Improving ~~large-scale river routing models for climate studies: the impact of~~ Large-Scale River Routing Models with ESA long-term CCI discharge ~~products on correcting multi-model hydrological simulations~~data assimilation: Advancing Accuracy for Climate Studies.

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Abstract. Large scale hydrological models like CTRIP and MGB are essential for simulating river dynamics and supporting large-scale climate studies. Their accuracy can be significantly improved through satellite data assimilation. This study leverages 20 years of high-resolution discharge data (2000–2020) from the ESA Climate Change Initiative (CCI) to enhance CTRIP and MGB models via ensemble Kalman Filter frameworks (HyDAS and HYFAA). Applied to the Niger and Congo basins, the models assimilate discharge data derived from altimetry and multispectral imagery, alongside water surface elevation (WSE) anomaly data, to evaluate their impact on model performance.

Discharge assimilation was more effective than WSE anomaly assimilation, as it provided a more direct input for improving model accuracy. In contrast, WSE anomalies were beneficial in poorly performing baseline simulations due to their lower observational uncertainty, but only when model and observed rating curves were well aligned. Temporal data density in discharge data assimilation was the key factor in reducing bias and enhancing the simulation of seasonal flow patterns, with spatial coverage and data quality also playing important roles. In the Niger Basin, the assimilation of denser discharge data resulted in a significant bias reduction, ~~which should improve the representation of~~ , which can support hydrological assessments related to long-term ~~climate trends~~variability. Furthermore, the higher temporal resolution allowed for better capture of flow variability, which is crucial for both seasonal climate studies and short-term predictions, such as extreme hydrological events.

The study also emphasizes the trade-offs between data resolution and quality, particularly in the Congo Basin. Future advancements include merging altimetry and multispectral discharge data, improving ~~the~~ discharge retrieval algorithms using SWOT data, and refining data assimilation techniques to ~~improve~~ support climate studies and river system modeling in complex, climate-impacted basins.

1 Introduction

Understanding Accurately modeling river discharge and water storage is essential for accurately modeling understanding the water cycle on a continental scale, especially at continental and global scales, particularly in regions where in-situ in situ hydrological data are sparse or unavailable. Large-scale hydrological models, such as ISBA-CTRIP and MGB, are effective tools for simulating (Decharme et al., 2019a) and MGB (Collischonn et al., 2007; Pontes et al., 2017), are widely used tools to simulate river hydrodynamics, but they are limited by uncertainties in input parameters and the simplifications needed by the simplifications required to represent complex local processes at larger scales (Emery et al., 2017; Paiva et al., 2013). As these models evolveTo address these challenges, integrating remotely sensed observations via through data assimilation (DA) has emerged as a key method to reduce uncertainties and improve model performance, enabling more accurate and dynamically consistent simulations (Wongchuig-Correa et al., 2020).

While a large number of studies have focused on the added value of water surface elevation (WSE) data assimilation into hydrological models like ISBA-CTRIP and MGB (Pedinotti et al., 2014; Paiva et al., 2013; Oubanas et al., 2018), recent studies have started to explore the assimilation of discharge data into these models. For examplehas also gained increasing attention in recent years. For instance, Paiva et al. (2013) applied discharge data alongside precipitation data from TRMM in estimates from TRMM into the MGB model to improve simulations of river dynamics in the Amazon Basin. Similarly, Wongchuig-Correa et al. (2020) explored simulated SWOT discharge data for the Solimões and Negro river basins, emphasizing the potential demonstrated the potential of assimilating SWOT-simulated discharge data over the Solimões and Negro rivers. Their results emphasized the benefits of discharge assimilation in improving model accuracy. Additionally, Emery et al. (2018) used data-sparse regions, particularly for improving peak flow simulations. Emery et al. (2018) further explored the assimilation of altimetry-derived discharge data to enhance estimates into ISBA-CTRIP, showing that discharge assimilation can enhance both river storage and discharge simulations in large-scale models like ISBA-CTRIP, showing the downstream discharge simulations. These studies underscore a growing interest in integrating discharge data, despite their inherent uncertainties, for more accurate hydrological modeling at large scales.

The European Space Agency (ESA) recognized the need for longer-term and refined temporal data In parallel, data assimilation itself has become a crutial tool in hydrological modeling, aimed at reducing uncertainty in model states and improving forecast skill. By updating model states and parameters with observational data dynamical integration, DA frameworks are particularly effective in addressing uncertainties in model inputs and structural representations, especially in large-scale applications. Clark et al. (2008) demonstrated how DA could enhance streamflow predictions through the assimilation of in-situ discharge measurements, significantly refining model forecasts. Michailovsky et al. (2013) extended this concept by incorporating remotely sensed water surface elevation (WSE) data into hydrological models, resulting in improved discharge estimates in regions with limited in-situ data.

Building on these foundational works, subsequent studies expanded the range of assimilated variables and refined methodological approaches. Paiva et al. (2013) investigated the assimilation of both in-situ and initiated the ESA satellite-derived discharge data into the MGB model for the Amazon Basin, showing marked improvements in river flow simulations and flood forecasting.

Wongchuig et al. (2019) further investigated the integration of simulated Surface Water and Ocean Topography (SWOT) mission data, demonstrating the potential of high-resolution satellite observations in refining hydrodynamic models. More recently, Feng et al. (2021) and Revel et al. (2023) advanced DA methodologies by incorporating transformed WSE data, leading to notable improvements in discharge predictions and model performance. Building upon these developments, Wongchuig et al. (2024) introduced the Multi-Observation Local Ensemble Kalman Filter (MoLEnKF), which simultaneously assimilates various satellite-derived hydrological variables, demonstrating significant improvements in large-scale hydrological predictions. This highlights a trend toward the integration of increasingly complex and multi-sensor observation strategies in hydrological DA systems.

Altogether, the progressive inclusion of both WSE and discharge data, whether in-situ or satellite-based, has reinforced the relevance of DA for improving hydrological model performance across a wide range of spatial and temporal scales. In large-scale hydrological models like ISBA-CTRIP and MGB, DA has been particularly valuable for mitigating biases related to parameter uncertainty and structural simplifications. While early efforts prioritized WSE assimilation (Pedinotti et al., 2014; Oubanas et al., , the increasing focus on discharge assimilation reflects both the growing maturity of satellite-derived discharge products and recent advances in DA techniques capable of handling multiple uncertain inputs.

Recognizing the importance of long-term, high-resolution data, the European Space Agency (ESA) initiated the Climate Change Initiative (CCI) Discharge Project to address the lack of ~~long-term, high-resolution river discharge data~~consistent discharge records over climate-relevant time periods. Although many satellite-derived hydrological data products exist, they are often limited in temporal resolution and do not cover long periods ~~necessary~~ relevant for climate studies. The ESA CCI ~~discharge products are designed to fill~~ products address this gap by providing ~~long-term~~globally distributed, quasi-daily ~~resolution data over two decades~~ WSE and discharge products over a 20-year period (2000–2020). This rich dataset offers the opportunity to capture the temporal dynamics of large river basins, allowing for the study of both seasonal and interannual variations, as well as the detection of extreme hydrological events~~. These high-resolution data over extended periods also enable the assessment of long-term trends and changes in river discharge patterns under varying climatic conditions, helping to understand the impacts of climate change on hydrological systems by capturing variability and shifts in hydrological processes over time. Although this study does not address hydro-climatic aspects, it focuses on evaluating how the assimilation of these new long-term high-resolution data impacts model outputs and performance~~, and can support the construction of hydrological reanalyses. They are thus particularly well-suited for supporting climate-relevant modeling applications, especially in large and complex river basins.

~~While existing research has~~ While previous studies have explored the assimilation of long-term satellite-derived ~~data,~~ variables—such as terrestrial water storage from ~~missions like GRACE (Girotto et al., 2016; Getirana et al., 2017), these efforts have not specifically focused on assimilating river discharge or water surface elevation (WSE) data, nor have they~~ GRACE (Girotto et al., 2016; Getirana et al., 2017)—few have investigated the assimilation of long-term WSE and discharge data, especially at quasi-daily resolution extended over two decades. ~~The specific use of~~ This remains a significant gap, especially given the growing interest in using satellite-based observations to support hydrological reanalyses and long-term ~~WSE and discharge data in DA remains underexplored. Studies like Emery et al. (2018) have~~ monitoring. Emery et al. (2018) demon-

strated the benefits of assimilating altimetry-derived discharge time series for reducing bias in large-scale models. However, comprehensive assessments of long-term ~~data assimilation in reducing model bias and enhancing the accuracy of river discharge predictions.~~ satellite-based discharge and WSE data assimilation over large river basins at climate-relevant timescales, remains largely missing from the literature.

Previous research has highlighted that the ~~success of DA~~ effectiveness of data assimilation depends not only on the accuracy of ~~the satellite products~~satellite products, but also on how well their spatial and temporal characteristics align with the ~~model's scale and objectives (Oubanas et al., 2018; Emery et al., 2020). For the Niger and Congo basins, where hydrological complexities abound, integrating these satellite-based discharge data into large-scale river routing models like ISBA-CTRIP and MGB presents both opportunities and challenges.~~

~~Building on these findings, the long-term assimilation of satellite-derived data, including WSE and discharge provided by the CCI products, is anticipated to lead to more stable and accurate hydrological simulations. This is achieved by effectively capturing both seasonal variations and extreme hydrological events over time. By addressing the gaps in existing literature—specifically the lack of~~ scale and design of the target model (Oubanas et al., 2018; Emery et al., 2020). In this study, we evaluate the assimilation of long-term ~~(20 years) assimilation studies focused on~~ discharge and WSE ~~—this research leverages the superior temporal and spatial resolution of CCI products to significantly enhance model performance in large and complex river basins such as the Niger and Congo.~~

~~This study builds on the existing literature by focusing on the assimilation of the new long-term, high-resolution CCIdischarge products into two~~ products from the ESA Climate Change Initiative (CCI) into two contrasting large-scale ~~river routing models, CTRIP and MGB~~hydrological models: CTRIP (Decharme et al., 2019a) and MGB (Collischonn et al., 2007; Pontes et al., 2017) . The models employed span two ends of the hydrological modeling spectrum. CTRIP is a continental-scale~~River Routing Model (RRM), coupled to ISBA, a Land-Surface Model (LSM), that integrates large spatial scales with simplified processes, making it suitable for global-scale applications (Decharme et al., 2019a)~~, uncalibrated river routing model designed for use within Earth system modeling chains. In contrast, MGB is a ~~distributed~~ basin-scale~~hydrological model that provides more detailed spatial representation and is primarily~~ , calibrated, distributed hydrological model commonly used for flood forecasting and ~~hydrological assessments~~at the basin level (Paiva et al., 2013). ~~The key difference between these models lies in their scale and resolution: CTRIP operates at a coarser scale, focusing on large-scale hydrodynamics, whereas MGB focuses on local basin processes with a finer spatial resolution~~water resource assessments.

~~In the context of data assimilation into large-scale hydrological models,~~ Rather than comparing model performance, we explore how the same CCI-derived data interact with these different model architectures, spatial scales, and parameterizations. The study focuses on two major African basins, the Niger and the Congo, which represent distinct hydrological regimes and offer diverse challenges in terms of in-situ data sparsity, seasonal variability, and hydrological processes complexity. These basins also represent contrasting hydrological regimes, making them ideal case studies for assessing the performance of satellite-based ~~observations, particularly water surface elevation (WSE) and discharge , offer distinct advantages~~ data assimilation across multiple scales and configurations. ~~WSE data, while having lower uncertainty, can present challenges when~~

~~integrated into models like CTRIP and MGB due to mismatches with typical hydrological model outputs and simplified river geometries~~

To isolate the effect of these satellite products, this study deliberately excludes in-situ discharge and mixed-product datasets. This design choice enables a clear and focused evaluation of the stand-alone value of CCI-derived data for assimilation. Moreover, our objective is not to optimize the assimilation scheme or model calibration, but to assess how assimilating these products improve model performance under operational constraints in two distinct hydrological frameworks.

In the context of DA, both WSE and discharge present distinct advantages and limitations. WSE is directly measurable from altimetry and typically less uncertain, but often misaligned with model simplified river geometry. In contrast, discharge ~~data more closely aligns with model simulations, but the process of deriving discharge from WSE , as one of the products of the CCI project (Gal et al., 2024), introduces additional uncertainties. The newly available discharge product derived from multispectral imagery (ESA CCI ATBD , 2023) carries even higher uncertainties due to the complexity of their production chain~~estimates align closely with model outputs but are derived indirectly from WSE or multispectral imagery, introducing additional uncertainties through empirical rating curves and processing chains (Gal et al., 2024; ESA CCI ATBD , 2023). By testing both types of products in DA applications over the Niger and Congo basins, this study examines the trade-offs between spatial coverage, uncertainty level, and data-model compatibility.

The primary objective of this study is to assess how ~~these~~ the assimilation of ESA CCI WSE and discharge products, despite their varying levels of uncertainty, improve ~~model performance when assimilated through DA~~hydrological model simulations through data assimilation. Specifically, we seek to ~~address two~~ answer three key questions: ~~(1)~~

1. Does the assimilation of ~~higher uncertainty river~~ higher-uncertainty discharge data improve model performance more than ~~lower uncertainty water surface elevation data? (2)~~ the assimilation of lower-uncertainty WSE data?

2. How do trade-offs between spatial coverage, temporal resolution, and the quality of satellite-derived products impact the effectiveness of ~~DA for correcting hydrological model simulations across large basins ?~~ satellite-based DA for large-scale hydrological modeling?

3. How do these impacts vary across models with differing scales and levels of calibration (MGB vs. CTRIP) and across basins with different hydrological characteristics (Congo vs. Niger)?

Through this analysis, we aim to provide insights into the added-value of long-term, satellite-based data assimilation in improving model accuracy and variability representation, especially in the context of developing reliable hydrological reanalyses for climate-relevant applications. Although this study does not explicitly perform climate attribution or hydroclimatic trend analysis, it contributes to climate-oriented hydrology by evaluating how assimilating these long-term satellite datasets affects model performance, internal consistency, and the ability to represent variability over multi-decadal periods.

The paper is organized as follows: Section~~2 covers~~ 2 presents the study area~~and the models used, MGB and CTRIP, also providing a detailed explanation of~~ , the modeling systems, and the CCI satellite products used, along with the data assimilation ~~approach and the satellite-derived CCI products that were assimilated. Section3~~ framework. Section 3 explains the experimental setup. Section~~4~~ 4 presents the results ~~, starting with the models' performance in Open-Loop mode and moving on to~~

a duo-model analysis of the impact of assimilating CCI discharge products, including the added value of multispectral and altimetry discharge data. Section5 of the assimilation experiments. Section 5 explores the trade-offs between different satellite data types, focusing on spatial and temporal resolution and their influence on model accuracyimpact on DA performance. Finally, Section6 concludes the paper, summarizing 6 summarizes the key findings and suggesting proposes future research directions in the context of using long-term satellite data to improve large-scale datasets in climate-relevant hydrological modeling.

2 Study domain, model and data used

2.1 Selected basins

Two basins were selected for this study This study focuses on two large and hydrologically significant African river basins: the Niger and the Congobasins. This choice relies on existing versions of the MGB model , which has been set up and calibrated in previous studies.

2.1.1 Niger basin

Originating in the Guinean highlands, These basins were selected based on the Niger River is availability of pre-existing model implementations and previous studies, access to satellite and in-situ observations, and their contrasting hydrological and climatic regimes (Figure 3). Their differences provide a valuable basis for assessing the robustness of data assimilation methods under diverse climatic and modeling conditions.

The Niger River, the third longest river in Africa(in Africa, spans over 4,200 kilometres), crossing kilometers and drains a basin of approximately 1.5 million km^2. It originates in the Guinean Highlands and flows through nine countries (Benin, Burkina Faso, Cameroon, Chad, Côte d'Ivoire, Guinea, Mali, Niger, and Nigeria) and providing water to about 100 million people (Figure ??). It ends in Nigeriabefore reaching the Atlantic Ocean, discharging through a massive delta into the Gulf of Guinea within the Atlantic Ocean. On its way through Mali, it traverses (Figure 3). Its hydrology is characterized by strong seasonality and the presence of the Inner Delta, a vast floodplain called the Inner Deltathe river traverses in Mali, averaging 73,000 square kilometreskm, which dissipates a significant proportion of the water flowing in the river its flow through absorption and evaporation (Andersen and Golitzen, 2005).

Downstream of the Delta, the river continues its course until till Niamey, receiving water mainly from a set of three intermittent rivers in the Niger right bank which are three intermittent right-bank tributaries responsible for a hardly predictable flood in Niamey, called event known as the "red flood" (Cassé et al., 2015). On the left bank, most channels are not connected to the river system. The basin has an average active area of about 1.5 million square kilometers. The socio-economic situation of the Basin countries relies on many river-related activities (agricultural productions, freshwater fishing, and livestock farming), making water availability a critical issue for the development of its population.

The Niger ~~basin traverses very different~~ Basin traverses diverse climatic zones, from the ~~tropical humid~~ humid tropical Guinean coast, where it generally rains every month of the year, to the ~~desertic~~ arid Saharan region with very little precipitation. Its hydrological regime is highly dependent on ~~the monsoon's rainfalls, whose uncertainties remain the main source of modeling errors in streamflow.~~

~~Map of the Niger River with the Niger River Basin in green (source : Niger Basin Authority)~~

2.1.1 ~~Congo basin~~

monsoonal rainfall, and uncertainties in this seasonal forcing remain a primary source of streamflow modeling errors.The socio-economic situation of the basin countries depends heavily on river-related activities such as agriculture, freshwater fishing, and livestock farming, making water availability a critical development issue.

The Congo River Basin (CRB)~~is~~ , the second-largest ~~basin on earth and drains more than~~ in the world, drains over 3.7 million km^2. Despite ~~this~~ its major contribution to the ~~world's~~ global freshwater cycle, its hydrological behavior ~~is not fully understoodyet~~remains insufficiently understood. The Congo's mean annual flow is around 41,000 m^3/s (Laraque et al., 2013)~~.~~ ~~This mean flow is remarkably stable~~ , with remarkably stable interannual variability (Spencer et al., 2016), which makes it an interesting singularity among large tropical rivers. Despite its critical importance ~~to~~ for local, regional, and global water and carbon cycles, the CRB has ~~not received as much attention as the Amazonor other large river basins~~received less attention than others like the Amazon.

In the CRB, most people rely on local water resources, which are ~~strongly impacted~~ increasingly affected by climate change and water availability ~~(Youssoufa Bele et al., 2013). Hence, the ongoing climate changes are expected to have severe implications for the populations. The mean temperature is approximately 25°C, whereas the mean annual rainfall varies between 2~~issues (Youssoufa Bele et al., 2013). The basin receives between 1,000 ~~mm/year in the central parts of the basin and 1~~and 2,000 mm ~~/year both northward and southward. The annual potential evapotranspiration is~~ of rainfall annually, with average temperatures near 25°C and potential evapotranspiration around 1,000 mm/year ~~and~~ that slightly varies across the basin.

~~The basin~~ It is characterized by four ~~main~~ major drainage systems (Ubangi ~~River in the northeast, Sangha River in the northwest, Kasai River in the southwest~~(northeast), Sangha (northwest), Kasai (southwest), and Lualaba ~~River in the southeast)~~(southeast)) that converge to form the main Congo River (Figure ~~??)~~3), and includes numerous lakes and wetlands that influence its hydrology.

~~Topography of the Congo River basin derived from the MERIT digital elevation model. Red and black triangles represent, respectively, the gauge stations with current (> 1994) and historical observations (Kitambo et al., 2022).~~

The selection of these two basins was guided by both scientific and operational considerations. They provide contrasting hydrological regimes and climate conditions, ranging from the monsoon-driven variability of Niger to the relatively stable flows of the equatorial Congo basin. They also have different hydrological characteristics: the Niger includes the Inner Delta with substantial evaporative losses, while the Congo includes an extensive tributary network, lakes and wetlands that buffer

and redistribute flow. These physical and climatic contrasts provide both a scientific rationale and a valuable opportunity to evaluate the performance of data assimilation across basins with diverse hydrological challenges.

Their selection was further guided by operational factors, including model availability and data coverage, as discussed below.

In terms of in-situ observations, the Niger Basin benefits from relatively dense discharge gauge networks. In contrast, the Congo basin has experienced a significant decline in active hydrological stations since the 1960s (Tourian et al., 2023), making it an ideal testbed to evaluate the potential of satellite-only data assimilation approaches. Both rivers are among the largest in Africa and play a critical role in shaping regional water resources, ecosystems, and livelihoods.

