Global NEST Journal, Vol 24, No 4, pp 562-568

Artificial neural network and weighted arithmetic indexing approach for surface water quality assessment of the Brahmani river

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Received: 01/08/2022, Accepted: 25/09/2022, Available online: 27/09/2022
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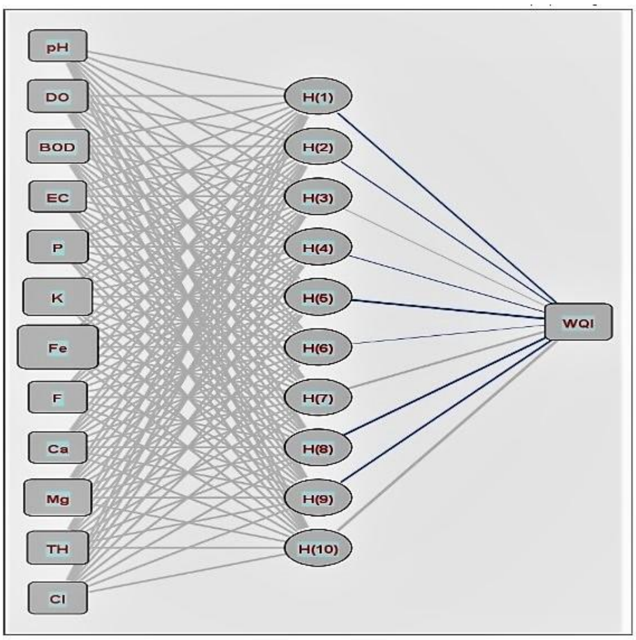
https://doi.org/10.30955/gnj.004414

Graphical abstract



Abstract

An approach was used in this study to relate the predicted and calculated water quality index (WQI) of the Brahmani River. The WQI was predicted using an artificial neural network (ANN) tool, and the weighted Arithmetic Index technique was used to calculate the WQI (WAI). The WQI is calculated using physicochemical parameters as input data. Pollution Control Board (India) data was utilised to train and evaluate the model, as well as to forecast WQI. The ANN model is trained using the feed-forward back-propogation approach. 70 percent of the data was used for training, whereas 30 percent was used for testing and validation (15 percent) (15 percent). The regression coefficients for all of the stations were greater than 0.9, indicating that ANN modelling produced successful results. For all stations, the average percent of variance between anticipated and computed WQI is 8.63 percent. According to the findings of this study, the ANN model may be useful for predicting the WQI of both surface and groundwater.

Keywords: ANN, Brahmani river, CWC, PCB WQI, WAI.

1. Introduction

As a consequence of fast industrialization and growing pollution, the usage of freshwater for household and industrial reasons has grown day by day. Overuse of water leads to an increase in water demand (Srinivasan *et al.*, 2022; Srinivasan *et al.*, 2022). Thousands of new toxins have emerged in recent years as a result of human activity (Sujatha *et al.*, 2022). Some new pollutants are routinely produced by the cosmetics industry, and heavy metals are discharged by a variety of industrial processes (Gokulan *et al.*, 2022; Praveen *et al.*, 2022). Water is one of the most important resources for manufacturing and processing (Gokulan *et al.*, 2021). They used industrial water that had to be treated before being dumped into neighbouring bodies of water. Many industries, such as dyeing, tannery, sugar, and paper and pulp, need a large amount of water for a variety of purposes (Gokulan *et al.*, 2021; Praveen *et al.*, 2021). However, these industries will require proper treatment facilities (Senthil Kumar *et al.*, 2021). Physical, chemical, and biological processes are the three types of wastewater treatment procedures (Joga *et al.*, 2021; Sivarethinamohan *et al.*, 2021). The treated wastewater must be recycled in industries before being released into the environment (Murugadoss *et al.*, 2021). Surface and groundwater pollution will arise if this effluent is not appropriately treated (Kalyani *et al.*, 2021). In India, several factories are located adjacent to rivers (Mahendran *et al.*, 2021). Rivers are one of the most important sources of surface water. These industries utilize these rivers for taking the water for their processing and also discharging the wastewater into the river (Lenin Sundar *et al.*, 2021; Praveen *et al.*, 2021). The toxins in the wastewater will be degraded by the natural process, as rivers are recognised for their self-purification. However, when pollutants are mixed in large quantities with the river, the river's self-purification ability is lost, and the entire waste stream is polluted, causing serious environmental difficulties (Praveen *et al.*, 2021; Madhu *et al.*, 2021). This contaminated water has been linked to a number of water-borne disorders (Gaddam *et al.*, 2020; Priya *et al.*, 2020). The degradation of surface and groundwater was caused by these contaminants (Damtew, 2021). Assessment of groundwater and surface water has become a requirement all across the world (Mohanty *et al., 2004*). Water contamination has necessitated numerous quantitative methods to evaluate water quality during the past decade. Researchers have developed a variety of methods for measuring water quality by incorporating its physicochemical and biological characteristics. (Şener *et al.*, 2017; Bora and Goswami, 2016). Instead of considering numerous additional parameters, as a single measure, water quality is judged by the WQI values (Hameed *et al.*, 2016; Ho *et al.*, 2019). Since various national and international authorities frequently monitor and study water quality (Horton *et al., 1965;* Judran and Kumar, 2020), the water quality index is derived using several criteria. As a result, many WQIs tailored to specific locales and with varying degrees of application have been established around the world (Khuan *et al.*, 2002).

