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# Estimating river discharge from earth observation measurement of river surface hydraulic variables

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## Abstract

River discharge is a key variable to quantify the water cycle, its fluxes and stocks at different scales, from local scale for the efficient management of water resource to global scale for the monitoring of climate change. Therefore, developing Earth observation (EO) techniques for the measurement or estimation of river discharge is a major challenge. A key question deals with the possibility of deriving river discharge values from EO surface variables (width, level, slope, velocity the only one accessible through EO) without any in situ measurement. Based on a literature study and original developments, the possibilities of estimating water surface variables using remote-sensing techniques have been explored, mainly RADAR altimetry as well as across-track and along-track interferometry.


## 1 Introduction

Traditionally, the river discharge is estimated using frequent in situ measurements. Periodically, the water flow velocity, the channel cross-section surface and the water level are recorded on gauging station. Several stations are dispatched along river basin in order to monitor the whole basin. These instantaneous pictures of the river configuration are used to build or adjust rating curves linking the water level to the discharge (Franchini et al., 1999). Henceforth the continuous measurement of the level allow an estimation of the discharge at a specific gauging station. Since the last two decades, Acoustic Doppler Current Profiler (ADCP) considerably eased and increase the accuracy of rivers monitoring (Gordon, 1989; Morlock, 1996; Oberg and Mueller, 2007). However, gathering reliable, long term and consistent information on river discharges worldwide or on large trans-boundary river basins is an extremely complex task, if ever achievable, as Hydrologic Services in different countries have heterogeneous acquisition strategies and data policies. This lead mainly to a leveling reference issues (Kosuth et al., 2006), data transmission delay or unsynchronized measurements periodicity.





HESSD

7, 7839–7861, 2010

Therefore, developing Earth Observation (EO) techniques for the measurement or estimation of river discharge is a major challenge.

Although in situ data acquisition is and will remain a keystone of hydrological monitoring and hydrological knowledge, an important question deals with the possibility of deriving river discharge values without any in situ measurement, based exclusively on river surface variables accessible through EO techniques, namely river width, level, surface slope and surface velocity. Such a method would allow a global monitoring of river discharges worldwide, and would usefully complement high accuracy in situ measurement networks.

The problem can be organized into two separated questions:

1. to which extent can EO techniques provide reliable measurement of river surface variables and what is the corresponding accuracy?

2. how can we derive discharge estimates from these surface variables?

The possibility of using EO techniques to measure river surface variables has been developed and commented in numerous papers, from optical or SAR imagery for river width (Zhang et al., 2004; Xu et al., 2004; Smith et al., 1995, 1996) to RADAR or LIDAR altimetry for river level (Coe and Birkett, 2004; Alsdorf et al., 2001; Costa et al., 2000), and from RADAR across-track interferometry for surface slopes (LeFavour and Alsdorf, 2005) to along-track interferometry for surface velocity (Thompson et al., 1994; Macklin et al., 2004; Romeiser et al., 2007). The scientific and technological progress in these domains is very rapid and mobilizes large combined efforts by the scientific community, space agencies and industrials (Alsdorf et al., 2007). However the accuracy of these data is still limited and, while improving it is a major challenge, should be carefully taken into account in any discharge estimation methods.

Assuming these river surface variables can be measured by EO with a given satisfying accuracy, we can concentrate our efforts on the second question of this problem. A method has been developed in order to estimate river discharge from these variables.





HESSD
7, 7839–7861, 2010

The goal of this paper is to present this discharge estimation method using remotely sensed hydrological variables and discuss its results.

## 2 Presentation of a statistical approach

It appears in literature that a statistical approach of this problem has already been investigated (Bjerklie et al., 2003, 2005). The method relies on different combinations of surface variables extracted from the Manning-Strickler equation and the flux expression of river discharge. Using the relationships between hydraulic variables, five expressions of the river discharge are achieved:

$$Q = c_1 L^a Y^b I_s^d \tag{1}$$
$$Q = c_2 L^e V^f I_s^g \tag{2}$$
$$Q = c_3 L^e V^f \tag{3}$$
$$Q = c_4 L_m^g Y_m^h I_s^i Y^j \tag{4}$$
$$Q = c_5 L_m^k Y_m^l I_s^m L^n \tag{5}$$

with $Q$ the river discharge, $L$ river width, $Y$ river depth, $V$ mean velocity and $I_s$ water surface slope, $L_m$ et $Y_m$ represent the maximum value of width and depth.

