Discharge Estimation via Assimilation of Multisatellite-Based Discharge Products: Case Study Over the Amazon Basin

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Abstract

River flows are an essential component of the water cycle and are directly accessible for human consumption and activities. River water flux (i.e. river discharge) can be measured locally at in situ gauges, but can also be estimated at larger scales with River Routing Models. However, the number of in situ gauges is declining worldwide while emerging river-related products from satellites are becoming more available. Especially, discharge products based on satellite altimetry water elevations are emerging. These altimetry missions provide different spatial and temporal coverage and may not provide the same amount of information. In this study, discharge products from two satellite altimetry missions (ENVISAT and JASON-2), were assimilated into the large-scale hydrologic model ISBA-CTRIP using an Ensemble Kalman filter, to correct the simulated discharge. This work investigates whether it is better to assimilate products with a dense spatial coverage but a lower temporal sampling (ENVISAT) or the opposite (JASON-2). Three experiments have been performed: the first two assimilated each product separately, the last one assimilated the combined product. The openloop normalized Root Mean Square Error evaluated against in situ discharge (RMSEn) is 69%. RMSEn is decreased for all experiments. Specifically, it is slightly lower when assimilating ENVISAT-based discharge product (51%) than JASON-2 product (53%), as the ENVISAT-based product spatial coverage is denser. Best results are obtained when both products are assimilated (RMSEn=49%). These results are very encouraging and could be improved when the future Surface Water and Ocean Topography (SWOT) wide swath altimetry mission discharge product will be available.

Index Terms

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I. Introduction

For the last two decades, hydrologic remotely-sensed data has increased considerably [1], leading to a numerous studies dedicated to merging this data with hydrologic models using Data Assimilation (DA) e.g. [2]. In river hydrology, an essential variable of interest is the river discharge as it quantifies the water fluxes over the continental surface and is crucial for closing the continental water budget. Thus, many studies have focused on correcting the simulated river discharge with data assimilation to generate improved and more realistic estimations of river flows. These studies used either in situ measurements e.g. [3] or remotely-sensed data from past/current [4] and future [5] missions via Observation System Simulation Experiments.

It is still impossible to directly measure discharge from space. Nonetheless, remote-sensed surface elevation products are provided by nadir altimetry missions. Then, it is possible to convert them into an equivalent discharge using rating curves built from in situ discharges [6] or simulated discharges from models [7].

The coming Surface Water and Ocean Topography (SWOT) satellite mission, scheduled for launch in 2021, will provide measurements of water surface elevations with a global coverage [8]. It stands out with its wide-swath instrument [9] in contrast with current nadir measurements. Also, spatially-distributed discharge products based on SWOT observables are currently in development [10]–[12].

However, these products are not yet available. Nonetheless, even if their spatial and temporal coverage is more limited, discharge products from nadir altimetry missions have emerged and can be already used for real-data applications [4].

The objective of this study is to assess the value of such nadir altimetry discharge products for large-scale hydrological model applications. The data assimilation method is tested over the Amazon basin. By investigating the impact of different satellite spatial/temporal coverage on estimated discharge correction, we wish to answer the following question: is it better to assimilate a product with a dense spatial coverage (implying a coarse temporal resolution) or rather assimilate a product with a high temporal repeat cycle (meaning a coarse spatial resolution)? This question is explored by assimilating the discharge from the ENVISAT and JASON-2 nadir altimeters (whose spatial/temporal coverage are opposite) into the large-scale hydrologic model ISBA-CTRIP.

II. Method

A. Hydrological model

ISBA-CTRIP [13] is a large scale hydrological model defined globally at a resolution of $0.5° \times 0.5°$. ISBA [14] is a classic Land Surface Model (LSM): at each grid cell, ISBA computes the water and energy budget given the input meteorological forcing and the soil and vegetation properties. More particularly, it gives a diagnostic of the surface runoff and gravitational drainage that are both used as input to the CTRIP [13] River Routing Model (RRM). CTRIP is dedicated to the lateral transfer of water from one cell to the other, up to the continent-ocean interface following a river network. The CTRIP version used in this study consists in a system of three water reservoirs: the surface reservoir, S, representing the river, the groundwater reservoir, G, and the floodplain reservoir, F.

