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A Study on the Flux of Total Suspended Matter in the Padma River in Bangladesh Based on Remote-Sensing Data

Zhuoqi Zheng ¹, Difeng Wang ^{1,2,*}, Fang Gong ^{1,3}, Xianqiang He ^{1,2} and Yan Bai ^{1,3}

- State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, MNR, Hangzhou 310012, China; zzq@sio.org.cn (Z.Z.); gongfang@sio.org.cn (F.G.); hexianqiang@sio.org.cn (X.H.); baiyan@sio.org.cn (Y.B.)
- ² Marine Resources Big Data Center of South China Sea, Southern Marine Science and Engineering Guangdong Laboratory, Zhanjiang 524088, China
- ³ National Earth System Science Data Center, Beijing 100101, China
- Correspondence: dfwang@mail.org.cn

Abstract: The flux of total suspended matter (TSM), F_{TSM} , output by several large rivers in Asia, has been in decline due to human activities. As the estuary of the Ganges–Brahmaputra River, the Padma River transports a significant amount of suspended matter (SM) to the Bay of Bengal each year. In this study, the TSM concentration (C_{TSM}) and F_{TSM} in the Padma River in the period 1991–2019 were calculated based on the data acquired by the Landsat series satellites and an empirical TSM algorithm model for large, high-turbidity rivers. The results showed that the maximum and minimum F_{TSM} values (318 ± 62 and 73 ± 29 mt, respectively) in the Padma River occurred in 2011 and 2015, respectively. On average, F_{TSM} in the Padma River decreased at an annual rate of 3.3 mt (p < 0.01). The impact of human activities on C_{TSM} contributed more significantly to the changes in F_{TSM} (R = 0.76) than natural factors (R = 0.44). Due to a lack of water conservancy facilities within the river basin, changes in the water and soil retention capacity due to the changes in vegetation coverage were an important human factor (R = -0.79).

Keywords: total suspended matter; Bay of Bengal; Landsat; flux estimation

1. Introduction

Total suspended matter (TSM) is an important index for evaluating the water quality in water bodies. In water-quality management, both the concentration and flux of TSM (C_{TSM} and F_{TSM} , respectively) depend on the gross primary productivity, the concentration of heavy metals, and the flux of substances such as radionuclides and organic micropollutants [1]. The concentration of total suspended matter, similarly, has a significant impact on the biogeochemical properties of coastal oceanic waters. The presence of TSM reduces the underwater transmittance of a water body [2] and alters its optical properties. For inland water bodies (e.g., rivers and lakes), TSM also plays a substantial role in maintaining ecosystem equilibrium and controlling the habitat of aquatic organisms. The C_{TSM} value in a water body can help to maintain its ecosystems only when controlled within a suitable range. For example, an extremely high C_{TSM} may cause wear damage to the eggs of aquatic organisms or directly lead to the death of their larvae [3]. On the other hand, some prey fish can evade their natural enemies by taking advantage of turbid water [4,5]. In addition, TSM and sediment can provide the environments and nutrients needed for the development of estuarine ecosystems.

Monitoring and studying the changes in the flux of TSM in large rivers is currently a focus area for research. Recent studies have shown that the flux of SM transported by large deltaic rivers is in decline, especially in Asia [6]. The transfer of both water and sediment to the sea will decrease as more dams and other river projects are built and utilized [7]. In the past 60 years, the flux of sediment transported seaward by the nine major



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). rivers in China [8] as well as the Mekong River [9] have shown a statistically significant negative trend due to the construction of reservoirs. At present, the traditional calculation methods of F_{TSM} are mainly based on measured hydrological data [8], hydrological climate model [9], isotope analysis [10], UAV measurement [11], and so on. The above method has the disadvantages of a large amount of calculation, difficult data acquisition, and excessive research cost [12]. In large tropical rivers such as Padma River, the installation and maintenance of in situ stations is a very costly task, limiting the data available for both river discharge and sediment load trend assessment. For these reasons, assessment of F_{TSM} in large rivers by remote sensing monitoring has received increasing interest from the scientific community [13]. As an efficient, low-cost, long-term indirect observation technique, remote sensing plays a vital role in several research fields including hydrology.

The Padma River is the estuary of the Ganges–Brahmaputra River. Glacial meltwater from the Tibetan Plateau, known as the "Asian Water Tower", is a primary source of freshwater for the Ganges–Brahmaputra River [14]. After converging in the Padma River, the water in the Ganges–Brahmaputra River flows into the Bay of Bengal, significantly affecting the eco-environmental changes in its northern waters. Many researchers have conducted relevant studies on the water constituents in the northern Bay of Bengal, including the measurement and monitoring of parameters such as the concentration of heavy metals [15], nutrients [16], dissolved oxygen [17], chlorophyll [18], and sediment [19]. Other researchers have observed this region over a large area through satellite remote sensing [20]. However, to date, few studies have monitored and estimated the flux of SM at the mouth of the Ganges River based on high-resolution satellite remote-sensing data.