Discharge is therefore expressed as the product of some hydraulic variables powered by constants. The coefficients and power of the hydraulic variables of five expressions are then fitted to in-situ measurements realized on a huge dataset among many different rivers around the world.

This method appears to give a satisfactory mean estimation of global discharge (with a mean error within a 10% range) on a whole measurements dataset and is consequently, theoretically, applicable on any river of the world.

In facts two major problems appears:



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HESSD

7, 7839–7861, 2010

Estimating river discharge from EO

J. Negrel et al.

1. two of the five expressions (1, 4) rely on the depth of the river information. But this hydraulic variable can not be measured from space using RADAR techniques, which can not penetrate water, or LIDAR techniques which are limited to shallow (less than 6 or 7 meters) and non turbulent water (Wang and Philpot, 2007).

2. if the method is really accurate to estimate the global amount of fresh water going to the ocean, this does not give any information for the ability to estimate a unique measurement on a given river.

In order to verify this last assumption, we applied these estimation methods on ADCP measurements dataset realized on the Amazon basin as well as on simulated dataset. The results of this test confirmed our doubts. Depending on the dataset used, the different models give us contrasted results, excepted the last model which always gives a wrong estimation of the discharge. More detailed results and comparison with our proposed model are discussed in Sect. 4.4.

## 3 Proposed method

The rationale of the proposed method consists into three steps:

1. Expressing the discharge $Q$ in a river section as a function of the sole surface variables and hydraulic parameters, based on a simplified formulation of the fundamental Saint-Venant hydrodynamic equations and a set of clearly identified hypothesis.

2. Mass conservation equation and energy conservation equation lead to two estimates of the river discharge, namely $Q_1$ and $Q_2$, which must be consistent over the full range of hydraulic regime. Therefore determining the values of the hydraulic parameters can be formulated as minimizing an error criteria between the two estimates of the discharge, over a set of surface variables measured at different stages of the river cycle.

3. Once the hydraulic parameters have been determined the two consistent estimates $Q_1$ and $Q_2$ can be quantified, and merged in a unique discharge estimate $Q^*$, using for example the mean between the two estimations of a discharge.

The measurable surface variables are width $L_s$, water level $Z_s$, surface velocity $V_s$ and surface slope $I_s$; the hydraulic parameters are bottom width $L_b$, bottom level $Z_b$, bottom slope $I_b$, Strickler roughness coefficient $K$ and $\alpha$, the ratio between surface velocity and mean velocity.

Saint-Venant river section is simplified assuming to have a rectangular cross-section represented by its mean bottom level and width. Based on a set of surface variables measurement at different dates and hydrological regimes, the methods estimates the values of the mean bottom level and mean Manning coefficient. Therefore, to be applied, the method requires a reasonable number of measurements along the complete hydrological cycle.

This lead to the formulation of the six following hypothesis to simplify the expression of the discharge:

H1 Permanent flow configuration at each measurement

H2 Rectangular cross-section, which lead to $L_s = L_b = L$. This hypothesis is motivated by the ratio appearing between width and depth (around 50), in this case a river can be considered as a thin film.

H3 Strickler formulation of the linear energy slope

H4 Strickler coefficient $K$ constant in time for each station

H5 $\alpha$ ratio constant in time and space.

H6 and finally uniform flow configuration

We can express the river discharge using two different expression:

– the mass conservation equation





HESSD
7, 7839–7861, 2010

– and the Strickler relationship.

This last equation links the linear energy slope $J$ to the hydraulic variables as it follow:

$$J = \frac{Q^2}{K^2 \cdot S^2 \cdot R^{4/3}} \tag{6}$$

which lead to the equation:

$$Q^2 = J \cdot K^2 \cdot S^2 \cdot R^{4/3} \tag{7}$$

with $Q$ the discharge ($m^3 s^{-1}$) $K$ the Strickler roughness coefficient ($m^{1/3} s^{-1}$), $S$ the cross-section surface and $R$ the hydraulic radius ($m$). $J$ is usually expressed as a negative while oriented downstream.

