Flow Forecasting and Measuring Environmental Flow Using Machine Learning Techniques

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Research Article

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Abstract

Flow alteration study in rivers persuaded by damming is well studied and reported significant flow failure. But how far the existing flow is ecologically ambient, in near future and what will be such situation are less addressed. Particularly, no such work is available in Atreyee river, a transboundary river between India and Bangladesh, the present area of interest. But it is essential from socio-ecological and ecosystem standpoints. Considering this, the present study has tried to predict river flow and assess its ecological relevance using soft computing advanced machine learning techniques like ANN, SVM and RF. Eco-deficit and surplus were assessed using a flow duration curve (FDC). The results indicate all the months' recorded eco-deficit conditions. Estimated environmental flow is moderately modified at present as per Environmental Management Class (EMC). The observed flow is 37.8m^3/sec which is less than FDC estimated environmental flow (42.3m^3/sec). Predicted flow in 2028, as per the best suited ANN, would be 56% lesser than present indicating the further departure of flow from the required environmental flow. It will perhaps pose an excessive burden to the ecosystem and socio-ecological fabrics.

1. Introduction

Amongst numerous reasons of hydrological modifications in a river like climate change (IPCC 2014; Chang et al. 2015), arresting water for hydro-electricity generation through the dam (Pal 2015), diversion and lifting of water for irrigation purposes across the river (Kingsford et al.2011; Arfanuzzaman and Syed 2018; Saha and Pal 2019b), hydrological alteration triggered by dam and barrages are prominent throughout the world (Tebakari et al. 2012; Pal 2015; Talukdar and Pal 2017). The increasing frequency of dams for taming the river for human use has been mounting the problem (Csiki and Rhoads 2010; Li et al.2013). As a consequence, in most cases, flow availability in the downstream section of the river is reduced. For example, in river Ganga, flow volume is reduced by 48% in the Post-Farakka period (Rahman and Rahaman2018); in Punarbhaba river of Barind region of India and Bangladesh, it is attenuated by 36% in the Post-Komardanga period (1992). Walling and Fang (2003) documented that nearly 22% of the world's rivers registered a noteworthy diminishing tendency in annual stream-flow in recent decades and the decrease of the annual stream-flow which cause great environmental problems as reported in the study of Pal(2015),Pal(2016),Rahman and Rahaman(2018),Talukdar and Pal (2017a), Pal and Talukdar (2018a),Pal and Saha (2018), Talukdar and Pal (2018).Graf (2006) inspected 36 US rivers detained by very large dam(s) and communicated that rapid maximum flow is diminished by 67% based on evaluations between river gauge records for unregulated stream segments and experimental regulated reaches. Such attenuation often causes flow below ecological needs. Eco-flow depicts the amount of flow, periodicity, quality of water that are needed to sustain the existing ecosystem and socio-ecological system depends on it (Li et al. 2020; Morid et al. 2019; Gosselin et al. 2019; Gostner et al. 2019). So, it is important both from an ecosystem and livelihood point of view. Improper maintenance of the downstream ecological flow sometimes exerts crisis on the existing ecosystem (Macpherson and Salazar 2020; O'Sullivan et al. 2020), species richness (Jarvis and Closs 2019), fish passages (Asaeda et al 2005; Dockery et al. 2019; Magaju et al. 2020; Moser et al. 2019; Plesinski et al. 2020), breeding, spawning of fishes (Harris et al. 2019; De-Miguel-Gallo et al. 2019; da Silva et al. 2020; Klopries et al. 2020), dependent likelihood of the stakeholders (Gallagher et al. 2020). It also imparts influence on changing channel morphology (Pal 2015), flood characteristics (Talukdar and Pal 2019), cropping pattern (Hao et al. 2020) and so on. As a consequence of damming, the water-rich area has turned into a water scarce area as modelled by Pal and Sarda (2021), Khatun et al. (2021) and such low flow persuaded eco-deficit causing species loss in the river and riparian wetland. Saha et al. (2021) has clearly predicted the influence of damming on the areal extent and depth of water in riparian wetland explains the fact that damming is not only the cause for hydro-ecological deterioration of the river itself but beyond that. Dam-induced eco-deficit is distinguished in Tangon river (Pal et al. 2018), Punarbhaba river, Yantez river (Wang et al. 2017). Talukdar and Pal (2018) documented 11 faunal and 7 floral species loss in the post-Komardanga dam period, Rahman and Rahaman(2018) identified 109 species that were lost in the Post-Farakka period. Eco-deficit is caused not only for reducing stream flow but also for turbulence in timing, high and low flow pulses, hydro-duration and flow fluctuation consistency of seasonal flow (Lin et al. 2014; Li et al. 2017; Talukdar and Pal 2019; Vega-Jácome et al. 2018). Artificial flow directive is principally caused for such indiscretion inflow and growing unpredictability in ecosystem stability (Friberg 2010; Rolls etal. 2012).

Growing intervention on river flow through damming often causes lowering flow below ecological minima and it is of great concern. In the last few decades, environmental flow appraisal has obtained priority. Many scholars have quantified ecological flow across the globe intending to flow reinstatement and long term supervision of the river, riparian ecosystem and the livelihood of the stakeholders (Liu et al. 2011; Beilfuss and Brown 2010; Joshi et al.2014; Adams2014; Liu et al. 2016; Pastor et al. 2014). Table 1 shows the methods concerning the assessment of the ecological flow of a river. Among these techniques Range of Variability Approach (Richter et al.1997), Flow Duration Curve Analysis (Tharme 2003) are frequently used techniques are present. The application of the Global Environmental Flow Calculator for calculating environmental flow for diverse ecological management classes is one of the signposts in this progress (Smakhtin and Anputhas 2006; Salik et al. 2016; Abdi and Yasi 2015). If all the existing methods are taken into consideration and categorized, there are four types i.e. (1) Hydrological or historic flow methods (2) Habitat methods (3) Hydraulic methods and (4) Holistic methods. Hydrological or historic flow methods are based on the records of the historical flow regime. Tennant (1976)method, for example, determines the EF as a percentage of the average annual flow. Hydraulic methods are dealt with the hydraulic geometry of a channel. Collings(1974) method is a customary one that defines the minimum flow based on the relationship between discharge and wetted perimeter. Habitat methods are based on the physical habitats simulation concerning flow. The stream-flow incremental methodology suggested by Bovee (1998) is a quite good example of this group. Holistic methods focus on water resource management about the riverine ecosystem as a whole. Precise estimation of eco-flow can extend an appropriate scope for restoration of the river and riparian ecosystem. So, this task is quite essential. In the developed nations, such work has been done affluently but there is an acute dearth of such work in the developing nations (Pal and Talukdar 2020). A clear report about the flow condition and ecological needs of each river should be in hand of the concerned policy makers for designing and implementing suitable strategies for its restoration and prevention.

Table 1
Different methods of Environmental flow estimation exercised across the world

Organisation	Source	Category of Methods	Sub-category/Example
IUCN	Dyson et al. (2003)	Look-up table	Q95 index
			Tennant method
		Desktop	Richter method
			Wetted perimeter
		Functional analysis	BBM
			Expert panel assessment
			Benchmarking method
		Habitat modeling	PHABSIM
IWMI	Tharme (2003)	Hydrologic index	Tennant Method
			RVA
			Flow duration curve (FDC)
		Hydraulic rating	Wetted Perimeter Method
		Habitat simulation	IFIM
			PHABSIM
		Holistic methods	Building Block Methodology
			DRIFT
			DRM
The World Bank	King et al. (2003)	Prescriptive	Tennant method
			Wetted perimeter method
			BBM
		Interactive	IFIM
			DRIFT

Eco-flow measurement about present flow condition is not only a prudent task. Since the flow alteration is observed in a particular direction, flow prediction and comparing predicted flow with the ecological needs are essential to make the strategies long-standing and effective (Gao et al. 2018). Flow prediction and eco-flow estimation have been done by the scholars separately (Lamouroux et al. 2015; Forio et al. 2015) lacking the integration of two vital issues for long-term inclusive hydro-ecological management of a river. This gap of research was the source of inspiration to carry on this research to estimate environmental flow, forecast flow and integrating these two issues for inclusive planning support. It will help to compare whether the predicted flow will be able to meet the needs of ecological flow requirements. Flow simulation and predictions based on statistical and mathematical predictors have got appropriate concentration over the last two or three decades. Although diverse methods are there, the use of machine learning techniques in this field has made new options for precise prediction of flow believing not only its net rise but also timing, high and low flow pulses, duration (Hoang et al. 2010; Wei et al. 2012; Yaseen etal. 2018; Zahiri and Azamathulla 2014). Few popular machine learning techniques are Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF). Table 2 shows brief pieces of literature on the application of machine learning methods in this regard and their success. In most cases, the applications of these methods have been done in developed countries and these are rarely applied in the country like India and Bangladesh. Considering the success of predictability, the present study has also relied on ANN, SVM and RF methods for flow forecasting and simulating. However, focusing on the issues of integration between eco-flow and flow forecasting for supporting effective strategies to the policy makers, the present work has tried to estimate eco-flow about historical flow and forecast flow to judge whether the predicted flow keeps in parity with ecological needs.