2. Materials and Methods

2.1. Study Area

The Padma River is the estuary of the Ganges–Brahmaputra River. The estuaries of three large rivers, namely, the Ganges, the Brahmaputra, and the Meghna, flow into the Bay of Bengal through Padma River (see Figure 1). Each year, the Ganges–Brahmaputra river system, which has the world's largest annual sediment discharge, approximately 100 billion tons [21,22], transports a significant amount of freshwater and SM into the Bay of Bengal [23]. The northern Bay of Bengal is home to the world's largest mangrove forest—the Sundarbans—which discharges 18 million tons of SM and organic matter into the Bay of Bengal via various small tributaries, resulting in a complex ecosystem in the coastal waters of the northern Bay of Bengal [24].

The Padma River—a main tributary of the Ganges River—converges in the downstream region with the Meghna River—a tributary of the Brahmaputra River—and eventually flows into the Bay of Bengal. Since 1966, approximately 660 km² of land have been eroded by the Padma River [25].

2.2. Hydrological Data

The reanalysis data used in this study included discharge and precipitation. The discharge data originated from the global modelled daily river discharge data from the Global Flood Awareness System [26]. Specifically, the monthly mean discharge data for the period 1991–2019 with the resolution $0.1^{\circ} \times 0.1^{\circ}$ were used. There were a total of 348 data records.



Figure 1. Illustration of the location of the study area. The image on the left-hand side shows a map of the East Asian continent with digital elevation model (DEM) data downloaded from USGS as the background. The blue lines signify six large rivers originating from the Tibetan Plateau. The area within the black outline is the Ganges–Brahmaputra River Basin, while the area within the red box is the study area. The image on the right-hand side is an example of a Landsat 5 TM image of the Padma River (taken on 17 October 1994).

The precipitation data originated from the Global Precipitation Climatology Project [27], which is a satellite precipitation product (resolution: $0.5^{\circ} \times 0.5^{\circ}$) produced by the Global Precipitation Climatology Center through combining the infrared (IR) and microwave data acquired by dozens of geostationary and polar-orbit satellites and correcting the resulting data against the data acquired by multiple ground stations worldwide. Specifically, the monthly mean precipitation data (data format: netCDF4) for the period 1991–2019 were used in this study. There were a total of 348 data records.

The Bay of Bengal has a sub-tropical monsoon climate with high temperature all year round and distinct monsoon and non-monsoon seasons. The monsoon season is from May to October, and about 84% of the rainfall occurs from June to October. The precipitation is concentrated. In addition, the terrain is low and flat, and the drainage is not smooth, which is easy to lead to flood disasters. The dry season is from November to April. Affected by the northeast monsoon, there is drought and less precipitation. Meanwhile, the water in non-monsoon season is not enough to meet the requirements of irrigation and shipping, nor to maintain the minimum environmental flow of the river [28].

2.3. Remote-Sensing Data

Landsat data, including Landsat-8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) L1 products (resolution: 30 m) and Landsat-5 Thematic Mapper (TM) L1 products (resolution: 30 m), were used as experimental satellite data in this study. Sentinel-2 L2A reflectance products (resolution: 10 m) were used to perform spectral validation on the Landsat satellite data. These satellite data were downloaded from the official website of the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/ (accessed on 22 July 2020)). The Landsat products, covering the period from 1991 to 2019, provided images of the non-tidal reaches of the Padma River (row and column numbers: 137–044). At least one image was selected for each season. After the unusable data covered by cloud were removed, a total of 85 images were obtained. The number of effective values of each pixel can be seen in Figure 2.



Number of effective values of each pixel

Figure 2. Location of the section selected for calculating F_{TSM} . The color bar shows the number of effective values of each pixel. The section was selected from the branchless part of the river with a relatively large amount of available data. North of the section are mostly input tributaries, while south of the section are mostly distributories. The contributions of the tributaries were also considered when the flux was calculated.

The Landsat data used in this study were obtained from the official website of the USGS. Specifically, the L1 standard data (which had been geometrically corrected) were downloaded. In addition, the remote-sensing data were corrected based on the DEM data. Further, the following processes were performed to obtain more accurate reflectance data.

2.3.1. Radiometric Calibration

When remote-sensing data acquired at different times and locations or by different sensors are compared, it is necessary to convert the grey values of images to absolute radiance values to facilitate the calculation of the spectral reflectance or radiance of ground features [29]. In this study, radiometric calibration was performed using the Radiometric Calibration function within the Radiometric Correction tool in the ENVI 5.3 software package.

