A quantile function approach to discharge estimation from satellite altimetry (ENVISAT)

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[1] The publicly available global discharge database is limited in spatial and temporal coverage. Although regional exceptions exist, the population of the database has declined over the past several years. As discharge is one of the most important parameters for modeling hydrological interactions, alternative measuring techniques must be sought. In the recent past, satellite altimetry has been investigated as an alternative for monitoring inland water level. In the present study, altimetry footprints in the vicinity of river gauging stations for the Amazon, Amur, Brahmaputra, Danube, Don, Mekong, Niger, Ob, and Vistula rivers are analyzed for a functional relationship between the water level measurements from altimetry and discharge from the gauging stations. Such a functional relationship is conventionally established via a rating curve computed using simultaneous data. This study proposes a statistical approach based on quantile functions to infer this functional relation without the need for having synchronous data sets. The statistical approach provides the opportunity of extracting discharge values from altimetry data for rivers like the Mekong, Brahmaputra, Don, and Vistula for which the discharge measurements at the selected gauges were made before the age of satellites. The algorithm is then validated over those rivers which do have discharge measurements available within periods of altimetry. Our validation shows that our algorithm is in the same quality range as the conventional approach. We are thus able to salvage presatellite altimetry discharge data and turn them into active use for the satellite altimetry time frame.

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1. Introduction

[2] Freshwater supply is crucial to human life. Surprisingly, human knowledge of the spatial and temporal dynamics of the surface freshwater variations and discharges is limited [*Alsdorf et al.*, 2007]. Measuring the components of the hydrological cycle and modeling their interactions help us understand the freshwater behavior. Despite the overall success of hydrological models, they are far from perfect. Comparing different models and gauged observation reveals large model error, sometimes greater than 100% [*Alsdorf and Lettenmaier*, 2003]. A large difference between models underlines the necessity of in situ measurements for improving and validating the models. However, this becomes increasingly problematic as the worldwide number of gauging stations has been decreasing since the 1970s [*Milzow et al.*, 2011; *Fekete and Vörösmarty*, 2007]. This decrease seems to be more unsatisfactory in the case of discharge as it plays an important role in hydrological studies, being an output from hydrological models and input to many hydrological interactions. The discharge database is limited and is declining steadily over the past few decades (Figure 1), which emphasizes the need for independent sensors like space-borne sensors to monitor the surface water [*Bjerklie et al.*, 2003].

[3] Among the space-borne sensors, satellite altimetry can provide surface water height successively with repeat periods of 10 and 35 days [*Fu and Cazenave*, 2001]. Although satellite altimetry was initially designed for oceanography, four decades of altimetry missions have provided an opportunity to study the continental hydrological cycle as well [*Alsdorf and Lettenmaier*, 2003; *Calmant and Seyler*, 2006; *Papa et al.*, 2006, 2010; *Crétaux and Birkett*, 2006; *Berry et al.*, 2005]. Particularly, usage of satellite altimetry has mainly focused on monitoring water levels in large rivers and lakes by topex/poseidon (tp) and ENVISAT missions [*Birkett*, 1995; *Cazenave et al.*, 1997; *Stanev et al.*, 2004; *Frappart et al.*, 2006, 2008; *Crétaux et al.*, 2011]. Moreover, the capability of satellite altimetry

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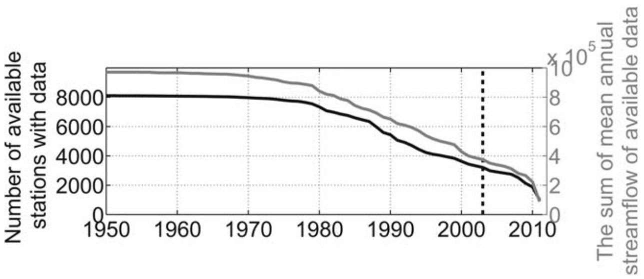

Figure 1. Number of available stations with discharge data according to GRDC database is depicted for different years together with the sum of mean annual stream flow of available data. Among the 8424 stations around the world for 3323 gauging stations, data are available after launching of the ENVISAT.

for estimating river discharge in large rivers has been assessed [*Kouraev et al*., 2004; *Zakharova et al*., 2006; *Leon et al*., 2006; *Coe and Brikett*, 2004; *Papa et al*., 2010; *Getirana and Peters-Lidard*, 2012].

[4] Within previous altimetry based studies, the river discharge at the selected gauges is typically determined from an empirical functional relation between water level estimated by satellite altimetry and measured discharges. This relation, referred to as a *rating curve*, is specific to each gauging station and location of altimetry. However, it is known that this technique has certain limitations, which will be discussed in the following and also have been addressed by *Alsdorf et al*. [2007] and *Papa et al*. [2010].

[5] On the one hand, first, this technique is limited by the availability of in situ discharge measurements simultaneous with altimetry data. In case of using ENVISAT altimetry, simultaneous measurements mean that the discharge data should be available after the year 2003. This becomes a serious restriction as among the 8424 recorded gauging stations in Global Runoff Data Center (GRDC) database, only 40% of stations provide discharge data after 2003 (Figure 1).

[6] On the other hand, the location of the altimetry footprint can also limit the usage of the technique. It becomes problematic and critical in two ways, one being a footprint dissimilar with gauge in terms of geomorphology [*Papa et al*., 2010] and the other is the low-quality altimetric water level time series driven by an inappropriate location of footprint.

[7] If in situ discharge measurements and high-quality altimetric water level time series are available, the performance of the methodology is restricted by sampling problems [*Papa et al*., 2012]. In other words, establishing the rating curve is possible if the measurements of altimetric water level and of in situ discharge are consistent in statistical sense. This consistency is challenging as satellite altimetry provides only 10 or 35 days interval time series and discharge measurements are often available in daily or monthly time scales. Therefore, certain statistical tests should be employed to check the consistency of water level and in situ discharge measurements.

[8] In this study, we propose to use a statistical modeling approach using quantile functions to create the rating curve without the requirement of simultaneous measurements. This statistical algorithm provides the opportunity of estimating discharge from satellite altimetry (altimetric discharge) for a river with no available in situ measurements within the altimetry time frame. We are thus able to salvage presatellite altimetry data and turn them into active use for the satellite altimetry time frame. In order to validate the estimated discharge using the statistical algorithm with the discharge from common methodology, hereafter empirical algorithm, over rivers with available in situ discharge measurement within altimetry time period.

[9] We perform this analysis at gauges for the Amazon, Amur, Brahmaputra, Danube, Don, Mekong, Niger, Ob, and Vistula rivers. We choose these case studies as they have different characteristics, which brings the opportunity of assessing the proposed algorithm thoroughly. The Amazon, Amur, Ob, Danube, Mekong, Niger, and Brahmaputra are broad enough to be captured by altimetry, while the Don and Vistual are narrower rivers with a width of 0.3 km. The Ob River is located in the boreal region and is covered with snow and ice most of the time. The Amazon and Niger flow in the tropics, where high water levels occur during the wet season. Also, in terms of discharge data availability, these rivers behave differently. For the Amazon, Amur, Danube, Niger, and Ob rivers, the discharge is available within the time period of altimetry, which is not the case for the Brahmaputra, Don, Mekong, and Vistula. Moreover, Amazon and Ob are the rivers for which the discharge was estimated by *Birkett et al*. [2002], *Kouraev et al*. [2004], and *Zakharova et al*. [2006], which allows us to compare results.

[10] The paper starts with a description of data sets and location of altimetry footprint close to the gauging station in section 2. The statistical consistency of available satellite altimetry and in situ discharge measurements are discussed in section 3. In section 4, we propose our statistical algorithm based on quantile functions of data sets. The discharge is then estimated from the established statistical rating curves and compared with the discharge derived from empirical approach and the results are discussed in section 5. Furthermore, the results of discharge estimation are then validated in section 6 against the in situ measurements. In this section, the estimated discharge is also investigated to assess if our methodology brings better estimation in comparison to the *monthly mean* discharge. Finally, we conclude with a discussion in section 7.

2. Data Sets

[11] In this study, the virtual stations of the Amazon, Amur, Brahmaputra, Danube, Mekong, Vistula, and Ob are defined upstream of the discharge gauge and downstream for the Niger and Don (Figure 2). The water level time series for the virtual stations are achieved by employing an algorithm, which conforms to a large extent to the standard processing of altimetry data in hydrological applications [*da Silva et al*., 2010]. Our algorithm mainly relies on the Ice-1 retracker, which according to *Frappart et al*. [2006] and *da Silva et al*. [2010], provides the best estimate of inland water level variations. However, the water level measurements are optimized by employing information from the other retrackers as well.

