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Assessment of the Present State and Future Fate of River Saraswati, India: Water Quality Indices and Forecast Models as Diagnostic and Management Tools

Sasanka Pramanik, Jayanta Kumar Biswas, Anilava Kaviraj, and Subrata Saha**

Water quality assessment is key to the conservation and management of rivers. River Saraswati, a distributary of the river Ganga, serves as a lifeline to many villages in the district Hooghly in West Bengal, India. As the river is gradually dying due to diverse man-made pollution, ten water quality parameters in two sampling spots (PR-1 and PR-2) in the river are monitored month-wise from March 2017 to February 2020, and these are compared with those from a reference pond. The water quality index (WQI) is determined for the two riverine spots and the reference pond based on the Canadian Council of Ministers of Environment WQI (CCMEWQI) and weighted arithmetic WQI, respectively. In addition to actual observations, three different forecasting methods, exponential smoothing, autoregressive integrated moving average, and artificial neural network, are used to predict WQI for the next two years. This study indicates that free CO_2, dissolved oxygen, and turbidity are the key parameters to evaluate this river's anthropogenic stress and health. The actual and forecasted results reflect the precipitous degradation of CCMEWQI in PR-2. Therefore, the immediate intervention of all stakeholders is required to adopt an integrated and comprehensive river management plan to save the river from utter obliteration.

1. Introduction

Aquatic pollution is caused by diverse anthropogenic activities such as wastewater discharge, poor sanitation processes, fertilizers, pesticide application in the agricultural field, animal husbandry activities, inefficient irrigation practices, industrial effluents, and domestic sewage discharge. They degrade the water quality of the aquatic ecosystem and overall aquatic health.[1–3] Rivers serve as lifelines of India to deliver a vast array of environmental services, including water resource provisioning for diverse human usages. But many of them are already dead, dying, or seriously threatened because of the massive loading of environmental pollutants, particularly industrial effluents and domestic sewage flowing through the city drainage system. About 70% of river water in India is misused, disused, exploited, or overexploited and is heavily polluted to a different degree, with pathological symptoms manifested in their degraded physicochemical profiles.[4] For example, originating from Gomukh of the Himalaya, the river Ganga, the colossal national river of India on its way to join the Bay of Bengal, runs through densely populated cities and receives 8250 million liters wastewater per day from industrial and domestic sources.[5] As a consequence, the physicochemical attributes of the river Ganga have been immensely degraded and heavily burdened with pathogenic and nonpathogenic microorganisms.[6] The Ganga Action Plan was introduced by the Government of India in 1985 to reduce the wastewater load and improve water quality, costing around six billion rupees.[6] But it was later considered an "environmental failure," and the river Ganga is still experiencing heavy water pollution while passing through cities and industrial constellations.[7]

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In India, agriculture is the leading source of pollution in rivers and streams. Discharging an unlimited amount of municipal, domestic, and industrial wastewater is also a significant threat to rivers and other water bodies.[8] Discharges from agricultural fields (e.g., fertilizers, pesticides, herbicides, and plant hormones) and industries (e.g., metals, metalloids, and polycyclic aromatic hydrocarbons) find their way into the rivers and other freshwater ecosystems.[9–13] Recently, micro- and nanoplastics have also been reported to affect freshwater systems and their biota.[14] Eutrophication, a nutrient enrichment impact of agrochemicals, emerged as a severe threat to many Indian riverine systems. It increases the turbidity of the water and often creates severe diurnal and vertical fluctuation of dissolved oxygen (DO), resulting in respiratory disturbance of aquatic organisms in the water body.[10,15]

The Hooghly estuary, the lower stretches of the river Ganga does not only receive a massive load of effluents from industries situated on both banks along with the cities of Kolkata, Howrah, Hooghly, and Nadia but also retain the pollutants for a long period due to tidal action of the estuary.[16,17] The river Saraswati is an important distributary of the river Ganga in its lower stretch, flowing across the Hooghly district, West Bengal, India. It was an important river in ancient Bengal province (as noted in Mangal-Kavya, composed more or less between the 13th and 18th centuries), and its inland port Adisaptagram was a major port in ancient and medieval times.[18] The Saraswati river was large, even 50–60 years ago, and was the lifeline for different trading classes and fishers. The river gradually decayed over the last few centuries and now survives as a shallow, nonperennial, nearly discontinuous stream.[19] But at present, the river has become a narrow water channel and has lost its importance due to pollution load from agricultural runoffs, discharge of organic wastes from growing human settlements on both banks of the river, siltation, and unscientific fishing practices emerging on the river beds. The large portion of this river, covering 285.69 km^2, flows through Polba-Dadpur of district Hooghly.[18] In addition, the construction of a chain of brick kilns along the river course has contributed to the stagnancy of the riverine flow regime.[20] It receives heavy organic loading from diverse anthropogenic activities such as agricultural and surface runoff, discharge of domestic wastewater, seasonal jute retting,[21] and effluents from some small beer and brick kiln factories.[22] These interventions and unauthorized land use on river beds have been instrumental in degrading the river environment.[6] The state of the river Saraswati has not been evaluated, notably the spatiotemporally water pollution of the river in recent years.

Pollutants can alter aquatic ecosystems' physicochemical profile and water quality.[23] Traditionally, limnological parameters such as DO, free carbon dioxide (CO_2), and biochemical oxygen demand (BOD) are used as indicators of environmental conditions and the health of the riverine system. This often lacks realism and fails to tell the whole story. When pollutants from different sources alter the physicochemical profile of a water body comprising multiple water quality parameters, the deficiency related to the above "single indicator" approach can partly be overcome if these are accommodated together to formulate an index called the water quality index (WQI) of that aquatic system. Therefore, we aimed to explore the spatial and seasonal variation of the river's water quality through various WQI and compare the WQI for three different spots. In the present study, we used a set of ten basic but critical physicochemical water quality parameters of water such as temperature, pH, DO, free CO_2, BOD, chemical oxygen demand (COD), turbidity, salinity, alkalinity, total dissolved solids (TDS), and conductivity. These parameters have "consanguineous" relationship with the physicochemical profile and aquatic ecosystem health. We determined WQI based on the weighted score of the parameters.[24]

The concept of WQI measures was initiated by Horton[25] and was widely used to evaluate the quality of the aquatic environment. Till now, a large number of WQIs have been developed for assessing water quality, such as the Prati Index of Pollution, Bhargava Index, Oregon WQI, National Sanitation Foundation (NSF) WQI, Canadian Council of Ministers of Environment WQI (CCMEWQI), and Weighted Arithmetic WQI (WAWQI).[24] The WQI has now become state-of-the-art metric for investigating water quality in polluted aquatic ecosystems.[26–31] Measuring WQI is a critical concern for environmentalists and policymakers to design intervention plans for river management, reduce the adverse effects of water pollution in rivers, and control anthropogenic activities.[32,33] Since the individual WQI method suffers from several weaknesses, it may not be sufficient to identify the impacts of pollution on the water quality status of the freshwater system under study, which calls for a multi-WQI approach. In the present study, we used CCMEWQI for determining the WQI of the river and WAWQI for determining the WQI for the reference ponds. The respective selection of the WQI method was based on the conventional relative preference, i.e., CCMEWQI for the lotic (running) water body and WAWQI for the lentic (standing) water body.

