Closure Report

File Number : ECR/2017/000740

Project Title : Development of Eutrophication Model for Rural Water Bodies of Assam, India

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Total Sanctioned Amount 21,18,493 (INR)

Total Released Amount : 21,78,674 (INR)

Start Date of the 18 Jul, 2017

Date of completion: 17 Jul, 2020 (36 months)

Approved Objectives :

The objective of this study is to develop an eutrophication model targeted at lakes or water bodies of rural Assam. The model will predict primarily pH, DO and biomass of primary producers under dynamic conditions, to yield better understanding of the biological, chemical and physical performance of such ponds or water bodies. The model will be calibrated and validated on data from the two constructed ponds at the test site and will be tested under controlled environment. Following objectives can be outlined 1. To develop an eutrophication model that could simulate water quality. 2. The developed eutrophication model should help in developing an understanding of the processes affecting the water quality. 3. The model should predict changes in water quality in due course of time. 4. Predict the response of the eutrophic lake to external nutrient loadings. 5. Identify potential critical source areas in using different empirical models.

Deviation made from original objectives (If Any) :

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Ph.D. Produced/ Likely to be : 1

Technical Personnel Trained : 1

Total Expenditure : 21,18,493 (INR)

Concise Research Accomplishment :

In recent times, ecological modelling has come out to be an effective tool for lake restoration and eutrophication management in terms of its better predictive capacity. However, most of the lake modelling works available till date is developed with lake specific parameters collected for a large span of time like ten to twelve years periodically. When prolonged dataset is not available for water bodies under threat of eutrophication; management and restoration of the same with mathematical modelling becomes vague. Therefore, in this research work a completely new approach has been adopted for development of lake eutrophication models to be used as a predictive tool in natural waterbodies in Assam, India with investigated dataset on artificially simulated lake systems. Three model tanks were constructed to artificially replicate lake eutrophication process and continuous monitoring of water quality data had been done which were used for model development. For modelling work, data driven tools like artificial neural network (ANN) has been used. After development of the models, to check accuracy of the models to be used as a predictive tool in natural lake condition, the models were tested against natural lake data from samples collected from some water bodies in Assam. Initially experimental investigations on two artificial lakes (concrete tanks) was conducted and two eutrophication models for common indicators dissolved oxygen (DO) and secchi depth (SD) has been developed. A multilayer perceptron (MLP) and a time delay neural network (TDNN) approach were used for development of the same. Thereafter, a second set of experimental investigation was conducted on a concrete tank and an artificial pond system. The dataset was used for development of more models for DO and SD, and chlorophyll-a (chl-a) using ANN and adaptive neuro-fuzzy inference system (ANFIS). In both cases, lake eutrophication scenario was successfully replicated by continuous addition of waste water into artificially constructed lakes. Trophic status index (TSI) was estimated for the studied lakes that indicated transition of the lakes from a clear water oligotrophic to hypereutrophic stage. All the models developed with data from artificially simulated lake systems were able to predict eutrophication indicators in natural waterbodies with considerable accuracy. A thorough analysis of the experimental and modelling results have been done and to predict lake eutrophication, the most suitable approach out of the presented methodology also has been proposed. This type of data driven modelling approach with laboratory investigated data on artificially simulated lake systems could be an alternate solution to eutrophication management of waterbodies where prolonged water quality data is unavailable for the same. Moreover, effect of nutrient concentration on eutrophication and trophic status of waterbodies can be easily assessed quantitatively.

Closure Details

Experimental/ Theoretical Investigation carried out

Two model tanks were constructed initially to simulate lake eutrophication scenario (Fig. 1). These tanks were artificial concrete tanks with rectangular shape in cross section. The tanks were initially filled with clear water and thereafter periodic application of wastewater was done. Wastewater in the tanks was added in alternate days and homogeneity in sampling and test run timings has been taken care of to minimize error. Samples of wastewater, tank water prior to addition of wastewater as well as tank water after addition of wastewater were collected in standard procedure for conducting water quality investigations in the laboratory. Tests for water quality parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), biochemical oxygen demand (BOD), secchi depth (SD), turbidity, total nitrogen as nitrite and nitrate (TN), total phosphorus (TP) and water temperature were regularly conducted after collection of samples. All the laboratory investigations were carried out according to Standard Methods for the Examination of Water and Wastewater. One set of experimental investigations (1st Set Up) were carried out for around six to seven months and thereafter complete deterioration of water quality has been observed for the studied artificial lakes (Tank-I and Tank-II). The investigated dataset was then utilized for development of models for eutrophication indicators DO and SD using multilayer perceptron (MLP) and time delay neural network (TDNN) architecture. Thereafter one more tank (Tank-III) was constructed as natural pond in ground having trapezoidal cross section (Fig. 1). All the experimental investigations were initiated once again on the Tank 1 and Tank 3 following the same methodology and with one additional important water quality parameter i.e. chlorophyll-a (chl-a) (2nd Set Up). Then data driven modelling approach artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) had been used to model eutrophication indicators DO, SD and chl-a from the experimental investigation of 2nd Set Up. The experimental investigations were carried out for around six to seven months period and thereafter complete deterioration of water quality has been observed with heavy algal growth and subsequent degradation for all the studied artificial lakes. To justify occurrence of eutrophication in the studied artificial lakes mathematically, the investigated parameters were used for trophic status index (TSI) evaluation following the protocol suggested by Carlson. During this period proper care had been taken to maintain a controlled environment in the Tank-I and Tank-II for eutrophication to occur in an ideal condition. Heavy rainfall was also protected during rainy seasons with shades so that dilution of water may not hinder the chemical process of eutrophication. But in case of Tank-III, such measures were not taken to simulate a natural lake eutrophication condition. General description of the model tanks constructed for experimental investigation is presented in Table 1.

