A framework for satellite retrieval of river discharge without in situ measurements

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A FRAMEWORK FOR SATELLITE RETRIEVAL OF RIVER DISCHARGE WITHOUT IN SITU MEASUREMENTS

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ABSTRACT

The development of radar altimetry over rivers along the past 20 years has shown a strong potential to provide hydrologist with valuable information on river water level dynamics. The development of new sensors and satellite mission concepts such as spatial interferometry or temporal interferometry opens midterm (10-20 years) perspectives for the spatialized measurement of river surface variables such as width W, water level Z, surface slope I_s and surface velocity V_s.
Although not as accurate as in situ measurements can be, satellite measurements would ensure exhaustive and homogeneous global coverages, and provide repetitive and near real time information on these variables. Therefore a key question arises for hydrologists : assuming the availability of satellite measured river surface variables, with known uncertainty levels, would it be possible to estimate river discharge without any in situ measurement, and what would be the resulting uncertainty on discharge estimate?
We developed a method to estimate river bottom parameters (river bottom elevation Z_b, bottom slope I_b, velocity profile coefficient α and Manning coefficient n) from a time series of synchronous surface variable measurements $(W(t_i), Z(t_i), I_s(t_i), V_s(t_i))_{(t_i\ i=1\cdots N)}$ realized on a given river section at different stages along the hydrological cycle. The method relies on the forcing of equality (or minimization of deviation) between two expressions of the river discharge : velocity integration on the section and Manning head loss equation. Various criteria have been developed based on the quadratic difference between these two expressions, and minimization techniques have been tested and optimized to estimate the river bottom parameters. The method has been implemented both on simulated data (without noise or with added measurement noise), and on real data (Amazon river). Additionnaly, the robustness of the method to surface variable uncertainty has been explored.
A simplified version of the method, with fixed value of the Manning coefficient,results in a 8% discharge estimation with a 25% standard deviation over the Amazon dataset (12 stations). The full method, while giving relevant estimates of river bottom parameters and river discharge on exact simulated data and on some in situ gauging stations, leads to inaccurate results on most of in situ gauging stations as well as on simulated data with significant measurement noise. Current works are dedicated to improve its robustness.

Key words: Remote sensing, Hydrology, Discharge, Radar interferometry, SWOT.

1. INTRODUCTION

River discharge is a key variable for quantifying the water cycle, its fluxes and stocks at different scales. These scales range from a local scale for the efficient management of water resources to a global scale for the monitoring of climate change. Therefore, developing Earth observation (EO) techniques for the measurement or estimation of river discharge addresses a major challenge. A key question deals with the possibility of deriving river discharge values from EO measured surface variables (width W, level Z, slope I_s, and surface velocity V_s are the only such variables accessible through EO) without any in situ measurement.

Traditionally, river discharge is estimated using sets of in situ measurements. Several gauging stations are located along the river network to monitor the entire basin. Periodically, the water flow velocity profile, the channel cross-section area and the water level are recorded at each gauging stations. These instantaneous pictures of the river hydraulics are used to build or adjust rating curves that link the discharge value to the water level to the discharge [1]. Hence, continuous water level measurement at a specific gauging station allows the estimation of the discharge time series.

However, gathering reliable, long-term and consistent information on river discharges worldwide or on large trans-boundary river basins is an extremely sensitive and complex task [2, 3, 4]. Developing Earth Observation (EO) techniques for the measurement or estimation of river discharges is a major issue.

Although not as accurate as in situ measurements, satellite measurements would ensure exhaustive, homogeneous and repetitive, near real time, information on river surface variables. A method to derive discharge from these measurements would enable global river discharge monitoring, and would usefully complement high accuracy in situ measurement networks.

The possibility of using EO techniques to measure river surface variables, from optical or SAR imagery and interferometry, has been developed and discussed in numerous papers [5, 6, 7, 8, 9, 10, 11, 12]. Scientific and technological progress achieved in these domains has been very rapid and has mobilized large, combined efforts from the scientific community, space agencies and industry [13]. However, the accuracy of these data is still limited.

