RESEARCH ARTICLE

Impact of river flow modification on wetland hydrological and morphological characters

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Abstract
A good number of researchers investigated the impact of flow modification on hydrological, ecological, and geomorphological conditions in a river. A few works also focused on hydrological modification on wetland with some parameters but as far the knowledge is concerned, linking river flow modification to wetland hydrological and morphological transformation following an integrated modeling approach is often lacking. The current study aimed to explore the degree of hydrological alteration in the river and its effect on downstream riparian wetlands by adopting advanced modeling approaches. After damming, maximally 67 to 95% hydrological alteration was recorded for maximum, minimum, and average discharges. Wavelet transformation analysis figured out a strong power spectrum after 2012 (damming year). Due to attenuation of flow, the active inundation area was reduced by 66.2%. After damming, 524.03 km² (48.9% of total pre-dam wetland) was completely obliterated. Hydrological strength (HS) modeling also reported areas under high HS declined by 14% after post-dam condition. Wetland hydrological security state (WSS) and HS matrix, a new approach, are used to explore wetland characteristics of inundation connectivity and hydrological security state. WSS was defined based on lateral hydrological connectivity. HS under critical and stress WSS zones deteriorated in the post-dam period. The morphological transformation was also well recognized showing an increase in area under the patch, edge, and a decrease in the area under the large core area. All these findings established a clear linkage between river flow modification and wetland transformation, and they provided a good clue for managing wetlands.

Keywords Flow alteration · Wetland hydrology · Wetland fragmentation · Active flood plain · Hydrological strength modeling · Machine learning models · Wetland security state

Introduction

People have been continuously changing river systems to meet their water demands through various activities, and one of these activities is the construction of dams across rivers, which dramatically modify the natural river flow regime in its downstream (Wang et al. 2019; Zheng et al. 2019; Arévalo-Mejía et al. 2020). This direct regulation-related effect will undoubtedly continue to have an impact on rivers in the future decades, with potentially significant and unexpected consequences for their morphodynamics and ecosystems, as well as the concerned flood plain areas (van Oorschot et al. 2018; Zheng et al. 2019; Pal and Sarda 2020). River flow alterations seem like the most significant modification of the fluvial landscape on the earth’s surface (Wang et al. 2020; Chen et al. 2021; Pal and Sarda 2021a). A good number of researchers have shown that flow modification is one of the emerging challenges since it changes the downstream flow regime in terms of total flow, size, timing, length, rate of change, and water quality (Pal et al. 2019; Huang et al. 2019; Amenuvor et al. 2020; Du et al. 2020; Pal and Sarda 2020; Pal et al. 2020). As a result, it can reduce the connection of the main channel with the flood plain, and it not only arrests the water supply to the flood plain but also limits the natural dispersion of fish and macroinvertebrate species toward the flood plain for
sustaining the flood plain biodiversity (Rolls et al. 2012; Bunn and Arthington, 2002; Zhang et al. 2012). Li et al. (2017) documented since 1991 to 2009, the average flow of Southeast Asia’s Mekong river was decreased by 82%. Pal (2016b) showed that the Rubber dam on the Atreyee river in Bangladesh has attenuated 84% maximum flow and 56% average flow. As per Xue et al. (2017), damming in the Tarim river basin of China, downstream flow was reduced by 68.7%, which made the hydrological shortage and ecological stress. According to Pal and Talukdar (2020) in the case of the Punarbhava river in India-Bangladesh, the average flow was decreased by 36% due to dam installation. Ali et al. (2019) reported 17–27% attenuation of the flow of the Yangtze River after damming and warned of water shortages without the implementation of suitable management techniques. Wang et al. (2018), Pal et al. (2019) observed the significant hydrological modification in the Yangtze and Tangon rivers throughout the world.

The construction of a dam not only changed the hydrological system of a river (Pal 2016a) but also modified the hydro-ecological regime and morphological character of the riparian wetlands by reducing flood frequency, magnitude, and squeezing active flood plain area, fragmenting the wetland landscape, and so on (Gain and Giupponi 2015; Pal and Saha 2018; Zheng et al. 2019; Saha and Pal 2019b; Wang et al. 2019; Duc et al. 2020; Smith et al. 2020; Pal and Sarda 2020; Pal and Sarda 2021b). Wetlands are the world’s most unique, transitional, and productive ecosystems, carrying only 6–8% of the earth’s terrestrial area. However, it supports approximately 45% of the overall economic value of all global ecosystems (Finlayson 2013; Mitsch and Gosselink 2015). Changes in land use/cover, increase in population and their demands, and changing lifestyles and requirements are all putting pressure on these wetlands. In comparison to other economic activities, these lands have always been treated as less valuable (Duc et al. 2020; Pal and Sarda 2020; Smith et al. 2020).

Several studies have discovered that damming has an unfriendly influence on the river zone, although the fact that the dam is not the sole responsible factor for all such changes undoubtedly, it is a dominant factor for altering riparian wetland hydrological and morphological character (Zheng et al. 2019; Pal et al. 2020; Talukdar and Pal 2020). In recent times, the research community and the victims both have paid attention to studying this issue and trying to find some reasonable solution, because it is strongly related to ecological survival and livelihood sustainability (Pal and Saha 2018; Wang et al. 2019; Zheng et al. 2019; Pal and Sarda 2020). According to Zheng et al. (2019), hydrological changes were recognized in the lower portion of the Nenjiang River in Northeast China after the dam building, and these changes contributed significantly to the 44% decline in

The average flow in the river basin was increased by 34% after damming across the Taprobane river in India and Bangladesh reduced the active floodplain by 39.7% enhancing the stress of wetlands beyond the active floodplain limit. When a wetland is hydrologically affected adversely, its ecological function abilities, natural resource yield in forms of goods and services, and morphological characteristics also change accordingly (Bregoli et al. 2019; Aghsaei et al. 2020; Orimoloye et al. 2020). According to Kundu et al. (2021), flow change has an indicative impact on the state of wetland fragmentation as well as ecosystem services. Furthermore, shallowing water depth promotes agriculture extension inside wetland, which leads to wetland fragmentation (Saha and Pal 2019a).