Detailed Analysis of result

Results of 1st Set Up: Eutrophication process was recreated effectively with periodic application of waste water to the studied artificial lakes (Fig. 2). The waste water had been gathered from a constant source all through the period having average pH, EC, TDS and turbidity values as 7.54, 689.80 µS/cm, 344.71 ppm and 178.65 NTU respectively. The nutrient concentration of the applied waste water was high with average TN and TP concentrations of 0.48 mg/L and 2.79 mg/L respectively. The results of experimental investigation for different physio-chemical properties of water samples collected from the prototype lakes are given in Table 2. The investigated dataset were used for calculation of TSI of the studied artificial lakes and the maximum, minimum and average values of TSI based on TP and SD values for the investigated artificial lakes are presented in Table 3. The concentration of TP during the initial period of investigation was quite low (0.01 mg/L) and water was transparent upto the full depth of the lakes. For this condition, TSI value was assessed as less than 40 indicating that the studied lakes were in the oligotrophic state. With gradual application of nutrients to the artificial lakes, the water quality of the lakes deteriorated considerably with higher TP concentration and lower SD values. In this condition, calculated value of TSI was well in excess of 70 both for TP and SD standards inferring that lake water quality had changed to a hypereutrophic stage from a freshwater stage. As such, the lake eutrophication phenomenon was replicated in controlled environment successfully and thereafter investigated dataset were used for model training in ANN. From the experimental dataset of 1st Set Up, two types of ANN models were used to predict DO and SD in eutrophic lakes as these are one of the common indicators of lake eutrophication. First one is a static type multilayer perceptron (MLP) and second one is dynamic type time delay neural network (TDNN). ANN models were developed with neural network toolbox in MATLAB. For simplicity of the model, a single hidden layer was considered. Number of neurons in the hidden layer was fixed using a trial and error approach. 20 and 12 numbers of neurons were found as optimum values for DO and SD model respectively and thereafter post processing was carried out with the same number of neurons for both the MLP and TDNN (two step ahead predictions) models. In the present study, a stepwise model-based approach was used for selection of best combination of input parameters for the proposed models. All the investigated water quality parameters were chosen for optimization to be used as model input parameters and DO model having 7 input parameters and SD model having 4 input parameters were finalized based on its lowest mean squared error and highest correlation values (Table 4). After selection of input parameters for DO and SD models, all the input and output data were normalized in the range 0.15 to 0.85 to increase the training efficiency. The predicting performance of the trained models was evaluated by using common statistical parameters coefficient of determination (R2), Nash-Sutcliffe efficiency (E), mean absolute error (MAE) and root mean square error (RMSE). The model performance results for both DO and SD models trained under MLP and TDNN topology are presented with Table 5 and the relation between the observed and predicted model values are presented in Fig. 3. It is evident from the figure that both the developed model based on TDNN and MLP, for the prediction of DO and SD, an acceptable correlation exists between observed values and model predicted values. For the trained DO models with MLP and TDNN, R2 and E values were obtained as greater than 0.95. For trained MLP SD model a slightly lower value of R2 and E were observed compared to the TDNN model. Overall, prediction capacity of TDNN model was found to be superior compared to the MLP models as reflected in the higher value of coefficient of determination and Nash efficiency and lower values of errors. Relative influence (RI) of each input parameters on prediction of output parameter were calculated with Garson equation it has been observed that for DO prediction, all the seven input parameters had equal amount of influence on prediction of output parameter. However, pH was observed as the major influencing parameter having highest relative contribution of 16.78% and TP having lowest relative contribution of 10.92% on the prediction of DO. Similarly, pH, EC and turbidity were found as major contributing parameters compared to temperature for prediction of SD in eutrophic lakes. To check sensitivity of the input parameters, data perturbation technique was used. Input parameters were increased or decreased by 20% one at a time fixing other inputs as constants. BOD and TN were observed as most sensitive input parameters for DO prediction having sensitivity percentage slightly higher than 100%. Compared to the DO model, input parameters in SD model were found to be less sensitive and changes in input parameters were found having lesser effect on SD prediction performance (Table 6). Feasibility of the adopted modelling approach to be used as eutrophication predictor in natural waterbodies is evaluated by checking the model performance with samples collected from a few natural water bodies in Assam. As the prediction capacity of the model should be flawless under normal to extraordinary ecological conditions a vast dataset were gathered to check accuracy of the developed models to be used in natural water bodies in Assam. Water samples were collected from two sampling points of Deepor Bil, a world heritage RAMSAR wetland in Guwahati city as well as from a marsh, a manmade lake and a village pond in and around Tezpur University campus in Tezpur city. All the previously mentioned water quality parameters were investigated on the samples collected during both monsoon and winter seasons. Model simulation results of the DO and SD models revealed that the developed models were able to predict the output values within considerable accuracy. R2 values of 0.916 and 0.853 were obtained for the DO and SD models respectively. E, RMSE and MAE values of 0.914, 0.527 mg/L and 0.480 mg/L were obtained for DO model testing with natural lake data. Similarly, for SD model testing E, RMSE and MAE values of 0.754, 6.785 cm and 5.275 cm were obtained. Results of 2nd Set Up: Lake eutrophication scenario was replicated successfully in the 2nd experimental set up also by continuous addition of waste water to the model tanks (Fig. 4). The statistical summary of the results of different water quality parameters monitored during the set up are presented in Table 7. For TSI calculation the average and maximum values of SD, chl-a and TP were considered and the same had been reported in Table 8 for the investigated artificial lakes. TSI values were determined for each parameter individually and thereafter mean value was considered for trophic status evaluation. In the initial period of investigation lower concentration of TP (0.01 mg/L) and chl-a (0 µg/L) was observed in the lakes and SD value was not obtained as the water was completely transparent to the full lake depth. Corresponding to this condition minimum value of TSI was obtained as less than 40 for TP, chl-a and SD consideration indicating that the studied lakes were initially at oligotrophic stage. However, during progressive deterioration of water quality maximum values of TP, chl-a and minimum value of SD were recorded and for that condition calculated maximum value of TSI was obtained as more than 70 for the three considered criteria. This indicated that the studied lakes had reached hypereutrophic stage and at that point the experimental investigation was terminated and evaluated dataset were used for development of ANN and ANFIS models for DO, SD and chl-a prediction respectively. From the experimentally investigated dataset of 2nd Set Up, three eutrophication models for indicators DO, SD and chl-a were developed using conventional ANN and sophisticated ANFIS topology, following the same methodology as discussed earlier. For DO, SD and chl-a prediction 5, 5 and 9 parameters were found as model input parameters respectively (Table 9). Five empirical methods from previous research works were used to calculate the number of neurons required for the hidden layer in a ANN model and thereafter several neural networks were created between the minimum and maximum values. Based on its mean squared error (MSE) and correlation coefficient (R) between the output and target values, each network was evaluated, and optimum number of neurons was finalized. 8, 7 and 18 number of neurons in the hidden layer were found as optimum for DO, SD and chl-a prediction respectively in ANN topology. In ANFIS topology, the input parameters as selected in ANN architecture were used for predicting the desired outputs and the whole normalized input dataset were randomly divided into 4:1 ratio as training and testing datasets. A subtractive clustering method with a hybrid learning algorithm was used in this work to formulate best fitting ANFIS model for the desired output parameters. Using a comprehensive methodology, testing different parameter combinations of subtractive clustering, the best structure of ANFIS was finalized with parameters 0.5 (range of influence), 1.5 (Squash factor), 0.5 (Accept ratio), 0.15 (Reject ratio) and 100 (no. of epoch). Based on the laboratory investigation results from the two artificially simulated eutrophied lakes, two ANN as well as ANFIS models were trained for each indicator parameters. The models trained with Tank-I data are denoted as DO-I, SD-I and chl-a-I respectively and that trained with Tank-III data are presented as DO-III, SD-III and chl-a-III respectively in the succeeding sections. The results of model training were illustrated as time series plot between the observed and predicted values in Fig. 5. The model performance was evaluated with correlation parameters R2 and E and error estimation parameters RMSE and MAE; results for which were shown in Table 10. It was observed that in case of the ANN models, the performance of DO and chl-a models were quite satisfactory as reflected by R2 and E parameters where values greater than 0.95 had been found for the models respectively. The RMSE and MAE between observed and predicted values were also low considering range of DO and chl-a dataset. Compared to DO and chl-a models, the goodness of fit for SD-I and SD-III ANN models were inferior with R2 and E values slightly higher than 0.90. RMSE and MAE values of 3.02 cm 2.33 cm were observed for SD-I model and for SD-III model these values were 3.15 cm and 2.46 cm respectively which are acceptable under considered database. In case of the ANFIS models, very fine correlation was observed between actual and forecasted values for all the model types developed with negligible error in prediction and it was found that models trained under ANFIS topology had better prediction accuracy compared to corresponding ANN models Sensitivity analysis was performed on the developed models with data perturbation method by changing the input parameters by ±20% in succession. Results of the sensitivity analysis revealed that for DO prediction with ANN and ANFIS, chl-a was found to be the most sensitive parameter followed by temperature. Out of the nine input parameters for chl-a prediction pH, DO, increase in nutrient concentration (TN and TP) and increase in temperature were most influential parameters. Compared to the DO and chl-a models, input parameters in SD model were found to be less sensitive. Results of the sensitivity analysis revealed that similar trends for ANN and ANFIS models were observed, however, effect of input perturbation on target prediction was smaller in case of ANFIS models compared with the ANN models. The trained ANN and ANFIS models were finally tested with natural waterbody data as discussed in preceding section and simulation results of the DO, SD and chl-a models revealed that the developed models were able to predict the output values within considerable accuracy. R2 values greater than 0.8 was obtained between observed and predicted values for all the DO, SD and chl-a models trained under ANN and ANFIS environment. Model simulation results were compared with statistical parameters R2, E, RMSE and MAE respectively and are reported in Table 11. Prediction capacity of trained ANFIS models were found superior to trained ANN models in general, except for SD-1 model where performance of ANN was slightly better compared to ANFIS. Comparing the testing results different ANN and ANFIS models developed with Tank-I and Tank-III data, it was found that for ANFIS models trained with Tank-III data, higher testing accuracy was achieved.

Fig.1: Construction of artificial tanks to simulate lake eutrophication

Fig. 2: Images of water quality deterioration of Tank-I water with time from 1st Set Up

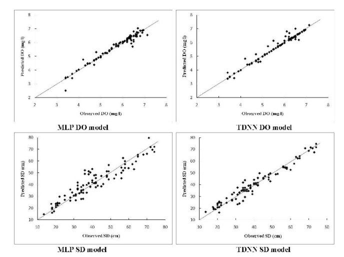

Fig. 3: Observed vs Predicted plot for the developed models from 1st Set Up

Fig. 4: Images of water quality in the artificial pond during studied period from 2nd Set Up

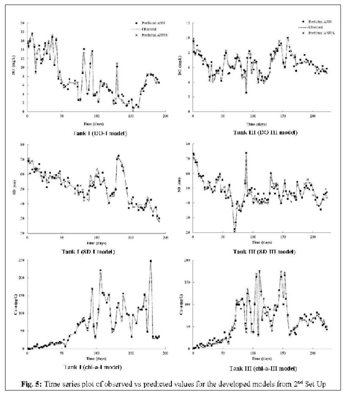

Fig. 5: Time series plot of observed vs predicted values for the developed models from 2nd Set Up

Table 1: General Description of Test Arrangement

	Tank-I (Concrete Tank)	Tank-II (Concrete Tank)	Tank-III (Natural Pond)
Location	Tezpur University, Tezpur, Assam	GIMT Campus, Tezpur, Assam	Tezpur University, Tezpur, Assam
Tank Dimension	2.61m × 1.63m × 0.73m	2.5m × 2.5m × 0.85m	3.0m x 2.5m x 0.90m
Side Slope	NIL	NIL	1 (H) : 1.8 (V)
Initial Free Board	0.11 m	0.15 m	0.30 m
Initial Volume of clear water added	2.637 m^3	4.375 m^3	3.20 m^3
Quantity of Sewage addition	5 L/alternate day	8 L/ alternate day	5 L/alternate day
Sampling frequency	Alternate day	Alternate day	Alternate day

Table 2: Statistical summary of investigated water quality variables

	pH	EC (µS/cm)	TDS (ppm)	Turb (NTU)	TN (mg/L)	TP (mg/L)	Temp^r (°C)	BOD (mg/L)	DO (mg/L)	SD (cm)
Max	10.32	837.00	561.50	68.90	5.77	9.62	36.00	51.80	7.13	74.00
Min	6.93	164.80	61.31	2.30	0.00	0.01	25.00	0.00	3.40	13.50
Avg	8.67	363.67	189.00	17.75	0.71	2.60	31.40	12.99	5.64	40.94
St. Dev.	0.90	155.44	100.60	15.07	1.03	1.95	2.51	10.31	0.97	15.29

* Turb= Turbidity, Max= Maximum, Min= Minimum, St Dev.= Standard Deviation

Table 3: Calculated TSI values of studied artificial lakes

TSI_{TP}			TSI_{SD}		
Min^m	Max^m	Avg.	Min^m	Max^m	Avg.
37.37	136.48	117.61	<40	88.90	72.89

Table 4: Selection of input parameters for DO and SD models

Sl. No.	Input Parameters	R	MSE
	DO model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, SD, Temp^r	0.897	0.0121
2	pH, EC, TDS, TN, TP, Turbidity, Temp^r	0.901	0.0101
3	**pH, EC, BOD, TN, TP, Turbidity, Temp^r**	**0.936**	**0.0094**
4	pH, EC, TDS, TN, TP, Temp^r	0.788	0.0203
5	pH, EC, TN, TP, Temp^r	0.804	0.0204
6	pH, EC, TN, TP	0.755	0.0214
	SD model		
1	pH, EC, TDS, DO, TN, TP, Turbidity, Temp^r	0.883	0.0110
2	pH, EC, TDS, DO, TN, TP, Temp^r	0.771	0.0175
3	pH, EC, Turbidity, TN, TP, Temp^r	0.845	0.0120
4	pH, EC, TN, TP, Temp^r	0.783	0.0198
5	TN, TP, Turbidity, Temp^r	0.748	0.0118
6	**pH, EC, Turbidity, Temp^r**	**0.921**	**0.0033**

Table 5: Performance results of trained DO and SD models

Model	R^2		E		RMSE		MAE	
	MLP	TDNN	MLP	TDNN	MLP	TDNN	MLP	TDNN
DO	0.956	0.964	0.956	0.963	0.2027	0.1842	0.118	0.090
SD	0.886	0.961	0.925	0.959	4.1472	3.0356	3.257	2.321