In each grid cell, the river discharge is defined as the water flow leaving the cell and is estimated from the river storage and a space and time-varying flow velocity based on the Manning formula [15]. In the current study, the model is run in offline mode using the external atmospheric data from the Global Soil Wetness Projet 3 (GSWP3, http://hydro.iis.u-tokyo.ac.jp/GSWP3) over the Amazon river basin.

B. *Remotely-sensed measurements*

1) Satellite-based discharge virtual stations: The remotely-sensed discharge products used in this study are derived from water surface elevations measured by both the ENVISAT (ENV) Radar Altimeter-2 and the JASON-2 (J2) Poseidon-3 altimeter instruments at Virtual Stations (VS). VS are computed where the altimeter track crosses the river stream. The water surface elevations measured over the Amazon basin were initially generated by [16]. Both products have vertical precisions ranging from 12 cm to 30-40 cm (related to errors the instrument design, signal corrections and the surrounding topography).

The rating curves used to convert the water surface elevations into discharge were built and validated by [7] using the discharge from the calibrated MGB hydraulic-hydrologic model [17]. The ENV nominal orbit has a 35 days repeat period and an 80 km inter-track distance at the equator while J2 has a shorter repeat period of 10 days and a wider inter-track distance at the equator of 315 km. ENV and J2 operated together from June 2008 when J2 was launched to October 2010 when ENV orbit was changed.

Each VS is coupled to a model grid cell to compare the altimetry-based dicharges to the simulated ones. Mostly, the grid cell containing the VS is selected. However, at some locations, the CTRIP pixel that contains the VS does not correspond to the river reach observed by the altimeter, because of the coarse model resolution. In these cases, the closest grid cell depicting the same tributary as the VS is selected. This process allowed us to associate most of the VS to a unique CTRIP cell. Indeed, some VS were located on tributaries that are too small to be represented on the CTRIP river network. In this case, the VS were not included in the study. Also, some VS could be located within the same CTRIP cell. In the first study in [4], when several VS were associated to the same grid cell, only the VS with the largest drainage area was conserved. Now, in the present study, it was decided to keep all of the VS associated to a same grid cell. We assume that all VS can be consistently compared to the simulated discharge, regardless of their remoteness to the grid cell output. Indeed, the ”model coarseness error” remains large compared to errors from neglecting river flow propagation at subgrid-scale between the VS and the pixel center. The advantage is that we avoid losing any information from the satellite products while also increasing the number of points in the discharge time series. Therefore, over all 767 ENV and 117 J2 VS initially available, 665 ENV and 115 J2 VS were actually included in the study.

2) Merging satellite-based discharge time series: Even if a VS can be associated to the same CTRIP equivalent river reach (i.e. same grid cell), they are located at different points along the river stem or can even be positioned on close tributaries with a very different hydrologic regime. Therefore, a specific treatment is applied to merge discharge time series into one coherent time series. The resulting VS will be hereafter denoted as SVS for Super Virtual Stations.

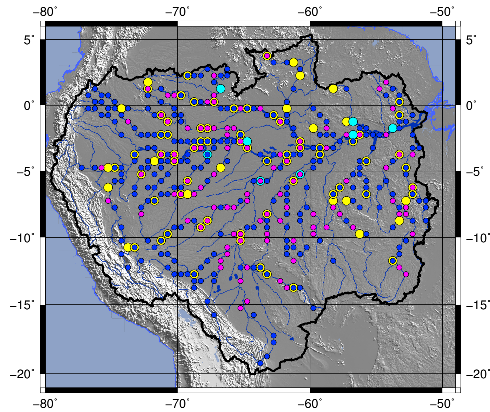

Fig. 1. Virtual stations network over the Amazon basin: ENVISAT VS (small blue markers), ENVISAT SVS (small magenta markers), JASON-2 VS (large yellow markers) and JASON-2 SVS (large cyan markers).