Beyond their geographic and hydrological significance, the suitability of these basins is reinforced by the availability of well-established modeling frameworks. In particular, both large-scale hydrological models used in this study (CTRIP and MGB) have been previously implemented over these basins, providing a consistent and well-informed experimental setup. MGB, which has been applied in both basins, is also used for flood forecasting and enables us to assess the added value of data assimilation in flood-prone areas such as Niamey. CTRIP, as a global model, has previously been applied in the Congo Basin (Munier et al., 2022) and offers complementary insights into how data assimilation performs in an uncalibrated, coarse-resolution setting. This dual-model setup offers a robust platform to test the effectiveness of data assimilation strategies under differing spatial scales and levels of calibration.

Yet, despite the relevance of these basins, their potential in advancing satellite-based data assimilation remains underexplored. This study contributes to filling that gap by applying and evaluating the assimilation of long-term WSE and discharge products from the ESA CCI into large-scale hydrological models. In doing so, our objective is to advance satellite-based DA practices for long-term hydrological modeling in African river basins, where robust long-term simulations are essential for supporting water resource planning and adaptation strategies in the face of observational gaps, increasing climate variability, and growing water demand.

2.2 Large-scale hydrological models

This study relies on two large-scale hydrological models that differ significantly in structure, spatial resolution, and intended use: the ISBA-CTRIP global river routing model and the MGB regional hydrological model. Their combined use enables a broader assessment of data assimilation (DA) strategies across diverse hydrological modeling contexts. The objective here is not to compare performances between the two hydrological models but rather to evaluate the potential of CCI discharge assimilation within those two conceptually different models.

2.2.1 CTRIP global river routing model

~~The CTRIP model~~ CTRIP is a physically based river routing model coupled to the ISBA land surface model (Figure ~~??~~1). While ISBA represents the vertical exchanges of water and energy at the soil-atmosphere interface, CTRIP simulates river flows over an entire hydrographic network (Decharme et al., 2019a). The ISBA and CTRIP models are used, in particular, in climate models such as the CNRM-CM6 that participated in the sixth phase of the Coupled Model Intercomparison Project

(Eyring, 2016, CMIP6) as a contribution to the IPCC Sixth Assessment Report (AR6). CTRIP is based on a regular grid with a resolution of 1/12° (i.e. around 8 km at the Equator) obtained by the upscaling of the MERIT-Hydro global hydrographic network (Yamazaki et al., 2019), available at a resolution of 90 m and currently considered to be the most accurate on a global scale.

A number of hydro-geomorphological parameters, such as the lengths and slopes of river sections, are obtained from high-resolution data from MERIT-Hydro, while other parameters, such as widths, depths, and roughness, are obtained from empirical formulae ~~(Munier and Decharme, 2022)~~(Munier and Decharme, 2022). It is assumed that each grid cell contains one and only one river reach, represented as a reservoir flowing into the downstream grid cell. The Manning equation is used to calculate the flow velocity as a function of the volume of water in the section, itself updated by the inflows from the upstream reaches and the runoff from the ISBA model.

The ~~CTRIP~~ model also benefits from a two-dimensional representation of aquifer dynamics and groundwater-river exchanges (Vergnes and Decharme, 2012). Finally, surface processes linked to vegetation (including real evapotranspiration) and snow cover (including sublimation and melting) are taken into account in the ISBA model.

It is also important to note that because the prior objective of CTRIP is to be integrated into climate models, it is based on quite simple approximations of rivers and aquifers dynamics. Consequently, unlike most hydrological models, the CTRIP model does not benefit from a parameter calibration stage. This choice ensures spatial consistency when the model is used in other regions of the world—or even globally—where few observations are available~~.~~

~~Schematic representation of the ISBA land surface model coupled to the CTRIP river routing model (Decharme et al., 2019a)~~ , particularly in climate projections. It follows a physically based parameterization strategy to ensure consistency across basins and scales.

2.2.2 MGB regional hydrological model

The MGB model ~~(Collischonn et al., 2007; Pontes et al., 2017) (“~~("Modelo de Grandes Bacias~~” or “~~" or "Large Basins Model~~”~~")~~ is a semi-distributed hydrological model that uses physically and conceptually based equations to simulate ~~the continental phase of the hydrological cycle (Figure ??)~~rainfall-runoff processes and river hydraulics using a two-way coupling scheme between hydrological and hydrodynamic modules (Collischonn et al., 2007; Pontes et al., 2017). It has been ~~evaluated on large basins around the world~~ extensively applied to large river basins such as the Amazon, and has shown good ability to represent complex processes, such as ~~those governing the dynamics of flooded areas (Paiva et al., 2013). The particularity of this version is that it utilizes a two-way coupling scheme between hydrological and hydrodynamic modules, allowing for a more dynamic representation of wetlands~~ floodplain dynamics (Paiva et al., 2013).

~~Specifically,~~ A key feature of MGB is its explicit simulation of wetlands and floodplain processes. It includes infiltration from flooded areas into unsaturated soil columns~~is accounted for~~, which is crucial in regions where dry soils are inundated by exogenous floodwaters, such as the Niger Inner Delta. ~~Additionally, the model dynamically simulates changes in~~ The model also dynamically simulates evapotranspiration and open water evaporation based on ~~land cover variations during flooding~~flood-driven land cover variation, capturing the differing effects of bare soil and vegetation across flooded zones. ~~The~~

~~routing function simulates the movement of water through the river network, accounting for~~ River routing includes flow propagation, backwater effects, and ~~complex~~ hydrodynamics in large floodplains (Figure 1). A full description ~~of the model can be found~~ is provided in Fleischmann et al. (2018).

~~Main processes represented in MGB model ((Fleischmann et al., 2018)). PC: precipitation; ET: evapotranspiration; EI: evaporation of intercepted water; P : precipitation discounted by EI; Dsup: surface flow; Dint: sub-surface flow; Dbas: groundwater flow.~~

MGB is used for real-time and near real-time flood forecasting in various regions, including the Amazon basin, where it has been operational for flood forecasts and water resource management (Paiva et al., 2013; Siqueira et al., 2018; Fleischmann et al., 2020). Similar real-time forecasting applications have been implemented in the Paraná basin and other regions, showcasing the model's adaptability for hydrological forecasting at both local and large scales.

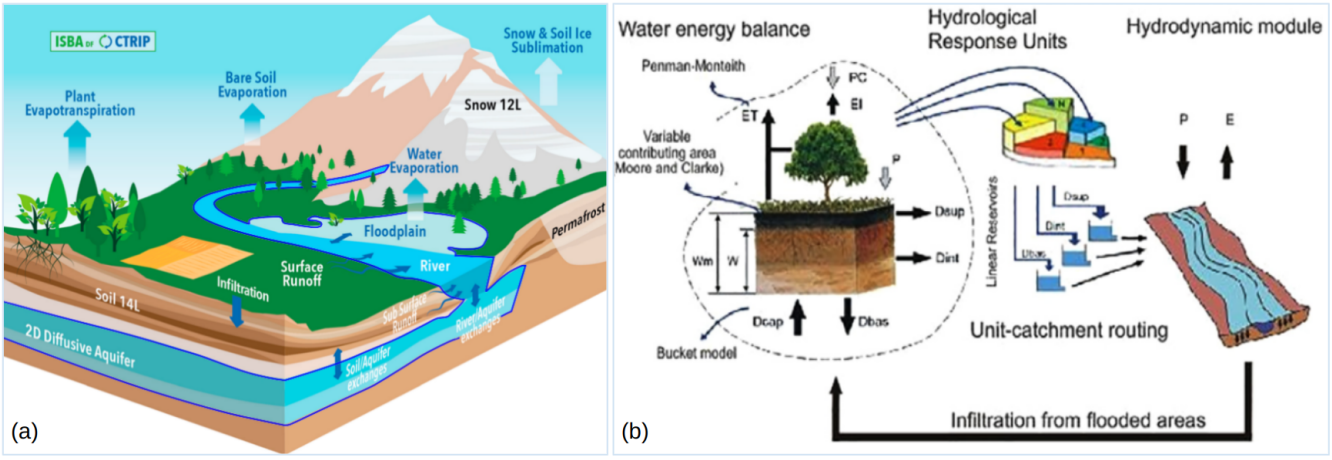

Figure 1. Schematic representation of the two large-scale hydrological models used in this study. Panel (a) illustrates the ISBA-CTRIP model (Decharme et al., 2019a), a global river routing model coupled to the ISBA land surface model, which simulates river discharge at continental scale. Panel (b) presents the MGB model (Collischonn et al., 2007; Pontes et al., 2017), a semi-distributed hydrological model incorporating two-way coupling between hydrology and hydrodynamics, enabling the explicit simulation of floodplain processes such as evapotranspiration from inundated areas.

2.2.3 Models implementation over the Niger and Congo basins

Both ISBA-CTRIP and MGB hydrological models require meteorological forcings, including precipitation, surface temperature and air humidity, wind, and radiation forcings. The choice of forcing datasets differs based on each model's design and application.

~~In this study, the~~ ISBA-CTRIP is forced with ERA5 reanalysis ~~was used to force the ISBA land surface model~~data, which is chosen for its global coverage, temporal resolution and consistency, with its intended use for climate studies and water resource assessments (Dee et al., 2011; Hersbach et al., 2020). A bias-correction process of ERA5 precipitation was applied following

Szczypta et al. (2012) to improve its accuracy in the hydrological context. The configuration of ISBA and CTRIP models is the one used for global scale simulations, as described in ~~Munier and Decharme (2022)~~Munier and Decharme (2022), except that the floodplain scheme was not activated. It is important to note that no observations were used to calibrate the model parameters.

~~The MGB model setup used in this study over the Niger basin is a resampled application of Fleischmann et al. (2018), discretized into~~ In contrast, MGB is designed for basin-scale hydrology and operational forecasting. For the Niger Basin, MGB is based on the setup from Fleischmann et al. (2018), with 11,595 ~~unit-catchments~~ unit catchments and river reaches of approximately 10 km. The model ~~was forced using the GSMAP precipitation dataset (Ushio et al., 2003) , together with~~ is forced using GSMAP precipitation (Ushio et al., 2003) and CRU 10′ long-term climatology data (monthly climate normals of wind speed, solar radiation, relative humidity, air pressure ~~,~~ and air temperature) (New et al., 2002) ~~for computation of~~ to calculate the model evapotranspiration. ~~The model was calibrated against in-situ discharge time series and validated against in-situ discharges, satellite altimetry, and flooded areas.~~

~~In~~ For the Congo Basin, ~~the model is discretized into~~ MGB is implemented with 9,220 ~~hydrological units of approximately~~ units (20 km ~~2 and is~~ resolution) and forced by IMERG ~~rainfall data (Huffman et al., 2018).~~ precipitation (Huffman et al., 2018) . These datasets were chosen for their improved spatial and temporal representation of tropical precipitation (Kubota et al., 2020; Gosset et a , which better aligns with the needs of short-term and flood forecasting.

~~For both basins and both models, simulations~~ MGB was calibrated against in-situ discharge and evaluated using altimetry and flood extent data, while CTRIP follows an uncalibrated, physically based approach.

The dual-model setup allows for a broader assessment of data assimilation performance across modeling contexts. CTRIP represents a global uncalibrated framework designed for integration into climate modeling systems, while MGB is a calibrated, regionally focused model that explicitly simulates floodplain dynamics and wetland processes. Rather than comparing absolute model performance, the objective is to examine how long-term satellite-derived discharge and WSE assimilation improve simulations under these different model structures.

Simulations are conducted over the period 2000–~~2020.~~ 2020 for both basins and models, ensuring a consistent and comparable framework for DA evaluation.

2.3 Data Assimilation schemes

Two distinct data assimilation (DA) frameworks are embedded within the CTRIP and MGB hydrological models: CTRIP-HyDAS and MGB-HYFAA. While both rely on ensemble-based Kalman filtering techniques, they differ in their implementation, model structure, and operational contexts. Their joint use allows us to explore the robustness and adaptability of DA across hydrological models with different configurations.

2.3.1 CTRIP-HyDAS and MGB-HYFAA

CTRIP-HyDAS (Hydrological Data Assimilation System) is a hydrological data assimilation system embedded ~~into the CTRIP model. It has been developed~~ within the CTRIP routing model. Developed since the early 2010s~~and is particularly~~ , it is

primarily designed to assimilate observations from satellite altimetry missions. The system has been previously applied over the Amazon basin (Emery et al., 2018, 2020a, b), ~~either to assimilate nadir altimetry data~~ where it was used to assimilate either nadir altimetry or SWOT-like observations. With this system, it is possible to correct model states (mainly river storage) or parameters (such as roughness).

In past studies, the assimilation of SWOT-like data was implemented in twin-experiment ~~OSSEs~~ Observing System Simulation Experiments (OSSEs) since real SWOT observations were not available yet. Some pseudo-OSSEs have also been conducted by using a different model (namely MGB) to simulate SWOT observations~~(Figure ??)~~, thus providing more realism in the differences between the dynamics of CTRIP and reality. More recently, CTRIP-HyDAS ~~is currently being extended to be applied at the global scale at the~~ has been extended to operate globally at 1/12° resolution in the context of the SWOT mission. ~~Here, only states are corrected via the assimilation of~~ In this study, only model states are updated, using either water surface elevation (WSE) anomalies or river discharge as observation input. Assimilated data are those derived in this CCI Discharge project.

~~Schematic of the pseudo-OSSE to assess the CTRIP-HyDAS over the Congo basin. SWOT observations are simulated using the MGB model and a large scale simulator that accounts for realistic SWOT orbit and noise. Simulated SWOT data are then assimilated into~~

~~HYFAA (Figure ??~~HYFAA (Hydrological Monitoring and Forecasting Framework for Assimilation Applications) is a ~~Python scheduler developed for hydrological monitoringand forecastingpurposes. Its processing module manages the launch~~ Python-based scheduler developed to support hydrological monitoring, forecasting, and assimilation tasks using MGB model. It manages the sequantial execution and communication between three components: the MGB hydrological model, an Ensemble Kalman Filter (EnKF), and an observations database.

In its forecasting mode, the ~~scheduler's tasks can be divided into~~ HYFAA wokflow includes three main steps:

1. Pre-processing~~: Updates~~ , which updates local forcing and assimilation databases from external sources, converts data to the required format, and keeps track of changes in data.

2. Processing~~: Launches hydrological simulations . When assimilation data is available, the processing module launches~~ , which launches hydrological simulations and, when observations are available, runs the EnKF to update the model state varaibles and/or parameters consistently with the observation and model uncertainties. The MGB model state variables and parameters are ~~given as inputs~~ passed to the EnKF, which returns corrected ~~state variables and parameters~~ values as new inputs to the MGB model. The processing module manages these exchanges of data.

3. Post-processing~~: Keeps~~ , which keeps track of the simulated or analyzed model states in an SQL database.

~~The~~ Beyond forecasting applications, HYFAA platform has also been used in various OSSE studies to assess the contribution of future satellite missions (SWOT, SMASH), as well as to evaluate the relevance of current observation systems, their spatial and temporal resolutions, and their uncertainties in estimating discharge over large river basins around the world.

Both CTRIP-HyDAS and MGB-HYFAA rely on Ensemble-based Kalman Filter (EnKF) approches to assimilate observations into their respective hydrological models. While based on the same core principles, the two systems employ slightly different variants:

1. CTRIP-HyDAS implements the Local Ensemble Transform Kalman Filter (LETKF), which updates the ensemble mean and perturbations separately to preserve the statistical structure of the ensemble (spread and statistical properties)

2. MGB-HYFAA uses the Local Ensemble Kalman Filter (LEnKF), which directly updates each ensemble member based on the observations and the model's error statistics

To better illustrate the methodological differences between the two data assimilation systems, Table 1 summarizes their main characteristics. It presents a comparative overview of model architecture, routing schemes, meteorological forcings, and assimilation strategies.

Table 1. ~~Conceptual scheme~~ Summary of the ~~HYFAA platform architecture and components~~data assimilation frameworks used in this study

Feature	**CTRIP-HyDAS**	**MGB-HYFAA**
Hydrological model	ISBA-CTRIP (global river routing)	MGB (distributed hydrology-hydrodynamics)
Spatial resolution	1/12°	10–20 km unit catchments
Main application	Climate and Earth system modeling	Operational flood forecasting, hydrological monitoring
River routing scheme	Kinematic wave, single reach per cell	Muskingum-Cunge scheme, full 1D hydrodynamics with floodplain exchange
Land-surface coupling	Coupled with ISBA LSM (for vertical water and energy fluxes)	Includes land cover–dependent evapotranspiration
Calibration	None (physically based parameterization)	Calibrated using in-situ discharge, altimetry and flood extent
Precipitation forcing	ERA5 (bias-corrected, (Szczypta et al., 2012))	GSMaP (Niger) (Ushio et al., 2003), IMERG (Congo) (Huffman et al., 2018)
DA method	LETKF (Local Ensemble Transform Kalman Filter)	LEnKF (Local Ensemble Kalman Filter)
DA system architecture	Embedded module (Fortran-based) module	External Python scheduler managing MGB + EnKF
Assimilated variables	Water surface elevation (WSE) anomalies, discharge	
Localization approach	Hydrological local patch based on variogram range from 20-year model run (Revel et al., 2019)	
Ensemble generation	EOF-based perturbation (Munier et al., 2015)	Stochastic pixel-wise multiplicative perturbation using Gaussian noise

2.3.2 ~~The Ensemble Kalman Filter (EnKF)~~

Evaluating the performance of data assimilation within both different hydrological frameworks is set to draw broader conclusions on how these long-term satellite-derived discharge and WSE products can enhance hydrological modeling under varied conditions of models configuration, scale, and data availability.

2.3.2 HYFAA: Local Ensemble Kalman Filter (LEnKF)

The Kalman filter (Kalman, 1960) is a foundational sequential data assimilation technique extensively used in hydrological sciences. At each ~~time~~ assimilation step, it integrates observations with the forecasted state ensemble to produce an updated analysis state, effectively addressing both observational and model errors. ~~Originally~~ Although originally developed for linear systems with Gaussian errors, the Kalman filter has been adapted for nonlinear models, with the Ensemble Kalman Filter (EnKF) being a notable extension (Evensen, 2009). ~~In this study, we used LETKF, which is a variant of the EnKF enabling high reductions of numerical costs. As in Revel et al. (2019),~~

In the ~~analysis equation becomes~~EnKF framework, an ensemble of model states is propagated forward in time, and at each assimilation step, observations are used to update the ensemble members. The general update equation for each ensemble member X_i is:

$$X_i{}^a = X_i{}^f + E^f V D^{-1} V^T (H E^f)^T \frac{R}{w}^{-1} K (Y^o + \varepsilon_i - H X H X_i{}^f) + \sqrt{(m-1)} V D^{-1/2} V^T \quad (1)$$

where ~~X^a is the posterior state estimator (or assimilator), X^f is the prior state estimator (or forecast) , Y^o~~ X_i^f is the forecast state of the i-th ensemble member, X_i^a is the updated (analysis) state, Y^o is the observation vector (here, WSE or river discharge), ~~H is~~ ε_i is a perturbation sampled from the observation error distribution, H is the ~~observation operator, which is used to convert the model state to model equivalent of observations, m is the size~~ observation operator mapping model states to observation space, and K is the Kalman gain matrix, computed as:

$$K = P^f H^T (H P^f H^T + R)^{-1} \quad (2)$$

where P^f is the forecast error covariance matrix, and R is the observation error covariance matrix, determined from the uncertainty of the measurements.

HYFAA scheduler uses the Local Ensemble Kalman Filter (LEnKF) as DA approach, which directly updates each ensemble member based on the observations and the model's error statistics.

Finally, a localization strategy has been implemented into HYFAA, as described in Section 2.3.4.

2.3.3 HyDAS: Local Ensemble Transform Kalman Filter (LETKF)

The assimilation in CTRIP-HyDAS follows the Local Ensemble Transform Kalman Filter (LETKF). The LETKF updates the ensemble mean and perturbations separately, preserving the statistical structure of the ensemble. The analysis update in LETKF is given by (Revel et al., 2019):

$$X^a = X^f + E^f \left[VD^{-1}V^T (HE^f)^T \left(\frac{R}{w}\right)^{-1} (Y^o - HX^f) + \sqrt{(m-1)} VD^{-1/2}V^T \right] \quad (3)$$

where X^a is the posterior state estimator, X^f is the prior state estimator (or forecast), E^f is the prior state error covariance, which is obtained directly from the ensemble, ~~R is the observation error covariance, determined from the uncertainty of the measurements,~~ w is the weighting term for the observation localization (described Section 2.3.4), and VDV^T is given by:

$$VDV^T = (m-1)I + (HE^f)^T R^{-1} HE^f \quad (4)$$

where I is the unit matrix with dimension m equal to the size of the ensemble. $VD^{-1}V^T$ and $VD^{-1/2}V^T$ can be calculated from the eigenvalue decomposition of VDV^T. It is important to highlight that R is consistently assumed to be diagonal, indicating independence among observation errors.

~~The localization, described by w in the analysis equation, is used to limit~~ This approach allows for efficient assimilation of observations by transforming the ensemble in a way that accounts for both model and observation uncertainties.