Assuming that these river surface variables will be measured by EO with a satisfactory accuracy in the near future, we developed a method to estimate river discharge from surface variables.

2. METHOD RATIONALE

The proposed method relies on three main steps:

1. expression of the river discharge as a function of surface hydraulic variables and bottom hydraulic parameters;
2. estimation of the bottom hydraulic parameters (α, Z_b, I_b, n) for a given river section from a series of N synchronous measurements of the four surface variables $(W(t_i), Z(t_i), I_s(t_i), V_s(t_i))_{(t_i\ i=1\cdots N)}$;
3. calculation of the discharge value for any measured set of the four surface variables using the estimated river bottom parameters.

To express the discharge as a function of the surface variables and bottom parameters, the fundamental Saint-Venant hydrodynamic equations were simplified based on a set of five limiting assumptions :

- A1 close to steady flow regime for each measurement;
- A2 rectangular cross-section of a wide and shallow river ($R = h = (Z - Z_b)$ and $A = W \cdot h$, where R (m) is the hydraulic radius, h (m) the water height and A (m^2) the area where the flow occurs);
- A3 Manning formulation of the linear energy slope S

$$S = \frac{n^2 \cdot Q^2}{A^2 \cdot R_h^{4/3}} \tag{1}$$

- A4 Manning coefficient n constant in time for each station;
- A5 α ratio ($\alpha = V_m/V_s$, with V_m the mean flow velocity) constant in time and space.

These assumptions lead to the two following discharge expressions :

- the flow rate expression

$$Q_1 = \alpha \cdot V_s \cdot W \cdot (Z - Z_b) \tag{2}$$

- and the Manning-Strickler relationship.

$$Q_2 = L \cdot \frac{1}{n} \cdot (Z - Z_b)^{\frac{5}{3}} \cdot I_s^{\frac{1}{2}} \cdot \left(1 + \frac{(Z - Z_b)^{\frac{1}{3}}}{n^2 \cdot g} \cdot (I_s - I_f)\right)^{\frac{-1}{2}} \tag{3}$$

These two discharge formulas should be equal at any moment, which allows to derive the river bottom hydraulic parameters from a series of surface variable measurements realized at different stages. Various criteria related with the difference between equations Eq.2 and Eq.3 are used to adjust the river bottom parameters through a minimization process.

3. CRITERIA DEVELOPMENT, METHOD IMPLEMENTATION ON SIMULATED DATA

3.1. Criteria design

Based on the difference between equations Eq.2 and Eq.3, we built two main minimization criteria. The first criterion J_1 is the direct expression of the difference between Q_1 and Q_2

$$J_1 = \sum_{i=1}^{N} [Q_{1_i} - Q_{2_i}]^2 \tag{4}$$

This criterion cannot be solved linearly due to the parameter Z_b in the powered expressions of $(Z - Z_b)$. We developed a gradient descent method to solve the minimization problem.

A second criterion J_2 was derived from J_1 to allow an easier solving method. J_2 is build using a uniform regime assumption. This assumption considers the difference between the surface slope I_s and bottom slope I_b as negligible, resulting in a simplification of equation Eq.3

$$Q_{2U} = L \cdot h^{5/3} \cdot I_s^{1/2} \cdot \frac{1}{n} \tag{5}$$

This leads to the following equation :

$$Q_1 = Q_{2U} \Leftrightarrow Z = Z_f + (n \cdot \alpha)^{3/2} \cdot \left(\frac{V_s}{I_s^{1/2}}\right)^{3/2} \tag{6}$$

Therefore, the J_2 criterion is expressed as :

$$J_2 = \sum_{i=1}^{N} \left[Z_i - Z_f - (n \cdot \alpha)^{3/2} \cdot \left(\frac{V_{s_i}}{I_{s_i}^{1/2}}\right)^{3/2} \right]^2 \tag{7}$$

This linear formulation can be easily solved using the mean squares matrix inversion to retrieve Z_b and n.