[12] For evaluating the derived altimetric water level, in situ water level close/at the virtual station is needed (Table 1). Among the aforementioned rivers, we have only access

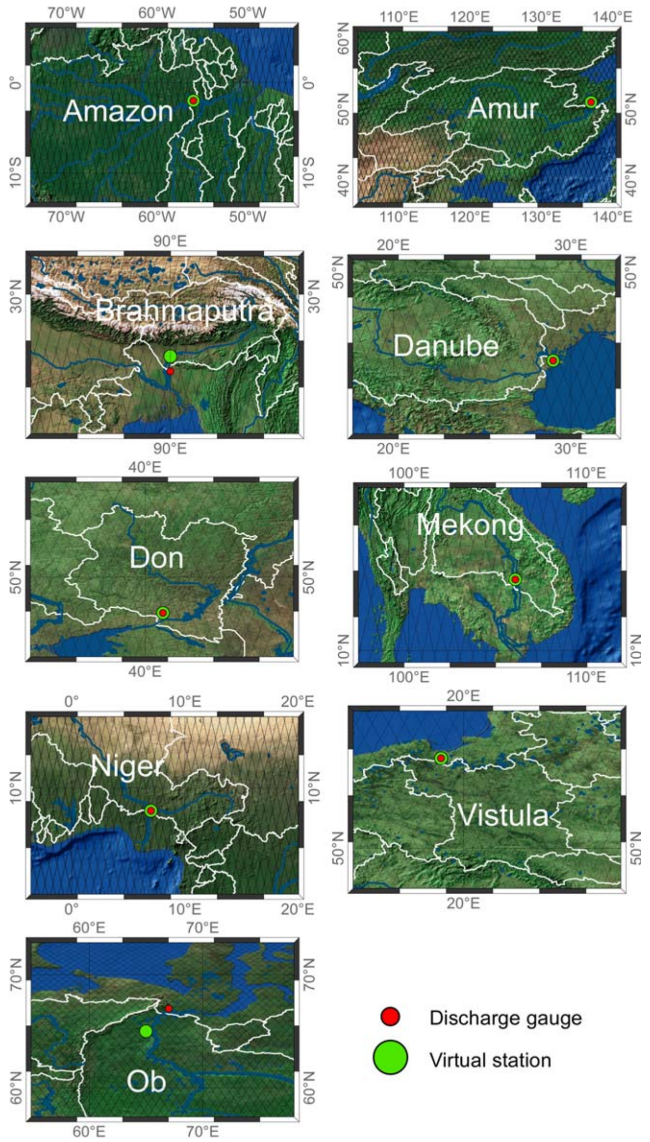

Figure 2. Different river basins under study with the ground tracks of ENVISAT. The virtual stations of the Amazon, Amur, Brahmaputra, Danube, Mekong, Vistula, and Ob are defined upstream of discharge gauge and downstream for the Niger and Don.

to the in situ water levels of Amazon, for which the correlation coefficient of 0.98 and Root Mean Square Error (RMSE) of 0.44 m are obtained from comparison with altimetric water level (see Appendix A).

[13] As depicted in the Figure 2, Ob is the only river, in which the virtual station is defined about 170 km away from the gauging station and not at the closest possible virtual station. In fact, due to the presence of ice and snow water level time series in the boreal region become noisy, which forced us to avoid using them for further investigation. Practically, assuming more than one virtual station for each river requires a number of considerations like concordance of channel width, slope correction, etc. Hence, for this study, only one virtual station close to the discharge gauge of each river is defined. Moreover, similar challenges are raised when multimission altimetry is used for investigation over rivers, so this study focuses only at the ENVISAT.

[14] For discharge, monthly and daily measurements in units of cubic meter per second are collected from different sources: (1) GRDC, (2) Arcticrims project, (3) Ore hybam project (Table 1).

[15] The discharge measurements are then converted to *specific discharge* by dividing the value to the area of the catchment and multiplying by 86.4 to achieve the unit of millimeter per month. This allows to assess the amount of river discharge with respect to the size of the upstream catchment. In the entire paper when river discharge appears, we refer to the specific discharge with unit millimeter per month. From the data availability, we distinguish between Group 1, consisting of rivers with available discharge measurements synchronous with the time period of altimetry (the Amazon, Niger, Danube, Amur, and Ob rivers), and Group 2, consisting of those without discharge measurement (the Mekong, Brahamputra, Don, and Vistula rivers).

3. Consistency Check

[16] ENVISAT brings in the best case a water level time series with 35 days time interval, while discharge data are available at daily or monthly sampling. Being just a snapshot, altimetry provides neither daily nor monthly sampling. However, discharge extraction from a desired functional relationship is only possible at the times of altimetry measurements. As 35 day sampling is sufficiently close to a month, we decided to turn the snapshot measurements into monthly discharge. This raises two important questions:

1. Which time resolution of discharge corresponds better with altimetric water level for creating a functional relationship: daily discharge at the day of altimetry considered as monthly value (hereafter quasi-monthly) or true monthly discharge? For the former, we multiply the daily discharge at the day of altimetry by the number of days of that month. For the latter, we sum all daily values at the month of altimetry (Figure 3).
2. Is the statistical distribution of the observed discharge at the times of altimetry measurements consistent with the statistical distribution of the complete discharge data set?

[17] The first question concerns the dynamic behavior of the river, where in case of stationary flows monthly and quasi-monthly discharge will be similar. They will be dissimilar in rivers with highly fluctuating water regime. The example of Figure 3 shows the principle of difference between monthly and quasi-monthly discharge. Figure 4 shows the comparison of monthly and quasi-monthly discharge values for the Danube and Niger rivers, that overall represents similar behavior of monthly and quasi-monthly discharge.

[18] The second question expresses the performance of the rating curve. If the statistical distribution of the observed discharge at the times of altimetry measurements does not represent the distribution of discharge, the derived rating curve would not be able to model every possible value of discharge within the range of distribution. Answering this question also justifies the ability of altimetry to map extreme values.

[19] In order to compare the distribution of both sets of data, the corresponding empirical Cumulative Distribution

Table 1. Virtual Stations (VS) Close to the Discharge Gauging Stations With Their Characteristics for Rivers Under Consideration[a]

		Virtual Station		River	Discharge Gauging Station				
	Area (km2)	Latitude [deg]	Longitude [deg]	Width [km^2]	Name	Distance to VS [km]	Latitude [deg]	Longitude [deg]	Available Data
Amazon	4,672,876	−1.89	−55.59	3.7	Obidos Porto	+10	−1.94	−55.51	1927–2010
Amur	1,949,471	50.50	137.04	2.0	Komsomolsk	+14	50.63	137.12	1940–2004
Brahmaputra	521,828	25.73	89.76	10.0	Bahadurabad	+61	25.18	89.67	1985–1992
Danube	771,277	45.25	28.54	1.5	Ceatal Izmail	+13	45.21	28.71	1931–2008
Don	378,180	47.50	40.56	0.3	Razdorskaya	−8	47.54	40.64	1952–1995
Mekong	640,708	13.78	105.97	1.4	Stung Treng	+32	13.53	105.94	1960–1994
Niger	2,100,508	7.85	6.91	1.6	Lokoja	−17	7.80	6.76	1970–2006
Ob	2,926,321	65.13	65.28	2.3	Salekhard	+170	66.57	66.53	1954–2003
Vistula	186,147	54.16	18.84	0.3	Tczew	−8	54.10	18.80	1900–1994

[a]The distance between the gauging station and virtual station is also shown.

Function (CDF) of monthly and quasi-monthly values are compared. The statistical comparison of distributions has been done using the Kolmogorov-Smirnov (k-s) test, which is a nonparametric test for the equality of one-dimensional probability distributions from two samples [*Massey*, 1951]. The null hypothesis of this test is that the samples are drawn from the same distribution. Therefore, the k-s statistic quantifies a distance between the empirical distribution functions of two samples to assess the similarity of the distributions. A smaller test statistic implies a stronger similarity. The more similar distributions of monthly or daily discharge within the time period of altimetry with the whole distribution of monthly or daily discharge, the better the model to extract river discharge. Therefore, the test statistic can be also employed as a tool to answer the first question where the lower test statistic offers to choose quasi-monthly or monthly discharge for building the rating curve. However, addressing the mentioned questions and performing the rating curve should be dealt with differently for rivers in groups 1 and 2.

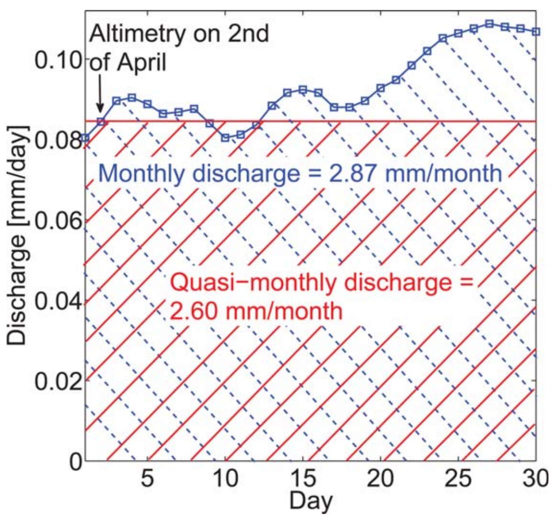

Figure 3. Daily discharge of the Niger River in April 2004. ENVISAT flies over the virtual station of the Niger River on 2 April 2004. The quasi-monthly discharge for April 2004 is 0.086 mm/day × 30 = 2.60 mm/month and the monthly discharge is 2.87 mm/month.