We also employed forecasting methods to explore the future WQI of the river, in general, to help policymakers prepare appropriate intervention plans. In recent years, river WQI forecasting has gained considerable attention from researchers. Generally, forecasting methodologies fall into the two main categories of statistical (e.g., moving average, exponential smoothing, autoregressive integrated moving average [ARIMA]) and computational intelligence (e.g., artificial neural networks [ANN], support vector machine [SVM], long short-term memory [LSTM]) methods.[34–36] There are differences between these two categories of forecasting. Statistical forecasting methods such as ARIMA assume that the time series contains only linear components. In contrast, computational intelligence methods such as ANNs can capture nonlinear patterns in time series. Several researchers used the ANN model to predict DO, temperature, pH, conductivity, and turbidity of water in different aquatic ecosystems across the globe.[37–40] In the present study, we used a portfolio of three state-of-the-art statistical (exponential smoothing), and computational intelligence models (ARIMA and ANN) to better anticipate the water quality and environmental health of the river Saraswati and to determine the fate of the river in the near future. One can apply the wavelet-based regression model or the wavelet-based artificial neural network model,[41] back propagation neural network[42] but this model requires large data points to ensure higher accuracy. The key focus was to explore the nature of WQI to obtain an overview of water pollution for both the river and surroundings for future intervention. A plethora of forecasting techniques has been developed to improve accuracy. Still, to the best of our knowledge, no study so far has brought out

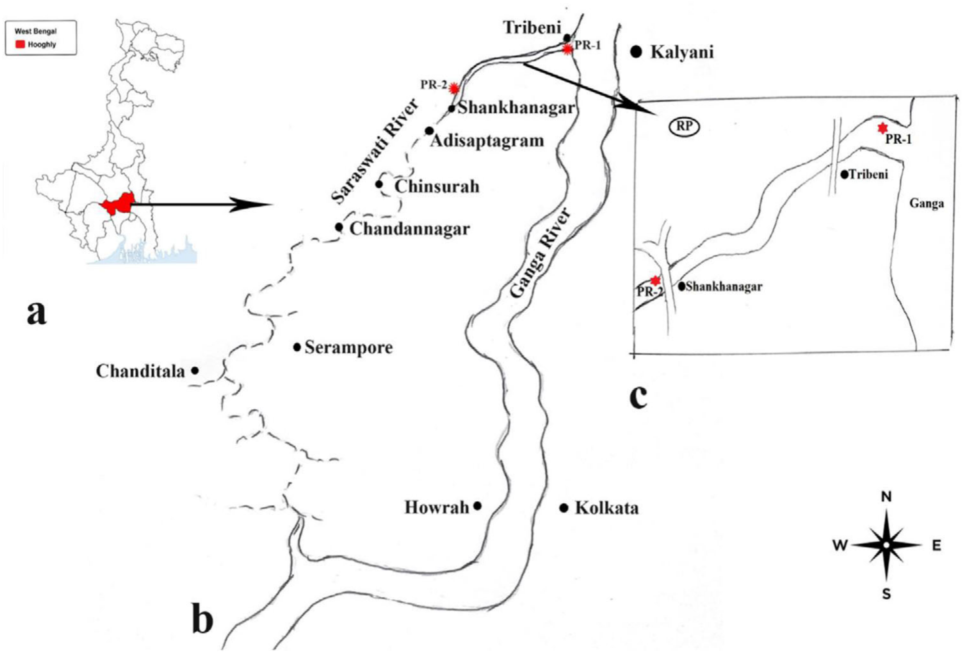

Figure 1. Map showing the course of the river Saraswati including b) its meeting point with the river Ganga and c) location of the sampling spots PR-1, PR-2, and RP of the river Saraswati a) passing through Hooghly, West Bengal, India. Here, the continuous line indicates the existing river course, while the dashed line indicates its historical presence and missing link.

the best of both worlds by combined use of WQIs and forecast models for diagnosis of the present pathological condition of the riverine ecosystem and prescription of management intervention measures and mitigation means. The present study adopted such an innovative integrated approach shifting from a piecemeal approach to an integrated systems approach for a comprehensive assessment of the present state and projection of the future fate of river Saraswati.

2. Experimental Section

2.1. Study Area

Three spots were selected for this study, two on the river Saraswati and one in a pond near to these spots as the reference spot. Spot 1 (PR-1) represents the site where the river Saraswati meets with the Ganga and is not much affected by pollutants generated from diverse human activities. Spot 2 (PR-2) is about 4 km away from PR-1 toward the southwest of the river Saraswati (**Figure 1**). PR-2 receives heavy organic loads from agricultural and surface runoffs and diverse anthropogenic activities such as discharge of domestic wastewater, seasonal jute retting, and effluents from some small- to medium-scale beer and brick kiln factories.

2.2. Collection of Water Samples and Physicochemical Analyses

The water samples were collected from the selected sampling sites of the river (PR-1 and PR-2) and the reference pond (RP) once a month during the study period from March 2017 to February 2020 to analyze the physicochemical parameters of water. The months of March to May represent the first quarter (Q1) of the year, the summer season; June to August represent the monsoon season (Q2); September to November represent the post-monsoon (Q3); and December to February represent the winter season (Q4). Water temperature, pH, TDS, turbidity, salinity, and electric conductivity (EC) were determined in the collected samples using a digital water and soil analysis kit (Model 172, Electronics India). The concentrations of DO, free CO_2, BOD, and COD were measured as per the standard methods.[43] The values of each parameter were subjected to one-way analysis of variance (ANOVA) followed by Fisher LSD test.[44]

2.3. WQI and Forecasting Methods

This subsection presents an overview of the methodology and WQI index used in this study. **Figure 2** shows the detail of the computational scheme used in this study. We used three years of actual data and applied three forecasting methods to each of the ten parameters. Based on that, we made forecasting for additional two years to obtain our final impact analysis. We present the detail of WQI in the following subsection.

2.4. Determination of WQI

Based on ten physicochemical parameters of water, WQIs were calculated season-wise for PR-1, PR-2, and RP. The water quality was evaluated by the WAWQI and the CCMEWQI. The standard values of water parameters, recommended by WHO,[45] BIS,[46] and ICMR[47] were used as "benchmarks" for assessing the quality of individual parameters while calculating both kinds of WQIs