WQI is a critical and unique assessment that displays the complete quality of water through time and aids in the selection of the best treatment technique to solve the issues (Banerjee *et al.*, 2011). The advantages are as follows:

1. This approach uses data from a range of water quality factors to create a mathematical equation that scores the water body's health as a sequence of integers. (Gazzaz *et al.*, 2012).
2. In comparison to total water quality parameters, fewer parameters are required for a specific application.
3. Useful for giving general water quality information to concerned citizens and policymakers.
4. Important for water quality evaluation and management (Goswami and Brahma, 2019) because it reflects the combined influence of various factors.

Artificial Neural Networks are a very effective tool for prediction that has been used in recent years (ANN). A neural network (ANN) is a mathematical model that predicts the output from a set of input data (Gupta *et al.*, 2021; Kadam *et al.*, 2019). Multiple hidden neurons make up an artificial neural network (ANN), which is used to train, test, and verify data sets. Recently, ANN has emerged as one of the most hopeful technologies for predicting non-linear and difficult events (Karimi *et al.*, 2013; Ghadai *et al.*, 2018). Water quality indices can be used to create artificial neural network models using a variety of methods, including a backup neural network, a modular neural network, and a radial base function network (Gupta *et al.*, 2019). Water quality parameters in the Saf-Saf River were used to develop a water value (WQI) forecasting model utilising neural networks and multivariate techniques. Three-layer forward feed-forward MLP gradient (GD) networks, Broyden–Fletcher–Goldfarben–Shanno (BFGS), and context conjugate gradient (CG) learning were used to study the association between water quality measures and WQI. In comparison to other types of MLP models, which have a low root mean square error (RMSE=0.007) and a high determination value (R2=0.811), their studies demonstrated that the MLP model with BFGS gives the maximum potential output. As a result, the current research begins by (i) evaluating a river with several stations, (ii) calculating WQI using the WAI method, (iii) predicting WQI using ANN, and (iv) comparing WQI between predicted and computed values.

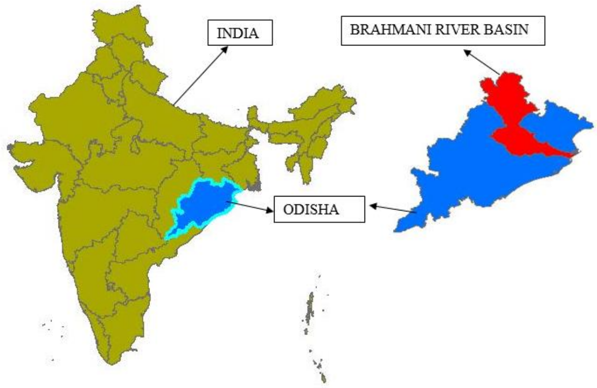


Figure 1. Study area.

2. Materials and methods

2.1. Study area

The Brahmani River, which comes from the continental Chotanagpur Plateau, is the subject of investigation (Figure 1). This is the second longest river and occupies 15% of the geographical area of the state. The river was formed by two major tributaries, Sankh and Koel, which originate in the state of Jharkhand. From 20^0 28' north to 25^0 35' north, and 80^0 52' east to 82^0 30' east, the river runs. The river's catchment spans Chattisgarh, Jharkhand, and Odisha, with the majority of the water flowing through Odisha. Sundergarh, Keonjhar, Sambalpur, Deogarh, Angul, Dhenkanal, Jajpur, and Kendrapada are the eight districts of Odisha that make up the river delta. Concerning the importance of the use of water from the Brahmani river, the river basin has been divided into several groups. By considering the types of the area with respect to agriculture and industry nine stations have been selected for research purposes. In this study, the selected sampling stations individually are of specific use. The stations like RSP Nala, Panposh, Talcher, and Kamalanga are sounded by major industries. The rest of the stations i.e. another five stations (Tilga, Jaraikela, Gomlai, Nandira, and Jenapur) are the main points for agriculture. So, by considering these nine stations we can analyse the water quality as a mixed influence of daily uses of water. This analysis can provide a fruitful result for our investigation (Figure 2).