Finally, using our hypothesis and the previous Strickler expression, we get the two following expression of the river discharge:

$$\begin{aligned} Q_1 &= V_{\mathrm{moy}} \cdot S \\ &\approx \alpha \cdot V_{\mathrm{s}} \cdot L \cdot (Z - Z_{\mathrm{b}}) \end{aligned} \tag{8}$$

$$\begin{aligned} Q_2 &= J^{1/2} \cdot K \cdot S \cdot R^{2/3} \\ &\approx I_{\mathrm{s}}^{1/2} \cdot K \cdot L \cdot (Z - Z_{\mathrm{b}})^{5/3} \end{aligned} \tag{9}$$

with $R \approx (Z - Z_{\mathrm{b}})$, $S \approx L \cdot (Z - Z_{\mathrm{b}})$ (hypothesis H2 the rectangulare cross-section) and $J = I_s = I_b$ thanks to uniform hypothesis. As this two discharge expression must be consistent, Eqs. (8) and (9) must be equal:

$$\alpha \cdot V_{\mathrm{s}} \cdot L \cdot (Z - Z_{\mathrm{b}}) = I_{\mathrm{s}}^{1/2} \cdot K \cdot L \cdot (Z - Z_{\mathrm{b}})^{5/3} \tag{10}$$





HESSD
7, 7839–7861, 2010

Estimating river discharge from EO

J. Negrel et al.

This lead to:

$$Z = Z_b + \frac{\alpha}{K}^{3/2} \cdot \frac{V_s^{3/2}}{I_s^{3/4}} \tag{11}$$

$$Z = A \cdot X + Z_b \tag{12}$$

with $A = \frac{\alpha^{3/2}}{K^{3/2}}$ and $X = \frac{V_s^{3/2}}{I_s^{3/4}}$.

The water level $Z$ is now presented as a linear expression of two unknown parameters ($A$ and $Z_b$) and a variable $X$, combination of measured surface variables $V_s$ and $I_s$. This linear expression is used to estimate the unknown parameters $Z_b$ and $A$, with a set of surface variable measurements $(Z_i, V_{s\,i}, I_{s\,i})_{(i=1 \cdots N)}$ at different dates and phases of the hydrological cycle. This estimation is achieved using mean square method to minimize a criteria $J$ which represent the root mean square error of the water level estimator:

$$J = \sum_{i=1}^{N} \left[ Z_i - Z(V_{s\,i}, I_{s\,i}) \right] = \sum_{i=1}^{N} \left[ Z_i - Z_b - A_i \cdot X_i \right] \tag{13}$$

The problem appearing on this formulation of the error criterion (13) is the impossibility to estimate the $\alpha$ parameter and the Strickler coefficient $K$ from the estimated parameter $A$. The $\alpha$ parameter is widely admitted to be constant around 0.85 for small river and 0.90 for wide river (Rantz, 1982; Costa et al., 2000). Therefore, we decided to fix it once for all and then it becomes possible to calculate the Strickler coefficient $K$ easily from the $A$ estimated parameter: $K = \frac{\alpha}{A^{2/3}}$.

Nevertheless, a study of the different gauging station ADCP measurements, verified the validity of this fixed value of the $\alpha$. On the global dataset, as well as on gauging station taken individually, the mean value of mean$(\alpha) = 0.9$ has been checked with a standard deviation is 0.06.





HESSD
7, 7839–7861, 2010

## 4 Result and discussion

The presented method has been developed and tested on a dataset of measurements realized on several stations on the Amazon basin (HyBAM ANA-IRD Project). To apply the method, the datasets are constructed directly form ADCP measurments for the surface velocities and surface width, while water level and longitudinal river slopes are provided by in situ monitoring of leveled gauging stations and relevant technique to derive the longitudinal profile and slope (Bercher, 2008). This method has been tested on different stations of the Amazon basin and gives satisfactory results on some of them but discrepancies on others. At this stage it appears to give more robust results than the Bjerklie's equations.

### 4.1 Dataset

To test the discharge estimation methods, severals datasets have been used. The first one come from several gauging station on the Amazon basin. We concentrate our efforts on the data from the Manacapuru (Table 1) and Obidos stations because these two stations give us the greatest number of measurements and also the less noisy acquisitions. Simulated data, generated by SIC, a 1-D hydrodynamic model (Baume et al., 2005), were also used for the discharge estimation in order to control the noise response of the models.

### 4.2 Model results on ADCP data

On a first time, the model has been applied on the Manacapuru and Obidos datasets. The estimation on the Manacapuru station data is quite satisfactory, as shown on Fig. 1. The mean relative error of the estimation is 5.98%, with a standard deviation of 0.0517. The estimated bottom level (−3.86 m) is consistent with the computed one from ADCP data (−5.63 m) compared the height of the water column (between 17 and 27 m). The estimated Strickler coefficient (36.98) is also consistent the computed one (34.24). On the contrary the process could not successfully estimate the hydraulic parameters with Obidos dataset. The estimated bottom level is $-4.67$ m while ADCP measurements give us a mean bottom level at $-39.46$ m. The problem is the same for the Strickler parameter, we estimated 28.48 wile we can found 65.03 from ADCP data. Consequently it's no surprise to obtain a discharge estimation which represent around 25% of the actual discharge (Fig. 2). However, even if the discharge estimations are not as expected using Obidos dataset, it appears that the two equations $Q_1$ and $Q_2$ give similar results, which is encouraging on the mean square criterion. The estimation error may come from one or more hypothesis.

