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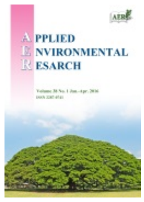

Prediction of Groundwater Quality Index in the Selected Divisions of Srikakulam Using Artificial Neural Networks Approach

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Abstract

Applicability of artificial neural network (ANN) modelling in predicting the water quality index (WQI) and in turn to ascertain the suitability of the water for human consumption has been presented in the paper. In the light of the present study, seventy-nine (79) groundwater samples were collected from two mandals (divisions) Veeraghattam (VGT) and Palakonda (PLKD) and analyzed for physicochemical parameters during the pre-monsoon and post-monsoon seasons of 2015 and 2016. In computing the WQI, physicochemical parameters such as pH, EC, TDS, TH, Ca, Mg, chlorine, fluoride, nitrite, DO and TA have been considered. From the results it was found that the WQI varies from 43.9 to 46.5 and 31.4 to 34.7 in VGT and PLKD divisions respectively. ANN tool in MATLAB has been used to predict the WQI. Back propagation methodology and LM algorithm has been chosen for the study. To train the network, physicochemical parameters have been given as inputs and the already computed WQI values as output. A particular season has been chosen for testing the network. After simulating the network, the results obtained were compared with the experimental value and found to have an error of 0.6%. It is inferred that the chosen model fits apt for the prediction of WQI in the present study.

Keywords: WQI; Artificial Neural Networks (ANN); Srikakulam

Introduction

Water is the predominant substance on earth and is utilized in farming, industry, business, rising of livestock, production of hydropower, as well as for drinking and domestic needs. The increasing rate of water contamination and the consequent increase of water borne diseases are compelling evidence of danger to public health and all living organisms [1]. By 2025, it is anticipated that water withdrawals will increase in the developing nations by 50% and by 18% in the developed countries [2]. In India, just 28,000 out of 2.5 village councils have acquired the status of being in extremely good condition [1, 3]. According to the World Bank reports, 21% of infectious diseases in India are due to

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contaminated water and lack of hygiene practices [4]. The United Nations Organization did an examination of the appraisal of water quality in 122 nations throughout the world. Among those 122 nations, India was positioned at 120, indicating that the water was terribly contaminated. In the other report of the UN, on the accessibility of freshwater, India ranked 133 out of 180 nations participating. Water contamination is the cause of a wide variety of diarrheal disorders, including cholera, guinea worm diseases, filarial diseases, dysentery, viral gastroenteritis, and amebiasis. In addition, around 250 million people are infected worldwide, of which 10–20 million die, mostly in developing countries [5–6]. The quality of water therefore determines the human quality of life and, in brief, the existence of human beings and other life forms is unlikely without water. The water quality index (WQI) is one of the premier productive tools for passing on information on water quality to affected residents as well as policymakers. Along these lines, it changes into a legitimate boundary for the evaluation and organization of groundwater. The WQI is portrayed as an evaluating tool reflecting the consolidated effect of different parameters present in groundwater. The WQI is registered for the suitability of groundwater for everyone's use [7].

The Artificial Neural Network (ANN) approach is a type of artificial intelligence that, through its architecture, aims to replicate and mimic the biological structure of the human brain and nervous system. The neural network is composed of simple, simultaneous processing elements called neurons, which are inspired by the biological nervous system [8]. The general ANN network consists of the input, hidden or middle, and output layers.

The ANN model involves high precision in the planning, production, and expansion of technological components. The input raw data is then structured and calibrated to avoid undue declination in the allocated weights. Standardized data is used to improve the level of transmission and accuracy of the results of ANN. Artificial neural networks are typically a designer-completed structure and input data weights are automatically trained using an optimization algorithm such as the back-propagation method [9].

The main advantages of ANN can be high efficiency of computation in dealing with large quantities of data and nonlinear relationships between parameters (especially for water quality) and data transfer during the calculation process, which enables its accuracy in water quality assessment or simulation. A memory capacity of large capacity can store large volumes of water quality data and the corresponding relationship between inputs and outputs. A combination of high speed of computation and high speed of computation will inevitably enhance the intelligence level of water quality assessment and simulation [10–11]. Learning ability avoids some processes such as mechanism analysis, boundary and initial hypothesis, parameter estimation and calibration in establishing groundwater quality simulation. Only model training is necessary to determine the input-output relationship, which greatly simplifies the model setup procedure. The ANN program was discovered to be utilized to estimate the water quality of the samples analyzed. The results were computed using the ANN toolbox in MATLAB; the back propagation methodology was used. The TRAINGLM model was used to train the network. To run the network, physicochemical characteristics assessed for four seasons were given as inputs and the WQI computed for the same four seasons was used as targets to train the network. The network was validated using physicochemical characteristics from one season and WQI was predicted for the remaining season. The WQI for the same season was calculated and compared to the predicted values by the ANN model. The ANN model computed the testing and validation regression analysis. R^2 values for the same were determined to be well within the permissible ranges. In this way, the author predicts the groundwater WQI of the two divisions by using the ANN tool. This study was aimed to appraise the groundwater quality of a total of 79 sample stations in the Palakonda and Veeraghattam divisions using the WQI method, and also predicting the integral groundwater quality through ANN. The key findings from this analysis might be very helpful information for water authorities and policy makers in the study area.