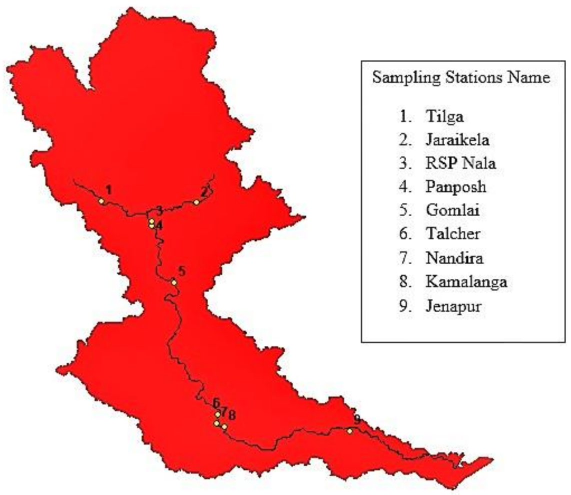


Figure 2. Sampling Stations on the Brahmani River.

2.2. WQI calculation

For calculating the water quality index, the weighted arithmetic index approach has been frequently used. Each influencing parameter's quality rating or sub-index (qn), which is a number that shows the relative intensity of the parameter in contaminated water in relation to its standard permitted value, is computed first in this procedure (Ramakrishnaiah *et al.*, 2009). The quality index for the specific parameter is then calculated by multiplying this value by a weightage factor (Yadav *et al.*, 2010; Mohanraj *et al.*, 2015). The various quality indices are then combined to get an overall quality index. The rating is generated using the current guidelines after collecting the whole water quality index. The necessary equations are shown below (Tables 1 and 2).

$$q_n = 100 * [(V_n - V_0)/(S_n - V_0)]$$

Where, qn=The nth water quality parameter's quality rating,

V_n=The nth water quality parameter of the obtained sample's estimated value,

S_n=The nth water quality parameter's standard allowable value and

V_o=Ideal water quality parameter nth value.

The unit weight (Wn) is then calculated as an inverse function of the parameter's suggested standard value Sn.

$$W_n=1/S_n$$

Where W_e=The nth water quality parameter's unit weight,

S_n=The nth water quality parameter's standard allowable value and

By linearly aggregating the quality rating and unit weight, the overall water quality index (WQI) is obtained.

$$WQI=(q_n Wn) / \Sigma W_n$$

Where, q_n=Water quality parameter quality rating

W_e=Different water quality parameters' unit weight

Table 1. WQI (WAI) rating scale

***WQI* Ranges**	**Quality of water**
0–25	Excellent
26–50	Good
51–75	Poor
76–100	Very poor
100	Unsuitable for drinking

3. Ann model

The “nntool” toolbox in MATLAB is used to generate models using a neural network in this study. Two windows in the MATLAB window are dedicated to the task of model generation (Mohanraj *et al.*, 2012). The workspace window and the command window are the two. The data is input in the workspace window, and the neural network toolbox "nntool" is activated in the command window. Physico-chemical parameters are all input data, but WQI considers them output or response (Target) data.

Table 2. ANN Modeling Input & Target (Response) Data

Input	pH (pH units)
	(i) Biochemical Oxygen Demand (BOD)
	(ii) Dissolved Oxygen (DO)
	(iii) Total Phosphorus (P)
	(iv) Electrical Conductivity (EC)
	(v) Iron (Fe)
	(vi) Potassium (K)
	(vii) Calcium (Ca)
	(viii) Fluoride (F)
	(x) Manganese (Ma)
	(xi) Chlorides (Cl)
	(xii) Total Hardness (TH)
Output	WQI