First, in each cell with a potential SVS, the climatology (monthly discharge averaged over all years of data) of all VS is estimated and compared to a chosen reference climatology. The reference climatology is chosen as the VS with the smallest error budget in [7]. Among the set of VS, only those highly coherent with the reference VS are kept (see Figure S1 of the supplementary). This steps allows the elimination of all of the VS that are not on the cell main stem but also VS with different dynamic.

Then, another processing is applied if several VS provide data for the same day. First, all available VS time series are interpolated daily to give a range of observed discharge values. Then, at a day with any available observed discharge, the merged discharge is the mean value within the range of possible values. Ultimately, at the ISBA-CTRIP resolution, the ENV dataset contains 362 VS+SVS, the J2 dataset contains 91 VS+SVS and the combined-ENV-J2 dataset is composed of 386 VS+SVS. Figure 1 displays the location of all of the VS and SVS over the Amazon basin.

3) Satellite-based discharge errors: The observation error model was defined as white noise whose standard deviation is a fraction (η^o) of the instantaneous discharge value. For simple VS, the fraction, η^o, is station-dependent but constant in time: see [7] and [4] for more details. At SVS, the η^o varies in time due to the merging of several VS together. On a day where a merged discharge is generated, the ratio of the discrepancy between the minimum and maximum interpolated discharge compared to the resulting merged discharge is estimated. Then, it was arbitrarily chosen to add 50% of this ratio to the reference fraction, η^o. Consequently, SVS error is generally larger than VS error. This approach was chosen to take into consideration potential large gaps between some VS time series that have been merged.

An example of the full merging procedure is illustrated in Figure S1 of the supplementary material.

C. Data assimilation algorithm

An Ensemble Kalman Filter (EnKF, [18]) with a static localization procedure as in [4] is used. The localization is applied to the control error covariance matrices such that, for a given grid cell, only VS within a fixed radius

- based on the mean flow velocity and direction - are assimilated. The EnKF is an extension of the classical Kalman Filter (KF) for models with slightly nonlinear dynamics. It overcomes the linear assumption of the KF by stochastically estimating the error covariance matrices from an ensemble of model runs. In the present study, the EnKF is used to assimilate remote-sensed discharges (see Section II-B) to correct the discharge estimates of the large-scale hydrological model ISBA-CTRIP (see Section II-A). The localization procedure has been inserted to deal with the scale difference between the model and the observations..

D. Experimental design

Three experiments have been conducted. The first assimilates the ENV dataset, the second assimilates the J2 dataset and the last experiment assimilates the combined ENV-J2 dataset. Each experiment starts on January 1st, 2009, and lasts for an entire year. Finally, the assimilation is performed using an ensemble with 100 members.

For each experiment, the assimilation performance is evaluated by calculating the normalized Root Mean Square Error (RMSEn) on daily discharges, following:

$$\text{RMSEn}_i^{*,\dagger} = \frac{100}{\overline{Q_{i,\bullet}^{\dagger}}} \times \sqrt{\frac{1}{K^{\dagger}} \sum_{k=1}^{K^{\dagger}} \left(Q_{i,k}^{*} - Q_{i,k}^{\dagger} \right)^2} \quad \left[\text{m}^3.s^{-1}\right], \tag{1}$$

where $K^{\dagger}$ represents the total number of available observed discharge values $Q_i^{\dagger}$ at the $i-$th VS and $\overline{Q_{i,\bullet}^{\dagger}}$ corresponds to the time-averaged $Q_{i,k}^{\dagger}$. The "$*$" upperscript stands for the discharge time-series to be evaluated while the "†" stands for the reference discharge.