Integrated development of hydrological strength (HS) is very difficult since the hydrological data are often not readily available (Jeziorska 2019). HS refers to the nature of hydrological consistency, length of water appearance, and maintenance of sustainable water depth in a wetland or each wetland pixel. Based on the nature of consistency in water appearance, water depth range, and hydro-period, its degree of strength could be determined. Pal and Sarda (2020), Khatun et al. (2021), and Pal et al. (2022) applied water presence frequency approach for wetland consistency analysis. A consistent wetland is good for hydrological strength. Water indices based on time series wetland maps were used for this. Water depth is also a prevalent hydrological component, and such data is scarce. Khatun et al. (2021), Kundu et al. (2021), Pal and Sarda (2021a), and Pal and Sarda (2021b) tried to develop it from satellite images. Onyango and Opiyo (2021), Pal and Sarda (2021b), Saha et al. (2021), and Sahour et al. (2022) used Normalized difference water index (NDWI) for preparing water depth layers through a field-driven database calibration process. Hydro-period means the period of water stagnation in the wetland in a year. Özelkan (2020), Kundu et al. (2021), Pal and Sarda (2021b), and Teng et al. (2021) attempted to develop it through monthly water index-based images. For compositing, the hydrological components and interpreting the overall change in the hydrological environment in wetland, modeling approaches like statistical, data-driven, and machine learning (ML) algorithms are recommended. Among these, ML modeling provides a good scope for solving non-linear relationships of the applied parameters in a very robust way. A good many ML methods like random forest (RF) (Shaikhina et al. 2019; Han et al. 2020; Rahmati et al. 2020), artificial neural networks (ANN) (Tian et al. 2019b; Nhu et al. 2020), reduced error pruning tree (REPtree) (Chen et al. 2019; Ghasemain et al. 2020; Arabameri et al. 2021), support vector machines (SVM) (Xiong et al. 2019; Singha et al. 2020; Bouramtane et al. 2021), and similar others such

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ML were applied by the scholars for predicting risk, the vulnerability of different kinds, and reported credible result. Considering this, the present study also applied ML models for developing hydrological strength models using image-driven hydrological components. Since flood water is a reliable source of wetland, assessing flood extent over time and analyzing wetland within or beyond flood extent is also very useful (Greet et al. 2020; Karim et al. 2020). Flood simulation is a reliable approach for this which is applied in this present case. Based on this, the wetland was classified into para- and ortho-fluvial wetland by Ward and Stanford (1989). Para-fluvial wetlands are those that are directly linked to the river (Deforet et al. 2009; Mondal and Pal 2018); on the other side, ortho-fluvial indicates the wetlands are disconnected from the river and do not receive water regularly. Due to this, ortho-fluvial wetlands are not as ecologically viable (Wantzen et al. 2008). Based on the nature of hydrological connectivity, the wetland hydrological security state (WSS) was recognized in this present work. 

From the literature survey, it is very clear that a good many studies dealt with river flow modification and its hydro-ecological, geomorphological consequences in downstream rivers (Yan et al. 2010; Li et al. 2017; Tonkin et al. 2018; Wang et al. 2018). A few works are also devoted to exploring hydrological dynamics in the riparian wetland as a consequence of hydrological modification in a river (Chakraborty et al. 2018; Zheng et al. 2019; Pal and Sarda 2020; Pal and Sarda 2021a; Pal and Sarda 2021b; Pal et al. 2022). As far the knowledge is concerned, there is a dearth of literature that link river hydrological modification with riparian wetlands and hydrological modification focusing on hydrological parameters like water depth, water presence consistency, hydro-period, river flood water connectivity, etc. But, integrated spatial scale (pixel) analysis of hydrological conditions of wetland and measuring the degree of hydrological modification in a river triggered by damming is very vital for understanding the effect of it on wetland and devising sustainable planning for wetland management. A few case studies used field-driven data for doing such work, but there is a lack of work covering a wider geographical area. However, it is essential from the planning point of view. Therefore, the current study aimed to examine the degree of hydrological modification in the river and dependent riparian wetland due to damming and linking them. The work also sets another question, i.e., can hydrological modification bring noticeable changes in wetland morphology promoting other factors of wetland transformation?

Study area

Atreyee river (390 km long), a tributary of the Brahmaputra river, is an India-Bangladesh transboundary river with various aquatic ecosystems (Adel 2013). In the lower portion of this basin, a lot of rain-fed and flood water-fed wetlands are available, and they are generally located close to the main river (Figure 1). The majority of the wetlands are seasonal and highly intermittent in water appearance. Water furnish to the wetlands depends on occasional rainwater and the frequency, duration, and magnitude of inundation of the Atreyee river (Pal and Saha 2018; Pal and Sarda 2020, 2021a). Water harvesting from the mainstream for different economic and domestic purposes has gradually been expanded. For upgrading irrigation supply, the Mohanpur rubber dam was built over the Atreyee river in 2012, and this episode has enhanced the water shortage in the downstream main river and its wetlands. The time after the development of the dam (2012 onward) is considered a post-dam stage. After the damming impact, the river and riparian scene experienced a huge alteration in the hydrological regime (Pal and Sarda 2020). River damming is brought about by 30.9% and 64% of discharge curtailed during pre-monsoon and post-monsoon seasons, and it is additionally caused for dwindling water accessibility in the wetland (Pal 2016b; Pal and Saha 2018; Pal and Sarda 2020). This is also a very evident reason for wetland hydrological alteration. Considering this, the lower Atreyee river basin has been considered a special case.

Materials

To fulfill the objectives, we considered 3-h interval discharge and water level data (from 1993 to 2018) that were obtained from the Joda bridge river gauge station in Balurghat for monitoring hydrological modification, 2D flood modeling in the post-dam period. Specifically, for 2D floodplain modeling, the SRTM DEM was employed. Landsat-TM satellite images characterize crucial and ongoing recordings of the earth’s surface. We have separated the complete temporal spectrum dataset into two phases — pre- and post-dam for pre- and post-monsoon seasons to recognize the dam’s influence. Over the last 33 years (1987–2020), cloud-free Landsat TM and OLI were used to detect and monitor the inundation state of wetlands. Detail descriptions of the images are provided in the supplementary section (Table S1).
Methods

Measuring flow alteration (heat mapping)

There are many methods of measuring flow alteration like the range of variability approach (Richter et al. 1998; Yang et al. 2008; Cheng et al. 2018; Ali et al. 2019; Tian et al. 2019a), revised range of variability approach (Ge et al. 2018), histogram comparison approach (Huang et al. 2017), and histogram matching approach (Shiau and Wu 2008; Huang et al. 2016). Among these approaches, the range of variability approach was adopted to measure the flow alteration of the Atreyee river. Besides, heat mapping is a good data visualization technique showing the changes in the magnitude of the phenomenon in a gradient of color in two dimensions (Barter and Yu 2018). In this present context, a heat map was prepared using the time series change of discharge data and the degree of its change in pre- and post-dam years (1997 to 2018) for each month to explore and visualize the time series degree of hydrological modification. Hydrological alteration of the post-dam period was computed about the discharge of the pre-dam period. The data matrix for the pre-dam period does not show any alteration but rather shows an anomaly of yearly discharge from the average of each respective month.

