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# Daily river discharge estimates by merging satellite optical sensors and radar altimetry through artificial neural network

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**Abstract**— Thanks to the large number of satellites, the multi-mission approach is becoming a viable method to integrate measurements and intensify the number of samples in space and time for monitoring the Earth system. In this study, we merged data from different satellite missions, i.e. optical sensors and altimetry, for estimating daily river discharge through the application of the Artificial Neural Networks (ANN) technique. ANN was selected among other retrieval techniques because it offers an easy but effective way of combining input data from different sources into the same retrieval algorithm. The network is trained in a calibration period and validated in an independent period against in situ observations of river discharge for two gauging sites: Lokoja along the Niger River and Pontelagoscuro along the Po River. For optical sensors, we found that the temporal resolution is more important than the spatial resolution for obtaining accurate discharge estimates. Our results show that Landsat fails in the estimation of extreme events by missing most of the peak values due to its long revisit time (14-16 days). Better performances are obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS). Radar altimetry provides results in between MODIS-TERRA and MODIS-AQUA at Lokoja, whereas outperforms all single optical sensors at Pontelagoscuro. The multi-mission approach, involving optical sensors and altimetry, is found to be the most reliable tool to estimate river discharge with relative root mean square error of 0.12% and 0.27% and Nash-Sutcliffe coefficient of 0.98 and 0.83 for the Niger and Po rivers, respectively.

**Index Terms**— Rivers, Radar altimetry, Remote sensing

## I. INTRODUCTION

RIVER discharge has been identified as a fundamental physical variable and is included among the Essential Climate Variables by the Global Climate Observing System (GCOS) [8, 9]. Notwithstanding river discharge is one of the most measured components of the hydrological cycle, its monitoring is still an open issue. Collection, archiving and distribution of river discharge data, globally, is limited [11], and

the network currently in operation is inadequate in many parts of the Earth and the number of sensors is declining [20, 28]. Remote sensing has great potential in offering new ways to monitor river discharge, through the measurements of the connected hydraulic variables. Indeed, because of its nature, river discharge cannot be directly measured, and both satellite and traditional monitoring are referred to measurements of other hydraulic variables, e.g. water level, flow velocity, water extent and slope, which are proficiently inserted in the traditional hydraulic formulas to derive river discharge [2, 3, 7, 10]. In this context, the strong advantage provided by remote sensing sensors is the regular, uniform and global monitoring of observables for a long period due to the large number of satellites launched during the last 20 years. Moreover, the different nature of the available sensors permits taking advantage of their complementarity in the observations and to benefit from the potential of combining them.

The recent advances in radar altimetry technology offer important information for water level monitoring of rivers and the increased accuracy of the sensors encourages its use as a validation tool for many applications from simple routing approaches [2, 21] to complex hydraulic models [5, 6, 18]. However, the spatial-temporal sampling of the altimetry mission is currently a limitation. The number of measurements along the rivers is dependent on the inter-track distance of the orbit which at the equator ranges from 80 km (ENVISAT-series including SARAL/AltiKa) to 315 km (TOPEX-series including JASON satellites). The temporal resolution ranges from 10 to 35 days depending on the satellite mission (i.e. JASON-2 and ENVISAT). With such temporal resolution, the fast dynamic behavior of rivers (from some days to some hours) remains unmonitored. Recent studies conducted by Tourian et al. [25, 26] partially overcame this issue by introducing the concept of altimetry data densification along the river to improve the temporal resolution to about 3 days. Despite the approach considers a simplified law for the flow routing, it has the potential to be applied for different sections along the river and

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for rivers of medium to large size (up to a width of 300 m), depending on the accuracy of the altimetry measurements.

Alternatively, optical sensors, thanks to their frequent revisit time (nearly daily) and large spatial coverage, could support the evaluation of river discharge variations [22, 23, 27]. Studies conducted on the Moderate Resolution Imaging Spectroradiometer (MODIS) demonstrated that the reflectance variation can be a proxy of discharge and can be used not only for river discharge estimation but also for forecasting purposes [12, 24]. Van Dijk et al. [27] proposed the evaluation of monthly discharge for over 8,000 gauging stations located all over the world using optical MODIS instrument and passive microwave sensor. Despite the coarse spatial resolution of the microwave data, their complementary use with optical data enables to improve the results in areas where cloud cover is a limitation for optical sensors. Indeed, in the case of cloudy sky, the optical images are not usable, resulting in data outages in the measurements. A possible remedy in these conditions is to collect data from more satellite missions of the same nature (optical), to enlarge the sample size or to benefit from satellite missions with different characteristics (active and passive microwave sensors). In a similar context, a multi-mission approach, if implemented with sensors that work in different electromagnetic bands, fosters the monitoring also in different conditions [1, 19]. Therefore, an alternative approach is to merge the optical image observation with altimetry data in order to catch information also during flood events, when the cloud coverage can last several days.

On these bases, this study has two main purposes: (a) compare the performance of different satellite optical sensors for river discharge estimation, analyzing the impact of the spatial and temporal resolution; and (b) merge satellite optical and altimetry data in order to obtain daily discharge estimates. To this end, we focus on the near-infrared (NIR) bands of the optical satellite sensors, i.e. MODIS, MERIS and Landsat, and on the altimetry data from ERS-2, Topex/Poseidon, Envisat/Ra-2, Cryosat-2 and Jason-2, for estimating river discharge. Our approach is tested in two different countries - Nigeria (Niger River) and Italy (Po River) - to demonstrate its efficacy in two completely different rivers in terms of dynamics and morphology. The procedure of merging is carried out using the Artificial Neural Network (ANN) technique, which represents an effective method for merging data from multiple sources into a single retrieval approach, by simply adding or removing inputs in the ANN configuration and updating the training accordingly. Therefore, ANN is also particularly suitable for evaluating the significance of each sensor to the final estimate of river discharge.

## II. MATERIALS AND METHODS

This section contains a brief description of the study area and the observed time series of river discharge, satellite data from optical and altimetry sensors, procedure for the estimation of river discharge, ANN technique and the performance indices used for the assessment of the results.

### A. Study areas and in situ datasets

We focused on two study sites: (a) Nigeria and, specifically, along the confluence between the Niger and Benue rivers at Lokoja station; and (b) Italy along the Po River at Pontelagoscuro station. The two study sites were selected for two main reasons: (i) they have been monitored with an in situ gauging station for more than 15 years; and (ii) they represent two different regimes of discharge.

Niger River at Lokoja has a width of about 2,800 m and the discharge ranges from 820 to 31,692 m<sup>3</sup>/s, which is strongly affected by the seasonal cycle due to the monsoon season that alternates from long periods of high flows (July to October) to long periods of low flows (November to June) (Fig. 1(a)). The analysis investigates the discharge anomalies (total discharge minus the seasonal cycle) in the period from January 2004 to April 2012. In situ discharge data are provided by the Nigeria Hydrological Services Agency (NIHSA) in cooperation with the Federal Ministry of Agriculture and Rural Development (FMARD), Nigeria.

Po River at Pontelagoscuro has a width of about 350 m and moderate flow regimes ranging from 168 to 8674 m<sup>3</sup>/s with two seasonal peaks during spring (May-June) and autumn (November) [15]. The seasonal cycle of the Po River is less significant than the Niger River (see Fig. 1(c)). The analysis investigates the total discharge of the Po River at Pontelagoscuro in the period from January 2006 to April 2012. In situ river discharge data are published each year by the Po River Basin Authority (Agenzia Interregionale per il Fiume Po [AIPO]) and are also available online (<https://www.arpae.it/documenti.asp> - in Italian).