Table 6: Result of sensitivity analysis with data perturbation

Parameters	DO Model		SD model	
	+20%	-20%	+20%	-20%
pH	86.17	93.46	36.17	57.84
EC	86.45	89.74	64.21	58.24
TN	102.83	66.46	-	-
TP	84.69	95.29	-	-
Temperature	97.43	95.33	57.35	67.08
BOD	121.26	98.18	-	-
Turbidity	95.74	89.93	59.36	85.69

Table 7: Statistical summary of the experimental investigation on the studied artificial lakes

		Concrete Tank (Tank-I)				Artificial Pond (Tank-III)			
	Waste water quality	Max^m	Min^m	Avg.	St. Dev.	Max^m	Min^m	Avg.	St. Dev.
pH	7.34	10.17	6.83	8.40	0.94	10.01	6.22	7.68	0.94
EC (µS/cm)	703.80	596.20	206.80	396.94	90.12	354.98	53.60	156.71	70.17
TDS (mg/L)	344.70	267.90	109.70	189.91	37.58	185.21	25.47	77.61	36.58
BOD (mg/L)	30.00	58.80	0.00	14.10	10.73	57.50	2	18.51	12.85
DO (mg/L)	6.10	17.30	0.50	7.80	4.68	10.00	2.50	6.48	1.46
Turb (NTU)	215.30	78.80	1.00	16.46	12.95	180.7	2.40	31.68	37.74
TN (mg/L)	0.48	0.71	0.00	0.11	0.15	1.01	0.01	0.09	0.15
TP (mg/L)	2.79	3.38	0.00	1.04	0.85	3.04	0	0.55	0.61
SD (cm)	--	72.00	28.00	52.01	10.79	75.00	21.00	47.78	8.94
$Temp^r$ (°C)	--	34.10	22.80	28.53	2.77	34.00	21.70	29.15	2.78
Chl-a (µg/L)	24.52	246.03	0.00	64.98	57.05	174.11	0	61.10	43.86

*Max^m = Maximum, Min^m = Minimum, Avg. = Average, St. Dev. = Standard deviation

Table 8: Trophic status estimation results of investigated lakes

	TSI (SD)		TSI (chl-a)		TSI (TP)		TSI_{MEAN}		Remarks
	Max^m	Avg.	Max^m	Avg.	Max^m	Avg.	Max^m	Avg.	
Tank-I	78.37	69.43	84.57	71.51	121.40	104.30	94.78	81.76	Hypereutrophic
Tank-III	82.52	70.66	81.18	70.90	119.84	95.20	94.51	78.92	Hypereutrophic

Table 9: Combinations for input parameter selection

Sl. No.	Input Parameters	R	MSE
	DO model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, Chl-a, $Temp^r$	0.9266	0.0106
2	pH, EC, TDS, TN, TP, Turbidity, $Temp^r$, Chl-a	0.9227	0.0079
3	pH, EC, BOD, TN, TP, Turbidity, Chl-a , $Temp^r$	0.9198	0.0062
4	pH, EC, BOD, TN, TP, Chl-a, $Temp^r$	0.9073	0.0104
5	pH, EC, TN, TP, Chl-a, $Temp^r$	0.9351	0.0036
6	pH, EC, TN, TP, Chl-a	0.9340	0.0166
7	pH, EC, TN, TP, $Temp^r$	0.8899	0.0061
8	**pH, EC, TP, Chl-a, $Temp^r$**	**0.9600**	**0.0029**
9	pH, TDS, TP, Chl-a, $Temp^r$	0.9132	0.0085
10	pH, TDS, Chl-a, $Temp^r$	0.8998	0.0100
	SD model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, Chl-a, $Temp^r$	0.891	0.0036
2	pH, EC, TDS, TN, TP, Turbidity, Chl-a, $Temp^r$	0.9053	0.0050
3	pH, EC, Turbidity, TN, TP, Chl-a, $Temp^r$	0.8829	0.0236
4	pH, EC, TN, TP, Chl-a, $Temp^r$	0.7554	0.0337
5	**pH, EC, Turbidity, Chl-a, $Temp^r$**	**0.9135**	**0.0035**
6	TN, TP, Turbidity, Chl-a, $Temp^r$	0.8824	0.0079
7	pH, EC, Chl-a, $Temp^r$	0.8267	0.0279
8	pH, EC, $Temp^r$, Turbidity	0.8591	0.0085
9	pH, TDS, Turbidity, Chl-a, $Temp^r$	0.8555	0.0173
10	EC, TDS, Turbidity, Chl-a, $Temp^r$	0.7801	0.0036
	chl-a model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, DO, $Temp^r$	0.8827	0.0160
2	pH, EC, TN, TP, BOD, Turbidity, DO, $Temp^r$	0.8428	0.0093
3	pH, EC, TN, TP, Turbidity, DO, $Temp^r$	0.8668	0.0097
4	pH, TN, TP, Turbidity, DO, $Temp^r$	0.8469	0.0088
5	pH, TN, TP, Turbidity, DO, BOD, $Temp^r$	0.8978	0.0084
6	pH, TN, TP, DO, BOD, $Temp^r$	0.8374	0.0237
7	pH, TN, TP, BOD, Turbidity, DO, SD, $Temp^r$	0.8841	0.0108
8	pH, EC, TDS, TN, TP, BOD, Turbidity, DO, SD, $Temp^r$	0.9024	0.0067
9	**pH, EC, TN, TP, BOD, Turbidity, DO, SD, $Temp^r$**	**0.9161**	**0.0022**
10	EC, TN, TP, BOD, Turbidity, DO, SD, $Temp^r$	0.8389	0.0180

Table 10: Performance result of ANN and ANFIS model training

Model	R^2	E	RMSE	MAE
ANN Models				
DO-I	0.977	0.978	0.453 mg/L	0.328 mg/L
DO-III	0.955	0.959	0.495 mg/L	0.376 mg/L
SD-I	0.913	0.920	3.020 cm	2.330 cm
SD-III	0.908	0.909	3.150 cm	2.460 cm
Chl-a-I	0.989	0.989	5.750 µg/L	3.970 µg/L
Chl-a-III	0.958	0.967	7.820 µg/L	6.820 µg/L
ANFIS Models				
DO-I	0.997	0.997	0.213 mg/L	0.144 mg/L
DO-III	0.993	0.994	0.114 mg/L	0.071 mg/L
SD-I	0.950	0.953	2.320 cm	1.680 cm
SD-III	0.958	0.960	1.780 cm	1.080 cm
Chl-a-I	0.999	0.999	0.010 µg/L	0.008 µg/L
Chl-a-III	0.999	0.999	0.010 µg/L	0.006 µg/L

Table 11: Performance result of model validation with natural waterbody data

Parameters	DO		SD		chl-a	
	ANN	ANFIS	ANN	ANFIS	ANN	ANFIS
Tank-I (*Concrete Tank*)						
R^2	0.827	0.867	0.868	0.814	0.910	0.914
E	0.829	0.855	0.860	0.809	0.890	0.923
RMSE	1.06 mg/L	0.97 mg/L	4.10 cm	6.09 cm	12.27µg/L	10.14 µg/L
MAE	0.77 mg/L	0.82 mg/L	3.58 cm	4.52 cm	10.06 µg/L	7.89 µg/L
Tank-III (*Artificial Pond*)						
R^2	0.829	0.902	0.809	0.831	0.918	0.960
E	0.836	0.905	0.820	0.840	0.920	0.962
RMSE	1.04 mg/L	0.79 mg/L	4.56 cm	4.27 cm	10.27 µg/L	7.10 µg/L
MAE	0.77 mg/L	0.66 mg/L	4.07 cm	3.76 cm	8.38 µg/L	5.67 µg/L

Conclusions

To predict lake eutrophication in waterbodies in Assam, India, a novel approach has been adopted in this presented work. From the results of the experimental and modelling investigations, the following major conclusions can be drawn. i. Lake eutrophication scenario was successfully replicated by continuous addition of waste water into artificially constructed lakes. Trophic status index (TSI) was estimated for the studied lakes that indicated transition of the lakes from a clear water oligotrophic to hypereutrophic stage. Data monitored during this process was used for development of eutrophication models for indicators DO, SD and chl-a using multilayer perceptron (MLP), time delay neural network (TDNN) and adaptive neuro-fuzzy inference system (ANFIS). The architecture of the developed models were chosen rigorously and input parameters were chosen based on a model based data pruning method to obtain optimum parameters. Results of sensitivity analysis revealed that all the dependent variables were logically chosen for target prediction. ii. The MLP and TDNN models developed from the 1st experimental set up for prediction of DO and SD, it was concluded that both type of models was able to predict the eutrophication indicators with considerable accuracy. Results of TDNN models were found to be superior in compared with MLP models during both training and testing stage. iii. All the models trained using ANN and ANFIS topology from the 2nd experimental set up were able to predict the eutrophication indicators DO, SD and chl-a with reasonable accuracy. Overall performance of the trained ANFIS models for prediction of DO, SD and chl-a were found to be superior compared to ANN models. Models trained with concrete tank (Tank-1) and artificial pond (Tank-3) data were found to be more or less consistent under ANN and ANFIS. However, ANFIS models trained with artificial pond (Tank-3) data produced best prediction performance. Compared to ANN models, ANFIS models were more reliable for forecasting eutrophication indicators when tested against actual natural waterbodies. iv. This type of data driven modelling approach with laboratory investigated data on artificially simulated lake systems could be an alternate solution to eutrophication management of waterbodies where prolonged water quality data is unavailable for the same. From the test results of this study, it can be concluded that ANFIS modelling approach with artificially simulated pond system can be a promising solution for forecasting and mitigating lake eutrophication in natural waterbodies in Assam, India.