Table 2
Literatures on applied ML methods for flow forecasting

Applied ML methods	Applied in river	Model performance/Validation methods with the success rate	Reference
ANN, GP, MT	Narmada basin, Rajghat, India	R (0.7, 0.75 and 0.72), RMSE (3240.23, 3059.52 and 3204.34)	Londhe and Charhate, 2010
ANN, SVM	Changjiang River, EastChina	MAE (2922.15 and 2567.0), MRE (22.11 and 19.73) and R^2 (0.795 and 0.834)	Guo et al., 2011
ANN, ARIMA, LSSVM, SOM-LSSVM	Bernam River, Penisular Malaysia	MAE (0.06, 0.076, 0.045 and 0.037), RMSE (0.083, 0.104, 0.061 and 0.049) and R (0.86, 0.584, 0.876 and 0.922)	Ismail et al., 2012
ANN	Upper White watershed, USA	NSE (0.7115)	Kasiviswanathan and Sudheer, 2013
ANN, ANFIS, SVM	Pailugou catchment, northwestern China	R (0.938, 0.936 and 0.947), RMSE (388.255, 392.530 and 364.555), MARE (12.802, 13.637, and 11.713) and NSE (0.871, 0.869 and 0.887)	He at al., 2014
ARIMA, LSSVM, WLSSVM	Klang River, Malaysia	RMSE (4.63, 3.47 and 2.71), MAE (3.56, 2.83 and 2.07) and R (0.66, 0.84 and 0.89)	Shabri, 2015
ELM, SVR, GRNN	Tigris River, Middle East	R (0.799, 0.761 and 0.468), NSE (0.578, 0.378 and 0.144), WI (0.853, 0.802 and 0.689), RMSE (87.906, 124.155 and 135.35) and MAE (71.544, 108.36 and 112.60)	Yaseen et al., 2016
ANN, SVM	Hunza river, Gilgit–Baltistan	RMSE (161.59 and 147.01) MAE (94.87 and 86.68) and R^2 (0.869 and 0.872)	Adnan et al., 2017
SVR, M5, FOASVR	Aji Chay River, Iran	RMSE (9.22, 9.79 and 8.99), MAE (5.53, 4.62 and 3.71), R (0.53,0.75 and 0.81) and BIC (834.27, 771.78 and 703.64)	Samadianfard et al, 2019
ANN, SVM, HW-ANN, RF	Punarbhaba river, India and Bangladesh	RMSE (1.24, 1.16, 0.32 and 0.45), MAE (1.53, 1.27, 0.51 and 0. 63), MAPE (1.34, 1.22, 0.41 and 0.51), R (0.836, 0.853, 0.884 and 0.866)	Pal and Talukdar, 2020
Note: ANN: Artificial Neural Network; GP: Genetic Programming; MT: Model Trees; SVM: Support Vector Machine; ARIMA: Autoregressive Integrated Moving Average; LSSVM: Least Squares Support Vector; SOM-LSSVM: Self Organizing Map-LSSVM; ANFIS: Adaptive Neuro-Fuzzy Inference System; WLSSVM: Hybrid Wavelet-least Square Support Vector Machines; ELM: Extreme Learning Machine; SVR: Support Vector Regression; GRNN: Generalized Regression Neural Network; HW-ANN: Wavelet ANN, RF: Random forest; M5: M5 model tree; FOASVR: Fruit fly Optimization Algorithm-SVR			
R: Coefficient of correlation; RMSE: Root mean square error; MAE: Mean absolute error; MRE: mean relative error; NSE: Nash-Sutcliffe efficiency coefficient; MARE: mean absolute relative error; MAPE: Mean absolute percentage error, WI: Willmott's Index; R^2: Determination coefficient; BIC: Bayesian Information Criterion.			

2. Study Area

About 390km long Atrai or Atreyee river has started its journey from Sivoke district (lat. 26°48'46.14"N long. 88°29'13.68"E) of the Jalpaiguri of West Bengal, finally debouched into the Brahmaputra River also known as Jamuna in Bangladesh near Ratanganj (lat. 24°4'16.18"N long. 89°39'34.60"E) of Bangladesh passing through the Chalan wetland (Fig. 1). Old Himalayan Piedmont Plain, the Teesta mega-fan, the Barind region, and the Ganga floodplain are the catena of this basin from source to confluence. The neo-tectonically uplifted Barind tract (11-48m amsl), a Pleistocene older alluvium terrace covers the entire middle and lower catchment of the basin (Rashid et al. 2013; Rashid and Islam 2015; Rashid et al. 2015). The average annual rainfall in this basin is about 1500mm and Out of the total rainfall, 81% takes place during the monsoon season, influenced by the southwesterly monsoon (Hossain et al. 2019; Rahaman et al. 2016;Mukherjee et al. 2007). Agriculture is the mainstay of the region's economy, but now the region is facing water crisis for many crops (Rashid et al. 2013). So, to supply huge irrigation water and to receive greater productivity, a Rubber Dam (135m long and 4.5m high, with 12km of the dam in the river and dam capacity of 7,290,000m^3) was constructed in 2012 at Mohanpur (lat. 25°32'23.28"N long. 88°45'35.39"E) in Bangladesh (Fig. 1), bringing a significant modification in the hydrological regime both upland downstream of the dam, especially in India portion 55km of river course over two blocks Kumarganj and Balurghat of West Bengal.

3. Materials And Methods

3.1 Materials

Three hours interval discharge data (Joda bridge gauge station, Balurghat) from 1993 to 2018 have been collected from Irrigation & Waterways Dept. Balurghat, Govt. of West Bengal and Irrigation & Waterways Dept. under North Bengal Planning Division, Malda for analyzing it's changing the hydrological regime and prediction of river flow.

3.2 Periodicity Analysis

Wavelet transformation is a very useful technique for analyzing long-term time-series trends, variations, and periodicity. According to Santos et al. (2018),wavelet transformation is a strong mathematical signal processing approach that can provide both time and frequency information from both stationary and non-stationary data sets, which is difficult to get by other standard methods. Where, Fourier transformation can only give either time or frequency domain (Smith et al. 1998), On the other side, the wavelet transformation method was developed by modifying it to get both time and frequency domain information (Wang et al. 2018; Liu et al. 2016; Amezquita-Sanchez & Adeli 2015). In addition, this approach can build a multi-resolution analysis. For instance, at a low scale of wavelet transformation, it produces good quality time resolution and in the case of high scale, the result shows exactly the opposite. This information for time series analysis is very imperative.

Therefore, wavelet transformation has become a more accepted technique to crack time series problems (Amezquita-Sanchez & Adeli2015). The non-stationary time series data (mean, variance, covariance and autocorrelation are changed over time and not able to get back in their previous original state) are most suitable to run the wavelet analysis to discover the variability of the data. So, the wavelet transformation method is employed on the hydro-meteorological time series data assessment because of its non-stationary nature.

Goupillaud et al. (1984) considered first wavelets as a family of functions built from the translations and dilations of a single function, which is called the “mother wavelet”. The wavelet transformation is defined by Eq. (1)

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

Where, the scale parameter is represented by ‘’ that evaluates the degree of compression, whereas, translation parameter that computes the time location of the wavelet is represented by ‘’. The ‘’ parameter in the mother wavelet will be characterized by 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 corresponds to lower frequencies. Therefore, wavelets have time widths that are adapted to their frequencies that are the actual reason behind the achievement and exclusive usefulness of the Morlet wavelets in signal processing and time-frequency signal analysis.

3.3 Measuring the hydro-ecological states

Estimation of eco-deficit and eco-surplus are two inclusive measures for assessing the overall impact of flow modification in a river. Vogel et al. (2007) recommended the non-dimensional metrics of eco-deficit and eco-surplus based on the flow duration curve (FDC). FDC of unregulated and regulated periods are plotted to illustrate eco-deficit and surplus. The area between regulated FDC and unregulated FDC indicates the amount of water now unavailable in the river due to flow alteration caused by the water diversion. Eco-deficit is the ratio of this area over the total area under the unregulated median of annual FDC. This ratio emphasizes the portion of stream flow is no longer existing in the river during that period. On the other hand, eco-surplus is the area above the unregulated FDC and below the regulated FDC divided by the total area under the unregulated median FDC. Thus, eco-deficit and eco-surplus are dimensionless measures that present the deficit or surplus of stream flow resulting from flow regulation, as a fraction of the mean stream flow in a definite time scale. Vogel and Fennessey (1995) also employed eco-deficit and eco-surplus techniques for direct ecological measures like habitat suitability.

3.4 Predicting flow

For predicting river flow, three machine learning techniques are applied i.e. (1) Artificial Neural Network (ANN), (2) Support vector machine (SVM), and (3) Random forest (RF). As per literature, all the models can produce a dependable result but as the present study area experiences a drastic change in river flow, three such advanced methods are applied to choose a better predictable model.

