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Water discharge estimates from large radar altimetry datasets in the Amazon basin

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Abstract

In this study, we evaluate the use of a large radar altimetry dataset as a complementary gauging network capable of providing water discharge in ungauged regions within the Amazon basin. A rating-curve-based methodology is adopted to derive water discharge from altimetric data provided by Envisat at 444 virtual stations (VS). The stage-discharge relations at VS are built based on radar altimetry and outputs from a global flow routing scheme. In order to quantify the impact of modeling uncertainties on rating-curve based discharges, another experiment is performed using simulated discharges derived from a simplified data assimilation procedure. Discharge estimates at 90 VS are evaluated against observations during the curve fitting calibration (2002–2005) and evaluation (2006–2008) periods, resulting in mean relative RMS errors as high as 52 % and 12 % for experiments without and with assimilation, respectively. Without data assimilation, uncertainty of discharge estimates can be mostly attributed to forcing errors at smaller scales, generating a positive correlation between performance and drainage area. Mean relative errors (RE) of altimetry-based discharges varied from 15 % to 92 % for large and small drainage areas, respectively. Rating curves produced a mean RE of 54 % versus 68 % from model outputs. Assimilating discharge data decreases the mean RE from 68 % to 12 %. These results demonstrate the feasibility of applying the proposed methodology to the regional or global scales. Also, it is shown the potential of satellite altimetry for predicting water discharge in poorly-gauged and ungauged river basins.

1 Introduction

In the last decades, the hydrological sciences community has experienced significant advances in the understanding of water storage and transport over the continents using remote sensing data. In particular, radar altimetry, firstly designed to monitor the oceans, has motivated the development of techniques attempting to improve our

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understanding of inland water fluxes worldwide. It has been shown that radar altimetry, in the form of virtual stations, or VS (location where satellite ground tracks transect open-water surfaces), can significantly contribute to the monitoring of poorly gauged or ungauged areas. Most applications have attempted to retrieve water discharges from stage-discharge relations derived from altimetric data and observed discharges from gauging stations located in the vicinity of the VS. These relations are commonly represented by rating curves and allow one to predict water discharges from observed water levels, with accuracy varying as a function of input data and flow regime characteristics. As examples, river discharges have been estimated from altimetric data in the Chari River (Coe and Birkett, 2004), Ob River (Kouraev et al., 2004), Ganges-Brahmaputra Rivers (Papa et al., 2010), Amazon River (Zakharova et al., 2006) and Zambezi River (Michailovsky et al., 2012). Although errors between predicted and observed water discharges are relatively small in most applications, the use of such methods is restricted to VS located near gauging stations. Some studies preparing for the upcoming Surface Water Ocean Topography Mission (SWOT; Alsdorf et al., 2007) have combined virtual swath altimetric measurements with hydrodynamic models using data assimilation methods in order to improve modeled depth and discharge on river reaches (e.g., Andreadis et al., 2007). These studies show the potential of upcoming altimetric measurements, but the application of the proposed techniques implies that bathymetry must be known. Recent works in the Amazon basin have addressed these limitations (need for observed discharges and river cross sectional information at VS) by using discharge estimates derived from routing schemes and rainfall-runoff models at the regional scale (Leon et al., 2006; Getirana et al., 2009). These approaches allow one to take advantage of larger radar altimetry datasets. On the other hand, they are constrained by uncertainties of simplified model representations of physical processes and input forcings.

A recent effort in acquiring altimetric data resulted in an unprecedented dataset composed of Envisat satellite time series at several hundreds of virtual stations within the Amazon basin (da Silva et al., 2010). Even though the Amazon basin is responsible

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for about 15% of the water flow from continents to oceans, it is poorly gauged and its hydrological processes are still unknown in many areas at the meso and regional scales. Taking advantage of da Silva's et al. dataset, the present study extends the application of the rating curve approach for discharge forecasts at the large scale, investigating whether is possible to predict water discharges from current large scale radar altimetry datasets based on rating curves and quantifying the accuracy of retrieved discharge estimates. Specifically, this study evaluates a methodology where stage-discharge relations are based on rating curves derived from Envisat data and simulated discharges provided by the Hydrological Modeling and Analysis Platform (HyMAP) flow routing scheme (Getirana et al., 2012) coupled in off-line mode with the Interactions Sol-Biosphère-Atmosphère (ISBA) (Noilhan and Mahfouf, 1996) land surface model (LSM). The results of this study point toward a general methodology capable of predicting water discharges at the continental or global scale from the next generation of satellite missions such as the SWOT mission.

