

Impact of river flow modification on wetland hydrological and morphological characters

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1 **Impact of river flow modification on wetland hydrological and morphological characters**

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29 **Abstract**

30 A good number of researchers investigated the impact of flow modification on hydrological,
31 ecological, geomorphological conditions in a river. A few works also focused on hydrological
32 modification on wetland with some parameters but as far the knowledge is concerned, linking
33 river flow modification to wetland hydrological and morphological transformation following an
34 integrated modeling approach is almost absent. The current study aimed to explore the degree of
35 hydrological alteration in the river and its effect on downstream riparian wetlands adopting
36 advanced modeling approaches. After damming maximally 67 to 95% hydrological alteration
37 was recorded in respect to maximum, minimum, and average discharges. Wavelet transformation
38 analysis figured out a strong power spectrum after 2012 (damming year). Due to attenuation of
39 flow, the active inundation area was reduced by 66.29%. After damming, 524.03 km² (48.97% to
40 total pre-dam wetland) was completely obliterated. Hydrological strength (HS) modeling also
41 reported areas under high HS was declined by 14% after post-dam condition. WSS and HS
42 matrix, a new approach, used to feature wetland coupling inundation connectivity and current
43 hydrological state. HS under critical and stress wetland hydrological security zones deteriorated
44 in the post-dam period. The morphological transformation was also well recognized showing an
45 increase of area under the patch, edge, and decrease of the area under large core area. All these
46 findings established a good linkage between river flow modification and wetland transformation
47 and it provided a good clue for managing wetland.

48 **Keywords**

49 Flow alteration, Wetland hydrology, Wetland fragmentation, Active flood plain, Hydrological
50 strength modeling, Machine learning models, and Wetland security state.

51 **1. Introduction**

52 People have been continuously changing river systems to meet their water demands through
53 various activities, and one of these activities is the construction of dams across river, which
54 dramatically modify the natural river flow regime in its downstream ([Wang et al., 2019](#); [Zheng et
55 al., 2019](#); [Arévalo-Mejía et al., 2020](#)). This direct regulation-related effect will undoubtedly
56 continue to have an impact on rivers in the future decades, with potentially significant and
57 unexpected consequences for their morphodynamics and ecosystems, as well as the concerned
58 flood plain areas ([van Oorschot et al., 2018](#); [Zheng et al., 2019](#); [Pal and Sarda, 2020](#)). River flow
59 alterations seem like the most significant modification of the fluvial landscape on the earth's

60 surface (Wang et al., 2020; Chen et al., 2021; Pal and Sarda, 2021a). A good number of
61 researchers believe that flow modification is one of the emerging challenges since it changes the
62 downstream flow regime in terms of total flow, size, timing, length, rate of change, and water
63 quality (Pal et al., 2019; Huang et al., 2019; Amenuvor et al., 2020; Du et al., 2020; Pal and
64 Sarda, 2020; Pal et al., 2020). As a result, it can reduce the connection of the main channel with
65 the flood plain and it not only arrests the water supply to the flood plain but also limits the
66 natural dispersion of fish and macroinvertebrate species towards the flood plain for sustaining
67 the flood plain biodiversity (Rolls et al., 2012). Li et al. (2017) documented since 1991 to 2009,
68 the average flow of Southeast Asia's Mekong river was decreased by 82 percent. Pal (2016b)
69 showed that the Rubber dam on the Atreyee river in Bangladesh has attenuated 84 percent
70 maximum flow and 56 percent average flow. As per Xue et al. (2017), damming on Tarim river
71 basin of China, downstream flow was reduced by 68.7%, which made the hydrological shortage
72 and ecological stress. According to Pal and Talukdar (2020) in the case of the Punarbhaba river
73 in India-Bangladesh, the average flow was decreased by 36% due to dam installation. Ali et al.
74 (2019) reported 17-27% attenuation of the flow of the Yangtze River after damming and warned
75 for water shortages without implementation of suitable management techniques. Wang et al.
76 (2018), Pal et al. (2019) observed the significant hydrological modification in Yangtze, Tongon
77 rivers throughout the world.

78 The construction of the dam not only changed the hydrological system of a river (Pal, 2016a) but
79 also modified the hydro-ecological regime and morphological character of the riparian wetlands
80 by reducing flood frequency, magnitude, squeezing active flood plain area, fragmenting the
81 wetland landscape, and so on. (Gain and Giupponi, 2015; Pal and Saha, 2018; Zheng et al., 2019;
82 Saha and Pal, 2019b; Wang et al., 2019; Duc et al., 2020; Smith et al., 2020; Pal and Sarda,
83 2020; Pal and Sarda, 2021b). Wetlands are the world's most unique, transitional, and productive
84 ecosystems, holding around 6-8 percent of the earth's terrestrial area and indicating
85 approximately 45 percent of the overall economic value among all global ecosystems (Finlayson,
86 2013; Mitsch and Gosselink, 2015). Changes in land use/cover, increase of population and their
87 demands, changing lifestyles and requirements are all putting pressure on these wetlands. In
88 comparison to other economic activities, these lands have always been treated as less valuable
89 (Duc et al., 2020; Pal and Sarda, 2020; Smith et al., 2020).

90 Several studies have discovered that damming has an unfriendly influence on the riparian zone,
91 although, the fact that the dam is not the sole responsible factor for all such changes undoubtedly
92 it is a dominant factor for altering riparian wetland hydrological and morphological character
93 (Zheng et al., 2019; Pal et al., 2020; Talukdar and Pal, 2020). In recent times, the research
94 community and the victims both have paid their attention to study this issue and trying to find
95 some reasonable solution, because it is strongly related to ecological survival and livelihood
96 sustainability (Pal and Saha, 2018; Wang et al., 2019; Zheng et al., 2019; Pal and Sarda, 2020).
97 According to Zheng et al. (2019), hydrological changes were recognized in the lower portion of
98 the Nenjiang River in Northeast China after dam building, and these changes contributed
99 significantly to the 44 percent decline in riparian wetlands. Saha and Pal (2019a) reported that
100 45% of the active flood plain was lost after damming in the Atreyee river basin. According to
101 Talukdar and Pal (2020), damming across the Punarbhaba river in India and Bangladesh reduced
102 the active floodplain by 39.72% enhancing the stress of wetland beyond the active flood plain
103 limit. When a wetland is hydrologically affected adversely, its ecological function abilities,
104 natural resource strength, and morphological characteristics also change accordingly (Bregoli et
105 al., 2019; Aghsaei et al., 2020; Orimoloye et al., 2020). According to Kundu et al. (2021), flow
106 change has an indicative impact on the state of wetland fragmentation as well as ecosystem
107 services. Furthermore, shallowing water depth promotes agriculture extension inside wetland,
108 which leads to wetland fragmentation (Pal and Saha, 2019a).

109 Integrated development of hydrological strength is very difficult since the hydrological data are
110 not readily available (Jeziorska, 2019). Pal and Sarda (2020), Khatun et al. (2021), Pal et al.
111 (2022) applied a water presence frequency approach for wetland consistency analysis. A
112 consistent wetland is good for hydrological strength. Water indices based on time series wetland
113 maps were used for this. Water depth is also a prevalent hydrological component and such data is
114 scarce. Khatun et al. (2021), Kundu et al. (2021), Pal and Sarda (2021a), Pal and Sarda (2021b)
115 tried to develop it from satellite images. Onyango and Opiyo (2021), Pal and Sarda (2021b),
116 Saha et al. (2021), Sahour et al. (2022) used Normalized difference water index (NDWI) for
117 preparing water depth layers through a field-driven databased calibration process. Hydro-period
118 means the period of water stagnation in the wetland in a year. Özelkan (2020), Kundu et al.
119 (2021), Pal and Sarda (2021b), Teng et al. (2021) attempted to develop it through monthly water
120 indices-based images. For compositing, the hydrological components and interpreting the overall

121 change in the hydrological environment in wetland, modeling approaches like statistical,
122 knowledge-driven, and machine learning (ML) algorithms are recommended. Among these, ML
123 modeling provides a good scope for solving non-linear relationships of the applied parameters in
124 a very robust way. A good many ML methods like Random forest (RF) (Shaikhina et al., 2019;
125 Han et al., 2020; Rahmati et al., 2020), Artificial neural networks (ANN) (Tian et al., 2019; Nhu
126 et al., 2020), Reduced Error Pruning Tree (REPTree) (Chen et al., 2019; Ghasemian et al., 2020;
127 Arabameri et al., 2021), Support vector machines (SVM) (Xiong et al., 2019; Singha et al., 2020;
128 Bouramtane et al., 2021) and many more were applied by the scholars for predicting risk, the
129 vulnerability of different kinds and reported credible result. Considering this, the present study
130 also applied ML models for developing hydrological strength models using image-driven
131 hydrological components. Since flood water is a reliable source of wetland, assessing flood
132 extent over time and analyzing wetland within or beyond flood extent is also very useful (Greet
133 et al., 2020; Karim et al., 2020). Flood simulation amongst is a reliable approach for this which is
134 applied in this present case. Based on this, the wetland was classified into para and ortho-fluvial
135 wetland by Ward and Stanford (1989). Para-fluvial wetlands are those that are directly linked
136 with the river (Deforet et al, 2009; Mondal and Pal, 2018). Following their thinking, the wetland
137 hydrological security state (WSS) was recognized in this present work.