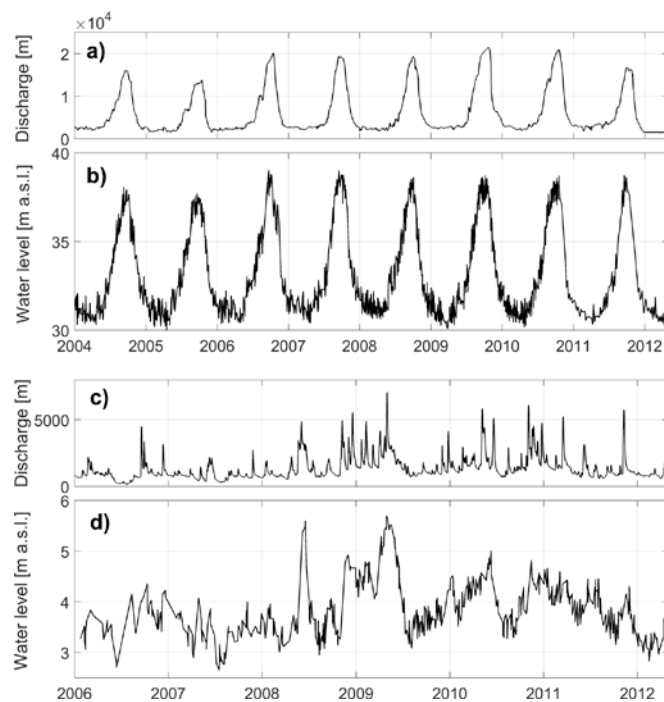


Fig. 1. Discharge and altimetry-derived water level for Niger (a and b), and Po (c and d) Rivers.

TABLE I  
MAIN CHARACTERISTICS OF THE OPTICAL SATELLITE SENSORS USED IN THE ANALYSIS

	MODIS TERRA	MODIS AQUA	MERIS	LANDSAT
Product	MOD09GQ	MYD09GQ	MER_FRS_2P	Landsat / ETM+
No. band (spectral range [nm])	2 (841-876)	2 (841-876)	13 (855-875)	4 (772-898)
Spatial resolution [m]	250	250	270	30
Temporal resolution	1 per day	1 per day	1 per 2 days	1 per 15 days
Total number of images	2,286 (Niger) 2,304 (Po)	2,286 (Niger) 2,309 (Po)	1,874 (Niger) 1,227 (Po)	123 (Niger)
Cloud-free images	900 (Niger) 1,149 (Po)	1,167 (Niger) 1,083 (Po)	521 (Niger) 495 (Po)	55 (Niger)

### B. Satellite radar altimeter dataset for water level

We used data from different satellite altimetric missions to derive water level time series: two in the Niger River and five in the Po River. In the following the main characteristics of the altimetric sensors are described, whereas more information of the altimetry data can be drawn from Tourian et al. [25, 26].

TOPEX/POSEIDON (August 1992 – September 2002) and Jason-2 (June 2008 – October 2016) are joint satellite missions between National Aeronautics and Space Administration, NASA and Centre national d'études spatiales, CNES. They use the orbit configuration with a cross-track resolution of about 315 km at the equator and a repeat cycle of 10 days. From September 2002 to October 2005, TOPEX/POSEIDON assumed a new orbit midway between its original ground tracks. We distinguished this different orbit by calling TOPEX/POSEIDON-XT.

ERS-2 and ENVISAT were two European Space Agency, ESA, missions flew from April 1995 to September 2007 and May 2002 to October 2010, respectively. They used the same orbit configuration with a cross-track resolution of about 80 km and a repeat cycle of 35 days. In 2010, ENVISAT changed its orbit, until April 2012 when the signal totally disappeared. We called the temporal series from drifted orbit as ENVISAT-XT.

Cryosat-2 is an ESA mission launched in April 2010. Its orbit has a full repeat cycle of 369 days, resulting in a so-called drifting ground track and a very dense spatial sampling pattern with an across-track distance of only 7.5 km at the equator.

Over the Niger River, overall, 68 virtual stations were defined among them 6 for Jason-2 and the rest for ENVISAT. Over the Po River, 40 virtual stations from TOPEX/Poseidon, TOPEX/Poseidon-XT, ENVISAT, and ENVISAT-XT together with around 400 measurements from multiple crosses of CryoSat-2 are used to obtain densified water level time series.

### C. Satellite optical datasets and pre-processing

The analysis considered three different satellite missions for the optical images, that are described below, mainly focusing on the spatial and temporal resolutions (see Table I).

MODIS is a multispectral sensor on board the TERRA and AQUA satellites, acquiring image data in 36 bands ranging in wavelength from 0.4  $\mu\text{m}$  (visible) to 14.4  $\mu\text{m}$  (thermal infrared). Data are available from the year 2000 (2002) from TERRA (AQUA) with spatial resolutions of 250, 500 and 1,000 m, and a temporal resolution of 1-2 days. In this study, level-2 products

MOD09GQ and MYD09GQ from TERRA and AQUA, respectively, at a daily resolution are used. Specifically, band 1 and band 2 surface reflectance in NIR (620-670 and 841-876 nm) at 250 m are exploited (available at the Earth Data website - <https://earthdata.nasa.gov/>). Band 2 provides the river discharge signal, but the filtering of the clouds is carried out by exploiting band 1. The total number of images after the cloud filtering is reduced to about 50%. The subsample is again quite robust for the analysis (see Table I).

Medium Resolution Imaging Spectrometer (MERIS) was one of the main instruments on board the European Space Agency (ESA) ENVISAT platform. It produced multispectral images in 15 selected spectral bands between 390 nm and 1,040 nm. The spatial resolution of this instrument was about 260 m x 300 m over land. The swath width was equal to 1,150 km and allowed MERIS to reach global coverage every 3 days. MERIS data has been available worldwide from May 2002 to April 2012, but due to the long time needed for data processing, periods starting from 2004 for Niger and 2006 for Po were extracted. Images from the level 2 Full Resolution Full Swath Geophysical (FRS) products were pre-processed through the Basic ERS & ENVISAT (A) ATSR and MERIS Toolbox, BEAM (<http://www.brockmann-consult.de/cms/web/beam/>). Specifically, the ortho-rectification was carried out by selecting the UTM-WGS84 geodetic datum and the GETASSE30 Digital Elevation Model. Band 13 (band center 855 nm, bandwidth 20 nm) and band 7 (band center 655 nm, bandwidth 10 nm) are chosen to make the analysis consistent with the MODIS bands. In particular, band 7 is used to realize a filter able to exclude the images of MERIS affected by cloud coverage. After filtering, the final number of selected images is drastically reduced to 72% for Lokoja and 60% for Pontelagoscuro (see Table I).

LANDSAT is a series of satellites that provide the longest temporal record of moderate resolution multispectral data of the Earth's surface on a global basis (40 years). Within the selected period, in Nigeria, only LANDSAT 7 ETM+ is available. The observation bands of this sensor are seven. We analyzed band 3 (band center 660 nm, bandwidth 30 nm) and band 4 (band center 837.5 nm, bandwidth 62.5 nm). The sensor on this satellite has a high spatial resolution, i.e. 30 m, but also a long grounding track repeat cycle. This low temporal resolution reduces the number of available images at Lokoja to 123, further reduced by the cloud filter to 55 images. Due to the big computational effort for processing Landsat images, the analysis is limited to the Niger River.

Each optical image is extracted to a box with a dimension of

TABLE II  
TEMPORAL RESOLUTION (IN DAYS) OF THE ALTIMETRIC AND OPTICAL DATASETS. FOR OPTICAL DATASET THE MEAN AND THE STANDARD DEVIATION IS CALCULATED AFTER THE REMOVING F CLOUDY IMAGES

		Altimetry	MODIS TERRA	MODIS AQUA	MERIS	LANDSAT
Niger	mean	2.27	2.56	2.00	5.80	42.07
	standard deviation	2.21	3.05	1.67	9.76	45.29
Po	mean	5.94	3.20	4.14	4.67	-
	standard deviation	8.25	4.13	5.59	6.66	-

40 x 40 km for the Niger River and 20 x 20 km for the Po River, centered on the gauged stations of Lokoja (Niger) and Pontelagoscuro (Po) in order to compare the simulated and observed discharge. We prefer to consider two sizes for the boxes because the case studies are significantly different. Indeed, Lokoja is near the confluence of two large rivers and the scene takes into account the width of the two branches. At Pontelagoscuro station, the river has a moderate width and it flows in a large meander without any division of flows in more watercourses.

The cloud filter logic is the same for every optical dataset. A threshold on the band in NIR close to 660 nm is fixed at 0.2 to remove all the pixels with a high value of reflectance, typical of the cloud pixels. These pixels are masked out in the images at ~850 nm band. Finally, a visual inspection polished the non-filtered images in which the river is not clearly visible.