### 4.2.1 Fixed $\alpha$

Firstly, we decided to fix the $\alpha$ ratio, this could induce an estimation error with an inappropriate value of $\alpha$. But on Obidos station dataset, the mean value of the $\alpha$ ration appear to be 0.90 (with a standard-deviation of 0.06), the hypothesis seems thus correct. Moreover, if the discharge is calculated using Eq. (8) with the fixed value of $\alpha$ and the measured mean bottom level, the results on Obidos data become satisfactory (mean relative error = 0.13 with a standard-deviation = 0.04), and are equivalent to the ones using our estimation method on Manacapuru data. This hypothesis is therefore correct.

### 4.2.2 Fixed Strickler coefficient $K$

Unfortunately, there is no way to measure directly this coefficient to check this hypothesis. As for the $\alpha$ ratio, the values of the Strickler coefficient $K$ has been computed using the ADCP measurements and the discharge equations defined previously, this time using Eq. (9).

It seems that both stations have a varying Strickler coefficient with a similar standard deviation (2.89 for Obidos and 2.23 for Manacapuru). So it's impossible to affirm that the variation of the Strickler coefficient is problematic with our hypothesis or not. One





HESSD
7, 7839–7861, 2010

interesting thing is the correlation ($r^2 = 0.86$) between discharge and the value of the Strickler coefficient appearing on Obidos data. This correlation, which does not exist on Manacapuru dataset, does not seem to modify considerably the estimation of the discharge. If the discharge is estimated on Obidos station using the mean estimated Strickler coefficient and the mean measured bottom level, like previously, the results gets satisfactory with a mean relative error of 0.09 and a standard-deviation of 0.05. This hypothesis is also valid.

### 4.2.3 Uniform hypothesis

This last hypothesis is clearly not valid. It has been assessed that the water surface slope equal the linear energy slope equals the bottom slope ($I_s = I_b = J$). As the bottom slope is the ground, it's not suppose to move, but the surface slope is varying in time. The problem is surface slope vary on both gauging station dataset and the model still works on Manacapuru station dataset. This difference might come from the amplitude of the variation of the slope. At Obidos station dataset, the mean slope is $1.39 \times 10^{-05}$ m m$^{-1}$ with a standard-deviation of $3.27 \times 10^{-06}$, while Manacapuru station dataset has a mean slope of $2.09 \times 10^{-05}$ m m$^{-1}$ with a standard-deviation of $2.57 \times 10^{-06}$ which is noticeably inferior, regarding the mean value of the slope. This difference might explain the difference in results gets with the estimation model.

An other point seems important about the surface slope, it is extracted using the derivation of a function fitted to the water level series between 4 gauging stations upstream and downstream Obidos gauging station. Considering the scale of value of the slope, the precision of this estimation could be considered as a possible error source as well. This issue could only be solve by ground truth verifications.

### 4.2.4 Variability of $Z_b$

One last possible source of error is the movements of the local topography of the river bed. We assumed the bottom level to be constant and equal to the level minus the mean depth. In fact, Amazon river bed has huge dune movement, consequently, depending where and when the ADCP measurements have been realized, the bottom level might appear extremely variable for a single gauging station.

On Obidos station the amplitude of the bottom level found from the ADCP measurements is 15.66 m around a mean bottom level of −39.46 m (the standard-deviation is 3.54 m). On Manacapuru station, this variation of the bottom level is noticeable too, but with an amplitude of 7.10 m around the mean bottom level of −5.63 m (the standard-deviation is 1.76 m).

We can see that both the amplitude and the standard deviation on Manacapuru data are the half of the ones computed on Obidos data. This issue might jeopardize our approach of the discharge estimation problem on large river with similar characteristics.

### 4.3 Model results on simulated data

The discharge estimation model has been applied on the simulated dataset, with no noise addition on the surface variables. As for the ADCP dataset, the uniform flow hypothesis is not validated because of the variables surface slope: the mean surface slope is $5.88 \times 10^{-05}$ m m$^{-1}$ with a standard-deviation of $6.94 \times 10^{-06}$. Therefore, perfect discharge estimation is not expected, but it can verify the impact of variable surface slope on the model.

