Assessing the Performance of SWOT Simulator in Estimating River Discharge of a Tropical Basin

Taha Aawar, M. S. Adarsh, and C. T. Dhanya

Abstract River discharge, one of the most informative hydrologic variables for different applications such as water resources management, flood forecasting, and long-term change studies in the water cycle, is measured only across a few stations, however. The measurement and maintenance of river discharge data at in situ hydrological observations (HO) stations are challenging due to the cost involved and the accessibility. Hence, studies often rely on remote sensing methods, particularly satellite data, as a complementary source for estimating river discharge. Interest in space-based observation for remote sensing of river discharge has gained momentum recently due to continuous availability and open access of multiple satellites such as optical, microwave, and altimetry at various spatial and temporal scales globally. Surface Water and Ocean Topography satellite mission (SWOT), to be launched in 2022, aims to estimate discharges in rivers wider than 100 m directly. This study aims to assess the applicability of the SWOT mission to estimate the discharge of Gopalkheda station in the Tapi river basins, a tropical basin in India, using SWOT-like data. In situ, HO station data and satellite data are used in a SWOT Simulator along with multiple river discharge estimating algorithms used by SWOT satellite to derive the discharge series. The results are compared with the in situ river discharge to assess the performance of SWOT-derived river discharge.

Keywords River discharge · Remote sensing · Satellite data · SWOT satellite mission

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The original version of this chapter was revised: The author Taha Aawar's name has been updated. The correction to this chapter can be found at https://doi.org/10.1007/978-981-19-9147-9_45.

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1 Introduction

River discharge has a significant role in water resources management; thus, understanding river discharge is advantageous for mitigating and controlling floods, drought, etc. Discharge estimation using satellite data is a complicated process due to numerous limitations like temporal and spatial resolution of satellites, type of satellites available, and accuracy of the satellite images [1, 2]. Based on the literature, the global discharge database information has been regularly downsizing throughout the last few years. This issue leads to understanding the importance of remote sensing techniques and applications in measuring rivers' height, width, and slope [3–6]. Recently, remote sensing and GIS techniques have been widely used to estimate river discharge through calibration in situ observation data [7–9]. Various studies have been conducted to estimate the discharge using satellite and remote sensing data products in the last few decades [2, 3, 9–18]. The river discharge through satellite products data is estimated by measuring its different hydraulic components, such as river width, depth, or velocity either solely or jointly [19–21]. The Surface Water and Ocean Topography (SWOT) satellite mission planned to be launched in 2022 can estimate discharge by simultaneously measuring water surface elevation, river width and slope, using a temporally and spatially continuous Ka-band radar interferometer [22, 23]. SWOT is the first such satellite devoted to terrestrial hydrology, which was developed by the National Aeronautics and Space Administration (NASA) and French: Centre National D'études Spatiales (CNES) with contributions from the Canadian Space Agency (CSA) and The United Kingdom Space Agency (UKSA) [24–31].

The SWOT mission satellite is designed to complete one earth cycle observation within 21 days at an altitude of 800–1000 km generating a large amount of data. This satellite carries a payload module containing a KaRIn radar interferometer to measure ocean water level, Jason class altimeter, DORIS antenna, microwave radiometer, X-band antenna, laser reflector assembly, and GPS. Likewise, the SWOT mission can observe the ocean water level, estimate inland water bodies wider than 250 × 250 m with a target of 10,000 square metres, and discharge rivers more than 100 m wide [32, 33]. One of the most remarkable points of the SWOT is that it can accurately measure soil, snow, and vegetation layers with less penetration using KaRIn. KaRIn is the first satellite instrument to completely dissolve surface water bodies with high altitude accuracy [34, 35].

In order to investigate the capabilities of SWOT, identify applications, and develop algorithms to process the large output data, studies have been carried out by generating synthetic SWOT-like observations by corrupting the observed or modelled data with SWOT error characteristics [25, 36]. Using the CNES SWOT Hydrology Simulator [34], proxy SWOT-like data are produced that account for additional measurement error sources and produce outputs that are comparable to those expected from actual SWOT products.