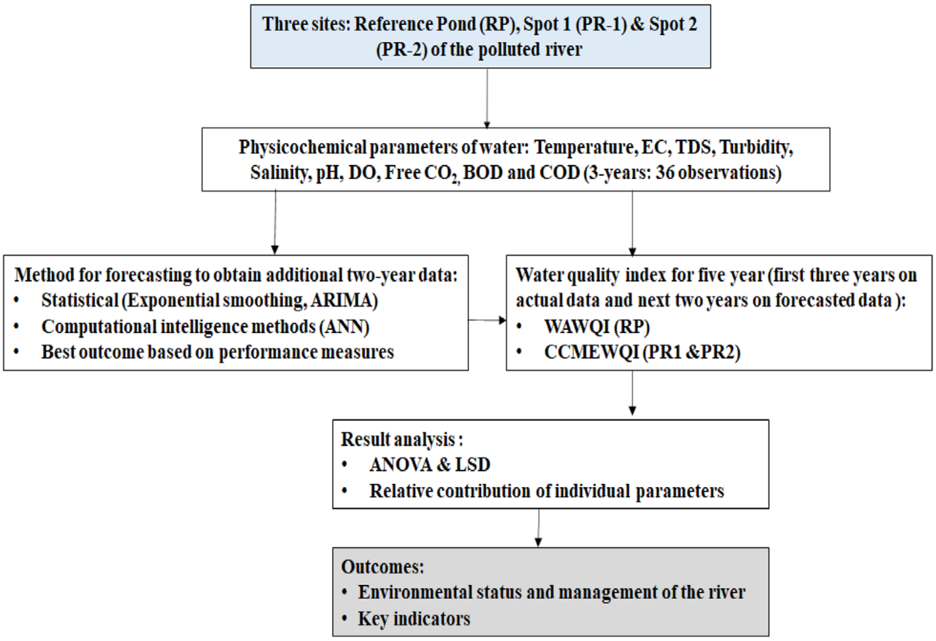

Figure 2. Overview of analysis.

(Table S1, Supporting Information). The method characterizes the water quality of a water body depending on its physicochemical parameters (Table S1, Supporting Information). We used Equation (1) to calculate the WAWQI.[48]

$$\text{WAWQI} = \frac{\sum_{i=1}^{n} W_i Q_i}{\sum_{i=1}^{n} W_i} \tag{1}$$

where n, W_i, and Q_i represent the total number of variables of parameters, relative weight of the nth parameters, and water quality rating of the nth parameters, respectively. CCMEWQI is based on three measurements: factor 1 (F1) represents the scope, factor 2 (F2) represents the mean frequency, and factor 3 (F3) represents the amplitude.[49] The values of F1, F2, and F3 are calculated using Equation (2) that follows CCME[50]

$$\text{F1} = \frac{\text{Number of failed variables}}{\text{Total number of variables}} \times 100,$$

$$\text{F2} = \frac{\text{Number of failed tests}}{\text{Total number of tests}} \times 100,$$

$$\text{F3} = \frac{nse}{0.01\,nse + 0.01} \tag{2}$$

where nse stands for normalized sum excursion, which is derived as the ratio between the sum of excursion and the total number of tests. Finally, the value of CCMEWQI was calculated by using the following equation

$$\text{CCMEWQI} = 100 - \frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732} \tag{3}$$

The vector length can reach = 173.2, so division by the factor 1.732 is only to adjust CCMEWQI into 0–100 scale.[51] The mode of representation for the WQIs considered here is the opposite of the scale taken to each other. In CCMEWQI, a lower value (<44) indicates poor water quality, and a higher value (95–100) indicates excellent water quality. On the other hand, in WAWQI, a lower value (0–25) indicates excellent water quality, and a higher value (>100) indicates unsuitable for drinking (Table 3). We refer to **Table 1** for quality scales for two indices.

Table 1. Different scales used for determining water quality as per CCMEWQI and WAWQI.

Index method	Range of WQI value	Inference about water quality status
CCMEWQI	<44	Poor
	45–64	Bad
	65–79	Marginal
	80–94	Good
	95–100	Excellent
WAWQI	0–25	Excellent
	26–50	Good
	51–75	Poor
	76–100	Very poor
	>100	Unsuitable for drinking

Note: WQI, water quality index; CCMEWQI, Canadian Council of Ministers of the Environment WQI; WAWQI, weighted arithmetic WQI

2.5. Forecasting Methods

We employed three different forecasting methods: i) exponential smoothing,[52,53] ii) ARIMA model,[54,32] and iii) ANN.[55,56]

2.5.1. Exponential Smoothing

The exponential smoothing method is widely used for forecasting where weighted averages of past observations and the weights decaying effect of older observations are jointly considered. The key idea is to obtain a stable time series trend, and it is suitable for short/medium-term forecasting with reasonable accuracy. Exponential models used in the study are presented below

$$y_t = a_t + s(t) + \epsilon_t,$$
$$\text{where } a_t = \alpha(y_t - S_{t-s}) + (1-\alpha) A_{t-1;}$$
$$S_t = \delta\left(y_t - A_{t-s}\right) + (1-\delta) S_{t-s} \tag{4}$$

$$y_t = a_t + b_t t + s(t) + \epsilon_t,$$
$$\text{where } a_t = \alpha\left(y_t - S_{t-s}\right) + (1-\alpha)\left(A_{t-1} - B_{t-1}\right);$$
$$B_t = \gamma\left(A_t - A_{t-1}\right) + (1-\gamma) B_{t-1}, S_t = \delta\left(y_t - A_{t-s}\right) + (1-\delta) S_{t-s} \tag{5}$$

a_t, b_t, and $s(t)$ represent the time-varying mean, time-varying slope, and time-varying seasonal component, respectively. A_t and B_t are smoothed level that estimates a_t and b_t, respectively. S_{t-j}, $j = 0, ..., s-1$ estimates of the $s(t)$. The last components ϵ_t represent the exogenous random shocks. We further assume that α, γ, and δ represent level, trend, and seasonal smoothing weight, respectively.

2.5.2. ARIMA

Time series data for water quality measures frequently experienced trends, seasonal patterns and might be nonstationary, and ARIMA (p, d, q) models are widely used for forecasting,[57] where p, q, and d are positive integer numbers, referring to the order of the autoregressive, moving average, and integrated parts, respectively. In an ARIMA model, the future value of a variable is assumed to be a linear function of several past observations plus random errors. For example, the autoregression or AR (p) and moving average or MA (q) models can be formulated as follows

$$y_t = c_1 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{6}$$

$$y_t = c_2 + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \varepsilon_t \tag{7}$$

where y_t and ϵ_t are the actual value and random error, assumed to be independently and identically distributed with a mean of zero and a constant variance of σ_2; at period t, respectively; c_1 and c_2 are the intercepts; ϕ_p is a finite set of parameters, determined by linear regression. In this study, augmented Dickey-Fuller (ADF) test is used to measure the degree of stationarity. A null hypothesis is constructed when using the ADF test, stating that the data are not stationary if the p-value is >0.05. Therefore, data differentiation is used to make the data stationary. Finally, the Akaike information criterion (AIC) is used for estimating how well a model fits the data.

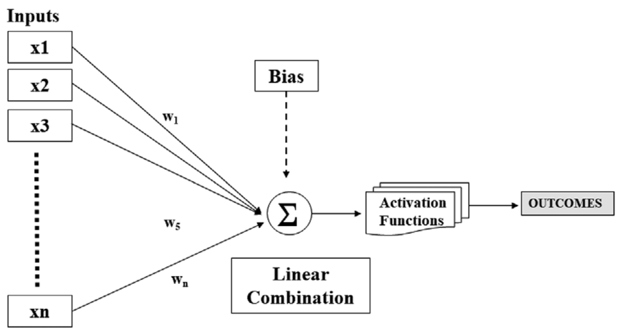

Figure 3. Structure of ANN.