2.3.4 Localisation Approach

Both CTRIP-HyDAS and MGB-HYFAA adopt the same localization strategy to constrain the spatial influence of ~~each observation. We used the same methodology as Revel et al. (2019)to compute the length of~~ observations, reducing the risk of spurious long-distance correlations and improving the numerical stability of the filter. The observations localization weight w, introduced in Equation 3, is computed using the method proposed by Revel et al. (2019), specifically adapted to the ~~localization for~~ structure of river networks. Rather than solely relying on simple Euclidean distances or topological river-network distances, this approach defines spatial local patches based on the spatial correlation structure of hydrological variables.

For each pixel (or river reach) of the domain~~. The method is based on the semi-variogram from~~ , a Gaussian semi-variogram is computed based on a long-term (20-year) free run of the model. ~~For each pixel of the domain, the basic idea is to compute the correlation between the discharge time series at this pixel and at pixels connected via the river network~~ (The semi-variogram is fitted to time series of discharge or WSE anomalies, and its estimated range parameter determines the distance over which the variable is spatially correlated. This range is then used as a threshold to define the spatial extent of the local patch. For each observation, only the pixels within this hydrologically connected patch, both upstream and downstream~~). Then, with a given threshold, we delimitate the pixels that will be corrected if an observation is available at the original pixel~~, are updated during the assimilation process. This localization method is therefore more adapted to hydrology than ~~more classical methods simply based on geographical distance or on the distance within the river network~~classical methods as it accounts for the dynamic dependencies in river discharge and improves the physical consistency of the data assimilation procedure.

Figure 2 shows ~~an example of the localization for some~~ examples of the local patches for three pixels in the Congo basin, with the color bar representing the observation localization weight w.

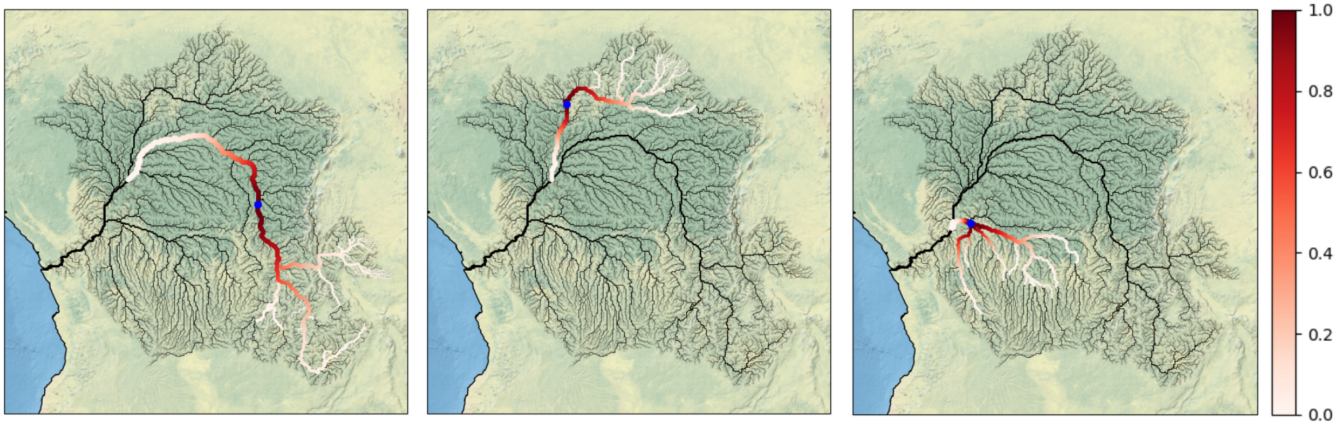

Figure 2. Examples of the localization for three pixels of the Congo basin. The color bar represents the observation localization weight w, which indicates the spatial influence of an observation on nearby hydrologically connected pixels during the assimilation process.

2.3.5 Ensemble Generation

The ensemble of model states, representing the best operating estimate, is systematically generated through the introduction of perturbed meteorological forcing. It is highlighted that only meteorological forcing is assumed to be subject to uncertainties, with the model structure and parameters assumed to be devoid of errors that could significantly impact the model outputs. Perturbing the model parameters is also a possible way to create the model ensemble, and it is particularly useful when parameters are corrected during the analysis step.

Here, we used the method developed in Munier et al. (2015). The approach involves perturbing statistically significant modes obtained through the decomposition of the precipitation field into Empirical Orthogonal Functions (EOFs). Mathematically, for a variable X representing meteorological forcing (here precipitation), the decomposition can be expressed as:

$$X_{ijk} = X_{\text{ref},jk\,\text{mean},jk} + \sum_{l=1}^{\ell=1}{}^{\text{NEOFs}} U_{l,jk\,\ell,jk} V_{i,l\,i,\ell} \tag{5}$$

Here, X_{ijk} represents the meteorological forcing variable at time step i, latitude j, and longitude k. ~~$X_{\text{ref},jk}$~~ $X_{\text{mean},jk}$ is the temporal mean of X at latitude j and longitude k. ~~$U_{l,jk}$~~ $U_{\ell,jk}$ denotes the spatial patterns, and ~~$V_{i,l}$~~ $V_{i,\ell}$ represents the temporal coefficients of mode ℓobtained through the EOF analysis. The sum is taken over the retained EOFs, with NEOFs being the number of retained modes.

The leading modes, explaining 95% of the variance, are retained, with the perturbations applied as:

$$\tilde{X}_{ijk} = X_{\text{ref},jk\,\text{mean},jk} + \sum_{\ell=1}^{\text{NEOFs}} U_{\ell,jk} + \sigma\epsilon_{\ell} U_{\ell,jk} V_{i,\ell} + \sigma V_{i,\ell} \tag{6}$$

Here, ~~X~~ $\tilde{X}$ represents the perturbed variable, and ~~σ is the standard deviation~~ ϵ_{ℓ} is the perturbation coefficient of the respective EOF mode, following a gaussian distribution centered in 1 and with a variance of 0.4 (a value obtained by trial and error to

ensure a relevant discharge ensemble spread). This methodology ensures a realistic representation of meteorological forcing uncertainties, critical for generating the ensemble of model states for subsequent assimilation experiments.

2.4 Observations - Assimilated satellite products

2.4.1 ~~Assimilated satellite products~~

~~Within~~ In this study, three satellite-based products are evaluated within data assimilation schemes: ~~altimetric~~ (i) water surface elevation (WSE) ~~, altimetry-based discharge~~ rom satellite altimetry, (ii) discharge estimates from altimetry-based WSE (Qalti), and ~~multispectral imagery-based discharge~~ (iii) discharge estimates based on multispectral remote sensing imagery (Qmultispec). These three products are part of the ESA Climate Change Initiative (CCI) River Discharge project (Gal et al., 2024).

The first product, WSE time series, is derived from the merging of data from multiple nadir altimetry satellite missions (Biancamaria et al., 2024), including ERS-1 and -2, Envisat, SARAL, Topex-Poseidon, Jason-1, -2 and -3, Sentinel-3A and –3B, Sentinel-6A and Cryosat-2. Time series are derived at reference virtual stations (VS), preferably located on the Jason-3 ground track since the Jason series is the longest continuous series of altimeter missions. To ensure consistency across missions, inter-mission biases are corrected by subtracting the mean difference between overlapping time series. In cases where missions do not overlap, intermission bias is corrected by computing the difference between the time average of time series of the two consecutive missions. Additionally, when VS from different missions are located within 10 km of each other, with no major tributary between them, their time series can be merged using fitted relationships with the reference VS ~~(?Biancamaria et al., 2017)~~(Biancamaria et al., 2024, 2017).

The second product corresponds to river discharge derived from altimeter-based WSE (Qalti). Different methodologies have been developed, but only the first one was used for data assimilated in this work. It relies on the existence of in-situ river discharge observations and the calibration of a rating curve between in-situ discharge and altimetry WSE. A comprehensive uncertainty analysis has been conducted to derive uncertainties associated with each discharge value. These uncertainties have been used in the assimilation experiment, in comparison with constant values to assess the importance of providing realistic uncertainties along with observations. For detailed methodologies and additional context regarding Qalti, refer to the Algorithm Theoretical Basis Document (ATBD) by Gal et al. (2024) and the relevant published studies (Kouraev et al., 2004; Paris et al., 2016; Zakharova et al., 2020, 2021; Tourian et al., 2013, 2017) which explore various approaches for deriving discharge from satellite altimetry.

The third product corresponds to river discharge based on multispectral images (Qmultispec) Gal et al. (2024). The multispectral images used comes from Landsat-5/7/8/9, TERRA and AQUA (MODIS sensors), Sentinel-2, and Sentinel-3 (OLCI) platforms. It assumes that the differences between the passice response of the reflectance signal from the soil and that from the water can be used to identify a change in the land area near the river channel that is strongly correlated with river discharge. In this approach, different reflectance indices are computed for each considered VS where in-situ discharge is available. Then, the estimation of discharge from these indices is very similar to the rating curve approach applied for the water levels by altimetry.

Here, the relationship is based on the evaluation of a non-linear regression relationship between the multi-mission time series and the observed river discharge values. It is important to note that no uncertainties were computed in this approach, and only constant theoretical error values were used in the assimilation experiment. Tarpanelli et al. (2013), Filippucci et al. (2022) ~~, and Filippucci et al. (in preparation)~~ provide more details on the generation of these products and the application of multispectral imagery data for estimating river discharge.

Table 2 summarizes the available stations and data periods for the different CCI products used in the experiments for both Niger and Congo basins.

Table 2. Data availability for WSE, Qalti, Qmultispectral products and in-situ discharge observations in Niger and Congo basins.

Basin	Station	WSE (v1.1) / Qalti (v1.1)	Qmultispectral (v1.2)	Q in-situ
Niger	Mandiana	-	-	[2010–2018]
	Banankoro	-	-	[2010–2017]
	Koulikoro	[1995–2023]	[2000–2022]	[2010–2018]
	Ke-Macina	-	-	[2010–2018]
	Nantaka	-	-	[2010–2018]
	Akka	-	-	[2010–2017]
	Dire	-	-	[2010–2018]
	Ansongo	[1995–2023]	[2002–2022]	[2010–2018]
	Alcongui	-	-	[2010–2017]
	Niamey	[2017–2023]	[2000–2022]	[2010–2022]
	Malanville	[1995–2023]	[2013–2022]	[2010–2017]
	Makurdi (Benue)	-	-	[2010–2016]
	Ibi (Benue)	[2002–2023]	[2000–2022]	-
	Lokoja	[2010–2016]	[2000–2022]	[2010–2018]
Congo	Chembe-Ferry	[2002–2023]	[2002–2022]	-
	Ouesso	-	-	[1947–2020]
	Bangui / Oubangui	[2002–2023]	[2000–2022]	[1911–2020]
	Kinshasa	[2002–2023]	[2000–2022]	[1947–2023]

The locations of the stations where data will be assimilated into both models are presented in the two maps shown in Figure3.

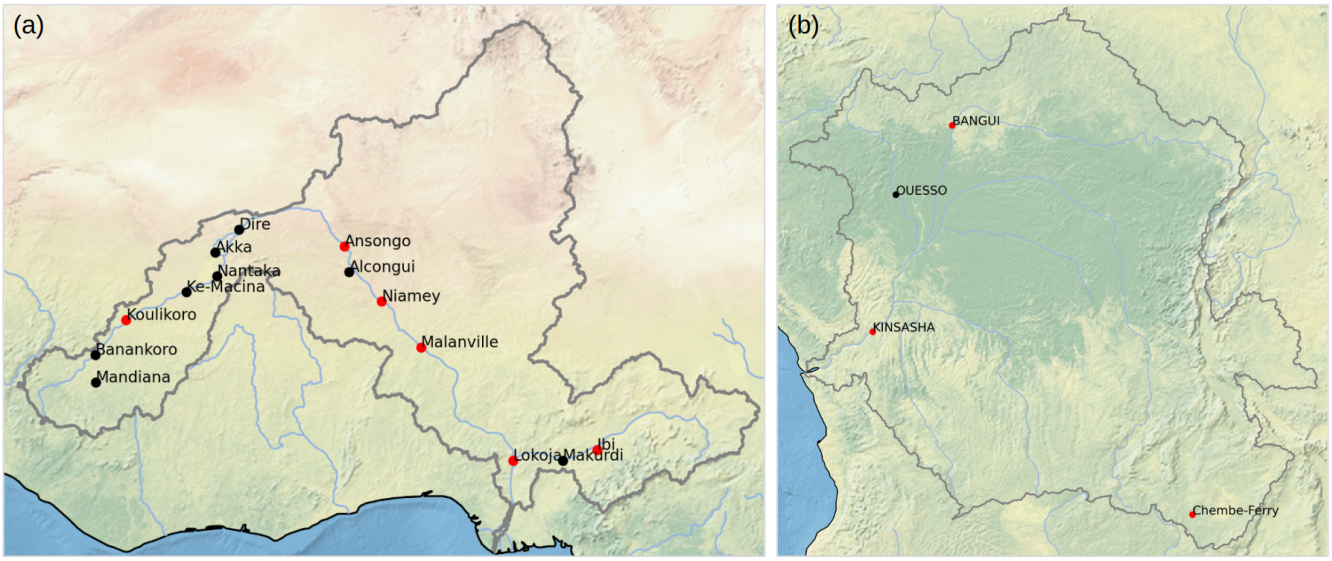

Figure 3. Maps showing the locations of stations in both the Niger and Congo basins. Red markers represent stations where data assimilation is conducted, and black markers indicate the remaining stations with in-situ data used for performance assessment of the assimilation experiments in both the MGB and CTRIP models.

2.4.1 ~~Comparison with in-situ observations~~

~~This section presents a comparison between the CCI discharge products and independent in-situ data from two different sources. For the Niger Basin, we compare the CCI data with 13 stations from the Niger Basin Authority (ABN) network, covering the period from approximately 2010 to 2017. In the Congo Basin, the comparison is made with the So-Hybam database, which includes two stations that overlap with the CCI data, providing a longer temporal record from 1947 to 2020 (Table 2).~~

~~Figure ?? illustrates the performance of the KGE index and its three components — β (bias), r (correlation), and γ (internal variability) — for the CCI discharge productsacross stations in the Niger and Congo basins, with Q_{alti} represented in blue and $Q_{\text{multispec}}$ in green. Following this, Figure ?? presents the time series of discharge estimates from satellite altimetry~~ To assess the reliability of the assimilated satellite discharge products, we compared both altimetry-based (Q_{alti}) and ~~multispectral~~ imagery multispectral-based ($Q_{\text{multispec}}$) ~~compared to~~ discharge estimates against independent in-situ ~~observations for five stations~~ measurements in the Niger ~~basin and two stations in the Congo basin, with an overview of the period from 2010 to 2020.~~

and Congo basins. In the Niger basin, ~~the analysis of the 20-year time series (2000–2020) across stations such as Koulikoro, Ansongo, Niamey, Ibi, and Lokoja reveals distinct patterns in the performance of Q_{alti} and $Q_{\text{multispec}}$ products. Figure ?? shows that~~ Q_{alti} ~~data generally capture the seasonal hydrological cycle well, particularly in upstream stations like Koulikoro and Ansongo, where the correlations with in-situ data are 0.99~~ generally captures the seasonal cycle and ~~0.92, respectively.~~

However, Q_{alti} high-flow dynamics well at upstream stations (e.g., Koulikoro, Ansongo), though it tends to overestimate high flows, as indicated by biases of 1.35 at Koulikoro and 1.06 at Ansongo. At Niamey, the availability of Q_{alti} data starting only from 2017 limits the analysis. However, the two-peak hydrological cycle is reasonably well-represented, with a strong correlation of 0.96, although the peak flowsare slightly underestimated (bias of 0.85).

Further downstream , Ibi, which is located on the Bénoué River (a significant tributary of the Niger River), shows a different pattern.Here, Q_{alti} tends to underestimate discharge during both high and low flows, with a bias of 0.59.Despite this underestimation, the seasonality is well captured with a correlation of 0.99, as shown in Figure **??**. At Lokoja, near the Niger River's outlet, a similar underestimation is observed with a bias of 0.90, but the seasonality remains well represented, with a correlation of 0.79.

KGE score rate and its 3 components (r, β, γ) for CCI discharge products at stations where in-situ observations are available (Niger Basin left, Congo Basin right): altimetry-based discharge (Qalti) in blue and multispectral imagery discharge (Qmultispec) in green.

peak flows. Further downstream (e.g., Lokoja, Ibi), the accuracy decreases slightly, with growing underestimation of discharge. In contrast, $Q_{multispec}$ data provide denser coverage, particularly during low-flow periods, as seen in Figure **??**. However, this increased data density comes at the cost of increased noise, leading to generally lower performance scores compared to Q_{alti}. For instance, at Ansongo, the correlation with in-situ data drops significantly to 0.40 for $Q_{multispec}$, compared to 0.92 for Q_{alti}. This decrease in performance is largely due to a temporal shift in the hydrological cycle representation, as well as greater data dispersion, particularly during high-flow periods.

At Koulikoro, $Q_{multispec}$ data perform better in high-flow periods but exhibit a slight lag during the recession phase, resulting in a correlation of 0.76 compared to 0.92 for Q_{alti}. Despite these issues, $Q_{multispec}$ data show improved representation of low flows, closer to in-situ observations, compared to Q_{alti}. Downstream at Lokoja, $Q_{multispec}$ continues to underperform, with a bias of 0.70 compared to 0.90 for Q_{alti}, and lower correlations due to increased noise and data dispersion.

At Niamey, the performance of the $Q_{multispec}$ product against in-situ observations is subpar, with a KGE score of 0.65 for daily data, and dropping further to 0.57 for monthly data. This underperformance is primarily due to two factors: offers denser temporal coverage but shows greater noise and a temporal lag in the representation of the hydrological cycle and the failure to accurately reproduce the double peak characteristic of the flow at Niamey . The first peak, which results from the contributions of a nearby tributary, is particularly missed. This temporal lag significantly reduces the correlation, with a monthly correlation of only 0.62, compared to 0.97 for the Q_{alti} product derived from altimetry data.

capturing hydrological peaks — especially at Niamey and Lokoja. In the Congo basin, where comparisons were limited to results are available for Bangui and Kinshasadue to the lack of independent in-situ data (not available at Chembe-Ferry), Q_{alti} data show strong performance, closely aligning with in-situ observations. At both stations, , where Q_{alti} achieved KGE scores exceeding 0.92, with correlations greater than 0.93 and minimal bias(1), demonstrating a robust representation of the internal variability of the hydrological cycle, as shown in Figure **??**. In contrast, performs well, closely tracking observed discharges with high correlations and low bias. While $Q_{multispec}$ data, while showing similar correlation and internal variability

representation shows acceptable performance at Kinshasa, suffer from greater data dispersion, leading to a lower daily correlation of 0.8 and a KGE score of 0.8.

At Bangui, however, the $Q_{\text{multispec}}$ data are less reliable, showing significant dispersion and failing to accurately represent the hydrological cycle. This is reflected in a very low correlation of 0.11 daily and 0.02 monthly, and a poor KGE score of 0.07, indicating that while $Q_{\text{multispec}}$ can offer denser temporal data, the quality and reliability are significantly compromised in certain locations.

Despite the poor quality of the multispectral imagery discharge products , these data have been retained in the analysis for comparison purposes. Currently, the calibrated multispectral data is available only for Niamey in the Niger basin and for Kinshasa and Bangui in the Congo basin. This limitation constrains the analysis of the added value of dataassimilation over the MGB model, considering the size of the basins, it fails to reproduce the hydrological signal at Bangui, with low correlation and restricts the ability to conduct a coherent comparison with other experiments (dH, Q_{alti}). The calibrated versions are expected to be available in Phase 2 of the CCI Discharge project, covering all analyzed stations. It will be valuable to revisit and reassess this work with the calibrated datasets once they become available to evaluate their performancepoor representation of seasonality. A full evaluation of the CCI discharge products against in-situ data, including KGE scores and hydrograph comparisons, is presented in the Supplement.

Discharge time series comparing altimetry-based discharge (Qalti, blue), multispectral imagery discharge (Qmultispec, green), and in-situ observations (black) at five stations in the Niger Basin (first five panels) and two stations in the Congo Basin (last two panels).

3 Experimental Setup

To evaluate the impact of assimilating CCI discharge products Altimetry-based (Q_{alti}) and Multispectral-imagery based ($Q_{\text{multispec}}$) and water surface elevation anomaly (dH) into the CTRIP (with HyDAS scheme) and MGB (HyFAA schemewith HyFAA) models, a series of 8 experiments were conducted . First, both models were forced using over the 2000–2020 period in both the Niger and Congo basins.