This paper attempts to evaluate the SWOT satellite's performance with the observation data in one of India's prominent rivers, the Tapi river basin. We use existing satellites and in situ observations data to supply inputs for SWOT Simulator to generate SWOT-like output data and compare with in situ observation.

2 Study Area, Material, and Method

2.1 Study Area

Based on Central Water Commission (CWC), India has 20 river basins in which 12 are prominent, and rest eight rest are composite and small basins. A seasonal tropical river basin with high intensity of rainfall and flood is located in central India called Tapi River Basin. Tapi River Basin has a 724 km length and 65,145 km^2 catchment area divided into upper Tapi river (Multai to Hathnur dam), middle Tapi river (Hathnur dam to Ukai dam), and lower Tapi river (Ukai dam to the Arabian Sea). Tapi river basin has three discharge gauge stations of which two located in the upper part of the basin, and the rest is in the middle part. In this study, the Gopalkheda gauge station is selected as in situ reference data. This station belongs to the branch of the Purnais river which located in the Akoal district of Maharashtra. The total average rainfall in this area is 704.7 mm [37]. Figure 1 shows the study area map.

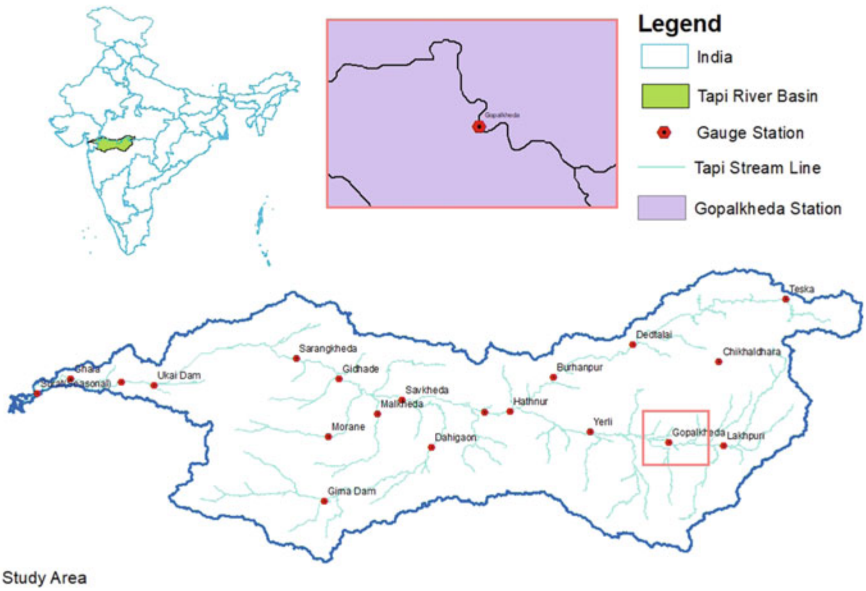

Fig. 1 Tapi River Basin—Study area

2.2 *In Situ* Data Requirement

The monsoon season in India generally peaks between July and October of every year. Our study focussed on these months and selected HO observations for each year from 2010 to 2017. Accordingly, we obtained discharge and water surface elevation data from India-WRIS (www.indiawris.gov.in) Website for the study area.

2.3 *Surface Water Extend from Satellite*

One of the inputs for the SWOT simulator is the river surface water extent at the study location. In order to obtain the water extent, we used images from multiple satellites such as the Sentinel-1 SAR satellite and Landsat-5, 7, 8 and Sentinel-2 Satellites. The images were processed to extract the surface water extent and converted to polygon shapefiles for use in SWOT Simulator.

2.4 *CNES SWOT Hydrology Simulator*

Amongst the inputs that the CNES SWOT hydrology simulator uses are radar parameters (power, bandwidth, baseline, thermal noise level, etc.), SWOT orbit, a land coverage map referred to as a water mask, and a digital elevation model (DEM).

A simulator run begins with finding all ascending and descending orbits intersecting the area of interest and selecting the ones to use. In the next step, the simulator calculates the complex interferograms by taking into account the chosen orbit, the DEM, the land cover mask, the water topography, and the instrument characteristics. A complex output image reflects the magnitude of the backscattering of the surface (corrupted by speckle), and the phase reflects the topography of land and water (with thermal noise).