2.3.2. Atmospheric Correction

In this study, atmospheric correction was completed using the FLAASH Atmospheric Correction Model within the Radiometric Correction tool in the ENVI 5.3 software package. The FLAASH Atmospheric Correction Model, developed through improving the Moderate Resolution Atmospheric Transmission model, has relatively high accuracy in correcting hyperspectral and multispectral data [30]. Specifically, based on the geographical location of the study area, the Tropical Atmospheric Model and Maritime Aerosol Model were selected.

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2.4. C_{TSM} Inversion Model

The C_{TSM} algorithm for the estuary of the Yangtze River developed by Liu et al. (2019) [31] was selected in this study for C_{TSM} estimating based on the following considerations (see Table 1):

- 1. The estuarian waters of both the Yangtze and Ganges Rivers are high in C_{TSM} and contain TSM mostly from terrestrial sources [31].
- 2. The estuaries of the Yangtze and Ganges Rivers are similar in terms of C_{TSM} and the content ranges of main water constituents (e.g., chlorophyll) [18].
- 3. The sensitive bands of the Landsat TM sensor for the TSM and main water constituents (e.g., chlorophyll) in both the estuaries of the Yangtze and Ganges Rivers are identical.
- 4. The regions where the estuaries of the Yangtze and Ganges Rivers are located share the same rainy season. Therefore, high discharges and high *C*_{TSM} values occur at the same time in the estuaries of the Yangtze and Ganges Rivers.

Table 1. Comparison	of the characteristics of the	Yangtze and Padma Rivers.
		0

River	C _{TSM} in the River	Sensitive Bands for TSM	Rainy Season	Average Chlorophyll Concentration at the Estuary	Data Sources
Yangtze River	30.5–735.4 mg/L	B4 and B1	May-October	3.60 mg/L	Liu et al. (2019) [31]
Padma River	32.2–821.7 mg/L	B4 and B1	May-October	5.54 mg/L	Rahman et al. (2016) [12] and Jutla et al. (2012) [18]

Thus, the algorithm developed by Liu et al. (2019) [31] is also applicable to the estuary of the Ganges River. The C_{TSM} was calculated using the following algorithm:

$$\begin{cases} \log_{10}(\text{TSM}) = a \times \text{Ratio}^b, \\ \text{Ratio} = (\text{band4})/(\text{band1}), \end{cases}$$
(1)

where *a* and *b* are both fitting coefficients (a = 2.1454 and b = 0.2945 for Landsat-5 TM data; a = 2.1012 and b = 0.2953 for Landsat-7 Enhanced TM Plus (ETM+) data; the absolute relative errors for Landsat-5 TM and Landsat-7 ETM+ data are 13.69% and 13.46%, respectively) and band 4 and band 1 are the reflectance values of bands 4 and 1 of the Landsat-5/7 sensors, respectively.

To apply the above algorithm to the Landsat-8 OLI, the ETM+/OLI transformation functions established by Roy et al. (2016) [32] (see Table 2) were used.

Table 2. Transformation functions between ETM+ and OLI top-of-atmosphere reflectance sensors developed through ordinary-least-squares (OLS) regression (Roy et al. [32]).

Band	Sensor Transformation Functions	n	R^2 (<i>p</i> Value)	Mean DifferenceOLI— ETM+ (Reflectance)	Mean Relative Difference OLI—ETM+ (%)	Root-Mean-Square Deviation (Reflectance)
Blue (~0.48 μm)	OLI = 0.0173 + 0.8707 ETM+ ETM+ = 0.0219 + 0.8155 OLI	29,697,049	0.710 (<0.0001)	0.0013	0.69	0.0259
Near infrared (~0.85 µm)	OLI = 0.0374 + 0.9281 ETM+ ETM+ = 0.0438 + 0.7660 OLI	29,767,214	0.711 (<0.0001)	0.0194	6.45	0.0637

The Mann–Kendall (M–K) test [33,34] is a climate diagnosis and prediction technique that can be used to determine whether an abrupt climate change occurred from a climate data series and, if so, its time of occurrence:

$$S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} \operatorname{sign}(X_i - X_j),$$

$$\begin{cases}
Z = \frac{S-1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & S > 0, \\
Z = 0 & S = 0, \\
Z = \frac{S+1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & S < 0,
\end{cases}$$
(2)

where X_n is the value of the variable. A positive *Z* value suggests an upward trend in the variable, a negative *Z* value suggests a downward trend in the variable, and absolute *Z* values greater than 1.28, 1.64, and 2.32 signify the passing of significance tests at confidence levels of 90%, 95%, and 99%, respectively. The test result (i.e., *Z* value) reflects the overall trend of the variable.