2.5.3. ANN

ANN is a data-driven non-parametric forecasting method that emulates human brain operations in processing information. ANNs with a single hidden layer and the single neuron comprises p data inputs $x_i \epsilon X$, used in this study. The final outcome value is computed by summing weighted inputs and a bias. The output of the neuron is computed by sending the net value to an activation function. The weights of the perception are adjusted by performing the learning process during a predefined determined number of iterations, and the overview of ANN is depicted in **Figure 3**.

A single hidden layer feed-forward ANN is one of the extensively used forecasting tools.[58] The ANN creates a nonlinear functional mapping from past observational data (y_{t-1}, y_{t-2}, ... y_{t-p}) to future value y_t. Based on Khandelwal et al.,[32] the mathematical formulation of the relationship between the output (X) and the inputs (Y) is as follows

$$y_t = \phi_0 + \sum_{j=1}^{q} \phi_j g(\theta_0 j + \sum_{i=1} p\theta_{ij} y_{t-1}) + \epsilon_t \tag{8}$$

where, $\phi_j (j = 0, 1 ..., q)$, θ_{ij}, $(i = 0, 1, 2, ..., p; j = 1, 2, ..., q)$, ϵt is the white noise. We used the logistic and tan-hyperbolic functions as the hidden layer activation functions g.

Three performance measures, namely, i) mean absolute error (MAE) $= \frac{1}{n}\sum_{t=1}^{n} |y_t - f_t|$, ii) mean absolute percentage error (MAPE) $= \frac{1}{n}\sum_{t=1}^{n} |\frac{y_t - f_t}{y_t}|$, and iii) root mean squared error (RMSE) $= \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - f_t)^2}$ are used to evaluate accuracy among methods.

3. Results

The descriptive statistics for ten parameters during the study period are presented in **Table 2**.

ANOVA conducted among the three sampling sites (RP, PR-1, and PR-2) revealed significant variations in EC ($F_{2105} = 7.379$, $p < 0.001$), TDS ($F_{2105} = 13.397$, $p < 0.001$), turbidity ($F_{2105} = 17.01$, $p < 0.001$), pH ($F_{2105} = 194.08$, $p < 0.001$), DO ($F_{2105} = 74.51$, $p < 0.002$), free CO_2 ($F_{2105} = 692.52$, $p < 0.001$), BOD ($F_{2105} = 94.32$, $p < 0.001$), and COD ($F_{2105} = 40.44$, $p < 0.001$) and statistically insignificant variations for temperature ($F_{2105} = 0.077$, $p < 0.466$)

Table 2. Physicochemical parameters of water from the river Saraswati (PR-1 and PR-2) and reference pond (RP) during 2017 to 2019.

Sampling area	Statistical method	Temperature [°C]	EC [mS cm^{-1}]	TDS [ppt]	Salinity [ppt]	Turbidity [NTU]	pH	DO [mg L^{1}]	Free CO_2 [mg L^{-1}]	BOD [mg L^{-1}]	COD [mg L^{-1}]
PR-1	Mean	29.63	400	0.29	0.17	30.16	7.58	3.41	34.33	5.31	18.50
	SD	4.77	150	0.10	0.11	18.25	0.23	1.21	5.01	2.01	3.93
	Min	20	200	0.16	0	6	7.1	1	23	2.5	10.9
	Max	37.2	850	0.56	0.4	85	7.9	5.32	44	10	26.2
PR-2	Mean	29.35	520	0.37	0.18	26.25	7.35	1.92	58.59	8.06	28.02
	SD	5.02	190	0.11	0.1	15.69	0.20	1.19	9.08	2.30	6.51
	Min	19	220	0.16	0	4	7.05	0.2	35.5	4.2	15.4
	Max	36.8	870	0.65	0.5	80	7.8	4.5	75	12.5	38.73
RP	Mean	30.69	520	0.40	0.23	13.02	8.66	7.13	3.59	2.22	20.59
	SD	4.7	70	0.06	0.08	4.07	0.41	2.74	3.27	0.62	2.97
	Min	22	420	0.32	0.1	4	7.9	3.8	0	1.08	15
	Max	38	870	0.52	0.4	19	9.6	15.9	11	4.19	27.24

Note: PR-1, spot 1 of polluted river; PR-2, spot 2 of polluted river; RP, reference pond; EC, electrical conductivity; TDS, total dissolved solids; DO, dissolved oxygen; BOD, biochemical oxygen demand; COD, chemical oxygen demand

and salinity ($F_{2105} = 2.559$, $p > 0.05$) of water. We refer to Figure S1 (Supporting Information) for a detailed overview of the actual data.

The LSD test indicated that the mean EC value of PR-1 was significantly ($p < 0.001$) lower than for PR-2 and RP. The EC value in both the river spots gradually increased in winter and became maximum during summer. The mean EC value of summer and winter differed significantly from monsoon and post-monsoon. The water turbidity in both the river spots was much higher than that in the RP. A distinct variation (LSD test; $p < 0.001$) in mean values of turbidity was observed between the two study spots of the river and the RP, and the value ranged in the following order: PR-1 (30 ± 18.25 NTU) > PR-2 (26.25 ± 15.69 NTU) > RP (13.02 ± 4 NTU). In both PR-1 and PR-2, the mean turbidity value was lower in summer and exhibited an increasing trend during monsoon and post-monsoon, followed by a drastic decrease in winter. The mean DO concentration of water exhibited significant spatial variation, and the value ranged in the following order: RP (7.13 ± 0.45 mg L^{-1}) > PR-1 (3.41 ± 0.2 mg L^{-1}) > PR-2 (1.92 ± 0.19 mg L^{-1}) (LSD test; $p < 0.005$). There was also significant seasonal variation in DO concentration; it increased during post-monsoon and declined during winter. The mean concentration of free CO_2 among the three spots showed significant variations (LSD test; $p < 0.001$) and the values ranged in the following order: PR-2 (58.59 ± 9.08 mg L^{-1}) > PR-1 (34.33 ± 5.01 mg L^{-1}) > RP (3.59 ± 3.27 mg L^{-1}). There was a significant difference in the mean concentration of BOD among the study spots; the measure ranged in the following order: PR-2 (8.06 ± 2.3 mg L^{-1}) > PR-1 (5.31 ± 2.01 mg L^{-1}) > RP (2.22 ± 0.62 mg L^{-1}), as revealed by LSD test; $p < 0.001$. The BOD value peaked in summer and declined during the following seasons. A similar trend was observed for COD. Next, we applied all three forecasting methods and used performance measures to obtain the best forecast results for each parameter. The detailed overview of forecasted results is presented in **Table 3**.