Each model was first run in an Open-Loop (OL) configuration, without data assimilation, to establish a reference baseline. CTRIP was forced with ERA5 data (2000-2020), with MGB incorporating GSMAP and IMERG precipitation datasets for reanalysis data (Hersbach et al., 2020), while was driven by ERA5 atmospheric variables and GSMaP (Ushio et al., 2003) and IMERG (Huffman et al., 2018) precipitation products in the Niger and Congo basins, respectively (with unbiasing work done previously for MGB), to establish a baseline in Open-Loop modesee Section 2.2.3). A 25-member ensemble generated by the Ensemble Kalman Filter (EnKF) scheme was used in both Open-Loop and assimilation experiments was generated in each experiment using EOF-based perturbations of the precipitation field to account for uncertainties in input forcingsmeteorological forcing uncertainties (see Section 2.3.5).

Following the Open-Loop experiments, 8 Eight assimilation experiments were then carried out, with each CCI product tested at two-three two to three uncertainty levels:

- WSE anomaly (dH): computed errors, 0.2 m, 0.4 m. Anomalies are computed by subtracting the mean WSE from a 20-year open-loop reference simulation [2000-2020] in both models.
- Altimetry-based discharge Q_{alti}: computed errors, 30%, 50% constant uncertainty.
- Multispectral-imagery based discharge $Q_{\text{multispec}}$: 30% and 50% constant uncertainty.

For each assimilated product, two levels of uncertainty have been chosen corresponding to the standard uncertainty usually applied to remotely sensed WSE or discharge. In addition, for WSE and altimetry-based discharge, the uncertainty computed during the generation of the products have also been used as additional experiments.

The performance of assimilation experiments was evaluated against independent in-situ discharge data. The validation datasets include 13 stations from the Niger Basin ~~(ABN: 13 stations, 2010–2017) and~~ Authority (ABN, 2010–2017) and three stations from the So-HyBAM database in the Congo Basin (~~So-HyBAM: 3 stations, 1950–2020~~ 1950–2020).

~~The experimental setupis summarized in Figure 4, showing~~ An overview of the experimental setup, including the models, forcing datasets, and ~~the assimilation products tested~~assimilated observations, is presented in Figure 4.

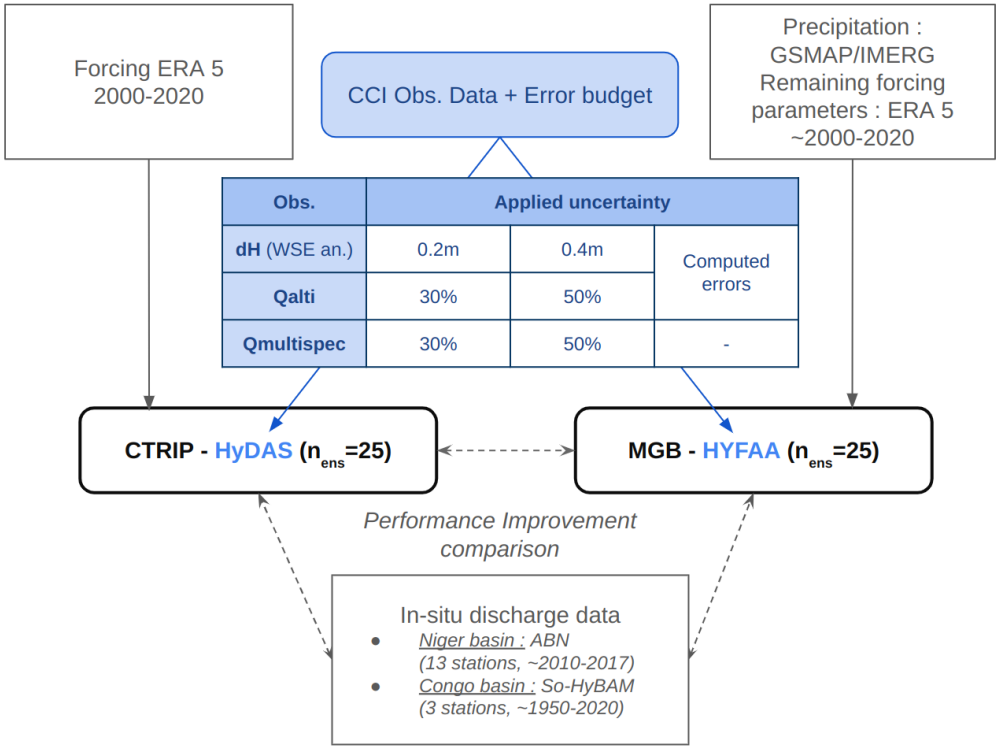

Figure 4. ~~Schematic overview~~ Overview of the experimental setup for the assimilation of ESA CCI discharge ~~product assimilation~~ products into the CTRIP and MGB hydrological models. The models were forced with ERA5 reanalysis data (GSMaP/IMERG precipitation data for MGB in the Niger and Congo Basins respectively) and run in both Open-Loop mode and with data assimilation. The three assimilated observation types are: (1) water surface elevation anomalies (dH) derived from satellite altimetry, (2) altimetry-based discharge (Qalti), and (3) discharge estimated from multispectral imagery (Qmultispec). The EnKF framework (HyDAS for CTRIP and HYFAA for MGB) was used to update model states based on these observations

4 Results

To correctly understand the impact of the assimilation of satellite derived WSE or discharge, it is first important to analyze the performances of both models without assimilation (Open-Loop), which is described in the following section.

4.1 ~~Open-Loop performance~~Open-loop Performance - Key issues in both models

4.1.1 ~~Niger Basin~~

~~The MGB model demonstrated overall good performance across the Niger Basin in its Open-Loop mode. It generally captured the broad hydrological dynamics of the basin, with all stations—except Nantaka—showing a Nash-Sutcliffe Efficiency (NSE) score above 0.5. The correlation coefficient exceeded 0.8 basin-wide, with a median of 0.93, indicating the model successfully~~

reproduced flow patterns during both high and low-flow periods. However, the MGB model tends to overestimate discharge during high-water periods, particularly upstream of stations like Koulikoro and Ansongo, with a median bias around 20%. The overestimation is particularly pronounced in the Inner Niger Delta, where it reaches 40% at Nantaka.

In contrast, the CTRIP model performs poorly across most of the basin, with a median NSE score of around -4 and values consistently below 0. This poor performance is primarily due to pronounced overestimations during high-flow periods. In the region between Ke-Macina and Niamey, discharge overestimations reach up to 2.3 times the observed median values, largely due to the model's inability to account for the significant evaporation and complex hydrodynamics of the Inner Niger Delta.

Moreover, CTRIP tends to underestimate discharge during low-flow periods, particularly along the Benue tributary and near the Niger outlet at Lokoja. In contrast, the MGB model accurately captures low-flow conditions, especially in the downstream sections of the basin. However, MGB slightly underestimates internal variability, with a median KGE γ value of 0.9, a discrepancy more evident in the central basin after the river passes through the Inner Delta.

Discharge time series at same 8 stations within the Niger basin, comparing CTRIP (red) to MGB Open-Loop (green) and in-situ observations

In the Upper Niger (Banankoro, Mandiana, and Koulikoro), both models generally reproduce the basin's hydrological dynamics, capturing the seasonal peaks and low flows with correct timing. However, the key issue lies in the representation of high-flow events. The MGB model performs strongly here, with NSE scores consistently above 0.65 and correlations exceeding 0.9. Meanwhile, the CTRIP model, although showing correlations above 0.8 in these stations, exhibits significant overestimation during high-flow periods, often doubling the observed high flows, as seen in panels (a) and (b) of the discharge time series (Figure **??**).

In the Inner Niger Delta (Ke-Macina, Nantaka, Akka, Dire), both models encounter difficulties due to the region's complex hydrodynamics, where the river splits into multiple branches and experiences significant water losses from evaporation. The MGB model overestimates discharge by over 20% during high flows, particularly at Nantaka, where the peak discharges are nearly doubled. The CTRIP model performs even worse, with exaggerated flow biases, particularly downstream of stations like Dire and Ansongo (panels (d,e) Figure **??**). The overestimation grows from twice the observed values at Ke-Macina to three times at Ansongo. The failure to represent evaporation and the delta's complex branch dynamics leads to these inflated discharge estimates in CTRIP . Additionally, CTRIP struggles to capture the gradual shift in the high-water season from September to December/January, particularly between Nantaka (panel e) and Niamey (panel f), where the correlation drops below 0.5 as the flow moves downstream.

In the Middle Niger (Ansongo, Alcongui, Niamey, Malanville), the MGB model continues to show strong performance, particularly at Niamey, where it captures the bimodal hydrological cycle driven by the Sirba tributary (panel (c), Figure **??**) (NSE = 0.8, r = 0.96). However, MGB overestimates the second flow peak by 20%. The CTRIP model continues to struggle in this region, with difficulties in capturing both the magnitude and timing of high flows. In Alcongui (Gorouol tributary), both models encounter challenges due to intermittent flows driven by seasonal rainfall, with correlation scores of r close to 0.8 in MGB and r close to 0.5 in CTRIP.

~~Discharge time series comparing MGB (green) to in-situ observations on Koulikoro, Ansongo, Niamey and Lokoja (Niger basin)~~

~~In the Lower Niger (Makurdi on the Benue tributary, and Lokoja near the Niger outlet), CTRIP performs relatively well compared to its performance upstream. While it underestimates discharge during both high and low flows, the hydrological cycle is reasonably well reproduced at Lokoja (panel h, Figure **??**). This is largely because CTRIP's parameters—such as channel width, slope, and Manning's roughness coefficient—are globally adjusted based on empirical relationships and global datasets to ensure consistent performance at the outlets of large river basins without region-specific calibration (Decharme et al., 2019b) . However, CTRIP still struggles with high flow overestimation and low flow underestimation. The MGB model performs better at Lokoja (panel d, Figure **??**), as it is calibrated for each specific basin to accurately capture local hydrological processes. While the hydrological cycle is accurately reproduced, MGB tends to underestimate discharge during high flows, with about 10% underestimation at Lokoja, likely due to difficulties in fully representing the Benue's high flows.~~

4.1.1 ~~Congo Basin~~

~~Considering the significantly limited access to in-situ station data across the Congo Basin, the performance analysis of the MGB and CTRIP models remains constrained. The available in-situ data from the So-HyBam database includes only three stations, which cover two of the four main drainage systems: Ouesso on the Sangha tributary and Bangui on the Ubangui tributary. The third station is located at Kinshasa, downstream of the confluence of the four tributaries, on the Congo river. The models are therefore evaluated based on their performance at these three stations.~~

~~The MGB model shows overall good performance in reproducing the hydrological dynamics of the Congo Basin, though certain biases and errors persist. With a median correlation score of 0.88, the model successfully captures the general flow patterns across the three stations. The best performance is observed at Bangui, with a correlation of 0.94, while Ouesso and Kinshasa also perform consistently, with correlation values exceeding 0.87. However, the Nash-Sutcliffe Efficiency (NSE), with a median score of 0.4, suggests moderate accuracy in predicting discharge magnitudes, pointing to areas where the model could improve, especially in terms of magnitude prediction.~~

~~On a monthly scale, the MGB model generally performs well, particularly in terms of correlation (r), internal variability (γ), and NSE. This indicates good internal consistency and a strong ability to capture the seasonal and intra-annual variability in discharge. At Bangui and Kinshasa, KGE γ monthly values are close to 1, reflecting the model~~A detailed evaluation of the Open-Loop (OL) simulations was conducted for both CTRIP and MGB models across the Niger and Congo basins to establish a baseline prior to data assimilation. The analysis, presented in the Supplement, compares model outputs with in situ discharge observations, and focuses on the models' ~~s strength in reproducing seasonal cycles (panels d,f, Figure **??**). However, short-term hydrological fluctuations present more challenges, as evidenced by the increased variability in daily scores, particularly at Ouesso (panel a, Figure **??**). Here, the model overestimates internal variability by around 20%, especially in the first peak of the bimodal cycle, highlighting difficulties in predicting short-term fluctuations.~~

~~In contrast, the CTRIP model exhibits weaker overall performance, particularly near the outlet at Kinshasa, where NSE score falls below -4. On the tributaries, the model shows slightly better performances, with NSE values ranging between -0.7~~

ability to reproduce key hydrological features, including seasonal flow dynamics, the magnitude of high and ~~0.3. The median correlation coefficient of 0.8 suggests that while CTRIP accurately captures seasonal flow patterns, the model struggles with overall discharge magnitudes. Discharge is largely underestimated, with a median bias of -43% across the basin, particularly near Kinshasa (panels e,f, Figure ??).~~

~~Discharge time series over the period 2010-2017 and climatologies comparing CTRIP (red), MGB (green), and in-situ observations (black) at three stations: Ouesso (a, b), Bangui (c, d), and Beach Brazzaville/Kinshasa (e, f)~~

~~At the tributary stations (Ouesso and Bangui), both models demonstrate reasonable performance in capturing the evolution of the annual hydrological cycle. The MGB model tends to overestimate discharge during high-flow periods, with overestimations of 17% at Ouesso (Sangha tributary) and 8% at Bangui (Ubangi tributary). For CTRIP, the annual cycle is well represented at both tributaries, but the model consistently underestimates discharge. The relative bias is 0.56 at Bangui and 0.32 at Ouesso, indicating a clear underestimation (panels b, d). Despite this, the correlation coefficients are satisfactory, with values close to 0.8 at both stations, reflecting a fairly accurate representation of the hydrological cycle.~~

~~At Kinshasa, the MGB model underestimates discharge by 19% across both high and low-flow periods. This underestimation is most pronounced during the second peak of the bimodal cycle (April to June), which is significantly underrepresented in the model, leading to an NSE score of 0 at Kinshasa. For CTRIP, the underestimation of discharge at Kinshasa is less pronounced compared to the tributaries, especially between February and April, when discharge is reasonably well captured. However, the model consistently underestimates discharge in the following months, with a relative bias of 0.63, likely due to underestimations of rainfall within the catchment area, leading to a shortfall in the observed water input and contributing to the systematic bias in discharge predictions at this station (Figure ??, panels e, f). Additionally, the correlation coefficient at Kinshasa drops to 0.46~~low flows, and internal variability. These results provide a necessary benchmark for understanding how data assimilation may improve model performance.

4.1.1 ~~Key issues in both models~~

The Open-Loop performance of the MGB and CTRIP models across the Niger and Congo basins reveals several key limitations. MGB generally performs well but tends to overestimate discharge during high-flow periods in both basins, particularly in the Inner Niger Delta and at Ouesso and Bangui in the Congo basin. It also slightly underestimates internal variability, leading to difficulties in reproducing short-term fluctuations, especially in the central Niger Basin. Additionally, at Kinshasa, the model underestimates discharge by 19%, indicating a bias in the overall flow magnitude.

In contrast, CTRIP faces significant challenges, with large overestimations during high flows—up to 2.3 times the observed values in the Niger Basin —(mainly due to evaporation in the Inner Delta not represented in the model) and considerable underestimations, particularly during low flows, across both basins. In the Congo basin, CTRIP struggles with discharge underestimations of around 43% at Kinshasa, although it captures seasonal flow patterns relatively well in the tributaries. It has to be noted that improvements can be expected with the CTRIP model when coupled to the ISBA land surface model to account for evaporation, namely. Yet, as CTRIP is also used for large scale hydrological studies, we preferred to use this configuration in the present study.

These ~~model issues~~ baseline limitations highlight opportunities for improvement, where data assimilation has the potential to reduce biases, improve discharge magnitudes, and refine flow timing in both models. The next section explores how different assimilation products can address these challenges and enhance model performance, taking into account the quality and temporal resolution of the assimilated products (~~Section ??~~Supplement, Figures S1,S2), and also the uncertainties set to the different data (Section ~~??~~3).

4.2 Assimilation Impact

4.2.1 Overview

The impact of data assimilation for both models (MGB-HYFAA and CTRIP-HyDAS) across the Niger and Congo basins is first presented through a general overview of the performance changes observed across the different assimilation experiments. To ensure ~~the~~ clarity of the figures, only the ensemble means for each experiment are considered, given the number of assimilation experiments. It is worth noting that, for both CTRIP and MGB, the dispersion between ensemble members (standard deviation) has consistently decreased following data assimilation compared to the Open-Loop simulations.

The following initial comparison highlights the overall trends and improvements brought by the integration of observation products, which will then lead into a more detailed analysis in the following subsections.

In the Niger basin, when assessing the performance of MGB in assimilating discharge and WSE anomalies, Qalti shows the highest improvement in NSE (Figure 5, panel 1a), with a median value of 0.83 at 50% uncertainty, followed by WSE anomalies (NSE: 0.73-0.76). In terms of correlation, Qalti assimilation performs best, raising the median correlation to 0.94 (Panel 1b), while WSE anomalies maintain a similar value to the Open Loop (0.93). Although Qmultispec exhibits the lowest NSE (0.68-0.72) and correlation due to its higher data noisiness, it compensates by performing best in reducing bias and correcting internal variability (panels 1c,1d). Bias is best reduced by Qmultispec, improving the median from 1.2 to closer to 1 (Figure 5, panel 1c). In terms of internal variability, Qmultispec also outperforms, with KGE γ nearing 1.0 at 30-50% uncertainty, while Qalti and WSE anomalies range between 0.91-0.94 (Figure 5, panel 1d). Therefore, while Qalti leads in improving flow magnitude and correlation, Qmultispec proves superior in bias and internal variability correction.

In CTRIP-HyDAS, the Niger basin exhibits limited improvement due to the model's already poor performance in Open Loop. However, Qmultispec performs better than both Qalti and WSE anomalies in bias reduction and overall improvement of internal variability. The CTRIP model demonstrates improvements in NSE, where Qmultispec assimilation leads to a 15% increase in performance, whereas WSE and Qalti show more modest gains in both bias and correlation (panels 2a, 2b, 2c, 2d, Figure 5).

For the Congo basin, assimilation experiments reveal a more nuanced picture. The analysis is limited to only two of the four main tributaries and Kinshasa at the lower Congo, making the scope of conclusions more constrained. While MGB displays noticeable improvements with Qmultispec in the Niger basin, the product does not perform as well in the Congo basin, largely due to lower data quality and temporal density (Figure ~~??~~S2, Supplement). Here, Qalti delivers the best performance, notably improving NSE from 0 to 0.1 at Kinshasa. Correlation scores improve by about 5% at Kinshasa and other stations (Panels 1a,

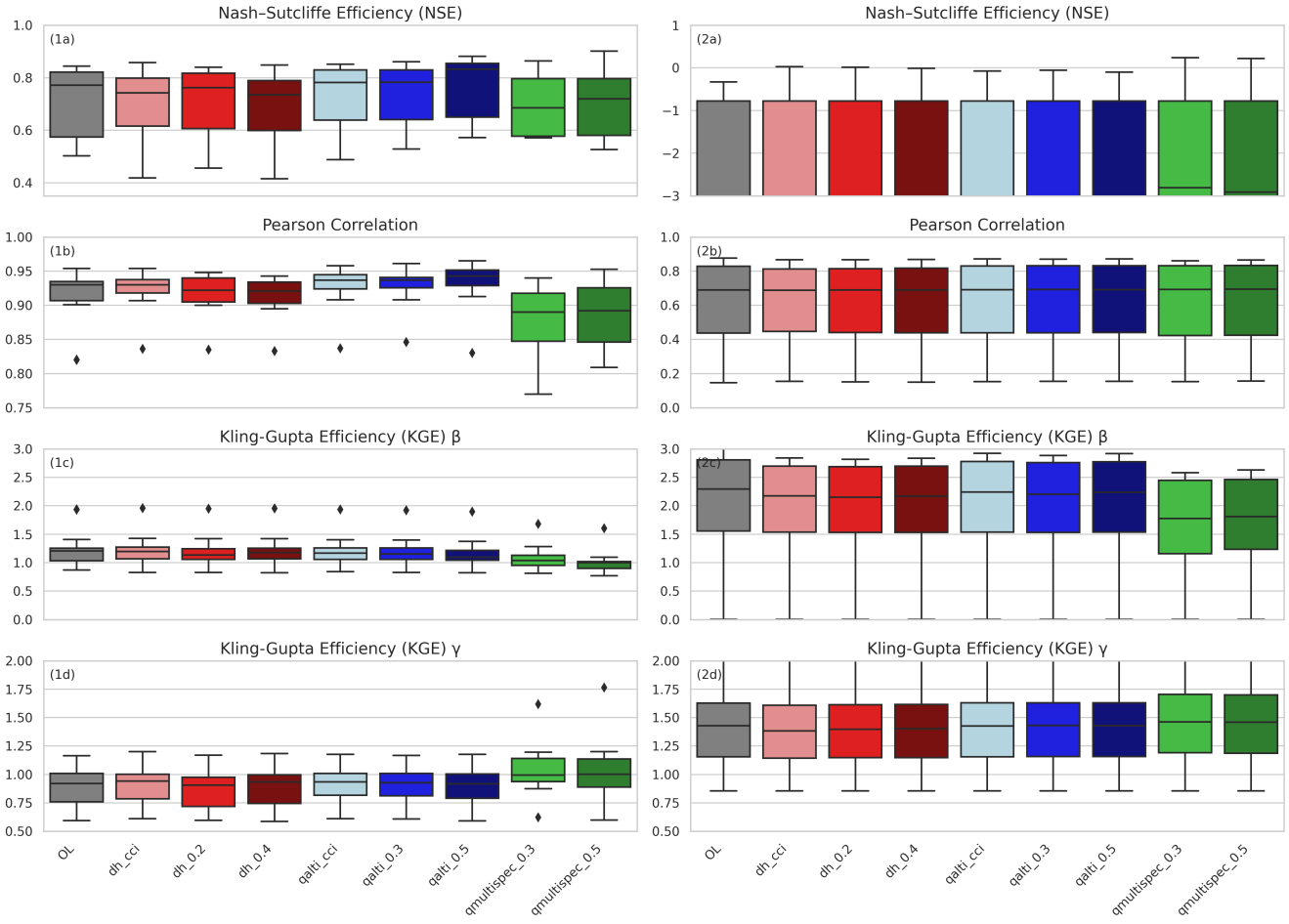

Figure 5. Distribution of NSE (a), correlation (b), bias (c), and internal variability (KGE γ, panel d) scores for MGB (1) and CTRIP (2) simulated discharge at 11 in-situ stations (Niger Basin, 2000-2020): comparison of open-loop (grey) and assimilation of water level anomalies (dH, red), altimetry-based discharge (Qalti, blue), and multispectral imagery discharge (Qmultispec, green) with different uncertainties. The lightest colours for dH and Qalti experiments represent uncertainties from computed errors, followed by the lowest values, while the darkest indicate the highest errors. For Qmultispec, the shades of green transition from light to dark based on increasing theoretical uncertainties.

