WATER QUALITY DURING PRE-MONSOON AND POST-MONSOON AND MODELLING OF TOTAL DISSOLVED SOLIDS FOR TAMIRAPARANI RIVER, TAMILNADU, INDIA

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ABSTRACT

The research was performed to investigate the water quality of Tamiraparani river situated in the district of Tirunelveli and Tuticorin, from source to sea. The river is about 128 kilometers long and is the only perennial river in Tamil Nadu. The samples were collected from 12 major places Papanasam, Cheranmadevi, Kokirakulam, Murapanadu, Thiruvudaimarudur, Ambasamudram, Authoor, Eral, Kallidai Kurichi, Srivaikuntam, Vellakovil and Sivalaperi. To understand the water quality, parameters were identified via the examination of pH, turbidity, alkalinity, chloride, hardness, calcium, magnesium and TDS. Test results showed that the analyzed parameters were within the World Health Organization's allowable limits. Although the parameters of water were in the acceptable range, the overall findings indicate that the effects on the wetland environment should be best addressed. From the results obtained, the average WQI is calculated to be 64.1 which falls borderline. This indicates the poor quality of the river due to the presence of pollutants. Prediction of total dissolved solids was performed with the results using MATLAB. These WQI results point to take required actions to avoid water pollution and TDS predication will be useful for planning and managing water quality.

Keywords: Water Quality, Monsoon, Water Quality Index, Modelling.

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INTRODUCTION

Water is an indispensable natural resource on the planet. Healthy drinking water is a human being's primary requirement. Owing to over-exploitation and wastewater discharge, freshwater has become a precious asset. The risk of river water pollution is due to the mixing of hazardous materials, fertilizers and unsafe processing of agricultural liquid waste. Numerous human exercises and their side-effects can affect surface and subsurface water without fitting waste administration methodologies.¹ The quality assessment of transitional water is regarded as an important extension of such studies about the assessment of environmental quality.²

Polluting materials released into the water resources leads to deteriorating the quality of water which majorly impacts the freshwater bodies and marine ecosystems. Evaluating and comparing the water quality with standards are consequential for supervising and enhancing the water quality.^{3,4}

The water quality index is quite possibly the best apparatuses to convey facts on the quality of water to the concerned people. It, hence, turns into a significant boundary for the evaluation and management of surface water. WQI is characterized as a ranking mirroring the complex impact of diverse river quality properties. WQI is determined from the perspective of the suitability of surface water for social utilization.⁵

The ANN strategy is adequately adaptable to oblige extra limitations that may emerge during its application. Also, the ANN model can uncover concealed connections in authentic information, in this way encouraging the prediction and anticipating of water quality.⁶ Artificial neural organizations for foreseeing the water quality segments in a few contextual investigations. The author had expressed that artificial intelligence methods have appropriate execution for modeling and foreseeing the inward connection between the water quality parts and demonstrating their time arrangement. Assessing and predicting water quality proves to be an important factor for water conservation and development projects and artificial intelligence techniques have been proposed for modeling the water quality.^{7,8}

The main purpose of this study is to calculate WQI based on the physical and chemical parameters and to develop ANN model to assess the water quality of Tamiraparani River. The model can be used for understanding and managing water quality.

Study Area and Data

The sample was collected from 12 major places they are Papanasam, Cheranmadevi, Kokirakulam, Murapanadu, Thiruvaidamarudur, Ambasamudram, Authoor, Eral, Kallidai Kurichi, Srivaikuntam, Vellakovil and Sivalaperi. Parameters were analyzed for the water quality of Tamiraparani river is pH, turbidity, alkalinity, chloride, hardness, calcium, magnesium and TDS. All the parameters were measured in mg/l except for pH and turbidity. pH has no unit and turbidity was measured in NTU.

Table-1: Water Quality for Selected Area during pre-monsoon

	pH	Turbidity	Alkalinity	Chloride	Hardness	Calcium	Magnesium	TDS
Min	6.5	2.22	4	6	12	3.2	0.97	28
Max	7.1	8.08	68	125	218	56	19	380
Mean	6.8	4.739	18.17	32	65.5	19.3	4.193	104.33
Median	6.75	4.095	10	14.5	49	14.5	2.675	67
Mode	6.7	-	4	8	50	9.6	0.97	-
Standard Deviation	0.18	2.119	20.08	36.868	59.409	16.816	5.003	105.73
Variance	0.03	4.49	403.24	1359.27	3529.6	282.79	25.035	11178.1

Tamiraparani River plays significant role in marine resources in Tirunelveli and Tuticorin districts. This river originates from Agastiar foothill of Western Ghats, and spreads towards the Bay of Bengal Punnaikayal and Pazhayakayal Estuarine, part of Gulf of Mannar. Study area Tamiraparani Estuarine is located between latitude 8.641316N and longitude 78.127298E. Samples were collected during early morning time of pre-and post-monsoon. All parameters were estimated in the laboratory by using standard methods as prescribed by WHO. The obtained values were tabulated as in Tables-1 and 2.