#### D. Water level from radar altimetry

Water levels are derived using a multi-mission approach developed by Tourian et al. [25, 26] that connects hydraulically more individual altimetric time series along the river in order to obtain a water level time series with an improved temporal resolution (about every three days). Altimetric measurements along the river are stacked after shifting their water level hydrographs according to a corresponding time lag. The time lag represents the time that stream flows from one virtual station to another downstream. For the time lag estimation, average river width from imagery together with the slope derived from satellite altimetry are used as inputs into a simplified hydraulic model. The temporal series for the Niger River is derived by considering ENVISAT/RA-2 and JASON-2 missions. For the Po River, 40 virtual stations along the river every ~11 km are used for reconstructing the water level time series, including ERS-2, Cryosat-2 and Topex-Poseidon [25]. Both the time series are available online at the HydroSat website (<http://hydrosat.gis.uni-stuttgart.de/php/index.php>).

Fig. 1(b) and (d) display the water level time series reconstructed for the gauged stations of Lokoja and Pontelagoscuro from radar altimetry.

#### E. Optical time series as a proxy for the discharge

The approach used for the estimation of river discharge is based on the different characteristics of the wet and dry pixels in the NIR band. The reflectance of a dry pixel (C) is higher than that of a wet pixel (M), even if noises due to vegetation and atmosphere affect the signals. The difference in reflectance between the two pixels is leveraged through the ratio  $C/M$  that allows a reduction in the noises.

Separately for each optical dataset, all the images have been

collected around the location of the gauged stations. Here, the pixels M and C have been selected based on the instructions described on previous papers [22, 24]. Unlike these studies in which the locations of C and M were calibrated in order to obtain the highest correlation with the in situ observations of river discharge, in this study, no calibration is used for selecting the pixels. Following the indications contained in these previous studies, the best location for the wet pixel M is near the river in a zone not completely full of water but sensitive to variations of inundated area during flood events. The dry pixel C of calibration is located outside the river in areas not surrounded by water and over urban areas, that are not affected by the seasonal cycle of vegetation. So, it is expected that the locations could be not optimal as in the previous studies and the ratio  $C/M$  could provide worst performance on the estimation of river discharge, if considered singularly.

Multiple images are analyzed to obtain time series of  $C/M$  that is smoothed with a low pass filter (averaging moving window), in order to achieve  $C/M^*$  time series. The performances of the time series of  $C/M^*$  from the different satellites in the estimation of river discharge is carried out through the comparison with the observed discharges.

#### F. Merging multiple satellite through an artificial neural network for the discharge estimation

The merging procedure is feasible if all the datasets are available for the same dates. The  $C/M^*$  ratio extracted from optical satellite sensors is affected by cloudy images while the water level altimetry time series is constrained to the passage of satellites over the river. These conditions generate missing data and make the time series not continuous. Moreover, the altimetry multi-mission satellites can be heterogeneous in terms of both the accuracy, depending from the altimeter used, and the number of satellites available in the same period. Looking at the Niger (Fig. 1), water level before October 2010 has much more high frequencies variability than later this date, mainly due to the working period of ENVISAT. For the Po the frequency is also lower (see Table II), due to the low number of altimeters available in the period.

The time series derived by optical sensors, have different temporal resolution, due to the repeat cycle of the satellites. Table II shows their temporal frequency: MODIS-derived time series have temporal resolution comparable to the altimetric time series in Niger, whereas it is lower in the Po. Landsat has on average a low temporal resolution (more than one month), whereas for MERIS the mean time step among the measurements is 5-6 days.

The differences in the frequency and accuracy between the

altimetric and optical sensors, can be mitigated by the multi-mission approach. Therefore, in order to make the time series at the same frequency, all the satellite datasets are interpolated linearly at daily scale, in a way which makes them consistent with the temporal resolution of ground observations. The missing daily data are replaced by interpolated values between the closer previous and next values in a linear way.

The daily datasets represent the inputs to the ANN.

ANN can be regarded as a statistical approach aimed at providing the minimum variance solution to the given problem. When properly trained, ANNs are able to reproduce almost any kind of input-output relationship [13, 14]. In particular, ANNs were largely employed for remote sensing applications, since they offer an easy but effective possibility of combining input data from different sources into the same retrieval algorithm [4, 16, 17].

In this study, we made use of the feed-forward multi-layer perceptron neural networks (MLP-ANNs) available in the Matlab® Neural Networks toolbox. In MLP-ANNs, each input is weighted and passed to the neurons of the first hidden layer, where is added to the other neuron inputs to produce an output value, also called activation. The activation value is then passed through a non-linear function known as transfer function and passed to the neurons of the second hidden layer (if present) or to the output layer. The most common transfer functions are linear, hyperbolic tangent sigmoid (tansig), and log-sigmoid (logsig).

The tansig is expressed by equation (1) and returns an output value between -1 and 1 when the input a value goes from  $-\infty$  to  $+\infty$ :

$$\tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}} \quad (1)$$

Logsig is expressed by equation (2) and its output goes from 0 to 1 when a varies between  $-\infty$  and  $+\infty$ .

$$g(a) = \frac{1}{1 + e^{-a}} \quad (2)$$

The MLP-ANNs training is based on the back propagation (BP) learning rule: BP is a gradient descent algorithm that adjusts iteratively the ANN weights and connection strengths

for minimizing the Mean Square Error (MSE) between the ANN output and the corresponding target value.

Several combinations of inputs have been implemented, considering each satellite sensor alone or in combination with others. For each combination, a dedicated ANN has been implemented and trained. In detail, ANNs have been implemented in nine different configurations. For each configuration, the optimal number of hidden layers and neurons have been defined through an iterative process that repeated the training by increasing the ANN architecture until the minimum error is found. Table III summarizes input combinations and optimal configuration for each ANN implementation. 50% of the data available for each configuration of inputs was considered for training the algorithm and the remaining 50% for validating it, by predicting the river discharge from a set of satellite data not considered for the training. In order to train the network efficiently, the training dataset must cover the whole range of discharge. In the case of Niger, the division of the dataset in two sequential periods, 2004-2008 for training and 2008-2012 for the validation, is not the best choice. Indeed, the river discharge has highest values during 2010 and 2011 and a neural network trained in the first period would fail during the following periods. Similar considerations can be done in the case of the Po, in which the period 2006-2008 has values of river discharge significantly lower with respect to the period 2009-2012.

Therefore, the training set is obtained by selecting data every other day, while the validation set comprised of the remaining data.

The training set was further subsampled randomly in 60%, 20% and 20% subsets: the first subset served for iteratively adjusting the ANN weights and connection strengths using BP; and the second and third subsets were used for validating the training and having a posteriori test at each training iteration. Based on the so-called “early stopping” rule, the training stops as soon as the errors on the three subsets are diverging, in order to prevent overfitting. The optimal ANN for the given problem was defined by increasing iteratively the ANN configuration from one hidden layer with a number of neurons equal to the number of inputs up to two hidden layers with a number of neurons each equal to three times the number of inputs. For reducing the risk of BP to find local minima of MSE, the training of each configuration was repeated 100 times, by resetting each time the initial ANN weights. This process was repeated for each transfer function available, among linear, tansig and the logsig: output of this process was the ANN giving the best results for each input configuration.

The transfer functions providing the best results were the hyperbolic tangent sigmoid (tansig) and the log-sigmoid (logsig), depending on the given configuration of inputs.

The ANN validation, to which the results presented in the following sections are referred, was obtained by applying each saved ANN to the corresponding validation set, comprised of the data excluded from the training, in order to keep training and validation as independent as possible.