3.2. Robustness analysis

To ensure the efficiency of the minimization process, the estimation of river parameters through minimization of criteria J_1 (Eq.4) and J_2 (Eq.7) have first been tested on simulated data, that respect the equality between Q_1 (Eq.2) and Q_2 (Eq.3). The simulated data are generated through to two methods :

i mathematical modeling, according to equation Eq.2 and Eq.3. This first dataset is fully consistent with our assumptions : data respect the equality between Eq.2 and Eq.3. The minimization process is expected to result in an exact estimate of river bottom parameters and river discharges.

ii 1-D hydrodynamic model. This second dataset is build using SIC 1-D hydrodynamic model [14, 15]. It is more realistic but shows a slight deviation between values from equations Eq.2 and Eq.3.

These dataset are used in two modes : “without measurement noise” or “with additional measurement noises” to simulate real conditions. These noises are generated randomly using a centered normal distribution defined by its standard deviation, a percentage of the mean value of each surface variable.

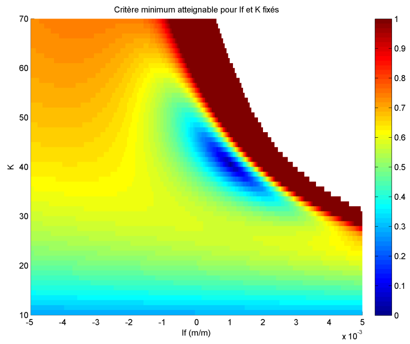
In the absence of measurement noises, minimization of criterion J_1 results in accurate estimate of discharge on both datasets, while criterion J_2 results in a systematic estimation bias of 10% in the discharge estimation. This bias is a consequence of the uniform flow hypothesis which is not strictly respected by the datasets.

When measurement noises are added to surface variables, either separately or simultaneously, discharge estimate move away from real values. The table Tab.1 resents the noise sensitivity, indicating for each variable the maximum allowable measurement noise intensity to ensure a 20% accurate estimate of the river discharge [16]. In contrast to results obtained with noiseless simulated data, criterion J_2 shows a higher robustness while criterion J_1 appears unable to estimate hydraulics parameters from noisy surface variables.

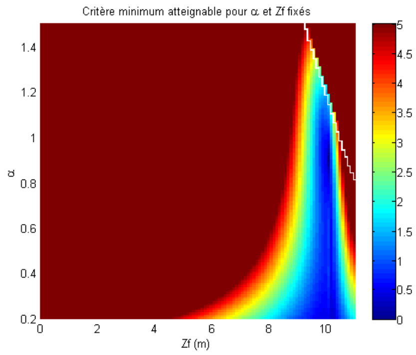
	V_s	Z	I_s	All
J_1	0%	0%	0%	0%
J_2	$\leq 5\%$	$\leq 10\%$	$\leq 2\%$	$\leq 2\%$

Table 1. Limit of noise intensity on surface variable to reach a 20% discharge estimation accuracy

The study of criterion J_1 topography from noiseless data shows an extremely flat minimum area around the actual solution (Fig.1(b) and Fig.1(a)). When noise is added to measured surface variables, this minimum is smoothed and drifted and the minimization algorithm converges toward mathematical local minima.



(a) Map of the minimal value reachable as a function of n and I_f, α and Z_f fixed to their exact value



(b) Map of the minimal value reachable as a function of α a Z_f, n and I_f fixed to their exact value

4. RESULTS ON REAL RIVER DATA

As no satellite system is curently able to provide accurate and synchronous measurement of the surface velocity V_s, surface slope I_s, water elevation Z and width W over river sections, a “real conditions” dataset has been built from ground measurements data. These data come from several gauging stations along the Amazon river network for now, the real test dataset is build on ground measurements (HyBAm, ANA-IRD, Project). At these stations, surface velocities and surface width are derived from ADCP measurements [17], whereas water level data result from daily in situ monitoring and longitudinal river slope result from relevant techniques to derive longitudinal profile and slope [18, 19].