The M–K abrupt-change test can be used to determine whether there exists an abrupt change. Similarly, for variable series x_n , we define the following:

$$S_{k} = \sum_{i=1}^{k} r_{i}, r_{i} = \begin{cases} 1, x_{i} > x_{j}, \\ 0, x_{i} < x_{j}, \end{cases}$$
(3)

$$E[S_k] = \frac{k(k-1)}{4}, \text{ var}[S_k] = \frac{k(k-1)(2k+5)}{72} \ 1 \le k \le n,$$
(4)

$$UF_{k} = \frac{(S_{k} - E[S_{k}])}{\sqrt{\operatorname{var}[S_{k}]}},$$
(5)

$$UB_{\mathbf{k}} = -UF_{\mathbf{k}}.\tag{6}$$

Then, whether there is an abrupt change in variable x_n can be analyzed based on the two statistics UF_k and UB_k . The point of intersection of the UF_k and UB_k curves is the abrupt-change point. The UF_k curve and UB_k curve signify the sequential and reversed time series for x_n , respectively. The critical values for the significance levels a = 0.05 and 0.01 ($U_{0.05}$ and $U_{0.01}$, respectively) are ± 1.96 and ± 2.32 , respectively. If the UF_k or UB_k value is greater than 0, it means that the series exhibits an upward trend; otherwise, the series exhibits a downward trend. If the curves exceed the critical straight lines, this indicates a significant upward or downward trend. The time period for which the curves exceed the critical lines is determined as the time period of the abrupt change. The point of intersection between the UF_k and UF_k curves within the critical lines corresponds to the starting time of the abrupt change.

2.6. Validation of Landsat Data with Sentinel Data

Sentinel-2 and Landsat-8 satellite data are extensively used in remote sensing of ocean colors. In addition, a large number of algorithms have been developed to integrate the data acquired by the sensors of these two satellites [35]. In this study, two Sentinel-2 L2A products were used to validate the atmospheric correction accuracy of the Landsat-8 data (see Figure 3). The two selected Sentinel-2 images were captured at 04:29:19 on 11 February 2020 and at 04:31:09 on 23 November 2019, respectively. The two corresponding Landsat-8 OLI/TIRS images were captured at 04:24:52 on 11 February 2020 and at 04:24:52 on 23 November 2019, respectively.



Figure 3. Location of the areas in the Landsat and Sentinel images (the image with a red border is the Sentinel image, and the image with a blue border is the Landsat image).

As mentioned above, the Landsat-8 OLI image was radiometrically calibrated and atmospherically corrected using the ENVI 5.3 software package. The image captured by the Multispectral Instrument (MSI) onboard the Sentinel-2 satellite was radiometrically calibrated and atmospherically corrected using the SNAP software. The difference between the OLI and MSI was eliminated using the sensor-transformation method developed by Zhang et al. (2018) [36] (see Table 3).

Table 3. Transformation functions between the Sentinel-2 MSI and Landsat-8 OLI developed through OLS regression (Zhang et al. [36]).

Band	Transformation Function	Sample Size	<i>R</i> ² (<i>p</i> Value)	Mean OLI—MSI Difference	Mean Relative OLI—MSI Difference (%)
Blue λ (~0.48 µm)	OLI = 0.0003 + 0.9570 MSI MSI = 0.0039 + 0.9383 OLI	65,347,909	0.8980 (<0.0001)	-0.0014	-4.64
Near infrared λ OLI = $0.0077 + 0.9644$ MSI (~0.85 µm) MSI Band 8A MSI = $0.0147 + 0.9355$ OLI	65,380,148	0.9022 (<0.0001)	-0.0003	-0.22	

2.7. Normalized Difference Vegetation Index (NDVI)

The NDVI is an important parameter that reflects vegetation coverage and can be calculated for Landsat datasets using the equation [37]:

$$NDVI = \frac{R_{NIR} - R_R}{R_{NIR} + R_R},$$
(7)

where R_{NIR} and R_{R} are the reflectance values in the NIR and red bands, respectively.

3. Results

3.1. Hydrology in the Study Area

The changes of discharge and precipitation in the Padma River Basin during the study period are shown in Figure 4. The discharge result is calculated from GloFAS data, and the precipitation change result is calculated from GPCP data, which is the total precipitation in the basin. From May, precipitation and discharge begins to increase, and begins to decrease after October. From the change of monthly average results, the change of discharge lags the precipitation. The time-series data for the discharge and precipitation in the Padma River were analyzed using the M–K test. The *Z* value and its rate of change were obtained respectively (discharge: Z = 0.5730, slope = 1.4077×108 , p > 0.5; precipitation: Z = -1.2784, slope = 0.0375, p > 0.5). The results show that there is no obvious trend in discharge and precipitation in the past 30 years.