138 From the literature survey, it is very clear that a good many studies dealt with river flow
139 modification and its hydro-ecological, geomorphological consequences in downstream rivers
140 (Yan et al., 2010; Li et al., 2017; Tonkin et al., 2018; Wang et al., 2018). A few works also
141 devoted to exploring hydrological dynamics in the riparian wetland in consequence of
142 hydrological modification in a river (Chakraborty et al., 2018; Zheng et al., 2019; Pal and Sarda,
143 2020; Pal and Sarda, 2021a; Pal and Sarda, 2021b; Pal et al., 2022). However, as far the
144 knowledge is concerned there is a dearth of work linking river and riparian wetland hydrological
145 modification selecting relevant hydrological parameters like pixel scale water depth, water
146 presence consistency, hydro-period, river flood water connectivity, etc. But integrated spatial
147 scale (pixel) analysis of hydrological conditions in the wetland concerning the degree of
148 hydrological modification in a river triggered by damming is very vital for understanding the
149 effect of it and devising sustainable planning for wetland management. Few case studies used
150 field-driven data for doing this, but there is a lack of work covering a large geographical area.
151 However, it is essential from the planning point of view. Therefore the current study aimed to

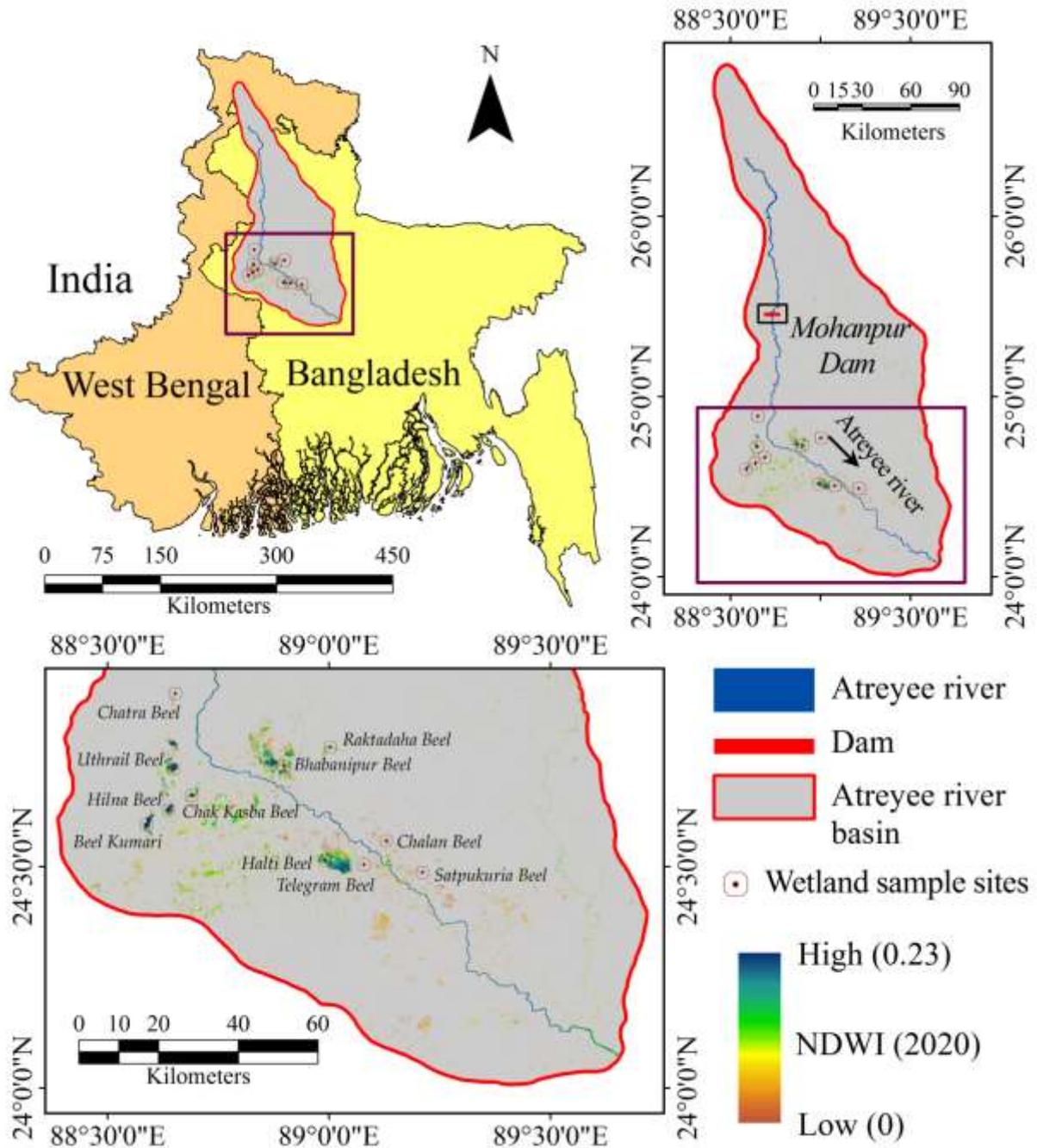
152 examine the degree of hydrological modification in the river and riparian wetland concerning
153 damming and linking them. The work was also in a question that can hydrological modification
154 bring noticeable changes in wetland morphology promoting other factors of wetland
155 transformation?

156 **2. Study area**

157 Atreyee river (390 km long), an India Bangladesh transboundary river with assorted aquatic
158 ecosystems (Adel, 2013). In the lower portion of this basin, a lot of rain-fed and flood water-fed
159 wetlands are available and they are generally located close to the main river (Figure 1). The
160 majority of the wetlands are seasonal and highly inconsistent in water appearance. Water furnish
161 to the wetlands depends on occasional rainwater and the frequency, duration, magnitude of
162 inundation of the Atreyee river (Pal and Saha, 2018; Pal and Sarda, 2020; Pal et al., 2021, Pal
163 and Sarda, 2021a). Water harvesting from the mainstream for different economic and domestic
164 purposes has gradually been expanded. For upgrading irrigation supply, the Mohanpur rubber
165 dam was built over the Atreyee river in 2012 and this episode has enhanced the water shortage in
166 the downstream main river and its alongside wetlands. The time after the development of the
167 dam (2012 onward) is considered as a post-dam stage. After the damming impact, the river and
168 riparian scene have experienced a huge alteration in the hydrological regime (Pal and Sarda,
169 2020). River damming is brought about by 30.97% and 64.01% discharge curtailed during pre-
170 monsoon and post-monsoon seasons and it is additionally caused for dwindling water
171 accessibility in the wetland (Pal, 2016b; Pal and Saha, 2018; Pal and Sarda, 2020). This is also a
172 very evident reason for wetland hydrological alteration. Considering this the lower Atreyee river
173 basin has been considered as a special case.

174

175



176

177 **Figure 1:** Location of the study area

178 **3. Materials**

179 To fulfill the objectives, consider three-hour interval discharge and water level data (from 1993
 180 to 2018) that were obtained from the Joda bridge river gauge station in Balurghat for monitoring
 181 hydrological modification, 2D flood modeling in the post-dam period. Specifically, for 2D
 182 floodplain modeling, the SRTM DEM was employed. Landsat-TM satellite images characterize

183 crucial and ongoing recordings of the earth's surface. We have separated the complete temporal
184 spectrum dataset into two phases-pre and post-dam for pre and post-monsoon season to
185 recognize the dam's influence. Over the last 33 years (1987-2020), cloud-free Landsat TM and
186 OLI were used to detect and monitor the inundation state of wetlands. Detail descriptions of the
187 images are provided in the supplementary section.