It appear, on Fig. 3, that we over-estimate the discharge on noiseless data, with a mean relative error of 0.06 with a standard deviation of 0.004. In fact, these simulated data, fit perfectly the first discharge expression $Q_1$ (Eq. 8) but not the second expression $Q_2$ (Eq. 9). As we fixed the Strickler parameter $K$ and the bottom level $Z_b$ for the simulation model, the only error source is the surface slope.

If a theoretical perfect surface slope is computed, fitting the the Eq. (9), a difference between the value of the simulated slope and the theoretical slope appear. The theoretical slope is 6% inferior to the simulated one. This explain the over-estimation of the discharge.

### 4.4 Results of Bjerklie models and comparison with the proposed one

The five statistical models described earlier in Sect. 2 have been applied on Manacapuru dataset , Obidos dataset and simulated dataset in order to compare the responses of these models to the estimation given by our model.

The Figs. 4, 5 and 6 represent the estimated discharge using the Bjerklie's and our models. Our model is still represented by the blue circles and red squares, like on previous figures, and the five statistical models are represented, respectively, by red stars, green cross, blue diamonds, purple pentagrams and yellow hexagrams, and finally, the blue line represent the ideal case.

The fifth model appear to give similar results in every cases: the estimated discharge is quasi-constant whatever the value taken by the measured discharge.

The other models give different results depending on the dataset used. On the simulated data, models (1) and (4) give similar results to our model: it overestimate discharge with a mean relative error of, respectively, 13% and 5%. On the Manacapuru dataset, it's the second model which gives us the best results, with a mean relative error of 18%. The fourth model is quite good as well (mean relative error of 19%) but for discharge superior to 140 000 $m^3 s^{-1}$, it dramatically overestimate the discharge which can not be satisfying. Finally, on the Obidos dataset, none of the five models give results really better than our own model. The second and the third models underestimate half of the discharge, but with a good coherence (respective standard deviation 0.09 and 0.06) while the first and fourth models overestimate the discharge twice with a huge dispersion of the estimation (respective standard deviation 0.42 and 0.29). Regarding this results, it seems impossible to determine which model would be suitable to estimate a river discharge in all cases.





HESSD
7, 7839–7861, 2010

## 5 Conclusion

Regarding the results reached on Manacapuru and simulated datasets, a relative error on the estimation of the discharge under 10%, our model seems promising. However the problem of the wrong estimation on Obidos dataset remains. As long as we can't verify the accuracy of our estimation of the surface slope, it seems impossible to isolate the source of this error for sure. Concerning the Bjerklie's models, as our approach consist in extracting the sub-surface hydraulic information from surface variables, we did not want to re-estimate the parameters of the Eqs. (1), (2), (3), (4) and (5) to fit the Amazon basin datasets. Regarding the results of these models on our different datasets, we consider them not suitable for our application.

Finally, in order to solve the problem of the varying surface slope, the development of the adaptation of the model to the non-uniform flow configuration is on going. And ground measurements of the water surface slope should be lead to validate the estimation method.

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HESSD
7, 7839–7861, 2010

Estimating river discharge from EO

J. Negrel et al.

**Table 1.** Set of measurements at the Manacapuru gauging station.

| | $Q$ ($m^3 s^{-1}$) | $L$ (m) | $Z_s$ (m) | $V_s$ ($m s^{-1}$) | $I_s$ ($m m^{-1}$) |
|---|---|---|---|---|---|
| 1 | 115 304 | 3180 | 20.14 | 1.48 | 2.04e−05 |
| 2 | 84 949 | 3216 | 16.83 | 1.30 | 1.97e−05 |
| 3 | 51 908 | 3074 | 10.68 | 1.07 | 2.18e−05 |
| 4 | 138 744 | 3108 | 22.93 | 1.66 | 2.23e−05 |
| 5 | 61 984 | 3210 | 14.09 | 1.08 | 1.55e−05 |
| 6 | 115 653 | 3241 | 19.87 | 1.56 | 2.43e−05 |
| 7 | 56 227 | 3219 | 11.29 | 0.97 | 1.43e−05 |
| 8 | 116 228 | 3140 | 21.23 | 1.52 | 2.12e−05 |
| 9 | 51 973 | 2901 | 11.47 | 1.03 | 1.75e−05 |
| 10 | 90 361 | 3208 | 16.71 | 1.35 | 2.16e−05 |
| 11 | 113 447 | 3246 | 19.82 | 1.50 | 2.22e−05 |
| 12 | 134 494 | 3255 | 22.45 | 1.61 | 2.21e−05 |
| 13 | 117 406 | 3250 | 20.91 | 1.45 | 2.09e−05 |
| 14 | 62 354 | 3157 | 12.53 | 1.14 | 2.08e−05 |
| 15 | 104 262 | 3236 | 18.39 | 1.48 | 2.19e−05 |
| 16 | 142 430 | 3154 | 23.41 | 1.71 | 2.18e−05 |
| 17 | 108 003 | 3288 | 18.55 | 1.52 | 2.43e−05 |
| 18 | 73 457 | 3187 | 14.23 | 1.25 | 2.34e−05 |
| 19 | 109 884 | 3456 | 19.93 | 1.47 | 2.16e−05 |
| 20 | 126 337 | 3276 | 22.65 | 1.55 | 2.11e−05 |