The dataset gathers a total 192 quads of surface variables measurement $(W(t_i), Z(t_i), I_s(t_i), V_s(t_i))_{(t_i\ i=1\cdots N)}$ over 12 gauging stations (Fig.1). Gauging stations have a minimum 5 and a maximum 22 surface variable measurement quads. The method has been implemented on the 12 river sections of the Amazon river under four versions :

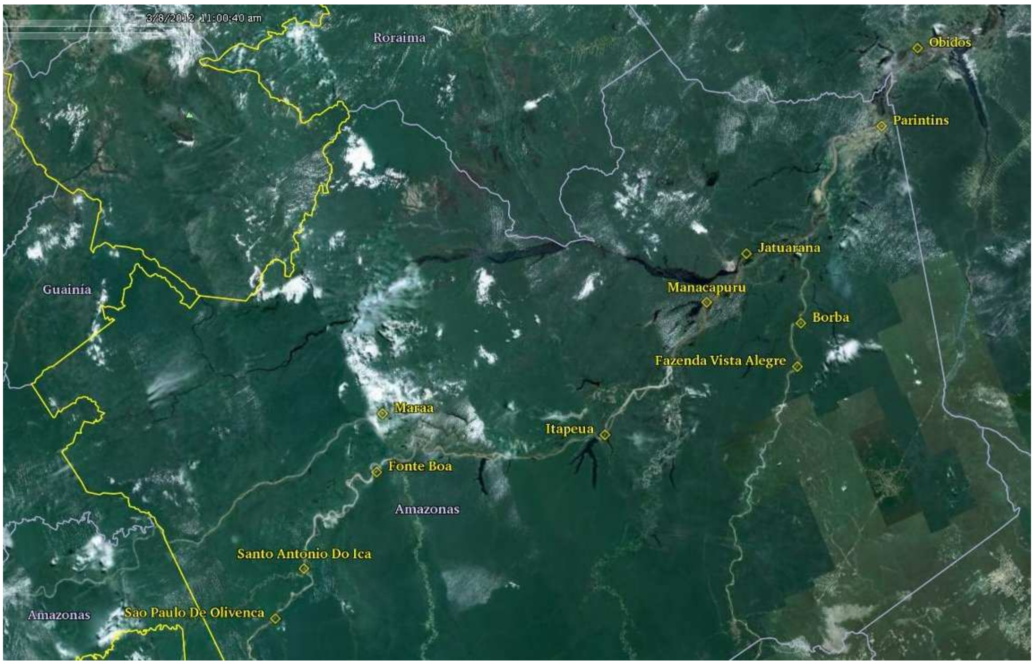


Figure 1. Map of the Amazonian gauging stations used in the dataset

- Full method deriving Z_b, I_b and n (setting α to a realistic 0.9 value) from J_1 or J_2
- Simplified method deriving Z_b, (setting α and n to respective realistic 0.9 and 0.033 value and ignoring I_b through the uniform regime hypothesis) from J_1 or J_2

Full method: When the J_1 criterion is applied to derive Z_b, I_b and n (setting α to a realistic 0.9 value), the algorithm converges toward a mathematical solution which remains far from any realistic parameters estimation. When the J_2 criterion is applied to derive Z_b and n (setting α to a realistic 0.9 value), Z_b and n are generally over-estimated. However, the J_2 criterion provides more realistic results and even gives satisfactory results for 2 stations out of 12, Manacapuru and Maraa.

The Manning coefficient n and the river bed elevation Z_b appears to compensate each other leading to an unsatisfactory mathematical solution.

Simplified method: In order to prevent the minimization algorithms from drifting towards unrealistic mathematical solutions, the method was simplified by adding an a priori knowledge to the process, and forcing the Manning coefficient to a fixed value ($n = 0.033$) suitable for large rivers.