Also, to evaluate the performance over the entire study domain, a global RMSEn ($\text{RMSEn}_{\text{global}}$) is determined as:

$$\text{RMSEn}_{\text{global}}^{*,\dagger} = 100 \times \frac{1}{\left(\sum_{i=1}^{I^{\dagger}} w_i\right)} \sum_{i=1}^{I^{\dagger}} w_i.\text{RMSEn}_i^{\dagger}, \quad [-], \tag{2}$$

where $I^{\dagger}$ denotes the total number of stations and w_i is a weighting constant depending on the maximal discharge at the i-th station ($\max_k \left(Q_{i,.}^{\dagger}\right)$) and the maximal discharge over the basin ($\max_{i,k}\left(Q_{.,.}^{\dagger}\right)$) such that:

$$w_i = \frac{\log_{10}\left[\max_k \left(Q_{i,.}^{\dagger}\right)\right]}{\log_{10}\left[\max_{i,k}\left(Q_{.,.}^{\dagger}\right)\right]}. \tag{3}$$

This weighting gives more importance to the main stem and cells containing the largest tributaries into the global statistics.

E. Validation data

To evaluate the performance of the assimilation independently from the assimilated remote-sensed product, we retrieved daily discharge time series from 120 in situ stations over the Amazon basin from the Brazilian water agency (Agencia Nacional de Agua, hidroweb.ana.gov.br). However, over the study period, only 81 stations have available data. Also, among those 81 stations, 56 correspond to VS (ENV or J2) while the remaining 25 are never observed by any remote-sensed product.

TABLE I

GLOBAL RMSEN (SEE EQ. 2) WITH RESPECT TO THE IN SITU DISCHARGE FOR THE OPENLOOP RUN AND THE MEAN ANALYSIS RUN FROM ALL THREE EXPERIMENTS

	Openloop	Analysis from assimilating		
		ENV	J2	ENV+J2
$\text{RMSEn}_{\text{global}}$	68.96	51.56	53.72	49.53

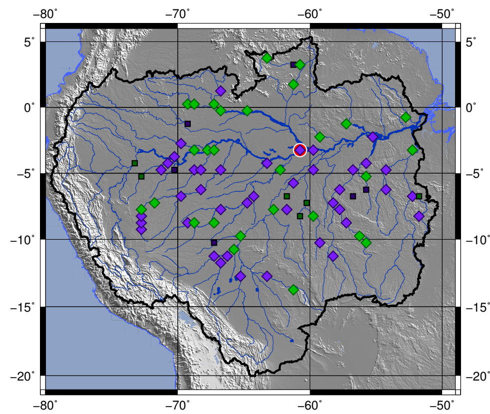

Fig. 2. Summary of assimilation results over the available in situ gauges. *Markers color is associated with experiments 1-2*: (purple) the ENV product assimilation performed better than the J2, (green) the J2 product assimilation performed better than the ENV product. *Markers shape is associated with experiment 3*: (large diamonds) the assimilation improved the simulated discharge, (small squares) the assimilation degraded the simulated discharge. The red circle indicates the individual Manacapuru in situ gauge.

III. RESULTS

A. General results

The global RMSEn defined in Eq. 2 are given in Table I. The assimilation is able to reduce the openloop RMSEn of 69% for all experiments to a RMSEn of 51%, 53% and 49% with the assimilation of the ENV-only, J2-only and combined product respectively. More detailed results maps and the resulting RMSEn at each VS for all experiments are given in Figure S2-3 and Table S4 of the supplementary material.

To interpret these results, we considered all products to be equivalently accurate (see Table S4, column 4). Thus, the assimilation performances are independent from the products relative accuracy. As it should be expected, the assimilation of the product with the best spatio-temporal coverage (i.e. the ENV-J2 product) gave the best assimilation results with an analysis RMSEn of 49%. Examining the analysis RMSEn, it appears that the more spatially dense the coverage of the product is, the better the analysis RMSEn are. These results suggest that, over the Amazon river basin, better results are obtained when the assimilated product has a denser spatial coverage. This assumption is further discussed in the coming sections.