Note that the ARIMA model ensures higher forecast accuracy, but the parameters vary considerably (Table S2, Supporting Information). Although several researchers reported that ANN performs better than the conventional methods, some authors reported that results remain inconclusive,[59] or when we compare results on different data sets, none of the forecasting techniques has shown performance that is superior to the others in general.[33] In the context of our study, we have 36 observations, and while we divide those into 6:2:2 ratio as training, test, and validation set, the model suffers from the decrease in data scale. Gui et al.[42] compared the outcome of the ARIMA model and back propagation neural network (BPNN) and the Hydrologic Simulation Program-FORTRAN (known as HSPF). It is also observed that the outcome are data point sensitive; the BPNN model leads to a lower R^2 value when applied in a data set with a limited number of observations. Because there is limited data available, as an alternative, one can also use the grey system model based on the linear differential equation.[60] Until we found the ANN model able to show the fluctuation, which cannot be achieved in the ordinary differential equation. Consequently, it leads to a higher error value when we apply ANN. Moreover, the exponential method is also not applicable to our study because high seasonality is observed for most of the parameters. Next, we computed two water quality indices based on the standard values of water parameters,[61] and the detailed results are presented in **Table 4**.

The average index values of CCMEWQI were lower in PR-2 (37.3 ± 5.61) compared to PR-1 (50.1 ± 7.53), showing the distinct order of variations PR-1 > PR-2 (one-way ANOVA; $F_{1,38} = 37.126$; $p < 0.01$). The assumption of homogeneity of variances was tested and satisfied based on Levene's test ($F_{1,38} = 2.478$, $p = 0.124$). According to the water quality rating of the CCMEWQI method, the water of PR-2 was rated as "poor" quality, and PR-1 was rated as "bad" quality, as shown in **Figure 4**. Based on the water quality rating of WAWQI, the water quality of RP (79.45 ± 7.73) was rated as very poor but much better than PR-2 of the polluted river.

In PR-1, the minimum value (39.34) of CCMEWQI was recorded in summer (Q1), and the maximum value (62.44) was recorded in winter (Q4). Results of ANOVA ($F_{3,16} = 30.125$,

Table 3. Physicochemical parameters of water from the river Saraswati (PR-1 and PR-2) and reference pond (RP) based on the forecasted data for two years (2017–2019).

Sampling area	Statistical analysis	Temperature (°C)	EC (mS cm^{-1})	TDS (ppt)	Salinity (ppt)	Turbidity (NTU)	pH range	DO (mg L^{-1})	Free CO_2 (mg L^{-1})	BOD (mg L^{-1})	COD (mg L^{-1})
PR-1	Mean	30.58	370	0.275	0.17	34.82	7.85	4.36	37.99	4.76	17.55
	SD	4.58	80	0.063	0.074	19.17	0.13	1.079	4.53	2.02	3.70
	Min	21.99	250	0.2	0.04	13.48	7.62	2.48	29.25	2.4	10.39
	Max	37	500	0.4	0.31	84.07	8.11	6.1	43.58	8.11	24.01
PR-2	Mean	30.58	370	0.27	0.17	34.82	7.85	4.36	37.99	4.76	17.55
	SD	4.58	80	0.06	0.07	19.17	0.13	1.07	4.53	2.02	3.70
	Min	21.99	250	0.2	0.04	13.48	7.62	2.48	29.25	2.4	10.39
	Max	37	500	0.4	0.31	84.07	8.11	6.1	43.58	8.11	24.01
RP	Mean	31.29	510	0.63	0.22	14.1	8.83	7.36	4.08	1.88	23.11
	SD	4.55	49	0.109	0.06	3.37	0.39	2.42	3.34	0.66	2.61
	Min	22.85	450	0.42	0.13	10.03	8.41	4.24	0.36	0.78	17.76
	Max	37.55	590	0.82	0.36	19.05	9.73	12.41	11.34	3.67	29.05

Note:PR-1, spot 1 of polluted river; PR-2, spot 2 of polluted river; RP, reference pond; EC, electrical conductivity; TDS, total dissolved solids; DO, dissolved oxygen; BOD, biochemical oxygen demand; COD, chemical oxygen demand

Table 4. WQI values for the spots studied. PR-1 and PR-2 values are based on CCMEWQI, while RP values are based on WAWQI. Q1, Q2, Q3, and Q4 denote four quarters of the study period 2017 to 2019 (actual) and 2020 to 2021 (forecasted).

	Q1			Q2			Q3			Q4		
	PR-1	PR-2	RP	PR-1	PR-2	RP	PR-1	PR-2	RP	PR-1	PR-2	RP
2017	39.34	34.73	82.44	45.99	37.72	88.22	55.31	46.46	67.56	62.28	45.65	69.09
2018	49.55	30.31	77.49	45.63	37.22	89.34	43.11	37.05	71.2	58.62	45.34	76.48
2019	46.12	30.21	84.17	44.15	36.07	89.89	49.95	43.26	69.57	62.44	45.08	78.28
2020	44.82	30.15	81.91	44.81	32.66	91.54	44.74	39.15	74.08	62.19	38.35	79.92
2021	44.69	29.74	82.49	45.72	31.42	88.95	50.46	35.76	68.97	62.24	39.68	77.55

Note:PR-1, spot 1 of polluted river; PR-2, spot 2 of polluted river; RP, reference pond; Q1, quarter 1; Q2, quarter 2; Q3, quarter 3; Q4, quarter 4

$p < 0.001$) followed by LSD test ($p < 0.001$) revealed that the mean CCMEWQI value of winter was significantly much higher (61.55 ± 0.73) than for the three other seasons (summer = 44.90 ± 3.67, monsoon = 45.26 ± 0.76, and post-monsoon = 48.71 ± 2.18). On the other hand, no seasonal variation was observed among the three other seasons (LSD test, $p > 0.001$). As per CCMEWQI standard, the water quality during summer, monsoon, and post-monsoon were poor, while it improved slightly to become bad water quality during winter. In PR-2, the minimum value of CCMEWQI was 30.21 recorded during summer, while the maximum value was 46.46 recorded during post-monsoon, exhibiting significant seasonal variation ($F_{3,16} = 12.649$, $p < 0.001$). However, the pattern of seasonal variation was different from PR-1. The mean CCMEWQI value, like PR-1, was the maximum during winter (42.82 ± 1.57). The value differed significantly (LSD test, $p < 0.001$) from summer (31.02 ± 0.93) and monsoon (35.01 ± 1.26), but the value was not significantly different (LSD test, $p > 0.05$) from post-monsoon (40.33 ± 1.98). As per the CCMEWQI standard, the water quality rating for all the seasons indicated poor water quality (Table 4). The WAWQI value of RP exhibited seasonal variation as validated by one-way ANOVA ($F_{3,16} = 42.519$, $p < 0.001$) followed by the LSD test, $p < 0.001$. According to the rating, post-monsoon and winter water quality was poor but in summer and monsoon was very poor. The observation revealed that the water quality of RP deteriorated throughout the summer and monsoon, then improved during the post-monsoon and winter.