188 **4. Methods**

189 **4.1 Measuring flow alteration (heat mapping)**

190 There are many methods of measuring flow alteration like the Range of variability approach
191 ([Richter et al., 1998](#); [Yang et al., 2008](#); [Cheng et al., 2018](#); [Ali et al., 2019](#); [Tian et al., 2019](#)),
192 Revised range of variability approach ([Ge et al., 2018](#)), Histogram comparison approach ([Huang](#)
193 [et al., 2017](#)), Histogram matching approach ([Shiau and Wu, 2008](#); [Huang et al., 2016](#)). Among
194 this range of variability approach adopted to measure the flow alteration of the Atreyee river.
195 Besides, heat mapping is a good data visualization technique showing the changes of the
196 magnitude of the phenomenon in a gradient of color in two dimensions ([Barter and Yu, 2018](#)). In
197 this present context, a heat map was prepared using the time-series change of discharge data and
198 change of discharge data in pre and post-dam years (1997 to 2018) about each month.
199 Hydrological alteration of the post-dam period was computed about the average of the pre-dam
200 period. The Data matrix for the pre-dam period doesn't show any alteration rather an anomaly of
201 yearly discharge about the average of each respective month.

202

203 **4.2 Flow periodicity analysis**

204 For analyzing long-term time series variability, trend, periodicity Wavelet transformation
205 technique is very useful ([Talukdar and Pal, 2020](#)). Wavelet transformation is a well-built
206 mathematical signal processing technique that can offer both frequency and time domain
207 information from both non-stationary and stationary data sets, which together is difficult to
208 obtain from other standard methods ([Santos et al., 2018](#)). Fourier transformation can only
209 provide time or frequency domain ([Smith et al., 1998](#)), however, the wavelet transformation
210 method was built by modifying the Fourier transformation to receive both time and frequency
211 domain information ([Liu et al., 2016](#); [Wang et al., 2018](#)). Additionally, this method can construct
212 a multi-resolution analysis. For an instance, at a low scale of wavelet transformation, it yields a
213 good quality time resolution and at a high scale, it is just the opposite. This information is very

214 imperative for any time series analysis like time series discharge change. In the case of non-
215 stationary time series data (mean, variance, covariance, and autocorrelation change over time but
216 cannot return to its original position again), this method is well accepted and will be applied for
217 hydro-meteorological data series.

218 Goupillaud et al. (1984) deemed first wavelets as a group of functions constructed from the
219 translations and dilations of a single function, which is known as the “mother wavelet”. The
220 wavelet transform is defined by equation (1)

$$221 \quad \psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right); a, b \in R; a \neq 0 \quad (\text{Eq. 1})$$

222 Where, the scale parameter is symbolized by ‘*a*’ that appraises the degree of compression,
223 whereas, translation parameter that calculates the time location of the wavelet is presented by ‘*b*
224 ’. The ‘*a*’ parameter in the mother wavelet will be conditioned by the higher frequencies
225 (smaller support in the time domain) when $|a|$ will be less than 1. When $|a|$ will be more than 1,
226 then $\psi_{a,b}(t)$ has a larger time width than $\psi(t)$ that will correspond to lower frequencies.
227 Therefore, wavelets have time widths that are adapted to their frequencies that are the actual
228 reason behind the achievement and exclusive usefulness of the Morlet wavelets in signal
229 processing and time-frequency signal analysis.

230

231 **4.3 Method for measuring hydrological modification of wetland**

232 **4.3.1 Modification about hydrological components**

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

238 For developing hydrological components of the wetland, month scale Normalized differences
239 water index (NDWI) was first developed following Mcfeeters (1996) (Eq. 2). Saha and Pal
240 (2018), Pal and Sarda (2020) endorsed that NDWI is a suitable water index for wetland
241 delineation for this region. NDWI value 0-1 signifies wetland.

242
$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (\text{Eq. 2})$$

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

253
$$WPF(\%) = \frac{\sum_{i=1}^N BF_{pij}}{N_s} \quad (\text{Eq. 3})$$

254
255 Hydro-period map was developed from monthly NDWI maps. Binary NDWI maps of twelve
256 months in a year were summed up following Pal and Sarda (2021a). The value may range from
257 0-12. 0 signifies no wet period in a year and 12 means perennial wetland. Both seasonal and
258 perennial wetlands are ecologically important but perennial wetland has a better opportunity for
259 species phenology over a long period and economic turnover (Milani et al., 2019). This approach
260 is very efficient since it provides pixel scale hydro-period information over wider geographical
261 areas. The finer temporal resolution may provide more authentic data for doing this than the
262 Landsat product (temporal resolution: 16 days).

263 Water depth data is very crucial for analyzing the hydrological state of a wetland, but pixel scale
264 data, even point scale data is almost lagging. Khatun et al. (2021), Kundu et al. (2021), Pal and
265 Sarda (2021b) successfully attempted image-based derivation of water depth data at different
266 points in time. Following them, the present work also applied this approach of water depth
267 calibration of water indices (NDWI) using 130 field-driven sample depth data of nine wetland
268 sites. The accuracy of this map largely depends on the number of field-driven data for calibration
269 and suitable water indices. Abnormal natural and anthropogenic intervention on wetland water
270 strongly withstand against establishing a relationship between spectral value and ground truth

271 (Talukdar and Pal, 2020). Gao (1996) stated that NDWI value is related to water thickness. Good
272 water depth is related to the hydrological strength of the wetland since it provides sample
273 ecological niches of varying characteristics.

274 **4.4 Developing hydrological strength model**

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

279 **4.4.1 Artificial neural network (ANN)**

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

295 **4.4.2 Random forest (RF)**

296 Random forest (RF), presented by Breiman (2001) is a notable ensemble-learning calculation
297 that is a blend of decision trees for gathering or backsliding to predict with a higher precision
298 level. Besides, the RF method is broadly utilized for land use land cover classification,
299 regression, and unsupervised learning (Behnia and Blais-Stevens, 2018; Camargo et al., 2019;
300 Chen et al., 2020). RF comprises an ensemble of classifiers to establish a connection among

301 factors and weight generation for each variable. The RF algorithm produces many trees during
 302 the training stage, and the last weight is created by averaging all the tree values. RF classification
 303 utilized the resampling procedure by randomly changing the predictive variables to build the
 304 variety in each tree (Arabameri et al., 2020). In this study, the datasets are of high dimensional
 305 nature so it is essential to join the effect of each component then the model can predict the water
 306 wealth of the wetland with a higher precision level.

307 4.4.3 Reduced error pruning tree (REPtree)

308 The Reduced error pruning tree is a fast machine learning algorithm, which consists of Reduced
 309 Error Pruning (REP) and the Decision Tree (DT) (Quinlan, 1987). The prime goal of this
 310 algorithm is to reduce the difficulty of the modeling procedure when utilizing enormous
 311 information (Mohamed et al., 2012). In this calculation, the DT is applied to rearrange the
 312 modeling strategy using a preparation dataset when the output of a decision tree is huge, and the
 313 REP was used to lessen the complicity of the structure of the tree (Mohamed et al., 2012). This
 314 strategy reduces the complexity of the decision tree model during the pruning process and limits
 315 the model error. The straightforward setup and pruning strategy gives better exactness and
 316 lessens the over-fitting issue (Pham et al. 2019). In pruning measure, a decision tree can be
 317 pruned into two different ways, for example, pre-pruning and post-pruning. Pre-pruning is
 318 quicker with less exactness whereas post-pruning gives better precision (Chen et al. 2019). In
 319 this examination, the post pruning strategy was used to generate a series of pruned trees and to
 320 recognize an exact sub-tree from the test dataset.