Study area

Srikakulam is one of the backward districts of north coastal Andhra Pradesh, India. Palakonda (PLKD) and Veeraghattam (VGT) divisions are rural divisions in this district. PLKD is located 43 km towards the north of the district headquarters with latitude 18.6019263 E and longitude 83.758423 N, and is located 59 km from the district headquarters in Srikakulam with latitude 18° 41' 11 "E and longitude 83 ° 36' 38" N. [7, 12]. The major sources of employment in both divisions are horticulture, agriculture, and animal husbandry, where approximately 80% of the labor force is engaged. The major industries are rice mills, food processing industries, mining, and stone crushing. Figure 1 shows the study area map.

Materials and methodology

To ascertain the seasonal variations in the groundwater quality, a total of 79 groundwater samples were collected during the pre-monsoon and post-monsoon seasons of December 2013 (S1), June 2014 (S2), December 2014 (S3), June 2015 (S4), December 2015 (S5), June 2016 (S6), and analyzed for various physico-chemical parameters such as pH, turbidity, EC, TDS, TH All chemicals used for analytical reagent grade and for preparation of solutions are made with triple distilled water [7]. The methodology flow chart for prediction of WQI through ANN is shown in Figure 2.

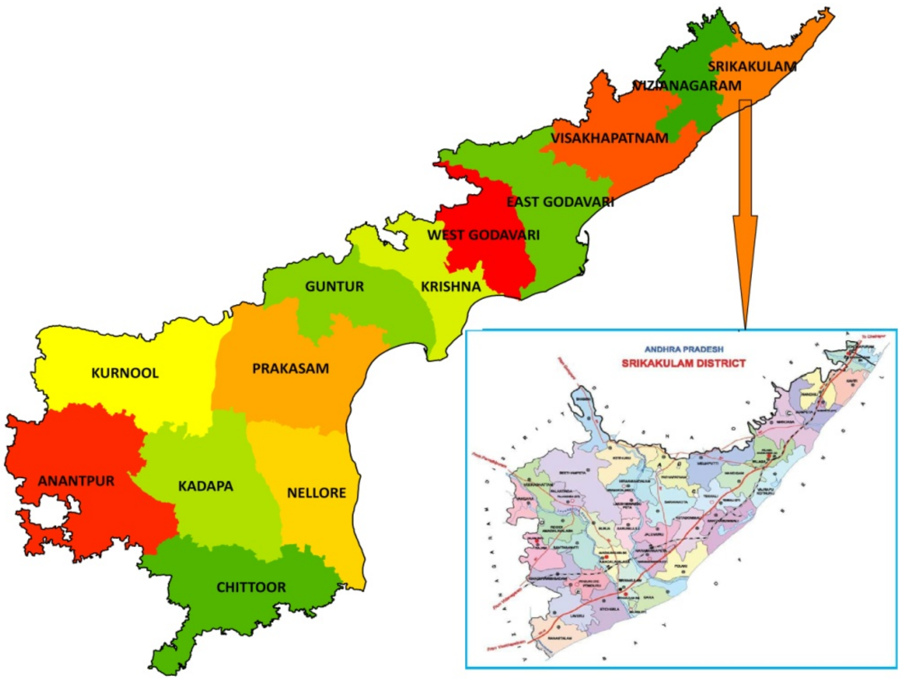

Figure 1 Sampling locations of the study area.