It is possible to simulate various situations by changing parameters, like the backscattering model for each class (land, water, etc.), or by adding a wind field that will locally modulate water roughness and backscattering. In the next step, the simulator generates a "pixel cloud" product, a water mask associated with geolocated heights and uncertainties, in which the water pixels are demonstrated as a point cloud. Land pixels are mostly disposed of or discarded.

We create the water extent at rivers using the polygon shapefile extracted from Satellite images. These shapefiles must contain attributes with water surface elevations input as "HEIGHT", River flag (RIV_FLG) with 1 for the river and 0 for the lake [34]. Figure 2 illustrates the river network and river pixel cloud (river mask), which SWOT Simulator generated at Gopalkheda.

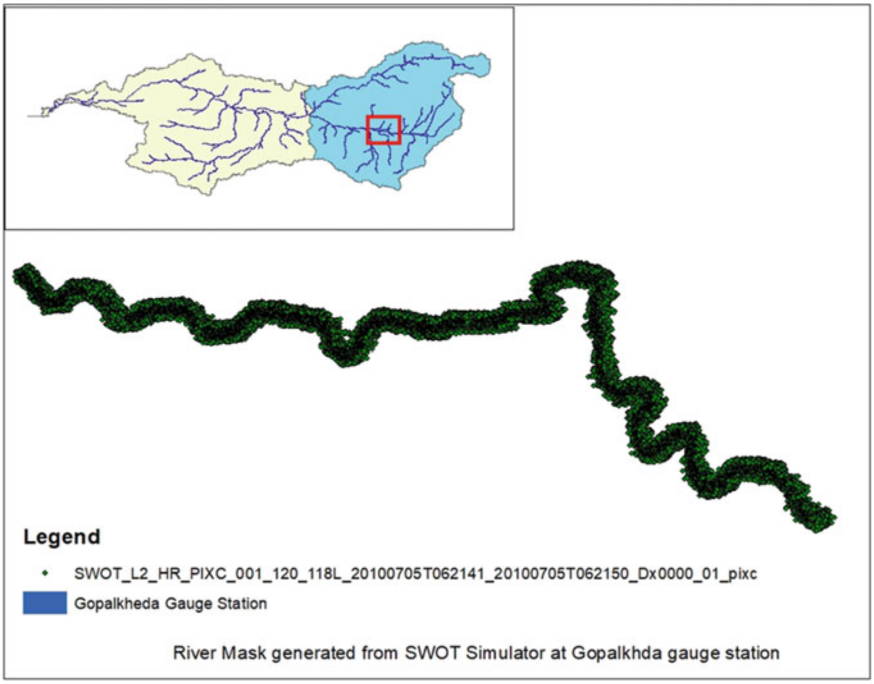

Fig. 2 Generated river mask for Gopalkheda gauge station

2.5 SWOT RiverObs Simulator

The resulting pixel cloud of water surface heights is processed with a RiverObs package in the SWOT simulator, which uses a priori information of river centerline and node database spaced at ~200 m along the river centerline and reaches database computed by aggregating nodes to ~10 km. It uses an offline SWOT River Database (SWORD), which contains the river feature in shapefiles through its global and satellite-related database [38]. Generated nodes that have average water level and river with are shown in Fig. 3 at the Gopalkheda HO station of the study area.

2.6 Empirical Equation

Discharge being a significant characteristic of the river, researchers have tried various methods to estimate discharge from satellite data products. [22, 39] used the stage-rating curve and hydraulic manning equation to estimate river discharge from satellite data products. [20, 40, 41] used an empirical method in order to carry out river discharge from satellite data. Sichangi et al. [40] developed the manning's equation form to derive discharge using satellite water level and river width with an assumption