Figure 4. Changes of Padma River discharge and precipitation in the basin during the study period. The figures on the left and right show the average annual discharge and precipitation and the average monthly discharge and precipitation, respectively.

3.2. Comparison of Atmospheric Correction Results between Landsat and Sentinel

The NIR-band/blue-band ratio was calculated for points randomly selected within the river area, and the results were then compared. Similar ratios ($R^2 = 0.9563$, root-mean-square error (RMSE) = 0.0811 in the 2020 image. $R^2 = 0.8963$, RMSE = 0.0440 in the 2019 image. $R^2 = 0.9461$, RMSE = 0.0596 in total) were obtained based on the data acquired by the two satellites (as shown in Figure 5), suggesting that the atmospherically corrected data were accurate and reliable.



Figure 5. Comparison of the NIR-band/blue-band ratios between the Landsat and Sentinel data.

3.3. Distribution of C_{TSM} in the Padma River

The arithmetic mean C_{TSM} was calculated for each season of each year in the period 1991–2019. On this basis, the seasonal distribution of C_{TSM} in the Padma River was obtained, as shown in Figure 6. In terms of the distribution trend, C_{TSM} in the Padma River was high in areas close to the banks and in the downstream region and low in areas away from the banks and in the upstream region. The waters with relatively high C_{TSM} values were distributed near the estuary in the downstream region, which was primarily due to the water and soil loss on the islands near the mouth of the estuary caused by the scouring of the water flow in the river as well as the convergence and resuspension of the matter (e.g., sediment) carried here by the water flow in the river from the upstream region. At a seasonal scale, C_{TSM} was the lowest in winter (December through February of the following year). The C_{TSM} remained below 150 mg/L in most parts of the river but reached up to 180 mg/L in some tributaries and 200 mg/L in the downstream region. There was a certain increase in C_{TSM} in spring (March through May). Compared to winter, C_{TSM} in spring exhibited an overall similar distribution trend but was higher in magnitude. The study area has a tropical monsoon climate with abundant precipitation in summer. Due to heavy precipitation and a large discharge, C_{TSM} displayed a relatively uniform distribution pattern and, overall, remained at a relatively high level in summer (June through August). As a result of the soil erosion caused by precipitation and high flow rates, high C_{TSM} values were distributed along both banks of the river and in the inland tributaries. The C_{TSM} in the river was almost above 150 mg/L. In addition, due to an increase in the discharge, the erosion and siltation zone at the mouth of the estuary shifted outward. Similar to summer, C_{TSM} in fall (September through November) remained above 150 mg/L in the main parts of the river, and high-C_{TSM} zones shifted downstream.



Figure 6. Distribution of C_{TSM} in the Padma River in: (a) winter, (b) spring, (c) summer, and (d) fall.

3.4. Interannual Variations of C_{TSM} in the Padma River

After the waters were separated from the land in the images, C_{TSM} in the waters was estimated using the algorithm equation introduced in Section 2.4. The arithmetic means of the pixels in each image of the section showed in Figure 2 was calculated to represent the mean C_{TSM} .

We also used Sentinel-2 data to calculate C_{TSM} from 2016 to 2019 based on the same algorithm. In order to ensure the consistency of the algorithm, the reflectance data of Sentinel-2 were converted to the reflectance bands of Landsat-8 OLI by using the equation in Table 3, and then converted to the reflectance bands of Landsat-7 ETM+ according to the formula in Table 2. Finally, the C_{TSM} of Sentinel-2 sensor was calculated through Equation (1). The results calculated by Sentinel-2 data with higher temporal and spatial resolution are similar to those calculated using Landsat data, which shows that the atmospheric correction and C_{TSM} algorithm have good accuracy. Here, there is a little systematic bias between the two satellites, which is probably caused by the reason that the $B_{\text{NIR}}/B_{\text{blue}}$ value of Sentinel-2 is slightly higher than that of Landsat (see in Figure 5). However, from the perspective of the overall change trend, we still believe that the results of the two are similar. Therefore, due to the advantages of Landsat data quantities and the fact that the

biases are within the acceptable range, we believe that Landsat satellites can be used to evaluate the flux of total suspended matter in the Padma River in the past 30 years.

Figure 7 shows the changes in the mean C_{TSM} in the Padma River in the period 1991–2019. During this period, the maximum and minimum C_{TSM} values (194.56 ± 54 and 58.97 ± 16 mg/L, respectively) occurred in 2011 and 2015, respectively. Overall, C_{TSM} displayed a downward trend in this period.