1b, Figure 6). However, bias and internal variability are only slightly corrected (less than 5% overall improvement), as seen in panels 1c and 1d of Figure 6.

Meanwhile, in CTRIP, the assimilation of WSE anomalies leads to better performance over the Congo basin compared to discharge assimilation. This is due to a more coherent alignment between the model's rating curve and observed WSE data (as shown in the following section 4.2.2), along with the lower uncertainty attributed to WSE compared to discharge. Panels 2b and 2d of Figure 6 show improvements in correlation (+13%) and variability (-7%), particularly noted at Kinshasa, where

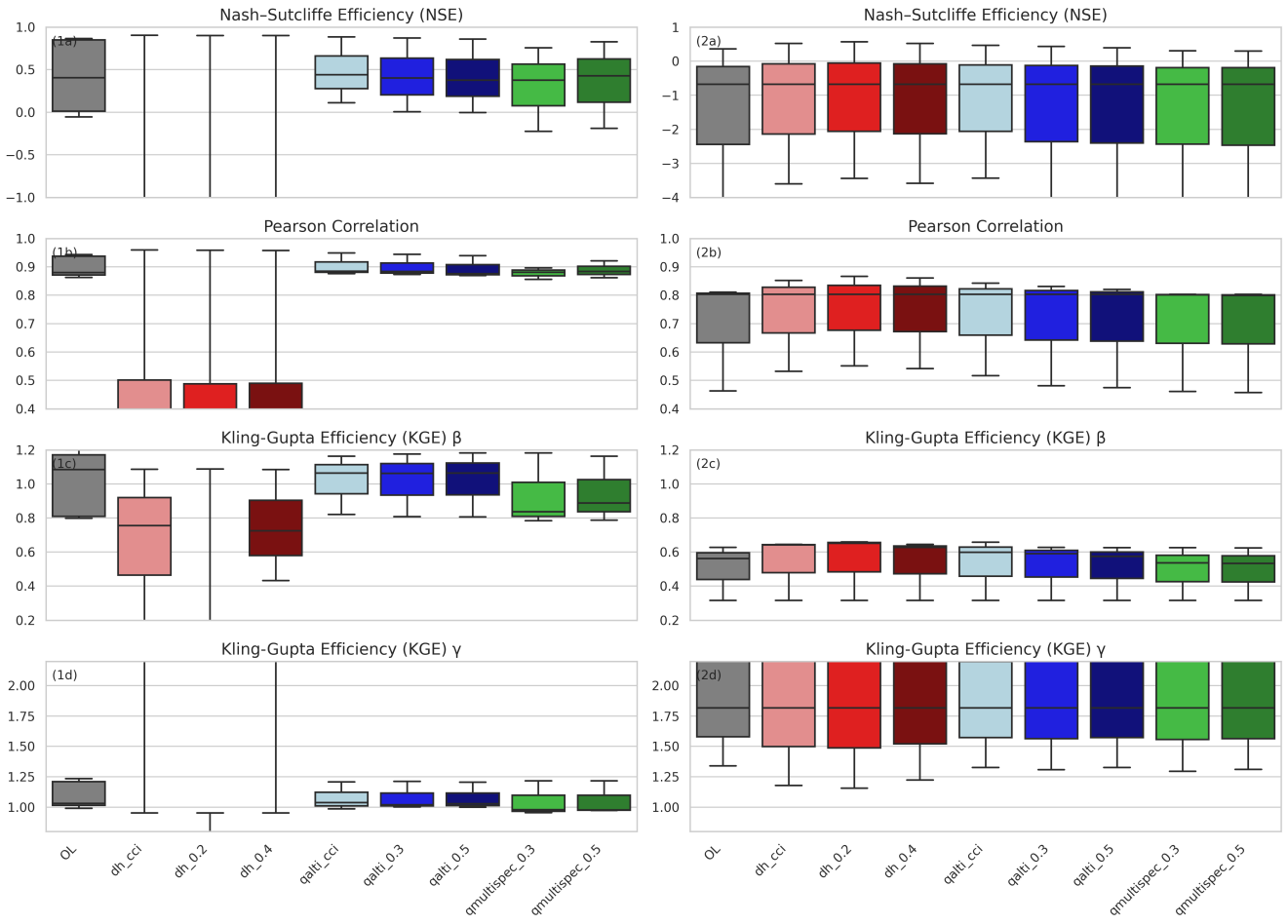

Figure 6. Distribution of NSE (a), correlation (b), bias (c), and internal variability (KGE γ, panel d) scores for MGB (1) and CTRIP (2) simulated discharge at the 3 in-situ stations (Congo Basin, 2000-2020): comparison of open-loop (grey) and assimilation of water level anomalies (dH, red), altimetry-based discharge (Qalti, blue), and multispectral imagery discharge (Qmultispec, green) with different uncertainties.

Qmultispec underperforms. In contrast, Qmultispec data quality deteriorates performance in both MGB and CTRIP for the Congo basin, particularly at Bangui and Kinshasa, where it fails to accurately represent the hydrological cycle.

When comparing the influence of the observations characteristics (spatial density, temporal frequency, and data accuracy) with uncertainty values, the distribution of performance indices across experiments shows that the characteristics of observed data play a more decisive role in both models and basins. Data assimilation is primarily driven by the spatial density of virtual stations, followed by temporal resolution and data accuracy, with uncertainty having a lesser impact. However, uncertainties become important in the presence of outliers, as higher uncertainty values reduce the likelihood of outlier assimilation, minimizing hashed effects in the analysis. This is evident in the assimilation of Qmultispec products in the Congo basin, where

poor data quality degrades model performance. Nevertheless, higher uncertainty (50%-60%) limits degradation compared to 30% uncertainty (Figure 6).

From these results, two key findings are highlighted to explore more specifically the contributions of the different CCI discharge products. In one hand, the comparison between discharge assimilation and WSE anomaly assimilation in large-scale hydrological models is examined. In the other hand, the added value of Qmultispec data is analyzed, particularly in the Niger Basin, where it outperforms Qalti in correcting bias and internal variability.

4.2.2 Assimilation of Discharge Compared to WSE Anomalies in Large-Scale Hydrological Models given same temporal and spatial resolution - Qalti vs dH

The comparative performance of dH and Qalti assimilation is influenced by several factors, including product uncertainty, model open-loop baseline simulation, and how well observations integrate with model dynamics. Among these, the mismatch in rating curves between models and observations emerge as a key recurring limitation for dH assimilation and is highlighted at relevant points throughout this section.

In the Niger Basin, MGB shows a clear advantage for discharge assimilation (Qalti) over water surface elevation anomalies (dH). Qalti improves Nash-Sutcliffe Efficiency (NSE) to 0.83 (+14%) and raises correlation to 0.94 (+18.5%), ensuring smoother flow predictions across stations.

As shown in Figure 7, at Ansongo and Malanville, discharge assimilation produces smoother results, while WSE introduces noise due to rating curve discrepancies between MGB and CCI observations. The hashed effect seen with dH assimilation is evident in several stations but absent in others like Ibi and Lokoja. This absence is due to the combined effect of low observation uncertainties and compatible rating curves between the model and observations at these stations.

This discrepancy is particularly evident at Ansongo (Figure 7), where MGB's rating curve diverges significantly from the CCI observations. Figure ~~??~~ 8 highlights this finding by comparing observed and simulated rating curves across both Niger Basin stations. This mismatch between the two curves at Ansongo implies additional errors when converting WSE anomalies to discharge, leading to noisy results. In contrast, Qalti, as a directly modelled variable, fits more naturally to the hydrological model~~, avoiding these complexities and providing more reliable results in terms of discharge simulation~~.

In addition to these structural mismatches, such as those seen in Ansongo, the behavior of the assimilation filter is also shaped by how observation uncertainties are handled in the EnKF. At Ansongo, the MGB model results for two experiments (dH 0.4m and Qalti 30%) from 2010-2020 reveal ~~additionnal~~ additional differences in assimilation, as shown in Figure 9. Panels ~~display time series for open-loop (black) , Analysis (blue) , and Observation to be assimilated (red). With dH assimilation , the MGB model shows near-zero residuals (otherwise~~ (1b) and (2b) represent the time series of increments, defined as the difference between the model analysis and the background (i.e., the forecast prior to assimilation). These increments quantify how much the model state was updated by the assimilation process. Panels (1c) and (2c) show the residuals, defined as the difference between the analysis and the assimilated observations: a low residual indicates the model is closely following the observations, while a large residual suggests a partial rejection of the observation. Finally, the innovation (not explicitly shown here) would

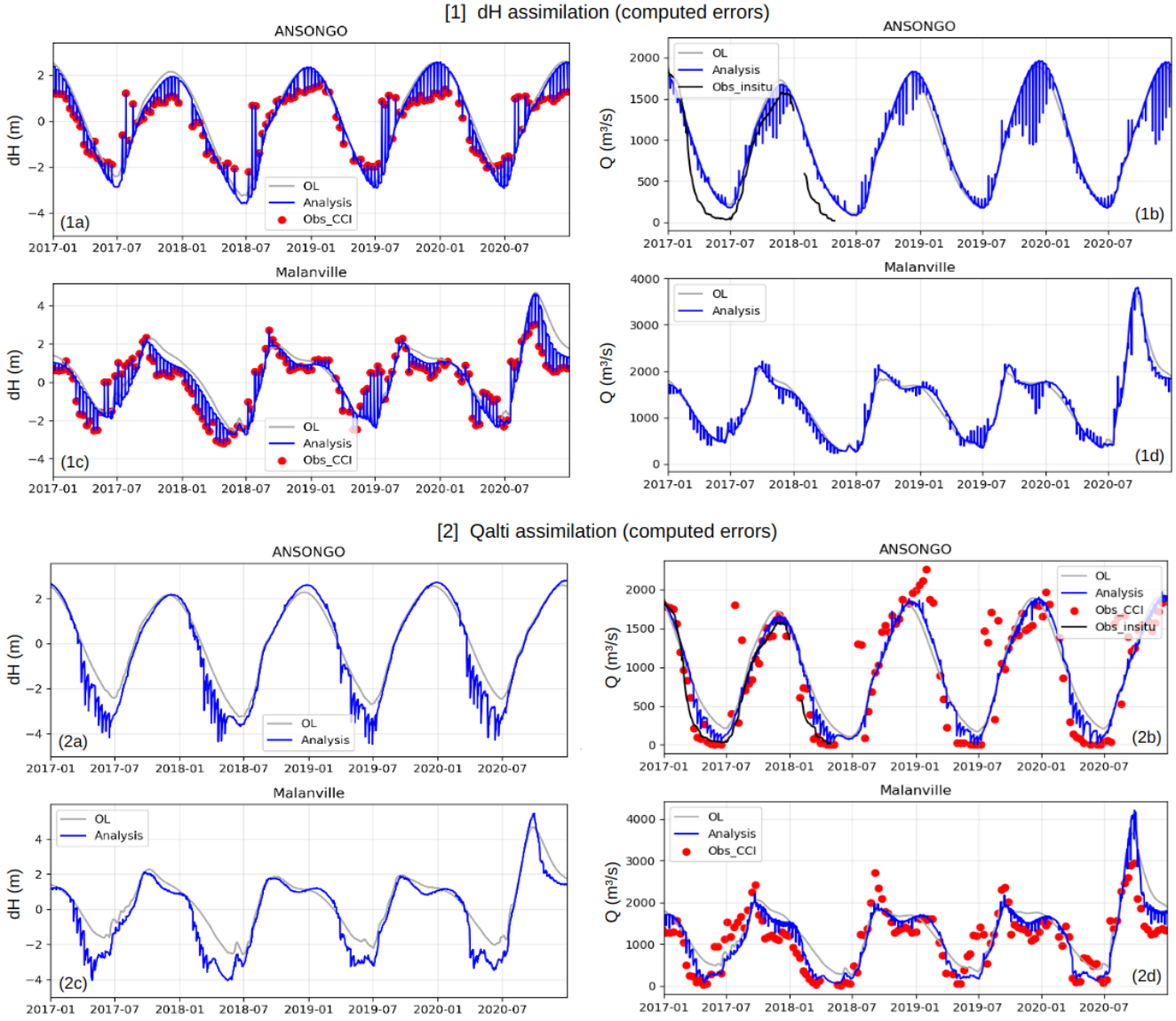

Figure 7. Comparison of water surface elevation (dH) and altimetry-based discharge (Qalti) assimilation with computed errors for Ansongo and Malanville stations (2017-2020), within MGB-HYFAA. Panel (1a-d): dH assimilation (computed errors) showing time series of dH (1a, 1c) and discharge (Q) (1b, 1d) for Ansongo and Malanville. Panel (2a-d): Qalti assimilation (computed errors) showing time series of dH (2a, 2c) and discharge (Q) (2b, 2d) for the same stations. *Obs CCI* represents water surface elevation (WSE) from satellite altimetry in panels (1a,1c) and altimetry-derived discharge in panels (2b,2d).

be the difference between the ~~CCI observations assimilated and the Analysis), meaning all observationsare assimilated with minimal corrections~~observation and the background (forecast), and shows the initial discrepancy before assimilation.

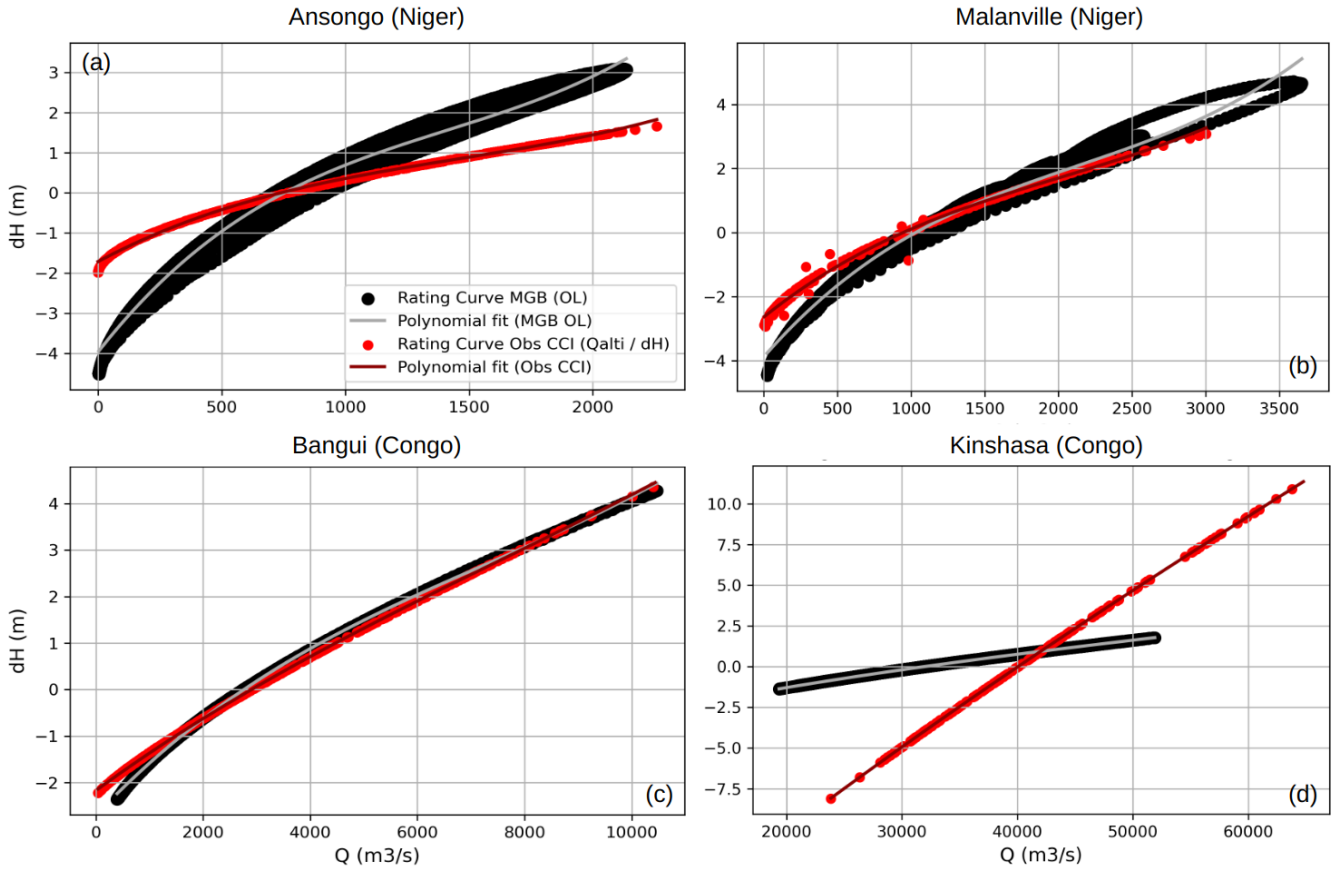

Figure 8. Rating curves from MGB (Open-Loop) vs. Obs CCI (dH, Qalti) at (a) Ansongo and (b) Malanville stations in the Niger basin, and at (c) Bangui and (d) Kinshasa stations in the Congo basin.

With dH assimilation, the model almost entirely follows the observations, as indicated by the near-zero residuals. The same pattern is observed for CTRIP. Due to their lower uncertainty compared to the other products, dH observations, even at 0.4m uncertainty value, are still assimilated even when they diverge from the model's theoretical WSE values. This introduces erroneous information into the model, which can disrupt the simulated discharge and amplify the hashed effect after assimilation.

Qalti, ~~on the other hand, even with~~ in contrast, despite its 30% uncertainty, ~~leaves persistent~~ results in larger residuals, especially during high flow periods~~, and this~~ . This is mainly because the error given to the discharge products is proportional, so the higher the discharge value, the higher the absolute uncertainty given to that value and the lower is the weight given to observation within the EnKF scheme compared to model background. These residuals help maintain more reliable results by preventing the full assimilation of outliers (Figure 9). This selective assimilation behavior of Qalti, driven by proportional uncertainty, is particularly useful for reducing the influence of extreme outliers during flood peaks. However, during low-flow periods, Qalti's uncertainty becomes very small in absolute terms, potentially leading the filter to overfit isolated or erroneous

low-flow observations. This limitation should be considered when evaluating Qalti assimilation performance across all flow regimes. dH is less sensitive to this effect due to its fixed absolute uncertainty.

Another key advantage of Qalti lies in its temporal continuity, since discharge is a mass-conserving quantity that evolves continuously over time steps, supporting more physically consistent updates throughout the river network. In contrast, dH values are tied to local rating curves and may produce temporally inconsistent discharge increments between time steps and across stations. A 0.4 m WSE anomaly may lead to a discharge correction that varies widely across the river network, depending on the local shape of the rating curve. In reaches with steep slopes or narrow channels, this may correspond to small discharge changes. In contrast, in flat floodplain areas or during low-flow periods, this can induce disproportionately large discharge corrections, potentially destabilizing the model.