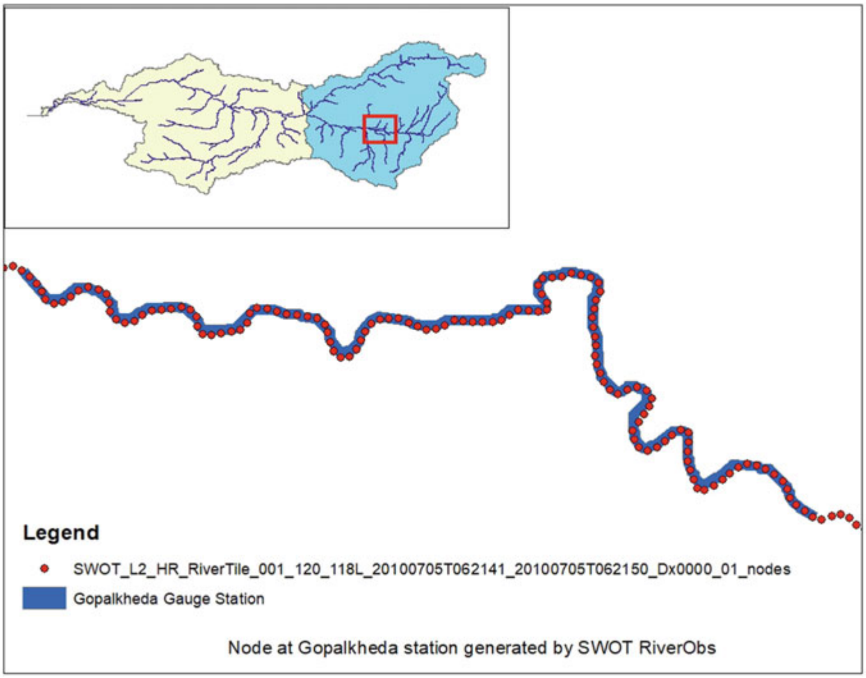

Fig. 3 Nodes generated from RiverObs at Gopalkheda gauge station

of the trapezoidal cross-section according to Eq. (1):

$$q = aWD^{\frac{5}{3}} + b \tag{1}$$

where a and b are constant, which can evaluate by calibration of in situ data, W is river width, q is the discharge, and D is water depth obtained from Eq. (2):

$$D = H - h \tag{2}$$

H is water level height, and h is the zero flow water level. Huang et al. [41] expand the Eq. 1 for various cross-section areas shapes, which result is shown in Eq. (3):

$$q = aW(H - h)^{\frac{5}{3}} \tag{3}$$

where a is the constant ratio between roughness and slope and can estimate from the least square fitting using calibrated in situ data (Huang et al., 2018).

For the present study, power-law fitting [42] as presented in Eqs. (4–6) is used in order to estimate discharge.

$$h = aQ^b \tag{4}$$

$$W = cQ^d \quad \text{m} \tag{5}$$

$$\begin{aligned} Wxh &= (a + c)Q^{(b+d)} \\ Wxh &= AQ^B \end{aligned} \tag{6}$$

where W is river width, h is water depth, and Q is discharge. A and B are constant slope roughness ratios.

3 Performance Evaluation

Nush–Sutcliffe efficiency (NSE) coefficient, root mean square error (RMSE), and relative root mean square error (RRMSE) are used according to the following formula to evaluate the discharge estimation performance.

$$\text{NSE} = 1 - \frac{(Q_{\text{Obs}} - Q_{\text{Est}})^2}{\left(Q_{\text{Obs}} - \overline{Q_{\text{Obs}}}\right)^2} \tag{7}$$

$$\text{RMSE} = \sqrt{\frac{(Q_{\text{Obs}} - Q_{\text{Est}})^2}{n}} \tag{8}$$

$$\text{RRMSE} = \frac{\text{RMSE}}{\overline{Q_{\text{Obs}}}} \times 100\% \tag{9}$$

4 Results and Discussion

SWOT satellite missions can simultaneously measure the water surface elevation (WSE) and river width (W), whilst other satellites do not have this ability. Consequently, the SWOT simulator estimated the time series of water surface elevation and river width on the Gopalkheda gauge station of the Tapi river basin plot in Fig. 4.