3.1. Consistency Check for Rivers in Group 1

[20] As discharge measurements are available during the time period of altimetry, the above two questions can be answered by performing the k-s test over the monthly and daily discharge at the time of ENVISAT measurements and the whole available discharge. Figure 5 shows the obtained CDF and results of k-s test at a significance level of 0.05 over the Niger River. The null hypothesis for all five rivers in group 1 is accepted, which means that the answer to the question 2 is *yes*. This supports the idea of establishing a rating curve using available discharge measurements and water level by altimetry. Table 2 shows the result of the k-s test for rivers in group 1. For the Amazon and Ob, the statistics from daily discharge indicate more similarity; the Niger, Danube and Amur statistics prefer monthly discharge. However, as the test statistics for both monthly and daily discharge data are very close to each other, they will both be used for further investigations.

3.2. Consistency Check for Rivers in Group 2

[21] Synchronous measurements of discharge and altimetry are not available for rivers in group 2. Therefore, the mentioned questions should be answered differently. We assume a randomly selected measurement epoch with 35 day interval as representative of the time of altimetry measurements within the available discharge time period. Then, the daily discharge measurements at the considered time

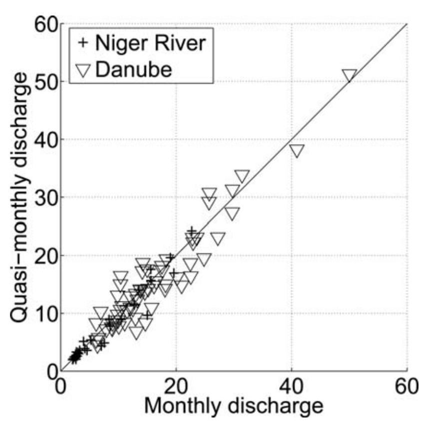

Figure 4. Scatter plot of quasi-monthly discharge versus the monthly discharge value of the Niger and Danube rivers for 2002–2012.

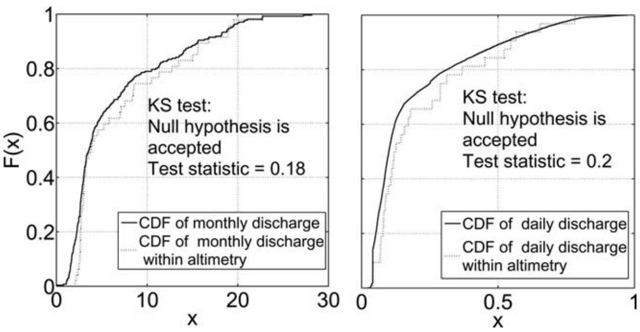

Figure 5. Comparison of empirical cumulative distribution functions of whole available monthly (left)/daily (right) discharge and monthly/daily discharge at the time of altimetry for the Niger River and the results of k-s test with significance level of 0.05.

are compared using k-s test with the whole daily discharge. The arbitrary epochs are moved day by day 34 times within the period of available measurements to cover all the possible cases. The test statistics for all 34 cases are then averaged and nominated as the test statistic of daily discharge (Table 2). The null hypothesis for these three rivers for all 34 cases is accepted at the 0.05 significance level. Daily discharge data are not available for Vistula river.

[22] Following the same procedure for monthly discharge leads to very small test statistics, as the monthly discharge at arbitrary epochs and whole monthly available discharge show very similar distributions. Therefore, answering question 2 relies more on the daily discharge measurements and their distribution. The obtained low statistics imply that the distribution of every 35 days sampled discharge data is similar to the distribution of all available discharge data. This similarity allows us to establish a rating curve from the available measurements. On the other hand, question 1 cannot be specifically addressed as there is no real epoch of ENVISAT altimetry within the available discharge data. Hence, both monthly and daily discharges are investigated to construct the rating curve.

4. Methodology

[23] As discussed before, one of the major problems to derive discharge from altimetric water level is the availability of discharge data within altimetry time period. This data limitation narrows the usage of the method used in the previous studies [*Kouraev et al.*, 2004; *Zakharova et al.*, 2006; *Leon et al.*, 2006; *Coe and Brikett*, 2004; *Papa et al.*, 2010], for which the rating curves are established based on simultaneous water level and discharge measurements. The conventional approach is to fit a smooth (rating) curve, for example, a quadratic curve, through the scatter of the simultaneous time series. Hereinafter, we call this the empirical approach. Therefore, we have motivated to model the relationship between asynchronous measurements of discharge and water level statistically. However, before modeling we should investigate the dependency of water level and discharge.

[24] Dependence of two sets is quantified here by Pearson's correlation (standard correlation) and rank correlation over those rivers with simultaneous data sets. In general, the correlation of two sets reveals linear dependency and the rank correlation measures the extent of monotonic relationship. Table 3 shows the estimated correlations and rank correlations between the altimetric water level and monthly and quasi-monthly discharge for rivers in group 1.

[25] All the altimetric water level time series in the Amazon, Niger, Danube, Amur, and Ob rivers show high correlations and rank correlations with measured discharge. The relative low correlations for Ob River might be explained by the large distance between the virtual station and gauging station of the discharge. In general, the high correlation and rank correlation values in Table 3 express the highly monotonic dependency between the data sets, which was expected physically. In fact, the monotonic relation between water level and discharge with positive rank correlation indicates that the function to derive discharge from water level is a nondecreasing function. This characteristic justifies a statistical approach, based on quantile function mapping.

[26] The quantile function, denoted by $Q(p)$, provides a way of describing the statistical distribution of a data set [*Gilchrist*, 2000]. The quantile functions for data sets of altimetric water level, $Q_W(p)$, and discharge from in situ measurements, $Q_R(p)$, are

$$Q_R(p) = \inf\{X_R \in R : p \leq F(X_R)\} \tag{1}$$

$$Q_W(p) = \inf\{X_W \in R : p \leq F(X_W)\} \tag{2}$$

Table 2. Kolmogrov-Smirnov Test Statistics With Significance Level of 0.05 for the Comparison of Distribution of Two Sets of Data[a]

River	Monthly	Daily
Amazon	0.09	**0.08**
Niger	**0.18**	0.20
Danube	**0.06**	0.08
Amur	**0.18**	0.29
Ob	0.06	**0.05**
Mekong	–	0.03
Brahmaputra	–	0.05
Don	–	0.02

[a]For group 1 rivers: monthly/daily discharge at the time of altimetry and whole monthly/daily discharge. For group 2 rivers: arbitrary daily discharge at the time of altimetry and whole daily discharge. The bold values represent the better statistic for each river.

Table 3. Computed Pearson's Correlation (Corr.) and Rank Correlation (Rank Corr.) Coefficient of Simultaneous Measurements of Quasi-Monthly/Monthly Discharge With Altimetric Water Level for Rivers in Group 1

River		Monthly	Quasi-Monthly
Amazon	Corr.	0.94	0.95
	Rank Corr.	0.96	0.97
Niger	Corr.	0.95	0.96
	Rank Corr.	0.90	0.90
Danube	Corr.	0.83	0.86
	Rank Corr.	0.86	0.87
Amur	Corr.	0.94	0.96
	Rank Corr.	0.88	0.94
Ob	Corr.	0.82	0.85
	Rank Corr.	0.79	0.83

where X_R and X_W refer to the discharge and water level values and $F(\cdot)$ represents the CDF. The quantile function specifies, for a given probability $0 < p < 1$, the maximum value that X_R or X_R can attain with that probability.

[27] In order to derive discharge from satellite altimetry, we should model a function $T(\cdot)$:

$$X_R = T(X_W), \tag{3}$$

[28] As we have demonstrated that the function $T(\cdot)$ is a nondecreasing function, the Q-transformation rule [*Gilchrist*, 2000] holds since a nondecreasing function $T(\cdot)$ of a nondecreasing function (quantile function) must itself be nondecreasing. Therefore, we propose to achieve the functional relationship between water level and discharge, $T(\cdot)$, by means of their quantile functions instead of the data itself:

$$Q_R = T(Q_W). \tag{4}$$

[29] In other words, since the time coordinate is not involved explicitly, we eliminate the requirement of synchronous data sets.

[30] To obtain the quantile functions of water level and discharge empirically, both the monthly values of water level and the measured discharge are sorted ascendingly. The rank of each data set is normalized:

$$p_i = \frac{k_i}{N+1} \tag{5}$$

where k_i is the rank of the sorted values, N is the number of measurements, and p_i is the probability of water level or discharge data. The sorted values of water level and discharge measurements versus their corresponding probability form the empirical quantile function cf. Figure 6 (middle).

[31] The quantile function particularly provides information on the probability that a particular flow or water level was exceeded over the available period. This can also be viewed as the complement of the CDF of the considered discharge or water level variations. Therefore, a direct connection between the quantile functions at the corresponding probability represents a relationship between discharge and water level, which can be referred to as a *statistical* relationship. In principle, the obtained relationship can be used as look-up table implying the desired rating curve. However, as this study aims to compare the statistical and empirical rating curves, a similar way of approximation for both is needed. In general, the rating curve can be approximated with different numerical and physically based methods like polynomial regression, power type equation, etc. In this study, the simple quadratic estimation is used for modeling the rating curve. Thus, the statistical rating curve is achieved by fitting a quadratic curve over the obtained statistical relationship. Figure 6 shows the empirical quantile functions for water level and monthly discharge for the Mekong River and the resulting statistical discharge-water level relationship that leads to a statistical rating curve for the virtual station on the Mekong River by fitting a quadratic curve. In fact, the rating curve is constructed here by eliminating the p coordinates, whereas conventionally t coordinate (time) is eliminated.