321 **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

322

323 4.5 Validation of hydrological strength models

324 Nampak et al. (2014) rightly stated that there is no merit in modeling with no scientific
 325 significance; therefore, the validity and uncertainty of models need to be assessed. To
 326 authenticate the performance of the wetland hydrological strength models, several statistical
 327 measures including Sensitivity (SE), Specificity (SP), Kappa statistic (K), Area under the curve
 328 (AUC) in receiver operating characteristic (ROC) curve, and Matthews's correlation coefficient
 329 (MCC) were applied in this study. SE, SP, AUC, K values usually range from 0-1. A value near
 330 1 signifies a higher level of predictive agreement (Yang and Zhou 2015; Warrens and Pratiwi,
 331 2016). MCC was used to check the quality of binary classification of machine learning models
 332 (Chicco and Jurman, 2020). This coefficient ranges from -1 (complete disagreement in
 333 prediction) to +1 (perfect agreement in prediction). The equations of the statistical measures are
 334 put from Eq. 4-7.

$$335 \quad SE = \frac{TP}{TP + FN} \quad (\text{Eq. 4})$$

$$336 \quad SP = \frac{TN}{TN + FP} \quad (\text{Eq. 5})$$

$$337 \quad \text{Kappa statistic} = \frac{W_o + W_e}{1 - W_e} \quad (\text{Eq. 6})$$

$$338 \quad MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (\text{Eq. 7})$$

339 Where, TP= True Positive; TN=True Negative; FP=False Positive; FN=False Negative; W_o and
 340 W_e = Observed and Expected agreement

341

342 **4.6 Modification about lateral hydrological connectivity**

343 **4.6.1 2D inundation modeling**

344 The US Army Corps of Engineers developed HEC-RAS software to simulate floods using one-
 345 dimensional (1D), two-dimensional (2D), and three-dimensional (3D) models. In the scenario of
 346 a uniform cross-section channel, the 1D model can be utilized whereas, in the case of a channel
 347 with different cross-sections, the 2D model is implemented. The 2D simulation model was

348 employed for both the pre-dam and post-dam phases of the Atreyee river, taking into account
 349 variable cross-sections.

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

$$360 \quad \frac{\partial h}{\partial x} + \frac{\partial s}{\partial m} + \frac{\partial t}{\partial n} = 0 \quad (\text{Eq. 8})$$

$$361 \quad \frac{\partial s}{\partial x} + \frac{\partial}{\partial m} \left(\frac{s^2}{wd} \right) + \frac{\partial}{\partial n} \left(\frac{st}{wd} \right) = - \frac{n^2 sg \sqrt{s^2 + t^2}}{wd^2} - vwd \frac{\partial h}{\partial m} + sf + \frac{\partial}{\partial m} (wd\tau_{mm}) + \frac{\partial}{\partial n} (wd\tau_{mn}) \quad (\text{Eq. 9})$$

$$362 \quad \frac{\partial t}{\partial x} + \frac{\partial}{\partial n} \left(\frac{t^2}{wd} \right) + \frac{\partial}{\partial m} \left(\frac{st}{wd} \right) = - \frac{n^2 tg \sqrt{s^2 + t^2}}{wd^2} - vd \frac{\partial h}{\partial n} + yf + \frac{\partial}{\partial n} (wd\tau_{nn}) + \frac{\partial}{\partial m} (wd\tau_{mn}) \quad (\text{Eq. 10})$$

363 Where, wd is the depth of water (m),

364 s and t are the definite flow in the m and n directions (m^2s^{-1}),

365 h is the surface height (m),

366 v is the increase of rate due to gravity ($m s^{-2}$),

367 r is the Manning resistance,

368 ω is the water density ($kg m^{-3}$),

369 τ_{mm} , τ_{nn} and τ_{mn} are the components of the effective shear stress and f is the Coriolis (s^{-1}).

370 After producing inundation maps for both the pre-dam and post-dam phases, current-day
 371 wetlands were superimposed on these maps, and it was determined which section of a specific
 372 wetland is beyond or within the pre-dam and post-dam active flood plains. Wetlands are
 373 classified into three types based on their probability of receiving frequent floodwater. Wetlands
 374 that exceed the pre-dam flood limits are classified as having a critical status. Wetlands that are
 375 inside the pre-dam active flood limit but beyond the post-dam active flood limit are classified as

376 stressed wetlands. Wetlands within the current flood limit are considered safe wetlands since
377 they may receive frequent flood water.

378 **4.6.2 Classifying wetland security state (based on flood zones)**

379 Wetlands of the basin were classified based on lateral inundation zones before and after
380 hydrological alteration due to damming. After overlapping inundation zones of pre and post-dam
381 conditions, three zones were identified like (1) area inundated both during pre and post-dam
382 periods (2) area beyond post-dam but within pre-dam inundation limits, and (3) area beyond both
383 pre and post-dam flood limits. Wetlands were under three inundation zones were respectively
384 treated as (1) safe, (2) stress, and (3) critical about hydrological security particularly in terms of
385 lateral hydrological connectivity. Since in the rain-induced fluvial-flood plain region where
386 floodwater is one of the dominant sources of wetland, classification on this basis is very crucial.
387 Moreover, flood not only supplies water to the para-fluvial wetland but also supplies nutrients,
388 fish seeds, different species seeds, remove pollutants, etc. So, analyzing flood water connectivity
389 and classifying wetland is very essential. Here, it is to be remembered that a critical wetland
390 doesn't mean the wetland is devoid of water, it may be supported by rainwater, seepage water
391 but deprived of flood services.

392 **4.7 Morphological change of wetland (Fragmentation/shape sizes)**

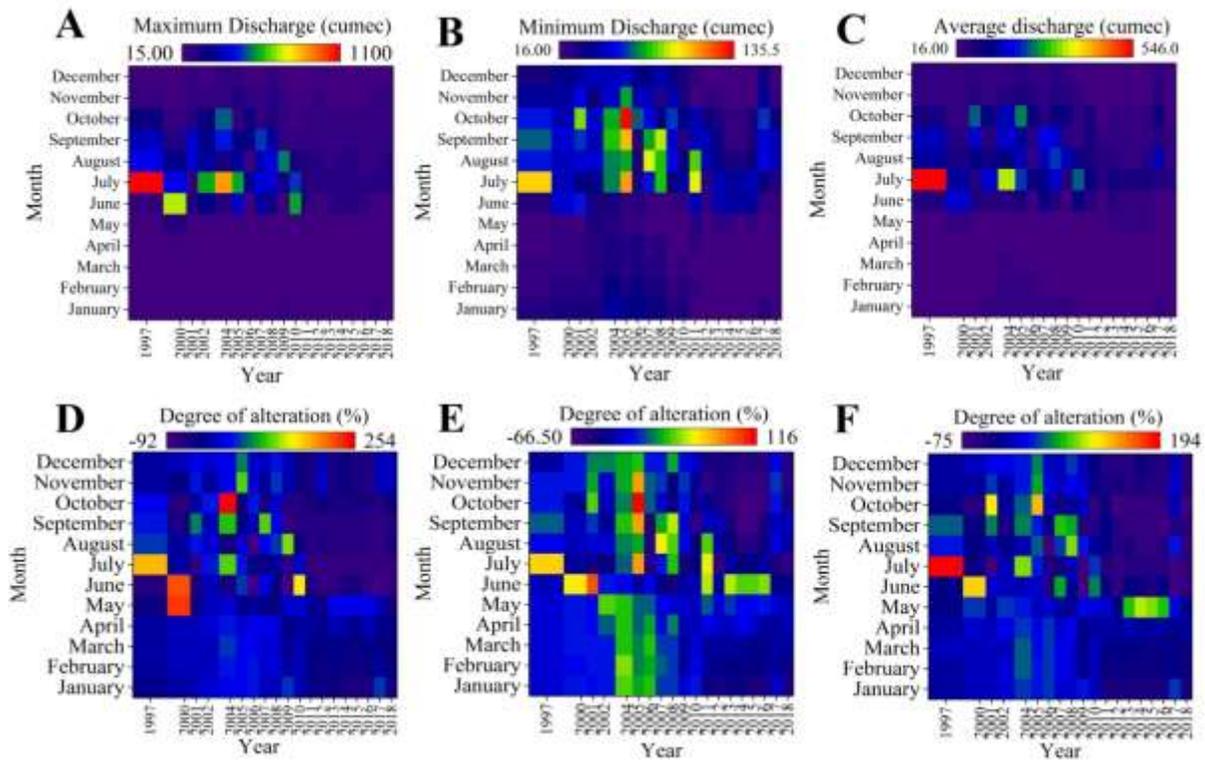
393 Landscape morphology is itself a good indicator of wetland hydrological dynamics. The
394 perennial and consistent wetland is less susceptible to morphological transformation than
395 seasonal, ephemeral wetlands that are hydrological irregular, erratic, and provide a scope of
396 activating invasive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

402 **4.8 Identifying associated modification**

403 There are different causes to be condemned for wetland loss, a hydro-ecological transformation
404 like agricultural, built-up land extension, infrastructure development replacing wetland,
405 attenuation of water availability, etc. However, the hydrological modification could be one
406 fundamental transformation of wetland that can also invite some other related causes (Das and

407 Pal, 2018; Pal and Sarda, 2020; Pal et al., 2022). Considering this the present section focused on
 408 some case studies exploring the nature of hydrological transformation and associated other
 409 causes directly from the field following the approach of the Millennium Ecosystem Assessment
 410 (MEA, 2005) report. Different drivers, driver's impact, current trend, etc were surveyed for each
 411 wetland.