HESSD
7, 7839–7861, 2010

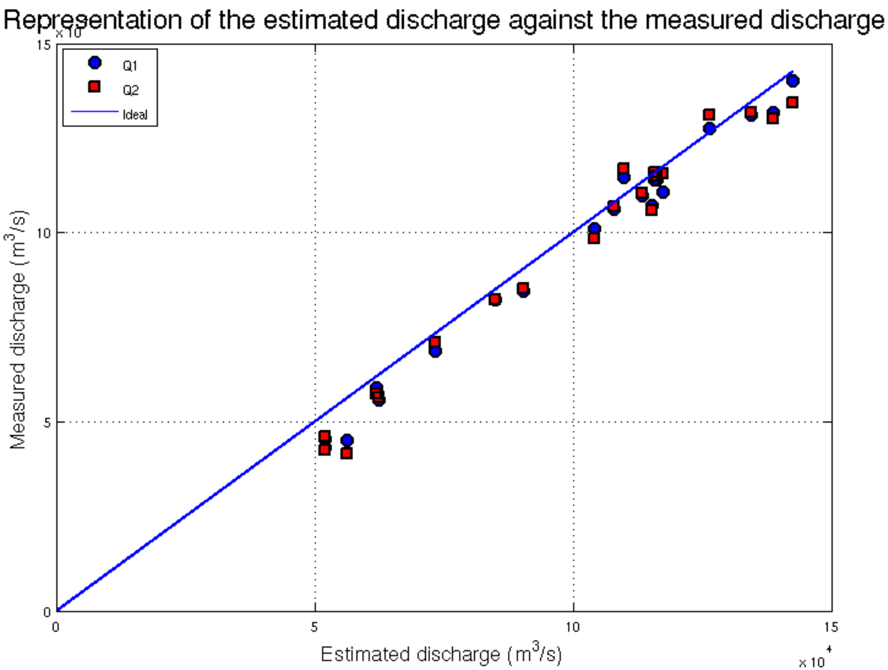


**Fig. 1.** Comparison of the estimated discharge using Eqs. (8) and (9) and ADCP discharge measurements at Manacapuru gauging station.



HESSD
7, 7839–7861, 2010

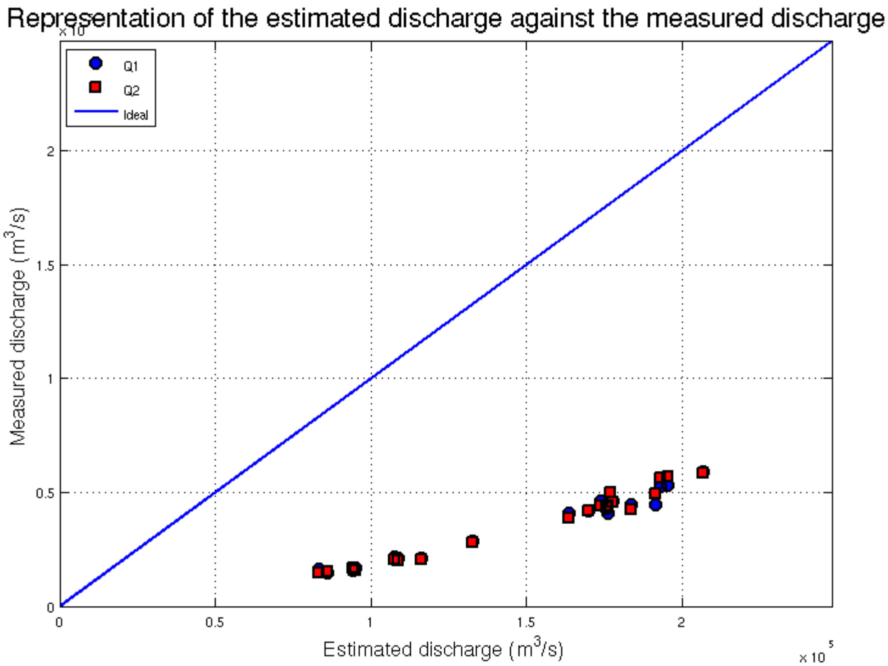


**Fig. 2.** Comparison of the estimated discharge using Eqs. (8) and (9) and ADCP discharge measurements at Obidos gauging station.