In the present study, Eqs. (4 and 6), as illustrated in Figs. 5 and 6, are used, respectively, to derive the discharge from joint estimation using SWOT data products and solo estimation using in situ data water level for the Gopalkheda gauge station, as shown in Table 1.

Based on Eq. 6, the SWOT river width product and in situ water level are used to calculate discharge at the Gopalkheda gauge station. The result demonstrated a comparable estimated discharge value in comparison with actual discharge. On the other hand, Eq. 4 is used to estimate discharge from in situ water level data. This process has been done in order to check the accuracy of the river width and

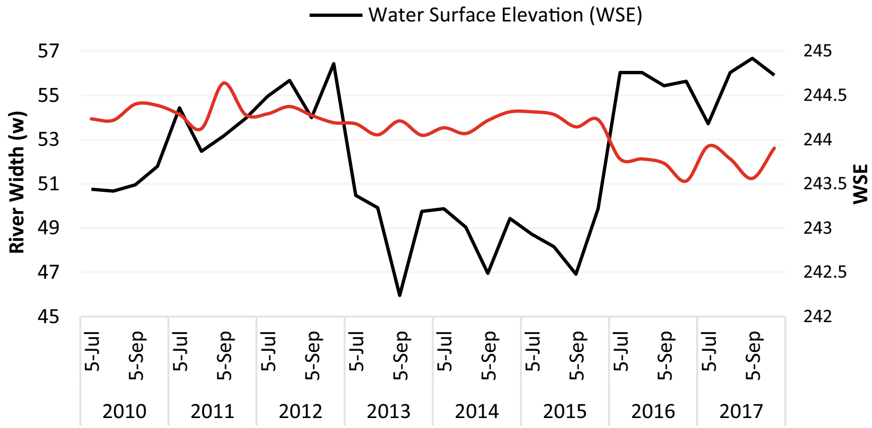

Fig. 4 River width and water surface elevation SWOT data

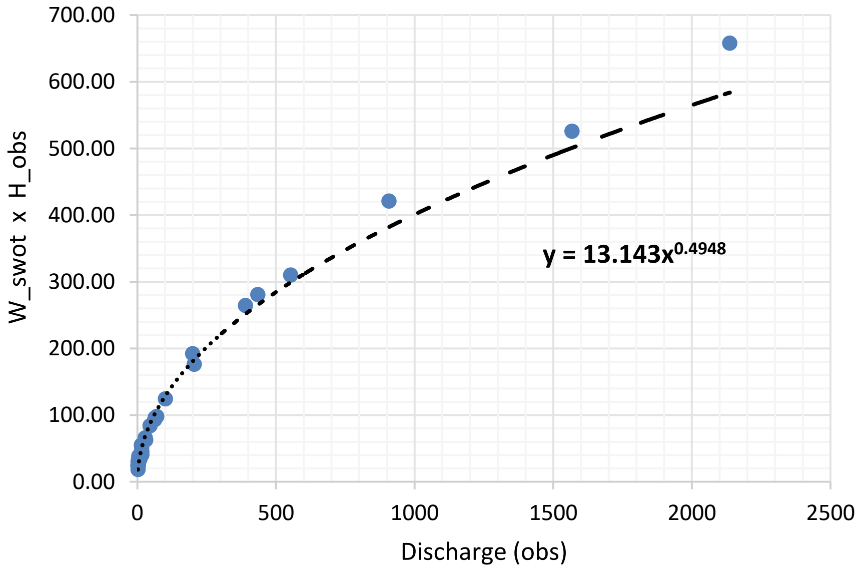

Fig. 5 Discharge via width to the height power equation

performance of SWOT satellite data. Appropriately, estimated discharge is showing consistency, as shown in Figs. 5 and 6.

Nush–Sutcliffe efficiency (NSE) coefficient, root mean square error (RMSE), and relative root mean square error (RRMSE) to calculate the performance of SWOT data products to estimate discharge using Eqs. 7, 8, and 9 are presented in Table 2.