4. Discussion

A suite of salient physicochemical and biological attributes shapes the water quality of an aquatic ecosystem. It serves as the *sine qua non* for its aquatic health and is a key determinant of ecosystem services.[62] Results of the present study indicate that the mean EC value of PR-1 (404 ± 152 mS cm^{-1}) was lower than that of PR-2 (522 ± 193 mS cm^{-1}) and RP (521 ± 78 mS cm^{-1}) while exceeding the standard limit (300 mS cm^{-1}) in all the sampling sites. The mean turbidity value was higher in both the spots (PR-1 = 125.26% and PR-2 = 95.16%) of the river compared to RP and crossed the standard limit (10 NTU). In both the spots of the river, the mean DO concentration always remained below the standard limit (5 mg L^{-1}), the concentration being very low (1.92 ± 0.19 mg L^{-1}) in PR-2, indicating a hypoxic condition in this spot. The free CO_2 concentration was 15-fold higher (58.59 ± 1.51 mg L^{-1}) in PR-2 in respect to RP (3.59 ± 0.54 mg L^{-1}) and about twofold higher than in PR-1(34.33 ± 0.83 mg L^{-1})

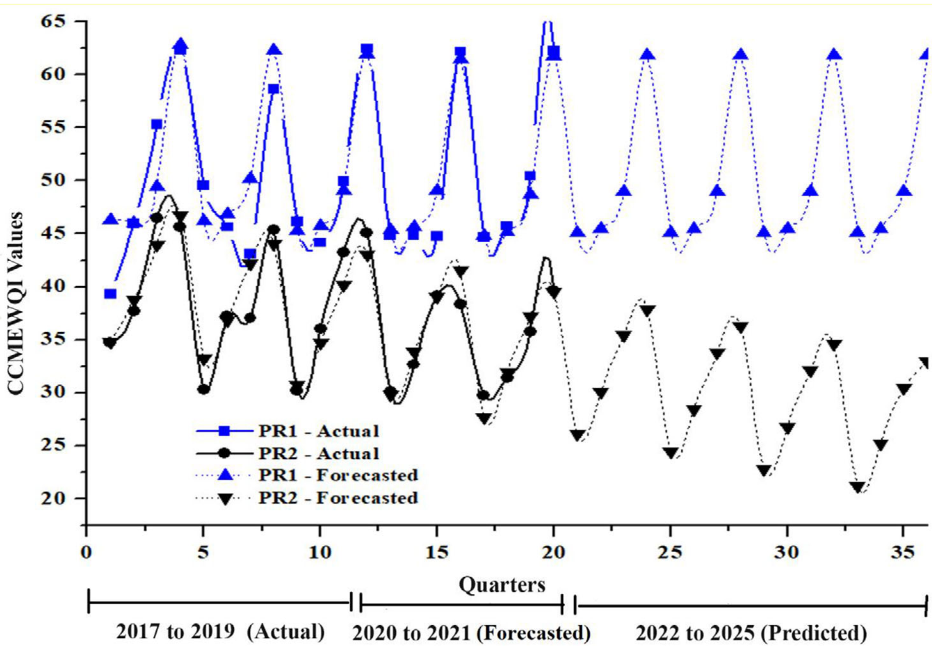

Figure 4. Variation of CCMEWQI in both the spots (PR-1 and PR-2) of the polluted river during 2017–2025. Here, the three types of values are represented as actual: 2017–2019; forecasted: 2020–2021; predicted: 2022–2025.

of the river. The mean concentration of COD (28.02 ± 1.08 mg L^{-1}) was moderately higher in PR-2, but the mean concentration of BOD was 263.06% higher in PR-2 (8.06 ± 0.38 mg L^{-1}) and 139.19% in PR-1 (5.31 ± 0.33 mg L^{-1}) compared to RP (2.22 ± 0.1 mg L^{-1}). A high concentration of free CO_2 and BOD levels indicated increased pollution in PR-2 due to organic loading from catchment areas.[63,64] High organic loading consumed DO to reduce it considerably, with a concomitant increase in free CO_2 concentration culminating in a semi-anoxic to almost anoxic condition.[65]

Among the ten physicochemical parameters of water, seasonal variation was observed only for five parameters (temperature, TDS, turbidity, DO, and free CO_2) in RP. In both the sampling spots (PR-1 and PR-2) of the river Saraswati, seasonal variation was more prominent in the mean value of temperature, EC, TDS, and turbidity, while the variation was less prominent in the mean concentration of DO, free CO_2, BOD, and COD. The seasonal variation was absent in the mean value of pH and salinity, implicating their minor role in determining the overall water quality status of the study sites. In PR-1, the mean turbidity values in monsoon and post-monsoon were nearly twofold higher than that in summer and one and half-fold higher than in winter. High turbidity value is typically attributed to the high concentration of the suspended solid particles of autochthonous (riverbed materiasl) or allochthonous origin (surface and agricultural runoff-borne materials) caused by heavy rainfall,[66] which has strong implications for the inferior water quality. Although turbidity cannot be used as the sole indicator of water pollution, it may be used as an "associate" indicator along with other critical water quality parameters.[67] The lowest concentration of dissolved oxygen in PR-2 was the combined effect of organic loading, lowered water volume, stagnancy, seasonal eutrophication, and almost no water influx from the river Ganga.

Pollutants from different sources can alter a multitude of physicochemical parameters of water that can be accommodated together to formulate a water quality index expressed as the WQI of that aquatic ecosystem.[68,69] Several methods have been used to estimate WQI based on the physicochemical and biological properties of water.[51]

Two different WQI methods, one for the polluted river (CCMEWQI) and another for the reference pond (WAWQI) were used in this study to assess the water quality status of the polluted river and the reference pond. The mean CCMEWQI score indicated "bad" quality for PR-1 and "poor" quality for PR-2, indicating the worst situation in PR-2. Conversely, the mean WAWQI score indicated comparatively better water quality in RP. The mean score value (F1) of PR-2 was higher (80) than for PR-1 (70), which indicated that eight and seven out of the ten physicochemical parameters crossed the respective limit of the standard value for PR-2 and PR-1. The values of mean frequency (F2) and amplitude (F3) were also greater in PR-2 (F2 = 63.33 and F3 = 51.36) than in PR-1 (F2 = 51.66 and F3 = 37.24) (**Figure 5**b). The amplitude depends on the sum excursion of those parameters that cross the standard value limit. Nearly 90% mean excursion of PR-1 was associated with free CO_2 (42.9%), turbidity (37.2%), and DO (9.7%), while in the case of PR-2, nearly 95% mean excursion was associated with free CO_2, (47.4%), DO (18.9%), turbidity (16.5%), EC (6.8), and BOD (5.9%) (Figure 5a). Thus, for PR-2, the scores of all the underlying determinants of CCMEWQI, i.e., F1, F2, and F3 showed the highest values in both spots. The overall index value of WAWQI is the summation of $W_i \times Q_i$ (W_i = unit weight and Q_i = quality rating of each parameter).