Scope of future work

The presented models were successful in predicting eutrophication indicators in natural water bodies in Assam. Considering the boundary conditions of the experimental set up as well as complex nature of eutrophication phenomenon, the presented models are suitable for application in tropical climatic conditions with high humidity like in Assam. Moreover, the major source of water pollution in the natural water bodies prone to eutrophication in Assam is due to domestic wastes. So, the applicability of the developed models is limited to use in the natural water bodies in Assam where major source of contamination is domestic wastes with high nutrient concentration and low BOD. Future research can be focussed on conducting more detailed investigation to understand eutrophication dynamics of the concerned lake, incorporating more number of parametric studies and with varying influent properties. Prediction of more number of water quality variables like total phosphorus, total nitrogen etc. may be done using additional data driven methods like Decision Tree, Support Vector Machines, and hybrid approaches such as genetic algorithm optimized neural networks (GA-ANN).

List of Publications (only from SCI indexed journals) :

Title of the Paper	List of Authors	Journal Details	Month & Year	Volume	Status	DOI No	Imp Fact
A review on lake eutrophication dynamics and recent developments in lake modeling	Biswajit Bhagowati and Kamal Uddin Ahamad	ECOHYDROLOG & HYDROBIOLOGY (International)	Jan-2019	19(1) (155-166)	Published	https://doi.org/10.1016/j.ecohyd.2018.03.002	1.66

List of Papers Published in Conference Proceedings, Popular Journals :

Title of the Paper	List of Authors	Journal Details	Month & Year	Volume	Status	DOI No	Imp Fact
Lake Eutrophication: Causes, Concerns and Remedial Measures || Book Chapter, Publisher: Springer, Singapore	Biswajit Bhagowati, Bishal Talukdar, Kamal Uddin Ahamad	Emerging Issues in the Water Environment during Anthropocene (International)	Dec-2020	(211-222)	Published	https://doi.org/10.1007/978-981-32-9771-5_12	

List of Patents filed/ to be filed :

Patent Title	Authors	Patent Type	Country/Agency Name	Patent Status	Application Grant No.
Not Available					

Equipment Details :

Equipment Name	Cost (INR)	Procured	Make & Model	Utilization %	Amount Spent	Date of Procuremen
BOD Incubator	1,24,770	No		100	0	
UV-Visible Spectrophotometer	5,43,520	No		100	0	
DO Meter	37,640	No		100	0	

Plans for utilizing the equipment facilities in future:

From the financial assistance of this research project three numbers of major equipment have been procured that includes a BOD incubator, a double beam UV/VIS Spectrophotometer and a digital DO meter. All these facilities are very useful and frequently used for most of the environmental investigations related with water and wastewater quality. These facilities were used extensively throughout conduction of the experimental investigations of this research work and will be used for similar endeavours in near future. BOD incubator is essentially required for determining the BOD value of wastewaters and so it will be quite useful in conduction of sewage and wastewater related investigations. UV/VIS Spectrophotometer has a very wide range of application in water quality analysis and is quite useful in determination of metal ion and nutrient concentration, organic compounds, bacterial contaminants etc. in water and wastewater samples. So, this instrument will be invaluable for future research work related with physio-chemical properties of water and wastewater. Digital DO meter provides a rapid means of estimating the DO concentration in water samples compared to conventional titration methods. This instrument will be used for determination of in-situ DO concentrations in surface waterbodies like lakes, ponds, and rivers etc. in future research works where DO level is a prime indicator of surface water quality. Apart from research works, the above facilities will be utilized for departmental academic purposes like conduction of laboratory classes and project works of B. Tech and M. Tech students.

Closure Report

Concise Research Accomplishment*

In recent times, ecological modelling has come out to be an effective tool for lake restoration and eutrophication management in terms of its better predictive capacity. However, most of the lake modelling works available till date is developed with lake specific parameters collected for a large span of time like ten to twelve years periodically. When prolonged dataset is not available for water bodies under threat of eutrophication; management and restoration of the same with mathematical modelling becomes vague. Therefore, in this research work a completely new approach has been adopted for development of lake eutrophication models to be used as a predictive tool in natural waterbodies in Assam, India with investigated dataset on artificially simulated lake systems. Three model tanks were constructed to artificially replicate lake eutrophication process and continuous monitoring of water quality data had been done which were used for model development. For modelling work, data driven tools like artificial neural network (ANN) has been used. After development of the models, to check accuracy of the models to be used as a predictive tool in natural lake condition, the models were tested against natural lake data from samples collected from some water bodies in Assam. Initially experimental investigations on two artificial lakes (concrete tanks) was conducted and two eutrophication models for common indicators dissolved oxygen (DO) and secchi depth (SD) has been developed. A multilayer perceptron (MLP) and a time delay neural network (TDNN) approach were used for development of the same. Thereafter, a second set of experimental investigation was conducted on a concrete tank and an artificial pond system. The dataset was used for development of more models for DO and SD, and chlorophyll-a (chl-a) using ANN and adaptive neuro-fuzzy inference system (ANFIS). In both cases, lake eutrophication scenario was successfully replicated by continuous addition of waste water into artificially constructed lakes. Trophic status index (TSI) was estimated for the studied lakes that indicated transition of the lakes from a clear water oligotrophic to hypereutrophic stage. All the models developed with data from artificially simulated lake systems were able to predict eutrophication indicators in natural waterbodies with considerable accuracy. A thorough analysis of the experimental and modelling results have been done and to predict lake eutrophication, the most suitable approach out of the presented methodology also has been proposed. This type of data driven modelling approach with laboratory investigated data on artificially simulated lake systems could be an alternate solution to eutrophication management of waterbodies where prolonged water quality data is unavailable for the same. Moreover, effect of nutrient concentration on eutrophication and trophic status of waterbodies can be easily assessed quantitatively.

Experimental/ Theoretical Investigation carried out*

Two model tanks were constructed initially to simulate lake eutrophication scenario (Fig. 1). These tanks were artificial concrete tanks with rectangular shape in cross section. The tanks were initially filled with clear water and thereafter periodic application of wastewater was done. Wastewater in the tanks was added in alternate days and homogeneity in sampling and test run timings has been taken care of to minimize error. Samples of wastewater, tank water prior to addition of wastewater as well as tank water after addition of wastewater were collected in standard procedure for conducting water quality investigations in the laboratory. Tests for water quality parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), biochemical oxygen demand (BOD), secchi depth (SD), turbidity, total nitrogen as nitrite and nitrate (TN), total phosphorus (TP) and water temperature were regularly conducted after collection of samples. All the laboratory investigations were carried out according to Standard Methods for the Examination of Water and Wastewater. One set of experimental investigations (**1st Set Up**) were carried out for around six to seven months and thereafter complete deterioration of water quality has been observed for the studied artificial lakes (Tank-I and Tank-II). The investigated dataset was then utilized for development of models for eutrophication indicators DO and SD using multilayer perceptron (MLP) and time delay neural network (TDNN) architecture. Thereafter one more tank (Tank-III) was constructed as natural pond in ground having trapezoidal cross section (Fig. 1).

Fig.1: Construction of artificial tanks to simulate lake eutrophication

All the experimental investigations were initiated once again on the Tank 1 and Tank 3 following the same methodology and with one additional important water quality parameter i.e. chlorophyll-a (chl-a) (**2nd Set Up**). Then data driven modelling approach artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) had been used to model eutrophication indicators DO, SD and chl-a from the experimental investigation of 2nd Set Up. The experimental investigations were carried out for around six to seven months period and thereafter complete deterioration of water quality has been observed with heavy algal growth and subsequent degradation for all the studied artificial lakes.

To justify occurrence of eutrophication in the studied artificial lakes mathematically, the investigated parameters were used for trophic status index (TSI) evaluation following the protocol suggested by

Carlson. During this period proper care had been taken to maintain a controlled environment in the Tank-I and Tank-II for eutrophication to occur in an ideal condition. Heavy rainfall was also protected during rainy seasons with shades so that dilution of water may not hinder the chemical process of eutrophication. But in case of Tank-III, such measures were not taken to simulate a natural lake eutrophication condition. General description of the model tanks constructed for experimental investigation is presented in Table 1.

Table 1: General Description of Test Arrangement

	Tank-I (Concrete Tank)	**Tank-II (Concrete Tank)**	**Tank-III (Natural Pond)**
Location	Tezpur University, Tezpur, Assam	GIMT Campus, Tezpur, Assam	Tezpur University, Tezpur, Assam
Tank Dimension	2.61m × 1.63m × 0.73m	2.5m × 2.5m × 0.85m	3.0m x 2.5m x 0.90m
Side Slope	NIL	NIL	1 (H) : 1.8 (V)
Initial Free Board	0.11 m	0.15 m	0.30 m
Initial Volume of clear water added	2.637 m^3	4.375 m^3	3.20 m^3
Quantity of Sewage addition	5 L/alternate day	8 L/ alternate day	5 L/alternate day
Sampling frequency	Alternate day	Alternate day	Alternate day

Detailed Analysis of result

Results of 1st Set Up:

Eutrophication process was recreated effectively with periodic application of waste water to the studied artificial lakes (Fig. 2).

Fig. 2: Images of water quality deterioration of Tank-I water with time from 1st Set Up

The waste water had been gathered from a constant source all through the period having average pH, EC, TDS and turbidity values as 7.54, 689.80 µS/cm, 344.71 ppm and 178.65 NTU respectively. The nutrient concentration of the applied waste water was high with average TN and TP concentrations of 0.48 mg/L and 2.79 mg/L respectively. The results of experimental investigation for different physio-chemical properties of water samples collected from the prototype lakes are given in Table 2.

Table 2: Statistical summary of investigated water quality variables

	pH	EC (µS/cm)	TDS (ppm)	Turb (NTU)	TN (mg/L)	TP (mg/L)	Temp^{r} (°C)	BOD (mg/L)	DO (mg/L)	SD (cm)
Max	10.32	837.00	561.50	68.90	5.77	9.62	36.00	51.80	7.13	74.00
Min	6.93	164.80	61.31	2.30	0.00	0.01	25.00	0.00	3.40	13.50
Avg	8.67	363.67	189.00	17.75	0.71	2.60	31.40	12.99	5.64	40.94
St. Dev.	0.90	155.44	100.60	15.07	1.03	1.95	2.51	10.31	0.97	15.29

* Turb= Turbidity, Max= Maximum, Min= Minimum, St Dev.= Standard Deviation

The investigated dataset were used for calculation of TSI of the studied artificial lakes and the maximum, minimum and average values of TSI based on TP and SD values for the investigated artificial lakes are presented in Table 3. The concentration of TP during the initial period of investigation was quite low (0.01 mg/L) and water was transparent upto the full depth of the lakes. For this condition, TSI value was assessed as less than 40 indicating that the studied lakes were in the oligotrophic state. With gradual application of nutrients to the artificial lakes, the water quality of the lakes deteriorated considerably with higher TP concentration and lower SD values. In this condition, calculated value of TSI was well in excess of 70 both for TP and SD standards inferring that lake water quality had changed to a hypereutrophic stage from a freshwater stage. As such, the lake eutrophication phenomenon was replicated in controlled environment successfully and thereafter investigated dataset were used for model training in ANN.