412 **5. Results**
 413 **5.1 Flow alteration (heat mapping)**



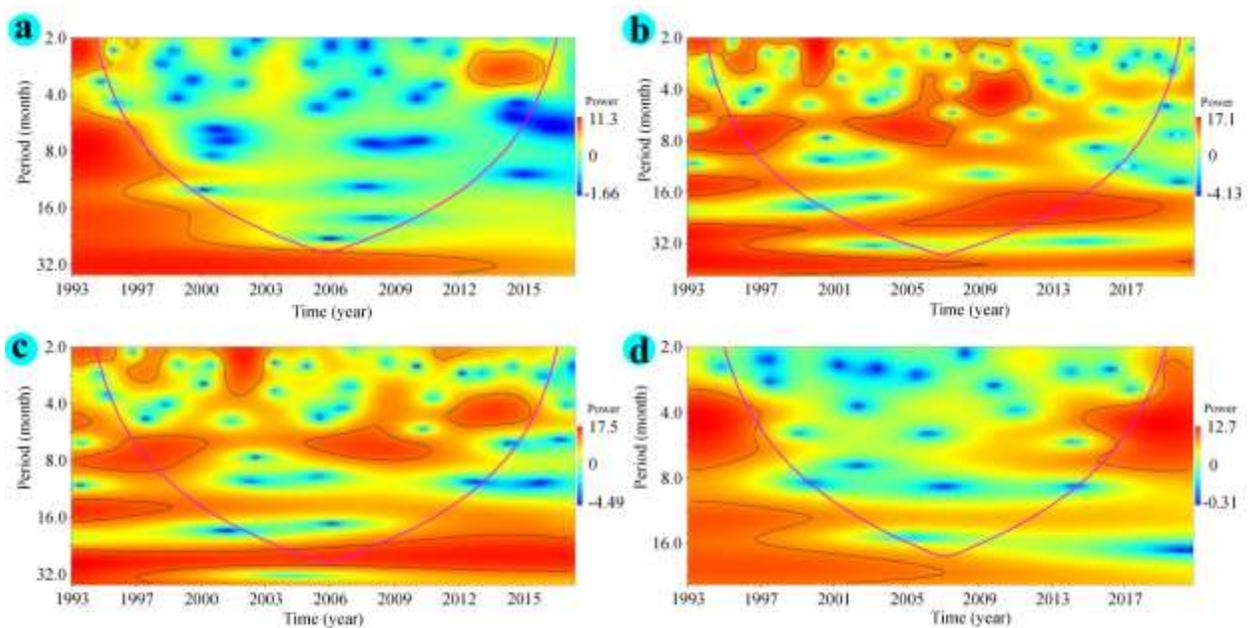
414
 415 **Figure 2:** Heat map showing flow alteration about absolute maximum, minimum and average
 416 discharge (A, B, C) and maximum, minimum and average discharge change rate (D, E, F). Here
 417 2012 is the damming year.

418 From the heat map of maximum, minimum and average discharge, and discharge change rate, it
 419 is very evident that in the pre-dam period discharge anomaly (positive and negative) is
 420 accountable for but its dynamics were highly observable in case of minimum discharge
 421 specifically in the monsoon months. After damming, the sharp decline of discharge without any
 422 incident of the anomaly was noticed (Fig. 2A, B, C). Similarly, the rate of discharge attenuation
 423 was found in post-dam conditions. For instance, it was up to 92%, 66.5%, and 75% in case of

424 maximum, minimum and average discharges respectively (Fig. 2D, E, F). Such change was
425 recognized more during monsoon months. Discharge increment rate was also recorded in these
426 heat maps, however; all such incidents were identified in the pre-dam period. It does mean there
427 were many years when maximum, minimum, and average discharge was greater than that of
428 respective average.

429 5.2 Periodicity Analysis

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

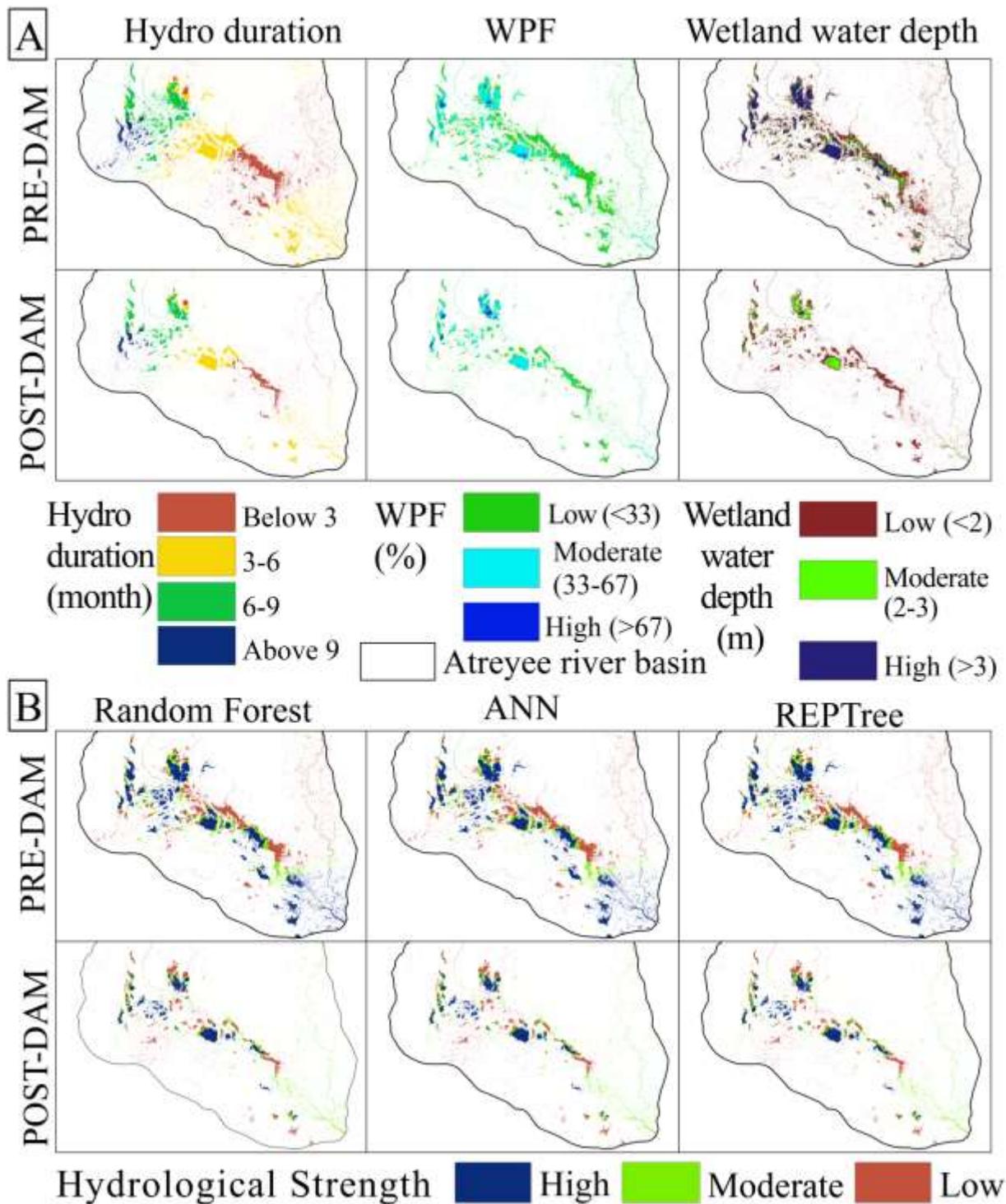


444 **Fig. 3** (a - d) Continuous wavelet power spectrum of average flow data from 1992 to 2018
445 recorded at Joda Bridge Gauge station over Atreyee river for (a) Pre-monsoon (b) Monsoon (c)
446 Post-monsoon and (d) Winter season. Red and blue represent stronger and weaker powers
447 respectively. A thick black contour line delineates a 5 % significance level against the red noise.
448 Conic concave area (border by pink color) shows the cone of interest within which significance
449 could be judged