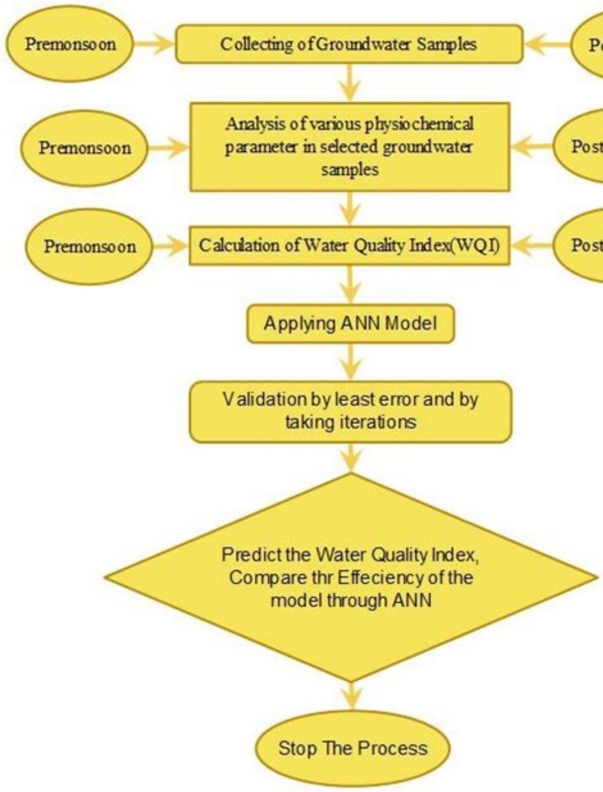

Figure 2 Flowchart for prediction of WQI through ANN architecture.

Water quality index (WQI)

The water quality index is portrayed as a ranking that reflects the integrated impacts of multiple potable water quality parameters on drinking water quality as a whole [7]. In order to assess the true status of the quality of the water resources, the WQI technique can be used [13]. The water quality evaluation for numerous uses, such as drinking, washing, and bathing, is carried out by the water quality indexes based on the BIS standards [14–15]. Weights for various drinking water quality parameters are presumed to be inversely proportional to the standards for the relevant parameters [7]. Weighted index method of WQI proposed by Brown [16–17] has been applied to evaluate the water quality status of groundwater [7, 15–17]. Out of total analyzed physicochemical parameters, including EC, pH, TDS, TH, Ca (II), Mg (II), Cl^-, F^-, NO_2^- and TA were used to calculate the WQI of groundwater in the PLKD [7], and VGT divisions. As suggested by Brown et al. [16–17], if the WQI value is in the range of 0–25, the water is "excellent", if it is 25–50, it is "good", if it is 50–75, it is "poor", if it is 76–100, it is "very poor", and if it is greater than 100, it is "unsuitable for drinking". The WQI is computed by using the following formula.

$$WQI = \frac{\Sigma QiWi}{\Sigma Wi} \quad \text{(Eq. 1)}$$

where Q_i is the quality rating of ith water quality parameter and W_i is the unit weight of nth water quality parameter.

The quality rating Q_i is calculated using the Eq. 2.

$$Q_i = 100 \left[\frac{V_i - V_o}{V_s - V_o}\right] \quad \text{(Eq. 2)}$$

where V_i is the actual amount of i^{th} parameter present, V_0 is the ideal value of the parameter, $V_0 = 0$, except for pH ($V_0 = 7$) and Vs is the standard permissible value for the ith

water quality parameter. Unit weight (W_i) is calculated using the Eq. 3.

$$W_i = \frac{k}{V_i} \qquad \text{(Eq. 3)}$$

where k is the proportionality constant and it is calculated using the Eq. 4.

$$K = \frac{1}{V_s} = 1, 2 \ldots n \qquad \text{(Eq. 4)}$$

Artificial neural network (ANN)

The specific utilization of ANN to build up an anticipating model for the expectation of WQI for the examination zone is an application that has not yet been researched. Therefore, the current examination starts by setting goals to assess the groundwater quality for drinking by computing the WQI, and another one for the prediction of WQI using the ANN model through the back-propagation algorithm.

The general ANN system comprises of three layers, in particular, the input layer, hidden layer, and output layer. The information sources are applied in the input layer for additional preparation. From the input hubs, the data is passed to the hidden layer. In the hidden layer, it is set between the input layer and the output layer and, in this manner, has no association with the outside world. The hidden layer carries out its operation and sends the results to the output layer. The data received from the secret layer is stored in the output layer, and the data is transferred to the outer world. The relationship between the layers in the network is allowed by the communication lines that hold the chosen weights. The output layer value is compared to the expected output of the circuit and the error is measured. In the next step, this error is used in the weight-updating phase, and the output layer result is fed back to the hidden layer. This process continues until the error is sufficiently small [1]. Ten input nodes are used in this function because 10 water quality parameters such as EC, pH, TDS, TH, Ca (II), Mg (II), Cl^-, F^-, NO_2^- and TA are selected in computing the WQI. The weights are carried out via the neural network and the measurement is carried out within the network. For this purpose, the author used MATLAB (MATLAB R2013a) programming software and chose the ANN tool from it. The back-propagation and L-M algorithm has been adopted as it is widely used over the globe to predict various other phenomena. The main steps involved in prediction using ANN are as follows;

1. Training the network chosen by prompting inputs.
2. Verifying the error. If an error exists, by adjusting epochs, train the network again and again until the errors become zero or less.
3. Simulation of the trained network
4. Prediction of the WQI

In Figure 3, the ANN networking model has been depicted. The pictorial representation of back-propagation is shown in Figure 4.