TABLE III  
INPUT CONFIGURATION AND CORRESPONDING OPTIMAL NUMBER OF  
NEURONS AND HIDDEN LAYERS

Inputs	No. of hidden layers	No. of neurons
MODIS-TERRA (MOD)	2	6
MODIS-AQUA (MYD)	2	6
MERIS (MER)	2	6
ALTIMETRY (ALT)	2	6
ME + ALT	2	8
MOD + MYD	2	8
MOD + MYD + MER	2	9
MOD + MYD + MER+ALT	2	12

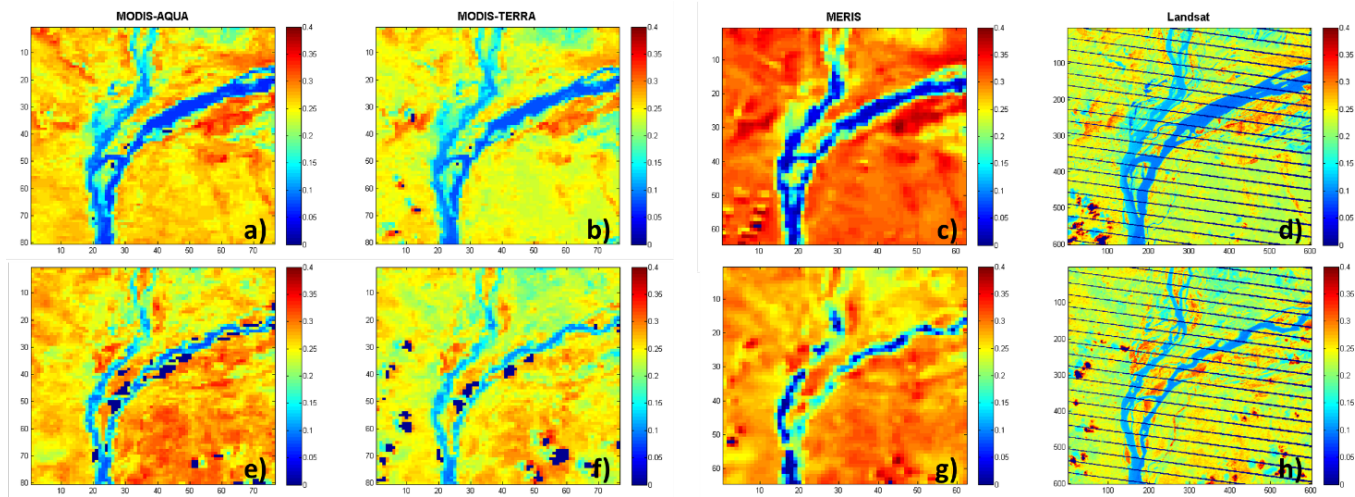


Fig. 2. Reflectance values at Lokoja box. Comparison between the four images from (a) and (e) MODIS-AQUA, (b) and (f) MODIS-TERRA, (c) and (g) MERIS, and (d) and (h) Landsat, acquired on November 21, 2011 (top) and March 28, 2012 (bottom).

### G. Performance indices

The capability to reproduce the observed temporal pattern of discharge is evaluated through the calculation of four performance indices at daily time scale: (1) Pearson coefficient of correlation ( $R$ ); (2) root mean square error (RMSE); (3) relative RMSE (RRMSE), defined as the ratio between the RMSE and the mean of the simulated discharge; and (4) the Nash-Sutcliffe efficiency (NS).

Additionally, three categorical metrics are examined: Probability of Detection (POD) defining the fraction of events correctly predicted (optimal value equal to 1), False Alarm Ratio (FAR) referring to the fraction of predicted events that are actually non-events (optimal value equal to 0) and Threat Score (TS) representing the number of events successfully estimated over the total of hit, missed and false events (optimal value equal to 1). For “events” we refer to the values of river discharge above a threshold (different for Lokoja and Pontelagoscuro). Taking in account the importance of the estimation of high discharge values for the flood risk purpose, our interest is to evaluate the performance of the procedure considering different thresholds, selected between the 50<sup>th</sup> and the 98<sup>th</sup> percentile of the observed total discharge.

## III. RESULTS AND DISCUSSION

This section describes the following: (i) comparison among the images of the four optical products (MOD, MYD, MERIS and Landsat); (ii) ratio of reflectance of dry and wet period is computed for each dataset, and compared against each other in order to select the satellite to be employed for the estimation of discharge; and (iii) results of the merging procedure used to calculate river discharge. In order to evaluate the performance of the procedure, in the following, all the analyses of the results refer to the independent period of validation. Only if expressly specified, we refer to training datasets.

### A. Comparison of optical satellites

A consistent comparison among the optical datasets includes a direct evaluation of the images during the same day of

acquisition. Because of the shift in the overpassing time, the images can observe different scenes due to the presence of clouds. An example is provided in Fig. 2 where the comparison in terms of reflectance between the images for a box surrounding the Lokoja station during two specific days is shown. The river was characterized by medium flow for November 21, 2011. However, for the image acquired on March 28, 2012, low flow conditions were observed. Despite the different time of acquisition of the satellites (MERIS overpassed the area at 9:29 UTC, Landsat overpassed at 9:44 UTC, MODIS-TERRA at 10:05 UTC and MODIS-AQUA in the afternoon at 13:05 UTC), the scenes are very similar.

Based on the reflectance, even if the bands of the satellite are close, some differences are found between the products. In one case (November 21, 2011), MODIS-AQUA, MODIS-TERRA and Landsat have very similar patterns, with median values between 0.22 and 0.26, whereas MERIS has higher values outside the river of about 0.30 as underlined also by the histograms shown in Fig. 3. For the image with low flow (March 28, 2012), MERIS (median of 0.28) is more similar to MODIS-AQUA (0.26), with values higher than MODIS-TERRA (0.24) and Landsat (0.23). As illustrated in Fig. 3, MERIS has the larger variability of the reflectance with respect to the other sensors: the standard deviation is equal to 0.05 and 0.07 for moderate and high flow, respectively, which is different from the other sensors for which the standard deviation ranges between 0.04 and 0.05. Moreover, the clear distinction between water and land (wet and dry pixels) is shown by the bimodal behavior of the histograms, visible in MODIS and MERIS, but not easily detectable in Landsat images.

### B. Temporal series of $C/M^*$ for optical sensors

In order to compare the performances of the different satellites, the computation of the time series for  $C/M^*$  is carried out selecting two boxes, one near the river in areas showing significant variation of water extent during flood events (wet pixel,  $M$ ) and the other far from the river in areas not covered

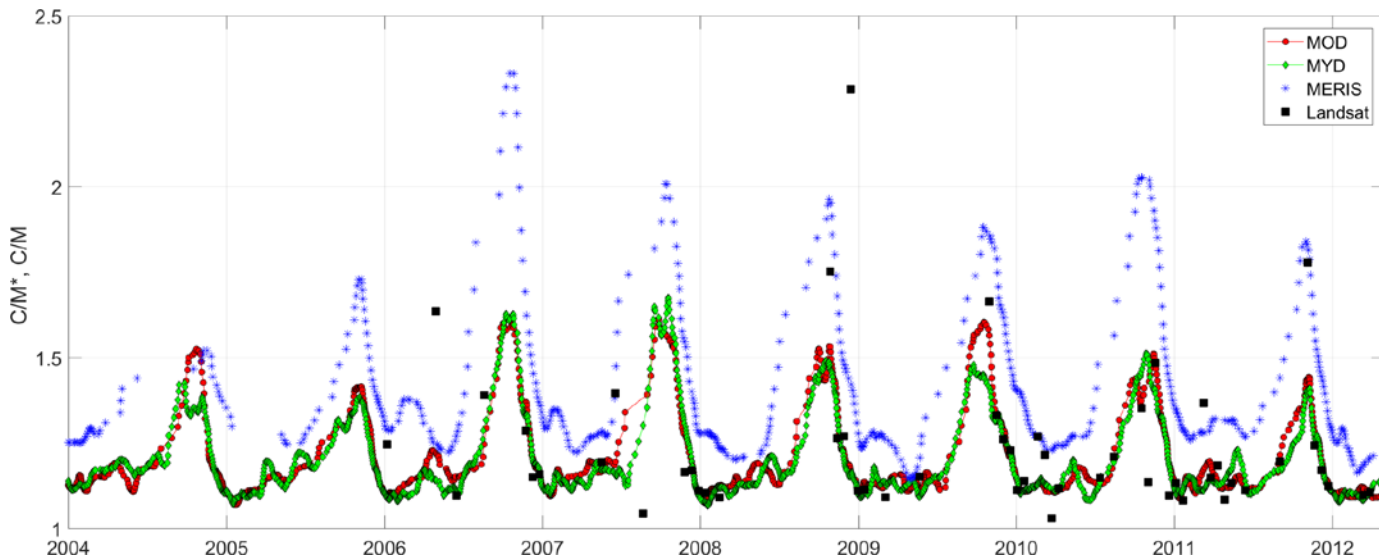


Fig. 5. Time series of  $C/M^*$  derived by different optical products for Niger River at Lokoja: MODIS-TERRA (MOD), MODIS-AQUA (MYD), MERIS and Landsat.

by water and in correspondence of urban areas (dry pixel, C). Fig. 4 shows the location of C and M pixels for Lokoja and Pontelagoscuero stations. Due to the different width of the rivers, the boxes are of different size: for Lokoja, the urban area on the right bank of the confluence (left of the image) is included in the box for C (about 2.5 km x 2.5 km), whereas a larger box is selected for M (5 km x 5 km). For the Po River, the size of the two boxes is smaller and equal to 600 m x 600 m.