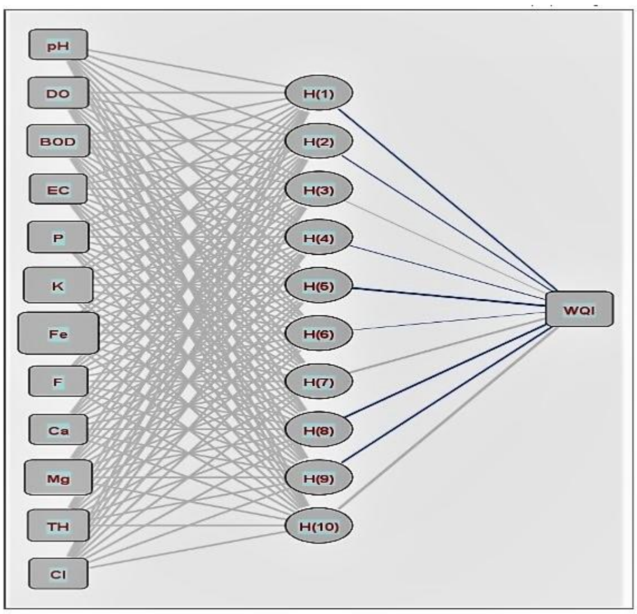


Figure 3. ANN Structure.

The feed-forward backpropagation approach was examined for WQI training and prediction. The data was utilised for training 70% of the time, validation 15% of the time, and testing 15% of the time. The regression coefficient (R) is increased until it approaches 1.0 (typically >0.8). Figure 3 shows how the TRAINLM and LEARNGDM training functions are used to model a hidden layer of 10 integers. The regression plots contain graphs for the test, training, and validation phases, as well as a complete regression graph.

4. Result and discussion

The performance of the models built is examined using two years of PCB data from all nine sites (2019 and 2020). Tables 3 and 4 show the WQI computed (WAI Method) and forecasted (ANN Model) for 2019 and 2020, respectively.

Table 3. WQI prediction (ANN Model) vs. calculated (WAI Method) – 2019

Station	ANN Model			WAI Method		
	Summer	Rainy	Winter	Summer	Rainy	Winter
Jarikela	130.66	119.69	119.69	173.08	138.39	137.52
Tilga	188.85	181.75	168.89	171.52	168.61	167.74
Rsp Nala	167.9	173.69	192.28	178.52	196.89	215.02
Panposh	122.07	99.73	101.22	177.96	141.41	110.37
Talcher	192.72	202.63	80.77	205.24	175.91	80.96
Gomlai	164.25	134.25	164.25	172.75	117.49	160.03
Kamalanga	130.07	221.92	180.67	140.95	205.44	178.44
Nandira	238.79	138.79	138.79	247.56	141.03	145.07
Jenapur	100.77	110.77	203.06	107.21	109.86	207.41

Table 4. WQI prediction (ANN Model) vs. computation (WAI Method) – 2020

Station	ANN Model			WAI Method		
	Summer	Rainy	Winter	Summer	Rainy	Winter
Jarikela	230.66	80.66	80.66	228.4	77.1	85.03
Tilga	67.23	330.97	99.97	89.61	334.18	113.86
Rsp Nala	101.76	112.36	109.78	106.12	114.99	107.83
Panposh	80.67	98.06	81.14	110.47	102.65	101.86
Talcher	88.33	96.34	89.05	101.97	97.58	88.74
Gomlai	92.62	112.62	92.62	99.61	109.73	106.02
Kamalanga	210.26	78.49	80.76	213.23	92.5	90.05
Nandira	98.79	88.79	108.79	108.91	96.24	105.28
Jenapur	140.77	140.77	110.77	176.45	131.1	110.83

The results show that for practically all stations and seasons, the agreement between the model and real values is pretty satisfactory. When comparing Panposh to other stations, it can be seen that the model values deviate more from the computed values. It should also be highlighted that the expected values for practically all stations and seasons are on the higher side. The anticipated values for the stations Panposh, RSP Nala, Gomlai, and Nandira are lower than the actual readings. When the WQI values for table no.1 are considered, it is clear that the water quality for maximum stations in all three seasons is unfit for human consumption. The river's surface water is used as a supply of water for domestic uses. For sources utilised for domestic purposes, the WQI should always be less than 100. The WQI scores at all nine locations indicate that the river is entirely contaminated and unfit for human consumption. The river became polluted as a result of industrial development and other activities. Common activities that may add to the pollution load in the river include solid waste dumping, sewage drainage, and the release of toxic effluents. When pollutants enter the river, they fully deplete the available dissolved oxygen and transform the aerobic zone to the anaerobic zone. The river's self-purification also suffers as a result of the frequent disposal of rubbish alongside the river. Table 3 further shows that all of the station WQI ranges are very high, greater than 100. It increases the severity of pollution levels, and the river is occupied with constant s loading of pollutants along its length. Talcher station will be exempt throughout the post-monsoon season. The anticipated and computed values indicate that the water quality at this site is quite bad. Table 4 depicts the changes discovered at each of the nine locations in 2020. Tables 3 and 4 show that the WQI for the year 2020 is significantly lower than it was in 2019. Many of the questions, including Tilga, Panposh, Talcher, Gomlai, and Nandira, were reduced to less than 100. For example, the average WQI for 2020 was reduced by 21, 17, and 35% for pre-monsoon, monsoon, and post-monsoon, respectively. The decrease in WQI values indicates that the quality of surface water has improved as a result of lower pollutant loads in the river. COVID 19 caused a nationwide lockdown in India after March 2020, resulting in the closure of many small and medium-sized businesses, the arrest of many recreational activists, the closure of public places, and a reduction in water consumption. As a result, may be pollution levels have decreased and water quality has improved. The regression analysis for the ANN model for Station Tilga is shown in Figure 4.