Table 3: Calculated TSI values of studied artificial lakes

TSI_{TP}			**TSI_{SD}**		
Min^{m}	Max^{m}	Avg.	Min^{m}	Max^{m}	Avg.
37.37	136.48	117.61	<40	88.90	72.89

From the experimental dataset of 1st Set Up, two types of ANN models were used to predict DO and SD in eutrophic lakes as these are one of the common indicators of lake eutrophication. First one is a static type multilayer perceptron (MLP) and second one is dynamic type time delay neural network (TDNN). ANN models were developed with neural network toolbox in MATLAB. For simplicity of the model, a single hidden layer was considered. Number of neurons in the hidden layer was fixed using a trial and error approach. 20 and 12 numbers of neurons were found as optimum values for DO and SD model respectively and thereafter post processing was carried out with the same number of neurons for both the MLP and TDNN (two step ahead predictions) models. In the present study, a stepwise model-based approach was used for selection of best combination of input parameters for the proposed models. All the investigated water quality parameters were chosen for optimization to be used as model input parameters and DO model having 7 input parameters and SD model having 4 input parameters were finalized based on its lowest mean squared error and highest correlation values (Table 4). After selection of input parameters for DO and SD models, all the input and output data were normalized in the range 0.15 to 0.85 to increase the training efficiency. The predicting performance of the trained models was evaluated by using common statistical parameters coefficient of determination (R^2), Nash-Sutcliffe efficiency (E), mean absolute error (MAE) and root mean square error (RMSE).

Table 4: Selection of input parameters for DO and SD models

Sl. No.	Input Parameters	R	MSE
	DO model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, SD, $Temp^r$	0.897	0.0121
2	pH, EC, TDS, TN, TP, Turbidity, $Temp^r$	0.901	0.0101
3	**pH, EC, BOD, TN, TP, Turbidity, $Temp^r$**	**0.936**	**0.0094**
4	pH, EC, TDS, TN, TP, $Temp^r$	0.788	0.0203
5	pH, EC, TN, TP, $Temp^r$	0.804	0.0204
6	pH, EC, TN, TP	0.755	0.0214
	SD model		
1	pH, EC, TDS, DO, TN, TP, Turbidity, $Temp^r$	0.883	0.0110
2	pH, EC, TDS, DO, TN, TP, $Temp^r$	0.771	0.0175
3	pH, EC, Turbidity, TN, TP, $Temp^r$	0.845	0.0120
4	pH, EC, TN, TP, $Temp^r$	0.783	0.0198
5	TN, TP, Turbidity, $Temp^r$	0.748	0.0118
6	**pH, EC, Turbidity, $Temp^r$**	**0.921**	**0.0033**

The model performance results for both DO and SD models trained under MLP and TDNN topology are presented with Table 5 and the relation between the observed and predicted model values are presented in Fig. 3. It is evident from the figure that both the developed model based on TDNN and MLP, for the prediction of DO and SD, an acceptable correlation exists between observed values and model predicted values. For the trained DO models with MLP and TDNN, R^2 and E values were obtained as greater than 0.95. For trained MLP SD model a slightly lower value of R^2 and E were observed compared to the TDNN model. Overall, prediction capacity of TDNN model was found to be superior compared to the MLP models as reflected in the higher value of coefficient of determination and Nash efficiency and lower values of errors.

Table 5: Performance results of trained DO and SD models

Model	R^2		E		RMSE		MAE	
	MLP	TDNN	MLP	TDNN	MLP	TDNN	MLP	TDNN
DO	0.956	0.964	0.956	0.963	0.2027	0.1842	0.118	0.090
SD	0.886	0.961	0.925	0.959	4.1472	3.0356	3.257	2.321

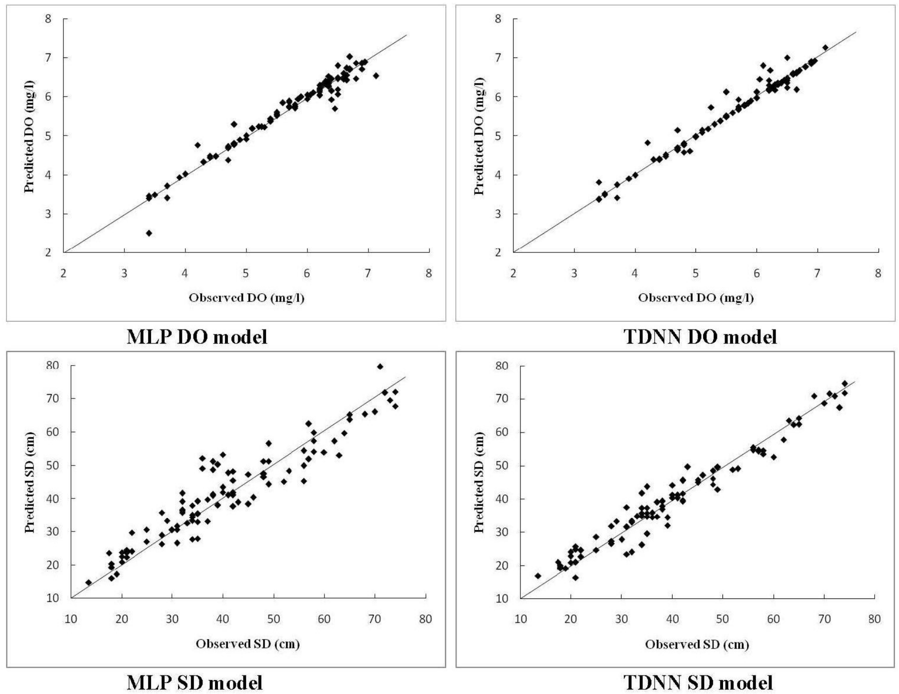

Fig. 3: Observed vs Predicted plot for the developed models from 1st Set Up

Relative influence (RI) of each input parameters on prediction of output parameter were calculated with Garson equation it has been observed that for DO prediction, all the seven input parameters had equal amount of influence on prediction of output parameter. However, pH was observed as the major influencing parameter having highest relative contribution of 16.78% and TP having lowest relative contribution of 10.92% on the prediction of DO. Similarly, pH, EC and turbidity were found as major contributing parameters compared to temperature for prediction of SD in eutrophic lakes.

To check sensitivity of the input parameters, data perturbation technique was used. Input parameters were increased or decreased by 20% one at a time fixing other inputs as constants. BOD and TN were observed as most sensitive input parameters for DO prediction having sensitivity percentage slightly higher than 100%. Compared to the DO model, input parameters in SD model were found to be less sensitive and changes in input parameters were found having lesser effect on SD prediction performance (Table 6).

Feasibility of the adopted modelling approach to be used as eutrophication predictor in natural waterbodies is evaluated by checking the model performance with samples collected from a few natural water bodies in Assam. As the prediction capacity of the model should be flawless under normal to extraordinary ecological conditions a vast dataset were gathered to check accuracy of the developed models to be used in natural water bodies in Assam. Water samples were collected from two sampling points of Deepor Bil, a world heritage RAMSAR wetland in Guwahati city as well as from a marsh, a manmade lake and a village pond in and around Tezpur University campus in Tezpur city. All the previously mentioned water quality parameters were investigated on the samples collected during both monsoon and winter seasons. Model simulation results of the DO and SD models revealed that the developed models were able to predict the output values within considerable accuracy. R^2 values of 0.916 and 0.853 were obtained for the DO and SD models respectively. E, RMSE and MAE values of 0.914, 0.527 mg/L and 0.480 mg/L were obtained for DO model testing with natural lake data. Similarly, for SD model testing E, RMSE and MAE values of 0.754, 6.785 cm and 5.275 cm were obtained.

Table 6: Result of sensitivity analysis with data perturbation

Parameters	DO Model		SD model	
	+20%	-20%	+20%	-20%
pH	86.17	93.46	36.17	57.84
EC	86.45	89.74	64.21	58.24
TN	102.83	66.46	-	-
TP	84.69	95.29	-	-
Temperature	97.43	95.33	57.35	67.08
BOD	121.26	98.18	-	-
Turbidity	95.74	89.93	59.36	85.69

Results of 2nd Set Up:

Lake eutrophication scenario was replicated successfully in the 2nd experimental set up also by continuous addition of waste water to the model tanks (Fig. 4).

Fig. 4: Images of water quality in the artificial pond during studied period from 2nd Set Up

The statistical summary of the results of different water quality parameters monitored during the set up are presented in Table 7.