Table-2: Water Quality for Selected Area during post-monsoon

	pH	Turbidity	Alkalinity	Chloride	Hardness	Calcium	Magnesium	TDS
Min	6.3	0.48	2	5.11	8	1.6	0.97	16
Max	7.16	8.6	23.4	63	65	21	2.65	115
Mean	6.7	2.45	9.66	18.33	21.25	6.85	1.29	47
Median	6.7	2.08	7	11.23	12	2.4	0.97	33
Mode	6.8	2.11	4	11.23	12	1.6	0.97	16
Standard Deviation	0.3	2.21	7.06	16.44	17.73	7.05	0.54	36.5
Variance	0.1	4.89	49.81	270.5	314.20	49.68	0.295	1333.6

Methodology

Along the waterway, twelve sites were carefully chosen for sampling. The pre-sterilized bottles were used for the collection of water samples from each site during two spells, i.e., pre-monsoon (August to October), post-monsoon (January to February) throughout 2019–2020. Field kits were used for measurements of pH and TDS. Till the analysis work was started in the laboratory, the samples were kept in a freezer at 4°C. 0.45-micron filters were used to remove the suspended particles in the samples and then they were analysed using standard procedures.⁹

To calculate water quality index, the sub-index (SI) needs to be determined for each water quality constraint, as mentioned below:¹⁰

$$SI_i = W_i \times q_i \quad (1)$$

Where,

q_i - quality rating,

C_i - concentration of each parameter in mg/l,

S_i - Indian drinking water standard in mg/l.

WQI is calculated using the below equation,

$$WQI = \sum SI_i - n \quad (2)$$

Where,

SI_i - sub-index of i^{th} parameter

W_i - relative weight of i^{th} parameter

q_i - rating of i^{th} parameter based on the concentration

n - number of chemical parameters

The statistical investigation was performed using SPSS software program to find the correlation coefficient which can be used for understanding the behaviour of the parameters.

ANNs were also utilized in water quality investigation and estimation. To enable modeling of nonlinear water quality parameters, feed-forward back-propagation training algorithm has been used with one or more hidden layers. A different set of input parameters were considered for the targeted parameter TDS.

RESULTS AND DISCUSSION

pH

If the pH is under 6.5, it suspends the creation of nutrients and minerals in the human body. If the pH is more than 8.5, it makes the water saltier. And the water causes eyes disorder and skin problems if pH is more than 11. For the pH of 5.5–6, the rainwater doesn't have any useful minerals and is unsafe to be utilized for drinking purposes.¹¹ In this study, pH was measured with pH electrode for pre-and post-monsoon. In Papanasam and Murapanadu, pH values are lesser than 6.5 in pre-monsoon and the values are not within the permissible limits.

Turbidity

The higher turbidity in water impedes the entrance of light. This will harm the aquatic life and fall apart the nature of the surface water.¹² In this study turbidity values are measured on Nephelo turbidity meter for pre-and post-monsoon for the selected locations. Throughout pre-monsoon, the turbidity is higher in Authoor location and during post-monsoon, it was higher in Kokirakulam, Vellakovil and Sivalaperi.

Alkalinity

Total alkalinity throughout the study area ranges from 2 mg / l to 23.4 mg / l in pre-monsoon and varies from 4 mg/l to 68 mg / l in post-monsoon especially higher at Authoor.

Chloride

Chloride is a normally happening component that is present in waters and is frequently found as a part of salt (sodium chloride) or sometimes in blend with potassium or calcium.¹³ Chloride in a water sample for all twelve locations within the permissible limit but compared to other locations Authoor has more chloride in pre- and post-monsoon.

Hardness

The hardness was higher in post-monsoon 218 mg/l at Authoor location and lower in pre-monsoon 8 mg/l at papanasam. Calcium ions make a major contribution to the hardness of river water.