For each image, and hence each time step, the reference value for the dry and wet pixel is calculated by the average of the reflectance of the pixels included within the boxes for C and M. The ratio  $C/M$  is filtered through the moving average window filter with N equal to 16 days in order to smooth the effect of the noise in the time series. The choice of 16 days comes from the revisit time of MODIS and can be well adapted for MERIS for which we used the same. Due to the temporal frequency of the Landsat (55 cloud-free images in 6 years), the filter cannot be applied because the period between one measurement and the successive one is on average of 42 days (Table II).

The resulting time series of  $C/M^*$  are shown for the Niger River at Lokoja in Fig. 5, including  $C/M$  for Landsat. Because of the dissimilarity between the sensors, the temporal series of  $C/M^*$  show large differences in the range of variability: the highest for MERIS and the lowest for MODIS. All the satellites capture very similar seasonal behavior of the river with periods of high and low flow. MODIS-AQUA and MODIS-TERRA well match even if flood events in 2004 and 2009 show some substantial differences in the high values. MERIS well follow the shape of the floods, but disagreements are found in the rising limb. Indeed, in the period 2006-2011, MERIS showed higher values than MODIS. Although the sensors of MERIS and MODIS are similar, the algorithm used to derive the reflectance of the water bodies is differences and this leads to sensitive variations in the reflectance values. For Landsat, despite the good agreement with MODIS in the falling limbs, dissimilarities are observed in 2006 and 2008. Due to the impossibility to apply the filter, the outliers are not smoothed

and the time series appear very different to the others. These high values of  $C/M$  are consistent to the  $C/M$  of the other sensors, but they cannot be used to capture the discharge variations. For Landsat, the high spatial resolution, and hence more detailed information, does not compensate its low temporal resolution that becomes unsuitable for the estimation of river discharge. Therefore, we decided not to consider the Landsat time series in the merging process. As an input to ANN, only MERIS, MODIS from TERRA (MOD), MODIS from AQUA (MYD) and time series of altimetry are processed.

*C. Merging optical sensors and altimetry data for river discharge estimation*

Fig. 6 and 7 show the outcomes of the ANN application. Specifically, in subplots a to d of both Fig. 6 and 7, ANN was applied to the four single products for both the anomaly discharge in the case of Niger River and the total discharge in

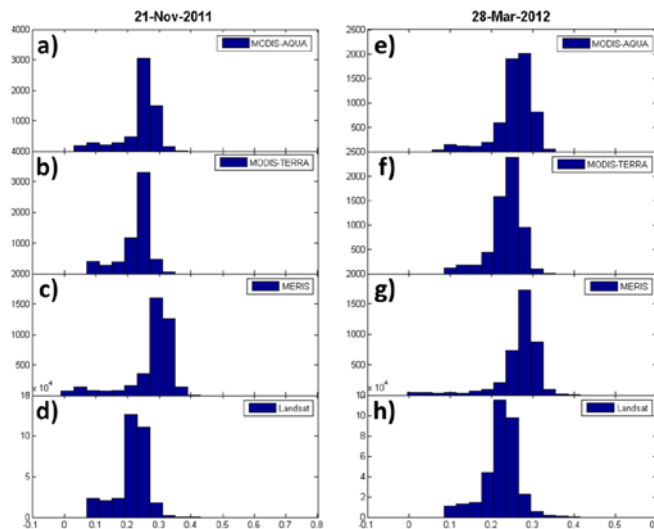


Fig. 3. Histogram of the images in Fig. 1 for Lokoja station and for the four images from (a) and (e) MODIS-AQUA, (b) and (f) MODIS-TERRA, (c) and (g) MERIS, and (d) and (h) Landsat, acquired on November 21, 2011 (left) and March 28, 2012 (right).



the case of Po River. Unlike previous studies conducted by Tarpanelli et al. [17, 19] where good discharge estimates were obtained using MODIS products, the use of a single product (MODIS or MERIS) here does not properly represent the river discharge. This is mainly due to two factors: first, the optimization of the location for M and C pixels, which is not carried out in this analysis and, second, the interpolation process of the input dataset for providing daily data which introduces a high number of interpolated values with respect to the original time series. In the case of single product of altimetry, the river discharge retrieved by ANN slightly improves the estimation with respect to the rating curve based on a simple regression law of second order between the water level and the discharge ( $R = 0.71$ ,  $NS = 0.50$ ). Strong improvements are achieved, only if the products are combined. In particular, the merging of optical sensors MOD, MYD and MERIS provides discharge estimates with  $R$  equal to 0.87 and  $NS$  equal to 0.76 for the discharge anomalies of Niger River. With the contribution of the altimetry, the performances reach values quite satisfying with  $R$  equal to 0.89,  $NS$  equal to 0.78 and  $RMSE$  equal to  $728 \text{ m}^3/\text{s}$ . In Fig. 6h the scatter plot is close to the fit 1:1.

Fig. 8 shows the same comparison but in terms of temporal

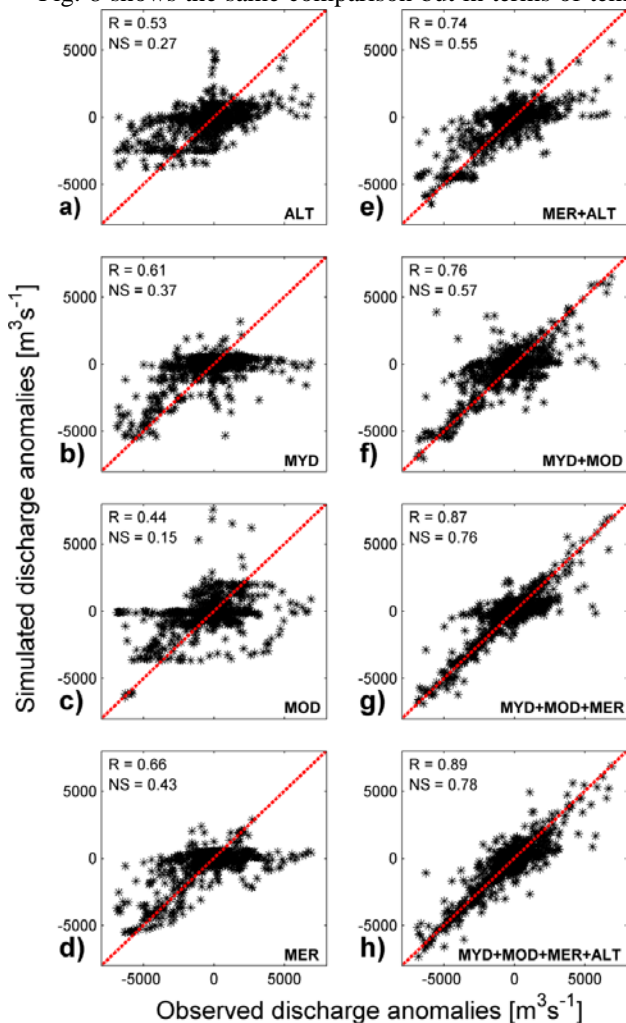


Fig. 6. Observed and simulated discharge anomalies in the testing period for Niger River at Lokoja station (ALT is for altimetry, MYD is for MODIS-AQUA, MOD is for MODIS-TERRA, and MER is for MERIS).

series. The temporal behavior is well reproduced in terms of both anomalies and total discharge. If the total discharge is calculated by adding the observed seasonal cycle to the discharge anomalies, the performance increases:  $R$  and  $NS$  reach a value of 0.99 (for both the calibration and validation periods) and the observed and estimated time series appear coincident (see Fig. 8(b)). In terms of  $RRMSE$ , good performance is obtained equal to 0.11 in calibration and 0.12 in validation.

For the Po River at Pontelagoscuro, similar conclusions are drawn from the analyses, where improvements in the results are obtained when more products are merged. Different from the Niger River, here, the network trained on the altimetry data shows good quality. Lower performances are observed for the two MODIS products (see Fig. 7). If they are merged with MERIS, the resulting discharge closely matches observations as demonstrated by the good performance indices. The best solution is again the merging of all the sensors considered in the analysis with coefficient of correlation equal to 0.91,  $NS$  equal to 0.83 and  $RRMSE$  of about 0.27. The resulting time series are compared with the observations in Fig. 8(c).