2 The stage-discharge relation

The stage-discharge relation is a hydraulic property of a river reach or cross section and it is unknown a priori. The hydrologist must define it based on an approximated representation by a rating curve, traditionally built based on in situ measures and supported by the analysis of streamflow parameters (Jacon and Cudo, 1989). In general, the rating curve of a specific river location can be expressed by mathematical expressions representing successive linear reaches or curves. The most frequently used form is the exponential one defined as $Q = a \cdot h^b$, where Q [$\text{m}^3 \text{s}^{-1}$] is the estimated discharge and h [m] the water depth related to a given zero-flow-equivalent water height, z (see below for details). In general, the coefficient a reproduces the relief of the river reaches, including surface roughness and sinuosity, and b the geometry of river banks. If the Manning equation for wide rectangular canals is considered as a reasonable representation of the truth, these coefficients can be expressed as $a = S_o^{1/2} \cdot n^{-1}$ and

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$b = 5/3$, where S_o is the river slope and n the river flow roughness coefficient. However, as in most applications, a and b are estimated by curve-fitting, and they do not necessarily represent their physical characteristics. Due to changes in the river geometry, rating curves must be updated periodically. Also, scatter around the curve can exist as the relation is derived from approximations of observations. Errors can be in the order of 10–15%, varying as a function of the river geometry, numerical approximation and quantity and quality of measurements.

Radar altimetry provides us with the height, H [m], which represents the instantaneous measurement of the Earth's surface height referenced to a specified ellipsoid. In this sense, H corresponds to the height of the reflecting surface that receives and reflects the satellite radar echoes. The river depth h can be derived from H by subtracting the mean river bed elevation, or the zero-flow water height, z ($h = H - z$). This leads to the general formulation of the rating curve equation defined as

$$Q = a \cdot (H - z)^b \quad (1)$$

However, as in most cases, the zero-flow water height z is an unknown variable. A straightforward way to estimate this parameter is by minimizing errors of curve-fitting between stage and discharge observations at a given location and period using the linear form of Eq. (1):

$$\ln(Q) = \ln(a) + b \cdot \ln(H - z) \quad (2)$$

3 Methods

The methodology used to predict water discharges is based on rating curve fitting by combining radar altimetry with simulated discharges in Eq. (2). Maximizing the coefficient of determination, R^2 , is performed to optimize z and parameters a and b . R^2 is computed for the best fit between Q and $H - z$, as denoted by Eq. (2), and ranges between zero and 1, where 1 represents the optimal value. For a given z , a and b are

5 estimated by a linear statistical regression. Exploring the range of possible values of z allows the function $R^2 = f(z)$ to be built up. In cases where convergence is not reached, i.e., $R^2 = f(z = \infty)$, the search procedure stops when a differential R^2 (dR^2) between two search steps is equal or less than 10^{-6} . These cases will be called “non-converging curve fittings” hereafter (and the opposite case “converging curve fittings”).

10 The current Envisat radar altimetry dataset covers several large rivers, lakes and floodplains within the Amazon basin, being composed of over 1500 VS. After selection of VS located over rivers with sufficiently long and consistent time series, 444 VS remained (see Fig. 1 for the spatial distribution of VS). The ranges used in this study are those issued by the ICE-1 algorithm (Bamber, 1994). Absolute errors of altimetric time series within the Amazon basin are in the order of tens of centimeters (da Silva et al., 2010). Selected VS cover most Amazon River’s tributaries and other small rivers, with drainage areas ranging from 10 000 km² to 5 238 800 km². Time series length varies from 23 to 63 altimetric observations for the 2002–2009 period. Details about the data extraction, retracking and evaluation against in situ observations are reported in da Silva et al. (2010). In this study, the water heights provided by Envisat were converted to altitudes using the GRACE static solution of GGM02C geoid model (Tapley et al., 2004).