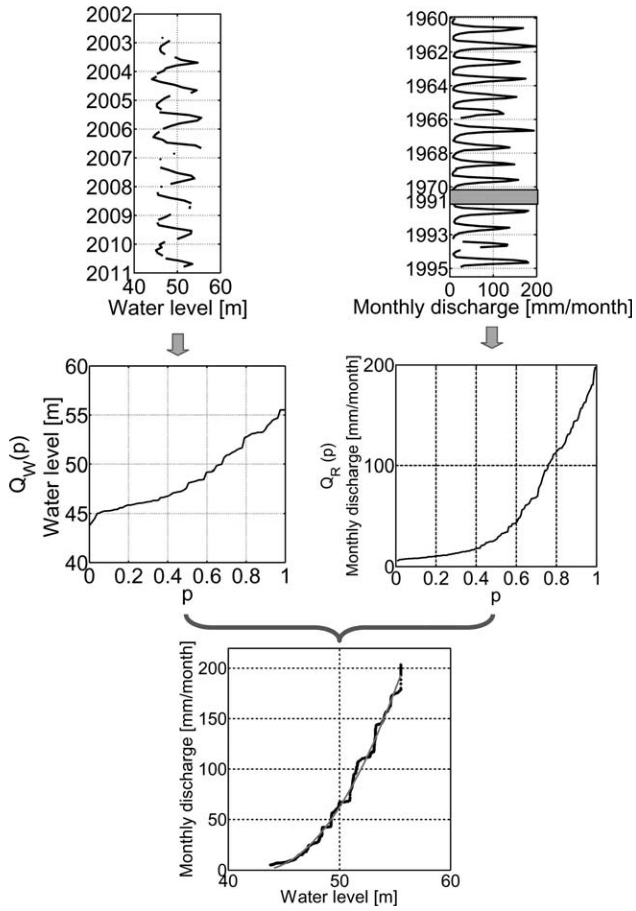

Figure 6. Estimated water level from satellite altimetry and available discharge for the Mekong River (top) are transferred to the quantile functions (middle). From the corresponding probabilities, the scatter plot of discharge versus water level is constructed. A smoothened rating curve is then obtained by fitting a quadratic line to the scatter (bottom). Note the dissimilar time axes of the two data sets (top).

[32] A similar approach can be used to derive the rating curve from daily discharge data. To that end, daily discharge values are converted to quasi-monthly discharge and a corresponding quantile function is achieved. A careful comparison of the quantile functions from monthly and quasi-monthly discharge data reveals that the extreme daily values can overestimate the quantile function belonging to monthly discharge. As an example, Figure 7 shows the different behavior between the quantile functions from monthly and quasi-monthly discharge due to the existence of extreme values in daily discharge data.

[33] We deal with that problem in the following way. The daily discharge values within each year are converted to quasi-monthly discharge and used to form the quantile functions individually for each year. The number of available daily discharge measurements in a year is interpreted as a weight for that year. We have then calculated the weighted median of quantile functions of different years. This allows a robust estimation of a quantile functions from quasi-monthly values, in which the problem of extreme values is tackled (Figure 8). This quantile function is then

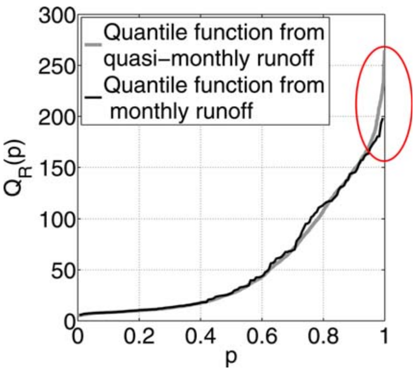

Figure 7. Quantile functions from monthly and quasi-monthly discharge of the Mekong River achieved from sorting the whole monthly and quasi-monthly discharge descendingly and normalizing the ranks. The dissimilar part at extreme daily values is highlighted.

used to directly connect its probabilities to the probabilities of the quantile function from water levels and establish the statistical rating curve.

5. Results

[34] The proposed methodology can be applied to rivers in group 1 and 2 on both monthly and quasi-monthly data to build the rating curves and consequently estimate the discharge. Figure 9 shows the estimated statistical rating curves for group 2 (quadratic models are provided in Figure S2, supporting information). As expected, the rating curves show a nondecreasing behavior except for the rating curve from the quasi-monthly data of the Don River. For this river, rare extreme daily values exist in the data set, which lead to some extreme monthly values and consequently influence the quantile function of monthly discharge. On the other hand, as our method for deriving the quantile function of quasi-monthly values uses the weighted median of quantile functions of different years, the rare extreme values cannot be captured via the weighted median quantile function. Therefore, the rating curves from monthly and quasi-monthly values of Don River depicted in Figure 9 show dissimilar behavior.

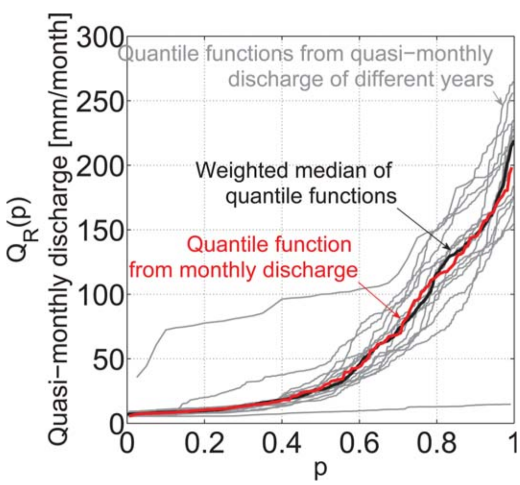

Figure 8. Quantile functions from quasi-monthly discharge of the Mekong River constructed for each year separately. The weighted median of different years' quantile values belong to each probability representing the quantile function from the quasi-monthly discharge data, which is comparable with the depicted quantile function from monthly discharge.

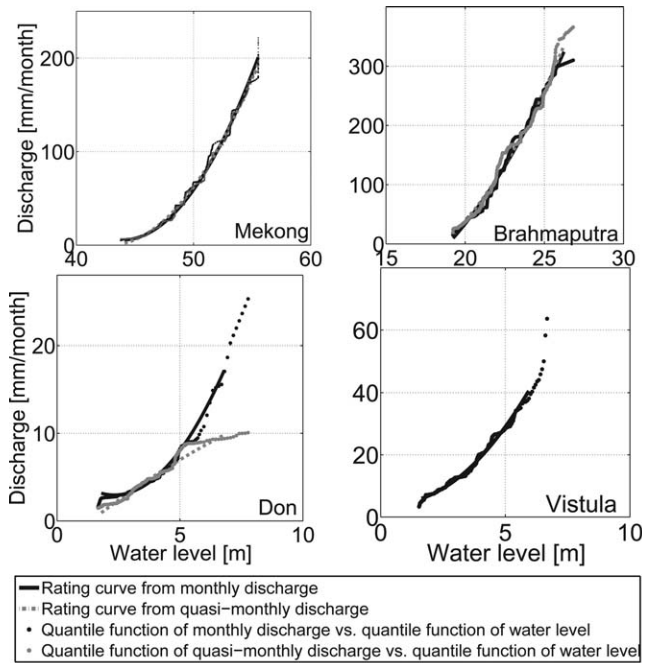

Figure 9. Scatter plots of discharge versus the altimetric water levels for rivers in group 2, produced from the respective quantile functions. Fitted quadratic model represents the obtained statistical rating curve for monthly and quasi-monthly discharge.

[35] In a next step, we convert altimetric water level into discharge for group 2, c.f. Figure 10. As an internal comparison, discharge estimations from quasi-monthly and monthly discharge data are compared to each other and RMSE of 2.3, 1.7, and 1.2 mm/month are achieved for the Mekong, Brahmaputra, and Don, respectively. These RMSE values correspond to an error of 1%, 1%, and 8% with respect to the range of discharge (max. − min.) of these three rivers. Without daily discharge data, the intercomparison for Vistula is not available.

[36] For rivers in group 1, in situ discharge measurements are available within time period of altimetry. We are thus motivated to establish a conventional/empirical rating curve together with our new statistical rating curve for rivers in group 1. The empirical rating curve, which was also used by, e.g., *Kouraev et al*. [2004], *Zakharova et al*. [2006], *Leon et al*. [2006], *Coe and Brikett* [2004], and *Papa et al*. [2010], is established by fitting a quadratic curve over simultaneous measured monthly or quasi-monthly discharge and the altimetric water level (Figure S1, supporting information). The comparison of this empirical and the proposed statistical rating curve helps to assess the statistical methods. Figure 11 shows both types for monthly and quasi-monthly discharge data over rivers in group 1.