450 **5.3 Hydrological modification of wetland**

451 **5.3.1 Modification about individual hydrological components**

452 Figure 4 (A) shows the hydrological components of the wetlands like hydro-duration, WPF, and
453 water depth. Each map was sub-classed and the area under each was documented in table 2.
454 About the hydro-period, the absolute area under longer hydro-duration (>9 months) was reduced
455 from 69.04 to 42.81 km² in between pre and post-dam periods. however, in terms of the
456 proportion of area, there was no significant change. The hydro-period below three months also
457 shows the significant reduction of the area indicating the improvement of hydrological state but
458 practically since the larger extent of area under this was completely obliterated in the post-dam
459 period. The same trend was also noticed in the case of WPF. Low WPF (<33%) zone was
460 squeezed from 743.12 km² (68.44%) to 332.57 km² (60.89%) in between pre and post-dam
461 periods (Table 2). High WPF was noticed slightly increased from 1.59% to 4.14%. In the case of
462 water depth, a significant increase (48.94% to 79.26%) of the proportion of wetland area was
463 noticed in the low water depth class (<2 m) and a decrease in high depth (>3m.) was observed.
464 High depth class area was declined from (371.31 km²) 34.70% to (10.49 km²) 1.92%. Some
465 areas were recognized where water depth was recorded low but despite having relatively greater
466 WPF and hydro-period. These areas may be highly susceptible to hydrological transformation in
467 the coming days. Figure 4 portrays that areas under each hydro-period, WPF, water depth sub-
468 class was substantially decreased in the post-dam period.



469

470 **Figure 4:** (A) Hydrological components of wetland like hydro-period, WPF, and water depth (B)

471 hydrological strength state models using different ML models for both pre and post-dam periods

472

473

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

Parameters	Period	Parameter sub-class	Area in km ²	% of area
Hydro-period (month)	Pre-dam	Below 3	299.83	28.02
		3 to 6	477.11	44.58
		6 to 9	224.22	20.95
		Above 9	69.04	6.45
	Post-dam	Below 3	114.86	21.03
		3 to 6	235.58	43.13
		6 to 9	152.92	28.00
		Above 9	42.81	7.84
WPF (%)	Pre-dam	Low	743.12	69.44
		Moderate	310.03	28.97
		High	17.05	1.59
	Post-dam	Low	332.57	60.89
		Moderate	191.01	34.97
		High	22.59	4.14
Wetland water depth (m)	Pre-dam	Low (<2)	523.72	48.94
		Moderate (2-3)	175.17	16.37
		High (>3)	371.31	34.70
	Post-dam	Low (<2)	432.89	79.26
		Moderate (2-3)	102.79	18.82
		High (>3)	10.49	1.92

476

477 5.3.2 Modification in reference to Hydrological strength (HS) models

478 Figure 4B shows the hydrological strength (HS) using ANN, RF, and REPTree ML models both
 479 for pre and post-dam periods. High HS was widely found across the river basin covering both
 480 upper and lower catchments during the pre-dam period but a huge area under this category was
 481 squeezed in the post-dam period. A large part of the wetland with high HS in the lower part of
 482 the basin was lost showing maximum degree of conversion. A large tract of wetland with high
 483 HS astride of river was also witnessed wetland transformation from high HS to moderate and

484 low. Table 3 depicts the area under different HS zones computed for each applied model.
 485 Noticeably, it was found that the area under the high HS zone was about 47% as per all the
 486 models but it was reduced to about 32% with very little inter-model areal fluctuation. The area
 487 under moderate HS zone was declined about the absolute area (210 km² to 187 km²) however in
 488 terms of relative area, it was increased by 14%. The area under high HS was shifted to a
 489 moderate HS zone. Applied ML HS models showed that there was no significant variation in
 490 areal extents and geographical positions of high, moderate, and low HS zones and thus, all those
 491 models could be valid. However, conventionally, it requires validation for finding out the most
 492 suited one.

493 **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)

494
 495 **5.3.3 Validation of HS models**
 496 From the applied statistical measures of validation, it is clear that all the applied models have an
 497 excellent agreement between map and ground conditions and therefore, could be accepted. AUC
 498 values range from 0.89 to 0.92, sensitivity from 0.89 to 0.9, specificity from 0.88 to 0.92, kappa
 499 coefficient from 0.89 to 0.94 indicating the acceptability of all the models. However, to select the
 500 best representative model, a comparative analysis of those values was done and the REPTree
 501 model was recognized as the best suited since all the measures show the highest agreement
 502 (Table 4). MCC value was also found 0.82 in the case of REPTree both during pre and post-dam
 503 periods and this value is greater than MCC produced by the other models.

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

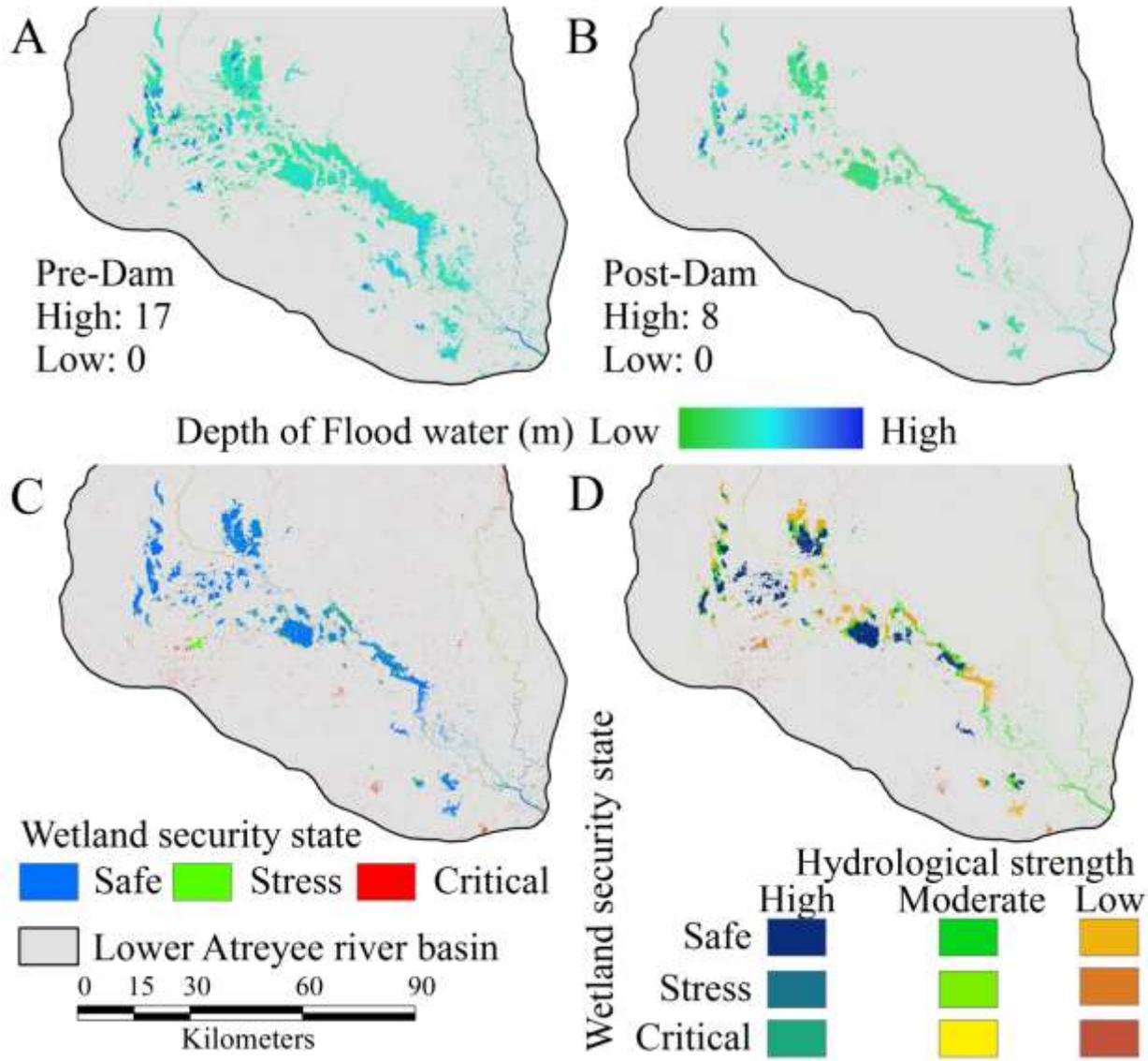
Phases	Models	AUC (ROC)	Sensitivity	Specificity	MCC	Kappa coefficient (K)
--------	--------	-----------	-------------	-------------	-----	-----------------------