20 Simulated discharges (Q_{sim}) are provided at a daily time step and 0.25° spatial resolution by HyMAP, coupled in off-line mode with ISBA (Noilhan and Mahfouf, 1996). HyMAP is a global scale flow routing scheme capable of simulating flow velocity, water discharge, depth and storage in rivers and floodplains, among other hydrological variables. The runoff and baseflow generated by ISBA (see Decharme et al., 2011, for a full description of ISBA parameterization and forcings) are routed using a kinematic wave formulation through a prescribed river network to oceans or inland seas. Details about the HyMAP parameterization considered in this study are described in Getirana et al. (2012). The uncertainty of simulated discharge varies spatially as a function of both the size the drainage area (A) and quality of LSM inputs, notably the precipitation field. The relative error (RE) of simulated discharges ranges from 0.155 (or 15.5 %) for

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large basins ($A > 10^6 \text{ km}^2$) to 1.105 ($\sim 110\%$) for smaller areas ($A < 10^5 \text{ km}^2$). RE values are closely related to the vertical water balance, which is highly sensitive to precipitation and LSM parameterization. Altimetric data was combined to simulated discharge at grid cells representing the river reaches where virtual stations are located.

Two experiments were performed in order to evaluate the impacts of simulated discharge uncertainties on rating curve fitting. The first one uses simulated discharge from the standard HyMAP model configuration as described in Getirana et al. (2012). The second one takes advantage of the assimilation of observed daily discharges (Q_{obs}) at 135 gauging stations (see spatial distribution of stations in Fig. 1) during the HyMAP run by directly replacing simulated discharges by observations at the outlet of the corresponding grid cells. Gauging stations are operated by the Brazilian Water Agency (ANA) and have at least one year of observed discharges within the study period. The discharge data assimilation assures that uncertainties in the curve fitting at VS located near gauging stations are mainly due to altimetric data rather than discharge. Finally, two different discharge forecasts can be provided by rating curves at each VS: (1) discharge derived from curve fitting without assimilation (Q_{rc0}); and (2) with assimilation (Q_{rc1}). Curve fitting was performed during the 2002–2005 calibration period for the whole set of VS. However, only 90 VS located near gauging stations had discharge forecasts compared against observations. In order to quantify the impacts of radar altimetry data on discharge forecast from rating curves, H_{sat} at these same selected virtual stations was compared to stage observations for both calibration and validation periods. The distances between the selected VS and gauging stations do not exceed 30 km. Based on the geographical proximity, it was considered that these stations have the same hydrological response, since the incremental area within the reaches are irrelevant if compared to the total drainage areas upstream the stations. The evaluation of predicted water discharges by rating curves was performed in the 2006–2008 period. The accuracy of discharge estimates was determined by using three performance coefficients: the normalized root mean square error (NRMSE), the Nash-Sutcliffe (NS) coefficient and the relative error (RE).

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$$\text{NRMSE} = \frac{\text{RMSE}}{(y_{\max} - y_{\min})} \quad (3)$$

$$\text{NS} = 1 - \frac{\sum_{t=1}^{nt} (y_t - x_t)^2}{\sum_{t=1}^{nt} (y_t - \bar{y})^2} \quad (4)$$

$$\text{RE} = \frac{\sum_{t=1}^{nt} x_t - \sum_{t=1}^{nt} y_t}{\sum_{t=1}^{nt} y_t} \quad (5)$$

5 where t is the time step, nt the total number of days disposing of observed data, x and y are, respectively, the simulated and target (observed) signals at time step t , and y_{\max} , y_{\min} and \bar{y} are respectively the maximum, minimum and mean values of the target signals for the entire period. NS ranges from $-\infty$ to 1, where 1 is the optimal case and zero is when simulations represent observed signals as well as the mean
 10 value. NRMSE and RE vary from zero to $+\infty$, where zero is the optimal case. One can obtain NRMSE and RE values in percentage by multiplying them by 100.

4 Results and discussion

4.1 Curve fitting

15 Figure 2 shows the spatial distribution of R^2 values and curve coefficients (a , b and z) derived from the calibration procedure for both experiments. From a total of 444 VS, 205 had rating curves converging to optimal z values in experiment 1 (without data assimilation). The other 239 VS had the calibration procedure interrupted based on the

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$dR^2 \leq 10^{-6}$ criterion. R^2 values used as the objective function in the calibration varied from 0.21 to 0.95. The mean R^2 value of converging rating curves was 0.54. Diverging rating curves had a higher mean R^2 of 0.67 which implies that non-convergence does not necessarily indicate bad curve fitting. This deduction will be addressed in next section.