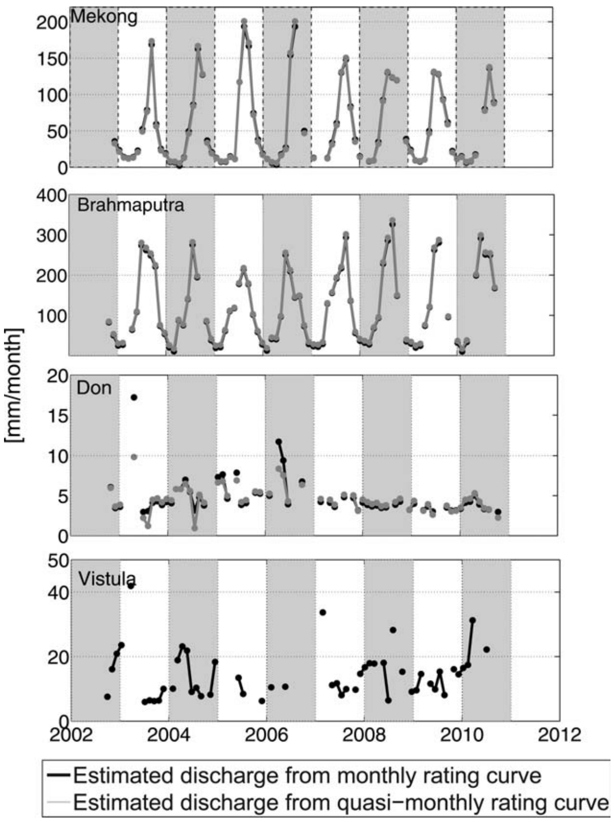

Figure 10. Estimated discharge in millimeter per month from the statistical rating curves obtained from the statistical method of performing rating curves out of asynchronous measurements of water level and discharge for group 2 rivers. Intercomparison of monthly and quasi-monthly discharge leads to RMSE of 2.3, 1.7, and 1.2 mm/month for the Mekong, Brahmaputra, and Don, which correspond to 1%, 1%, and 8% error, respectively.

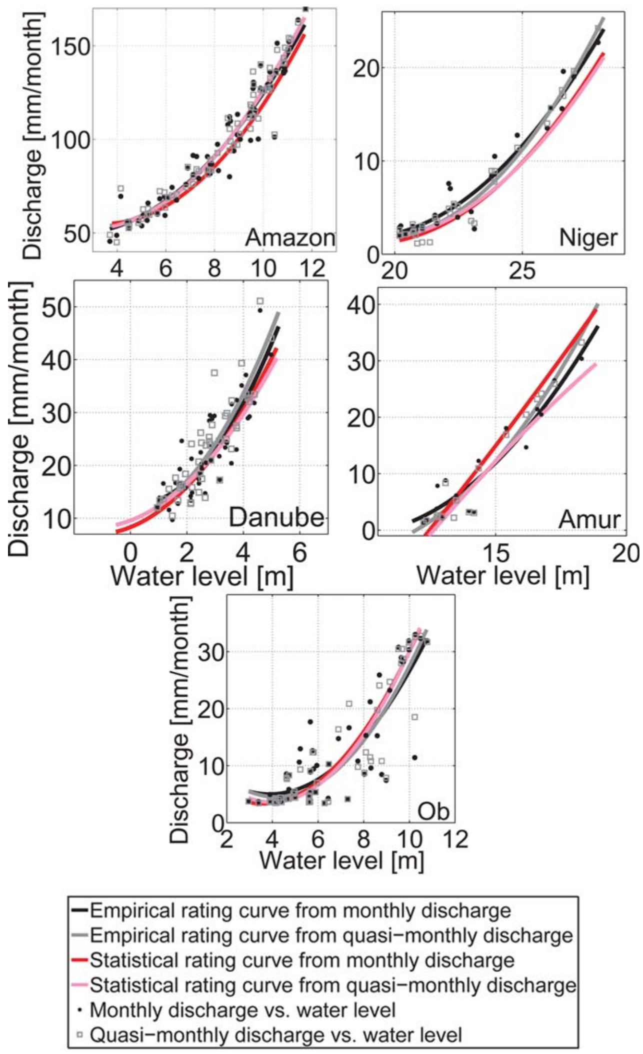

Figure 11. Scatter plot of simultaneous measurements of discharge versus altimetric water level with the fitted quadratic conventional/empirical and our new statistical rating curve models for the quasi-monthly and monthly discharge data of rivers in group 1.

[37] Both methods lead to very similar rating curves for the virtual stations of the Amazon, Danube, and Ob. For the Niger River, both types of rating curves do follow the same pattern, yet with a distinctive bias between curves, c.f. 1.2 mm/month. On the other hand, the empirical and statistical rating curves are not consistent with each other for the virtual station of Amur River. The nonsimilarity for Niger and Amur can be explained by the difference of quantile functions of discharge data consisting of discharge values at the time of altimetry and quantile function of whole available discharge data. Actually, these differences could have been expected as the k-s test statistics from the consistency check in Table 2 show higher values for the Amur and Niger compared to the Amazon, Danube and Ob.

[38] For group 1, the estimated discharge can be compared with available measured discharge to address the error budget of estimation or goodness of modeling. However, this would not thoroughly verify the method as the measured discharge is also used for modeling the rating curve. The estimated discharge using statistical rating curves shows a good agreement with measured discharge, yet with some distinct unexpected fluctuations (e.g., March 2004 in the Amazon, January 2005 in the Niger) which are generated by noisy altimetry. Residuals are computed by subtracting the estimated monthly and quasi-monthly discharge from those measured. The computed root mean square (RMS) of residuals provides information about the error of estimation. The error budgets of approximately 8%, 7%, 10%, 10%, and 17% are achieved with respect to the range of discharge (max. – min.) for the Amazon, Niger, Danube, Amur, and Ob, respectively.

[39] The obtained errors of 9.1 and 8.3 mm/month of Amazon River, which leads to 8% accuracy are relatively high as the proper conditions for measuring water height by satellite altimetry are available. This particularly can be explained by an outlier from altimetry in March 2004 that produces approximately 20 mm/month error (Figure 12). On the other hand, high RMS error for Ob and Danube are not influenced by a single outlier. In this case, poor modeling of the rating curve seems to be responsible. This was already expected as water level and available in situ discharge measurements show low correlations (Table 3). Comparing the obtained RMS of residual for estimated

discharge using our proposed statistical approach with the estimated discharge using empirical approach reveals a similar range of error budget for both methods (Table 4). The comparable RMS values in Table 4 especially express that the statistical approach provides similar performance, despite using quantile functions of data instead of data itself.

[40] However, scatter plots of estimated discharge using the empirical and statistical approaches reveal nonlinear behavior for the Danube and Amur (Figure 13). This might be due to a change in discharge behavior over the years for these rivers. In fact, when discharge variation changes over time, the obtained statistical rating curves and empirical rating curves are not correspondent. On the other hand, linear scatter plot indicates similar rating curves, which are produced by similar discharge variations. This means that the discharge behavior after 2002 has been stationary in comparison with time before for the Amazon and Niger rivers.

6. Cross Validation

[41] Note that in the above validation of discharge estimation from the statistical approach against the one from the empirical approach, we did make use of simultaneous data in the construction of the statistical discharge data set. To that end, the proposed methodology should be validated against in situ measurements, when the ground truth is not used for modeling. Therefore, in this section, a leave-out validation is performed and the results are discussed. Hence, a modified discharge data set is produced by excluding the available discharge data within the time period of altimetry for group 1 rivers.

[42] Moreover, we emphasize that the proposed methodology in this study is mainly developed for the rivers with no available in situ measurements after launch of satellite altimetry. For such rivers, as the in situ discharge data is not available, it is common in the hydrologic community to employ the available annual cycle (monthly mean) of discharge for study of hydrologic interactions in the monthly time scale. Therefore, it is important to validate the estimated discharge against the monthly mean of discharge.

[43] For the first type of validation, the quantile functions are then constructed from the modified discharge data and directly connected to the quantile function of water level to establish the statistical rating curves for each river. Using the available altimetry data and the achieved rating curves, discharge values are then estimated for group 1 rivers. The validation is then conducted by comparing the estimated discharge with in situ measurement. Table 5 shows the computed RMS values, bias (mean of altimetric discharge minus mean of in situ discharge) and computed error budgets with respect to the derived range from altimetric and in situ discharge data for both monthly and quasi-monthly values of different rivers.