3.4.1 Artificial Neural Network (ANN)

An artificial neural network is an extensively exercised soft computing machine learning algorithm that is used for solving real problems. It is a parallel distributed information processing system that works like the human brain functioning that has encompassed numerous numbers of neurons that connect each other and form a network and transmit information to the brain. In a very analogous manner of the human brain, the neural network is structured by its architecture that consists of connecting nodes, its method of determining the connection weights and the activation function. The most commonly applied neural network structure is the feed-forward hierarchy. The nodes of the neural network are processing elements of the network and are known as neurons. It collects an input signal, processes it and transmits it as an output signal to the other interconnected neurons.

In the hidden and output layers, the net input to the unitis of the form as Eq. 2

$Z = \sum_{j=1}^{k} W_{ji}y_j + \theta_i$ (Eq. 2)

Where, W_{ji} = the weight vector of unit,

= the number of neurons in the layer above the layer that embraces unit,

y_j = the output from unit,

Y_i = the bias of the unit.

The weighted sum Z, an incoming signal of the unit is then transmitted by the transfer function to yield the computes $\hat{y}_i$for unit. The sigmoid function is continuous, differentiable universally, and monotonically escalating. The sigmoid transfer function, f_i, of unit , is of the form as Eq. 3

$\hat{y}_i = \frac{1}{1+e^{-z}}$ (Eq. 3)

Therefore, to solve the problems of the neural network, a training algorithm is essential. Generally, numbers of training algorithms are available but it is required to select an algorithm, which gives the best fit to the data. Recently, the multi-layer perceptron (MLP) is the most widely used neural network typologies. The MLP is characterized by the back propagation algorithm. The MLP with two hidden layers are a universal pattern classifier for static pattern classification.

The back-propagation rule propagates the errors by the networks of the neurons and permits adjustment of the hidden units. Two vital characters of the multilayer perceptron are: its nonlinear processing elements (PEs) and their massive interconnectivity first one have a nonlinearity that must be smooth (the logistic function and the hyperbolic tangent are the most widely used); and the second one reflects any element of a given layer feeds all the elements of the next layer.

3.4.2 Support vector machine (SVM)

Basically, the support vector machine model has been used for diverse reasons, such as classification, pattern recognition, regression analysis and forecasting. It shows good performance in the ages of artificial intelligence (Adnan et al. 2017; Garsole&Rajurkar 2015;Kisi 2015; Deo et al. 2017; Gong et al. 2016). The most important thing of the support vector machine is that it offers an extraordinary solution in the effect of the convex characteristics of the model problem and used a high-dimensional space set of kernel functions, which delicately incorporates nonlinear transformation. Consequently, it has no scientific assumption in functional transformation, which makes it indispensable to have linearly divisible data. Ashort explanation of the support vector machine is given below using Eq. 4. The main relationship for the statistical learning process is as follows:

$$z = f(y) = \sum_{i=1}^{P} w_i \phi_i(y) = w\phi(y) \text{ (Eq. 4)}$$

Where, the output of the model represents the part of linear P and the converter is presented by the nonlinear model by $\phi(y)$. This equation is converted as the below for using the support vector machine model:

$$z = f(y) = \left\{ \sum_{i=1}^{L} w_i K(Y_i, Y) \right\} - c \text{ (Eq. 5)}$$

Where, K represents the Kernel function, w_i and represents parameters of the model, is the total number of learning patterns and $Y_i$means the data vector for network learning and represents an independent vector. The parameters of the model are determined by maximizing the objective of the function.

3.4.3 Random forest (RF)

RF model usually uses the plan of a randomly chosen subset of m predictors to construct a binary tree, where each tree is produced on a bootstrap sample of the training data set (Breiman2001). This machine-learning algorithm is the amendment of bagging and a competitor to boosting (Polikar2012). The regression trees necessitate no suppositions of the distribution of data (Francke et al.2008). For every tree, the response data are clustered into two offspring nodes that strengthen the homogeneity and the best binary spilt is chosen. This chosen split of each offspring node is taken likewise to the original node and this procedure keeps on recursively until a stop criterion is assembled.

All the trees are grown to their maximum sizes and ultimate predictions are achieved from the average results (Breiman2001). In random forest modelling, three parameters are required to be specified: (1) the most imperative parameter is the required number of trees that grow in the forests (ntree), (2) at each node, the required number of randomly chosen predictor variables (mtry); and (3) the lowest number of observations at the terminal nodes of the trees (nodesize).

3.5 Modelling process

In the present study, the entire time-series datasets for the period of 1993-2018were used to extrapolate the discharge data for incoming years. To predict future forecasting for each year we have used all years for pre and post-dam, otherwise, it would have been difficult to predict future conditions.

A sequence of observations made sequentially in time is a time series. Time series forecasting effectively takes models and then applies them to historical data and then using them to predict future observations. For eg. min(s), day(s), month(s) before the measurement is used as an input to predict the next min(s), day(s), month(s).The steps that are considered to shift the data backward in the time(sequence) are called lag times or lags. Initially, the input data is time-series discharge data, when this data goes through the modelling process, the data gets divided and automatically convert to lag according to software needs. The model parameters have been optimized using a trial and error process, we have run the models many times by changing the values of the parameters, after getting the best result we fixed the model parameters. Additionally, a time series problem can be transformed into a supervised ML by adding lags of measurements as inputs of the supervised ML. Therefore, in the present study, we used 5 lags and one lag signifying five years of data, which were used as inputs for forecasting future discharge. We kept the lags the same for all models. We set 5 lags by evaluating 1–4 lags as the results are satisfactory for the 5 lags. Even, we also checked other parameters, such as rainfall to find a relation to the discharge and found that these parameters had very less control on the discharge generation (supplementary table 1). Therefore, it can be stated that the forecasting process is scientific and robust. For forecasting the discharge we have used WEKA (Waikato Environment for Knowledge Analysis, 3.8.2 version) software.

3.6 Validation of the models

For validating the predicted discharge as per the applied ML methods, simulation of existing flow (up to 2018) is done. Simulated result is compared with observed data on that span of time. Adjacency between simulated and observed flow data is computed using (1) Root Mean Square Error (RMSE) (2) Mean Absolute Error (MAE) (3) Mean Absolute Percent Error (MAPE)(Schaeffer, 1980;Willmott, C.J. and Matsuura, 2005) and (4) Pearson's correlation coefficient (Pearson 1896). It is supposed that if the simulated data is matched with existing data in an acceptable range, the predicted flow data could be treated as valid.

3.6.1 Root Mean Square Error (RMSE)

This statistic was obtained through the Eq. (6):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}} \left(P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right)^2 \text{ (Eq. 6)}$$

The less this statistic, the better is the function of the model.

3.6.2 Mean Absolute Error (MAE)

This statistic was obtained through the Eq. (7):

$$MAE = \frac{\sum_{i-1}^{n}\left|P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right|}{n} \text{ (Eq. 7)}$$

3.6.3 Mean Absolute Percent Error (MAPE)

This statistic was obtained through the Eq. (8):

$$MAPE = \left(\frac{1}{n}\sum \frac{|Observed.flow - predicted.flow|}{|Observed.flow|}\right) \times 100 \text{ (Eq. 8)}$$

3.6.4 Correlation between actual and simulated flow data

This statistic was obtained through the Eq. (9):

$$R^2 = \frac{\sum_{i=1}^{n}\left(P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right)\left(P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right)}{\sqrt{\sum_{i=1}^{n}\left(P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right)^2\left(P_{(predicted.flow)\,i} - Q_{(observed.flow)\,i}\right)^2}} \text{ (Eq. 9)}$$

3.7 Estimating environmental flow

3.7.1 Flow duration curve shifting method

Smakhtin and Anputhas (2006) established Global Environmental Flow Calculator (GEFC). Nowadays, this calculator is widely used to calculate the environmental flow requirements of a river. In global environmental flow calculator, 17 fixed percentiles (0.01, 0.1, 1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, 99, 99.9 and 99.99%) are used to wrap the whole range of flow variability from top to bottom. Smakhtin and Anputhas (2006) classify the ecological management classes into six categories, e.g. A, B, C, D, E, and F, and these classes evaluate the different ecology-friendly conditions of the river. This calculator can estimate the water requirements for these six ecological management classes. These six management ecological classes are presented by different names according to their characters (Table 3). For instance, classes A and B are represented as an original and largely natural state, on the other side E and F are considered as largely modified and ecologically unsuitable. Class D is considered as the marginally permissible management condition, while class C is considered an environmentally acceptable condition that maintains the ecosystem. The Flow Duration Curve is estimated for the 17 fixed percentiles and the first FDC curve is represented as an original reference curve. Then, the flow requirements of the ecological management class are estimated by the method of shifting the original reference to one percent. Lastly, environmental flow requirement is computed by dividing the total flow value of 17 fixed percentiles with each EMC class by the mean annual flow (MAF) and expressed as a percentage, which gives the percentage of MAF for each EMC class. The post dam reference FDC has been plotted along with the computed FDCs for six EMC classes to show the position of FDC within the wrap of six categories.