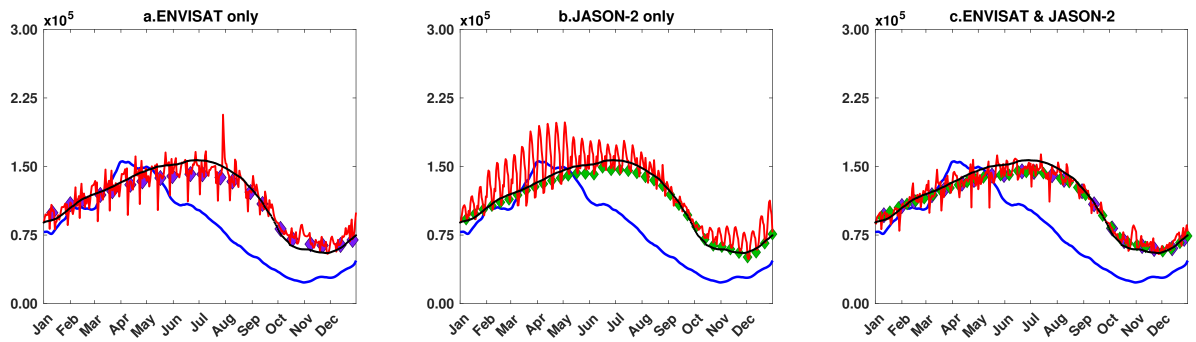

Fig. 3. Manacapuru station ensemble mean analysis discharge (red line, RMSEn=10% (a), =17% (b), =8% (c)) compared, over the year 2009, to the free run discharge (blue line, RMSEn=36%), the measured gauge discharges (black dots) and the assimilated remote-sensed product: (a) ENV (purple markers, RMSEn=8%), (b) J2 (green markers, RMSEn=5%), (c) combined ENV-J2 (ENV-issued purple markers and J2-issued green markers, RMSEn=6%). For each panel, the x-axis represents time (in days) and the y-axis represents discharge (in $m^3.s^{-1}$).

B. Assimilation of individual products

The markers color in Figure 2 is used to indicate which individual product performs best for each in situ gauge (whether the gauge had an associated VS or not): the ENV product performed better over 47 in situ gauges, including 13 gauges with no associated VS (purple markers in Figure 2) while the J2 product performed better over the other 34, including 12 gauges with no associated VS (green markers in Figure 2). These results depend on river flow dynamic. Over large-scale basin with strong and smooth seasonal cycle such as the Amazon river, observations with dense spatial cover might be more appropriate than observation with denser temporal. But the differences between assimilating ENV- or J2-based discharge products remain small.

C. Results at an individual gauge

Figure 3 displays the assimilation results at the Manacapuru in situ gauge (red circle in Figure 2), the most downstream gauge on the Amazon main stem with both an ENV and J2 SVS.

In all cases, the analysis discharge (red line) follows the observed seasonal cycle better than the openloop discharge but it is characterized by oscillations at the frequency of the assimilated observations. These oscillations are observed everywhere. The denser the assimilated product, the smaller the oscillation amplitude, as the model is constrained more often by neighboring observations in between assimilation times. However, the information from those nearby VS is sometimes spuriously spread - at the assimilation time - given the model correlations between adjacent grid cells; and propagated and amplified - at subsequent times - given the river propagation model (see Figure S5). They attest then of the limitations of our localization approach.

D. Assimilation of the merged product

Markers shape in Figure 2 details the performance of the combined ENV-J2 product. Out of the 81 available in situ gauges, 69 (85% of all in situ gauges) showed an improvement of the simulated discharge after assimilation (large diamond markers) while the remaining 12 were *apparently* degraded (small square markers).