[44] The estimated RMS values imply same range of error as indicated in Table 4. For all the rivers, the estimated errors are slightly worse in case of using modified discharge data. The maximum degradation happened in the estimation of quasi-monthly discharge for Ob River, where the estimated RMS increases from 4.3 to 4.9 mm/month, which is in the range of approximately 1%. On the other hand, the provided maximum, minimum, and range (max.–min.) in the

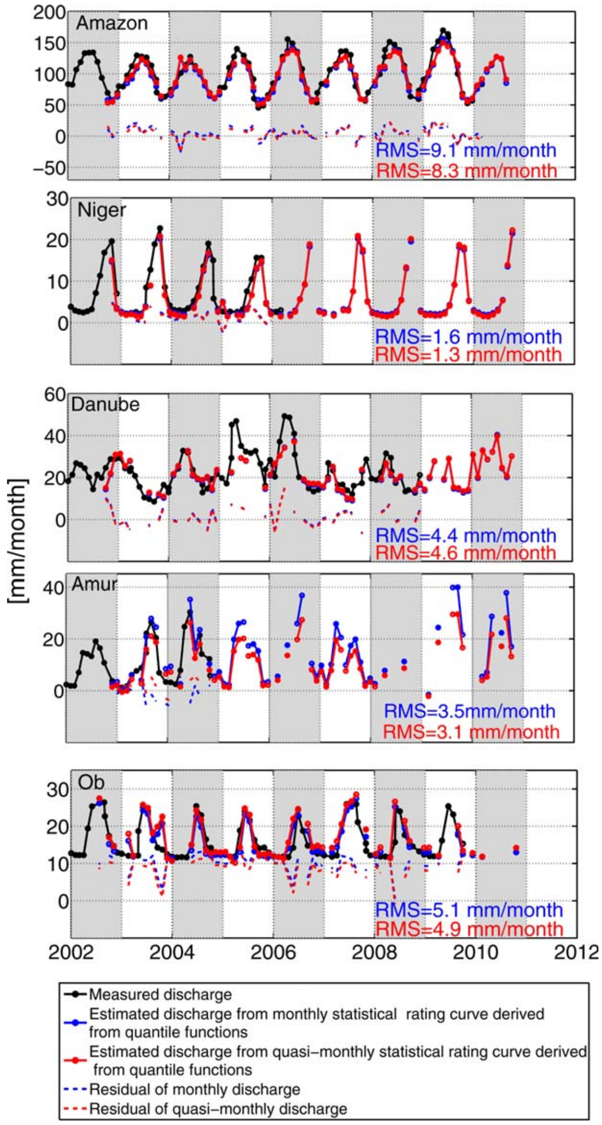

Figure 12. Estimated discharge from the rating curves obtained from the statistical methods of performing rating curve for rivers in group 1. Residuals are achieved by subtracting the estimated discharge from the in situ measurements discharge. The computed RMS values in millimeter per month for the residuals reveal the performance of statistical approach for constructing the rating curve.

Table 4. Computed RMS Values of the Residual of Empirical and Statistical Approach for Discharge Estimation Over Time in mm/Month for Rivers in Group 1

River		Empirical	Statistical	Error %
Amazon	Monthly	8.5	9.1	∼8%
	Quasi-monthly	7.3	8.3	
Niger	Monthly	1.4	1.6	∼7%
	Quasi-monthly	0.9	1.3	
Danube	Monthly	4.3	4.4	∼10%
	Quasi-monthly	4.3	4.6	
Amur	Monthly	2.9	3.5	∼10%
	Quasi-monthly	2.4	3.1	
Ob	Monthly	4.9	5.1	∼17%
	Quasi-monthly	4.3	4.3	

Table 4 reveal that the method can properly capture the maximum and minimum discharge values for most of the cases. This issue can be also be understood from the obtained similar error budgets computed by dividing the RMS by the in situ or altimetric discharge ranges. However, for some cases, mapping the maximum and minimum discharge seems to be problematic, i.e., quasi-monthly discharge of Amazon, monthly and quasi-monthly discharge of Danube. These cases can be explained by the difficulty of modeling an extreme value using quantile function approach.

[45] Moreover, the obtained bias values in Table 4 represent the long-term change of discharge behavior within altimetry time frame. In other words, as for designing the rating curve using statistical approach, the discharge values within time period of altimetry have not been used, any bias between the altimetric and in situ discharge time series indicates the long-term change after 2002. However, the obtained bias values for rivers under study seem to be negligible with respect to their discharge range except for Danube (1.3/ 41.6 = ~3%) and quasi-monthly estimation of Ob (~4%). Overall, the statistical approach seems to perform well.

[46] Given the relative error levels implied by the new discharge estimation methodology, the question seems to be justified, whether the whole effort of saving heritage discharge data into the satellite altimetry era was worth it.

[47] The hydrologic community commonly calculates the mean monthly discharge from heritage discharge data and employs it as representative of measured data. The question, therefore, is: Is the estimation of discharge by altimetry better than the annual cycle? Apart from comparison of estimated discharge with measured discharge and providing the error budget, the estimated discharge should be also compared with the annual cycle (monthly mean). In other words, by estimating the discharge using altimetry, we expect to have better estimation than the annual cycle, that is often used by hydrologists for modeling purposes.

[48] In fact, a good estimation should bring extra information for discharge in comparison to the annual cycle. Therefore, we have performed a test for rivers in group 1, in which we exclude in situ measurements that belong to a given year and compute the annual cycle. The computed annual cycle is then compared with estimated altimetric discharge using the statistical approach.

[49] This comparison is performed by computing the difference between altimetric X_{alt} and observed discharge X_{ins} and the difference between the computed mean annual cycle $\overline{X}_{\mathrm{ins}}$ for discharge and the observed discharge:

$$v_{\mathrm{alt}} = X_{\mathrm{alt}} - X_{\mathrm{ins}} \tag{6}$$

$$v_{\mathrm{mean}} = \overline{X}_{\mathrm{ins}} - X_{\mathrm{ins}} \tag{7}$$

where $\overline{X}_{\mathrm{ins}}$ for the j^{th} month of the i^{th} year is

$$\overline{X}_{\mathrm{ins}}(t_j) = \frac{1}{N}\sum_{i=1}^{N} X_{\mathrm{ins}}(t_{i,j}), \tag{8}$$

and N refers to the number of available years. If the residual values from altimetry v_{alt} are smaller than residual values from the mean annual cycle v_{mean}, it means that the estimation of discharge by altimetry provides information on the discharge variation better than the annual cycle.

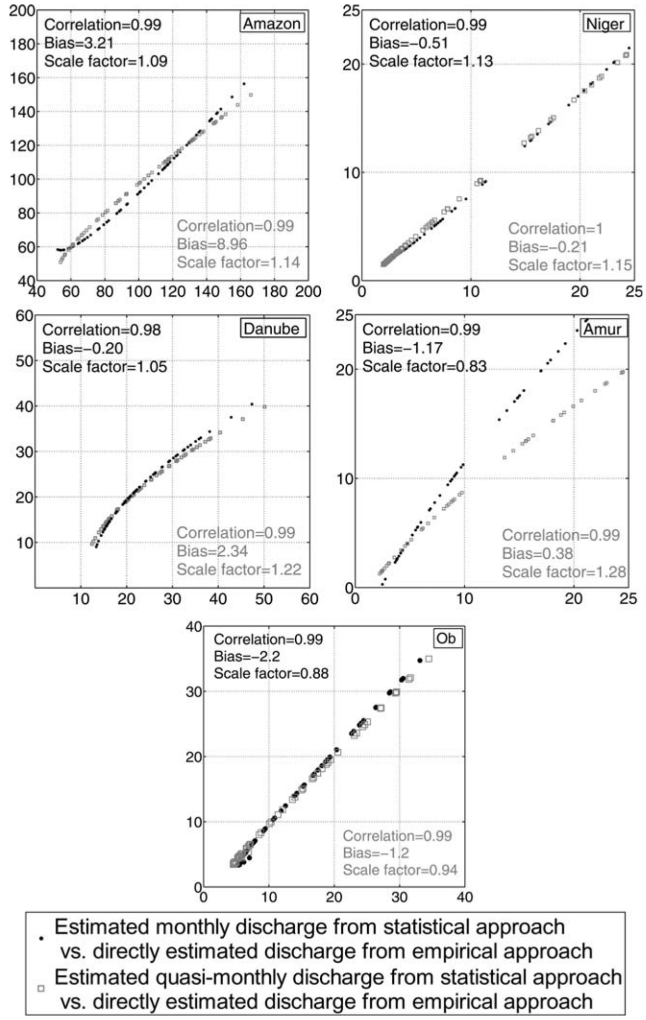

Figure 13. Scatter plots of estimated discharge from the statistical method versus estimated discharge from the empirical method. The statistical characteristics of scattered points represent the similarity of estimations.

Here we have computed the annual cycles by excluding each year in the available data individually and compared residual values from altimetry and residual values from the annual cycle for different rivers in group 1 (Figure 14).

[50] The scatter of Amazon, Danube, and Amur lies predominantly to the left (Figure 14). Thus, the estimated discharge at selected gauges of the Amazon, Danube, and Amur provide better estimation in comparison with the annual cycle for most of the months. Although the estimated RMS error for discharge at the selected gauge of the Niger River shows relatively low value (Table 5), the scatter plot in Figure 14 expresses that for some months the annual cycle provides a better estimation. Unlike the Niger, estimated discharge at the gauge in the Danube River provides better estimation than the annual cycle for most of the months, while the estimated error is higher (~10%).