In the Congo Basin, the ~~discrepancy~~ mismatch between the MGB model's rating curve and the observed altimetry data is even more pronounced, especially at Kinshasa. ~~Here, Qalti further~~ At this location, Qalti outperforms dH, as dH assimilation ~~struggles with large water level variations not well captured by~~ fails to capture the large observed WSE variations due to the model's flat rating curve (Figure ~~??~~8). At Kinshasa, the MGB model has a flatter slope, meaning that for similar discharges, the model produces much smaller changes in water surface elevation. In contrast, the observed rating curve from altimetry (dH and Qalti) shows a much steeper slope, indicating a larger variation in water surface elevation for the same discharge fluctuations. ~~When altimetry~~ Altimetry observations show dH variations reaching ~~as high as~~ up to $\pm$7 meters, while the MGB model's ~~dH remains near zero~~maintains nearly constant WSE values. This mismatch between modeled and observed rating curves, also noted in the Niger Basin (Ansongo, Figure 8), illustrates a broader structural limitation of dH assimilation in MGB when rating curve slopes differ significantly.

~~Rating curves from MGB (Open-Loop) vs. Obs CCI (dH, Qalti) at Bangui and Kinshasa stations in the Congo basin.~~

~~This mismatch causes EnKF divergence and so outliers and very~~ This mismatch leads to EnKF filter divergence, resulting in outliers and highly negative NSE values, ~~making~~ which makes dH assimilation unreliable ~~in stations like~~ at stations such as Kinshasa and Ouesso (Figure 10). Ouesso, correlated with Kinshasa through the localization matrix, is also impacted by the discrepancies observed at Kinshasa. These inconsistencies propagate backward to Ouesso, resulting in unstable discharge estimates with extreme fluctuations, including both excessively high and negative values. These issues lead to poor performance scores at Ouesso as well. It is worth noting that, in this version of MGB-HYFAA, the EnKF does not impose numerical constraints on discharge, which allows for negative values when unrealistic corrections deviate from physical plausibility, as seen in Figure 10.

~~In CTRIP, a contrasting result is observed~~While MGB benefits more from Qalti due to its compatibility with discharge as the primary modeled variable, CTRIP shows a different behavior. The assimilation of dH consistently outperforms Qalti across the stations in both basins. This difference is most notable in the Niger Basin, where the Open-Loop (OL) simulation performs poorly. ~~Given the low performance of CTRIP's OL, any satellite product leads to significant improvements. The uncertainty for WSE anomalies (dH) corresponds to much lower uncertainty levels compared to Qalti, which is logical since the discharge is a more indirect product.Also, in CTRIP~~In such cases, the EnKF favors the observation with the lowest uncertainty, typically dH, even when Qalti would be more consistent with the model's output. Since Qalti is indirectly derived from altimetry and

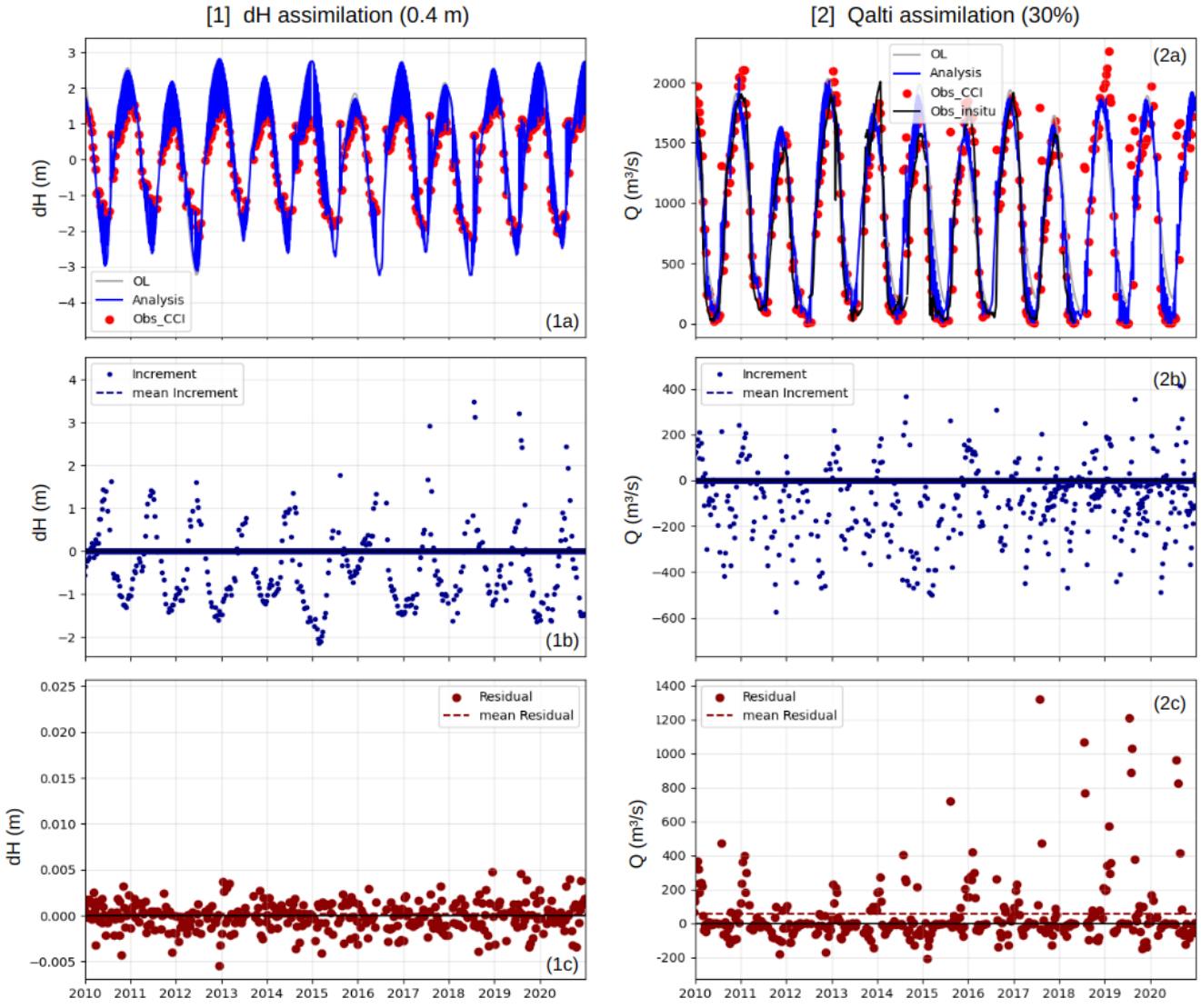

Figure 9. Comparison of dH and Q assimilation at Ansongo, Niger, over the 2010-2020 period: Top panels show time series of (a) dH assimilation with 0.4m uncertainty and (b) Qalti assimilation with 30% uncertainty, with open-loop, analysis, and observed data. The middle and lower panels show the corresponding innovation and residuals, with the mean innovation and residuals represented by dashed lines, illustrating the model's performance and adjustments after assimilation.

involves transformation through rating curves, it carries higher uncertainty and is thus assigned lower weight in the analysis.
830 This may lead to over-reliance on dH, even if the structural limitations (e.g., ~~for~~ flat rating curves) make it less appropriate.

dH assimilation is most effective in CTRIP when large model biases are present and when model rating curves align well with observations. In fact, CTRIP's rating curves closely match altimetry-based ones at most stations, ~~the model rating curve~~

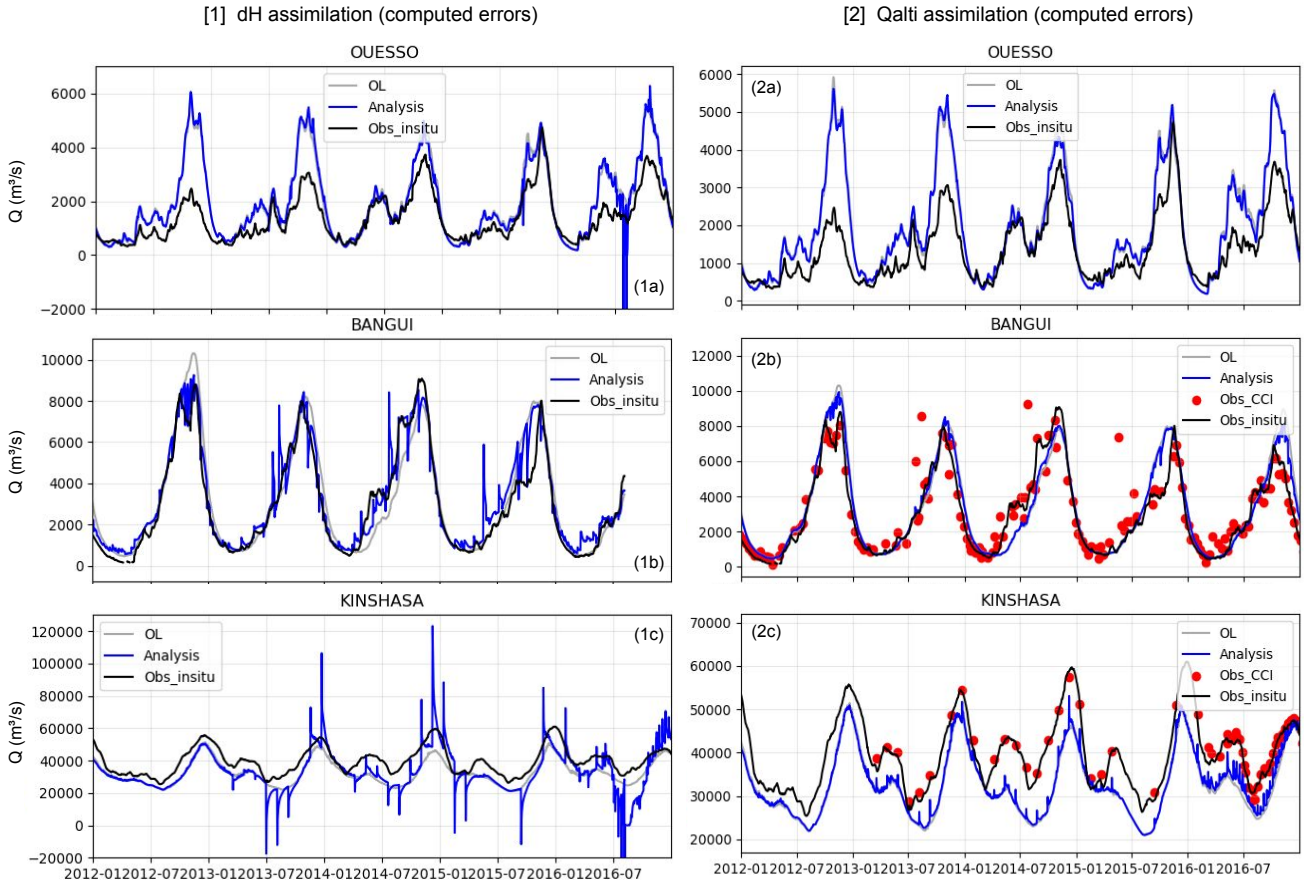

Figure 10. Comparison of dH (1) and Qalti (2) Assimilation in Ouesso, Bangui, and Kinshasa: OL Simulation in black, Assimilation Results in blue and Observed ~~CCIP~~ CCI Data in red.

~~matches the observed one from altimetry products (dH/Qalti). However, for products with equal temporal density~~including Niamey, as shown in Panel (c), Figure 11. Panel (a) shows that dH assimilation shows consistently higher KGE scores. Given equal temporal resolution, the lower uncertainty ~~assigned to~~ of dH (0.2~~m-0.4m)~~ –0.4 m) gives the observation more relative weight in the analysis, compared to Qalti (30~~%-50%)allows dH to provide more impactful corrections to the model~~–50%). ~~CTRIP model's rating curvesalong stations align closely with the observed altimetry data, as seen in Figure 11, allowing for near-total dH observation assimilation compared to Qalti, despite both products being derived from the same altimetry source (Figure~~

However, this comes at the cost of physical consistency and temporal continuity. Q is a mass-conserving variable that evolves continuously over time steps, supporting more physically consistent updates throughout the river network and therefore offering more stable integration with hydrological model dynamics. WSE anomalies, by contrast, do not conserve volume and require geometric assumptions through rating curves, which can reduce consistency between time steps.

In CTRIP, where structural errors, like missing evaporation downstream the Inner Delta in the Niger, lead to biased flow, dH assimilation leads to better improvements, but only when the model's rating curve matches observations (Figure 11). ~~The lower uncertainty of dH plays a crucial role in~~

In contrast, MGB includes explicit evaporation and provides a better OL simulation. In this case, ~~as it drives better assimilation outcomes by assigning more weight to the observed water surface elevations, resulting in smoother corrections to the model's discharge predictions~~Qalti proves more effective: it updates discharge directly and avoids transformation errors, and better reflects seasonal flow signals. Even at stations with good rating curve alignment (e.g., Malanville), Qalti outperforms dH assimilation (Figure 7). This is supported by comparisons with in-situ data (Supplement), which show CCI discharge capturing seasonal dynamics reliably.

These results indicate that discharge assimilation tends to be more effective when the model provides a reliable physical representation of the river system and the open-loop is not structurally too poor.

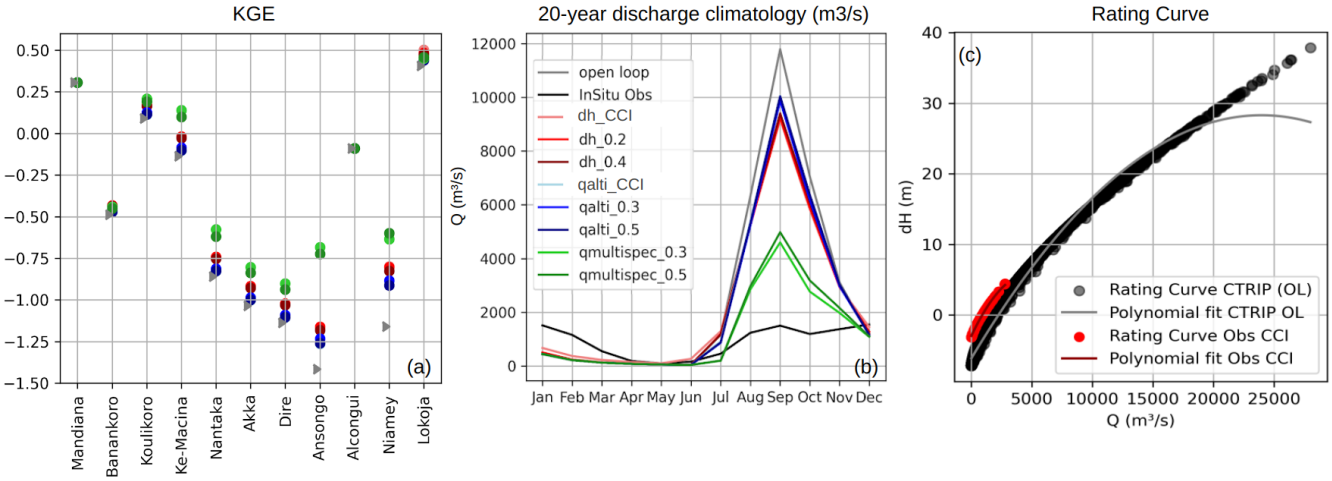

Figure 11. ~~Example of~~ Panel (a) presents the Kling-Gupta Efficiency (KGE) performance results from CTRIP for each assimilation experiment (colored markers) at 11 stations in the Niger Basin, with Open-Loop (OL) performance shown as grey triangles for reference. Panel (b) displays the corresponding discharge climatology at Niamey, comparing observed discharge (black) with Open-Loop simulations from CTRIP (grey) and different assimilation experiments (colored), illustrating seasonal variations in modeled and observed discharge. Panel (c) shows the rating curve ~~and climatology~~at Niamey from CTRIP Open-Loop (black), compared to Obs CCI (dH, Qalti) (red)

The preferred assimilation variable ~~depends on~~ thus depends on a combination of the model's open-loop performance, the uncertainty ~~assigned to each variable, and how they are represented in the model~~of the observation, and rating curve alignment. In CTRIP, structural limitations and accurate alignment with observed rating curves favor WSE assimilation. In contrast, Qalti assimilation in MGB is supported by stronger internal discharge simulation and more realistic physical representation. The issues with rating curve mismatches in MGB (Kinshasa, Figure ~~??~~8) and the ~~similar~~ close performance results between dH and Qalti in CTRIP (Figure 11) ~~demonstrate that, overall, discharge (Q) remains a more effective variablefor assimilation in~~

large-scale models. These findings underscore that despite some close comparisons, discharge offers a more reliable and direct integration into hydrological models, avoiding the complexities associated with converting water surface elevation (dH) to discharge. highlight the sensitivity of each variable's performance to model context.

The choice between dH and Qalti should consider not only uncertainty but also how well each variable aligns with the model's structure and dynamics. For large-scale hydrological models, whose primary objective is to accurately simulate discharge rather than water surface elevation (WSE), it is more robust to assimilate a variable directly related to the flows they simulate. Adjusting rating curves across model cells to accommodate dH is more complex and introduces errors, especially when the model's simplified river geometry does not match real-world conditions. Discharge integrates smoothly into models like MGB and CTRIP without requiring these complex conversions assimilation avoids these conversions and ensures consistency across both model cells and time steps, making it the more reliable choice overall. Thus, when the model is not too structurally biased, Qalti assimilation tends to outperform dH and is better suited for large-scale hydrological applications.

4.2.3 Bias and internal variability correction : Outperformance of Qmultispec assimilation over Qalti

In the Niger Basin, despite its lower performance in other metrics, Qmultispec outperforms in bias correction by significantly reducing flow overestimation in both models. This improvement is particularly notable in the upper Niger and Inner Delta within MGB, where the Open-Loop (OL) simulation consistently overestimates discharge. Koulikoro serves as a key example, where the bias is reduced by 17-20% (depending on the uncertainty levels), bringing the bias from 1.2 in the Open-Loop down to approximately 1. In fact, Qmultispec's higher temporal density enables better alignment with the observed rising and falling limbs of the hydrograph, providing more consistent results over the annual cycle.

Figure 12 illustrates in panels (a) the time series results for two experiments conducted at Koulikoro between shows time series at Koulikoro (2010and –2020(MGBmodel) : (1) Qalti and (2)Qmultispec assimilation, both at , MGB) for two experiments at 30% uncertainty. In panels (b), % uncertainty: Qalti (1a) and Qmultispec (2a). Panels (1b, 2b) show the time series of increment – which measures the difference between the analysis and the background– for each experiment are shown (Qalti in 1b and Qmultispec in 2b). We observe that with frequent and continuous data input, the bias correction occurs steadily over the annual cycles. Both the overestimation during high-flow periods and the underestimation during increments (analysis minus background). With frequent updates, bias corrections occur steadily throughout the hydrological year, correcting both high- and low-flow periods are corrected consistentlybiases.

As shown in panel Panel b of Figure 13 , the increment displays a notable reduction confirms that Qmultispec produces smaller mean increments during the high-flow period (Juneto November) , with a much lower mean increment for Qmultispec than for WSE (dH) –November) compared to dH or Qalti assimilation. At Koulikoro, Qalti actually overestimates discharge by 35% compared to in-situ data, while the MGB Open-Loop overestimates by 25%, and Qmultispec by 20%. Although the Qmultispec data is noisier, particularly during the recession phase, its high temporal resolution allows for continuous correction, preventing frequent updates prevent the model from reverting to its biased pre-assimilation , overestimated state. In panel (2b) of Figure 12, showing the increment over time, we see that updates occur continuously with a repetitive trend throughout the annual cycle. state.