A closer analysis of those 12 gauges showed that, for half of them, the in situ data were unreliable (lots of missing and/or nonphysical data) or the data were inconsistent with the associated remote-sensed data (those cases were already discussed in [7]). Therefore, the evaluation of the assimilation performance at these gauges is irrevelant. For the other half, the updating of the discharge is directly linked to the localization and the impact of nearby VS. Therefore, as discussed in [4], we can hope that a refinement of the localization method will prevent these kind of negative results.

It is worth noting that, as the same algorithm was used to convert both ENV and J2 water surface elevations into discharges, we were able to build a rather consistent combined ENV-J2 product. These results showed that it is possible to merge products from different missions to further improve assimilation performance.

IV. Conclusion

The study shows the possibility to assimilate remotely-sensed discharge products, either from a single mission or from the merging of several missions, into large-scale hydrological model such as ISBA-CTRIP.

The simulated discharge was best corrected when the ENV-J2 product was used, as it presents the best spatial and temporal cover among all products. However, it is worth keeping in mind that both individual products were fairly consistent. The assimilation of individual products also gave good performances. It appeared that the assimilation of the ENV product, with a better spatial coverage, is slightly more effective than the assimilation of the J2 product, with a better temporal sampling. This led us to conclude that the spatial coverage of the assimilated products is the most critical aspect to ensure good assimilation results, at least over the Amazon basin. Yet, this conclusion should be taken sparingly as the performance differences were not that large and the in situ network used to evaluate the was quite sparse. This could also be due to multiple factors, especially: our coarse model spatial resolution ($\sim$50km), the observed hydrological regime (long residence times and strong seasonal cycle) and the VS repeat period (35 days).

Moreover, the basic settings of our approach (notably the static localization method) do not allow to fully take advantage of the VS network coverage. Using the dynamical model and an appropriate travel time, one could propagate in space and time each VS information to grab their real spatial and temporal span (called *identifiability map* in [11]). Such approach would also help reduce the oscillations in the updated discharge.

Finally, in the perspective of the SWOT mission, the products are expected to have a better spatial coverage than the current altimeters as continental surfaces will be observed by two wide swaths of 50 km each with a repeat cycle of 21 days. In the assumption that a consistent discharge product will be produced using SWOT measurements, the assimilation of such product should have a significant contribution to better simulate river discharges globally. Other perspectives also include reviewing the localization method but also refining the coupling and merging procedure by including the river dynamic (as presented by [6]); along with applying this method to other basins with a different size and a different hydrologic regime to asses if the different temporal coverage of ENV and J2 result in larger difference than on the Amazon.

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REFERENCES

[1] D. P. Lettenmaier, D. Alsdorf, J. Dozier, G. J. Huffman, M. Pan, and E. F. Wood, “Inroads or remote sensing into hydrologic science during the wrr era,” *Water Resources Research*, vol. 51, pp. 7309–7342, 2015.

[2] R. H. Reichle, “Data assimilation methods in the earth sciences,” *Advances in Water Resources*, vol. 31, pp. 1411–1418, 2008.

[3] H. K. McMillan, E. O. Hreinsson, M. P. Clark, S. K. Singh, C. Zammit, and M. J. Uddstrom, “Operational hydrological data assimilation with the recursive ensemble kalman filter,” *Hydrology and Earth System Sciences*, vol. 17, pp. 21–38, 2013.

[4] C. M. Emery, A. Paris, S. Biancamaria, A. Boone, S. Calmant, P.-A. Garambois, and J. S. D. Silva, “Large scale hydrological model river storage and discharge correction using satellite altimetry-based discharge product,” *Hydrology and Earth System Sciences*, vol. 22, pp. 2135–2162, 2018.

[5] C. K. Fisher, M. Pan, and E. F. Wood, “Spatiotemporal assimilation/interpolation of discharge records through inverse streamflow routing,” *Hydrology and Earth System Sciences*, vol. in review, 2018.