Table 4 indicates that the model and real data agreement is excellent for practically all stations and seasons. In comparison to other stations, the variance is higher at Gomlai and Nandira. Except for Jarikela, the anticipated values are lower than the computed values for almost all stations. According to the anticipated values, the water quality for the stations Panposh and Talcher is very bad in all seasons, but the water quality is unacceptable according to computed values, which exhibit the highest variance in comparison to other stations. Table 5 summarises the R^2 (Regression Coefficients) predicted by ANN for all stations.

Table 5. Percentage deviations between compute WQI and actual

Station	2019			2020			Average
	Summer	Rainy	Winter	Summer	Rainy	Winter	
Tilga	-10.2	-7.9	-0.8	24.6	0.9	12	9.3
Jarikela	24.3	13.4	12.8	-1.1	-4.7	5	10.15
Panposh	31.2	29.2	8.2	26.7	4.4	20.1	19.97
Rsp Nala	5.9	11.7	10.5	4	2.2	-1.9	6
Gomlai	4.8	-14.3	-2.8	6.9	-2.8	12.5	7.25
Talcher	6	-15.3	0.2	13.2	1.2	-0.5	6
Nandira	3.5	1.5	4.2	9.2	7.6	-3.5	4.88
Kamalanga	7.6	-8.1	-1.4	1.3	14.9	10.2	7.18
Jenapur	5.9	-1	2	20.1	-7.5	0.1	6.02
Average*	11.02	11.27	4.7	11.88	5.07	7.23	8.53

Note: * Absolute deviation values are used in average computations.

Table 6. All stations' regression coefficients

Station	R^2			
	Test	Training	Validation	All
Tilga	0.9908	0.9601	0.9209	0.9677
Jaraikela	0.9998	0.9961	0.9944	0.9963
Panposh	0.9999	0.9250	0.9137	0.9881
RSP Nala	0.9998	0.9941	0.9999	0.9995
Gomlai	0.9999	0.9998	0.9998	0.9998
Talcher	0.9998	0.9996	0.9998	0.9996
Nandira	0.9997	0.9998	0.9999	0.9998
Kamalanga	0.9998	0.9984	0.9999	0.9985
Jenapur	0.9947	0.9996	0.9942	0.9988

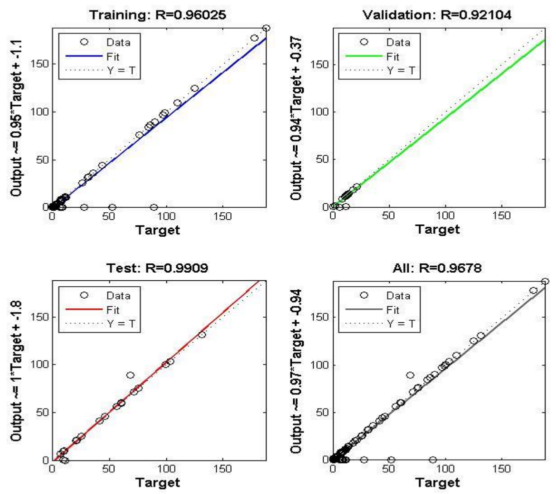


Figure 4: Regression Coefficient for the Station Tilga - ANN model.