Table 3
Description of different Environment Management Classes

Environmental Management Class	Ecological description	Management perspective	Environmental Flow Percentage*
A: Natural Flow	Minor modification of in stream and riparian habitat.	Protected rivers and basins. Reserves and national parks. No new water projects allowed.	82.3
B: Slightly Modified	Largely intact biodiversity and habitats despite water resources development and/or basin modifications.	Water supply schemes or irrigation development present or allowed.	69.4
C: Moderately Modified	The habitats and dynamics of the biota have been disturbed, but basic ecosystem functions are still intact. Some sensitive species are lost or reduced in extent. Alien species present.	Multiple disturbances associated with the need for socio-economic development, e.g. dams, diversions etc.	59.8
D: Largely Modified	Large changes in natural habitat, biota and basic ecosystem functions have occurred. A clearly lower than expected species richness. Much lowered presence of intolerant species. Alien species prevail.	Significant and clearly visible disturbances associated with basin and water resources development, including dams, diversion, habitat modification and water quality degradation.	51.9
E: Seriously Modified	Habitat diversity and availability have declined. A strikingly lower than expected species richness. Only tolerant species remain. Indigenous species can no longer breed. Alien species have invaded the ecosystem.	High human population density and extensive water resources exploitation.	45.1
F: Critically Modified	Modifications have reached a critical level and ecosystem has been completely modified with almost total loss of natural habitat and biota. In the worst case, the basic ecosystem functions have been destroyed and the changes are irreversible.	Management interventions are necessary to restore flow pattern, river habitats etc (if still possible/feasible)	39.2
Source: Smakhtin and Anputhas (2006)			
**Percentage of natural flow required to maintain the EFs for the selected EMC*			

4 Results

4.1 Hydrological alteration

Dam construction has curtailed the downstream discharge of the Atreyee river. In this view, Fig. 2 represents the average discharge of the Joda bridge gauge station in different seasons from1993 to 2018, denoting the year of damming (2012). For instance, in the post-monsoon season, the discharge in the pre-dam period was 77.54m^3/sec which is reduced to 34.68m^3/sec; in monsoon season, the discharge is attenuated from 165.6m^3/sec to 56.81m^3/sec in between pre to post dam periods. Maximum and minimum discharge is also changed in the same direction (Table 4). Pal (2016b) clearly identifies that the volume of reduction in some months specifically in pre and post-monsoon months is so high that it is beyond the ecological threshold limit.

Table 4
Maximum and minimum flow regime (cumec), fluctuation (%), trend in pre and post-dam of Atreyee river

Season	Discharge in cumec			% of Discharge gap	CV in %		Pre- dam		Post-dam	
	Pre- dam	**Post-dam**	**Discharge gap**		**Pre-dam**	**Post-dam**	**Trend (Y = a + bx)**	**R^2**	**Trend (Y = a + bx)**	**R^2**
Pre-monsoon	Max.: 29.9	Max.: 23.11	6.79	22.7	49.85	40.35	y = -0.025x + 30.32	0.000	y = 2.014x + 15.54	0.284
	Min.: 21.59	Min.: 18.80	2.78	12.91	18.40	9.35	y = 0.046x + 20.24	0.037	y = 0.237x + 17.61	0.135
Monsoon	Max.:410.88	Max.: 98.95	311.93	75.91	101.56	20.76	y = -9.773x + 799.5	0.231	y = 0.736x + 79.44	0.023
	Min: 59.30	Min.: 36.56	22.74	38.36	59.31	25.13	y = -0.201x + 67.05	0.016	y = -0.148x + 37.52	0.003
Post monsoon	Max.: 168.1	Max.: 66.95	101.15	60.17	142.98	43.55	y = -2.564x + 247.9	0.029	y = -5.015x + 73.34	0.426
	Min.: 49.87	Min.: 22.77	27.09	54.33	51.14	23.35	y = -0.324x + 59.28	0.044	y = -1.236x + 28.96	0.405

4.2 Periodicity Analysis

Figure 3 (a-d) represents the continuous wavelet power spectrum of average flow in pre-monsoon, monsoon, post-monsoon and winter seasons. Significant variability in the wavelet power spectrum is displayed in 3–5 years' band from 2012-onwards, in case of all seasonal stream flow. From observing the wavelet power spectrum, the highest power (represents the variance of flow) is found near the bands of 3–4 years from 2012 to 2015. It does mean that the entire flow nature has been changed more or less in the same direction and magnitude. In the pre-monsoon season, the strong power is recognized in 2–3 years' band from 2012 to 2015 (Fig. 3a). In the monsoon season, a strong wavelet power spectrum is displayed in 2–8 years' band from 2000 to 2009; in 16–30 years' band from 2012 to 2017 (Fig. 3b). In the post-monsoon season, a small amount of scattered significant spectrums are noticed. Among them, comparatively stronger significant spectrum is located in 2-2.8 years' band from 1995 to 2000, 4 to 7 years' band from 2012 to 2015 (Fig. 3c). In the winter season, few strong spectra are noticed after 2012. So, it can be stated that non-monsoon seasons are more susceptible to the change of flow regime. After 2012 strong variability is noticed both during post-monsoon and pre-monsoon seasons.

4.3 Hydro-ecological state

Vogel and Fennessey (1995) also use eco-deficit and eco-surplus techniques for direct ecological measures like habitat suitability measures. Figure 4portrays monthly FDCs for unregulated (pre-dam period) and regulated (post-dam period) flow states to show the ecological surplus and deficit. Unregulated FDC curve of unregulated flow above the regulated FDC does signify that in every point of flow probability discharge is larger than regulated flow state. From Fig. 4 it is revealed that all the months of the year show eco-deficit in post-dam condition although the gap between regulated and unregulated FDCs differs signifying the magnitude of eco-deficit. The magnitude of eco-deficit is very high in most of the months except pre-monsoon months. For instance, in July, discharge is > 300m^3/sec in unregulated flow conditions and it is < 100m^3/sec in regulated conditions. In other months of the year, shows the same picture with varying magnitudes. Regulation of flow through dam has also created such a situation in the Punarbhaba river (Talukdar and Pal2018), Tangon river (Pal et al. 2018) between India and Bangladesh, Yantze river (Wang et al.2017), Mekong river (Li et al.2017) and Rimac basin (Vega-Jácome et al.2018). This eco-deficit state is dangerous for the ecological sustainability of a significant number of species (Gain and Giupponi.2014). Various researchers found this kind of similar result in their study site and clearly reported eco-deficit state of post-hydrological alteration period such as Wang et al. (2018) on Yangtze River of China, Ren et al (2018) on Wei river in Guanzhong Plain of China, Dong et al. (2019) on upper Yangtze River.

4.4 Flow prediction and validation

Three flow prediction models (ANN, SVM and RF) are applied for predicting seasonal flow for the next 10 years using historical flow data. Historical flow data is also simulated and predicted for accuracy assessment as to when observed flow data is available (Kişi 2008; He et al. 2014;Ghorbani et al. 2020; Imrie et al. 2020)Fig. 5represents the simulated data from1993 to 2018 and Fig. 6shows predicted flow up to 2028 for pre-monsoon, monsoon, post-monsoon and winter seasons. Results of the used models indicate that in all the seasons, the predicted flow is likely to be declined but the predicted value is not uniform.

For instance, the predicted discharges in monsoon, 2018 are 186.45m^3/sec, 181.96m^3/sec and 185.16m^3/sec as per ANN, SVM and RF models respectively. In, pre-monsoon season, the predicted values are 17.64m^3/sec, 18.34m^3/sec and 19.22m^3/sec in the same order. In case of other seasons also, the discharge is curtailed by 35–43% with reference to 2018 in winter and post-monsoon seasons as predicted by the models. As the model-specific predicted discharge is different, it essential to justify the suitability of the predictive models in this case. For this, an accuracy assessment is required.

In this work, simulated discharge data is compared with observed discharge data from 1993 to 2018 and RMSE, MAE and MAPE errors are computed. Based on the error statistics, all the applied models can be treated as accepted but ANN model can best be applied for the discharge prediction purpose (Table 6). Pearson’s correlation coefficient and level of significance between observed and simulated flow data are shown in Table 5. Performances of all the models would have been far better if the post-dam discharge data series could have been excluded from the prediction process. A significant reduction of discharge was triggered by damming after 2012 where the maximum proportion of error is attributed. However, the predicted discharge is computed to understand the fact that whether the predicted discharge will be within the ambit of threshold categories.

For the Atreyee river, the yearly average flow requirement of different ecological management classes is represented by a table (Table 7) of flow values (percentiles) covering the entire range of probabilities of occurrence corresponding to 17 fixed percentage points: 0.01, 0.1, 1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, 99, 99.9, and 99.99%. Table 7 indicates the amount of water required for sustaining the river ecosystem based on the pre-dam phase water availability. Calculated post dam reference flow shows the amount of water between slightly modified to moderately modified EMC zone of 10–80 percent of the flow exceedance level, whereas 90-90.99% flow exceedance level the requirement of water is less than critically modified EMC zone.