Flow periodicity analysis

According to Weigend and Gershenfeld (1994) through periodicity analysis, we can get helps in predicting the behavior of time series data. Periodicity analysis requires specifying a period that determines the rate at which the time series is periodic. It expects that users either know the value of the period beforehand or are prepared to
experiment with different period values until satisfactory periodic patterns emerge (Elfeney et al. 2005). The wavelet transformation time-frequency technique is very useful for analyzing long-term time series variability, trend, and periodicity and making it more suitable for representation (Araghi et al. 2015; Talukdar and Pal 2020). It helps to understand the statistical significance of the hydrological alteration within a definite time. Wavelet transformation is a well-known mathematical signal processing technique that can offer both frequency and time domain information from both non-stationary and stationary datasets, which together is difficult to obtain from other standard methods (Santos et al. 2018). Fourier transformation can only provide time or frequency domain (Smith et al. 1998); however, the wavelet transformation method was built by modifying the Fourier transformation to receive both time and frequency domain information (Liu et al. 2016; Wang et al. 2018). Additionally, this method can construct a multi-resolution analysis. For an instance, at a low scale of wavelet transformation, it yields a good quality time resolution, and at a high scale, it is just the opposite. This information is very imperative for any time series analysis like time series discharge change. In the case of non-stationary time series data (mean, variance, covariance, and autocorrelation change over time but cannot return to their original position again), this method is well accepted and will be applied for hydro-meteorological data series.

Goupillaud et al. (1984) deemed first wavelets as a group of functions constructed from the translations and dilations of a single function, which is known as the “mother wavelet.” The wavelet transform is defined by Equation (1). More details regarding the wavelet analysis are available in the literature of Goupillaud et al. (1984).

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \Psi\left(\frac{t-b}{a}\right), a, b \in \mathbb{R}, a \neq 0$$

where the scale parameter is symbolized by “a” that appraises the degree of compression, whereas the translation parameter that calculates the time location of the wavelet is presented by “b.” The “a” parameter in the mother wavelet will be conditioned by the higher frequencies (smaller support in the time domain) when \(|a| \) will be less than 1. When \(|a| \) will be more than 1, then \(\Psi_{a,b}(t)\) has a larger time width than \(\Psi(t)\) that will correspond to lower frequencies. Therefore, wavelets have time widths that are adapted to their frequencies which are the actual reason behind the achievement and exclusive usefulness of the Morlet wavelets in signal processing and time-frequency signal analysis.

Method for measuring hydrological modification of wetland

Modification in hydrological components

Measuring hydrological modification at a spatial level over a larger geographical area is a very difficult task due to the limited spatial scale data availability. In this work, three major hydrological components were developed from multi-date image data at a pixel level. The components are (1) water presence frequency (WPF), (2) hydro-period (HP), and (3) water depth (WD).

For developing hydrological components of the wetland, month scale normalized differences water index (NDWI) was first developed following Mcfeeters (1996) (Eq. 2). Saha and Pal (2019a) and Pal and Sarda (2020) endorsed that NDWI is a suitable water index for wetland delineation for this study region. Here, NDWI value 0–1 indicates the wetland area.

$$\text{NDWI} = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}}$$

where NDWI = normalized difference water index; Green band = band 2 of TM and band 3 of OLI; NIR band = band 4 of TM and band 5 of OLI

WPF shows consistency of water appearance in a pixel over a considered time. The equation for computing WPF is Equation 3. WPF value ranges from 0 to 100%. A value near 1 means irregular water appearance in a pixel and 100% signifies that in all the considered years, water appeared in a pixel (Sarda and Das 2018). For the convenience of analysis, the WPF spectrum was classified into three classes (a) high WPF (> 67%), (b) moderate WPF (33–67%), and (c) low WPF (< 33%). For developing the WPF map from the satellite image, the first water index (normalized difference water index (NDWI)) (Eq. 2) of each year was computed for the post-monsoon season. Each NDWI map was converted into a binary map assigning 0 to non-wetland and 1 to wetland pixel. All the binary maps of pre- and post-dam periods were added separately and divided by the total number of considered years and expressed in percentage (Eq. 3).

$$\text{WPF(\%)} = \frac{\sum_{i=1}^{N} BF_{pi}}{N_s}$$

where \(BF_{pi}\) signifies that in all the considered years, water appeared in a pixel and 100% signifies that in all the considered years, water appeared in a pixel (Sarda and Das 2018). For the convenience of analysis, the WPF spectrum was classified into three classes (a) high WPF (> 67%), (b) moderate WPF (33–67%), and (c) low WPF (< 33%). For developing the WPF map from the satellite image, the first water index (normalized difference water index (NDWI)) (Eq. 2) of each year was computed for the post-monsoon season. Each NDWI map was converted into a binary map assigning 0 to non-wetland and 1 to wetland pixel. All the binary maps of pre- and post-dam periods were added separately and divided by the total number of considered years and expressed in percentage (Eq. 3).

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is very efficient since it provides pixel scale hydro-period information over wider geographical areas. The finer temporal resolution may provide more authentic data for doing this than the Landsat product (temporal resolution: 16 days).

Water depth data is very crucial for analyzing the hydrological state of a wetland, but pixel scale data, even point scale data is almost lacking. Khatun et al. (2021), Kundu et al. (2021), and Pal and Sarda (2021b) successfully attempted image-based derivation of water depth data at different points in time. Following them, the present work also applied this approach of water depth calibration of water indices (NDWI) using 130 field-driven sample depth data of nine wetland sites. The accuracy of this map largely depends on the number of field-driven data for calibration and suitable water indices. Abnormal natural and anthropogenic intervention on wetland water strongly withstand against establishing a relationship between spectral value and ground truth (Talukdar and Pal 2020). Gao (1996) stated that the NDWI value is related to water thickness. Good water depth is related to the hydrological strength of the wetland since it provides sample ecological niches of varying characteristics.

Developing hydrological strength model

Using WPF, HP, and WD, three machine learning (ML) algorithm-based hydrological strength models were developed to see the change in hydrological strength in pre- and post-dam periods. Artificial neural network (ANN), random forest (RF), and reduced error pruning tree (REPTree) hydrological strength models were built.

Artificial neural network (ANN)

ANN can work as a human mind and can powerfully anticipate the consequences of the countless driving factors (Zhao et al. 2019; Nguyen et al. 2020; Saha et al. 2021). This is the justification for why several specialists have widely applied this model in several fields of examination (Choi et al. 2020; Zhao et al. 2019; Nguyen et al. 2020; Pal and Sarda 2021a). Here the researchers have widely used the multi-layer perceptron (MLP) algorithm. MLP is one of the most huge executed neural frameworks which are constantly set up with the back-propagation calculation (Choi et al. 2020; Zhao et al. 2019). The backpropagation algorithm was applied in MLP for the development of the network till the least error is reached inside the result and expected upsides of the ANN. In this calculation, the connection between the information is noticed, and a transition rule is utilized to remove data from the fundamental layer (Paola and Schowengerdt 1995). The connections might be weighted in the given environment and are associated through unidirectional progressions of data produced from the input layer to concealed layer and lastly to the output layer. This sort of multi-layer ANN model is skilled to get significance from the components WPF, depth consistency, and hydro-period duration of the wetland considered as a dependable information building WR models.