Figure 7. Changes in *C*_{TSM} in the Padma River in the period 1991–2019, and the red area represents the duration of La Niña.

Especially, the strongest global La Niña event in the past six decades occurred in 2011 and 2012. In April of 2011, intense cyclones struck Bangladesh and brought heavy rainfall. In July of 2011, continuous heavy precipitation triggered floods and forced more than 10,000 people to evacuate. The flood caused by La Niña lasted until the summer of 2012. The floods caused a large amount of SM from terrestrial sources to rush into the Padma River, resulting in an abnormally elevated level of turbidity and an abnormally high mean C_{TSM} in 2011 and 2012. At the end of 2012, the impact caused by La Niña weakened, and the C_{TSM} level returned to the normal trend in 2013.

3.5. Changes in F_{TSM} in the Padma River

Due to the high flow rate and large discharge in the Padma River, we can approximately consider that the TSM in the Padma River was sufficiently mixed. In addition, the non-tidal reaches were selected in this study for analysis, and, therefore, the tidal effects do not need to be considered. Then, we can approximately consider that the TSM was uniformly distributed in the Padma River. The monthly mean F_{TSM} was calculated through the multiplication of the arithmetic mean C_{TSM} at the selected section (23°10′44″ N) estimated from the Landsat data by the arithmetic mean discharge at the selected section. On this basis, subsequent calculations were performed. Figure 8 shows the changes in F_{TSM} in the Padma River in the period 1991–2019. The maximum and minimum F_{TSM} values $(318 \pm 62 \text{ and } 73 \pm 29 \text{ mt, respectively})$ occurred in 2011 and 2015, respectively. Due to the impact of the 1998 flood, the discharge and C_{TSM} were at a high level, so the F_{TSM} increased significantly and returned to the normal level in 2000. At the same time, the low flow caused by the drought in 2006 also continued to reduce F_{TSM} and restored in the next year. In 2011, due to the flood disaster caused by La Niña, the discharge and C_{TSM} in Padma River increased significantly, resulting in a significant increase in F_{TSM} level. In 2012, the impact of La Niña continued. Although the discharge decreased, it remained at a high level. At the same time, the erosion of flood on land did not reduce C_{TSM} , so F_{TSM} was still at a high level. In 2013, the flood disaster was over, and C_{TSM} returned to normal level; F_{TSM}

also decreased. The time-series data for the changes in F_{TSM} were analyzed using the M–K test. The Z value and its rate of change were obtained (Z = -2.6073, slope = -33.27×10^5 , p < 0.01). In the past 30 years, F_{TSM} in the Padma River showed a relatively significant downward trend and, on average, decreased by 3.3 mt each year. The result passed the significance test at a confidence level of 0.01.

Figure 8. Changes in F_{TSM} in the Padma River in the period 1991–2019. The dotted line is the linear regression of F_{TSM} .

3.6. Changes of NDVI in the Padma River

The NDVI for the Padma River Basin was calculated based on the Moderate Resolution Imaging Spectroradiometer (MODIS) global monthly mean NDVI products. The resolution of MODIS NDVI product is 1 km, and the selected coverage covers the whole Padma River Basin. The monthly mean NDVI images for the period 2000–2019 were selected. On the other hand, NDVI along the Padma river is calculated from Landsat images. As shown in Figures 9 and 10, overall, the NDVI for the Padma River Basin displayed an upward trend, suggesting a notable increase in the vegetation coverage along the banks of the Padma River. This suggests that the significant increase in the vegetation coverage in the basin of the Padma River increased the water and soil retention capacity of the land, reduced the extent of soil erosion, and, to a certain extent, reduced the discharge of SM from terrestrial sources, thereby making some contribution to the decrease in the content of TSM in the Padma River.

Figure 9. Mean NDVI values from MODIS for the Ganges–Brahmaputra River Basin. (**a**) Mean NDVI value for the river basin in 2000. (**b**) Mean NDVI value for the river basin in 2019. (**c**) Changes in the mean NDVI value between 2000 and 2019.

Figure 10. Changes in the average NDVI value for the Landsat image as well as the C_{TSM} at the mouth of the river in the period 2000–2019.