As for experiment 2 (with data assimilation), 304 rating curves converged to optimal z values, representing an increase of 48 % in comparison with experiment 1. The assimilation of water discharge observations also improved R^2 values, varying from 0.21 to ~ 1 . Converging and diverging curve fittings had mean R^2 of 0.76 and 0.69, respectively. Improvements are clearly noticed downstream of gauging stations, especially in medium and large rivers. These results demonstrate a significant enhancement in the curve calibration when observed discharges are assimilated into the modeling system.

According to Fig. 2, the zero-flow equivalent depth, z , and coefficients a and b had similar values for both experiments. Coefficients were omitted at VS where calibration did not converge. z values are physically consistent at VS where the calibration converged, ranging from -1.45 m and -5.54 m (experiments 1 and 2, respectively) near Óbidos to about 314 m and 313 m in the Western Amazon basin, near the Andes mountains. Both coefficients a and b showed large ranges. The coefficient a varied from values lower than 10^{-3} to values as high as 10^3 while b ranged from 0.35 to 10. As these values result from an automatic calibration procedure, their physical meanings remain unclear and are not discussed in this study

4.2 Accuracy of discharge forecasts

Tables 1 and 2 list the performance coefficients (NRMSE, RE and NS) used to evaluate the accuracy of discharge estimates provided by the rating curves and modeling during the calibration and validation steps. Coefficients are presented as averages of drainage area (A) thresholds: small ($A < 10^5$ km²); medium (10^5 km² < $A < 10^6$ km²); and large ($A > 10^6$ km²) drainage areas.

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Although discharge estimates derived from experiment 1 (Q_{rc0}) had overall poor results (NRMSE = 28 %, RE = 54 % and NS = -3.73), performance coefficients can vary as a function of the drainage area. Virtual stations with smaller areas had discharge estimates with low accuracy (52 %, 92 % and -13.45 , respectively), while those draining medium (20 %, 46 % and 0.31) and large areas (13 %, 15 % and 0.76) provided much better results. Figure 3 shows NRMSE of selected VS as a function of the drainage area (A). Results of both experiments 1 and 2 are presented for the calibration period. According to the map in the right side of the figure, a larger concentration of VS with high errors is located in the western side of the basin. These results agree with the spatial distribution of performance coefficients for simulated discharge (Q_{sim}), revealing a positive correlation of 0.26 between the accuracy of Q_{rc0} and Q_{sim} .

A substantial improvement is obtained with the assimilation of discharge data into the modeling system performed in experiment 2. The mean values of coefficients NRMSE and RE for the set of 90 VS were reduced to 10 % and 19 %, respectively, and NS had a non-negligible increasing to 0.84. Mean NRMSE values for small, medium and large areas are 7.8 %, 10.1 % and 12 %, respectively. Q_{rc1} uncertainty can be mostly attributed to radar altimetry errors since curve fitting was performed using observed discharge. Although the NRMSE values of unbiased Envisat water levels can exceed 20 % for a single VS, the mean NRMSE is 7.4 % for all VS within the Amazon basin, varying from about 7 % for VS draining medium and large areas to 9 % for small areas (Fig. 3). Mean NRMSE varies from 8 % up to 12 % in the validation period according to the area threshold.

Another source of errors can be curve approximations. The methodology applied in this study is based on the calibration of coefficients (a , b and z) of a single rating curve by maximizing R^2 . Rating curves used by ANA may have been built using different criteria, including the representation of loop ratings caused by variable backwater effects, which also consider river slope.

Discharge estimated in the validation step performed almost as well as estimates in the calibration step, presenting a minor degradation of most coefficients (see Table 2).

In experiment 1, mean NRMSE and RE remained nearly the same (30% and 53%, respectively) with minor variation within VS groups. The mean Nash-Sutcliffe coefficient improved ($NS = -1.58$), explained by the increasing of the performance at VS with $A < 10^5 \text{ km}^2$. Other groups had NS values lower than those provided by the calibration step.