Random forest (RF)

Random forest (RF), presented by Breiman (2001), is a notable ensemble-learning calculation that is a blend of decision trees for gathering or backsliding to predict with a higher precision level. Besides, the RF method is broadly utilized for land use land cover classification, regression, and unsupervised learning (Behnia and Blais-Stevens 2018; Camargo et al. 2019; Chen et al. 2020). RF comprises an ensemble of classifiers to establish a connection among factors and weight generation for each variable. The RF algorithm produces many trees during the training stage, and the last weight is created by averaging all the tree values. RF classification utilized the resampling procedure by randomly changing the predictive variables to build the variety in each tree (Abarameri et al. 2021). In this study, the datasets are high dimensional, so it is essential to integrate the effect of each component. The model can then predict the available water resources, their variability, and hydro-duration of the wetland with a higher precision level.

Reduced error pruning tree (REPTree)

The reduced error pruning tree is a fast machine learning algorithm, which consists of reduced error pruning (REP) and the decision tree (DT) (Quinlan 1987). The prime goal of this algorithm is to reduce the difficulty of the modeling procedure when utilizing enormous information (Mohamed et al. 2012). In this calculation, the DT is applied to rearrange the modeling strategy using a preparation dataset when the output of a decision tree is huge, and the REP was used to lessen the complicity of the structure of the tree (Mohamed et al. 2012). This strategy reduces the complexity of the decision tree model during the pruning process and limits the model error. The straightforward setup and pruning strategy gives better exactness and lessens the over-fitting issue (Pham et al. 2019). In pruning measures, a decision tree can be pruned in two different ways example, pre-pruning, and post-pruning. Pre-pruning is quicker with less exactness whereas post-pruning gives better precision (Chen et al. 2019). In this examination, the post pruning strategy was used to generate a series of pruned trees and to recognize an exact sub-tree from the test dataset (Table 1).
Validation of hydrological strength models

To authenticate the performance of the wetland hydrological strength models, several statistical measures including sensitivity (SE), specificity (SP), Kappa statistic (K), area under the curve (AUC), and Matthews’s correlation coefficient (MCC) were applied in this study. SE, SP, AUC, and K values usually range from 0 to 1. A value near 1 signifies a higher level of predictive agreement (Yang and Zhou 2015; Warsens and Pratiwi 2016). MCC was used to check the quality of binary classification of machine learning models (Chicco and Jurman 2020). This coefficient ranges from −1 (complete disagreement in prediction) to +1 (perfect agreement between model and field reality (Eqs. 8–10)). The estimated kappa coefficients for pre- and post-dam periods, respectively, are 0.85 and 0.89, denoting high agreement between model and field reality (Eqs. 8–10).

The median flood period (7 days) were placed in the dam’s downstream sections, and flood simulation maps were created using the SRTM DEM. For the model’s validation, a total of 188 flooded locations were chosen from around the basin. A GPS survey of flood areas was conducted to acquire ground reference sites. People’s perspectives on the selected places were obtained to see if they were genuinely prone to flooding. Using field and model data, the Kappa coefficient was calculated. The estimated kappa coefficients for pre- and post-dam periods, respectively, are 0.85 and 0.89, denoting high agreement between model and field reality (Eqs. 8–10).

Modification about lateral hydrological connectivity

2D inundation modeling

The US Army Corps of Engineers developed HEC-RAS software to simulate floods using one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) models. In the scenario of a uniform cross-section channel, the 1D model can be utilized, whereas in the case of a channel with different cross-sections, the 2D model is implemented. The 2D simulation model was employed for both the pre-dam and post-dam phases of the Atreyee river, taking into account variable cross-sections.

The median flood discharge is estimated for both the pre-dam and post-dam eras before flood models are simulated. The years 1993 and 2014 were chosen as the representative median flood years for both phases. Discharge data from flood periods (7 days) were placed in the dam’s downstream sections, and flood simulation maps were created using the SRTM DEM. For the model’s validation, a total of 188 flooded locations were chosen from around the basin. A GPS survey of flood areas was conducted to acquire ground reference sites. People’s perspectives on the selected places were obtained to see if they were genuinely prone to flooding. Using field and model data, the Kappa coefficient was calculated. The estimated kappa coefficients for pre- and post-dam periods, respectively, are 0.85 and 0.89, denoting high agreement between model and field reality (Eqs. 8–10).

where: $TP = \text{true positive; } TN = \text{true negative; } FP = \text{false positive; } FN = \text{false negative; } W_o$ and $W_e = \text{observed and expected agreement}$

Table 1: Optimization statistics of the applied machine learning models

| Machine learning algorithms | Description of optimized parameters |
|----------------------------|-------------------------------------|
| ANN                        | Hidden layer-6, learning rate-0.3, momentum-0.2, seed-7, training time-500, validation threshold-20, Normal to binary filter-TRUE |
| RF                         | Batch size-100, seed-1, number of iteration-100, max depth-1, calc out of bag-TRUE, Compute attribute importance-TRUE |
| REPtree                    | Batch size-100, seed-3, max depth-1, minimum number-2.0, minimum variance proportion-0.001, spread initial count-TRUE |
Classifying wetland security state (based on flood zones)

Wetlands of the basin were classified based on lateral inundation zones before and after hydrological alteration due to damming. After overlapping inundation zones of pre- and post-dam conditions, three zones were identified (1) areas inundated both during pre- and post-dam periods, (2) areas beyond post-dam but within pre-dam inundation limits, and (3) areas beyond both pre- and post-dam flood limits. Wetlands under three inundation zones were, respectively, treated as (1) safe, (2) stress, and (3) critical to hydrological security, particularly in terms of lateral hydrological connectivity. Since in the rain-induced fluvial-flood plain region where floodwater is one of the dominant sources of wetland, classification on this basis is very crucial. Moreover, flood not only supplies water to the para-fluvial wetland but also supplies nutrients, fry, and different species of seeds and removes pollutants, etc. So, analyzing connectivity between river and wetland through flooding and classifying wetland based on this connectivity is very essential. Here, it is to be remembered that a critical wetland does not mean the wetland is devoid of water; it may be supported by rainwater and seepage water but deprived of flood services.