Based on the NSE value, the result shows a consistency between the estimated discharge using SWOT data and in situ using Eq. 6. Figure 7 shows the estimated

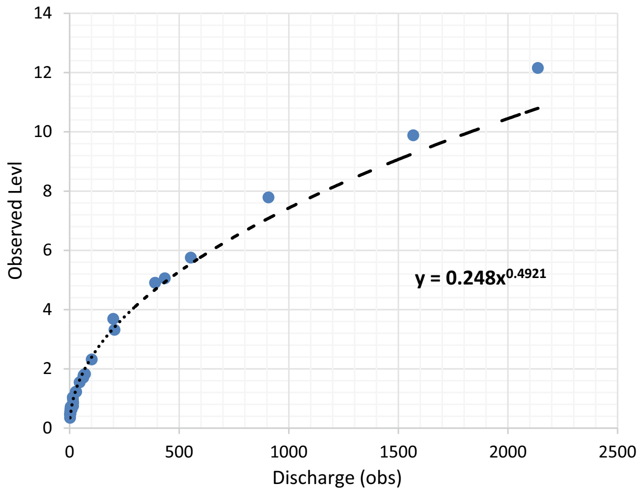

Fig. 6 Discharge via water level power equation

discharge using SWOT products and in situ observations. In addition, the RMSE in using SWOT satellite data shows improvement with respect to in situ data.

5 Conclusions

Recently, satellite data products have been widely used in order to estimate discharge amongst the researchers. This research attempted to use SWOT satellite mission synthetic data products to evaluate the performance of this satellite mission, which will be launched in 2022.

Although various methods to estimate river discharge from satellite data are used by many researchers, we used an empirical equation method to derive river discharge from the synthetic SWOT data products in the Gopalkheda gauge station in the Upper Tapi river basin. As shown in Fig. 7, the discharge is high during August, September, and October 2012, 2013, and 2015, which is the cause for the high value of RMSE by increasing the data time interval, this may decrease. NSE coefficient value for jointly used satellite river width and in situ water level express a good performance estimated value (0.94) near the ideal NSE value (1). Whilst for in situ data, NSE comes 0.94. Root mean square error indicates the improvement in the satellite data used compared with h solo in situ data. In order to obtain a temporally continuous estimate of water surface elevation using SWOT, it is recommended to input the height as a time series using Python wrapper to process the full time series through the CNES simulator quickly and efficiently [34]. The result of this study shows the applicability of SWOT satellite in Indian basin, promising to estimate river discharge reliably. The current study shall need to be scaled temporally and spatially to assess the performance of SWOT satellites data products in other basins of India.

Table 1 Estimation of discharge using SWOT data

Year	Date	Width (w) from SWOT	Water Surface Elevation (Observation)	Zero water Level	Observation Discharge (Q)	Water Depth h (h)	$w*h$	Estimated discharge from SWOT data (Q')	Estimated discharge from h solo (Q'')
2010	5-Jul	53.94	240.9	236	***390.29***	4.9	264.31	***430.94***	***429.63***
	5-Aug	53.88	241.75		***553.39***	5.75	309.81	***594.08***	***594.66***
	5-Sep	54.61	237.7		***62.6***	1.7	92.84	***52.01***	***49.98***
	5-Oct	54.55	236.74		***16.39***	0.74	40.37	***9.66***	***9.22***
2011	5-Jul	54.14	236.71	236	***5.53***	0.71	38.44	***8.75***	***8.48***
	5-Aug	53.5	236.55		***3.03***	0.55	29.43	***5.10***	***5.05***
	5-Sep	55.56	241.05		***435.03***	5.05	280.58	***486.25***	***456.78***
	5-Oct	54.13	236.69		***8.67***	0.69	37.35	***8.26***	***8.00***
2012	5-Jul	54.17	236.66	236	**8.15**	0.66	35.75	**7.56**	**7.31**
	5-Aug	54.5	237.54		**46.24**	1.54	83.93	**42.42**	**40.89**
	5-Sep	54.1	243.78		**907.84**	7.78	420.9	**1103.59**	**1099.27**
	5-Oct	53.77	237.82		**70.58**	1.82	97.86	**57.86**	**57.42**
2013	5-Jul	53.72	238.31	236	**101.57**	2.31	124.09	**93.50**	**93.20**
	5-Aug	53.22	239.31		**205.28**	3.31	176.16	**189.81**	**193.59**
	5-Sep	53.85	237.22		**28.58**	1.22	65.7	**25.86**	**25.47**
	5-Oct	53.2	245.88		**1568.23**	9.88	525.62	**1729.10**	**1786.45**