[51] On the other hand, the scatter plot of the Ob River in Figure 14 indicates that the estimation of discharge by altimetry does not bring extra information. This finding correlates with the high error range of ~17%. The scatter plot shows that, for the selected gauge at the Ob River, for

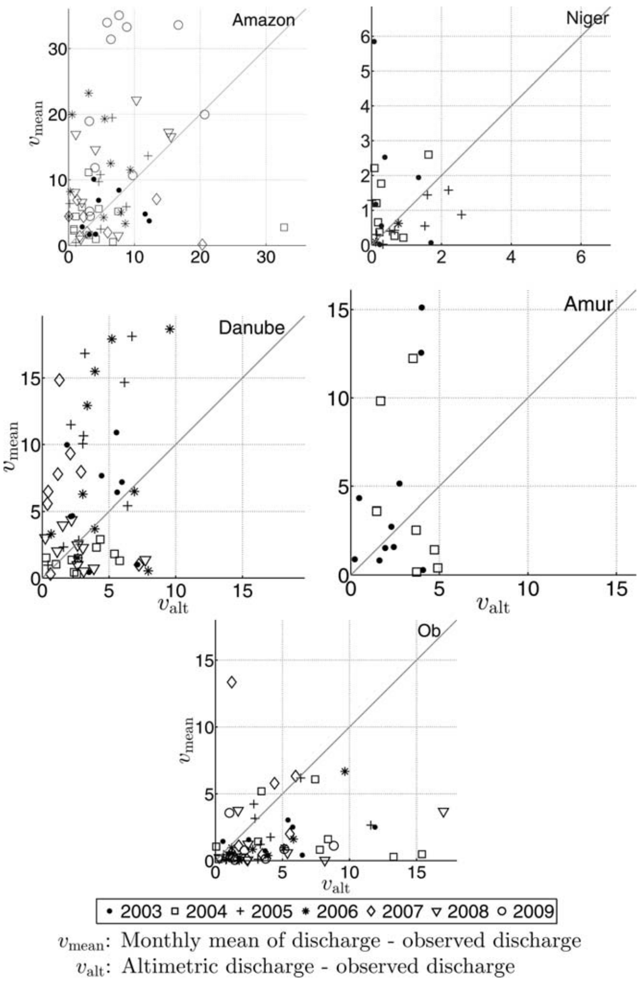

Figure 14. Comparison of estimated discharge by altimetry and the annual cycle computed by excluding data of different years over different rivers. Residuals are estimated by subtracting the observed discharge from altimetry discharge and the annual cycle, respectively.

many months over different years it is better to derive discharge from the annual cycle instead of using satellite altimetry. This can be explained by the long distance between the chosen virtual station and discharge gauge, which is forced by low-quality water level time series due to existence of ice in virtual stations near to the Salekhard station. In addition, according to *Kouraev et al*. [2004], for Ob at Salekhard (the selected gauge at this study), there exists at least two rating curves: flood rising and flood falling. Therefore, assuming a simple quadratic form for rating curve might lead to degradation of estimated discharge.

7. Conclusion

[52] We have introduced a statistical approach to derive discharge from river height through a rating curve based on quantile functions. This method was specially developed for rivers with only in situ discharge data available in the past, i.e., nonsimultaneous with satellite altimetry. Thus, in view of a declining global discharge database, if we assume stationarity behavior of discharge, our approach guaranties the employment of old in situ data in current applications.

[53] Our method of constructing the rating curve is based on a scatter diagram of quantile functions, thus eliminating the probability coordinate. In contrast, the conventional methods operate directly on time series and eliminate the time coordinate.

[54] We have employed our method over nine rivers with different channel width and from different climatic zones at their virtual station categorized into two groups. Group 1: rivers with available in situ discharge simultaneous with altimetry, i.e., the Amazon, Amur, Niger, Danube, and Ob. Group 2: rivers with available in situ discharge nonsimultaneous with altimetry, i.e., the Mekong, Brahmaputra, Don, and Vistula. For both groups, the method has been employed over monthly and quasi-monthly discharge data.

[55] The results show that the statistical approach based on the quantile functions of water level and discharge provides the same range of error as the common empirical method. Among the monthly and quasi-monthly data, quasi-monthly discharge performs better, although the differences are minor, cf. Table 5. Hence, for similar studies, we recommend to use daily or quasi-monthly discharge data when snapshot measurements of altimetry are involved. The good performance of the statistical approach supports the usage of altimetry to derive discharge over rivers, in which the data are not available after 2002. That would pertain to 60% of rivers in the global database (according to GRDC database). Thus, the statistical approach can be used as a tool to augment the discharge database around the world.

[56] The usefulness of the discharge database generated by satellite altimetry is supported by comparing the estimated altimetric discharge and available annual cycles for different years over different rivers. In fact, we could demonstrate that the estimated discharge at the gauges in the Amazon, Amur, and Danube provides better estimation than the mean annual cycle. However, for some rivers, the estimated altimetric discharge at the selected gauge of many months does not bring more information in comparison to the mean annual cycle, in spite of low-error budget obtained for estimated discharge, e.g., Niger. For the Ob River, the estimated discharge by altimetry has failed in the comparison. The annual cycle outperforms better discharge from our approach for most of the time within 2003–2009.

[57] Despite overall good performance, the main limitation of the quantile function approach is that it leads to erroneous discharge when discharge behavior of river is not stationary over time. This means that the method performs well if there is no change in the hydrological conditions of the discharge between the time periods of available in situ and altimetry records. This is specifically shown in Figure 13 where the nonstationary behavior of discharge over the time, e.g., the Amur River, causes changes in quantile function and dissimilar estimations of discharge from the empirical and statistical methods. On the other hand, similar to the empirical approach, the statistical approach is restricted by performing the model to the corresponding data set. This is highlighted in the Ob River where the noisy ice-contaminated water level time series of altimetry close to the gauging station of discharge forced a choice of virtual station far from the gauge and obtained an

Table 5. Computed RMS Values of the Residual of Empirical and Statistical Approach for Discharge Estimation Over Time in mm/Month Together With the Maximum, Minimum, and Range of In Situ and Altimetric Discharge and Corresponding Error and Bias for Rivers in Group 1

River		RMS of Residual (mm/month)	In Situ Discharge (mm/month)				Altimetric Discharge (mm/month)				Bias (mm/month)
			Maximum	Minimum	Range	Error %	Maximum	Minimum	Range	Error %	
Amazon	Monthly	9.3	155.6	34.3	121.2	7	154.4	58.9	95.4	9	3.8
	Quasi-monthly	8.6	169.7	45.1	124.6	7	147.6	51.4	96.2	9	3.3
Niger	Monthly	1.6	22.7	2.1	20.6	7	20.6	1.2	19.4	8	0.8
	Quasi-monthly	1.3	24.2	1.2	23.1	5	21.2	0.7	20.5	6	0.7
Danube	Monthly	4.5	49.3	8.4	40.8	11	38.9	8.9	30.1	14	1.1
	Quasi-monthly	4.5	51.1	9.4	41.6	10	38.9	9.8	29.1	15	1.3
Amur	Monthly	3.6	30.4	1.3	29.1	12	32.3	0.1	32.2	11	0.4
	Quasi-monthly	3.2	33.2	1.3	31.9	10	30.2	0.4	29.8	10	0.3
Ob	Monthly	5.1	33.0	3.4	29.7	17	34.2	3.2	30.9	16	0.3
	Quasi-monthly	4.9	32.7	3.2	29.5	16	36.9	1.1	35.8	14	1.4

erroneous model out of noncorrespondent water level and discharge values.

[58] As a final remark, discharge estimation from the obtained model from each empirical/statistical method is only possible at the time of altimetry. Since altimetric time series over rivers regularly have gaps, we will consequently have gaps in our discharge estimations. Moreover, noisy altimetry causes incorrect estimation of discharge. It would be therefore desirable to have an algorithm that covers the missing values and combines all available measurements with their uncertainties to provide an acceptable estimation. Using stochastic process models might be a way to achieve such an algorithm. Therefore, for our future work, we plan to use a stochastic process model to cope with this problem and improve our estimation.

Appendix A: Comparison of In Situ and Altimetric Water Level

[59] Among the nine rivers which have been studied here, we have only access to the in situ water levels of Amazon. Hence, we compared the altimetric water level (RSH) and in situ water level only for Amazon. Since a bias between time series does not play a role in this discussion, we removed it via the difference of average values of both time series. The comparison leads to correlation coefficient of 0.98 and 0.44 m standard deviation of the residual (Figure A1).

A.1. Consistency Check Between In Situ Water Levels and Discharges

[60] The consistency check is first investigated in terms of correlation of in situ water level and river discharge. The results are compared with the correlation of altimetric water level and in situ river discharge. As expected, the former shows better a correlation, yet the differences are not significant (Table A1).

[61] In order to verify whether the statistical distribution of in situ water level data at the time of altimetry matches that of the full in situ data set, the k-s test is employed. The k-s test is accepted in confidence level of 95% with test statistic of 0.05, which reveal similar statistical distribution for both data sets (Figure A2).