Table 5
Pearson’s correlation coefficient and level of significance between observed and simulated flow data

Models	Pre-monsoon		Monsoon		Post-monsoon		Winter	
	r	sig.	r	sig.	r	sig.	r	sig.
ANN	0.891	0.001	0.918	0.001	0.92	0.001	0.882	0.01
SVM	0.84	0.01	0.873	0.05	0.88	0.001	0.85	0.05
RF	0.81	0.01	0.827	0.01	0.86	0.05	0.84	0.05

Table 6
Computed RMSE, MAPE and MAE errors between observed and simulated discharge data for the used models

Models	Pre monsoon			Monsoon			Post monsoon			Winter		
	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE
ANN	1.654	5.332	1.208	14.675	16.082	9.873	4.358	8.320	3.287	1.547	5.011	1.322
SVM	3.741	5.055	1.449	4.061	1.978	1.295	22. 67	9. 643	6. 63	3.285	5.329	1.478
RF	2.619	7.752	1.971	51.449	42.47	37.849	22.042	18.951	12.945	3.382	7.639	2.408

Table 7
Yearly average flow requirement of different EMC classes for Atreyee river which calculated from global environmental calculator, value is in Million cubic meters (MCM)

Flow exceedance (%)	Pre dam reference flow	Natural	Slightly modified	Moderately modified	Largely modified	Seriously modified	Critically modified	Post dam reference flow
0.01	1985	1920	1402	867	590	338	227	548
0.1	1920	1402	867	590	338	227	154	536
1	1402	867	590	338	227	154	119	426
5	867	590	338	227	154	119	91	230
10	590	338	227	154	119	91	77.9	170
20	338	227	154	119	91	77.9	66.8	134
30	227	154	119	91	77.9	66.8	53.6	117
40	154	119	91	77.9	66.8	53.6	50.7	104
50	119	91	77.9	66.8	53.6	50.7	45.7	75.5
60	91	77.9	66.8	53.6	50.7	45.7	43.1	60.5
70	77.9	66.8	53.6	50.7	45.7	43.1	42.9	53
80	66.8	53.6	50.7	45.7	43.1	42.9	42.7	50.1
90	53.6	50.7	45.7	43.1	42.9	42.7	42.5	41.5
95	50.7	45.7	43.1	42.9	42.7	42.5	42.3	40.6
99	45.7	43.1	42.9	42.7	42.5	42.3	42	39.9
99.9	43.1	42.9	42.7	42.5	42.3	42	41.8	38.8
99.99	42.9	42.7	42.5	42.3	42	41.8	41.6	37.8

4.5 Environmental flow

Post-dam flow state about computed monthly EMC presented in Fig. 7. Predicted discharge is also compared with the EMCs to know the possible hydro-ecological security or poverty of the river in the coming days. It is vital for making future strategies for water management. Each EMC class estimates a specific ecological flow requirement at a specific probability level. As per the mechanism of calculation, the ecological flow requirement is high in the case of higher EMC (Poff et al.2010).

According to Sood et al.(2017), Richter et al. (2012) flow modification could be allowed up to moderately modified EMC. Largely, severely and critically modified EMCs are not ecologically sustainable enough, therefore interpretation of the present result is done with reference to the flow volume which is within moderate EMC or beyond it. Table 7shows the Yearly average flow requirement of different EMC classes as well as different flow exceedance level, from this, a general idea about the whole year of both periods can be obtained.

In all the months, the post-dam flow state is beyond moderately modified EMC. It does signify that the existing flow condition is ecologically hostile and thus not suitable for ecosystem health and vitality. If the percent probability of flow exceedance is considered, up to 30% probability of exceedance, the present flow condition is within severe to critical EMC which was almost double or more than that in pre-dam flow state in the respective months. The flow state is ecologically more adverse in pre and post-monsoon seasons compared to monsoon months. If the absolute discharge is taken into consideration, ecological flow requirements are 91.37, 60.41, 280.12,139.76 million cubic meters (mcm) in the months of January, May, September and November respectively. But, the observed availability of discharges is51.62, 43.83, 82.44 and 62.39 mcm of those months. It does indicate that observed flow is lower than the required discharge. In other months also the same result is found. If the predicted flow is compared with the computed EMCs, the ecological state is further to be degraded.

5. Discussions

Application of Range of variability approach (RVA) is rightly used for assessing ecological threshold limits of flow assessment of a river by many scholars like Wang et al. (2016), Gain et al. (2013), Yin et al. (2012), Gain and Giupponi (2014), Chen et al. (2010). Global Environmental Flow Calculator-based assessment of ecological management classes is an advanced approach and widely accepted among scholars and applied frequently in developed nations. It’s application is quite limited in developing countries. It computes the required volume of environmental flow at different probability levels. In the present study region, there is a seasonal rainfall regime that controls the flow regime of a river. The ecosystem and the species are accustomed to this regime. Therefore, the estimation of annual ecological flow is not a prudent approach. Considering this reality, the present work has estimated monthly ecological flow. It can guide the policymakers to make a comprehensive plan for flow regulation. Based on the dominant ecological species in the river and riparian environment, the flow requirement of a river should be decided and flow should be allowed accordingly. The application of machine learning techniques like ANN, SVM, RF is crucial for predicting the future flow trend. As these methods try to capture the historical flow frequency, magnitude and duration of high and low flow pulses and using them for predicting the flow, it’s credibility is high. Among the machine learning methods, it is very difficult to select the best method ubiquitously as the performance of these methods is not equal in all the fields of usage as well as in the different regions (Denil et al. 2013; Coates et al. 2011). Literature survey has stated that the application frequency and success rate of these methods are satisfactorily high. A good number of studies still recommended ANN, SVM and RF are suitable for predicting flow (Jajarmizadeh et al. 2015; Cid et al. 2016; Shafaeiand Kisi 2017). All three methods are applied for the same work considering the fact that they can give a comparative output and based on their performances, the best predicting methods could be selected. Prediction of flow is vital to adopt long-term flow management strategies of the river. It also helps to understand whether the predicted flow will meet the environmental flow. In the present study, it is found that flow is reduced in the post-dam period and it is likely to be reduced by 35–43% in the coming 10 years. This finding is quite similar to the findings of Poff and Zimmerman, (2010), Wang et al. (2016),Liu et al. (2016), Rahman et al. (2017), Kumar and Jayakumar (2018, 2021), Pal and Talukdar (2020), Mezger et al. (2020), Li et a. (2020). All these works validate the finding of the present work. In the present situation, the observed discharge is below the required water volume as per EMC and this situation is likely to be more grave in the coming days since the estimated discharge is likely to fall below the expected flow requirement. Previous works have estimated declining trend while predicting discharge in Changjiang river, Bernam river, Klang river, Upper White river, Hunza river but in those cases, whether the predicted discharge will meet the ecological flow requirement has not been addressed (Guo et al.2011; Ismail et al.2012; Kasiviswanathan and Sudheer, 2013; Shabri, 2015; Adnan et al.2017). Dyson et al. (2003), Beilfuss and Brown (2010), Lin et al. (2014), Gao et al. (2018), Kumar and Jayakumar (2018), Macpherson and Salazar (2020)have estimated eco-flow using different techniques and reported eco-hydrological deficit after damming which cross validates the finding of the present work. But, they have not extended their works about predicted flow pointing out the fact that whether the predicted flow will meet the EMC requirement. However, it is very much necessary for sustainable hydro-ecological management of a river and riparian environment. So, bridging these two issues is vital for effective and sustainable planning. This work has both predicted river flow and compared it with the ecological requirement in the predicted time. Since the result has clearly demonstrated the growing gap between flow volume and ecological requirement, it has figured out the fact that immediate measures are to be taken for restoring the river flow and ecological setup there over.

Flow alteration over and above ecological threshold flow provokes habitat and ecosystem vulnerabilities like increase of stress, hydrological poverty (Poff and Zimmerman 2010; Sahaand Pal 2019b; Pal and Talukdar 2018b). Eco-deficit in all the months as shown in Fig. 4with reference to flow state of the pre-dam period demonstrates the uprising hydro-ecological poverty. Significant reduction of discharge caused by the diversion of water through the dam and other forms of water extraction is one of the principal causes behind the growing eco-deficit state. The declining trend of flow was also reported by some previous scholars like Wang et al. (2017) in the case of Yangtze river; Li et al. (2017) and in the case of Mekong river. But they did not predict flow and compared it with ecological flow requirements in forecasted time. Sima and Saed (2017) also documented that flow reduction has not only invited the ecological degradation in the river but also the riparian flood plain wetland. Reduction of wetland habitat, lowering of wetland water depth, duration of water availability and increasing uncertainty in the rhythm of wetland hydrological dynamics are some direct consequences of the growing eco-deficit condition of the river (Yang et al. 2017; Talukdar and Pal 2019; Ziaul and Pal, 2017). Direct impact on the ecological species is not investigated in this study but previous works clearly mentioned simplification of species diversity and loss of species. For instance, Gain and Giupponi(2014)reported diversion of water through Farakka barrage (1975) in the river Ganga cause the destruction of breeding and hunting ground of 109 species of Gangetic fishes species, amphibians and other aquatic species. Hossain and Haque (2005) explored that more than 50 species have become rare in post Farakka period in Bangladesh part.