In RP, the overall index value (60%) was predominantly contributed by three water quality parameters comprising DO (24.3%), turbidity (20.5%), and pH (15.9%). The remaining index value (40%) was shared among BOD (13.8%), COD (6.4%),

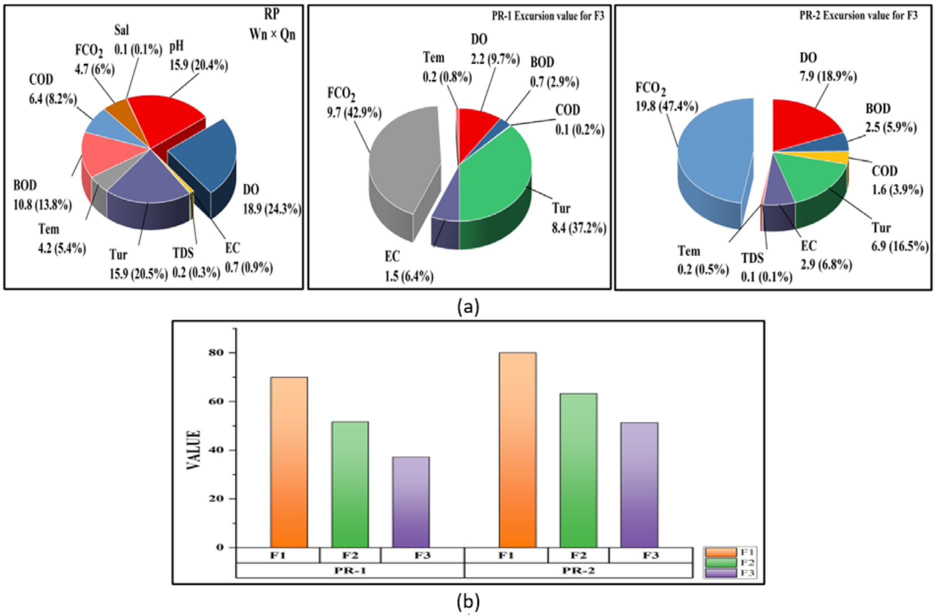

Figure 5. a) Relative contribution of individual water parameters in three spots (excursion value). b) The relative value of mean score (F1), frequency (F2), and amplitude (F3) of the two spots (PR-1 and PR-2).

free CO_2 (4.7%), and others (15%) (Figure 5). We refer to Figure S2 (Supporting Information) for the detailed overview of forecasting performance for some key parameters. A high concentration of free CO_2, turbidity, and BOD and a low DO concentration indicate high organic loading, sedimentation, and microbial activities.[70,71] Thus, for PR-2, the scores of all the underlying determinants of CCMEWQI, i.e., F1, F2, and F3, showed the highest values(Figure 5). The pollution level was found to be lower at PR-1 relative to PR-2 due to the dilution effect exerted by the influx of water from the river Ganga into PR-1, which acts as the bridge between the river Saraswati and the Ganga at PR-1. But the pollution intensity was found to increase upstream in the river Saraswati, where it passes through the localities and suffers from the reduced inflow of water, surface runoff containing organic loadings, the elevation of the river bed, and several anthropogenic activities. Thus, PR-2 was found as the most polluted spot in the river Saraswati. Figure 4 depicts the seasonal variations in the actual and forecasted values of CCMEWQI for both the sampling spots (PR-1 and PR-2) of the river Saraswati. The CCMEWQI value indicated persistently degraded water quality during the summer compared to other seasons. During the post-monsoon and winter seasons in PR-1, both actual and anticipated CCMEWQI values remained and would remain above 44 (i.e., the transitional value differentiating bad and poor water quality) for up to 35 quarters (2026).

On the other hand, in PR-2, the forecast CCMEWQI value (after 25 quarters, i.e., since 2025) always remained below 44, which implicated a perennially "poor" water quality status with a gradually degrading trend irrespective of the seasons.[27,49] Thus, the CCMEWQI projects a bleak future for the river Saraswati facing a looming crisis of an irreversible shift in its degraded water quality from "dying" to "dead" state, which would compromise the structural and functional integrity of the riverine ecosystem, with catastrophic consequences in rendering its ecosystem services. The degradation of water quality of river Saraswati finds resemblance to Jalangi River, a tributary of the Ganga River, which is primarily impacted by similar agricultural activities, domestic/municipal waste/wastewater discharges, and land use and land cover (LULC) changes.[72,73] The Yamuna river, considered the dirtiest river in India, showed higher organic loading reflected in its COD and BOD values.[74] The water quality status, nature of pollution, and the drivers and pressures responsible for the degradation of water quality, as revealed in the present study, earn conformity from Gikas et al.,[75] who adopted the CCMEWQI model of water quality indexing to show the degraded water quality status of the river resulting from organic loading and sedimentation (**Table 5**).

Table 5 presents an overview of different models of WQI adopted globally by several researchers to evaluate and monitor the water quality status of different rivers subjected to anthropogenic activities resulting in organic loading, chemical pollution, fecal contamination and hydrological alteration. While DO, free CO_2, and BOD have been considered by most authors as the key parameters to derive the CCMEWQI and evaluate a stressed aquatic ecosystem, the present study reveals free CO_2, turbidity, and DO as the primary parameters that influence CCMEWQI in the river Saraswati. EC, BOD, and COD values also secondarily influence the CCMEWQI, but these are primarily associated with DO, turbidity and free CO_2. Table 5 demonstrates that the key water quality parameters to be considered are not defined clearly. To simplify future studies and make policy planning, these three parameters can be considered as the key parameters.

5. Conclusions

It is concluded that the river Saraswati is in a heavily polluted and deadly decaying state, particularly upstream from its meeting point with the river Ganga. Forecasting methods are useful

Table 5. Contribution of the study to the present state-of-the-art of WQI as a tool for evaluating and monitoring the water quality status of rivers.

Study area	Parameter	Parameters used for WQI	WQI Indices	Key parameter	Remarks	Reference
Umia River, Limia River, Spain	Water temperature, pH, oxidation reduction potential, EC, turbidity, DO, percentage of dissolved oxygen (%), TDS, nitrogen, total phosphorus and orthophosphate	Temperature, pH, turbidity, DO, total phosphorus, nitrate	NFSWQI GQI TSI ICOTRO	Nitrogen and phosphorus	Nutrient pollution driven by storm water and agricultural runoff	[76]
Nestos/Mesta river, Europe	DO, EC, pH, TSS, BOD, COD, NO_2—N, NO_3—N, NH_4—N, TKN, OP, TP, Chl-a, some heavy metals	DO, pH, TSS, BOD, NO_2—N, NO_3—N, NH_4—N, PO_4—P, TP	WFD-MEEG CCMEWQI	BOD, COD, TKN and TP	Organic loading-induced nutrient pollution	[75]
Aksu river, Turkey	Temperature, EC, pH, DO, turbidity, COD, heavy metals (Pb, Cr, Mn) and some ions	pH, HCO_3^-, Cl, SO_4, Na, Ca, Mg, COD, NO_3^-, NO_2^-, Pb, Cr, and Mn	WQI according to WHO 2008; TSI-266, 2005	pH, COD, Mg	Chemical pollution from agricultural and industrial operations	[28]
Johor river, Malaysia	DO, pH, EC, Coliforms and *Escherichia coli*, COD, NO_2—N, NH_4—N, Ca, K, Mg, Na, trace metals (Pb, Cd, Cr, Mn, As, Ag, Se, Al, Ba, Cu, Fe, Ni, Zn), and some ions	All parameters	WQI_{MLR} WQI_{PCA} WQI_{AVG}	Total coliform and Mg COD for WQI_{MLR} Ba for WQI_{AVG}	Fecal contamination; chemical pollution; hydrological alteration due to changed climatic conditions change	[77]
The Lam Tsuen river, Hong Kong	BOD, COD, DO, EC, NO_3—N, NO_2—N, PO_4^{3-}, pH, temperature, and turbidity	All parameters	SVR, DTR and ETR model for WQI prediction	BOD, turbidity and phosphate	Organic loading and chemical nutrient pollution	[78]
Beheshtabad River, Iran	Temperature, pH, EC, DO, phosphate, nitrate, TS, BOD	All parameters	NSFWQI	TS, EC, BOD, and NO_3	Organic loading, nutrient pollution	[79]
Turnasuyu Stream, Eastern Black Sea Basin of Turkey	Temperature, pH, DO, EC, TDS, salinity, OP, turbidity, NH_4—N, NO_3—N, NO_2—N, TP, Cl, SO_4^{2-}, SiO_2, BOD, TSS, TA, TH, and trace metals	NO_3—N, NO_2—N, NH_4—N, Cl^-, TH, TDS, EC, pH, SO_4, Cu, Al, Fe, Mn, Zn)	WAWQI	NH_4—N, NO_3—N, NO_2—N, Mn	Nutrient and chemical pollution from agricultural and industrial operations	[80]
Kolong river; Assam, India	pH, EC, TDS, TSS, TA, TH, DO, BOD, chloride, sulfate	All parameters	WAWQI	DO and BOD	Organic loading	[81]
Ganga river Gaumukh to Haridwar, India	pH, temperature, EC, TDS, DO, BOD, COD, TH, Ca, Mg, Na, K, alkalinity	pH, TDS, alkalinity, chloride, hardness, calcium, and magnesium	WQI	TDS, EC, alkalinity, Ca^{2+}, and TH	Anthropogenic activities and surface runoff induced sedimentation and water quality degradation	[82]
Loktak lake, North-East India	Temperature, pH, turbidity, TDS, DO, TH, calcium, magnesium, potassium, sodium, chloride, sulfate, fluoride, phosphate, nitrite, nitrate, TOD, BOD, and COD	pH, DO, temperature, EC, TH, Na, BOD, NO_2, NO_3, TDS, and COD	WQI	DO, EC, nitrate, and COD	Chemical pollution	[83]