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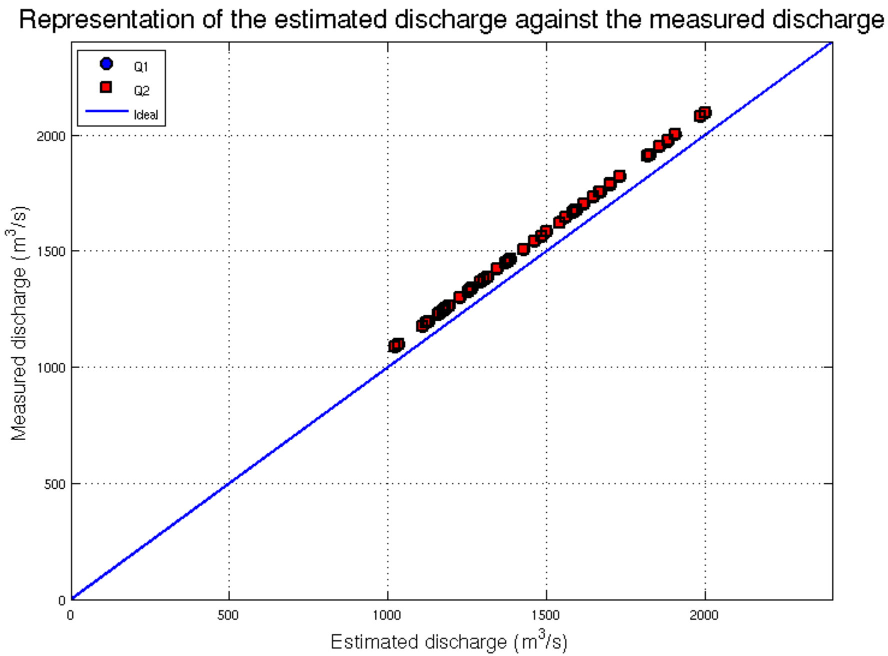