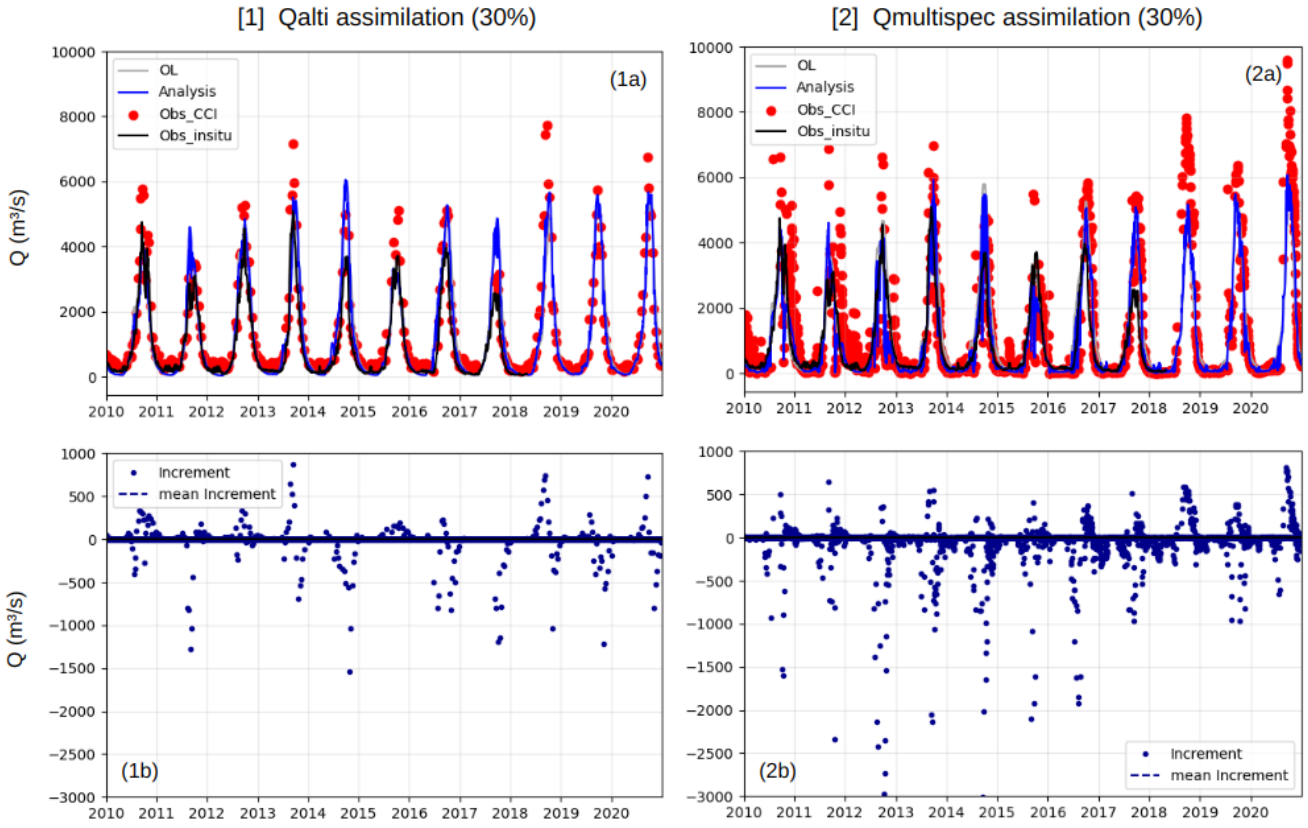

Figure 12. MGB model results at Koulikoro over 2010-2020 for two experiments: (1) Qalti with 30% uncertainty and (2) Qmultispec with 30% uncertainty. Time series for open-loop (black), Analysis (blue), and Observations to be assimilated (red) are shown in panels (1a) and (2a) for Qalti and Qmultispec, respectively. The increment (Analysis - Background) is shown in (b), and the residual (Obs CCI - Analysis) in (c). Dashed lines in (b) and (c) represent the mean innovation and residual over 20 years

In the CTRIP model, the ~~order of improvement follows a similar trend , with Qmultispec providing~~ trend is similar: Qmultispec provides the greatest reduction in bias, followed by ~~WSE anomalies (dH) and altimetry-based discharge (Qalti)~~dH and Qalti. This difference ~~stems~~ comes from the lower uncertainty levels of the WSE anomalies (0.2m-0.4m) compared to Qalti (30%-50%). In the Niger Basin, CTRIP's Open-Loop simulation overestimates discharge significantly, so all satellite products help reduce this positive bias. The ~~higher temporal resolution of Qmultispec prevents the model from reverting to its pre-assimilation state, reducing bias more effectively than the other products. This impact is particularly evident in the averaged monthly discharge values, where Qmultispec consistently shows better bias reduction than both WSE anomalies and Qalti assimilation, as seen in Niamey (Figure 11)~~frequent assimilation from Qmultispec helps constraining the model and reduces the tendency to revert to biased states (Open-Loop). This is particularly visible in the monthly climatologies, as shown at Niamey in Figure 11.

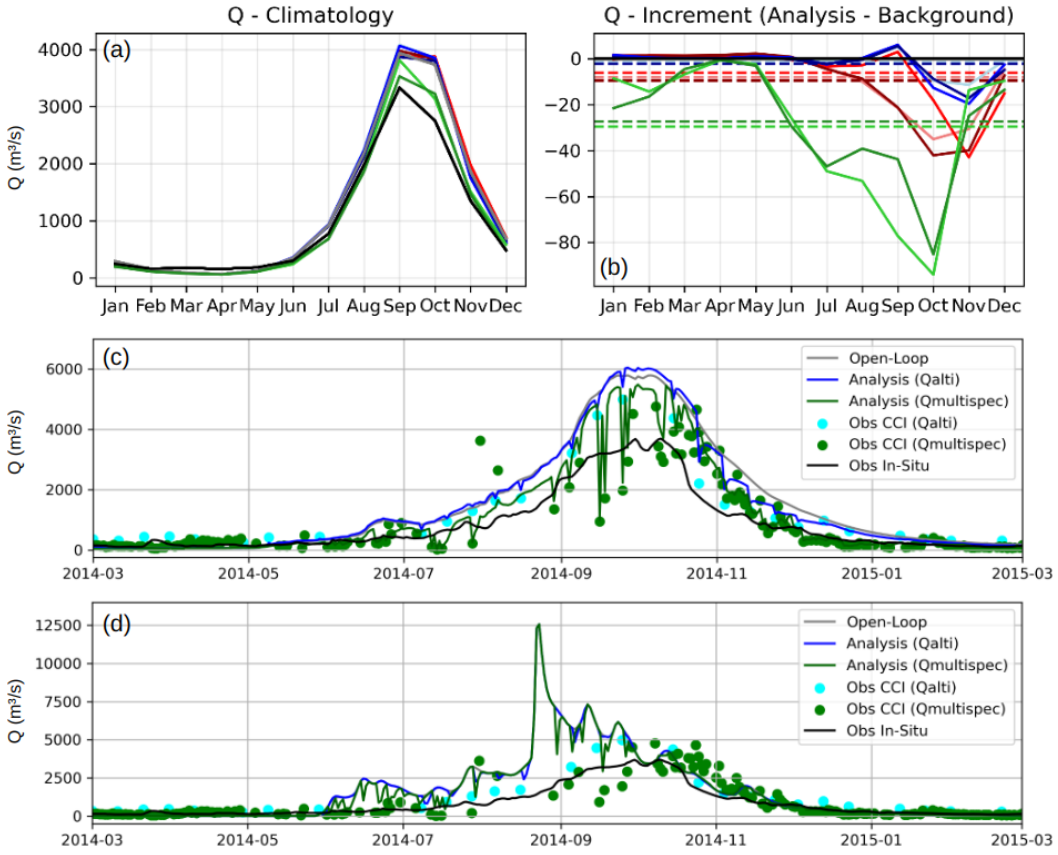

Figure 13. (a, b) MGB model results at Koulikoro for different experiments (dH in shades of red, Qalti in shades of blue, Qmultispec in shades of green); (a) Discharge climatologies, with in-situ observations in black. (b) Increment (Analysis minus Background) shows differences after assimilation, with mean increments indicated by dashed lines. (c, d) Example of assimilation results over a year (2014) for Qalti (blue) vs Qmultispec (green) at Koulikoro within MGB (c) and CTRIP (d), both CCI products assimilated at 30% uncertainty.

~~The dense temporal coverage of Qmultispec also ensures better capture of internal variabilityand long-term trends, more seen in MGBmodel results. Discharge data with higher temporal resolution provides a more dynamic correction, reducing the divergences in model simulations caused by~~ Beyond bias correction, Qmultispec also improves internal variability, particularly in MGB. With dense temporaly data coverage, it enables dynamic corrections that reduce simulation divergence caused by model internal errors or the omission of complex physical processes. This is evident in both the MGB and CTRIP models, as seen in Figure 13. It is worth noting that within the Niger basin, the internal variability is less effectively corrected by any of the products in CTRIP, largely due to the model's poor Open-Loop performance, which limits its ability to capture short-term fluctuations.

~~The outperformance of Qmultispecin internal variability correction compared to Qalti and WSE, makes this product~~ Qmultispec's improved capture of short-term fluctuations makes it particularly valuable for climate studies focusing on flow variability and

its evolution over time. Capturing this internal short-term variability is essential for modeling extreme events such as floods and droughts, which makes this product doubly relevant for MGB, as it is designed for forecasting applications.

Overall, in both models, Qmultispec ~~stands out as the most effective product for~~ outperforms Qalti and dH in reducing bias and correcting internal variability. ~~In particular, its higher temporal resolution provides continuous corrections to both high- and low-flow periods, reducing the existing biases in Open-Loop simulations. Despite the noisiness in the data~~ Despite some data noisiness, Qmultispec delivers more consistent and reliable performance compared to Qalti and WSE anomalies. This makes it particularly valuable for long-term studies on the evolution of discharge and water resources, such as those related to climate change, as well as for forecasting extreme events.

4.3 ~~Discussions~~

5 Discussions

This study demonstrates that ~~while~~ discharge data assimilation ~~yields more reliable results , especially in discharge-driven models, the use of WSE anomalies can introduce significant errors~~(Q) provides robust and physically consistent results in large-scale hydrological models. However, the effectiveness of WSE anomaly (dH) assimilation depends strongly on the model's structural realism and rating curve alignment with observations. For instance, in Kinshasa, the discrepancy between the modeled and observed WSE values resulted in poor model performance when assimilating dH ~~, due to mismatches between the model's rating curve and real-world conditions. Conversely, assimilation of discharge aligns better with the modeled variables, offering smoother and more consistent corrections, which are particularly vital for simulating dischargepatterns accurately~~in MGB, whereas Q assimilation provided more reliable discharge corrections. In CTRIP, dH assimilation produced better statistical scores than Qalti, but this was primarily due to the model's poor open-loop performance caused by missing evaporation processes. In such contexts, the EnKF filter tends to give more weight to the observation with the lowest uncertainty—dH—espe when the model's rating curve aligns well with altimetry data. This favorable alignment enables more efficient conversion of dH to Q, improving assimilation outcomes despite dH being less physically consistent than discharge. This underlines the need for careful consideration when integrating dH data into ~~discharge~~ discharge-driven models, especially in cases where the river bathymetry and geometry are not well represented.

Temporal data density plays a critical role in hydrological modeling, particularly for climate studies where capturing internal variability and correcting biases are essential. High-frequency data, like Qmultispec, provides continuous updates that ~~help correct~~ helps correcting seasonal and interannual flow patterns, which are important for modeling extreme events such as floods and droughts. In the Niger Basin, Qmultispec assimilation significantly improved the model's representation of seasonal flows and reduced systematic biases. However, a trade-off exists between data quality and temporal density. High-frequency datasets, such as Qmultispec, tend to be noisier compared to lower-frequency, but more accurate datasets like Qalti. In regions such as Bangui in the Congo Basin, where Qmultispec data was noisier, the assimilation led to poor model performance due to the excessive noise, despite its high temporal resolution. This highlights the importance of balancing the density of observations

with their quality to avoid degrading the model with inaccurate data. Figure 14 illustrates this trade-off, with high-frequency data improving flow timing but introducing noise into the analysis.

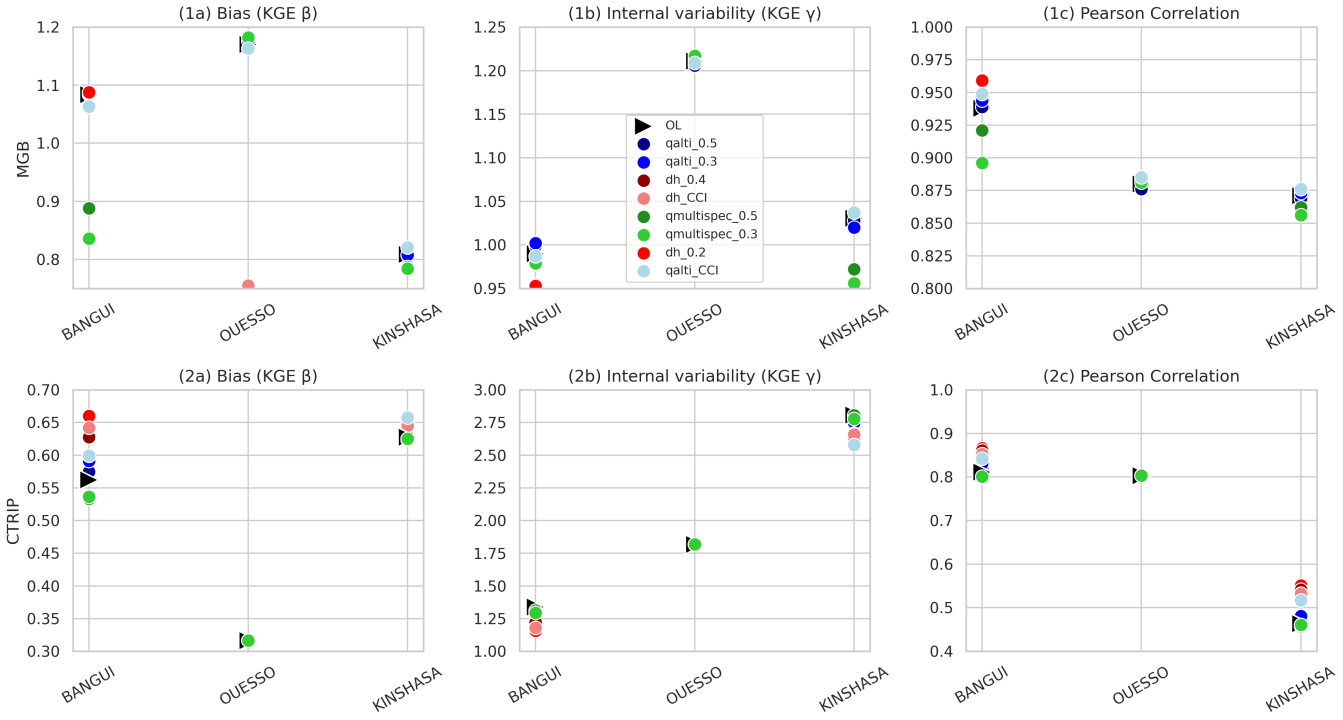

Figure 14. Comparison of bias (KGE β), internal variability (KGE γ), and Pearson correlation for different assimilation experiments in MGB and CTRIP models: daily scores at Ouesso, Bangui, and Kinshasa stations.

The trade-off between temporal density and data quality is especially evident in the Congo Basin, where Qmultispec performs poorly compared to its performance in the Niger Basin. In the Congo, the lower data quality and poorer temporal density reduce the effectiveness of Qmultispec, particularly in stations like Bangui and Kinshasa. While CTRIP is more influenced by WSE and discharge assimilation, the mismatches between the modeled and observed rating curves in MGB create additional challenges, leading to errors when assimilating dH. Furthermore, at stations like Ouesso, the high-water periods in Qmultispec are out of phase with the modeled output, diminishing the ~~impact of assimilation.~~ assimilation performance. This trade-off is critical for discharge assimilation, as the percentage-based uncertainty of discharge observations leads to seasonally variable correction weights. During high-flow periods, the larger absolute uncertainty reduces the influence of discharge data within the EnKF, limiting overcorrections, whereas in low-flow periods, the lower absolute uncertainty increases their relative weight, which may lead to overfitting of local or spurious fluctuations. These seasonal differences in correction weights should be taken into consideration when interpreting assimilation results.

Spatial data density is another critical factor in complex river basins like the Congo. The Congo's major tributaries contribute significantly to the overall discharge, necessitating adequate observation points for proper basin-wide hydrological

representation. For example, insufficient coverage in the upper tributaries of the Congo, such as the Chembe-ferry station, limits the overall influence of data assimilation across the basin. Figure 15 presents the normalized root mean square difference (NRMSD) between the Open-Loop and Qalti (0.20m) assimilation experiments over both basins. As shown in this figure, the impact of spatial coverage on data assimilation effectiveness is significant, especially when comparing the spatial coverage in the Niger Basin to the Congo Basin.

It is important to recall that this study was designed to isolate and evaluate the specific contribution of the long-term CCI discharge and WSE products. While combining them with other satellite datasets could enhance spatial coverage and improve assimilation performance—especially in data-scarce regions like the Congo Basin—this would make it difficult to isolate the specific effect of the CCI products. This proof-of-concept study focuses solely on the CCI products to analyse their added value for long-term, large-scale hydrological modeling. In future work (CCI Discharge Phase 2), we plan to explore how these products can be integrated with additional satellite observations to further improve model performance.

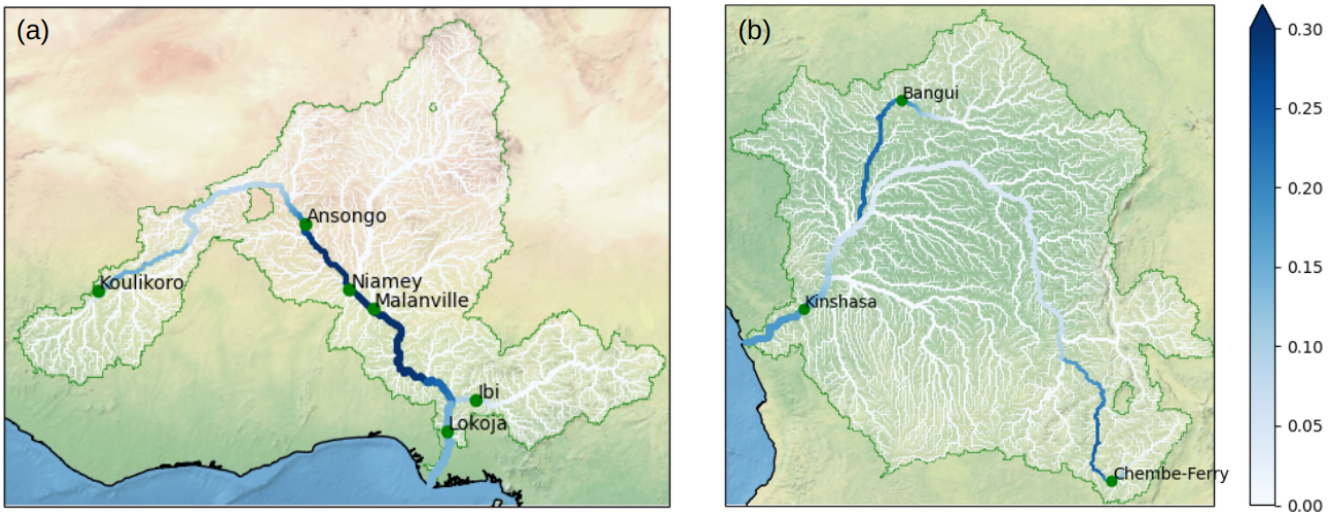

Figure 15. NRSMD comparison between Niger and Congo basins, illustrating the impact of spatial coverage on DA influence.

In summary, the effectiveness of data assimilation in large-scale hydrological models depends on several key factors: the type of data assimilated (discharge vs. WSE), the temporal and spatial density of observations, ~~and~~ the initial performance of the model~~. While~~ , and the consistency between modeled and observed rating curves. For similar data density, while discharge assimilation proves ~~to be~~ more reliable in models designed for flow dynamics, ~~the quality of the observation data~~WSE anomalies can still offer substantial benefits in poorly performing models when rating curves from model and observation are well aligned. The high temporal density of Qmultispec is a key asset of the CCI products, as it helps correcting seasonal and interannual biases more effectively; however, this advantage must be weighed against the potential noise associated with lower observation quality. Spatial coverage and observation quality, particularly in complex basins like the Congo, ~~plays a crucial role in~~ remain critical factors determining the success of assimilation experiments.

6 Conclusions and Perspectives

Hydrological models such as CTRIP and MGB are essential tools for climate studies and forecasting at large scales, including continental regions and large river basins. Their accuracy can be greatly enhanced through satellite data assimilation, which improves model performance by addressing key factors such as the model's initial open-loop performance, the temporal and spatial density of observations, and the quality of the assimilated data. Assimilating discharge data has proven more reliable than water surface elevation anomalies (dH) assimilation, particularly in models focused on discharge simulations. This is because direct discharge assimilation avoids the uncertainties involved in converting dH into discharge, especially in models with simplified river geometry. In contrast, dH assimilation often introduces errors in regions where discrepancies exist between observed and modeled water surface elevations. However, in poorly performing models with low open-loop skill and well-aligned rating curves, WSE anomalies can become more effective than Q, as their lower observation uncertainty leads to more impactful corrections. This underlines the importance of considering both the model structure and observation characteristics when selecting assimilation variables.

Temporal data density is also critical for improving model performance. High-frequency updates, such as those provided by Qmultispec, enable more continuous corrections, reducing bias and better capturing flow variability over time. However, noisy data can reduce model performance if not balanced with data quality, as seen in the Congo Basin at Bangui, where Qmultispec's higher temporal resolution introduced noise into the model. High-quality data like Qalti, which has lower uncertainty, consistently reduces bias and improves model accuracy, though its limited availability restricts the frequency of model updates. Spatial data density is equally important, particularly in complex river basins like the Congo, where major tributaries play a crucial role in the overall discharge. Insufficient spatial coverage can result in errors in basin-wide simulations, whereas better station coverage in regions like the Niger Basin has led to more consistent improvements.