6. Conclusion

The present study measures the environmental flow, analysis the periodicity of flow, simulation and prediction flow using advanced machine learning techniques. Periodicity of flow is noticed in all the seasons as displayed by the significant degree of spectral power (variability) in the continuous wavelet spectrum. After 2012, changes in river flow are clear. All the employed simulation models predicted showing a declining trend of flow in all the seasons however ANN model could be considered as the best for predicting flow. All the months show an eco-deficit condition clearly. This is a vital time to focus on this concern and adopt some proper strategies for restraining the flow alteration. Policymakers can decide the actual amount of water to be released from the Rubber Dam for the survival of the ecosystem based on these results. Predicted flow displays that such alteration continues in upcoming years and will go down below ecological requirements. So, it can be stated that this analysis has fundamental importance on remaking the running strategies of flow management and explore some alternatives of flow sustenance. A river is not represented as a pool for irrigation activities but an essential environmental part with multi-faceted socio-economic as well as hydro-ecological benefits. Considering this fact in mind, the release of ecologically sufficient flow is highly necessary for the survival of the river as well as riparian habitat health and ecosystem vitality.

Declarations

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Authors Contributions

All authors contributed to the study's conception and design. Conceptualization, methodology designing, writing, review and editing were performed by Dr. Swades Pal. Data curation, investigation, software, validation, and writing original draft were performed by - Dr. Tamal Kanti Saha. All the authors read and approved the final manuscript.

Availability of data and materials

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129. **Statements and Declarations**

Supplementary Tables

Supplementary Table 1 is not available with this version.

Figures

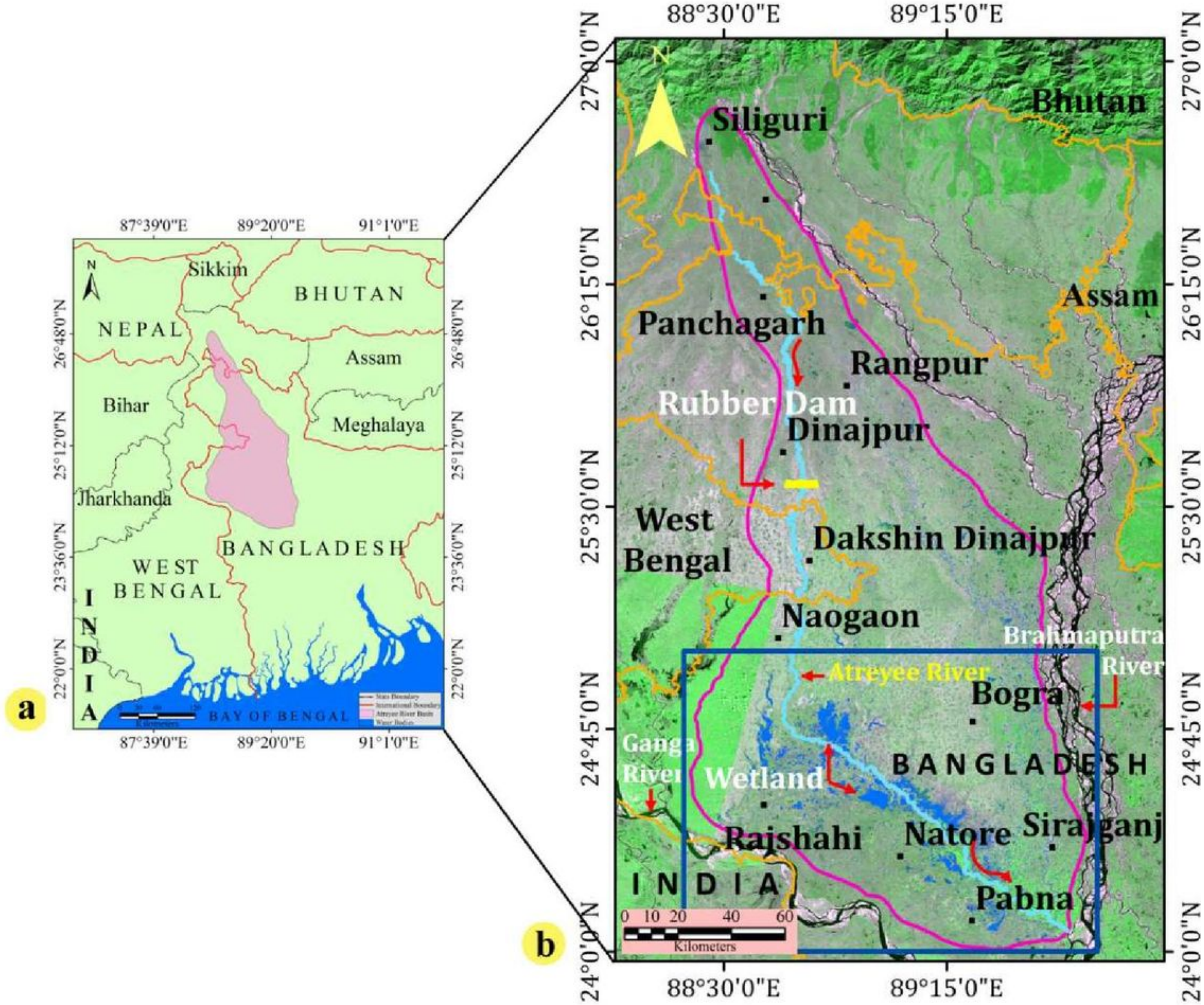

Figure 1

(a) Location of Study area, (b) thick pink colour line indicate basin boundary, blue colour patches indicate wetland in the river basin, and thick yellow horizontal line represent location of dam

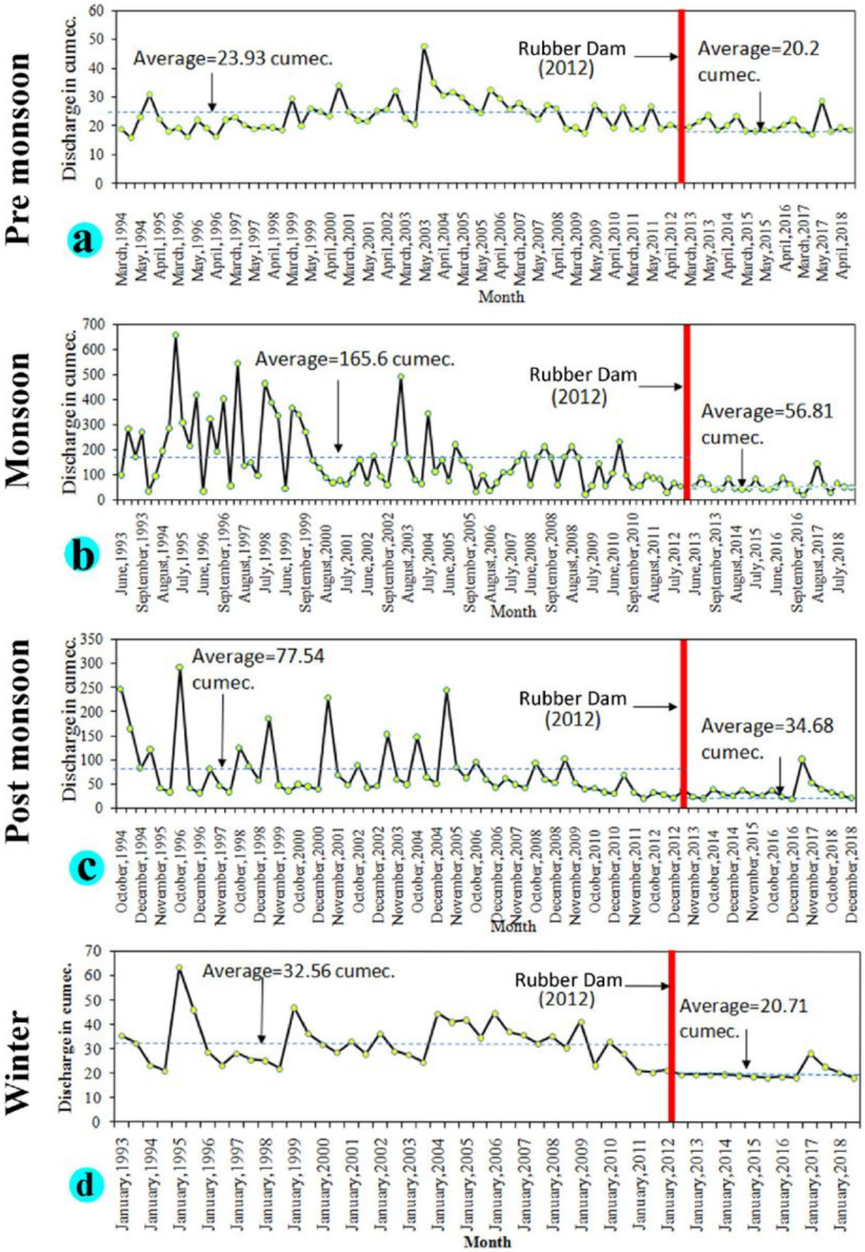

Figure 2

Average flow regime in different seasons- (a) Pre monsoon, (b) Monsoon, (c) Post monsoon and (d) Winter; red colour vertical line indicate dam construction year