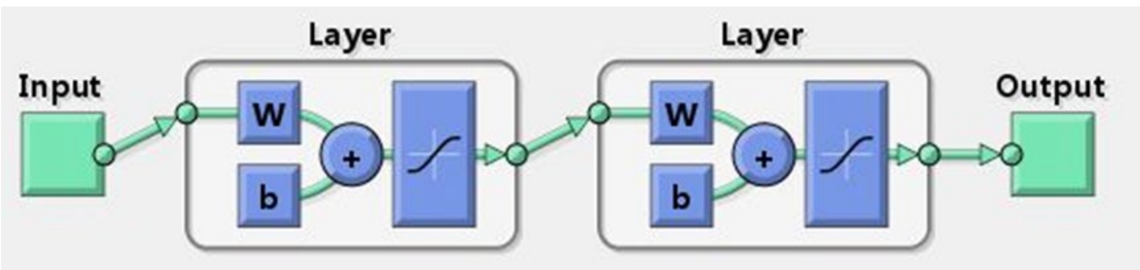

Figure 3 ANN feed-forward backdrop TRAINGM network.

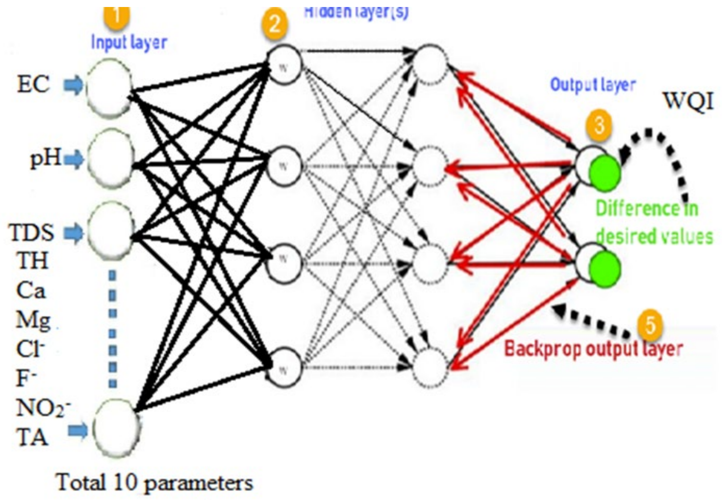

Figure 4 Back propagation algorithm for running ANN tool.

Results and discussion

1) Physicochemical analysis

The pH vacillates between mildly acidic and mildly alkaline in the two divisions. The hydrogen ion concentration in the VGT range is 6.56 –8.06 with a mean during the pre-monsoon of 7.36, and during the post-monsoon ranges from 6.61–8.1 with a mean of 7.47. The pH of groundwater samples in PLKD varied from 6.18–7.32 with a mean of 6.76 during the pre-monsoon, and during the post-monsoon varied from 6.25–7.7 with a mean of 6.87. This is in accordance with WHO standards (6.5–8.5) for drinking water [18]. The electrical conductivity of the water samples varied from 316–3541 µS cm^{-1} with a median of 1,261.63 µS cm^{-1} and 302–3,532 µS cm^{-1} with an average of 1,265 µS cm^{-1} in the VGT throughout the pre-and post-monsoon seasons. In PLKD, EC ranges from 326–3839 µS cm^{-1} with an average of 1428.46 µS cm^{-1}, and 330–3845 µS cm^{-1} with an average of 1434.31 µS cm^{-1} during the pre-monsoon and post-monsoon seasons. The electrical conductivity measured was very high in both seasons, according to WHO standards [18]. The turbidity of groundwater samples was found in the range of 0.14–6.04 NTU with a mean value of 1.56 NTU in the pre-monsoon and 0.16–6.22 NTU with a mean value of 1.60 NTU during the post-monsoon in VGT. In PLKD during the pre-monsoon ranged from 0.16– 8.8 NTU with an average of 1.72 NTU and 0.2 –9.18 NTU with an average of 1.80 NTU during the period. It was marginally higher in the post-monsoon season. The hardness of groundwater samples in VGT during the pre-monsoon was found to be in the range of 148–1826 mg L^{-1} with an average of 447.53 mg L^{-1}, and during the post-monsoon varied from 154–813 mg L^{-1} with a mean of 447.88 mg L^{-1}. In PLKD, TH was observed in the range of 148–1,536 mg L^{-1} with an average of 450.68 mg L^{-1}, and, 142–1,526 mg L^{-1} with a mean of 449.60 mg L^{-1} during the pre and post monsoon seasons respectively. The mean hardness value was calculated above the appropriate level (300 mg L^{-1}) of the Indian drinking water quality standard [19]. The Ca (II) concentration in VGT was observed in the range during the pre-monsoon was 9.19–185.4 mg L^{-1} with a mean of 65.98 mg L^{-1}, and during the post- monsoon it was 12.33–178.21 mg L^{-1} with an average of 63.38 mg L^{-1}. In PLKD, it was found in the range during pre-monsoon 13.46–114.87 mg L^{-1} with a mean value of 61.66 mg L^{-1}, and 20.2–109.31 mg L^{-1} with a mean value of 59.05 mg L^{-1}. In post-monsoon 14, (17.7%) and in pre-monsoon 10, (12.6%) samples are above the standard set by WHO [18]. The Mg (II) concentration in VGT varied from 18.06–391.23 mg L^{-1} with an average value of 5.92 mg