When the simplified method is applied on each of the 12 Amazon gauging stations (192 surface measurment quads), Z_b is correctly estimated and the discharge retrieval accuracy increases dramatically to 26% (RMSE). This allows discharge estimation with a mean estimation error of 8% and a 25% standard deviation.

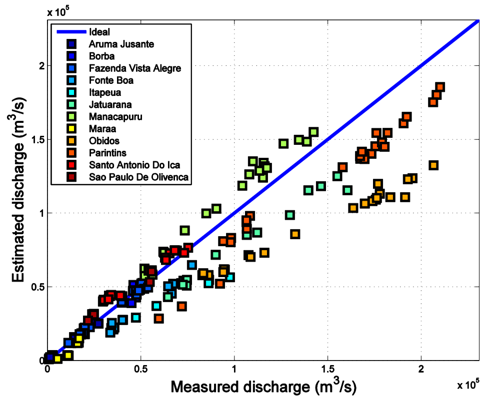
Fig.2(a) show the discharge estimation for each measurement, colored according to the gauging station and Fig.2(b) shows the distribution of the associated relative errors.

Results for Obidos gauging station presents important discharge estimation errors, showing a systematic underestimation bias. This explains the 35% error peak on histogram Fig.2(b). Our current analysis is that hydraulic assumptions of the method fail to catch the hydrological processes on this part of the Amazon river, thus biasing the estimation process.

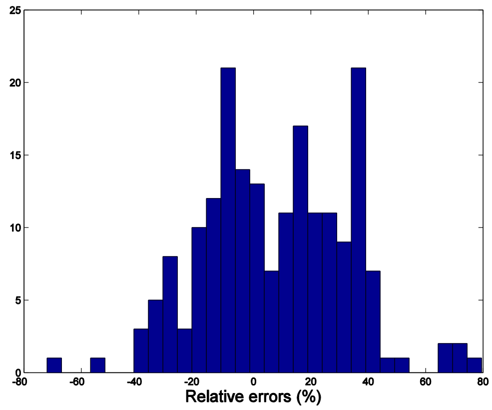
5. CONCLUSIONS AND PERSPECTIVES

A generic method has been developed to estimate river discharge from repetitive satellite measurement of river surface variables (width, water level, longitudinal slope and surface velocity), without in situ measurement. It consists in (i) retrieving river bottom hydraulic parameters through the minimization of the difference between two expressions of the river discharge, then (ii) estimating river discharge from these equations.

The simplified version of the method, using a uniform flow hypothesis and setting the Manning coefficient and the vertical velocity profile coefficient to realistic values, appears promising to estimate river discharges. It has proved able to retrieve river hydraulic parameters and to estimate river discharge with a 26% accuracy on a set of twelve Amazon river hydrometric stations.



(a) Estimated discharge versus measured discharge over the 192 surface measurements from the 12 Amazon gauging stations



(b) Distribution of the discharge estimation relative error for the 192 surface measurements dataset from 12 Amazon gauging stations

The full method, although mathematically sound, faces limits in terms of robustness to surface variable measurement noises. The uniform flow simplification appears to increase the robustness but the method is still unable, in most cases, to properly estimate the Manning coefficient n and the river bed elevation Z_b, Discharge estimate thus suffers systematic bias (under-estimation).

Further developments are ongoing, exploring various criterion shapes and optimization techniques (including constrained genetic algorithms), to increase the method robustness to measurement noises. Detailed analysis of the method efficiency for river reaches of the Amazon with diverse hydrological configurations (e.g. Obidos) is needed to understand the current over-estimation of hydraulic parameters.

ACKNOWLEDGMENTS

This work was supported by Irstea and the French space agency “Centre National d’Études Spatiales” (CNES). It benefited from a grant by CNES in the framework of the SWOT project (NASA-CNES).

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