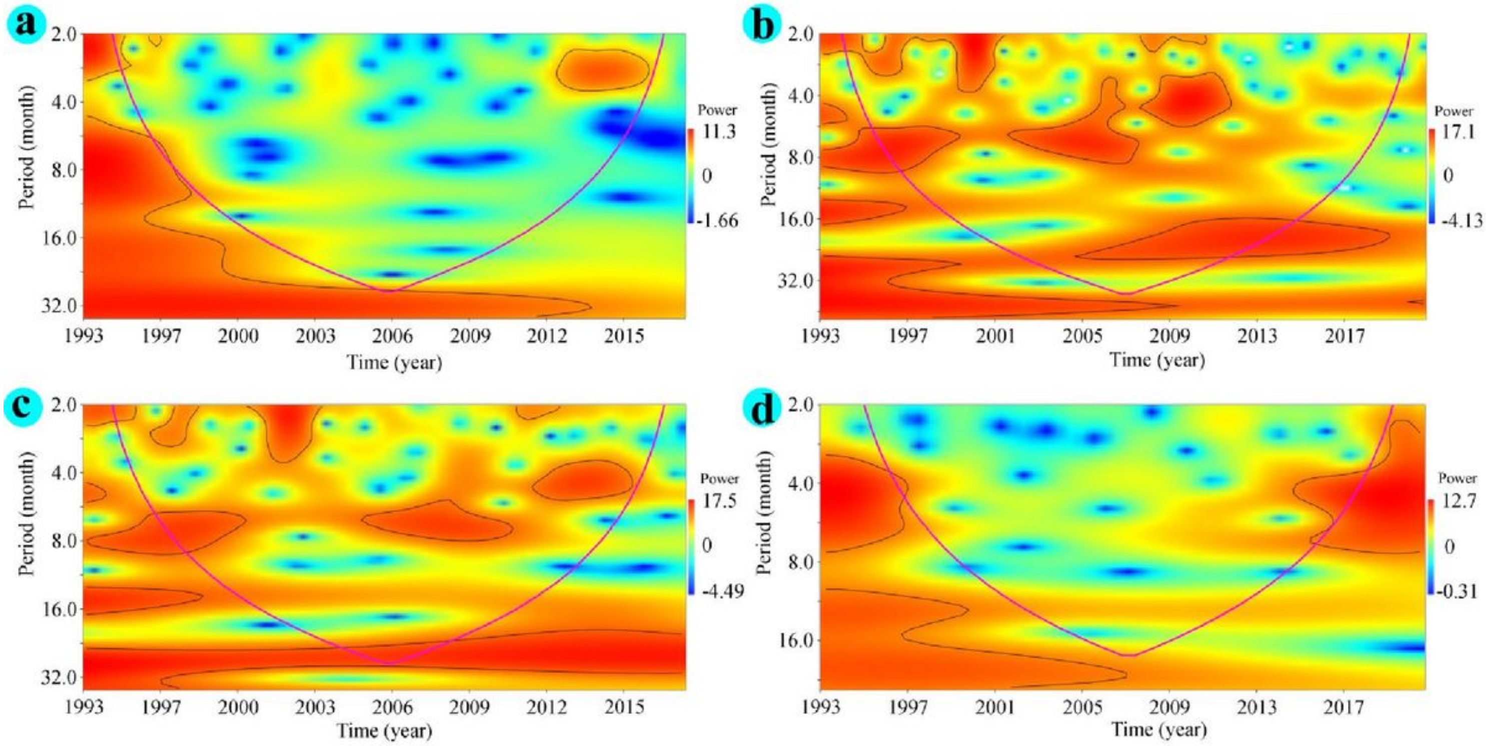

Figure 3

(a - d) Continuous wavelet power spectrum of average flow data since 1992 to 2017 recorded at Joda Bridge Gauge station over Atreyee river for (a) Pre-monsoon (b) Monsoon (c) Post-monsoon and (d) Winter season. Red and blue represent stronger and weaker powers respectively. A thick black contour line delineates a 5 % significance level against the red noise. Conic concave area (border by pink color) shows the cone of interest within which significance is judged

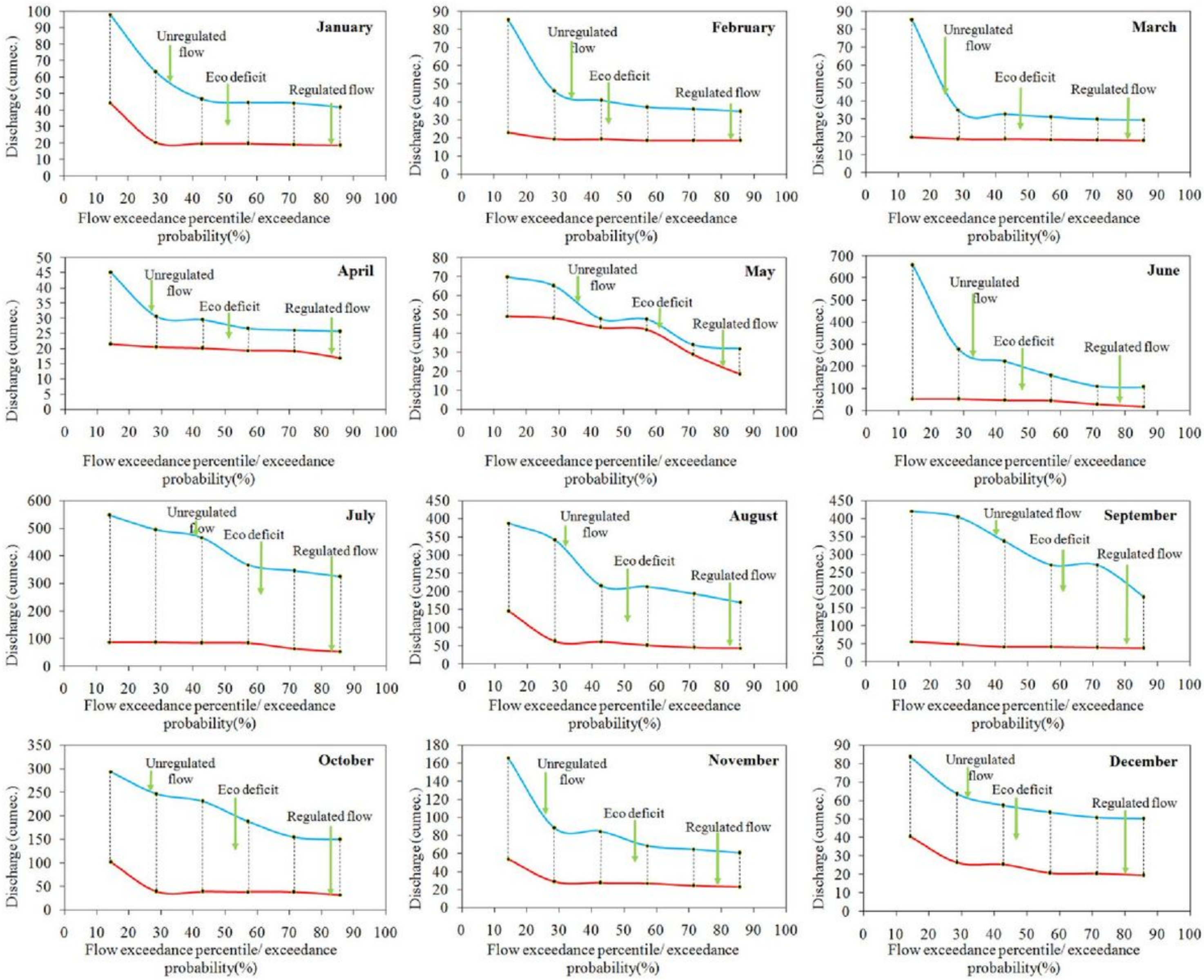

Figure 4

Monthly FDC for ecological surplus and deficit, blue colour line indicate unregulated flow and red line indicate regulated flow of Atreyee river, black colour vertical line indicate the gap between pre and post dam flow. This gap between unregulated and regulated flow as indicated is eco-deficit