Developing WSS and HS matrix

To clear discrimination of hydrological conditions, WSS and HS matrices were made. Both the WSS and HS maps were categorized into three classes, and when the matrix was built, nine distinct subclasses were obtained (like safe WSS and high HS; stress WSS and low HS, etc.). Each subclass provides a clear characteristic of both WSS and HS. Among the subclasses, low HS under stress and critical WSS zones are highly vulnerable from both hydrological and ecological standpoints.

Morphological change of wetland (fragmentation/shape sizes)

Landscape morphology is itself a good indicator of wetland hydrological dynamics. The perennial and consistent wetland is less susceptible to morphological transformation than seasonal, ephemeral wetlands that are hydrological irregular and erratic and provide a scope of activating invasive factors of wetland morphological change (Epting et al. 2018; Talukdar and Pal 2019; Lee et al. 2020). Using Fragstats software wetland landscape of both pre- and post-dam periods was classified into a patch, edge, perforated, small, medium, and large core, and the area under each category was accounted to show the morphological changes of the wetlands. Dynamics of patch frequency, area, edge area, and a core area in between pre- and post-dam periods help to explain the nature of influencing factors.

Identifying associated modification

There are different causes to be condemned for wetland loss, a hydro-ecological transformation like agricultural, built-up land extension, infrastructure development replacing wetland, attenuation of water availability, etc. However, the hydrological modification could be one fundamental transformation of wetland that can also invite some other related causes (Das and Pal 2018; Pal and Sarda 2020; Pal et al. 2022). Considering this, the present section focused on some case studies exploring the nature of hydrological transformation and associated other causes like habitat change, flow modification, climate change, biodiversity loss, inundation frequency, eutrophication, and built-up encroachment. These parameters were directly observed from the field and discussed with the stakeholders. Based on the field experiences and experience of the stakeholders, qualitative scaling was done. For showing drivers’ impact, the impact of the selected drivers was qualitatively measured on a scale of low, moderate, high, and very high. For illustrating the drivers’ current trend, four scale point was set decreasing impact of the drivers, increasing impact, very rapid increase, impact remaining same (continuing impact). These were presented using an integrated graph.

Results

Flow alteration (heat mapping)

From the heat map of maximum, minimum, and average discharge and discharge change rate, it is very evident that in the pre-dam period discharge, anomaly (positive and negative) is accountable, but its dynamics were highly observable in the case of minimum discharge specifically in the monsoon months. After damming, a sharp decline of discharge without any incident of the anomaly was noticed (Fig. 2A, B, C). Similarly, the rate of discharge attenuation was found in post-dam conditions. For instance, it was up to 92%, 66.5%, and 75% in case of maximum, minimum,
and average discharges, respectively (Fig. 2D, E, F). Such change was recognized more during monsoon months. Discharge increment rate was also recorded in these heat maps; however, all such incidents were identified in the pre-dam period. It does mean there were many years when maximum, minimum, and average discharge was greater than that of the respective average.

**Periodicity analysis**

The continuous wavelet power spectrum of average discharge in pre-monsoon, monsoon, post-monsoon, and winter seasons was presented in Figure 3. After damming (2012), significant periodicity in the wavelet power spectrum was identified in the 3–5 years band, particularly in different seasons. From the wavelet power spectrum, the highest power (represents the variance of flow) was found near the bands of 3–4 years from 2012 to 2015. It does signify that the nature of river flow was changed more or less in the same direction with quite varying magnitude. In the pre-monsoon season, a strong power is recognized in a 2–3 years time band from 2012 to 2015 (Fig. 3a). During the monsoon season, a few strong wavelet power spectrums were displayed in the 2–8 years band from 2000 to 2009 and in the 16–30 years band from 2012 to 2017 (Fig. 3b). In the post-monsoon season, three significant spectrums were noticed. Among them, a comparatively stronger significant spectrum was found in the 2–2.8 years band from 1995 to 2000 and the 4 to 7 years band from 2012 to 2015 (Fig. 3c). During the winter season, a few strong spectrums were portrayed after 2012 (Fig. 3d).

**Wetland area dynamics**

Time series wetland mapping using normalized difference water index of Mcfeeters (1996) explored that over the period, wetland area was squeezed. For instance, during the pre-dam period, wetland area was 1070.20 km². It was reduced to 546.17 km² in the post-dam period. Area loss was observed very prominent in the fringe area of the wetland and smaller patches. Over the progress of time, larger wetland patches appeared fragmented (Fig. 4). This trend of wetland loss is very common in the flood plain wetlands of other regions (Talukdar and Pal 2019), and the rate of depletion was identified as rapid in the case of damming river basin (Zheng et al. 2019).

![Fig. 2](image-url) Heat map showing flow alteration about absolute maximum, minimum and average discharge (A, B, C) and maximum, minimum, and average discharge change rate (D, E, F). Here 2012 is the damming year.
Hydrological modification of wetland

Modification about individual hydrological components

Figure 5A shows the hydrological components of the wetlands like hydro-duration, WPF, and water depth. Each map was sub-classed, and the area under each was documented in Table 2. About the hydro-period, the absolute area under longer hydro-duration (> 9 months) was reduced from 69.04 to 42.81 km² in between pre- and post-dam periods. However, in terms of the proportion of area, there was no significant change. The hydro-period below 3 months also shows a significant reduction in terms of the area. The results indicate the improvement of the hydrological state but practically since the larger extent of area under this was completely obliterated in the post-dam period. The same trend was also noticed in the case of WPF. Low WPF (< 33%) zone was squeezed from 743.12 km² (68.4%) to 332.57 km² (60.8%) in between pre- and post-dam periods (Table 2). High WPF was noticed slightly increased from 1.5 to 4.1%. In the case of water depth, a significant increase (48.9 to 79.2%) of the proportion of wetland area was noticed in the low water depth class (< 2 m), and a decrease in high depth (> 3 m.) was observed. High depth class area declined from (371.31
km$^2$) 34.7% to (10.49 km$^2$) 1.9%. Some areas were recognized where water depth was recorded low but despite having relatively greater WPF and hydro-period. These areas may be highly susceptible to hydrological transformation in the coming days. Figure 5A portrays that areas under each hydro-period, WPF, and water depth sub-class were substantially decreased in the post-dam period.