Based on the inputs and the trained ANN of these two case studies, we calculated also the weights given by the ANN to

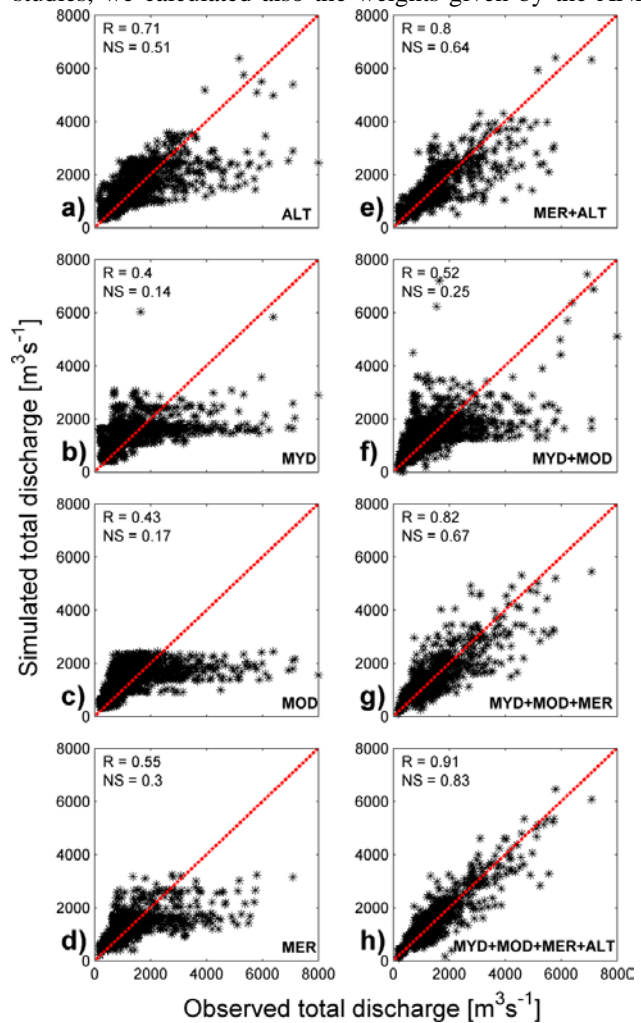


Fig. 7. Observed and simulated discharge anomalies in the testing period for Po River at Pontelagoscuro station (ALT is for altimetry, MYD is for MODIS-AQUA, MOD is for MODIS-TERRA, and MER is for MERIS).



Fig. 8. Comparison between the time series observed in situ and simulated by merging all the products through ANN, in terms of anomalies (a) and total discharge (b) for the Niger River and total discharge for the Po River (c).

each dataset. On average, all the datasets are needed and contribute similarly to the evaluation of the discharge. Specifically, MODIS-AQUA and MODIS-TERRA have similar weight for both the study areas around to 26-28 %, whereas altimetry has 26 % for Pontelagoscuro and 16 % for Lokoja. MERIS has lower weight for Pontelagoscuro (20 %) and higher weight for Lokoja (30 %).

Table IV shows the performance metrics of the final merging for both the calibration and validation periods over the Niger (for anomalies and total discharge) and Po (total discharge) rivers. The performances are very similar, with no sensible deterioration in the validation period, most probably caused by the selection procedure of calibration and validation datasets. Indeed, as already known, ANN is influenced by the range of variability of the input and if this shows considerable differences between the calibration and validation periods, the risk is to obtain a non-trained network. As the period of analysis is limited to 8 years for Niger and 6 years for Po and in these years the discharges are quite different, no alternative can be found for a more reliable selection procedure of calibration and validation datasets.

Generally, the performances are high, especially in the Niger River, for which improvement margins are obtained despite the seasonal cycle (in bracket) already showing high values of performance metric (RRMSE=0.25 and NS = 0.91 for both

calibration and validation). Overall improvements are obtained with respect to the previous analysis, that are carried out over the same study areas with single instruments. Table V resumes the main performances of previously published studies. In the Niger River, the use of multi-sensors data enhances the assessment of the discharge with respect to only use of optical data by MODIS AQUA and TERRA.

The merged time series show also improvements in terms of temporal resolution. The heterogeneity of the single time series (optical and altimetry), is overpassed by the interpolation at daily scale that has mitigated the effect of the not-consistent availability of the data.

A further investigation is carried out by analyzing the simulated and observed river discharge for the two case studies in terms of monthly statistics and the ability to reproduce the extreme events. For each month, we calculated the maximum, minimum and mean values of total observed and simulated discharges. We observed that, for Lokoja, the monthly statistical values are well reproduced by the simulated time series with coefficient of correlation very high (higher than 0.99) as shown in Fig. 9(a). On the other hand, the monthly analysis (Fig. 9(b)) underlines that the correlation between the simulated and observed discharge is dependent on the flows. Low flows in the period from January to June are characterized by coefficient of correlations lower than 0.65, whereas high

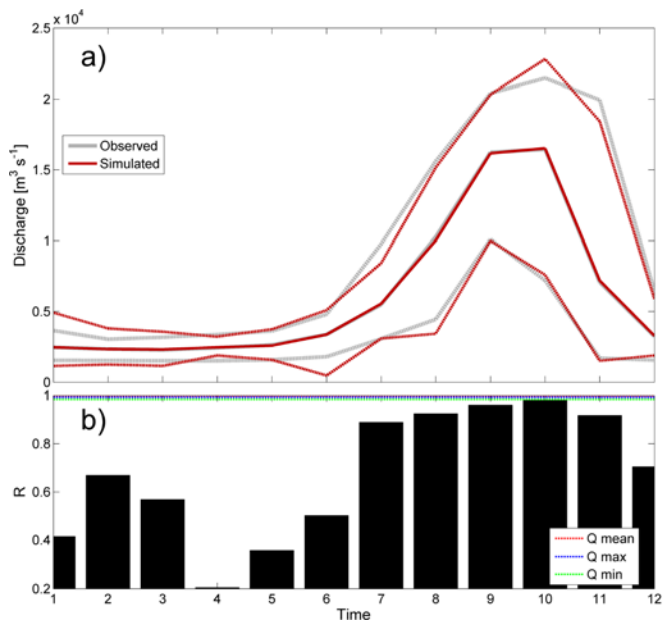


Fig. 9. Comparison between observed and simulated time series by merging discharge at Lokoja (Niger): (a) mean, maximum and minimum monthly discharge; (b) coefficient of correlation.

flows during the period from July to December are very well reproduced with correlation higher than 0.7, highlighting that the approach is able to detect high flow conditions. For the Po River (Fig. 10), the mean discharge is well reproduced by the simulated time series (correlation higher than 0.99), whereas for the maximum and minimum discharge, slight differences are detected (correlation equal to 0.83 and 0.75). At monthly scale, the observed and simulated time series show a good match with correlation higher than 0.77 except for October with a value of 0.64. As shown for the Niger River, the highest correlations are found for high flows in the period from April to July and in November.

The good performances for high flows is further analyzed in terms of categorical metrics. Fig. 11 illustrates the boxplot of the three indices POD, FAR and TS, obtained by using a variable threshold from 5,000 to 20,000 m<sup>3</sup>/s for Lokoja (a) and from 1,000 to 5,000 m<sup>3</sup>/s for Pontelagoscuro (b). For Lokoja, the high number of hits and low number of false alarms contribute to obtaining good values of TS which is, on average, above 0.9. For the Po River, the performances are slightly worse and TS is in the range 0.5-0.7. In both cases, the peculiarity of the proposed approach is to reproduce the observations,

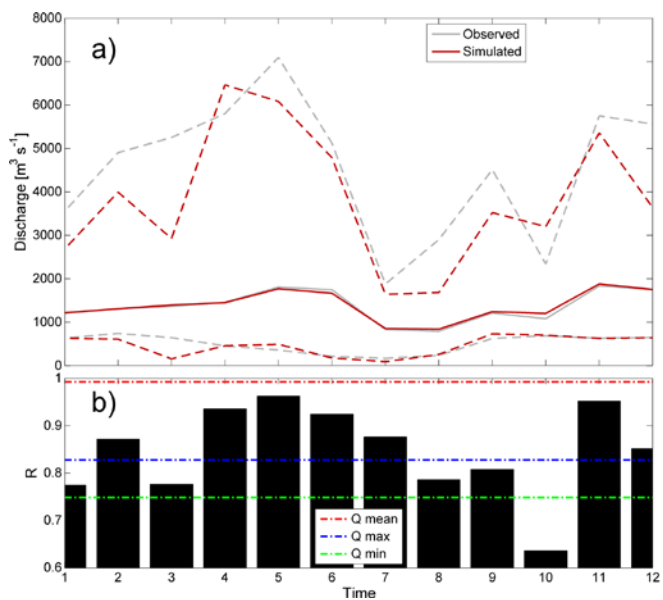


Fig. 10. Comparison between observed and simulated time series by merging discharge at Pontelagoscuro (Po): (a) mean, maximum and minimum monthly discharge; (b) coefficient of correlation.

especially for high flows, in order to obtain improvements in the estimation of extreme events and also forecasting these in future studies.