Experiment 2 provided a slightly higher degradation of mean NRMSE and NS (13% and 0.53, respectively), but RE stayed closely the same (20%). According to Fig. 3, NRMSE of H_{sat} is slightly higher in the evaluation period (2006–2008), averaging 9%. This explains the general increasing of discharge estimate uncertainty in that same period (mean NRMSE values are of 10% for Q_{rc0} and 13% for Q_{rc1}) and demonstrates a general agreement with results derived from the calibration step.

Figure 4 shows results of three VS selected from the dataset, each one representing a group of VS defined by drainage areas (see Fig. 1 for location of virtual stations): vs-8 represents large areas, located in the lower Amazon River near Óbidos, drains a surface of $4.7 \times 10^5 \text{ km}^2$ with a mean discharge of $\sim 173\,000 \text{ m}^3 \text{ s}^{-1}$; vs-217 is an example medium areas ($209\,200 \text{ km}^2$), mean discharge of $13\,700 \text{ m}^3 \text{ s}^{-1}$, near the Vila Bittencourt station on the Japurá River; and vs-479 for small areas ($16\,000 \text{ km}^2$), with mean discharge of $620 \text{ m}^3 \text{ s}^{-1}$ located near Palmeiras do Javari station on the Javari River. At virtual station vs-8, both curve-fitting experiments did not converge to a feasible z but the maximum R^2 values were of 0.98 and 0.92, respectively. The virtual station vs-217 showed a converging z value in the second curve-fitting experiment only ($z = 34.6 \text{ m}$), but R^2 of both experiments were relatively high (0.86 and 0.93, respectively). Finally, vs-478 had converging z values in both experiments with similar values (67.3 m and 66.5 m, respectively), but R^2 values significantly different (0.49 and 0.98, respectively). Although the accuracy of curve-based discharge estimates in experiment 1 varied as a function of the drainage area, all the cases provided improved discharges when compared to Q_{sim} . As for the calibration step (2002–2005), Q_{rc0} had relative errors of 7% (vs-8), 18% (vs-217) and 153% (vs-478) and NRMSE of 12%, 9% and 45%, respectively. The validation step (2006–2008) had similar results, with RE values of 8%, 12% and 213% and NRMSE of 10%, 8% and 48%. Data assimilation improved results of

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all the three VS, but significant changes are visible for vs-478, where RE and NRMSE were drastically improved to 8% and 4%, respectively, for the calibration step, and 10% and 4% for the validation step. Errors in Q_{rc0} for vs-8 are mainly due to overestimated peak discharge, as provided by HyMAP (see Fig. 4). As for vs-217, Q_{rc0} errors are derived from underestimated peaks, while vs-478 has overestimated discharges throughout the study period.

5 Concluding remarks

This letter presents a new methodology to predict water discharges from radar altimetry data in the Amazon basin. The technique is based on the calibration of rating curves using altimetric data and simulated water discharge at VS. A first evaluation (called experiment 1) was conducted by building rating curves at 444 VS within the basin combining Envisat data and simulated discharges derived from the HyMAP model. In order to evaluate the impacts of model uncertainties on rating curve accuracy, an additional experiment (experiment 2) was performed using model outputs resulting from a simplified discharge data assimilation procedure. Discharge estimates at 90 VS were compared against observations at nearby gauging stations. Based on the results obtained, we can say that discharge forecasts from current large scale radar altimetry datasets based on rating curves are feasible, but accuracy is highly sensitive to the quality of input data.

Overall, discharge forecasts provided by both experiments had good performance. In most cases, rating curve-based discharges performed better than model simulations. Results can be considered as optimistic if compared to previous related studies and are as acceptable for most hydrological applications. However, significant differences in experimental results were noted at smaller scales, i.e. VS with drainage areas $A < 10^5 \text{ km}^2$, where rainfall monitoring is usually inappropriate and model parameter uncertainties are higher (Getirana et al., 2012). Uncertainties of experiment 1 are closely related to simulated discharge errors. This is due to the noise reduction

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performed by the linear regression. The use of rating curves derived from this experiment at these locations should be more adequate to estimate monthly or annual discharges rather than daily. Experiment 2 provided better overall results. The assimilation of observed discharges eliminated the impact of simulated discharges on rating curve accuracy, resulting in a dominant influence of the low altimetric data uncertainty. Such differences between experiments are expected since precipitation and model uncertainties are eradicated by the assimilation of observed data.