Modification in reference to Hydrological strength (HS) models

Figure 5B shows the hydrological strength (HS) using ANN, RF, and REPTree ML models both for pre- and post-dam periods. High HS was widely found across the river basin covering both upper and lower catchments during the pre-dam period, but a huge area under this category was
squeezed in the post-dam period. A large part of the wetland with high HS in the lower part of the basin was lost showing a maximum degree of conversion. A large tract of wetland with high HS astride of river also witnessed wetland transformation from high HS to moderate and low. Table 3 depicts the area under different HS zones computed for each applied model. Noticeably, it was found that the area under the high HS zone was about 47% as per all the models, but it was reduced to about 32% with very little inter-model areal fluctuation. The area under the moderate HS zone declined about the absolute area (210 km² to 187 km²); however, in terms of relative area, it was increased by 14%. The area under high HS was shifted to a moderate HS zone. Applied ML HS models showed that there was no significant variation in areal extents and geographical positions of high, moderate, and low HS zones, and thus, all those models could be valid. However, conventionally, it requires validation for finding out the most suited one. Figure 5C depicts the degree of alteration in wetland HS models between pre- and post-dam phases built based on ML methods. Visual comparison of alteration maps of different phases clarified that negligible fringe wetland parts during the pre-dam phase were under a high HS zone, but it was negatively altered in the post-dam phase, and the wider part also experiences negative alterations. The core wetland part was turned into positive alteration and maintained hydrological strength during the post-dam period (Fig. 5C).

Validation of HS models

From the applied statistical measures of validation, it is clear that all the applied models have an excellent agreement between map and ground conditions and, therefore, could be accepted. AUC values range from 0.89 to 0.92, sensitivity from 0.89 to 0.9, specificity from 0.88 to 0.92, and kappa coefficient from 0.89 to 0.94 indicating the acceptability of all the models. However, to select the best representative model, a comparative analysis of those values was done, and the REPTree model was recognized as the best suited since all the measures show the highest agreement (Table 4).

**Table 2**: Area under different parameters used for identification of hydrological strength of the wetland

| Parameters                  | Period | Parameter sub-class | Area in km² | % of area |
|-----------------------------|--------|---------------------|-------------|-----------|
| Hydro-period (month)        | Pre-dam| Below 3             | 299.83      | 28        |
|                             |        | 3 to 6              | 477.11      | 44.5      |
|                             |        | 6 to 9              | 224.22      | 20.9      |
|                             |        | Above 9             | 69.04       | 6.4       |
|                             | Post-dam| Below 3            | 114.86      | 21        |
|                             |        | 3 to 6              | 235.58      | 43.1      |
|                             |        | 6 to 9              | 152.92      | 28        |
|                             |        | Above 9             | 42.81       | 7.8       |
| WPF (%)                     | Pre-dam| Low                 | 743.12      | 69.4      |
|                             |        | Moderate            | 310.03      | 28.9      |
|                             |        | High                | 17.05       | 1.5       |
|                             | Post-dam| Low                | 332.57      | 60.8      |
|                             |        | Moderate            | 191.01      | 34.9      |
|                             |        | High                | 22.59       | 4.1       |
| Wetland water depth (m)     | Pre-dam| Low (< 2)           | 523.72      | 48.9      |
|                             |        | Moderate (2–3)      | 175.17      | 16.3      |
|                             |        | High (> 3)          | 371.31      | 34.7      |
|                             | Post-dam| Low (< 2)          | 432.89      | 79.2      |
|                             |        | Moderate (2–3)      | 102.79      | 18.8      |
|                             |        | High (> 3)          | 10.49       | 1.9       |

**Table 3**: Area under different Hydrological strength state categories using ML methods

| Machine learning algorithms applied | Pre-dam | Post-dam |
|------------------------------------|---------|----------|
|                                    | Low     | Moderate | High    | Low     | Moderate | High    |
| ANN                                | 361.74 (33.80) | 209.67 (19.59) | 498.79 (46.61) | 184.38 (33.75) | 186.84 (34.20) | 174.96 (32.03) |
| RF                                 | 361.96 (33.82) | 210.11 (19.63) | 498.13 (46.55) | 192.24 (35.19) | 182.41 (33.40) | 171.52 (31.40) |
| REPTREE                            | 361.89 (33.82) | 209.52 (19.58) | 498.79 (46.61) | 185.8 (34.02)  | 186.9 (34.22)  | 173.47 (31.76) |
MCC value was also found 0.82 in the case of REPTree both during pre- and post-dam periods, and this value is greater than MCC produced by the other models.

**Modification in reference to lateral hydrological connectivity**

Flood water, river flow through water tie channels, and groundwater flow hydrologically connect the wetland with the river (Tootchi et al. 2019; Yabusaki et al. 2020). Disconnection of some wetlands from lateral flood spread limit deteriorates the water supply to the wetland. Figures 6A and B, respectively, represent the active inundation zones with possible floodwater depth in pre- and post-dam periods in the wetland domain. From the illustration, it is quite clear that the active inundation area in the pre-dam period was considerably greater than in the post-dam period. In the pre-dam period, the inundation area was 4827.82 km² which was reduced to 1627.30 km² in the post-dam period. Depth of floodwater ranged from 0 to 17 m in pre-dam and 0 to 8 m in post-dam period. Here, it is to be mentioned that extreme depth values were found only in a few pixels. This incident is directly linked to the dwindling of discharge and water level in the Atreyee river. Spilling of the riverbank and rainfall are

| Phases  | Models | AUC (ROC) | Sensitivity | Specificity | MCC | Kappa coefficient (K) |
|---------|--------|-----------|-------------|-------------|-----|----------------------|
| Pre-dam | REPTree | 0.91      | 0.9         | 0.92        | 0.82 | 0.91                 |
|         | RF     | 0.90      | 0.89        | 0.92        | 0.81 | 0.90                 |
|         | ANN    | 0.91      | 0.89        | 0.88        | 0.78 | 0.89                 |
| Post-dam| REPTree | 0.92      | 0.9         | 0.92        | 0.82 | 0.94                 |
|         | RF     | 0.9       | 0.89        | 0.92        | 0.81 | 0.92                 |
|         | ANN    | 0.89      | 0.89        | 0.88        | 0.78 | 0.92                 |

**Table 4:** Accuracy result of the wetland hydrological strength models using ML algorithm

Fig. 6: Active inundation flood-plain models of A pre-dam and B post-dam periods, C wetland hydrological security state (WSS) about the active inundation limits, D wetland matrix of WSS and HS showing HS under different WSS zones.
two major reasons behind rainfall in the flood plain region. Pal et al. (2022) also identified the same declining trend of active inundation and area and water depth in the post-dam period. River astride wetlands also witnessed considerable attenuation of water level, and this led to a reduction of inundated area.

**Wetland hydrological security state (WSS) concerning inundation**

Based on the active inundation zones of the pre- and post-dam period, the wetland was categorized into safe, stress, and critical, and definitions of each were mentioned in the concerned method section. About the lateral flood water connectivity, 85.74 km² (18.7%), 100.72 km² (22%), and 359.72 km² (78.8%) of wetland areas of the present time were classified into critical, stress, and safe wetland security. Wetland away from the main river was recognized as critical due to the linkage of floodwater (Fig. 6C).