The percent divergence of WQI between the ANN model projected values and WAI computed values is calculated and displayed in Table 5 to examine the success of the ANN methodology used at this time. The variance has been calculated using data from both 2019 and 2020. The model values' total average variance is predicted to be 8.3 percent. On the upper side, the greatest and lowest deviations for the 2019 pre-monsoon Panposh and 2019 post-monsoon Talcher values are + 31.2 percent and + 0.2 percent, respectively. The highest and lowest variances, respectively, are -15.3 percent (2019 monsoon Talcher) and -1 percent (2019 pre-monsoon Jaraikela). The regression coefficient analysis of two years of data with the help of the ANN model has strengthened the comparison between predicted and computed values. As we know, the closer the R-value is to 1, the closer the two data are related. As a result, the R values range between 0.91 and 1. Figure 4 shows a sample result from the Tilga station. In Table 6, the R values of all stations are listed.

5. Conclusion

Following are the conclusions reached after modelling, computation, and comparison.

- The current study used ANN modelling to create a model for predicting the WQI for a set of 12 factors for the river Brahmani.

- The regression coefficients for all of the stations were greater than 0.9, indicating that ANN modelling produced successful results.
- The average variation for all stations combined is 8.63 percent, which is a reasonable figure. The model values are often slightly higher than the real values in the majority of cases. Except for Jaraikela and Panposh, the average variance for all stations is less than 10%. Jaraikela and Panposh had average variances of 10.25 percent and 20.07 percent, respectively. When all stations are taken into account, the pre-monsoon ANN values are found to be about 11% for both years.
- The modelling shows the most accurate result in comparison to the computed value, and this is solely utilised for the Brahmani river to determine the ANN model's efficiency. Future predictions can be made using this method by providing suggestions on water contamination, which will be highly useful in allowing essential action to be taken ahead of time. This model can also be used to predict water quality in a variety of situations.

Conflicts of Interest

The authors state that they have no competing interests in the publication of this research.

References

Asfaw M.D. (2021). Evaluation of ground water quality with water quality index (WQI) in Woreillu Town, Ethiopia. *Journal of Environment and Earth Science*. doi:10.7176/jees/11-1-02.

Banerjee P., Singh V., Chatttopadhyay K., Chandra P., and Singh B. (2011). Artificial neural network model as a potential alternative for groundwater salinity forecasting. *Journal of Hydrology*, **398**(3–4), 212–220. doi:10.1016/j.jhydrol.2010.12.016.

Bora M., and Goswami D.C. (2016). Water quality assessment in terms of water quality index (WQI): Case study of the Kolong River, Assam, India. *Applied Water Science,* **7**(6), 3125–3135. doi:10.1007/s13201-016-0451-y.

Gaddam K., Perumal M.S., and Ravindiran G. (2020). Removal of lead metal ion using biowaste of *Pithophora cleveana wittrock* and *Mimusops elengi*. *Energy Source Part A: Recovery, Utilization and Environmental Effects*. https://doi.org/10.1080/15567036.2020.1831657 (SCI, I.F: 3.44).

Gazzaz N.M., Yusoff M.K., Aris A.Z., Juahir H., and Ramli M.F. (2012). Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors. *Marine Pollution Bulletin,* **64**(11), 2409–2420. doi:10.1016/j.marpolbul.2012.08.005

Ghadai M., Satapathy D.P., and Narasimham M.L. (2018). Water quality index computations at selected locations: a case study of Brahmani river basin, Odisha, India. *International Journal of Management, Technology and Engineering*, **8**(XII), 2249–7455.

Gokulan R., Balaji S., and Sivaprakasam P. (2021). Optimization of remazol black b removal using biochar produced from caulerpa scalpelliformis using response surface methodology. A*dvance in Materials Sciences and Engineering*, https://doi.org/10.1155/2021/1535823.

Gokulan R., Pradeepkumar S., and Elias G. (2021). Continuous sorption of remazol brilliant orange 3r using caulerpa scalpelliformis biochar. *Advances in Materials Science and Engineering*, **2021**, Article ID 6397137, 7 pages. https://doi.org/10.1155/2021/6397137.

Gokulan R., Praveen S., Avinash A., and Saravanan S. (2021). Soft computing-based models and decolorization of Reactive Yellow 81 using *Ulva Prolifera* biochar. *Chemosphere*, **287**(Part 4), Jan 2022, 132368 (Elsevier, SCI, IF: 7.08) https://doi.org/10.1016/j.chemosphere.2021.132368.

Goswami P., and Brahma H. (2019). River water level prediction modelling using artificial neural network and multiple linear regression. *International Journal of Engineering and Management Research,* **9**(6), 23–31. doi:10.31033/ijemr.9.6.4.