(*Continued*)

Table 5. (Continued).

Study area	Parameter	Parameters used for WQI	WQI Indices	Key parameter	Remarks	Reference
Godavari river, western to southern India	DO, fecal coliform, temperature, pH, total phosphate, nitrate, BOD, turbidity, TS	pH, DO, BOD, turbidity, TS for NSFWQI pH, DO, BOD for VWQI	NSFWQI VWQI	DO, fecal coliform, pH, BOD	Fecal contamination and organic loading	[84]
Saraswati river, West Bengal, India	Temperature, EC, TDS, salinity, turbidity, pH, DO, free CO_2, BOD, and COD	All parameters	CCMEWQI	Free CO_2, DO, and turbidity	Organic loading from domestic wastewater discharge, seasonal jute retting; anthropogenic activities and stormwater/agricultural runoff induced sedimentation	Present study

Note: GQI, General Quality Index; TSI, Trophic State Index; ICOTRO, Trophic Contamination Index; NSFWQI, National Sanitation Foundation Water Quality Index; CCMEWQI, Canadian Council of Ministers of Environment Water Quality Index; VWQI, Vedprakash Water Quality Index; EC, electrical conductivity; TDS, total dissolved solids; DO, dissolved oxygen; WFD-MEEG, Water Framework Directive proposed by the Ministry of Environment and Energy of Greece; TSS, total suspended solids; TKN, total Kjeldahl nitrogen; OP, ortho-phosphates; TP, total phosphorus; Chl-a, chlorophyll-a; COD, chemical oxygen demand; BOD, biochemical oxygen demand; TOD, total oxygen demand; WHO, World Health Organization; TSI, Turkish Standards Institution; WQI_{MLR}, WQI multivariate linear regression; WQI_{PCA}, WQI principle component analysis; WQI_{AVG}, average WQI; SVR, support vector regression; DTR, decision tree regression; ETR, extra tree regression; TS, total solids; TH, total hardness; TA, total alkalinity

for predicting the status of the river in the near future. A plethora of forecasting techniques have been developed to improve accuracy, but none of the techniques has shown performance superior to the others in general. We used three state-of-the-art forecasting techniques in this study to determine the fate of the river in the near future. Based on the actual data and the forecasting methods, it is clearly found that the water quality of the river is progressively degrading, which is alarming for the biodiversity and riverine ecosystem health of the river. Without immediate intervention, the river can die soon. Nonetheless, to stand with the reality check and reach more accuracy, such forecasting should be based on a robust reservoir of data derived from long-term studies, contrary to the present study of three years' duration. The WQI-forecast-based integrated approach is not an end in itself but a means of the continuous journey which needs to consider how the prospective intervention and restorative management measures improve the water quality and riverine health. Furthermore, remotely sensed satellite images (Landsat) of different periods need to be tied to track the long-term continuous change of this river and its floodplain areas. The present position and evolving problems of riparine floodplain areas could be identified from the conversions and changes in land use and land cover (LULC) and alteration in floodplain perimeters adopting geospatial tools and techniques.

Recently, the United Nations set goals to improve water quality by reducing pollution, eliminating dumping and minimizing the release of hazardous chemicals and materials, halving the proportion of untreated wastewater, and substantially increasing recycling and safe reuse globally by 2030. However, this study clearly demonstrates that the key water quality parameters are not unique across the globe to assess the ecological status of a polluted river. Therefore, identifying the critical parameters is necessary to evaluate a river. The present study clearly indicates that free CO_2, DO, and turbidity can be considered as primary parameters to evaluate the status of the river. The outcomes of the study can immensely benefit the policymakers to come up with future restoration plans to save the river. This calls for adopting the following set of strategies to restore the health of the river, inclusive of the riverine ecosystem and its goods and services: i) control of disposal of domestic and municipal wastes; ii) regulation of the discharge of industrial effluents; iii) management of agricultural and urban surface runoff; iv) prevention of unscientific soil digging and plundering by land sharks and brick kiln owners; v) dredging of sediment and other hydrodynamic manipulation for enhancing water influx from the river Ganga; vi) integrated river basin management; vii) ecotechnological and bio-manipulative water quality management, etc. In such context, an integrated, holistic, and comprehensive approach and sustainable riverine management strategies are warranted to reverse the river's water quality degradation, restore riverine health, and regenerate its ecosystem services, where conservation will be the "fulcrum" for wider change toward sustainability. This will definitely contribute to India's mission to realize the United Nations Sustainable Development Goals (SDGs) related to water resources.

In recent times, many rivers all over the globe have been deteriorating, shrinking, or vanishing unsung and untold, resulting in the cessation of their invaluable ecosystem services to humanity and society. The template of WQI and forecast models tested in this study can be adopted and implemented by the regulators and restoration practitioners for designing blueprints, framing plans, and formulating appropriate "down to earth" rejuvenation and revival strategies for saving the decaying and dying rivers from imminent extinction.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S.P.: formal analysis; data curation; methodology; validation ; writing – original draft; J.K.B.: conceptualization; data curation; supervision; methodology; validation; writing – original draft, review & editing; A.K.: writing – review & editing; validation; S.S.: conceptualization; formal analysis; methodology; validation; writing – original draft, review & editing.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Keywords

environmental degradation, forecasting tools, pollution load, riverine health, water quality index

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