It must be highlighted that in some cases, the calibrated rating curve parameters may not be reflective of the actual channel hydraulics. This relation will depend on the quality of data used as input for the curve calibration and hydraulic properties of the river at the station. For example, the stations located a short distance upstream from a confluence in flat regions may be influenced by backwater effects. In such cases, the stage at the station also depends on the stage at the confluence.

The continuous development of sophisticated physically-based flow routing schemes coupled with land surface models allows us to easily obtain gridded water discharge time series at the global scale with reasonable accuracy. However, these modeling systems are frequently constrained by quality or time length of global datasets, making it difficult to obtain accurate simulations of physical processes on a near real-time basis at poorly-gauged or ungauged locations. The combination of the present methodology with forthcoming altimetric and topographic missions (e.g., SWOT mission) will considerably improve the understanding of hydrological processes and streamflow estimates in unequipped basins. Ultimately, altimetry-based discharges can be used in a flow routing scheme framework to evaluate the feedback effects between the land surface and atmosphere and the vertical water and energy balances computed by LSMs.

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Water discharge estimates in the Amazon basin

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C. Peters-Lidard

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Table 1. Performance coefficients (NRMSE, RE and NS) of water discharges estimated by the rating curves at selected virtual stations for the calibration period (2002–2005). Coefficients of modeled discharges at gauging stations used in the evaluation are also provided. Values correspond to averages of drainage area thresholds.

	Thresholds of drainage area, A (km ²)			
	$A < 10^5$	$10^5 < A < 10^6$	$A > 10^6$	Total
Experiment 1 (Q_{rc0})				
NRMSE	0.521	0.202	0.128	0.282
RE	0.919	0.46	0.148	0.536
NS	-13.449	0.312	0.761	-3.727
Experiment 2 (Q_{rc1})				
NRMSE	0.078	0.101	0.12	0.098
RE	0.18	0.225	0.119	0.19
NS	0.907	0.837	0.759	0.842
HyMAP simulation (Q_{sim})				
NRMSE	0.372	0.247	0.134	0.262
RE	1.105	0.628	0.155	0.677
NS	-1.315	0.166	0.766	-0.159

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Table 2. Same as Table 1, but for the validation period (2006–2008). Simulated discharges are not available for this period.

	Thresholds of drainage area, A (km ²)			Total
	$A < 10^5$	$10^5 < A < 10^6$	$A > 10^6$	
Experiment 1 (Q_{rc0})				
NRMSE	0.522	0.233	0.158	0.298
RE	0.976	0.429	0.159	0.534
NS	-6.141	0.163	0.64	-1.582
Experiment 2 (Q_{rc1})				
NRMSE	0.097	0.128	0.16	0.126
RE	0.173	0.227	0.144	0.195
NS	0.73	0.388	0.602	0.529

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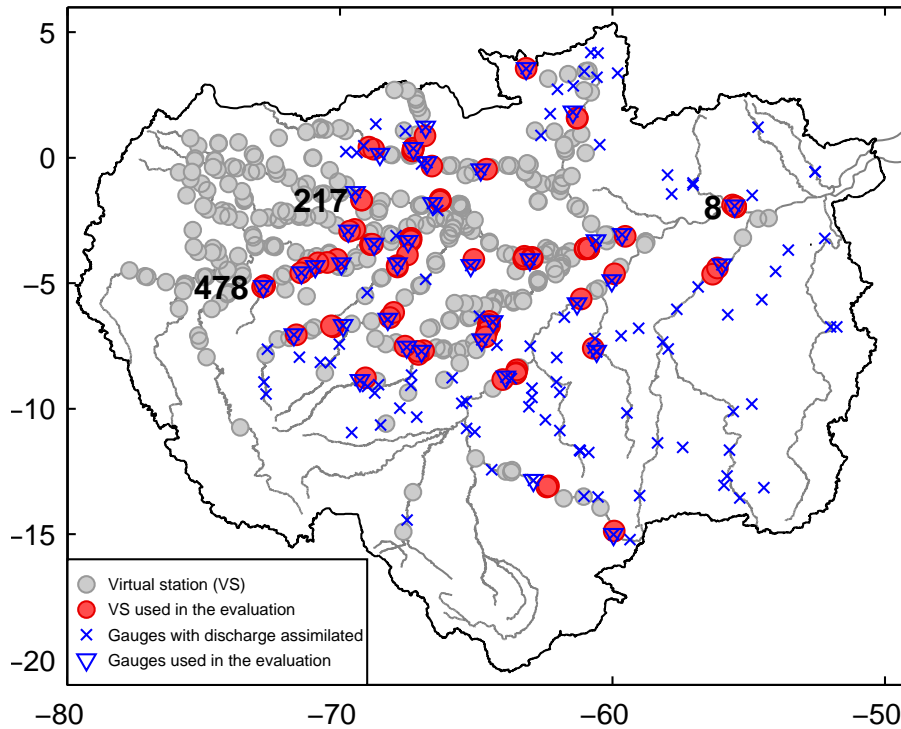