#### D. Limitations and potential application of the methodology

The procedure shown in the present study has potential applications also in other sites with different ranges of discharge and/or other climatic regions. Further tests should be carried out at large scale (more sites with different characteristics) to confirm the advantage to use more datasets with respect to single products. The current cloud computing platforms (i.e. Google Earth Engine, the new ESA  $\Phi$ -lab, ...) can be used for this purpose. Thanks to large storage, high performance and sizable computing resources, they are rather flexible to be employed for the development of applications at global scale.

Moreover, the application at large scale will assist the evaluation of discharge also for ungauged basin. By grouping rivers with similar characteristics, specific networks can be built by exploiting the available data in gauged sites, with the final purpose to estimate discharge for all the currently dismissing stations or ungauged sites, mainly in the developing

TABLE IV  
PERFORMANCES IN TERMS OF COEFFICIENT OF CORRELATION (R), ROOT MEAN SQUARE ERROR (RMSE), RELATIVE RMSE (RRMSE), NASH-SUTCLIFFE (NS) AND BIAS FOR NIGER AND PO RIVERS. PERFORMANCE OF THE SEASONAL CYCLE IN THE TOTAL DISCHARGE IN NIGER RIVER IS SHOWN WITHIN PARENTHESSES

	Niger - anomalies		Niger - total discharge		Po - total discharge	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
R	0.91	0.89	0.99 (0.96)	0.99 (0.96)	0.90	0.91
RRMSE	-	-	0.11 (0.25)	0.12 (0.25)	0.29	0.27
RMSE [m <sup>3</sup> /s]	666	728	666 (1588)	728 (1585)	402	374
NS	0.82	0.78	0.98 (0.91)	0.98 (0.91)	0.81	0.83
Bias	0.01	0.00	0.00 (0.04)	0.00 (0.04)	0.02	0.01

TABLE V  
COMPARISON OF THE PERFORMANCES IN TERMS OF COEFFICIENT OF CORRELATION (R) AND NASH-SUTCLIFFE (NS) FOR NIGER AND PO RIVERS FOR PREVIOUS PUBLICATIONS OF THE SAME AUTHORS.

	Niger - anomalies		Niger - total discharge		Po - total discharge	
	R	NS	R	NS	R	NS
Tarpanelli et al. 2013 RSE	-	-	-	-	0.73	0.78
Tarpanelli et al. 2013 RS	-	-	-	-	-	0.73-0.82
Tarpanelli et al. 2015 JSTARS	-	-	-	-	0.91	0.75
Tarpanelli et al. 2017 RSE	0.72 (Aqua) 0.63 (Terra)	0.52 (Aqua) 0.4 (Terra)	0.99 (Aqua) 0.99 (Terra)	0.97 (Aqua) 0.97 (Terra)	-	-

countries.

The spread application at large scale, will allow also to evaluate where the approach is more efficient. It is expected that in regions which are heavily covered with clouds during long periods, like Ganges, Brahmaputra or arctic rivers, the estimation of accurate and frequent river discharge is critical. Indeed, the linear interpolation of the datasets at daily scale could be not suitable for rivers affected by frequent cloud cover, where missing values can exceed the period of one week. In these cases, the linear interpolation can be too rough for representing the dynamic of the river. More elaborated interpolation algorithm should be considered.

A further limitation of the approach lies in the merging technique. Although ANN provides good results at Niger and Po rivers in the examined period, we should bear in mind that it cannot simulate accurately values outside the range of training dataset. Therefore, if a flood higher than the one measured will be experienced, the river discharge estimation can be not accurate enough. On this context, other machine learning approaches should be tested in order to find a good tradeoff between good performance and accuracy.

#### IV. CONCLUSIONS

The potential to estimate river discharge by merging more information coming from different satellite missions was demonstrated. The multi-mission approach which uses optical and radar altimetry within the ANNs demonstrated its value for river discharge estimation at the Niger (at Lokoja) and Po (at Pontelagoscuro) rivers.

In particular, the comparison between the optical sensors, i.e. MODIS (AQUA and TERRA), MERIS and Landsat, showed that the performances are more affected by the temporal resolution rather than the spatial resolution. Indeed, even if all images are contaminated by cloud cover that limits the number of available images, optical sensors such as Landsat fail in the estimation of extreme events, missing most of the peak values due to the long revisit time ( $\sim 14-16$  days). The best performances are obtained with the NIR bands from MODIS and MERIS that give similar results in the retrieval of  $C/M^*$  reflectance ratio, even if low performances are applied singularly, without any optimization for the location of the wet pixel (M) and dry pixel (C).

The ANN technique is demonstrated as being suitable to investigate the performance of the sensors. When it is applied to single sensors, it provides moderate performance, as

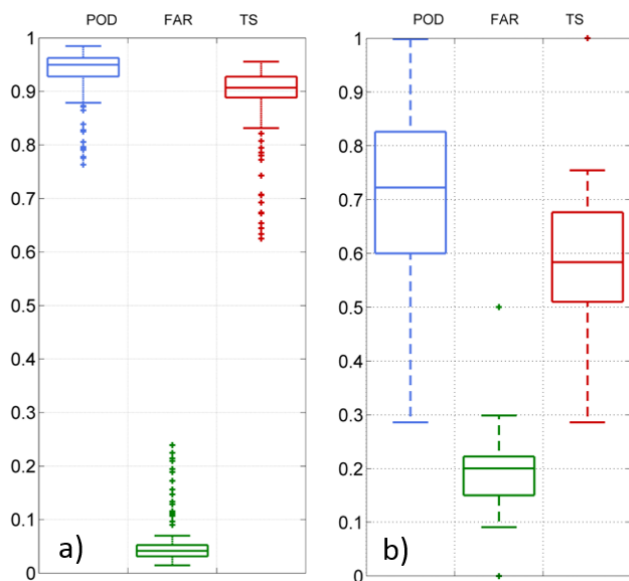


Fig. 11. Box plot of POD, FAR and TS for a discharge threshold ranging from 5,000 to 20,000 m<sup>3</sup>/s for Lokoja (Niger) (a) and from 1,000 to 5,000 m<sup>3</sup>/s for Pontelagoscuro (Po) (b).

demonstrated by the comparison with the observations. The combination of multiple sensors increases the performance as tested for the two case studies for which the regimes are very different: Niger River, with strong seasonality and high values of discharge (higher than 30,000 m<sup>3</sup>/s); and Po River, characterized by variable discharge during the year and maximum values of about 7,000 m<sup>3</sup>/s. Despite of different regimes of discharge, the multi-mission approach, merging sensors of different characteristics (radar altimetry and optical sensors), reproduces the daily river discharge observations well, considering both the discharge anomalies and the total values. The simulated discharge values obtained by the multi-mission approach are validated against in situ data, where NS of about 0.83 and 0.98 and RMSE equal to 374 and 666 m<sup>3</sup>/s are obtained for Po and Niger rivers, respectively.

Further, the discharge estimates are easily used for water resources management and flood forecasting, especially in medium and large basins. Further tests are required to identify whether the procedure can be used at a global level. In this context, cloud platforms and artificial intelligence, and Internet of Things (IoT) can enhance flood forecasting and early warning, and improve the dissemination of information to end users.

Further investigations will be addressed to the new Sentinel missions. The high spatial resolution ranging from 10 to 60 m for the MultiSpectral Instrument (MSI) on board Sentinel-2 can be exploited for estimating the discharge in a narrow river (width <100 m). In those cases, the revisit time of 5 days (with the constellation A and B) is expected to improve the performance with respect to the Landsat 7 (analyzed here), but it should be tested. On the other hand, Sentinel-3, with the Synthetic Aperture Radar Altimeter (SRAL) and the multispectral Ocean and Land Colour Instrument (OLCI), can guarantee continuity in the river monitoring at global scale.