**Fig. 3.** Representation of the estimated discharge using Eqs. (8) and (9) against simulated discharge measurements.





HESSD
7, 7839–7861, 2010

Estimating river discharge from EO

J. Negrel et al.

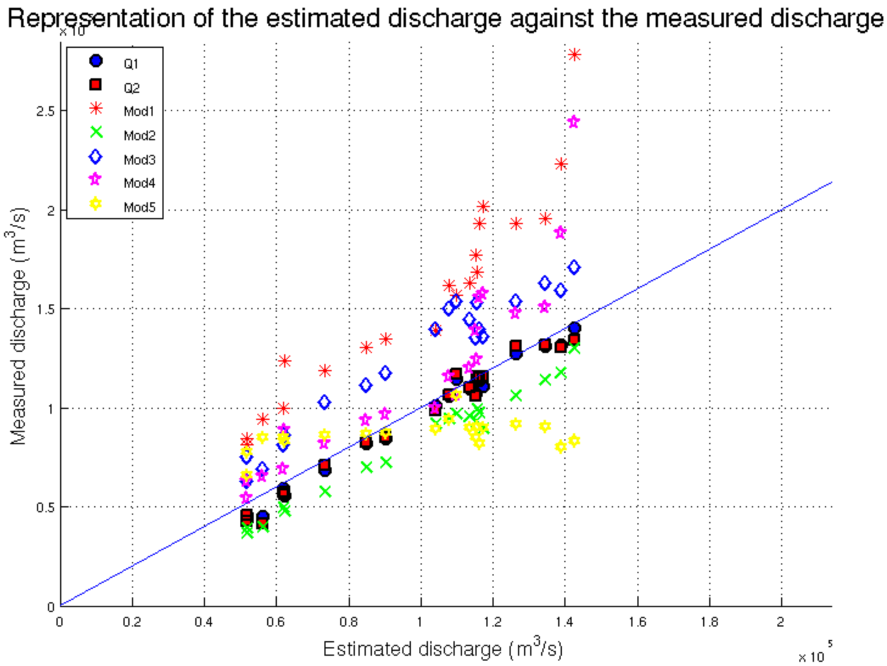


**Fig. 4.** Representation of the estimated discharge against ADCP discharge measurements on Manacapuru dataset.





HESSD

7, 7839–7861, 2010

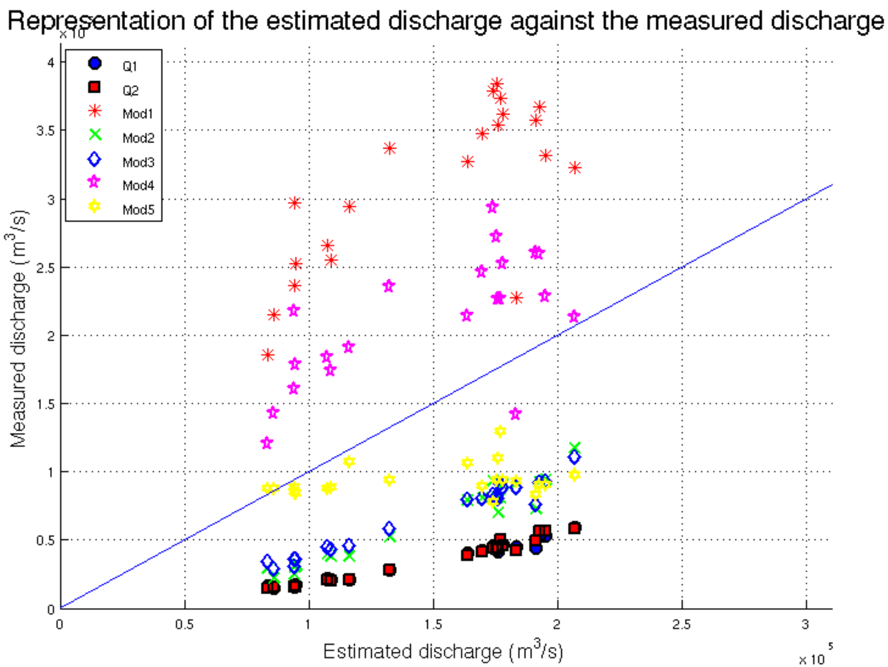


**Fig. 5.** Representation of the estimated discharge against ADCP discharge measurements on Obidos dataset.

HESSD
7, 7839–7861, 2010

Estimating river discharge from EO

J. Negrel et al.





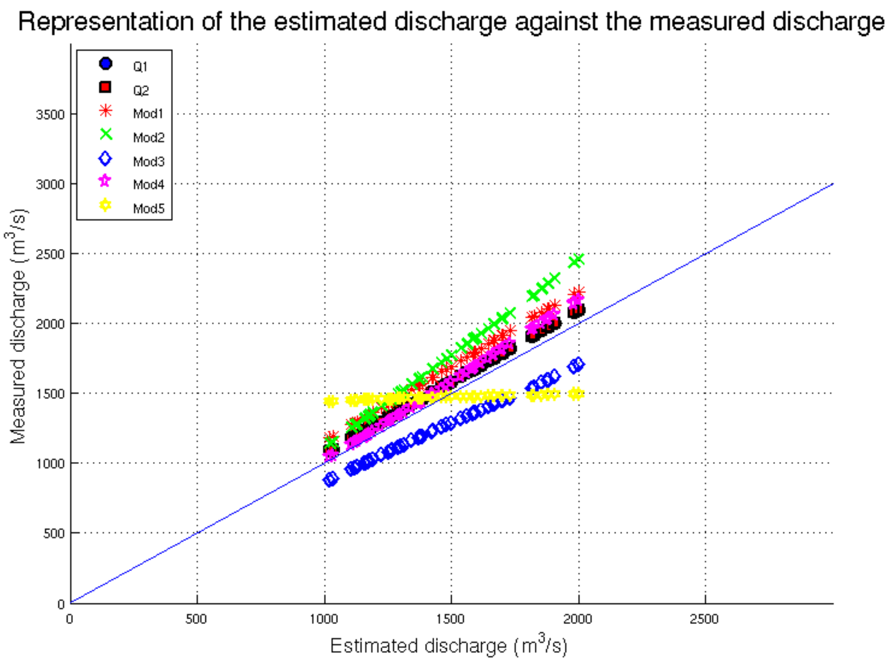


**Fig. 6.** Representation of the estimated discharge against simulated discharge measurements.