Looking ahead, Phase 2 of the CCI Discharge project presents ~~significant opportunities for improvement. The focus will shift to assessing how enhanced space-time sampling and uncertainty quantification influence the performance of data assimilation~~an opportunity to build on this proof-of-concept by expanding both the scope and methodological depth of data assimilation experiments. In particular, this next phase will investigate how the integration of CCI products with other available satellite observations can enhance hydrological modeling by improving spatial coverage and reducing uncertainty. By relying solely on CCI products in this study, we were able to isolate the specific contributions of long-term (20 years), high-temporal resolution discharge and WSE data. Future work will assess how these products interact with other data sources in a multi-sensor assimilation framework. In future research, we also plan to incorporate additional spatially distributed observations, especially in regions lacking in-situ stations, to enhance the localization process and improve model performance. The assimilation of combined WSE and discharge products will also be explored more systematically, especially in regions where spatial coverage is limited. By leveraging the spatial availability of dH and the physical consistency of Q, this combined approach is expected to densify the network of assimilated data, thereby enhancing the performance of models such as CTRIP and MGB. This phase will also incorporate outlier detection and combined data assimilation methods for both discharge and dH in order to densify the spatial coverage. By leveraging the high spatial coverage of dH and the direct relevance of Q, these combined

approaches are expected to enhance models accuracy like CTRIP, especially in regions with low observation density. ~~or the MGBmodel~~For MGB, challenges may arise with ~~certain rating curves, making dH less suitable for assimilation . However, in areas where~~ dH assimilation when simulated and observed rating curves ~~align, the combined assimilation of these datasets could prove beneficial~~diverge significantly; however, in areas where these align well, combining Q and dH assimilation could offer complementary benefits. Additional experiments will be conducted using newly developed datasets for large scale hydrological models, CTRIP and MGB, assessing the impact of combined assimilation on hydrological simulation.

To further explore the interaction between model structure and assimilated variables, future work will examine the behavior of routing reservoirs in MGB and relevant routing parameters in CTRIP. A seasonal analysis of assimilation performance could also help clarify the respective benefits of the different CCI products under different hydrological regimes.

Furthermore, the integration of SWOT (Surface Water and Ocean Topography) satellite data ~~will~~ offers distinct advantages for enhancing models accuracy through its detailed measurements of water surface slope~~, further reducing uncertainties in discharge predictions~~.The inclusion of remote sensing data such as river width and slope could enable joint state-parameter estimation, offering a more complete assimilation framework. These advantages, combined with the previously discussed improvements in space-time sampling and refined uncertainty quantification, will enable models to better represent critical parameters such as slope. This synergy is expected to significantly reduce uncertainties in discharge predictions and improve the overall performance of the models in simulating river discharge and water storage dynamics.

On the data assimilation side, future research should also evaluate the role of ensemble inflation and outlier handling strategies. While in this study, high-flow outliers were naturally down-weighted by the EnKF due to large observational errors, the impact of low-flow outliers remains less understood and deserves further investigation. A dedicated sensitivity analysis would help assess how the EnKF processes extreme values across different flow regimes and whether adjusted inflation settings could improve filter robustness.

Future improvements in data assimilation schemes will be crucial for further enhancing model performance, with one promising approach being the implementation of dynamic localization distances in models like CTRIP. This innovation will enable models to adapt to both natural variability and anthropogenic influences, such as the effects of dams and irrigation on river systems. By incorporating these dynamic localization techniques, models will be better equipped to account for changes in hydrological processes, thereby improving the reliability of hydrological forecasts.

As models continue to evolve, namely in improving parameterization or in integrating new processes (like evaporation over the Niger Inner Delta for the CTRIP model), the focus will be on refining data assimilation schemes to maximize the benefits of satellite data. The introduction of smoother methods, especially in Kalman filter-based systems, could mitigate the hashed effects observed in dH assimilation, ensuring more accurate corrections. Such methods could help refining corrections where dH assimilation currently leads to noisy or unstable updates, particularly during discharge assimilation where residual hashed effects remain. These advancements, combined with SWOT data integration, will address current gaps in data coverage and enhance the simulation of climate-impacted and human-modified river systems.

Data availability. The CCI-Discharge datasets are available at the following link: https://climate.esa.int/en/projects/river-discharge/ ("Data" section). The Product User Guides for each product are available in the "Key Document" section.

Author contributions. MS, GN, VP, and SM conceived the research design and experimental setup. MS and GN processed the data, ran the experiments, processed the results, and analyzed the findings. VP, SM, and KV assisted with data assimilation tools setup (SM and KV developed/improved HyDAS for CTRIP, and VP developed HYFAA in MGB) and contributed to the discussions. MS merged the findings of both models and wrote the initial draft, with input from GN, SM, and VP. CA, SB, and AA reviewed the paper and provided valuable insights. All authors contributed to the final version of the paper.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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References

Andersen, I. and Golitzen, K. G. (Eds.). (2005). *The Niger river basin: A vision for sustainable management*. World Bank Publications.

Paiva, R. C. D., Collischonn, W., and Bonnet, M. P. (2013). On the sources of hydrological prediction uncertainty in the Amazon. Hydrological Processes, 27(26), 4103-4110.

Siqueira, V. A., Paiva, R. C. D., and Collischonn, W. (2018). Flood forecasting and streamflow simulation using global hydrological information in the Amazon basin. Journal of Hydrology, 564, 743-757.

Fleischmann, A. S., Paiva, R. C. D., Siqueira, V. A., Pontes, P. R. M., and Fan, F. M. (2020). Large-scale hydrological and hydrodynamic modeling of the Amazon River basin. Water Resources Research, 56(1), e2019WR026086.

Biancamaria, S., ~~et al~~Blumstein, D., Tourian, M. J., Darrozes, J., Frappart, F., Paris, A., Grusson, Y. (2024). Water ~~Surface Elevation Time Series Derived from Multiple Nadir Altimetry Missions: A Long-Term Dataset for Hydrological Applications~~surface elevation time series derived from multiple nadir altimetry missions: A long-term dataset for hydrological applications. *Hydrology and Earth System Sciences*, In press.

Cassé, C., ~~et al~~Gosset, M., Vischel, T., Panthou, G., Quantin, G., Tanimoun, B. A. (2015). Modeling of the Congo River basin hydrology: The CRBH model – Version 1.0. ~~*Geoscientific Model Development, 8*(8), 2315–2333. https://doi. org/10.5194/gmd-8-2315-2015~~ *Geoscientific Model Development*, *8*(8), 2315–2333. https://doi.org/10.5194/gmd-8-2315-2015

Collischonn, W., et al. (2007). Development of the MGB-IPH model for large-scale hydrological and hydrodynamic modeling: Application to the Amazon basin. *Hydrological Processes*, 21(1), 114–131.

Decharme, B., Boone, A., Biancamaria, S., et al., 2019. Hydrological modeling at continental scale: The ISBA-CTRIP model applied to the European continent. *Geoscientific Model Development*, 12(3), 1009–1034.

Decharme, B., Delire, C., Minvielle, M., Colin, J., Vergnes, J. P., Alias, A., ... and Voldoire, A. (2019). Recent changes in the ISBA-CTRIP land surface system for use in the CNRM-CM6 climate model and in global off-line hydrological applications. *Journal of Advances in Modeling Earth Systems*, 11(5), 1207-1252.

Emery, C., Boone, A., Biancamaria, S., et al., 2017. Assimilation of satellite-derived data into large-scale hydrological models: Impacts on river discharge. *Journal of Hydrology*, 555, 420–437.

Emery, C., Oubanas, D., Boone, A., et al., 2018. Using satellite altimetry to enhance the simulation of river discharge and storage. *Hydrology and Earth System Sciences*, 22(4), 3029–3045.

Emery, C. M., Biancamaria, S., Boone, A., Ricci, S., Rochoux, M. C., Pedinotti, V., and David, C. H. (2020a). Assimilation of wide-swath altimetry water elevation anomalies to correct large-scale river routing model parameters. *Hydrology and Earth System Sciences*, 24(5), 2207–2233.

Emery, C. M., Paris, A., Biancamaria, S., Boone, A., Calmant, S., Garambois, P. A., ... and David, C. H. (2020b). Discharge estimation via assimilation of multisatellite-based discharge products: Case study over the Amazon Basin. *IEEE Geoscience and Remote Sensing Letters*, 19, 1–5.

Emery, C., Boone, A., Oubanas, D., et al., 2020. How to combine satellite altimetry and hydrological models for flood forecasting. *Remote Sensing of Environment*, 241, 111761.

Evensen, G. (2009). *Data Assimilation: The Ensemble Kalman Filter*. Springer, Berlin.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development, 9(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

European Space Agency (2023): Algorithm Theoretical Basis Document (ATBD) for River Discharge, CCI+ Phase 1. Available at: https://climate.esa.int/media/documents/CCI-Discharge-0012-ATBD-Discharge.pdf

Fleischmann, A. S., et al. (2018). Modeling hydrologic and hydrodynamic processes in large floodplain rivers: the Amazon Basin. *Water Resources Research*, 54(8), 6008–6032.

Gal, L., et al. (2024). Long-Term River Discharge Time Series from Altimetry and Multispectral Imagery: Methods and Applications. *Remote Sensing of Environment*, In press.

Getirana, A., Boone, A., Yamazaki, D., et al., 2017. Comparing satellite altimetry data assimilation techniques for flood forecasting: A case study for the Amazon basin. *Journal of Hydrology*, 552, 783–796.

Girotto, M., Reichle, R. H., Zaitchik, B. F., et al., 2016. Assimilation of GRACE terrestrial water storage data into a land surface model: Evaluation of benefits and limitations. *Hydrology and Earth System Sciences*, 20(3), 705–719.

Huffman, G. J., et al. (2018). Global Precipitation Measurement (GPM) IMERG early precipitation L3 1 month 0.1 degree x 0.1 degree V06. *NASA Goddard Space Flight Center*.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*, 82(1), 35–45.

Kitambo, W., et al. (2022). Impacts of Climate Variability on Water Resources in the Congo River Basin. *Journal of Water Resources and Climate*, 58, 220–236.

Laraque, A., et al. (2013). The Congo River, a case of hydrological stability in Central Africa. *Journal of Hydrology*, 496, 1–13.

Munier, S., Aires, F., Calmant, S., et al. (2015). Assimilation of Satellite Altimetry to Improve the Spatio-Temporal Water Storage Variations in Global Hydrological Models. *Hydrology and Earth System Sciences*, 19, 4149–4171. https://doi.org/10.5194/hess-19-4149-2015

Munier, S. and Decharme, B. (2022). Evaluation of river network models over continental domains. *Journal of Hydrology*, 600, 126516.

New, M., et al. (2002). A high-resolution data set of surface climate over global land areas. *Climate Research*, 21(1), 1–25.

Oubanas, D., Boone, A., Biancamaria, S., et al., 2018. Data assimilation of altimetry for flood modeling: Application to the Niger River Basin. *Hydrology and Earth System Sciences*, 22(4), 2217–2236.

Paiva, R. C. M., Collischonn, W., Bonnet, M.-P., et al., 2013. Large-scale hydrological and hydrodynamic modeling of the Amazon Basin using MGB-IPH model. *Hydrology and Earth System Sciences*, 17(7), 2753–2773.

Pedinotti, V., Boone, A., Decharme, B., et al., 2014. Impact of satellite-based surface water storage and discharge assimilation on the hydrological cycle in the Niger basin. *Journal of Geophysical Research: Atmospheres*, 119(15), 8231–8255.

Pontes, P. R. M., et al. (2017). A two-way coupled hydrological-hydrodynamic modeling framework with MGB and TELEMAC modeling system. *Environmental Modelling & Software*, 91, 77–97.

Revel, M., et al. (2019). Data assimilation for hydrological modeling: Evaluation of assimilation schemes for river discharge and water surface elevation. *Water Resources Research*, 55(9), 7171–7195.

Spencer, R., et al. (2016). Rainfall and flow variability in the Congo River Basin. *Water Resources Research*, 52(9), 7181–7194.

Ushio, T., et al. (2003). A combined microwave and infrared radiometer approach for daily precipitation estimation over the globe. *Journal of Geophysical Research*, 108(D3), 4699.

Vergnes, J. P. and Decharme, B. (2012). A simple groundwater scheme for hydrological and climate applications: Description and offline evaluation over France. *Journal of Hydrometeorology*, 13(4), 1149–1171.

Wongchuig-Correa, S., Boone, A., Oubanas, D., et al., 2020. Potential of SWOT data assimilation to improve hydrological modeling of large rivers. *Remote Sensing of Environment*, 236, 111507.

Yamazaki, D., et al. (2019). MERIT Hydro: A high-resolution global hydrography map based on latest topography datasets. *Water Resources Research*, 55(6), 5053–5073.

Youssoufa Bele, M., et al. (2013). Local communities' vulnerability to climate change and adaptation strategies in the Congo Basin forests of Cameroon. *Mitigation and Adaptation Strategies for Global Change*, 18, 757–771.

Gal, L., Tarpanelli, A., Filippucci, P. (2024). D3. River Discharge (Q) from Altimeters and Ancillary data, multispectral images and data combination - Algorithm Theoretical Basis Document (ATBD). CCI River Discharge precursor project technical document, CCI-Discharge-0012-ATBD, Issue 1.2 (available at https://climate.esa.int/fr/projects/river-discharge/).

Kouraev, A. V., Zakharova, E. A., Samain, O., Mognard, N. M., and Cazenave, A. (2004). Ob' river discharge from TOPEX/Poseidon satellite altimetry (1992–2002). Remote sensing of environment, 93(1-2), 238-245.

Paris, A., Dias de Paiva, R., Santos da Silva, J., Medeiros Moreira, D., Calmant, S., Garambois, P. A., and Seyler, F. (2016). Stage-discharge rating curves based on satellite altimetry and modeled discharge in the Amazon basin. Water Resources Research, 52(5), 3787-3814.

Zakharova, E., Nielsen, K., Kamenev, G., and Kouraev, A. (2020). River discharge estimation from radar altimetry: Assessment of satellite performance, river scales and methods. Journal of Hydrology, 583, 124561.

Zakharova, E., Agafonova, S., Duguay, C., Frolova, N., and Kouraev, A. (2021). River ice phenology and thickness from satellite altimetry: potential for ice bridge road operation and climate studies. The Cryosphere, 15(12), 5387-5407.

Tourian, M. J., Sneeuw, N., and Bárdossy, A. (2013). A quantile function approach to discharge estimation from satellite altimetry (ENVISAT). Water Resources Research, 49(7), 4174-4186.

Tourian, M. J., Schwatke, C., and Sneeuw, N. (2017). River discharge estimation at daily resolution from satellite altimetry over an entire river basin. Journal of Hydrology, 546, 230-247.

Gal, L., Filippucci, P., and Biancamaria, S. (2024). D10. Product User Guide (PUG). CCI River Discharge precursor project technical document, $D10_RD - CCI_0023_PUG$, Issue 2.0 (available at https://climate.esa.int/fr/projects/river-discharge/).

Biancamaria, S., Gal, L., Zakharova, E., Kitambo, B., and Vayre, M. (2024). D3. Water Surface Elevation (WSE) Algorithm Theoretical Basis Document (ATBD). CCI River Discharge precursor project technical document, Issue 1.2 (available at $https://climate.esa.int/media/documents/CCI-Discharge-0009-ATBD-WSE_v1-2.pdf$).

Biancamaria, S., Frappart, F., Leleu, A.-S., Marieu, V., Blumstein, D., Desjonquères, J.-D., Boy, F., Sottolichio, A., and Valle-Levinson, A. (2017). Satellite radar altimetry water elevations performance over a 200 m wide river: evaluation over the Garonne River. Advances in Space Research, 59(1), 128-146. http://dx.doi.org/10.1016/j.asr.2016.10.008.

Tarpanelli, A., Brocca, L., Lacava, T., Melone, F., Moramarco, T., Faruolo, M., and Pergola, N. (2013). Toward the estimation of river discharge variations using MODIS data in ungauged basins. Remote Sensing of Environment, 136, 47–55. doi:10.1016/j.rse.2013.04.010.

Filippucci, P., Brocca, L., Bonafoni, S., Saltalippi, C., Wagner, W., and Tarpanelli, A. (2022). Sentinel-2 high-resolution data for river discharge monitoring. Remote Sensing of Environment, 281, 113255. doi:10.1016/j.rse.2022.113255.

~~Filippucci~~

Collischonn, W., Allasia, D., Silva, B. C., & Tucci, C. E. M. (2007). The MGB-IPH model for large-scale rainfall–runoff modelling. *Hydrological Sciences Journal*, *52*(5), 878–895.

Pontes, B., Monzo, P., ~~Sahoo~~Gauthier, N. C., & Salbreux, G. (2017). Membrane tension controls adhesion positioning at the leading edge of cells. *Journal of Cell Biology*, *216*(9), 2959–2977.

Clark, M. P., Slater, A. G., Rupp, D. ~~P~~E., Woods, R. A., Vrugt, J. A., Gupta, H. V., Wagener, T., & Hay, L. E. (2008). Framework for Understanding Structural Errors (FUSE): A modular framework to diagnose differences between hydrological models. *Water Resources Research*, *44*(W00B02). https://doi.org/10.1029/2007WR006735

Michailovsky, C. I. B., McEnnis, S., Berry, P. A. M., Smith, R., & Bauer-Gottwein, P. (2013). River monitoring from satellite radar altimetry in the Zambezi River basin. *Hydrology and Earth System Sciences*, *16*(7), 2181–2192. https://doi.org/10.5194/hess-16-2181-2012

Wongchuig, C., Pedinotti, V., Boone, A., Calmant, S., Biancamaria, S., Decharme, B., & Frappart, F. (2019). Assimilation of SWOT simulated observations in a hydrological model of the Amazon Basin. *Remote Sensing*, ~~and~~ *11*(17), 1966. https://doi.org/10.3390/rs11171966

Feng, D., Beighley, R. E., & Famiglietti, J. S. (2021). Calibration and validation of hydrological models using transformed satellite altimetry data. *Journal of Hydrology*, *603*, 126979. https://doi.org/10.1016/j.jhydrol.2021.126979

Revel, M., Munier, S., Boone, A., Pedinotti, V., Biancamaria, S., Calmant, S., & Frappart, F. (2023). Improving discharge simulation by assimilating transformed water surface elevation observations using an ensemble Kalman filter. *Hydrology and Earth System Sciences*, *27*, 345–365. https://doi.org/10.5194/hess-27-345-2023

Wongchuig, C., Pedinotti, V., Boone, A., Biancamaria, S., & Frappart, F. (2024). A multi-observation local ensemble Kalman filter for assimilating SWOT hydrological variables. *Remote Sensing of Environment*, *312*, 114918. https://doi.org/10.1016/j.rse.2024.114918

Tourian, M. J., Papa, F., Elmi, O., Tarpanelli, A.~~(in preparation). Estimating River Discharge from Multispectral Sensors: A Near-Daily Dataset from 2000 Onwards for Climate Change Analysis. To be submitted to Remote Sensing of Environment~~, Biancamaria, S., Becker, M., Aires, F., et al. (2023). Current availability and distribution of Congo Basin's freshwater resources. *Communications Earth Environment*, **4**, 174. https://doi.org/10.1038/s43247-023-00836-z

Munier, S., Boone, A., Biancamaria, S., & Le Moigne, P. (2022). Assimilation of SWOT discharge versus water level into CTRIP-12D over the Congo Basin. In *Proceedings of the IAHS Scientific Assembly 2022*, Montpellier, France, 29 May–3 June 2022. https://doi.org/10.5194/iahs2022-657

Szczypta, C., Decharme, B., Carrer, D., Calvet, J.-C., Lafont, S., Somot, S., Faroux, S., & Martin, E. (2012). Impact of precipitation and land biophysical variables on the simulated discharge of European and Mediterranean rivers. *Hydrology and Earth System Sciences*, **16**(9), 3351–3370. https://doi.org/10.5194/hess-16-3351-2012

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., Van De Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., & Vitart, F. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, **137**(656), 553–597. https://doi.org/10.1002/qj.828

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., & Thépaut, J. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, **146**(730), 1999–2049. https://doi.org/10.1002/qj.3803

Kubota, T., Aonashi, K., Ushio, T., Shige, S., Takayabu, Y. N., Kachi, M., & Oki, R. (2020). Global Satellite Mapping of Precipitation (GSMaP) products in the GPM era. In *Satellite Precipitation Measurement* (pp. 355–373). Springer.

Gosset, M., Dibi-Anoh, P. A., Schumann, G., Hostache, R., Paris, A., Zahiri, E.-P., Kacou, M., & Gal, L. (2023). Hydrometeorological Extreme Events in Africa: The Role of Satellite Observations for Monitoring Pluvial and Fluvial Flood Risk. *Surveys in Geophysics*, **44**, 197–223.

Peterson, P., Heim, R., Kaiser, D., & Kunkel, K. (2015). Climate Hazards InfraRed Precipitation with Station data (CHIRPS). *Climate Data Guide*.