L^{-1} and from 25.25–387.78 mg L^{-1} with an average value of 85.54 mg L^{-1} during the pre and post monsoon seasons respectively. In PLKD, Mg (II) was in the range of 19.01–350.12 mg L^{-1} with a mean value of 93.05 mg L^{-1} during the pre-monsoon and 25.22–341.21 mg L^{-1} with a mean value of 88.78 mg L^{-1} during the post monsoon. As per the BIS limits, in pre-monsoon 68 (86%) samples, and in post-monsoon 73 (92.4%) samples are above the BIS standard [19]. The concentration of fluoride in VGT is in the range of 0.09–2.95 mg L^{-1} with a mean value of 0.87 mg L^{-1} and 0.1–3.02 mg L^{-1} with an average of 0.96 mg L^{-1} and in PLKD is varied from 0.01–1.65 mg L^{-1} with a mean value of 0.47 mg L^{-1} and 0.05–1.77 mg L^{-1} with an average of 0.58 mg L^{-1} during the pre and post monsoon season respectively. The Cl^- concentration in VGT samples varied from 36–760 mg L^{-1} with an average of 206.4 mg L^{-1}, and 39 to 774 mg L^{-1} with a mean value of 217.41 mg L^{-1} and in PLKD was 34–800 mg L^{-1} with an average of 249.62 mg L^{-1} and from 46–813 mg L^{-1} with a mean value of 260.68 mg L^{-1} during pre-monsoon and post-monsoon, respectively [7]. When compared to pre-monsoon in post-monsoon, the Cl^- content increases. According to BIS, the Cl^- in pre-monsoon 25 (31.6%) samples, and 28 (35.4%) samples in the post-monsoon exceeded, and remaining samples were within the standard limit of BIS. The TA in the VGT water samples varied from 177–938 mg L^{-1} with an average of 408.1 mg L^{-1} and 188–930 mg L^{-1} with an average of 402.18 mg L^{-1} during the pre and post monsoon seasons respectively. In PLKD, it varied from 118–897 mg L^{-1} with an average of 457.29 mg L^{-1} in the pre-monsoon, and during the post-monsoon it varied from 123–903 mg L^{-1} with an average of 463.94 mg L^{-1} [7]. According to BIS (2012), the TA values for all the analyzed samples in the research area were found to be higher in alkalinity in both seasons. The concentration of NO_2^- was observed in VGT in the range of BDL–0.29 mg L^{-1} and BDL–0.35 mg L^{-1} during the pre and post monsoon seasons respectively. In PLKD, it was found in the range of BDL to 0.45 mg L^{-1} in the pre-monsoon and BDL-0.48 mg L^{-1} during the post-monsoon. In the present study, all the samples were within the allowable limits [7]. The statistical data for physicochemical parameters is shown in Table 1 and Table 2.