**Hydrological strength in wetland hydrological security zone (WSS and HS matrix)**

For further discrimination of wetland characters, the hydrological strength of existing wetland under different was featured to know-how the wetland without having lateral inundation water connectivity. Table 5 explains the HS character in different WSS zones. Usually, it was hypothesized that critical and stress WSS zone will have poor HS and safe WSS zone will have a high HS state with a greater proportion. Out of a total of 85.74 km² of wetland under the critical WSS zone, 78.14 km² was characterized by low and moderate HS. In the stress, the WSS zone’s total area was 100.72 km², out of which 79.7 km² fall under the low and moderate HS zone (Table 5). On the other hand, out of a total of 359.72 km² of wetland in the safe WSS zone, 40.2% of wetland was characterized by a high HS state. The findings of the present WSS and HS matrix satisfied the adopted hypothesis (Fig. 6D).

**Morphological change of wetland**

Figure 7 depicts the wetland fragmentation status in pre- and post-dam periods. From the figure, it is very clear that there was well-defined long wetland tract alongside the main river during the pre-dam period. In the post-dam period, most of the continuous large wetland tract was found fragmented.

![Fig. 7: Wetland fragmentation showing patch, edge, perforated, small, medium, and large cores of a pre-dam and b post-dam periods](image-url)
For instance, in the pre-dam period, 10.8% and 22% of areas were under patch and edge areas, respectively, but these were inflated during the post-dam period (patch and edge areas are 22.2% and 27.4%) signifying enhancement of diverse situation of wetland morphology. Contrarily, the large core area was reduced from 52.1 to 33.7% in between pre- and post-dam periods (Table 6). Growing fragmentation means increasing the edge-area ratio which leads to the enhancement of anthropogenic intervention (Shen et al. 2019; Kundu et al. 2021). Such change is not only the alteration of landscape morphology, but it can adversely affect the service-ability of such precious natural capital (Lu et al. 2019).

**Identifying associated modification in some specific cases**

Ten wetlands from different parts of the study unit as mentioned in Figure 1 were taken for showing hydrological modification and associated other changes and their current trend (Figure 8). Driver-specific analysis endorsed the following findings: flow modification impact was high to moderate in maximum wetlands, and driver’s current trend at 60% cases was found to increase, and in 40% cases, the impact was continued as observed earlier. Inundation frequency was found to decrease in most of the cases, and inundation magnitude was found to decrease or remain as usual. In association with those hydrological transformations, agricultural encroachment, construction activities, water pollution, eutrophication, habitat change, biodiversity loss, etc. were found degraded in most of the selected wetlands. Hydrological strength is fundamental to an aquatic ecosystem (Meng et al. 2020; Li et al. 2021). Since the wetlands witnessed the adverse impact of hydrological transformation, it often promoted some other associated causes like habitat quality change, water pollution, and biodiversity loss. Some people residing near wetland areas also reported that after shallowing wetlands, inconsistent water appearance in wetland, people received an opportunity to convert the wetland into perennial agricultural land.

**Discussion**

From the result, it is very clear that damming brought a landmark hydrological change in the river and riparian wetlands. The squeeze of active inundation plain impacted adversely the wetland hydrological security. Poor hydrological strength was detected in critical and stress wetland insecurity zones. About 48.9% of wetland area was wiped out after damming. A large tract of the wetland along the confluence segment of the main river at its proximity was also hydrologically weakened. Now the question is how the hydrological modification and wetland loss are related to river flow modification?

Discharge attenuation after damming was well reported in this paper, and this finding is supported by similar works

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**Table 6: Proportion of area of landscape fragmentation for the post-monsoon season in pre- and post-dam periods**

| Landscape fragmentation | Wetland conditions in post-monsoon seasons | Pre-dam | Post-dam |
|-------------------------|--------------------------------------------|---------|---------|
|                         | Area (km²)                                 | Area (km²) |
| Patch                   | 116.01 (10.8%)                             | 121.30 (22.2%) |
| Edge                    | 235.77 (22%)                               | 149.81 (27.4%) |
| Perforated              | 15.30 (1.4%)                               | 10.87 (1.9%) |
| Low core                | 122.32 (11.4%)                             | 64.23 (11.7%) |
| Medium core             | 22.80 (2.1%)                               | 15.68 (2.8%) |
| Large core              | 557.68 (52.1%)                             | 184.11 (33.7%) |

**Fig. 8:** Current trends and degree of driver’s impact on the wetland of Atreyee river basin
conducted by Zheng et al. (2019), Amenuvor et al. (2020), Chen et al. (2021), and Gao et al. (2021) across the world. The rate of attenuation depends on the degree of anthropogenic control as reported by Fleischmann et al. (2019). Pal (2016b) investigated hydrological modification in the Atreyee river and reported that average flow was reduced by 53% and reduced overall flood frequency, and flood magnitude above extreme danger level was attenuated by 46%. Talukdar and Pal (2020) also documented the same trend of extreme hydrological change in the Punarbhaba river of Barind plain.

Since the flood plain wetlands are fed by rain and floodwater, the dynamics of the flood of a river are strongly linked to the riparian flood plain (Fritz et al. 2018; Vidon et al. 2019; Alafifi and Rosenberg 2020; Cui et al. 2021). The lowering of floodwater levels in the Atreyee river during monsoon season was identified as a prime reason behind the reduction of the active flood plain. Rainfall reduction (28.7%) was also identified as inflow availability in river and wetland reduction (Pal et al. 2022), and it is also a reason behind the active flood plain squeeze. Embanking rivers and restricting discharge up to an artificially elevated level also are major causes behind less spread flood water laterally (Galib et al. 2018; Sarkar et al. 2020). But if the embankment is breached anyway, it may cause the sudden spread of water laterally obliterating the natural and manmade infrastructures (Urzică et al. 2021). It can adversely affect the wetland hydrological stability and associated ecology. Since the water level was attenuated and the increased volume of water during extreme depression during monsoon was capacitated by the raised embankment, flood severity except during breach time was found weak. It is a well-explored cause of active flood plain squeeze. Mondal and Pal (2018) also reported an active flood plain squeeze incident in the Mayurarshiki river basin of Eastern India.