Table 7: Statistical summary of the experimental investigation on the studied artificial lakes

		Concrete Tank (Tank-I)				Artificial Pond (Tank-III)			
	Waste water quality	Max^{m}	Min^{m}	Avg.	St. Dev.	Max^{m}	Min^{m}	Avg.	St. Dev.
pH	7.34	10.17	6.83	8.40	0.94	10.01	6.22	7.68	0.94
EC (μS/cm)	703.80	596.20	206.80	396.94	90.12	354.98	53.60	156.71	70.17
TDS (mg/L)	344.70	267.90	109.70	189.91	37.58	185.21	25.47	77.61	36.58
BOD (mg/L)	30.00	58.80	0.00	14.10	10.73	57.50	2	18.51	12.85
DO (mg/L)	6.10	17.30	0.50	7.80	4.68	10.00	2.50	6.48	1.46
Turb (NTU)	215.30	78.80	1.00	16.46	12.95	180.7	2.40	31.68	37.74
TN (mg/L)	0.48	0.71	0.00	0.11	0.15	1.01	0.01	0.09	0.15
TP (mg/L)	2.79	3.38	0.00	1.04	0.85	3.04	0	0.55	0.61
SD (cm)	--	72.00	28.00	52.01	10.79	75.00	21.00	47.78	8.94
Temp^{r} (°C)	--	34.10	22.80	28.53	2.77	34.00	21.70	29.15	2.78
Chl-a (μg/L)	24.52	246.03	0.00	64.98	57.05	174.11	0	61.10	43.86

*Max^{m} = Maximum, Min^{m} = Minimum, Avg. = Average, St. Dev. = Standard deviation

For TSI calculation the average and maximum values of SD, chl-a and TP were considered and the same had been reported in Table 8 for the investigated artificial lakes. TSI values were determined for each parameter individually and thereafter mean value was considered for trophic status evaluation. In the initial period of investigation lower concentration of TP (0.01 mg/L) and chl-a (0 μg/L) was observed in the lakes and SD value was not obtained as the water was completely transparent to the full lake depth. Corresponding to this condition minimum value of TSI was obtained as less than 40 for TP, chl-a and SD consideration indicating that the studied lakes were initially at oligotrophic stage. However, during progressive deterioration of water quality maximum values of TP, chl-a and minimum value of SD were recorded and for that condition calculated maximum value of TSI was obtained as more than 70 for the three considered criteria. This indicated that the studied lakes had reached hypereutrophic stage and at that point the experimental investigation was terminated and evaluated dataset were used for development of ANN and ANFIS models for DO, SD and chl-a prediction respectively.

Table 8: Trophic status estimation results of investigated lakes

	TSI (SD)		TSI (chl-a)		TSI (TP)		TSI_{MEAN}		Remarks
	Max^{m}	Avg.	Max^{m}	Avg.	Max^{m}	Avg.	Max^{m}	Avg.	
Tank-I	78.37	69.43	84.57	71.51	121.40	104.30	94.78	81.76	Hypereutrophic
Tank-III	82.52	70.66	81.18	70.90	119.84	95.20	94.51	78.92	Hypereutrophic

From the experimentally investigated dataset of 2nd Set Up, three eutrophication models for indicators DO, SD and chl-a were developed using conventional ANN and sophisticated ANFIS topology, following the same methodology as discussed earlier. For DO, SD and chl-a prediction 5, 5 and 9 parameters were found as model input parameters respectively (Table 9).

Table 9: Combinations for input parameter selection

Sl. No.	Input Parameters	R	MSE
	DO model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, Chl-a, Temp^r	0.9266	0.0106
2	pH, EC, TDS, TN, TP, Turbidity, Temp^r, Chl-a	0.9227	0.0079
3	pH, EC, BOD, TN, TP, Turbidity, Chl-a , Temp^r	0.9198	0.0062
4	pH, EC, BOD, TN, TP, Chl-a**,** Temp^r	0.9073	0.0104
5	pH, EC, TN, TP, Chl-a, Temp^r	0.9351	0.0036
6	pH, EC, TN, TP, Chl-a	0.9340	0.0166
7	pH, EC, TN, TP, Temp^r	0.8899	0.0061
8	**pH, EC, TP, Chl-a, Temp^r**	**0.9600**	**0.0029**
9	pH, TDS, TP, Chl-a, Temp^r	0.9132	0.0085
10	pH, TDS, Chl-a, Temp^r	0.8998	0.0100
	SD model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, Chl-a, Temp^r	0.891	0.0036
2	pH, EC, TDS, TN, TP, Turbidity, Chl-a, Temp^r	0.9053	0.0050
3	pH, EC, Turbidity, TN, TP, Chl-a, Temp^r	0.8829	0.0236
4	pH, EC, TN, TP, Chl-a, Temp^r	0.7554	0.0337
5	**pH, EC, Turbidity, Chl-a, Temp^r**	**0.9135**	**0.0035**
6	TN, TP**,** Turbidity, Chl-a, Temp^r	0.8824	0.0079
7	pH, EC, Chl-a, Temp^r	0.8267	0.0279
8	pH, EC, Temp^r, Turbidity	0.8591	0.0085
9	pH, TDS, Turbidity, Chl-a, Temp^r	0.8555	0.0173
10	EC, TDS, Turbidity, Chl-a, Temp^r	0.7801	0.0036
	chl-a model		
1	pH, EC, TDS, TN, TP, BOD, Turbidity, DO, Temp^r	0.8827	0.0160
2	pH, EC, TN, TP, BOD, Turbidity, DO, Temp^r	0.8428	0.0093
3	pH, EC, TN, TP, Turbidity, DO, Temp^r	0.8668	0.0097
4	pH, TN, TP, Turbidity, DO, Temp^r	0.8469	0.0088
5	pH, TN, TP, Turbidity, DO, BOD, Temp^r	0.8978	0.0084
6	pH, TN, TP, DO, BOD, Temp^r	0.8374	0.0237
7	pH, TN, TP, BOD, Turbidity, DO, SD, Temp^r	0.8841	0.0108
8	pH, EC, TDS, TN, TP, BOD, Turbidity, DO, SD, Temp^r	0.9024	0.0067
9	**pH, EC, TN, TP, BOD, Turbidity, DO, SD, Temp^r**	**0.9161**	**0.0022**
10	EC, TN, TP, BOD, Turbidity, DO, SD, Temp^r	0.8389	0.0180

Five empirical methods from previous research works were used to calculate the number of neurons required for the hidden layer in a ANN model and thereafter several neural networks were created between the minimum and maximum values. Based on its mean squared error (MSE) and correlation coefficient (R) between the output and target values, each network was evaluated, and optimum number of neurons was finalized. 8, 7 and 18 number of neurons in the hidden layer were found as optimum for DO, SD and chl-a prediction respectively in ANN topology.

In ANFIS topology, the input parameters as selected in ANN architecture were used for predicting the desired outputs and the whole normalized input dataset were randomly divided into 4:1 ratio as training and testing datasets. A subtractive clustering method with a hybrid learning algorithm was used in this work to formulate best fitting ANFIS model for the desired output parameters. Using a comprehensive methodology, testing different parameter combinations of subtractive clustering, the best structure of ANFIS was finalized with parameters 0.5 (range of influence), 1.5 (Squash factor), 0.5 (Accept ratio), 0.15 (Reject ratio) and 100 (no. of epoch).

Based on the laboratory investigation results from the two artificially simulated eutrophied lakes, two ANN as well as ANFIS models were trained for each indicator parameters. The models trained with Tank-I data are denoted as DO-I, SD-I and chl-a-I respectively and that trained with Tank-III data are presented as DO-III, SD-III and chl-a-III respectively in the succeeding sections. The results of model training were illustrated as time series plot between the observed and predicted values in Fig. 5.

The model performance was evaluated with correlation parameters R^2 and E and error estimation parameters RMSE and MAE; results for which were shown in Table 10. It was observed that in case of the ANN models, the performance of DO and chl-a models were quite satisfactory as reflected by R^2 and E parameters where values greater than 0.95 had been found for the models respectively. The RMSE and MAE between observed and predicted values were also low considering range of DO and chl-a dataset. Compared to DO and chl-a models, the goodness of fit for SD-I and SD-III ANN models were inferior with R^2 and E values slightly higher than 0.90. RMSE and MAE values of 3.02 cm 2.33 cm were observed for SD-I model and for SD-III model these values were 3.15 cm and 2.46 cm respectively which are acceptable under considered database. In case of the ANFIS models, very fine correlation was observed between actual and forecasted values for all the model types developed with negligible error in prediction and it was found that models trained under ANFIS topology had better prediction accuracy compared to corresponding ANN models

Table 10: Performance result of ANN and ANFIS model training

Model	R^2	E	RMSE	MAE
ANN Models				
DO-I	0.977	0.978	0.453 mg/L	0.328 mg/L
DO-III	0.955	0.959	0.495 mg/L	0.376 mg/L
SD-I	0.913	0.920	3.020 cm	2.330 cm
SD-III	0.908	0.909	3.150 cm	2.460 cm
Chl-a-I	0.989	0.989	5.750 µg/L	3.970 µg/L
Chl-a-III	0.958	0.967	7.820 µg/L	6.820 µg/L
ANFIS Models				
DO-I	0.997	0.997	0.213 mg/L	0.144 mg/L
DO-III	0.993	0.994	0.114 mg/L	0.071 mg/L
SD-I	0.950	0.953	2.320 cm	1.680 cm
SD-III	0.958	0.960	1.780 cm	1.080 cm
Chl-a-I	0.999	0.999	0.010 µg/L	0.008 µg/L
Chl-a-III	0.999	0.999	0.010 µg/L	0.006 µg/L