Table 1 Statistical summary of the physicochemical parameter in VGT

VGT	**pre-monsoon-2015**				**post-monsoon-2016**				
Parameter	**Mean**	**Max**	**Min**	**Std. deviation**	**Mean**	**Max**	**Min**	**Std. deviation**	**BIS standards**
pH	7.36	8.06	6.56	0.35	7.47	8.10	6.61	0.36	6.5-8.5
EC	1261.6	3541	316	736.59	1265	3532	302	736.87	500
TDS	864.18	2921	44	586.47	873.35	2916	184	585.95	500
TH	447.53	1826	148	261.91	447.88	1813	154	267.70	300
Ca (II)	65.98	185.4	9.19	31.64	63.38	178.21	12.33	29.75	75
Mg (II)	85.92	391.23	18.06	58.63	85.54	387.78	25.25	58.52	30
F^-	0.87	2.95	0.09	0.71	0.96	3.02	0.1	0.71	1.5
Cl^-	206.4	760	36	146.28	217.41	774	39	147.29	250
TA	408.14	938	177	166.59	402.18	930	188	165.77	200
NO_2^-	BDL	0.29	0	0.05	BDL	0.35	0	0.06	0.02

Remark: All units except pH and electrical conductivity are in mg L^{-1}, min—minimum, max—maximum, mean—arithmetic mean, and *SD* standard deviation.

Table 2 Statistical summary of the physicochemical parameter in PLKD

PLKD	pre-monsoon-2015				post-monsoon-2016				
Parameter	**Mean**	**Max**	**MIN**	**Std. Deviation**	**Mean**	**Max**	**MIN**	**Std. deviation**	**BIS Standards**
pH	6.76	7.32	6.18	0.22	6.87	7.7	6.25	0.24	6.5-8.5
EC	1428.5	3839	326	860.71	1434.31	3845	330	859.56	500
TDS	969.26	2820	222	635.31	977.02	2827	230	632.91	500
TH	450.68	1536	148	249.22	449.60	1526	142	246.57	300
Ca (II)	61.66	114.87	13.46	23.37	59.05	109.31	20.2	20.11	75
Mg (II)	93.05	350.12	19.01	57.77	88.78	341.21	25.22	56.62	30
F^-	0.47	1.65	0.01	0.34	0.58	1.77	0.05	0.36	1.5
Cl^-	249.62	800	34	176.37	260.68	813	46	175.32	250
TA	457.29	897	118	181.60	463.94	903	123	181.55	200
NO_2^-	BDL	0.45	0	0.11	BDL	0.48	0	0.11	0.02

Remark: All units except pH and electrical conductivity are in mg L^{-1}, min—minimum, max—maximum, mean—arithmetic mean, and *SD* standard deviation.

2) Water quality index

As per the methodology [7] reported above, the WQI was calculated and the variations of the WQI of the groundwater ranged between 43.9–46.5 and 31.4–34.7 in different villages in the VGT and PLKD divisions, respectively (Table 4 to 7). As per the WQI ranges reported by Brown et al. [16–17], (Table 3), the present investigated region is fit for domestic as well as irrigation and industrial purposes.

Table 3 The range and type of water for WQI

Status	WQI range	Possible usages
Excellent	0–25	Drinking, irrigation and industrial
Good	25–50	Domestic, irrigation and industrial
Fair	51–75	Irrigation and Industrial
Poor	76–100	Irrigation
Very poor	101–150	Restricted use for irrigation
Unfit	Above 150	Proper treatment is required for drinking

3) Artificial neural network

The applicability of ANN was investigated to forecast WQI values in 79 groundwater samples from the investigated region. The performance of the back-propagation LM algorithm was evaluated by monitoring the error between the modeled output and the measured dataset. The number of neurons was optimized by keeping all other parameters constant. The database for the 10 parameters viz., EC, pH, TDS, TH, Ca (II), Mg (II), Cl^-, F^-, NO_2^- and TA were created [20–21]. In the data-base, the known limits for the range (min-max) in which the parameters can vary above and below the permissible limit should be considered as safe. The coding with respect to permissible ranges of the parameters is assigned. Values lying within the permissible range will be considered as safe and values lying either side will be considered as unsafe. The Levenberg–Marquardt three-layer with back-propagation algorithm has been studied for the dataset and modeled [22].

In the present study, to compute the WQI of the two divisions, the author trained the network by prompting inputs of all the physical and chemical parameters analyzed, such as pH, EC, TDS, TH, Ca (II), Mg (II), Cl^-, F^-, NO_2^-, and TA. For the same, the outputs were given as the computed WQI values. Regression equation analysis for different testing parameters for the trained network is shown in Figures 5 and 6. The network is trained several times to get the minimum or no epochs. The network is appropriately adjusted for each runtime. The aptness of the network that is trained is assessed by the correlation coefficient. From the results of the present study, it was found that for all the testing parameters, the value of R^2 was found to be 0.9998 and approximately close to 1. Therefore, it is considered that the network trained is fit for prediction of WQI of the study area.