4. Discussion

4.1. Natural Factors Affecting the Changes in the TSM in the Padma River

Changes in F_{TSM} depend on changes in the discharge and C_{TSM} . The discharge in the Padma River depends primarily on natural factors such as the precipitation and groundwater resources within the river basin and water sources (e.g., freshwater released from the melting of ice on the Tibetan Plateau). The time-series data for the discharge in the Padma River were analyzed using the M–K test. The Z value and its rate of change were obtained (Z = 0.5730, slope = 1.4077×10^8 , p > 0.5). The results showed that the discharge itself displayed no notable trend in the past 30 years. In addition, the correlation between the interannual changes in the discharge and F_{TSM} was analyzed. According to the results shown in Figure 11, there was little significant correlation between the changes in the discharge and F_{TSM} (R = 0.44, p < 0.05). Hence, the changes in the discharge might have had a limited impact on F_{TSM} .

Figure 11. Correlation between the changes in the discharge and F_{TSM} in the Padma River.

At the same time, the discharge may affect the degree of bank erosion of Padma river. Bank erosion is part of the river system's natural disruption [38]. The erosion of Padma River is highly irregular [39]. Anupom Halder et al. (2021) studied the change of Padma river bank in the past 40 years by using RS and GIS techniques. The results showed a linear relationship between the erosion and discharge ($R^2 = 0.9989$) [40]. From 1989 to 1999, char land of the Padma River continuously increased (see Figure 12). The island bars were most vulnerable during flooding. Combined with the change analysis of C_{TSM} , it can be seen that char land in Padma River is in a continuous growth state before 2010, and C_{TSM} is also at a stable high concentration level. Char land in Padma stops growing from 2010 to 2019, and C_{TSM} begins to gradually decrease. Unstable char land bar is a major source of TSM, and the area of unstable riparian lines determines the change of C_{TSM} . Therefore, during the study period, although the discharge itself has not changed significantly, the bank erosion of Padma River caused by large discharge and the change of fragile char land area caused by the change of bank line indirectly affect the change of C_{TSM} of Padma River, thus affecting the transportation of F_{TSM} .

4.2. Human Factors Affecting Changes in the TSM in the Padma River

While neglecting the changes in the discharge, we performed a correlation analysis on the annual mean changes in C_{TSM} and F_{TSM} (see Figure 13). A significant correlation (R = 0.76, p < 0.01) was found between the changes in C_{TSM} and F_{TSM} , suggesting that the changes in F_{TSM} in the Padma River depended heavily on the changes in C_{TSM} .

Figure 13. Correlation between the changes in *C*_{TSM} and *F*_{TSM} in the Padma River.

In the Padma River Basin, the changes in C_{TSM} were primarily a result of the changes in the discharge of TSM from terrestrial sources, including the discharge due to soil

erosion [41]. As no large reservoirs were constructed in the Ganges–Brahmaputra river system, the impact of water conservancy facilities on F_{TSM} can be excluded. In addition, relatively large discharges may lead to soil erosion and have a greater impact on C_{TSM} . This is particularly true for the Padma River—a river with highly unstable shorelines. The Padma River is relatively wide, with severe bank erosion near Harirampur in the district of Manikganj on its left bank and Naria Upazila in the district of Shariatpur on its right bank. Erosion on the left and right banks of the Padma River occurs at annual rates of 4.82 and 8.19 km², respectively [42].

Substitution of F_{TSM} series into the M–K abrupt-change test equation yielded UF_k and UB_k values, as shown in Figure 14. The point of intersection between the UF_k and UB_k curves correspond to the abrupt-change point of the time series. The abrupt change occurred in 2014. The UF_k value fluctuates near 0 before the point of intersection and remains within the a = 0.05 straight line, suggesting that before 2014, the Padma River was relatively stable and its F_{TSM} exhibited no notable trend of change. An abrupt change occurred in 2014, when F_{TSM} began to decrease. This is because, around 2014, the government of Bangladesh began to implement a series of environmental protection measures, adopted a sustainable development strategy, and participated in the Blue Economic Zone Cooperation in the Bay of Bengal [43]. In addition, the government of Bangladesh and non-governmental organizations vigorously carried out afforestation projects along the coast, resulting in a significant increase in the green land area. Vegetation planting, to a certain extent, reduced soil erosion in the coastal zones, thereby reducing the content of TSM [44]. To validate this hypothesis, the NDVI was analyzed.

Figure 14. M–K abrupt-change test results for F_{TSM} in the Padma River. The blue UF_k curve and red UB_k curve signify the sequential and reversed time series for F_{TSM} , respectively. The critical values for the significance levels a = 0.05 and 0.01 ($U_{0.05}$ and $U_{0.01}$, respectively) are ±1.96 and ±2.32, respectively.