Calcium

During pre-monsoon presence of calcium in water varies from 1.6 mg/l to 21 mg/l. Similarly, calcium was observed in water from 3.2 mg/l to 56 mg/l during post-monsoon. Higher presence of calcium observed in Authoor location during both pre-and post-monsoon. The concentration of Calcium was always greater than that of magnesium.¹⁴

Magnesium

Magnesium substance of water is considered as one of the main parameters in deciding the nature of water for agriculture usage.¹⁵ In the current investigation, the magnesium substance of the water of the river changes from 0.97 mg/l to 19 mg/l, which is reasonable for irrigation.

Total Dissolved Solids (TDS)

TDS are more significant estimations to be regarded when analyzing water quality. High TDS esteems makes unsafe impact the general wellbeing.¹⁶ It decides the reasonableness of water for horticulture uses. The scope of TDS falls between 16 mg/l to 115 mg/l in pre-rainstorm and 28 mg/l to 380 mg/l in post-storm. Overall, the TDS in water inside allowable constraint of 500 mg/l. The results of seasonal variation of water quality in Tamiraparani river can see in Fig.-1.

Water Quality Index

The observations in the current study briefed as WQI ranged from 16.87 to 135.60 before the rainy season and 40.53 to 122.15 after the rainy season. Based on WQI, the water quality at Authoor is poor during the pre-wet season as well as post-wet season. During rainy season the quality of water the downstream is poor due to the mixing of solid waste and domestic wastewater.

The percentage of variation in water quality is represented in Table-3.

Fig-1: Seasonal Variation of water quality in Tamiraparani River for (a) pH, (b) Turbidity, (c) Alkalinity, (d) Chloride, (e) Hardness, (f) Calcium, (g) Magnesium and (h) TDS

Table-3: Water Quality Index (WQI) range and percentage of different water types

WQI Range	Water Type	Percentage of Samples	
		Pre-monsoon	Post-monsoon
<50	Excellent Water	83.3	16.7
50-100	Good Water	8.3	41.7
100-200	Poor Water	8.3	41.7
200-300	Very Poor Water	0	0
>300	Not suitable for Drinking	0	0

The decision-making about the quality of water is a crucial issue because of the number of parameters involved in drinking water quality. Based on the water quality index better decisions can be made about the quality of water in any region.¹⁷ The comparison of water quality index between pre-monsoon and post-monsoon is shown in Fig.-2.

Fig.-2: WQI in pre-monsoon and post-monsoon

Correlation Analysis

In this examination, the relationship grid of 8 parameters for before and after rainstorm periods was figured utilizing SPSS programming. The simple correlation coefficient which is widely used shows the ability of one variable to forecast the additional variable. The correlation coefficient of the water quality parameter for pre-monsoon is shown in Table-4.

The connection between the parameters before and after seasonal rainfall has demonstrated roughly a closely resembling pattern. Strong ($r = 0.9$) to good ($r = 0.9$ to 0.5) relationships among the different

Physicochemical characters have been detected. Hardness and TDS are strongly corresponded (pre-storm $r = 0.955$; post-rainstorm $r = 0.993$).

The correlation coefficient of the water quality parameter for post-monsoon is shown in Table-5.

Table-4: Correlation Coefficient for pre-monsoon water quality

	pH	Turbidity	Alkalinity	Cl	Hardness	Ca	Mg	TDS
pH	1							
Turbidity	0.45269	1						
Alkalinity	0.84188	0.589831	1					
Chloride	0.61079	0.771781	0.862022	1				
Hardness	0.67137	0.745015	0.899519	0.97702	1			
Calcium	0.55950	0.605744	0.640702	0.80292	0.82443	1		
Magnesium	0.33908	0.749775	0.67429	0.91181	0.90679	0.7106	1	
TDS	0.70417	0.606223	0.89963	0.90381	0.95455	0.7368	0.8593	1

Table-5: Correlation Coefficient for post-monsoon water quality

	pH	Turbidity	Alkalinity	Cl	Hardness	Ca	Mg	TDS
pH	1							
Turbidity	-0.45434	1						
Alkalinity	0.75574	-0.12437	1					
Chloride	0.79054	-0.16436	0.988723	1				
Hardness	0.72573	-0.04984	0.989784	0.98290	1			
Calcium	0.72854	-0.09386	0.978474	0.96341	0.97730	1		
Magnesium	0.62078	0.043141	0.866357	0.87711	0.89809	0.78477	1	
TDS	0.75287	-0.10721	0.996808	0.9915	0.99306	0.96903	0.894615	1

After wet season TDS strongly correlated with alkalinity, chloride, hardness and calcium. In the same way alkalinity strongly correlated with chloride, hardness and calcium.