The results of the predicted WQI are tabulated in Table 4. From the results, it was found that the WQI values of the two divisions that were computed experimentally correlated with the values predicted by the network. An error of 0.6% was found for the predicted and experimentally computed values. This infers that the network trained for the present study fits perfectly for the prediction of WQI values.

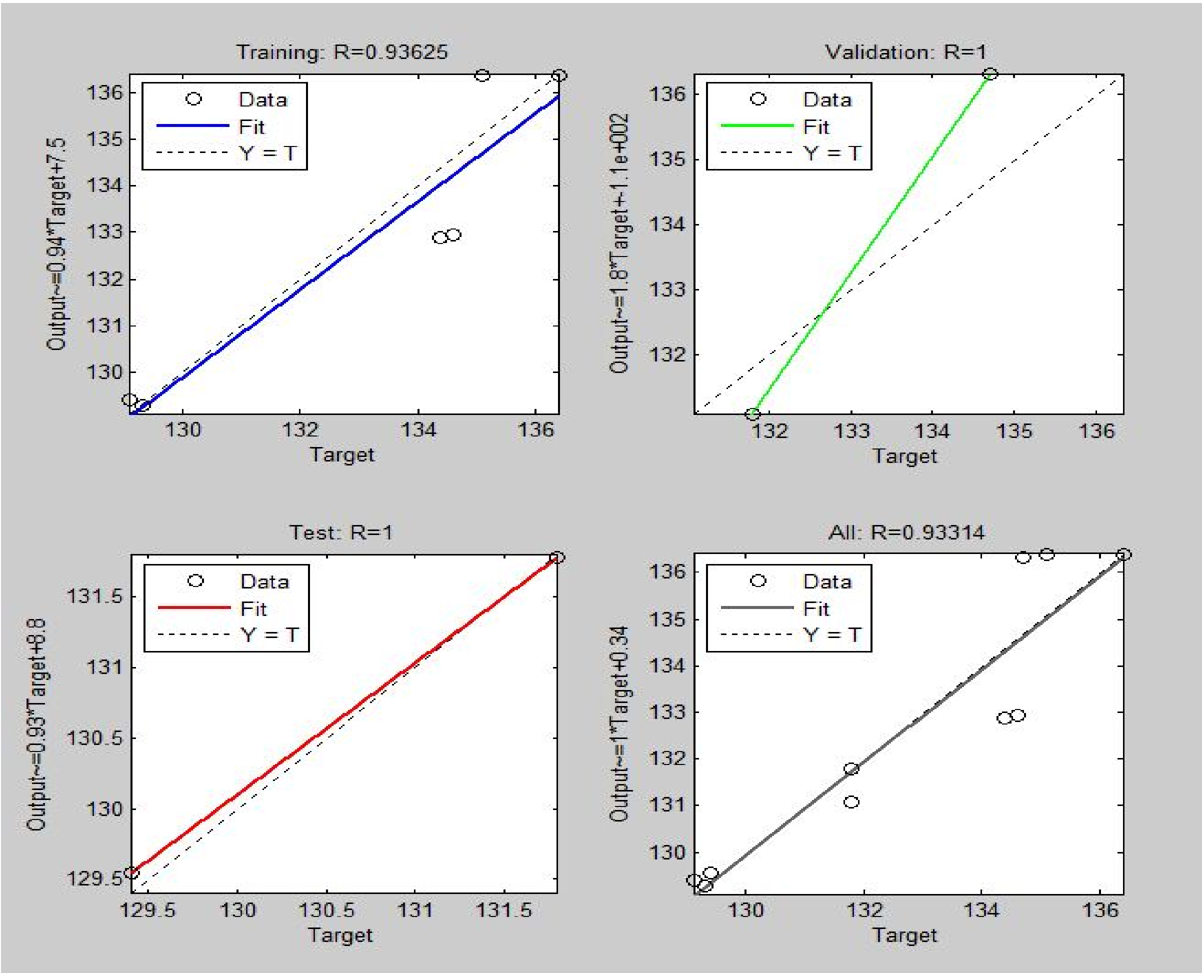

Figure 5 Regression equations for different parameters by ANN in PLKD.