4.3. Effects of the NDVI on the Changes in C_{TSM}

Mithun Kumar et al. (2021), in their monitoring and mapping of forest, cover changes in eastern Sundarban based on satellite remote sensing technology using the maximum likelihood classification approach [45]. The classification map shows that, from 1989 to 2014, the vegetation coverage in the study area decreased by 2.66%, while, from 2014 to 2019, the vegetation coverage increased by 2.22%. Water body and mudfat, low laying area, as well as intertidal zone have been increased with the decrease in vegetation cover. Using Landsat series satellite images separated by water and land, the NDVI mean of land in the image frame is calculated to obtain the change of average NDVI. The trend of the average NDVI in image was opposite to that of C_{TSM} (correlation coefficient R = -0.79, p < 0.01) (see Figure 15), indicating a significantly negative correlation between the NDVI and C_{TSM} . The results show that, from 2000 to 2019, under the background of the overall NDVI value rising in the basin, the NDVI level along the Padma River also shows an upward trend. At the same time, the downward trend before 2014 and the upward trend after 2014 can also be clearly seen. The research area of this study overlaps with that of Mithun et al. (2021) To a certain extent. Therefore, the similar conclusions of the two can also support the results of this study. It should be noted that the vegetation coverage is not completely related to the NDVI index, because in the study range, more vegetation in Padma River basin is transformed into water rather than bare land due to land erosion. At the same time, as mentioned above, in the last decade, due to environmental protection policies and policies to encourage planting, the level of NDVI has increased and the land retention has improved. The improvement of land conservation also slows down the generation of fragile bar lines, so it also slows down the growth of char land area. Thus, the land-based emission of TSM and C_{TSM} in Padma River are reduced. In conclusion, the vegetation cover level and NDVI of the Padma River Basin, especially the coastal land area, will affect the land conservation capacity, thus indirectly affecting the F_{TSM} transport of the Padma River.

Figure 15. Correlation between the mean NDVI value for the Landsat image and C_{TSM} at the mouth of the river in the period 2000–2019.

5. Conclusions

In this study, C_{TSM} in the Padma River Basin was estimated from the Landsat-8 OLI/TIRS and Landsat-5 TM L1 reflectance products for the period 1991–2019. In addition, the causes of the changes in C_{TSM} were analyzed based on the discharge, precipitation,

and NDVI data for the same time period. The main conclusions of this study can be summarized as follows:

(1) The C_{TSM} values in the Padma River were high in areas near the banks and in the downstream region and low in areas away from the banks and in the upstream region. The waters with relatively high C_{TSM} values were distributed in the downstream region near the mouth of the river. Across each year, C_{TSM} was the lowest in winter and spring and the highest in summer and fall.

(2) In the period 1991–2019, the maximum and minimum mean F_{TSM} values in the Padma River (318 ± 62 and 73 ± 29 mt, respectively) occurred in 2011 and 2015, respectively. Abnormally high F_{TSM} values occurred in the year with a strong La Niña event. Overall, F_{TSM} displayed a downward trend and decreased at an annual average rate of 3.3 mt.

(3) The F_{TSM} values in the Padma River depended collectively on the discharge and C_{TSM} at the mouth. Compared with natural factors (e.g., discharge) (R = 0.44, p < 0.05), the changes in C_{TSM} contributed more significantly to the changes in F_{TSM} in the Padma River (R = 0.76, p < 0.01). A significantly negative correlation was found between the NDVI and C_{TSM} (R = -0.79, p < 0.01), suggesting that the increase in the NDVI within the Ganges–Brahmaputra River Basin and the coastal bar line in the last decades led to a decrease in the discharge of TSM from terrestrial sources and C_{TSM} , and that changes in human factors (e.g., vegetation changes) negatively contributed to F_{TSM} in the Padma River. Hence, human activities were the dominant factor causing the changes in F_{TSM} in the Padma River (Ganges–Brahmaputra River system).

This study ensured the accuracy of atmospheric correction of satellite data and the accuracy of various algorithms. However, due to the climatic characteristics of the geographical location of the study area, it is difficult to obtain cloudless and high-quality remote sensing images, so the sufficiency of the amount of remote sensing data cannot be guaranteed. There may not be data available for the entire quarter in summer and autumn in some years. In this case, after calculating the TSM concentration of the seasons with data, we use the following method to make up for the gap in the cloudy season data: Take the multi-year arithmetic average of all TSM data in each season to obtain the C_{TSM} of the four seasons during the 30 years. Then the climatic distribution of each grid point is calculated, and the ratio of the four seasonal climatic C_{TSM} at each grid point is calculated. On this basis, the C_{TSM} of the missing season is calculated based on this ratio. Due to the numerical averaging of the climatic data, although the absolute value of the data may not be so accurate, it should be of good reference value when estimating the trend of the F_{TSM} changes. Because there are few hydrological data in the study area, and because they are difficult to obtain, this study can provide ideas for hydrological research in similar areas.

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