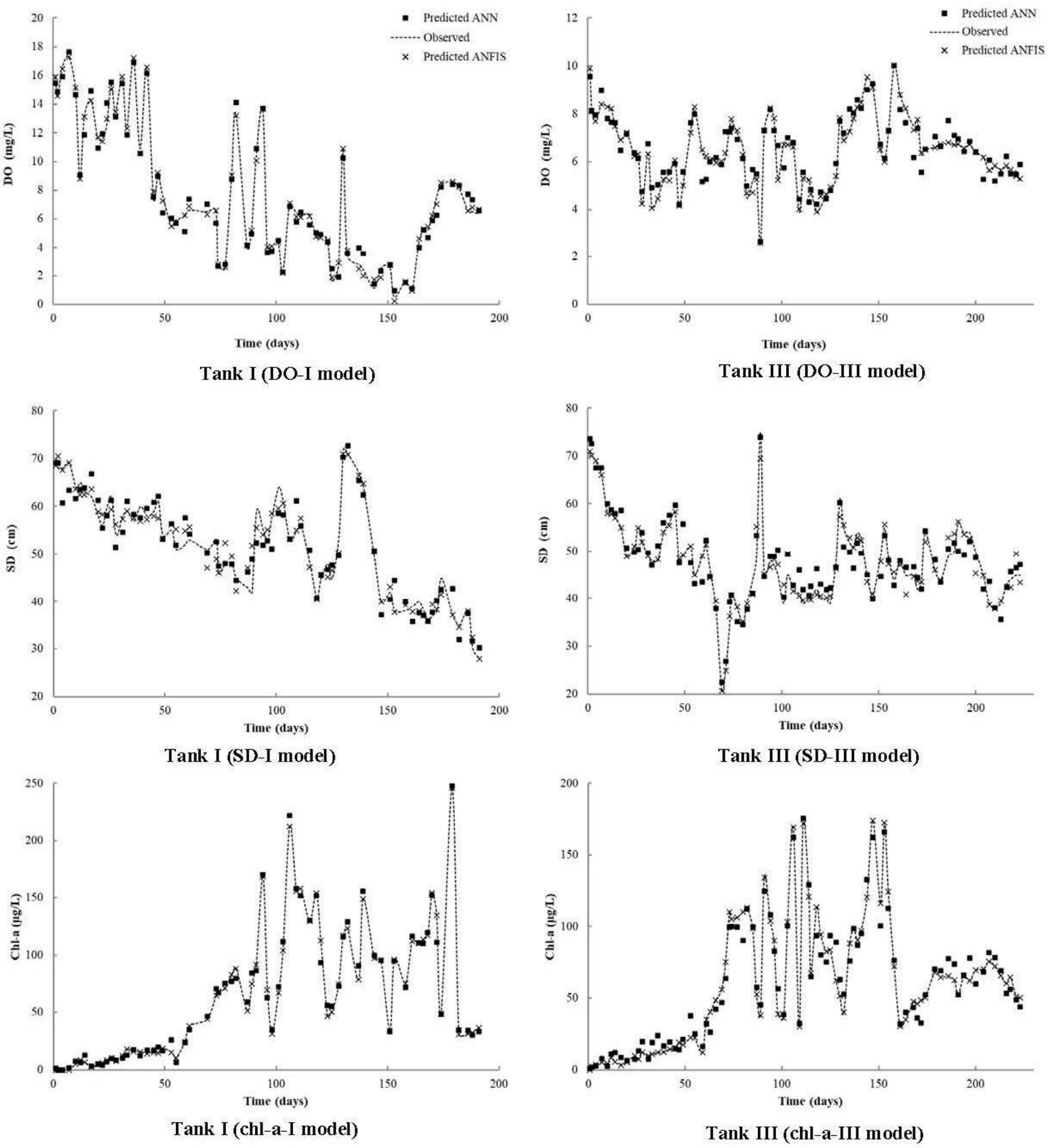

Fig. 5: Time series plot of observed vs predicted values for the developed models from 2nd Set Up

Sensitivity analysis was performed on the developed models with data perturbation method by changing the input parameters by ±20% in succession. Results of the sensitivity analysis revealed that for DO prediction with ANN and ANFIS, chl-a was found to be the most sensitive parameter followed by temperature. Out of the nine input parameters for chl-a prediction pH, DO, increase in nutrient concentration (TN and TP) and increase in temperature were most influential parameters. Compared to the DO and chl-a models, input parameters in SD model were found to be less sensitive. Results of the sensitivity analysis revealed that similar trends for ANN and ANFIS models were observed, however, effect of input perturbation on target prediction was smaller in case of ANFIS models compared with the ANN models.

The trained ANN and ANFIS models were finally tested with natural waterbody data as discussed in preceding section and simulation results of the DO, SD and chl-a models revealed that the developed models were able to predict the output values within considerable accuracy. R^2 values greater than 0.8 was obtained between observed and predicted values for all the DO, SD and chl-a models trained under ANN and ANFIS environment. Model simulation results were compared with statistical parameters R^2, E, RMSE and MAE respectively and are reported in Table 11. Prediction capacity of trained ANFIS models were found superior to trained ANN models in general, except for SD-1 model where performance of ANN was slightly better compared to ANFIS. Comparing the testing results different ANN and ANFIS models developed with Tank-I and Tank-III data, it was found that for ANFIS models trained with Tank-III data, higher testing accuracy was achieved.

Table 11: Performance result of model validation with natural waterbody data

Parameters	**DO**		**SD**		**chl-a**	
	ANN	ANFIS	ANN	ANFIS	ANN	ANFIS
Tank-I (*Concrete Tank*)						
R^2	0.827	0.867	0.868	0.814	0.910	0.914
E	0.829	0.855	0.860	0.809	0.890	0.923
RMSE	1.06 mg/L	0.97 mg/L	4.10 cm	6.09 cm	12.27μg/L	10.14 μg/L
MAE	0.77 mg/L	0.82 mg/L	3.58 cm	4.52 cm	10.06 μg/L	7.89 μg/L
Tank-III (*Artificial Pond*)						
R^2	0.829	0.902	0.809	0.831	0.918	0.960
E	0.836	0.905	0.820	0.840	0.920	0.962
RMSE	1.04 mg/L	0.79 mg/L	4.56 cm	4.27 cm	10.27 μg/L	7.10 μg/L
MAE	0.77 mg/L	0.66 mg/L	4.07 cm	3.76 cm	8.38 μg/L	5.67 μg/L

Conclusions

To predict lake eutrophication in waterbodies in Assam, India, a novel approach has been adopted in this presented work. From the results of the experimental and modelling investigations, the following major conclusions can be drawn.

i. Lake eutrophication scenario was successfully replicated by continuous addition of waste water into artificially constructed lakes. Trophic status index (TSI) was estimated for the studied lakes that indicated transition of the lakes from a clear water oligotrophic to hypereutrophic stage. Data monitored during this process was used for development of eutrophication models for indicators DO, SD and chl-a using multilayer perceptron (MLP), time delay neural network (TDNN) and adaptive neuro-fuzzy inference system (ANFIS). The architecture of the developed models were chosen rigorously and input parameters were chosen based on a model based data pruning method to obtain optimum parameters. Results of sensitivity analysis revealed that all the dependent variables were logically chosen for target prediction.

ii. The MLP and TDNN models developed from the 1st experimental set up for prediction of DO and SD, it was concluded that both type of models was able to predict the eutrophication indicators with considerable accuracy. Results of TDNN models were found to be superior in compared with MLP models during both training and testing stage.

iii. All the models trained using ANN and ANFIS topology from the 2nd experimental set up were able to predict the eutrophication indicators DO, SD and chl-a with reasonable accuracy. Overall performance of the trained ANFIS models for prediction of DO, SD and chl-a were found to be superior compared to ANN models. Models trained with concrete tank (Tank-1) and artificial pond (Tank-3) data were found to be more or less consistent under ANN and ANFIS. However, ANFIS models trained with artificial pond (Tank-3) data produced best prediction performance. Compared to ANN models, ANFIS models were more reliable for forecasting eutrophication indicators when tested against actual natural waterbodies.

iv. This type of data driven modelling approach with laboratory investigated data on artificially simulated lake systems could be an alternate solution to eutrophication management of waterbodies where prolonged water quality data is unavailable for the same. From the test results of this study, it can be concluded that ANFIS modelling approach with artificially simulated pond system can be a promising solution for forecasting and mitigating lake eutrophication in natural waterbodies in Assam, India.

Scope of future work

The presented models were successful in predicting eutrophication indicators in natural water bodies in Assam. Considering the boundary conditions of the experimental set up as well as complex nature of eutrophication phenomenon, the presented models are suitable for application in tropical climatic conditions with high humidity like in Assam. Moreover, the major source of water pollution in the natural water bodies prone to eutrophication in Assam is due to domestic wastes. So, the applicability of the developed models is limited to use in the natural water bodies in Assam where major source of contamination is domestic wastes with high nutrient concentration and low BOD. Future research can be focussed on conducting more detailed investigation to understand eutrophication dynamics of the concerned lake, incorporating more number of parametric studies and with varying influent properties. Prediction of more number of water quality variables like total phosphorus, total nitrogen etc. may be done using additional data driven methods like Decision Tree, Support Vector Machines, and hybrid approaches such as genetic algorithm optimized neural networks (GA-ANN).

Plans for utilizing the equipment facilities in future

From the financial assistance of this research project three numbers of major equipment have been procured that includes a BOD incubator, a double beam UV/VIS Spectrophotometer and a digital DO meter. All these facilities are very useful and frequently used for most of the environmental investigations related with water and wastewater quality. These facilities were used extensively throughout conduction of the experimental investigations of this research work and will be used for similar endeavours in near future. BOD incubator is essentially required for determining the BOD value of wastewaters and so it will be quite useful in conduction of sewage and wastewater related investigations. UV/VIS Spectrophotometer has a very wide range of application in water quality analysis and is quite useful in determination of metal ion and nutrient concentration, organic compounds, bacterial contaminants etc. in water and wastewater samples. So, this instrument will be invaluable for future research work related with physio-chemical properties of water and wastewater. Digital DO meter provides a rapid means of estimating the DO concentration in water samples compared to conventional titration methods. This instrument will be used for determination of in-situ DO concentrations in surface waterbodies like lakes, ponds, and rivers etc. in future research works where DO level is a prime indicator of surface water quality. Apart from research works, the above facilities will be utilized for departmental academic purposes like conduction of laboratory classes and project works of B. Tech and M. Tech students.