As a result of this squeeze of the active floodplain during the post-dam period, a good proportion of wetland was left beyond the present flood spread limit, and these wetlands were started to suffer from water scarcity, paucity of nutrients, fish seeds, and so on. Regular water supply to the wetland from the river in form of spill water can secure the water availability and different other ecological services to the wetland. For instance, spilled water often supplies fry and food for the fry and fishes which reduce the cost of fishing and thereby support the fishermen. The concentration of chemical fertilizers and pesticide residues within wetlands leads to a great ecological threat (Quintela et al. 2019) strengthening exotic species’ growth and arresting the growth of valuable endemic species (Maurya et al. 2019). Regular flooding can remove such noxious residues and refresh the wetland habitat (Liu et al. 2018). Considering mainly water service of flooding, the wetlands were categorized as safe, stressful, and critical. Critical wetlands are not used to receive floodwater since from pre-dam period, and they are solely dependent on rainwater and seepage water. Lowering groundwater tables and lessening rainfall (Pal et al. 2022) are therefore threats to the critical WSS. In the stress WSS zone, floodwater is usually not received but rarely received. So, the wetland within this zone is not hydrologically rich and ecologically prudent. Wetland within a safe zone receives regular flood water and nutrients and, therefore, is hydro-ecologically efficient. This sort of wetland classification was also done by Talukdar and Pal (2020).

Analysis of HS models identified that a large part of the wetland within critical and stress WSS zones suffers from hydrological weakness. For instance, inconsistent water appearance, narrow hydro-period, and shallow water depth were identified in these zones. Hydrological strength is considerably better in the safe WSS zone. However, all parts of the wetlands are not hydrologically stronger, some wetlands in very proximity to the main river within this zone were identified as hydrologically sick, and it is in fact due to the erection of an embankment astride the main river restricting natural flooding. In some cases, tie channels that connect river and wetland water were also reclaimed mainly for agriculture purposes (Mukherjee et al. 2018; Pal and Talukdar 2019). Case studies from the present study area also proved the loss of tie channels and hydrological degradation. Pal and Talukdar (2019) and Saha and Pal (2019) also reported hydro-ecological deterioration of wetland due to tie channel loss. Some tie channels were identified those were not reclaimed, but their aggraded bed level at the off-take points is quite above the normal water level, so they rarely get support from river discharge. These situations led to hydrological degradation of river proximate wetland despite tie channel linking.

Lowering water availability in wetland, irregular water appearance for a short time often invites agrarian people to invade the wetland. Initially, they used such area for seasonal cultivation, but gradually, they make it suitable for perennial agriculture land effacing its wetland characters (Wondie 2018). Often agricultural invasion is condemned as the most dominant cause behind wetland loss in the flood plain region (Saha and Pal 2019b). Das and Pal (2018), Saha and Pal (2019), and Saha and Pal (2019a) rightly pointed out hydrological deterioration can also promote this vector. It may also promote the expansion of the built-up area since the study region is densely populated. The increasing population demands more habitats for living. Often people reclaim this land without considering its priceless serviceability. If such land is public, the rate of reclamation is quite greater. All of these are caused for the morphological transformation of wetlands (Pal et al. 2022) as also found in this present study. Patch and edge dominated areas were increased, and the large core area was decreased in this present case. Increasing the edge area ratio after growing
fragmentation exerts extra pressure on wetland habitat and ecology (Mukherjee and Pal 2021). This trend of morphological wetland scape transformation is commonly found across the world (Shen et al. 2019; Cui et al. 2021; Das et al. 2021; Kundu et al. 2021).

For exploring hydrological change in wetland, image-driven hydrological components were used for overcoming the issues of spatial scale data scarcity. Image-driven pixel scale hydro-period, depth, and WPF data derivation is very useful for hydrological modeling over a wider geographical area time and cost-effectively. The approaches taken here for data derivation would be much more refined, and the resolution of the used images would be finer. In this regard, more research is required. One or two hydrological monitoring stations on wetland are not just enough to build a spatial hydrological strength model. So, it is now the chief alternative to fill the field-based data deficiency. Machine learning algorithms were applied for building the HS models to resolve the complex spatial relationship among the parameters and use the robustness of the models. Al-Abadi and Al-Najar (2020), Costache and Bui (2020), Pal and Paul (2020), and Pal and Sarda (2021a) recommended ML models over other statistical models. A multi-model approach was taken for justifying the best-suited model. Multiple statistical tests were applied for verifying the suitability of the model. If all the applied statistical test results figure out the suitability of a model, its acceptability will be very strong. In this study, REPTree was found as the best suited confirmed by all the test results. WSS and HS matrix is a new way of featuring wetland coupling inundation connectivity and current wetland hydrological conditions. This matrix yielded nine wetland types with the specific nature of WSS and HS.

Since the work clearly mapped the active flood plain zones after damming incidents and recognized wetland within and beyond, it would be a good instrument for adopting priority basis planning. Moreover, since the study further explored poor hydrological strength (HS) states within critical and stress WSS zones, flood restoration is an effective option to improve hydrological efficacy and wetland security. Maintaining water levels would be a panacea to resolving the ongoing and upcoming crisis. Detail study is further required for setting a viable amount of water flow that is to be released downstream. The study successfully linked the alteration in river flow and hydrological conditions of the wetland applying an integrated advanced hydrological modeling approach. This work would also be a good guide regarding the exploration of image-based pixel scale hydrological data resolving spatial scale wetland hydrological data scarcity. These are the novel contribution of this paper. However, by adopting the same approach or a more updated approach, high spatial and temporal resolution data could provide better output. Moreover, for analyzing the hydrological security of wetland, only inundation connectivity was focused but tie channel connectivity, and groundwater support in terms of vertical hydrological connectivity was not taken into consideration. Because of spatial scale data non-availability, these were not taken, but the inclusion of all these could yield more authentic results on wetland hydrological alteration.

Conclusion

From the result, it is very evident that damming was a major determinant of river flow, and in consequence of the attenuation of river flow, the active flood plain region was squeezed by 66.2% curtailing the water supply to the wetlands away from the current active flood plain limit. Flow alteration also leads to the loss of extensive wetland area, and existing wetland was also witnessed remarkable hydrological alteration. Hydrological strength models exhibited that area under high HS state was substantially reduced inflating area under relatively weaker HS state zones. Integrated analysis of wetland hydrological security state (WSS) based on lateral flood water connectivity and hydrological strength (HS) categories revealed that critical and stress WSS zones recorded relatively poor HS. Weakening hydrological strength was also identified as a major reason behind promoting wetland fragmentation as was noticed after damming in the present study.

The result itself is a vital instrument for wetland management and restoration. Reduction of flow is the primary reason behind attenuation of flood spread, and squeezing flood water spread is caused for enhancing wetland hydrological insecurity state. So, to formulate sustainable wetland management and restoration strategies, it is very essential to release the ecologically viable amount of water to the dam downstream segment. It can only revive the river and riparian wetland ecology. It can also help to restore the wetlands left beyond lateral hydrological connectivity.

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draft — were performed by Rajesh Sarda and Dr. Tamal Kanti Saha. All the authors read and approved the final manuscript.

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