[6] M. J. Tourian, A. Tarpanelli, O. Elmi, T. Qin, L. Brocca, T. Moramarco, and N. Sneeuw, “Spatiotemporal densification of river water level time series by multimission satellite altimetry,” *Water Resources Research*, vol. 52, pp. 1140–1159, 2016.

[7] A. Paris, R. C. D. Paiva, J. S. D. Silva, D. Moreira, S. Calmant, P.-A. Garambois, W. Collischonn, M.-P. Bonnet, and F. Seyler, “Stage-discharge rating curves based on satellite altimetry and modeled discharge in the amazon basin,” *Water Resources Research*, vol. 52, 2016.

[8] S. Biancamaria, D. P. Lettenmaier, and T. M. Pavelsky, “The swot mission and its capabilities for land hydrology,” *Survey of Geophysics*, vol. 37, p. 307337, 2016.

[9] L. L. Fu, D. Alsdorf, R. Morrow, E. Rodriguez, and N. Mognard, “Swot: the surface water and ocean topography mission: wide-swath altimetric elevation on earth,” Jet Propulsion Laboratory, National Aeronautics and Space Administration, Tech. Rep., 2012.

[10] M. Durand, C. J. Gleason, P. A. Garambois, D. Bjerklie, L. C. Smith, H. Roux, E. Rodriguez, P. D. Bates, T. M. Pavelsky, J. Monnier, X. Chen, G. D. Baldassarre, J.-M. Fiset, N. Flipo, R. P. d. M. Frasson, J. Fulton, N. Goutal, F. Hossain, E. Humphries, J. T. Minear, M. M. Mukolwe, J. C. Neal, S. Ricci, B. F. Sanders, G. Schumann, J. E. Schubert, and L. Vilmin, “An intercomparison of remote sensing river discharge estimation algorithms from measurements of river height, width, and slope,” *Water Resources Research*, vol. 52, p. 45274549, 2016.

[11] P. Brisset, J. Monnier, P.-A. Garambois, and H. Roux, “On the assimilation of altimetric data in 1d saint-venant river flow models,” *Advances in water resources*, vol. 119, pp. 41–59, 2018.

[12] H. Oubanas, I. Gejadze, P. O. Malaterre, M. Durand, R. Wei, R. P. Frasson, and A. Domeneghetti, “Discharge estimation in ungauged basins through variational data assimilation: the potential of the swot mission,” *Water Resources Research*, vol. 54, pp. 2405–2423, 2018.

[13] B. Decharme, D. C., M. Minvielle, C. J., V. J.-P., A. A. S.-M. D., S. R., S. S., and V. A., “Recent changes in the isba-ctrip land surface system for use in cnrm-cm6 climate model and global off-line hydrological applications.” *Journal of Advances in Modeling Earth Systems*, vol. 11, 2019.

[14] J. Noilhan and S. Planton, “A simple parameterization of land surface processes for meteorological models,” *Mon. Wea. Rev.*, vol. 117, pp. 536–549, 1989.

[15] R. Manning, “On the flow of water in open channels and pipes,” *Institution of Civil Engineers of Ireland*, vol. 20, pp. 161–207, 1891.

[16] J. S. D. Silva, S. Calmant, F. Seyler, O. C. R. Filho, G. Cochonneau, and W. J. Mansur, “Water levels in the amazon basin derived from the ers 2 and envisat radar altimetry missions,” *Remote Sensing of Environment*, vol. 114, pp. 2160–2181, 2010.

[17] R. C. D. Paiva, D. C. Buarque, W. Collischonn, M.-P. Bonnet, F. Frappart, S. Calmant, and C. A. B. Mendes, "Large scale hydrological and hydrodynamic modeling of the amazon river basin," *Water Resources Research*, vol. 49, pp. 1226–1243, 2013.

[18] G. Evensen, "Sequential data assimilation with a nonlinear quasi-geostropic model using monte carlo methods to forecast error statistics," *Journal of Geophysical Research*, vol. 99, no. C5, pp. 10 143–10 162, 1994.