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#### REFERENCES

- [1] F. Aires, L. Miolane, C. Prigent, B. Pham, E. Fluet-Chouinard, B. Lehner and F. Papa, "A global dynamic long-term inundation extent dataset at high spatial resolution derived through downscaling of satellite observations," *J. Hydrometeorol.*, vol. 18, no. 5, pp. 1305–1325, May 2017.
- [2] D. M. Bjerklie, S. L. Dingman, C. J. Vörösmarty, C. H. Bolster and R. G. Congalton, "Evaluating the potential for measuring river discharge from space," *J. Hydrol.*, vol. 278, no. 1–4, pp. 17–38, Jul. 2003.
- [3] D. M. Bjerklie, D. Moller, L. C. Smith and S. L. Dingman, "Estimating discharge in rivers using remotely sensed hydraulic information," *J. Hydrol.*, vol. 309, no. 1–4, pp. 191–209, Jul. 2005.
- [4] F. Del Frate, P. Ferrazzoli and G. Schiavon, "Retrieving soil moisture and agricultural variables by microwave radiometry using neural networks," *Remote Sens. Environ.*, vol. 84, no. 2, pp. 174–183, Feb. 2003.
- [5] A. Domeneghetti, A. Tarpanelli, L. Brocca, S. Barbeta, T. Moramarco, A. Castellarin and A. Brath, "The use of remote sensing-derived water surface data for hydraulic model calibration," *Remote Sens. Environ.*, vol. 149, pp. 130–141, Jun. 2014.
- [6] A. Domeneghetti, A. Castellarin, A. Tarpanelli and T. Moramarco, "Investigating the uncertainty of satellite altimetry product for hydrodynamic modelling," *Hydrol. Process.*, vol. 29, no. 23, pp. 4908–4918, Jul. 2015.
- [7] P.-A. Garambois and J. Monnier, "Inference of effective river properties from remotely sensed observations of water surface," *Adv. Water Resour.*, vol. 79, pp. 103–120, May 2015.
- [8] GCOS/GTOS plan for terrestrial climate-related observations, version 2.0. GCOS Rep. 32, 130 pp. [Available online at [www.wmo.int/pages/prog/gcos/Publications/gcos-32.pdf](http://www.wmo.int/pages/prog/gcos/Publications/gcos-32.pdf)].
- [9] GCOS Systematic observation requirements for satellite-based products for climate 2011 update: Supplemental details to the satellite-based component of the "Implementation plan for the global observing system for climate in support of the UNFCCC (2010 update). GCOS Rep. 154, 138 pp., 2011 [Available online at [www.wmo.int/pages/prog/gcos/Publications/gcos-154.pdf](http://www.wmo.int/pages/prog/gcos/Publications/gcos-154.pdf)].
- [10] C. J. Gleason, L. C. Smith and J. Lee, "Retrieval of river discharge solely from satellite imagery and at-many-stations hydraulic geometry: Sensitivity to river form and optimization parameters," *Water Resour. Res.*, vol. 50, no. 12, pp. 9604–9619, Dec. 2014.
- [11] D. M. Hannah, S. Demuth, H. A. J. van Lanen, U. Looser, C. Prudhomme, G. Rees, K. Stahl and L. M., Tallaksen, "Large-scale river flow archives: importance, current status and future needs," *Hydrol. Process.*, vol. 25, no. 7, pp. 1191–1200, Mar. 2011.
- [12] F. A. Hirpa, T. M. Hopson, T. De Groeve, G. R. Brakenridge, M. Gebremichael and P. J. Restrepo, "Upstream satellite remote sensing for river discharge forecasting: application to major rivers in South Asia," *Remote Sens. Environ.*, vol. 131, pp. 140–151, Oct 2013.
- [13] K. Hornik M. Stinchcombe and H. White, "Multilayer feedforward network are universal approximators," *Neural Networks*, vol. 2, no. 5, pp. 359–366, 1989.
- [14] A. Linden and J. Kinderman, "Inversion of multi-layer nets," in *Proc. Int. Joint Conf. Neural Networks*, vol. 2, pp. 425–430.
- [15] A. Montanari, "Hydrology of the Po River: looking for changing patterns in river discharge," *Hydrol. Earth. Syst. Sci.*, vol. 16, pp. 3739–3747, Oct. 2012.
- [16] S. Paloscia, P. Pampaloni, S. Pettinato and E. Santi, "A comparison of algorithms for retrieving soil moisture from ENVISAT/ASAR images," *IEEE Tran. Geosci. Remote Sens.*, vol. 46, no. 10, pp. 3274–3284, Oct. 2008.
- [17] E. Santi, S. Paloscia, S. Pettinato and G. Fontanelli, "Application of artificial neural networks for the soil moisture retrieval from active and passive microwave spaceborne sensors," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 48, pp. 61–73, Jun. 2016.
- [18] R. Schneider, P. N. Godiksen, H. Villadsen, H. Madsen and P. Bauer-Gottwein, "Application of Cryosat-2 altimetry data for river analysis and modelling," *Hydrol. Earth. Syst. Sci.*, vol. 21, pp. 751–764, Feb. 2017.
- [19] A. W. Sichangi, L. Wang, K. Yang, D. Chen, Z. Wang, X. Li, J. Zhou, W. Liu and D. Kuria, "Estimating continental river basin discharges using multiple remote sensing data sets," *Remote Sens. Environ.*, vol. 179, pp. 36–53, Jun. 2016.
- [20] N. Sneeuw, C. Lorenz, B. Devaraju, M. J. Tourian, J. Riegger, H. Kunstmann and A. Bárdossy, "Estimating runoff using hydro-geodetic approaches," *Surv. Geophys.*, vol. 35, no. 6, pp. 1333–1359, 2014.
- [21] A. Tarpanelli, S. Barbeta, L. Brocca and T. Moramarco, "River discharge estimation by using altimetry data and simplified flood routing modeling," *Remote Sens.*, vol. 5, no. 9, pp. 4145–4162, Aug. 2013a.
- [22] A. Tarpanelli, L. Brocca, T. Lacava, F. Melone, T. Moramarco, M. Faruolo, N. Pergola and V. Tramutoli, V. "Toward the estimation of river discharge variations using MODIS data in ungauged basins," *Remote Sens. Environ.*, vol. 136, pp. 47–55, Sep. 2013b.
- [23] A. Tarpanelli, L. Brocca, S. Barbeta, M. Faruolo, T. Lacava, and T. Moramarco, "Coupling MODIS and Radar Altimetry Data for Discharge Estimation in Poorly Gauged River Basins," *IEEE J. Sel. Top. Appl.*, vol. 8, no. 1, pp. 141–148, Jan. 2015
- [24] A. Tarpanelli, G. Amarnath, L. Brocca, C. Massari and T. Moramarco, "Discharge estimation and forecasting by MODIS and altimetry data in Niger-Benue River," *Remote Sens. Environ.*, vol. 195, pp. 96–106, Jun. 2017.
- [25] M. J. Tourian, A. Tarpanelli, O. Elmi, T. Qin, L. Brocca, T. Moramarco and N. Sneeuw, "Spatiotemporal densification of river water level time series by multitemission satellite altimetry," *Water Resour. Res.*, vol. 52, no. 2, pp. 1140–1159, Feb. 2016.
- [26] M. J. Tourian, C. Schwatke and N. Sneeuw, "River discharge estimation at daily resolution from satellite altimetry over an entire river basin," *J. Hydrol.*, vol. 546, pp. 230–247, Mar. 2017.
- [27] A. I. J. M. Van Dijk, G. R. Brakenridge, A. J. Kettner, H. E. Beck, T. De Groeve and J. Schellekens, "River gauging at global scale using optical and passive microwave remote sensing," *Water Resour. Res.*, vol. 52, no. 8, pp. 6404–6418, Aug. 2016.
- [28] C. Vörösmarty, A. Askew, W. Grabs, R. G. Barry, C. Birkett, P. Döll, B. Goodison, A. Hall, R. Jenne, L. Kitaev, J. Landwehr, M. Keeler, G. Leavesley, J. Schaake, K. Strzpek, S. S. Sundarvel, K. Takeuchi and F. Webster, "Global water data: A newly endangered species," *Eos Trans AGU*, vol. 82, no. 5, pp. 54–58, Jan. 2001.

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