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

505

506 **5.4 Modification in reference to lateral hydrological connectivity**

507 Flood water, flow of river water tie channel, groundwater flow connects the wetland with the
508 river (Tootchi et al., 2019; Yabusaki et al., 2020). Disconnection of some wetlands from lateral
509 flood spread limit deteriorates the water supply to the wetland. Figure 5 A and B respectively
510 represent the active inundation zones with possible floodwater depth in pre and post-dam periods
511 in the wetland domain. From the illustration, it is quite clear that the active inundation area in the
512 pre-dam period was considerably greater than the post-dam period. In the pre-dam period, the
513 inundation area was 4827.82 km² which was reduced to 1627.30 km² in the post-dam period.
514 Depth of floodwater ranged from 0 to 17 m. in pre-dam and 0 to 8 m. in post dam period. This
515 incident is directly linked with the dwindling of discharge and water level in the Atreyee river.
516 Spilling of the riverbank and rainfall are two major reasons behind rainfall in the flood plain
517 region. Pal et al. (2022) also identified the same declining trend of active inundation and area and
518 water depth in the post-dam period. River astride wetlands was also witnessed considerable
519 attenuation of water level and this led to reduction of inundated area.



520

521 **Figure 5:** Active inundation floodplain models of (A) pre-dam (B) post-dam periods (C) wetland
 522 hydrological security state (WSS) about the active inundation limits (D) wetland matrix of WSS
 523 and HS showing HS under different WSS zones

524 **5.5 Wetland hydrological security state (WSS) concerning inundation**

525 Based on the active inundation zones of the pre and post-dam period, the wetland was
 526 categorized into safe, stress and critical, and definitions of each were mentioned in the concerned
 527 method section. About the lateral flood water connectivity, 85.74 km² (18.79%), 100.72 km²
 528 (22.07%), and 359.72 km² (78.85%) of wetland areas of the present time were classified into

529 critical, stress and safe wetland security. Wetland away from the main river was recognized as
 530 critical due to the linkage of floodwater (Fig. 5C).

531 **5.6 Hydrological strength in wetland hydrological security zone (WSS and HS matrix)**

532 For further discrimination of wetland characters, the hydrological strength of existing wetland
 533 under different WSS zones was featured to know that how are the wetland without having lateral
 534 inundation water connectivity. Table 5 explains the HS character in different WSS zones.
 535 Usually, it was hypothesized that critical and stress WSS zone will have poor HS and safe WSS
 536 zone will have a high HS state with a greater proportion. Out of a total 85.74 km² wetland under
 537 the critical WSS zone, 78.14 km² was characterized by low and moderate HS. In the stress, the
 538 WSS zone total area was 100.72 km², out of which 79.7 km² fall under the low and moderate HS
 539 zone (Table 5). On the other hand, out of a total 359.72 km² wetland in the safe WSS zone,
 540 40.26% wetland was characterized by a high HS state. The findings of the present WSS and HS
 541 matrix satisfied the adopted hypothesis.

542 **Table 5:** Hydrological strength of wetland in different hydrological security states. The
 543 computed area under each zone is given in the table

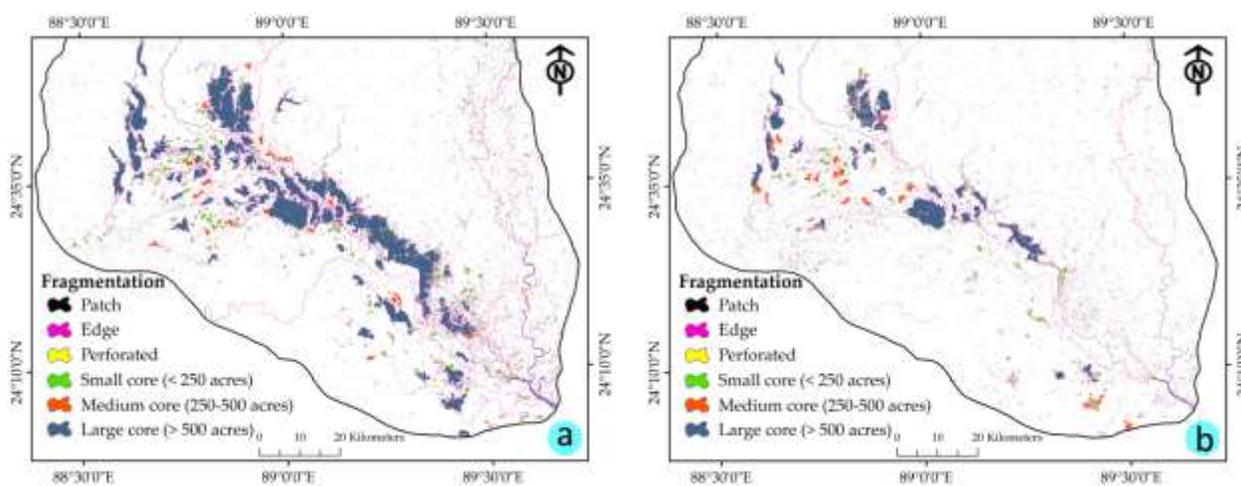
Wetland hydrological security state (WSS)	Hydrological strength (HS)	Area in post-dam period	
		Area in km ²	Area in %
Safe	High	144.84	26.52
	Moderate	96.36	17.64
	Low	118.52	21.70
Stress	High	21.02	3.85
	Moderate	43.37	7.94
	Low	36.33	6.65
Critical	High	7.60	1.39
	Moderate	47.26	8.65
	Low	30.88	5.65

544 **Note:** Wetland hydrological security state was determined based on lateral inundation
 545 connectivity and hydrological strength was determined based on hydrological components like
 546 WPF, HP and water depth

547

548 **5.7 Morphological change of wetland**

549 Figure 6 depicts the wetland fragmentation status in pre and post-dam periods. From the figure, it
 550 is very clear that there was well defined long wetland tract alongside the main river during the
 551 pre-dam period. In the post-dam period, most of the continuous large wetland tract was found
 552 fragmented. For instance, In the pre-dam period, 10.84% and 22.03% areas were under patch and
 553 edge area respectively but these were inflated during the post-dam period (patch and edge areas
 554 are 22.21% and 27.43%) signifying enhancement of adverse situation of wetland morphology.
 555 Contrarily, the large core area was reduced from 52.11% to 33.71% in between pre-and post-dam
 556 periods (Table 6). Growing fragmentation means increasing edge-area ratio which leads to the
 557 enhancement of anthropogenic intervention (Shen et al., 2019; Kundu et al., 2021). Such change
 558 is not only the alteration of landscape morphology, but it can adversely affect the serviceability
 559 of such precious natural capital (Lu et al., 2019).



560
 561 **Figure 6.** Wetland fragmentation showing patch, edge, perforated, small, medium, and large
 562 cores of (a) pre-dam and (b) post-dam periods
 563