Gupta R., Singh A.N., and Singhal A. (2019). Application of ANN for water quality index. *International Journal of Machine Learning and Computing*, **9**(5), 688–693. https://doi.org/10.18178/ijmlc.2019.9.5.859.

Gupta S.S., Singh R., and Chaudhary P. (2021). Advancing water quality assessment via artificial neural networks (ANNs). *Spectroscopy and Machine Learning for Water Quality Analysis*. doi:10.1088/978-0-7503-3047-3ch5.

Hameed M., Sharqi S.S., Yaseen Z.M., Afan H.A., Hussain A., and Elshafie A. (2016). Application of artificial intelligence (AI) techniques in water quality index prediction: A case study in tropical region, Malaysia. *Neural Computing and Applications*, **28**(S1), 893–905. doi:10.1007/s00521-016-2404-7.

Ho J.Y., Afan H.A., El-Shafie A.H., Koting S.B., Mohd N.S., Jaafar W.Z., and El-Shafie, A. (2019). Towards a time and cost-effective approach to water quality index class prediction. *Journal of Hydrology*, **575**, 148–165. doi:10.1016/j.jhydrol.2019.05.016.

Horton *et al.* (1965). An index number system for rating water quality. *Journal of the Water Pollution Control Federation*, **37**, 300–306.

Joga Rao H., Gokulan R., Ragunath S., and Praveen S. (2021). Optimization of process conditions using RSM and ANFIS for the removal of Remazol Brilliant Orange 3R in a packed bed column. *Journal of Indian Chemical Society*. https://doi.org/10.1016/j.jics.2021.100086.

Judran N.H., and Kumar A. (2020). Evaluation of water quality of Al-Gharraf River using the water quality index (WQI). *Modeling Earth Systems and Environment*, ***6***(3), 1581–1588. doi:10.1007/s40808-020-00775-0.

Kadam A.K., Wagh V.M., Muley A.A., Umrikar B.N., and Sankhua R.N. (2019). Prediction of water quality index using artificial neural network and multiple linear regression modelling approach in Shivganga River basin, India. *Modeling Earth Systems and Environment,* **5**(3), 951–962. doi: 10.1007/s40808-019-00581-3.

Kalyani G., Gokulan R., and Sujatha S. (2021). Biosorption of zinc metal ion in aqueous solution using biowaste of Pithophora cleveana wittrock and Mimusops elengi. *Desalination and Water Treatment*. 218, 363–371. https://doi.org/10.5004/dwt.2021.27005.

Karimi S., Kisi O., Shiri J., and Makarynskyy O. (2013). Neuro-fuzzy and neural network techniques for forecasting sea level in Darwin Harbor, Australia. *Computers & Geo-sciences,* **52**, 50–59. doi:10.1016/j.cageo.2012.09.015.

Khuan L.Y., Hamzah N., and Jailani R. (n.d.). Prediction of water quality index (WQI) based on artificial neural network (ANN). *Student Conference on Research and Development*. doi:10.1109/scored.2002.1033081.

Lenin Sundar M., Kalyani G., Gokulan R., Ragunath S., and Joga Rao H. (2021). Comparative adsorptive removal of Reactive Red 120 using RSM and ANFIS models in batch and packed bed column. *Biomass Conversion and Biorefinery.* https://doi.org/10.1007/s13399-021-01444-7.

Madhu K., Ravindiran G., Sivarethinamohan S., Pathanjali S.P.S., Saravanan P., Sellappan E. (2021). Biodecolorization of reactive Red 120 in batch and packed bed column using bio-char derived from Ulva reticulata. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-020-01268-x.

Mahendran S., Gokulan R., Aravindan A., Joga Rao H., Kalyani G., Praveen S., Bhagavathi Pushpa T., and Senthil Kumar M. (2021). Production of Ulva prolifera derived biochar and evaluation of adsorptive removal of Reactive Red 120: batch, isotherm, kinetic, thermodynamic and regeneration studies. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-021-01483-0.

Mohanraj M., Jayaraj S. and Muraleedharan C. (2012). Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems—A review. *Renewable and Sustainable Energy Reviews*, **16**, 1340–1358.

Mohanraj M., Jayaraj S. and Muraleedharan C. (2015). Applications of artificial neural networks for thermal analysis of heat exchangers e A review. *International Journal of Thermal Sciences*, **90**, 150–172.

Mohanty *et al.* (2004) Water quality index of four religious ponds and its seasonal variation in the temple city Bhubaneswar. In: Kumar A (ed) Water pollution. APH Publishing Corporation, New Delhi, pp 211–218.