Fig. 1. The Amazon basin and the geographical location of virtual and gauging stations used in this study.

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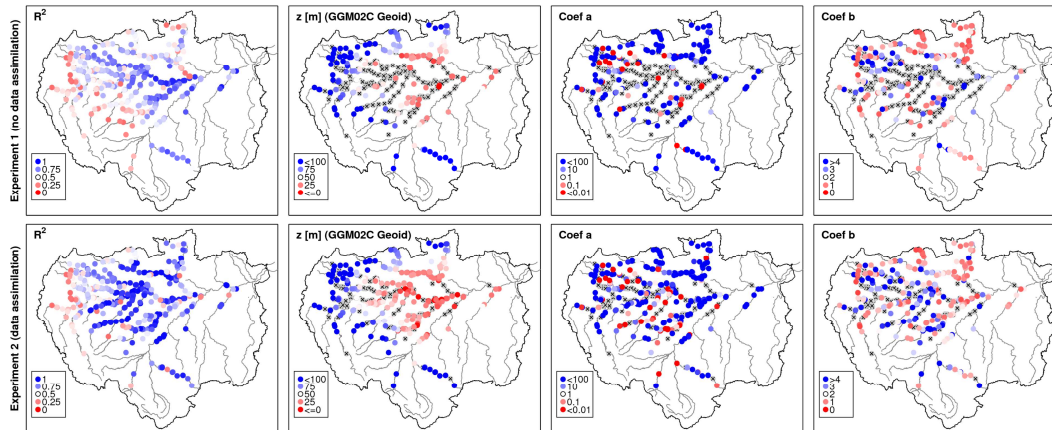


Fig. 2. Results of curve fitting at 444 virtual stations. Zero-flow equivalent depth (z) values and coefficients a and b are omitted (represented by crossed circles) at virtual stations with non-converging rating curves.

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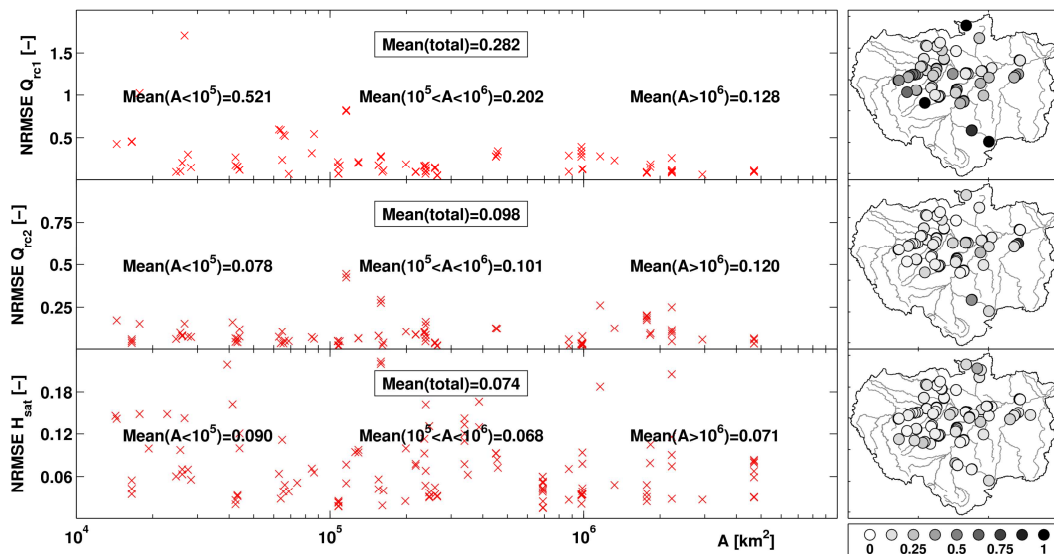