Modeling

ANN model architecture refers to the quantity of layers hidden and the layout of neurons. In most of the engineering, application feed-forward back-propagation training algorithm is used. In this work ANN model with a back-propagation algorithm is constructed to predict TDS values.

Pre-Monsoon

In the first model, pH and Turbidity were provided as input and targeted parameter TDS. While analyzing the data for the pre-monsoon period, the parametric studies on pH and turbidity are correlated with TDS which is the target parameter, and the graphical illustration is represented in the graph. In Fig.-3, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.80836$.

In the next model, pH, Turbidity and Alkalinity were provided as input, with targeted parameter TDS in pre-monsoon. In Fig.-4, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.95365$.

In the third model, pH, Turbidity, Alkalinity and chlorides were provided as input from pre-monsoon data and targeted with TDS. In Fig.-5, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.93696$.

In the fourth model, pH, Turbidity, Alkalinity, chlorides and Hardness were provided as input, with targeted value TDS. In Fig.-6, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.88544$.

In the fifth model, pH, Turbidity, Alkalinity, chlorides, Hardness and calcium used as input in ANN and targeted value as TDS. In Fig.-7 it is observed that the TDS parameter correlated with input parameters show an almost closer fit with $R=0.96772$.

In the final model, input data is provided as pH, Turbidity, Alkalinity, chlorides, Hardness, calcium and

magnesium with targeted parameter TDS. In Fig.-8, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.94758$.

Post-Monsoon

In the first model in post-monsoon, pH and Turbidity were fed as input and targeted parameters as TDS. It is observed in Fig.-9, the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.8405$.

In the second model, pH, Turbidity and Alkalinity were provided as input, with targeted parameter TDS in post-monsoon. It is observed in Fig.-10, that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.96744$.

Fig.-3: Comparison between NN outputs and targets for training and test data

Fig.-4: Comparison of predicted ANNs time series with observed values

Fig.-5: Comparison of predicted ANNs time series with observed values

Fig.-6: Comparison between NN outputs and targets for training and test data

Fig.-7: Comparison between NN outputs and targets for training and test data

Fig.-8: Comparison of predicted ANNs time series with observed values

Fig.-9: Comparison of predicted ANNs time series with observed values

Fig.-10: Comparison between NN outputs and targets for training and test data

Fig.-11: Comparison between NN outputs and targets for training and test data

Fig.-12: Comparison of predicted ANNs time series with observed values

Fig.-13: Comparison of predicted ANN time series with observed values.

Fig.-14: Comparison between NN outputs and targets for training and test data

In the third model pH, Turbidity, Alkalinity and chlorides were taken as input from post-monsoon data and targeted with TDS. It is observed in Fig.-11, that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.9576$.

In the fourth model, pH, Turbidity, Alkalinity, chlorides and Hardness were considered as input, with targeted value as TDS. It is observed in Fig.-12, that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.94893$.

In the fifth model, pH, Turbidity, Alkalinity, chlorides, Hardness and calcium were used as inputs in ANN and targeted value as TDS. In Fig.-13, it is observed that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.93528$.

In the final model, pH, Turbidity, Alkalinity, chlorides, Hardness, calcium and magnesium were fed into ANN as input and TDS as a targeted parameter. It is observed in Fig.-14, that the TDS parameter correlated with input parameters shows an almost closer fit with $R=0.83328$.

CONCLUSION

The preliminary concern for analyzing the water quality is to evaluate the effect of polluting materials that are released into the water resources leading to water quality deterioration which majorly impacts the freshwater bodies and marine ecosystems. The research analysis was performed across the Tamiraparani river basin. The water quality of the Tamiraparani river was predicted by an Artificial Neural Network model with a different set of input data and targeted parameter TDS.

In this examination, the calculated value of WQI fluctuated between 16.87 to 135.60 for pre-rainstorm and 40.53 to 122.15 for the post-storm season. As indicated by the WQI estimations, water quality at one area in pre-monsoon and five areas in post-monsoon periods was discovered inadmissible for drinking. High turbidity and TDS content were responsible for higher WQI values noted at the destinations inspected. The grouping of chloride and hardness additionally was a huge component for high WQI values at certain spots during the post-rainstorm period. The WQI shows that "great water" exists in the region during pre-rainstorm and "bad quality water" during the post-storm period. This proposes that a more noteworthy measure of draining and invasion of contaminations should be implemented for better water quality.

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