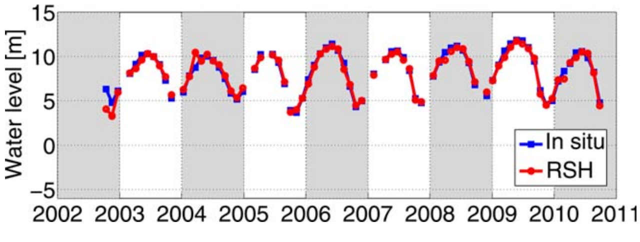

Figure A1. Comparison of in situ and altimetric water level for Amazon River at Obidos.

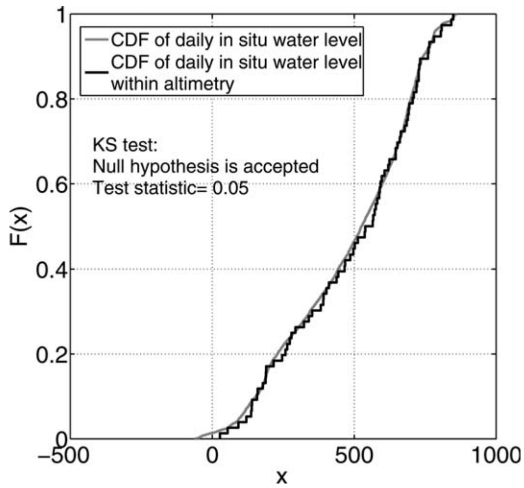

Figure A2. Comparison of empirical cumulative distribution functions of whole in situ data set and in situ water level data at the time of altimetry and the results of k-s test with significance level of 0.05.

Table A1. Computed Pearson's Correlation (Corr.) and Rank Correlation (Rank Corr.) Coefficient of In Situ and Altimetric Water Level With In Situ River Discharge of Amazon at Obidos

River		Monthly	Quasi-Monthly
In situ	Corr.	0.97	0.98
	Rank Corr.	1	1
Altimetric water level	Corr.	0.94	0.95
	Rank Corr.	0.96	0.97

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References

Alsdorf, D., and D. P. Lettenmaier (2003), Tracking fresh water from space, *Science*, *301*, 1491–1494, doi:10.1126/science.1089802.

Alsdorf, D., E. Rodriguez, and D. P. Lettenmaier (2007), Measuring surface water from space, *Rev. Geophys.*, *45*, RG2002, doi:10.1029/2006RG000197.

Berry, P. A. M., J. D. Garlick, J. A. Freeman, and E. L. Mathers (2005), Global inland water monitoring from multi-mission altimetery, *Geophys. Res. Lett.*, *32*, L16401, doi:10.1029/2005GL022814.

Birkett, C. M. (1995), The global remote sensing of lakes, wetlands and rivers for hydrological and climate research, in International Geoscience and Remote Sensing Symposium (IGARSS '95) on Quantitative Remote Sensing for Science and Applications', vol. *3*, pp. 1979–1981, IEEE, Firenze, doi:10.1109/IGARSS.1995.524084.

Birkett, C. M., L. A. K. Mertes, T. Dunne, M. H. Costa, and M. J. Jasinski (2002), Surface water dynamics in the amazon basin: Application of satellite radar altimetry, *J. Geophys. Res.*, *107*(D20), 8059, doi:10.1029/2001JD000609.

Bjerklie, D. M., S. L. Dingman, C. J. Vörösmarty, C. H. Bolster, and R. G. Congalton (2003), Evaluating the potential for measuring river discharge from space, *J. Hydrol.*, *278*(14), 17–38, doi:10.1016/S0022–1694(03)00129-X.

Calmant, S., and F. Seyler (2006), Continental surface waters from satellite altimetry, *C. R. Geosci.*, *338*, 1113–1122, doi:10.1016/j.crte.2006.05.012.

Cazenave, A., P. Bonnefond, K. Dominh, and P. Schaeffer (1997), Caspian sea level from TOPEX/Poseidon altimetry: Level now falling, *Geophys. Res. Lett.*, *24*(8), 881–884, doi:10.1029/97GL00809.

Coe, M. T., and C. M. Brikett (2004), Calculation of river discharge and prediction of lake height from satellite radar altimetry: Example for the Lake Chad basin, *Water Resour. Res.*, *70*, W102205, doi:10.1029/2003WR002543.

Crétaux, J.-F., and C. Birkett (2006), Lake studies from satellite radar altimetry, *C. R. Geosci.*, *338*(1415), 1098–1112, doi:10.1016/j.crte.2006.08.002.

Crétaux, J.-F., et al. (2011), SOLS: A lake database to monitor in the near real time water level and storage variations from remote sensing data, *Adv. Space Res.*, *47*, 1497–1507, doi:10.1016/j.asr.2011.01.004.

da Silva, J. S., S. Calmant, F. Seyler, O. C. R. Filho, G. Cochonneau, and W. J. Mansur (2010), Water levels in the Amazon basin derived from the ERS 2 and ENVISAT radar altimetry missions, *Remote Sens. Environ.*, *114*(10), 2160–2181, doi:10.1016/j.rse.2010.04.020.

Fekete, B. M., and C. J. Vörösmarty (2007), The current status of global river discharge monitoring and potential new technologies complementing traditional discharge measurements, in Predictions in Ungauged Basins: PUB Kick-Off, Proceedings of the PUB Kick-Off Meeting Held in Brasilia, 20–22 November 2002, IAHS Publ., 309, 129–136.

Frappart, F., S. Calmant, M. Cauhopé, F. Seyler, and A. Cazenave (2006), Preliminary results of ENVISAT RA-2-derived water levels validation over the Amazon basin, *Remote Sens. Environ.*, *100*(2), 252–264, doi:10.1016/j.rse.2005.10.027.

Frappart, F., F. Papa, J. S. Famiglietti, C. Prigent, W. B. Rossow, and F. Seyler (2008), Interannual variations of river water storage from a multiple satellite approach: A case study for the Rio Negro River basin, *J. Geophys. Res.*, *113*, D21104, doi:10.1029/2007JD009438.

Fu, L.-L., and A. Cazenave (2001), Satellite Altimetry and Earth Sciences: A Handbook of Techniques and Applications, Int. Geophys. Ser, *69*, Academic Press, Calif.

Getirana, A. C. V., and C. Peters-Lidard (2012), Water discharge estimates from large radar altimetry datasets in the Amazon basin, *Hydrol. Earth Syst. Sci. Discuss.*, *9*(6), 7591–7611, doi:10.5194/hessd-9-7591-2012.

Gilchrist, W. G. (2000), *Statistical Modelling with Quantile Functions*, Chapman and Hall, London.

Kouraev, A. V., E. A. Zakharova, O. Samain, N. M. Mognard, and A. Cazenave (2004), Ob' river discharge from TOPEX/Poseidon satellite altimetry (1992–2002), *Remote Sens. Environ.*, *93*(12), 238–245, doi:10.1016/j.rse.2004.07.007.

Leon, J., S. Calmant, F. Seyler, M.-P. Bonnet, M. Cauhop, F. Frappart, N. Filizola, and P. Fraizy (2006), Rating curves and estimation of average water depth at the upper Negro River based on satellite altimeter data and modeled discharges, *J. Hydrol.*, *328*(34), 481–496, doi:10.1016/j.jhydrol.2005.12.006.

Massey, F. J. (1951), The Kolmogorov-Smirnov test for goodness of fit, *J. Am. Stat. Assoc.*, *46*, 68–78.

Milzow, C., P. E. Krogh, and P. Bauer-Gottwein (2011), Combining satellite radar altimetry, SAR surface soil moisture and GRACE total storage changes for hydrological model calibration in a large poorly gauged catchment, *Hydrol. Earth Syst. Sci.*, *15*, 1729–1743, doi:10.5194/hess–15–1729–2011.

Papa, F., C. Prigent, F. Durand, and W. B. Rossow (2006), Wetland dynamics using a suite of satellite observations: A case study of application and evaluation for the Indian subcontinent, *Geophys. Res. Lett.*, *33*, L08401, doi:10.1029/2006GL025767.

Papa, F., F. Durand, W. B. Rossow, A. Rahman, and S. K. Bala (2010), Satellite altimeter-derived monthly discharge of the Ganga-Brahmaputra river and its seasonal to interannual variations from 1993 to 2008, *J. Geophys. Res.*, *115*, C12013, doi:10.1029/2009JC006075.

Papa, F., S. Biancamaria, C. Lion, and W. Rossow (2012), Uncertainties in mean river discharge estimates associated with satellite altimeter temporal sampling intervals: A case study for the annual peak flow in the context of the future swot hydrology mission, *Geosci. Remote Sens. Lett.*, *9*(4), 569–573, doi:10.1109/LGRS.2011.2174958.

Stanev, E. V., E. L. Peneva, and F. Mercier (2004), Temporal and spatial patterns of sea level in inland basins: Recent events in the Aral sea, *Geophys. Res. Lett.*, *31*, L15505, doi:10.1029/2004GL020478.

Zakharova, E. A., A. V. Kouraev, A. Cazenave, and F. Seyler (2006), Amazon river discharge estimated from TOPEX/Poseidon altimetry, *C. R. Geosci.*, *338*, 188–196, doi:10.1016/j.crte.2005.10.003.