Fig. 3. Normalized root mean square errors (NRMSE) of water discharge and level at 90 virtual stations during the calibration period (2002–2005): on the top, discharge estimates from experiment 1 (no assimilation of observed discharge); on the middle, discharge estimates from experiment 2 (assimilation of observed discharge); and on the bottom, water level fluctuation provided by Envisat. On the left, NRMSE values are presented as functions of the drainage area, A . On the right, NRMSE of virtual stations are spatially distributed within the Amazon basin.

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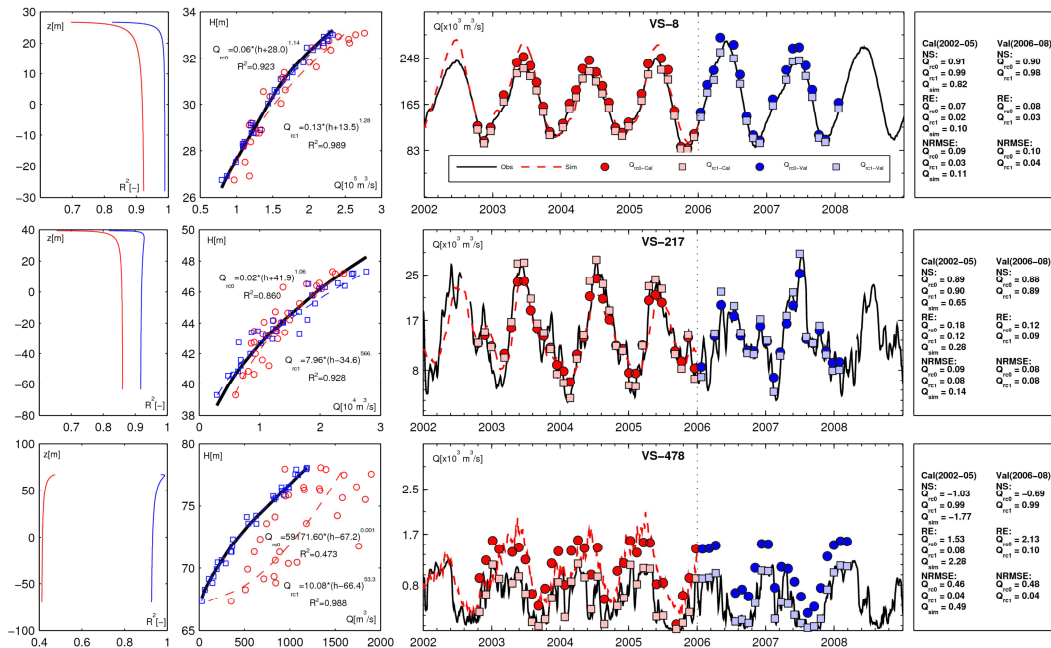


Fig. 4. Results from the curve fitting procedure for three virtual stations: vs-8, vs-217 and vs-478 (see location in Fig. 1). On the left, the optimization of $R^2 = f(z)$: red represents experiment 1 (Q_{rc0}) and blue is experiment 2 (Q_{rc1}). On the middle-left, the curve fitting for both experiments: red dots and lines stand for experiment 1 and blue squares and lines are derived from experiment 2. On the middle-right, observed and simulated daily discharges and curve estimates for both experiments during the calibration and validation periods (legend is provided). On the right, performance coefficients NS, RE and NRMSE of discharge estimates derived from experiment 1 (Q_{rc0}) and 2 (Q_{rc1}) for both calibration and validation periods. Coefficients for Q_{sim} are also provided for the calibration period.

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