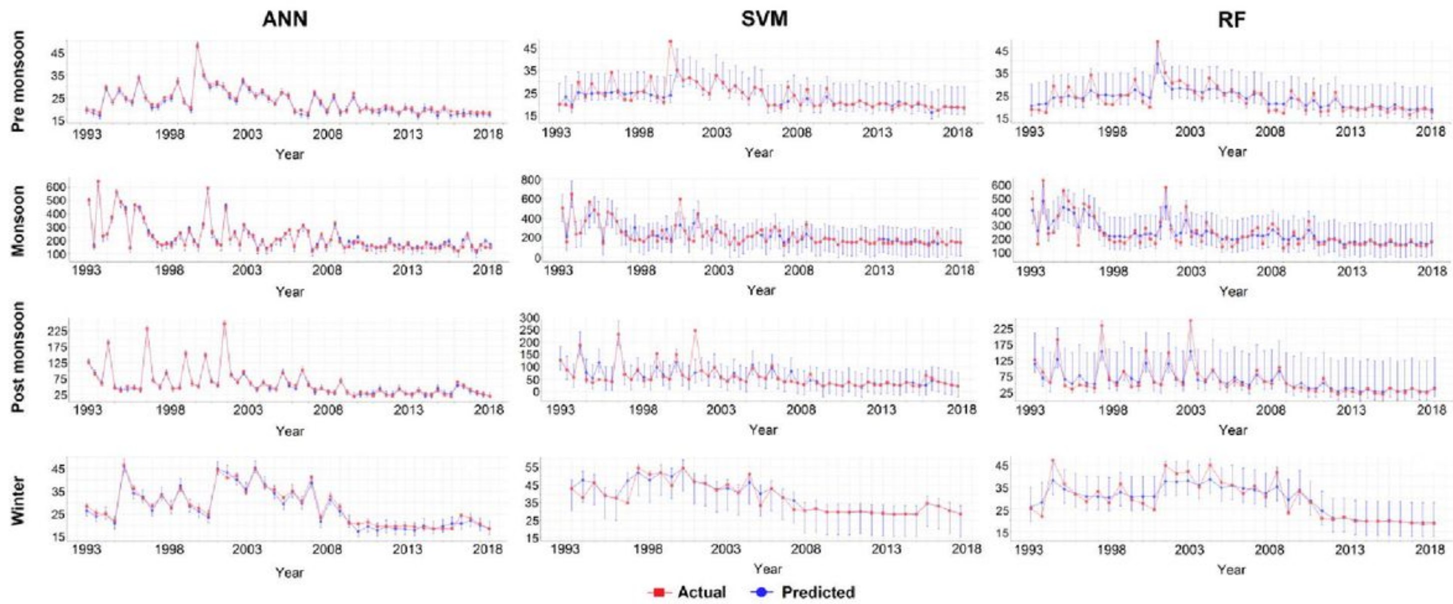

Figure 5

Stream flow simulation for 1993 to 2018 using ANN, SVM and RF for different seasons; dotted red colour line indicate actual flow, dotted blue colour line indicate simulated flow; the vertical line indicate 95% confidence interval

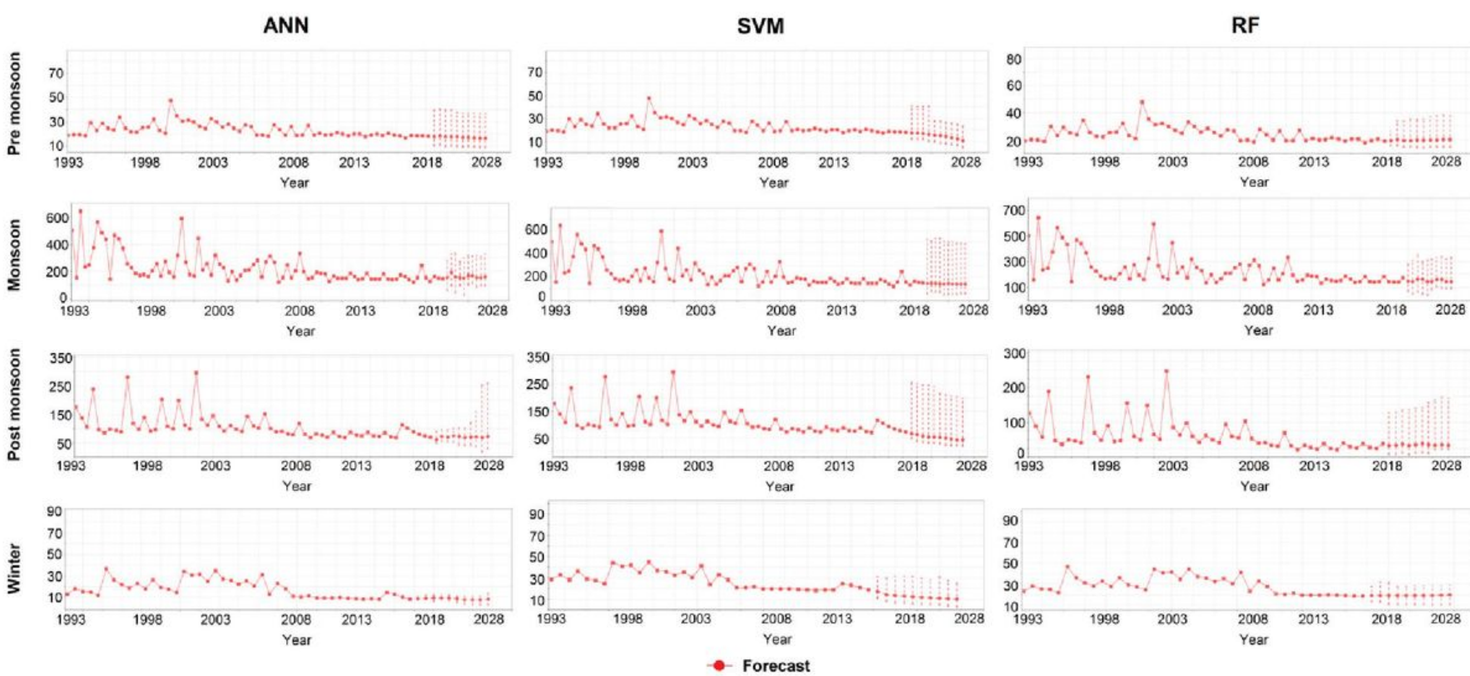

Figure 6

Stream flow forecasting for 2018 to 2028 using ANN, SVM and RF for different seasons; dotted red colour line indicate forecast flow, red colour vertical line indicate 95% confidence interval. In this graph, discharge showing from 1993 to 2018 is actual discharge and 2018 onward is predicted discharge

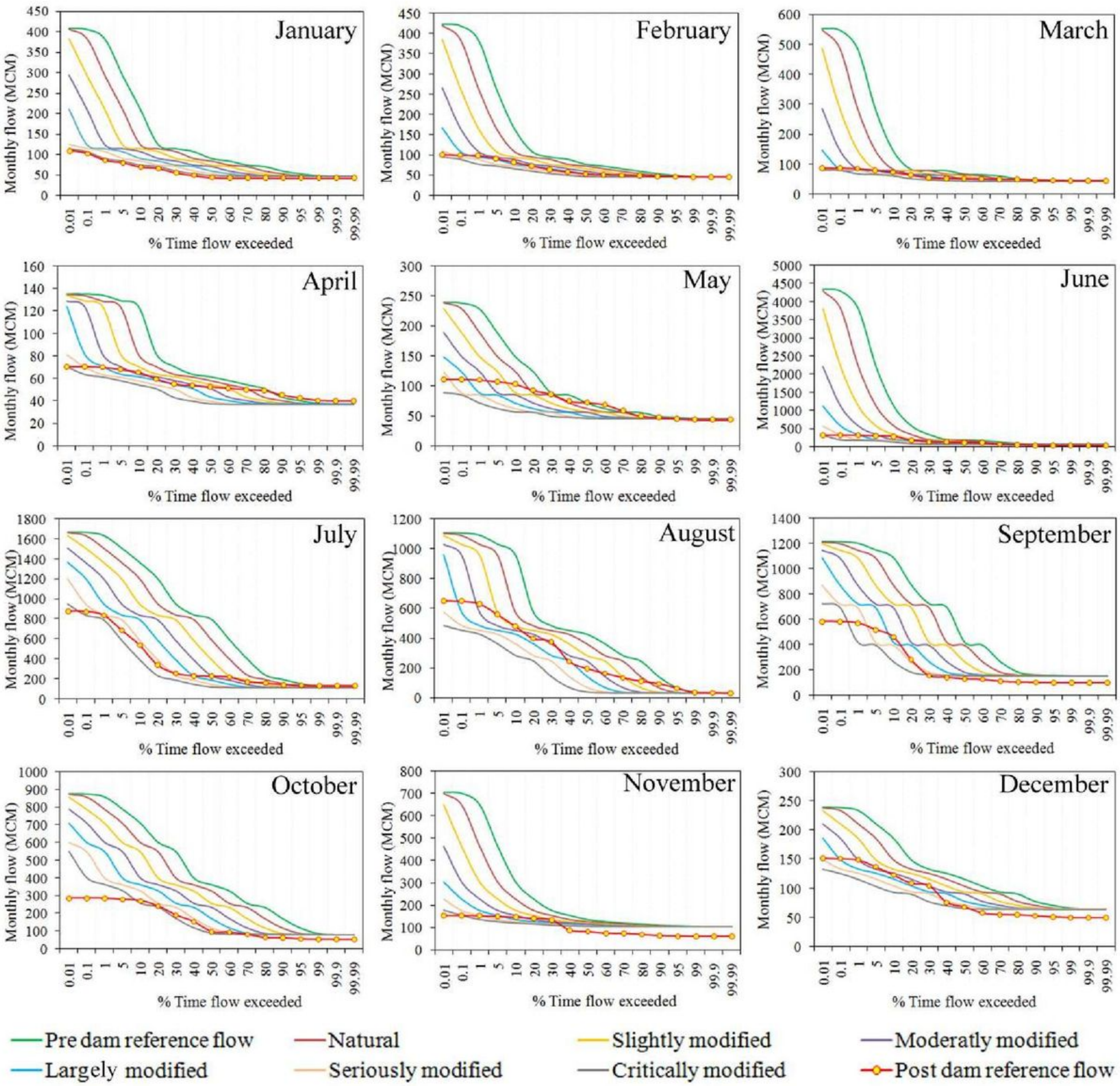

Figure 7

Showing the month wise computed EMC in respect to percentage of flow exceedance and compare with Post-dam flow condition (dotted red colour line), which indicates existing flow condition is ecologically hostile and not suitable for good ecosystem health