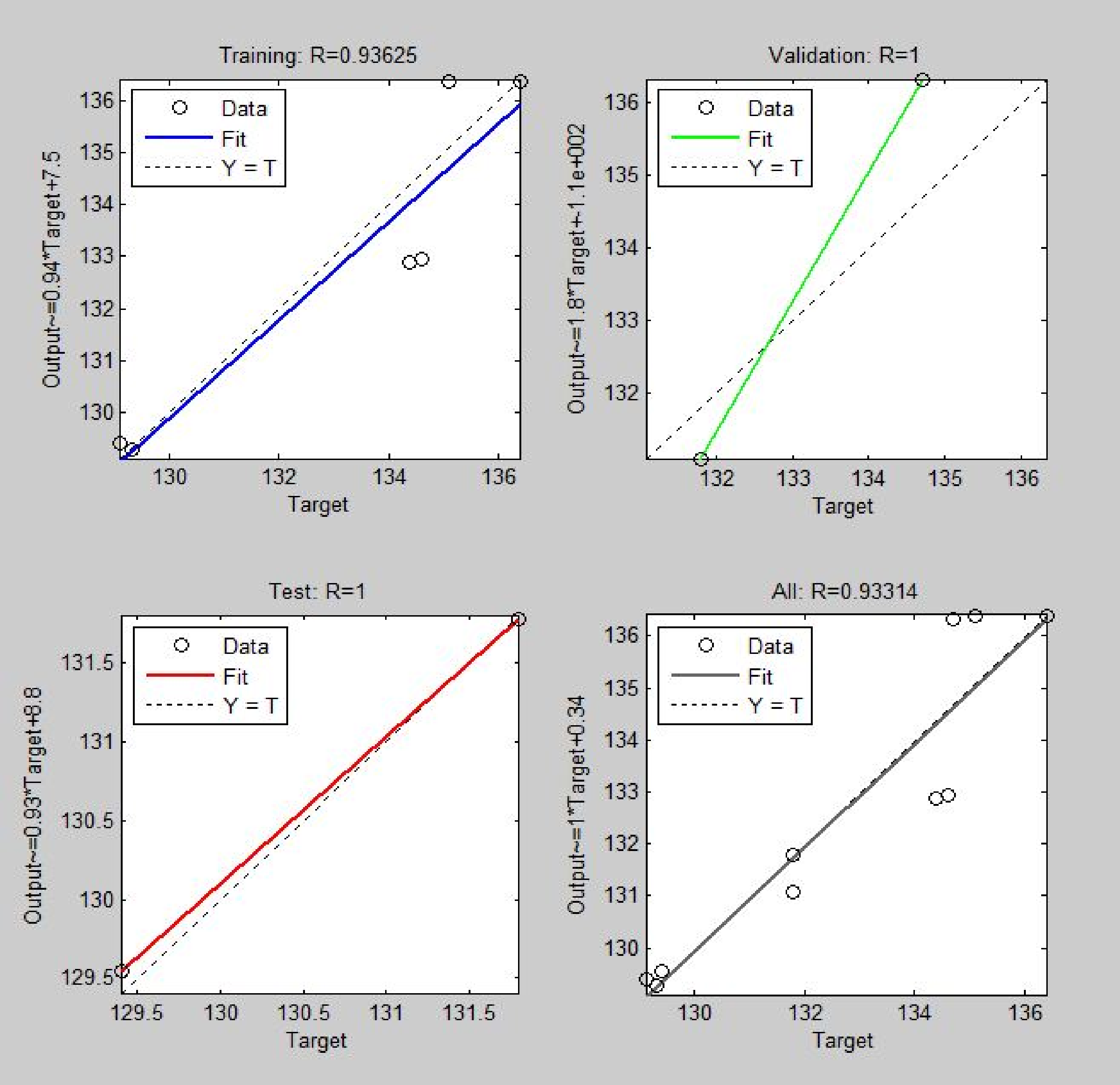

Figure 6 Regression equations for different parameters by ANN in VGT.

Table 4 Comparison between ANN predicted and experimental WQI values

Division	**Pre-monsoon-2015**		**Post-monsoon-2016**	
	Predicted	**Experimental**	**Predicted**	**Experimental**
PLKD	31.6	31.4	34.9	34.7
VGT	43.6	43.9	46.2	46.5

Conclusions

In this, an ANN model was developed to predict the WQI in the study region of PLKD and VGT divisions. The proposed model shows efficiency in forecasting the WQI in the groundwater samples. The result showed that the Levenberg–Marquardt three-layer with back-propagation algorithm network model prepared by ten different water quality parameters provided the R^2 value was found to be 0.9998 and approximately close to 1. Therefore, it is considered that the network is trained and fit for prediction of WQI of the study area. The results showed that the WQI values of the two divisions, which were computed experimentally, correlated with the values predicted by the network. An error of 0.6%was found for the predicted and experimentally computed values. This infers that the network trained for the present study fits perfectly for the prediction of WQI values. It has been observed that the WQI of groundwater in PLKD and VGT can be predicted using LM mode with both back-propagation network and acceptable accuracy using recurrent neural network. Hence, it is concluded that the ANN tool plays a significant role in water quality assessment too.

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