(continued)

Table 1 (continued)

Year	Date	Width (w) from SWOT	Water Surface Elevation (Observation)	Zero water Level	Observation Discharge (Q)	Water Depth h (h)	$w*h$	Estimated discharge from SWOT data (Q')	Estimated discharge from h solo (Q'')
2014	5-Jul	53.54	236.34	236	**2.5**	0.34	18.2	**1.93**	**1.90**
	5-Aug	53.28	237.03		**15.01**	1.03	54.88	**17.97**	**18.06**
	5-Sep	53.87	237.78		**64.55**	1.78	95.89	**55.52**	**54.88**
	5-Oct	54.26	236.73		**8.72**	0.73	39.61	**9.30**	**8.97**
2015	5-Jul	54.26	236.63	236	**5.84**	0.63	34.18	**6.91**	**6.65**
	5-Aug	54.14	248.15		**2136.8**	12.15	657.8	**2720.94**	**2719.66**
	5-Sep	53.58	236.73		**11.55**	0.73	39.11	**9.07**	**8.97**
	5-Oct	53.91	236.63		**9.85**	0.63	33.96	**6.82**	**6.65**
2016	5-Jul	52.13	236.86	236	**16.87**	0.86	44.83	**11.94**	**12.52**
	5-Aug	52.13	239.68		**199.5**	3.68	191.84	**225.50**	**240.11**
	5-Sep	51.93	236.97		**15.8**	0.97	50.37	**15.12**	**15.98**
	5-Oct	51.13	237.22		**30.63**	1.22	62.38	**23.29**	**25.47**
2017	5-Jul	52.71	236.47	236	**3.9**	0.47	24.77	**3.60**	**3.67**
	5-Aug	52.13	236.46		**1.96**	0.46	23.98	**3.37**	**3.51**
	5-Sep	51.25	236.63		**4.11**	0.63	32.29	**6.15**	**6.65**
	5-Oct	52.62	236.49		**4.39**	0.49	25.78	**3.91**	**3.99**

To highlight the key results of the model and guide the reader's attention, the numbers in the table are displayed in bold font. This emphasizes the importance of the data and encourages the reader to focus on the model's results.

Table 2 Performance evaluation metrics

Discharge estimate used	n	$\overline{\mathbf{Q}_{\mathrm{obs}}}$	$\sum(Q_{\mathrm{obs}} - Q_{\mathrm{Est}})^2$	$\sum\left(\mathbf{Q}_{\mathrm{obs}} - \overline{Q_{\mathrm{obs}}}\right)^2$	NSE	RMSE (Cumecs)	RRMSE (%)
River width from SWOT data	32	216.98	412,882.11	7,101,500.28	0.94	113.59	52.35
Height from in situ data	32	216.98	430,183.54	7,101,500.28	0.94	115.94	53.44

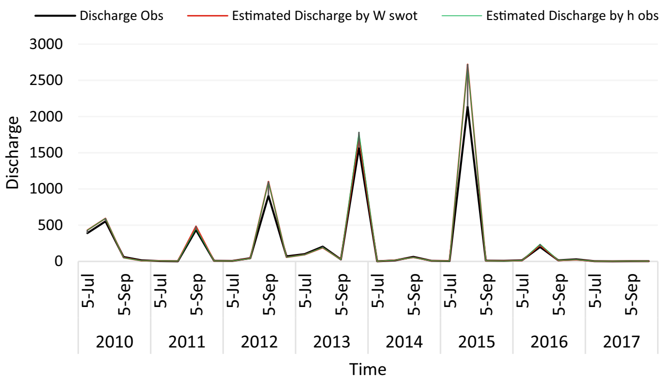

Fig. 7 Estimated discharge and in situ discharge graph

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