Praveen S., Jegan J., Bhagavathi Pushpa T., Gokulan R., and Bulgariu L. (Feb 2022). Biochar for removal of dyes in contaminated water: an overview. *Biochar*, **4**, Article ID: 10, 1–16. (Indexed in SCIE, Impact Factor: 5.22, Q2), ISSN: 2524-7972 (Doi: https://doi.org/10.1007/s42773-022-00131-8).

Praveen S., Jegan J., Pushpa T.B., and Gokulan R. (2021). Evaluation of the adsorptive removal of cationic dyes by greening biochar derived from agricultural bio-waste of rice husk. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-021-01415-y.

Praveen S., Jegan J., Pushpa T.B., Gokulan R. (2021). Artificial neural network modelling for biodecolorization of basic violet 03 from aqueous solution by biochar derived from agro-bio waste of groundnut hull: Kinetics and Thermodynamics. *Chemosphere*, 130191, https://doi.org/10.1016/j.chemosphere.2021.130191.

Praveen S., Jegan R.G.J., and PushpaT. B. Techno-economic feasibility of biochar as biosorbent for basic dye sequestration, *Journal of Indian Chemical Society*. https://doi.org/10.1016/j.jics.2021.100107.

Priya A.K., Gokulan R., Vijay Kumar A., and Praveen S. (2020). Biodecolorization of remazol dyes using biochar derived from *Ulva reticulata:* Isotherm, kinetics, desorption and thermodynamic studies. *Desalination and Water Treatment*, **200**, 286–295. https://doi.org/10.5004/dwt.2020.26098 (SCI, I.F:1.32).

Raja Murugadoss J., Kalyani G., Gokulan R., Sivaprakasam P., Maheandera Prabu P., Aravindan A., Praveen S., and Senthil Kumar M. (2021). Biochar from waste biomass as a biocatalyst for biodiesel production:an overview. *Applied Nanoscience*. https://doi.org/10.1007/s13204-021-01924-2.

Ramakrishnaiah *et. al.* (2009). "Assessment of water quality index for the groundwater in Tumkur Taluk", Karnataka State, India. *Journal of Chemistry*, **6**, 523–530.

Şener Ş, Şener E., and Davraz A. (2017). Evaluation of water quality using water quality index (WQI) method and GIS in Aksu River (SW-Turkey). *Science of The Total Environment, 584–585*, 131-144. doi:10.1016/j.scitotenv.2017.01.102.

Senthil Kumar M., Kalyani G., Mahendran S., Joga Rao H., Gokulan R., Someswaran R., Jenifa Latha C., and Palpandian M. (2021)., Treatment of RO rejects wastewater by integrated coagulation cum adsorption process. *Polish Journal of Environmental Studies*, **30**(5), 1–8.

Sivarethinamohan S., Ravindiran G., Hanumanthu J.R., Gaddam K., Saravanan P., Muniasamy S.K. (2021). Effective removal of remazol brillinat orange 3R using a biochar derived from Ulva reticulata, *Energy Source Part A: Recovery, Utilization and Environmental Effects*. https://doi.org/10.1080/15567036.2021.1943070.

Srinivasan K., Bobbili Aravind S.A., Gokulan R., Jodhi C., Muralikrishnan R., Ragunath S., Zunaithur Rahman D.R., and Nasar Ali R. (2022). Decolourization of reactive red 120 using agro waste-derived biochar. *Advances in Material Sciences and Engineering*, **2022**, Article ID 2689385, https://doi.org/10.1155/2022/2689385.

Srinivasan K., Bobbili Aravind S., Gokulan R., Balakumar S., Muralikrishnan R., Janakani Uday B., Bonu R., and Nasar Ali R. (2022). Effective removal of reactive yellow 145 (RY145) using biochar derived from groundnut shell. *Advances in Material Sciences and Engineering*, **2022**, Article ID 8715669. https://doi.org/10.1155/2022/8715669.

Sujatha S., Gokulan R., Zunaithur Rahman D.R., and Yogeshwaran V. Investigation of Mechanism of metal ion adsorption from aqueous solutions using prosopis julyflora roots: batch and fixed bed column studies. *Global NEST*, March 2022, (SCI, IF: 1.04) DOI: https://doi.org/10.30955/gnj.004061.

Yadav A.K., Khan P., and Sharma S.K. (2010). Water quality index assessment of groundwater in Todaraisingh Tehsil of Rajasthan State, India-A Greener Approach. *E-Journal of Chemistry,* **7**(S1). doi:10.1155/2010/419432.