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

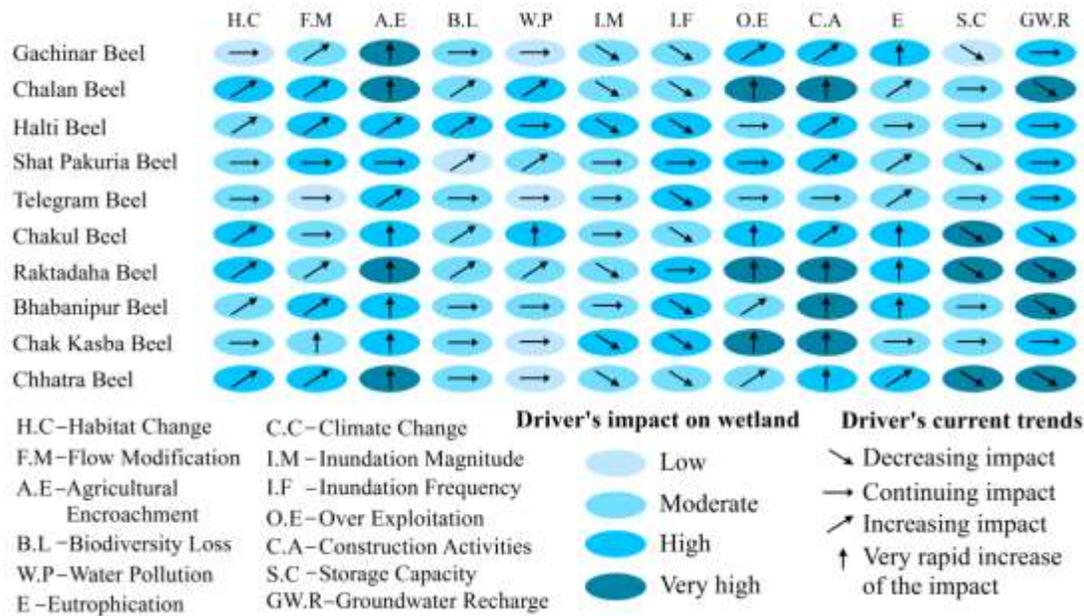
Landscape Fragmentation	Wetland condition in post-monsoon seasons	
	Pre-dam	Post-dam
	Area (km ²)	Area (km ²)
Patch	116.01(10.84%)	121.30 (22.21%)
Edge	235.77(22.03%)	149.81 (27.43%)

Perforated	15.30 (1.43%)	10.87 (1.99%)
Low core	122.32(11.43%)	64.23 (11.76%)
Medium core	22.80 (2.13%)	15.68 (2.87%)
Large core	557.68 (52.11%)	184.11 (33.71%)

566

567 **5.8 Identifying associated modification in some specific cases**

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



583

584 **Figure: 7** Current trends and degree of driver’s impact on the wetland of Atreyee river basin

585 **6. Discussion**

586 From the result, it is very clear that damming brought a landmark hydrological change in the
587 river and riparian wetlands. The squeeze of active inundation plain impacted adversely to the
588 wetland hydrological security. Poor hydrological strength was detected in critical and stress
589 wetland insecurity zones. About 48.97% wetland area was wiped out after damming. A large
590 tract of the wetland along the confluence segment of the main river at its proximity also
591 hydrologically weakened. Now the questions how the hydrological modification, wetland loss is
592 related to river flow modification?

593 Discharge attenuation after damming was well reported in this paper and this finding is
594 supported by similar works conducted by Zheng et al. (2019), Amenuvor et al. (2020), Chen et
595 al. (2021), Gao et al. (2021) across the world. The rate of attenuation depends on the degree of
596 anthropogenic control as reported by Fleischmann et al. (2019). Pal (2016b) investigated
597 hydrological modification in the Atreyee river and reported that average flow was reduced by
598 53%, reduced overall flood frequency, and flood magnitude above extreme danger level was
599 attenuated by 46%. Talukdar and Pal (2020) also documented the same trend of extreme
600 hydrological change in the Punarbhaba river of Barind plain.

601 Since the flood plain wetlands are fed by rain and floodwater, the dynamics of the flood of a
602 river are strongly linked with riparian flood plain (Fritz et al., 2018; Vidon et al., 2019; Alafifi

603 [and Rosenberg, 2020; Cui et al., 2021](#)). Lowering of floodwater level in Atrayee river during
604 monsoon season was identified as a prime reason behind the reduction of the active flood plain.
605 Rainfall reduction (28.76%) was also identified inflow availability in river and wetland reduction
606 ([Pal et al., 2022](#)) and it is also a reason behind active flood plain squeeze. Embanking rivers and
607 restricting discharge up to an artificially elevated level also is a major cause behind less spread
608 flood water laterally ([Galib et al., 2018; Sarkar et al., 2020](#)). But if the embankment is breached
609 anyway, it may cause the sudden spread of water laterally obliterating the natural and manmade
610 infrastructures ([Urzică et al., 2021](#)). It can adversely affect the wetland hydrological stability and
611 associated ecology. Since the water level was attenuated and the increased volume of water
612 during extreme depression during monsoon was capacitated by the raised embankment, flood
613 severity except during breach time was found weak. It is a well-explored cause for active flood
614 plain squeeze. Mondal and Pal ([2018](#)) also reported an active flood plain squeeze incident in the
615 Mayurakshi river basin of Eastern India.

616 As a result of this squeeze of the active floodplain during the post-dam period, a good proportion
617 of wetland was left beyond the present flood spread limit and these wetlands were started to
618 suffer from water scarcity, paucity of nutrients, fish seeds, and so on. Flood water supply at a
619 regular interval not only makes the wetland hydrologically secure but also ecologically efficient.
620 For instance, free nutrient and fish seed supply reduces the cost of fishing and thereby supports
621 the livelihood of the fishermen. The concentration of chemical fertilizers, pesticides residues
622 within wetlands leads to a great ecological threat ([Quintela et al., 2020](#)) like strengthening exotic
623 species growth and arresting the growth of valuable endemic species ([Maurya et al., 2019](#)).
624 Regular flooding can remove such noxious residues and refresh the wetland habitat ([Liu et al.,](#)
625 [2018](#)). Considering mainly water service of flooding, the wetlands were categorized into safe,
626 stress, and critical. Critical wetlands are not used to receive floodwater since from pre-dam
627 period and they are solely dependent on rainwater and seepage water. Lowering groundwater
628 tables and lessening rainfall ([Pal et al., 2022](#)) are therefore threats to the critical WSS. In the
629 stress WSS zone, floodwater is usually not received but rarely received. So, the wetland within
630 this zone is not hydrologically rich and ecologically prudent. Wetland within a safe zone receives
631 regular flood water and nutrients and therefore, is hydro-ecologically efficient. This sort of
632 wetland classification was also done by Talukdar and Pal ([2020](#)).

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

647 Lowering water availability in wetland, irregular water appearance for a short time often invites
648 agrarian people to invade the wetland. Initially, they used such area for seasonal cultivation but
649 gradually, they make it suitable for perennial agriculture land effacing its wetland characters
650 (Wondie, 2018). Often agriculture invasion is condemned as the most dominant cause behind
651 wetland loss in the flood plain region (Saha and Pal, 2019). Das and Pal (2018), Saha and Pal
652 (2019), Sarda and Pal (2021a) rightly pointed out hydrological deterioration can also promote
653 this vector. It may also promote the expansion of the built-up area since the study region is
654 densely populated. The increasing population demands more habitats for living. Often people
655 reclaim this land without considering its priceless serviceability. If such land is public, the rate of
656 reclamation is quite greater. All these are caused for the morphological transformation of
657 wetlands (Pal et al., 2022) as also found in this present study. Patch and edge dominated areas
658 were increased and the large core area was decreased in this present case. Increasing the edge
659 area ratio after growing fragmentation exerts extra pressure on wetland habitat and ecology
660 (Mukherjee and Pal, 2021). This trend of morphological wetland scape transformation is
661 commonly found across the world (Shen et al., 2019; Cui et al., 2021; Das et al., 2021; Kundu et
662 al., 2021).

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

680 **7. Conclusion**

681 From the result, it is very evident that damming was a major determinant of river flow and in
682 consequence of the attenuation of river flow, the active flood plain region was squeezed by
683 66.29% curtailing the water supply to the wetlands away from the current active flood plain
684 limit. Flow alteration also leads to loss of extensive wetland area and existing wetland was also
685 witnessed remarkable hydrological alteration. Hydrological strength models exhibited that area
686 under high HS state was substantially reduced inflating area under relatively weaker HS state
687 zones. Integrated analysis of wetland hydrological security state (WSS) based on lateral flood
688 water connectivity and hydrological strength (HS) categories revealed that critical and stress
689 WSS zones recorded relatively poor HS. Weakening hydrological strength was also identified as
690 a major reason behind promoting wetland fragmentation as was noticed after damming in the
691 present study.

692 The result itself is a vital instrument for wetland management and restoration. Reduction of flow
693 is the primary reason behind attenuation of flood spread and squeezing flood water spread is

694 caused for enhancing wetland hydrological insecurity state. So, to formulate sustainable wetland
695 management and restoration strategies, it is very essential to release the ecologically viable
696 amount of water to the dam downstream segment. It can only revive the river and riparian
697 wetland ecology. It can also help to restore the wetlands left beyond lateral hydrological
698 connectivity.

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

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1049 **Authors Contributions**

1050 All authors contributed to the study's conception and design. Conceptualization; Methodology
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1060 The datasets used and/or analyzed during the research work are available from the corresponding
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