GFR 12 – A [(See Rule 238 (1))]
UTILIZATION CERTIFICATE (UC) FOR THE YEAR 2020-21
in respect of NON-RECURRING
as on 17 July 2020 to be submitted to SERB

Is the UC ....*(Provisional/Audited)*
(To be given separately for each financial year ending on 31st March)

1. Name of the grant receiving Organization: **Tezpur University**
2. Name of Principal Investigator (PI): **Kamal Uddin Ahamad**
3. SERB Sanction order no. & date: **ECR/2017/000740 & 27 JUNE 2017**
4. Title of the Project: **DEVELOPMENT OF EUTROPHICATION MODEL FOR RURAL WATER BODIES OF ASSAM, INDIA**
5. Name of the SERB Scheme: **ECR**
6. Whether recurring or non-recurring grants: **NON-RECURRING**
7. Grants position at the beginning of the financial year

i.	Carry forward from previous financial year	:	Rs 60181
ii.	Others, If any	:	--
iii.	Total	:	Rs 60181

8. Details of grants received, expenditure incurred and closing balances: (Actuals)

Unspent Balance of Grants received previous years [figure as at Sl. No. 7(iii)]	Interest Earned thereon	Interest deposited back to the SERB	Grants received during the year			Total Available funds (1+2-3+4)	Expenditure incurred	Closing Balances (5-6)
1	2	3	4			5	6	7
			Sanction No.(i)	Date (ii)	Amount (iii)			
60181	NIL	NIL	NIL	NIL	NIL	60181	0	60181

Component wise utilization of grants:

Grants-in-aid- General	Grant-in-aid-creation forcapital assets	Total
NIL	NIL	NIL

Details of grants position at the end of the year

i.	Balance available at end of financial year	:	60181
ii.	Unspent balance refunded to SERB (If any)	:	60181 (DD number 535391 dated 15-11-2021)
iii.	Balance (Carried forward to next financial year) if applicable	:	--

GFR 12 – A [(See Rule 238 (1))]
UTILIZATION CERTIFICATE (UC) FOR THE YEAR 2020-21
in respect of NON-RECURRING
as on 17 July 2020 to be submitted to SERB

Is the UC ....*(Provisional/Audited)*

(To be given separately for each financial year ending on 31st March)

Certified that I have satisfied that the conditions on which grants were sanctioned have been duly fulfilled/are being fulfilled and that I haveexercised following checks to see that the money has been actually utilized for the purpose for which it was sanctioned:

i. The main accounts and other subsidiary accounts and registers (including assets registers) are maintained as prescribed in therelevant Act/Rules/Standing instructions (mention the Act/Rules) and have been duly audited by designated auditors. The figuresdepicted above tally with the audited figures mentioned in financial statements/accounts.
ii. There exist internal controls for safeguarding public funds/assets, watching outcomes and achievements of physical targets against the financial inputs, ensuring quality in asset creation etc. & the periodic evaluation of internal controls is exercised to ensure their effectiveness.
iii. To the best of our knowledge and belief, no transactions have been entered that are in violation of relevant Act/Rules/standing instructions and scheme guidelines.
iv. The responsibilities among the key functionaries for execution of the scheme have been assigned in clear terms and are not general in nature.
v. The benefits were extended to the intended beneficiaries and only such areas/districts were covered where the scheme was intended to operate.
vi. The expenditure on various components of the scheme was in the proportions authorized as per the scheme guidelines and terms and conditions of the grants-in-aid.
vii. It has been ensured that the physical and financial performance under ECR. **(CRG/NPDF/ECR.....etc.)** (Name of the scheme has been according to the requirements, as prescribed in the guidelines issued by Govt. of India and the performance/targets achieved statement for the year to which the utilization of the fund resulted in outcomes given at Annexure I duly enclosed.
viii. The utilization of the fund resulted in outcomes given at Annexure – II duly enclosed (to be formulated by the Ministry/Departmentconcerned as per their requirements/specifications.)
ix. Details of various schemes executed by the agency through grants-in-aid received from the same Ministry or from other Ministriesis enclosed at Annexure –II (to be formulated by the Ministry/Department concerned as per their requirements/specifications).

Date: 3/9/23

Place: Tezpur University

Signature of PI : ...K. U. Ahamad...	03/9/23 **Signature with Seal :**................. **Name:** CMA DR. BRAJA BANDHU MISHRA **Chief Finance Officer (Head of Finance)** Finance Officer Tezpur University	03/9/23 **Signature with Seal**........................ **Name:** DR. BIREN DAS......... Registrar **Head of Organisation** Tezpur University

GFR 12 – A [(See Rule 238 (1))]
UTILIZATION CERTIFICATE (UC) FOR THE YEAR 2020-21
in respect of *RECURRING*
as on 17 July 2020 to be submitted to SERB

Is the UC ....*(Provisional/Audited)*

(To be given separately for each financial year ending on 31st March)

1. Name of the grant receiving Organization: **Tezpur University**
2. Name of Principal Investigator (PI): **Kamal Uddin Ahamad**
3. SERB Sanction order no. & date: **ECR/2017/000740 & 27 JUNE 2017**
4. Title of the Project: **DEVELOPMENT OF EUTROPHICATION MODEL FOR RURAL WATER BODIES OF ASSAM, INDIA**
5. Name of the SERB Scheme: **ECR**
6. Whether recurring or non-recurring grants: **RECURRING**
7. Grants position at the beginning of the financial year

   i. Carry forward from previous financial year : Rs 165641
   ii. Others, If any : --
   iii. Total : **Rs 165641**

8. Details of grants received, expenditure incurred and closing balances: (Actuals)

Unspent Balance of Grants received previous years [figure as at Sl. No. 7(iii)]	Interest Earned thereon	Interest deposited back to theSERB	Grants received during the year			Total Available funds (1+2-3+4)	Expenditure incurred	Closing Balances (5-6)
1	2	3	4			5	6	7
			Sanction No.(i)	Date (ii)	Amount (iii)			
165641	**NIL**	**NIL**	--	--	**NIL**	**165641**	**217605**	**(-) 51964**

Component wise utilization of grants:

Grants-in-aid- General	Grant-in-aid-creation forcapital assets	Total
217605	NIL	217605

Details of grants position at the end of the year

i. Balance available at end of financial year : (-) 51964

ii. Unspent balance refunded to SERB (If any) : --

iii. Balance (Carried forward to next financial year) if applicable : (-) 51964

GFR 12 – A [(See Rule 238 (1))]
UTILIZATION CERTIFICATE (UC) FOR THE YEAR 2020-21
in respect of *RECURRING*
as on 17 July 2020 to be submitted to SERB

Is the UC ....*(Provisional/Audited)*

(To be given separately for each financial year ending on 31st March)

Certified that I have satisfied that the conditions on which grants were sanctioned have been duly fulfilled/are being fulfilled and that I haveexercised following checks to see that the money has been actually utilized for the purpose for which it was sanctioned:

i. The main accounts and other subsidiary accounts and registers (including assets registers) are maintained as prescribed in therelevant Act/Rules/Standing instructions (mention the Act/Rules) and have been duly audited by designated auditors. The figuresdepicted above tally with the audited figures mentioned in financial statements/accounts.

ii. There exist internal controls for safeguarding public funds/assets, watching outcomes and achievements of physical targets against the financial inputs, ensuring quality in asset creation etc. & the periodic evaluation of internal controls is exercised to ensure their effectiveness.

iii. To the best of our knowledge and belief, no transactions have been entered that are in violation of relevant Act/Rules/standing instructions and scheme guidelines.

iv. The responsibilities among the key functionaries for execution of the scheme have been assigned in clear terms and are not general in nature.

v. The benefits were extended to the intended beneficiaries and only such areas/districts were covered where the scheme was intended to operate.

vi. The expenditure on various components of the scheme was in the proportions authorized as per the scheme guidelines and terms and conditions of the grants-in-aid.

vii. It has been ensured that the physical and financial performance under **ECR** (CRG/NPDF/ECR.....etc.) (Name of the scheme has been according to the requirements, as prescribed in the guidelines issued by Govt. of India and the performance/targets achieved statement for the year to which the utilization of the fund resulted in outcomes given at Annexure– I duly enclosed.

viii. The utilization of the fund resulted in outcomes given at Annexure – II duly enclosed (to be formulated by the Ministry/Departmentconcerned as per their requirements/specifications.)

ix. Details of various schemes executed by the agency through grants-in-aid received from the same Ministry or from other Ministriesis enclosed at Annexure –II (to be formulated by the Ministry/Department concerned as per their requirements/specifications).

Date: 3/9/23

Place: Tezpur University

Signature of PI : ...K.U. Ahamed...	03/9/23 **Signature with Seal :..................** **Name:** CMA DR BRAJA BANDHU MISHRA **Chief Finance Officer** **(Head of Finance)** Finance Officer Tezpur University	**Signature with Seal........................** **Name:** DR. BIREN DAS........ Registrar **Head of Organisation** Tezpur University

Annexure-II

REQUEST FOR ANNUAL INSTALMENT WITH UP-TO-DATE STATEMENT OF EXPENDITURE

1. SERB Sanction Order No and date:**ECR/2017/000740 and27 June 2017**

2. Name of the PI:**Kamal Uddin Ahamad**

3. Total Project Cost:Rs **2426710**

4. Revised Project Cost: (if applicable)

5. Date of Commencement:**18 July 2017**

6. Statement of Expenditure:
(Month wise expenditure incurred during current financial year*1st April 2020-17 July 2020*)

Month & year	Expenditure incurred/ committed
April 2020	0
May 2020	0
June 2020	0
July 2020	217605 PAID FELLOWSHIP FOR MAR-2020 TO JUNE-2020 + CONSUMABLES
August, 2020	0
September, 2020	0
October, 2020	0
November, 2020	0
December, 2020	0
January, 2021	0
February, 2021	0
March, 2021	0

1. Grant received in each year
    a. 1st year : Rs **1255630**
    b. 2nd year :**Rs 485530**
    c. 3rd year :Rs **385550**
    d. 4th year
    e. Interest, if any : --
    f. Total (a + b + c + d) : Rs **2126710**

Statement of Expenditure

Sr No (I)	Sanctioned Heads (II)	Total Funds Allocated (indicate sanctioned or revised (III)	Expenditure Incurred				Total Expenditure till 17th July 2020 VIII = IV + V + VI +VII	Balance as on (date) IX = III – VIII	Requirement of Funds upto 31st March 2021	Remarks (if any)
			1st Year (18 July 2017 to 31st March 2018) (IV)	2nd Year (1st April 2018 to 31st March 2019) (V)	3rd Year (1st April to 31st March 2020) (VI)	4th Year (1st April to 17th July 2020) (VII)				
1.	Manpower costs	900900	132000	330000	315700	123200	900900	0	0	
2.	Consumables	274699	110317	61760	0	94405	266482	8217	0	
3.	Travel	75598	0	33569	42029	0	75598	0	0	
4.	Contingencies	148949	27528	76114	45307	0	148949	0	0	
5.	Others, if any	0	0	0	0	0	0	0	0	
6.	Equipment	609919	609919	0	0	0	609919	0	0	
7.	Overhead expenses	116645	45960	24725	45960	0	116645	0	0	
8.	Total	**2126710**	**925724**	**526168**	**448996**	**217605**	**2118493**	**8217**	**0**	

Name and Signature of Principal Investigator:

KAMAL UDDIN AHAMAD

Date: 2 Nov 2021

Signature of Competent financial authority: 03/11/2021

(with seal) Date: Finance Officer Tezpur University