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# ACCURATE PREDICTION OF WATER QUALITY INDEX USING ARTIFICIAL NEURAL NETWORK MODELING IN THE SOUTH-WESTERN REGION OF VIZIANAGARAM DISTRICT, ANDHRA PRADESH, INDIA

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## ABSTRACT
Groundwater quality deterioration is a growing concern in rural India, where aquifers serve as the primary drinking water source. This study evaluates and predicts the quality of groundwater in the selected villages of the South-Western region of Vizianagaram District, Andhra Pradesh, using a Water Quality Index (WQI) integrated with Artificial Neural Network (ANN) modelling. A total of 864 Groundwater samples from 24 locations were collected during 2018–2021 and analysed for fifteen physicochemical parameters following APHA procedures and calculated WQI using the weighted Arithmetic method. WQI classification indicated 58.33% of samples fall under good quality, 29.17%poor, 4.17% very poor, and 8.33% unsuitable for drinking. To minimise the dependence on extensive laboratory analyses, A feed-forward back-propagation ANN model with architecture 15–5–1 trained using the Levenberg–Marquardt algorithm was developed and obtained excellent predictive performance ($R^2$=0.999, RMSE=0.7940, MAE=0.5098, MBE=−0.01965). It can be applied to similar hard-rock aquifer regions, particularly in areas with limited monitoring infrastructure and financial constraints. It provides a foundation for future research to explore hybrid and advanced machine learning techniques for improved prediction accuracy and model robustness. From a practical perspective, the model serves as an efficient decision-support tool for policymakers, facilitating proactive planning and sustainable utilisation of groundwater resources. The findings emphasise the importance of intelligent modelling techniques in improving water quality monitoring, safeguarding public health, and ensuring long-term environmental sustainability.
**Keywords:** Groundwater Quality, ANN Modelling, Water Quality Index, Prediction, Water Resource Planning, Sustainable Development, Hydrochemistry
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## INTRODUCTION
Groundwater is an essential source of freshwater for drinking, irrigation, and household needs, especially in the hard rock regions of India. Although it is generally less exposed to contamination than surface water, its quality is still affected by natural factors such as geological formations and aquifer characteristics, as well as by fertiliser application and other human-induced influences. In recent decades, increasing population pressure, expansion of agricultural practices, and various anthropogenic interventions have contributed to the degradation of groundwater quality, creating significant concerns for human health and environmental sustainability.[1] Therefore, evaluating groundwater quality is important to determine its appropriateness for drinking and to support sustainable management of the resource. To simplify the interpretation of complex hydrochemical information, different water quality indices have been introduced that combine multiple parameters into a single representative value for assessing drinking water suitability.[2] Among these, the Weighted Arithmetic Water Quality Index[3] is one of the most commonly applied approaches for water quality assessment. However, conventional WQI methods are descriptive and lack predictive capability. Recent advances in Artificial Neural Networks (ANNs) have enabled the modelling of nonlinear relationships among hydrochemical variables, offering improved predictive accuracy.[4-6] From the literature, it states that several studies[7-10] have demonstrated ANN effectiveness for water quality prediction, yet modelling-based investigations in inland regions of Vizianagaram District remain limited.[11-14] To fill this research gap, the present study develops an


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integrated WQI–ANN framework for predictive groundwater quality assessment in the Southwestern region, a hard-rock aquifer system with limited monitoring infrastructure. This study is consistent with Sustainable Development Goal 6[15], which focuses on ensuring the availability and sustainable management of safe drinking water for all through improved water quality and effective monitoring systems.[16] By providing a reliable and cost-effective predictive tool, this study contributes to data-driven groundwater management and supports global efforts toward achieving water security and sustainable development.[17]

## EXPERIMENTAL

### Study Area and Sampling

The study was carried out in selected villages of the southwestern region (lies between 17°51′–18°06′N latitudes and 83°01′–83°19′E longitudes), covering ~527.98 km² in Vizianagaram District, Andhra Pradesh. The study area map is generated using QGIS software and shown in Figure-1.Groundwater level of the study area lies at 4-8m. Groundwater from fractured hard-rock aquifers is the primary drinking water source. The region is characterised by hard-rock aquifers dominated by Khondalite Group formations of the Eastern Ghats. The climate is tropical monsoonal, with seasonal recharge influencing groundwater chemistry. Groundwater is the principal source of drinking water for rural and tribal communities.

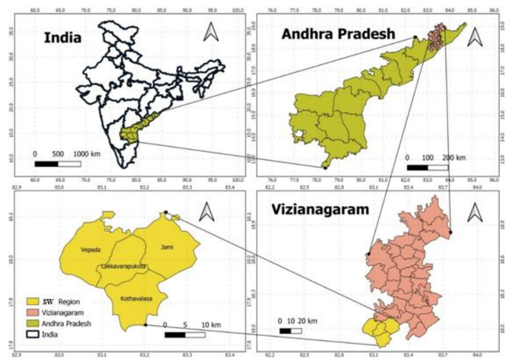


Fig.-1: Study Area Map

A total of 864 samples of twenty-four sampling locations were collected from bore wells/hand pumps between November 2018 and October 2021(one sample per month from each location) at a depth of 25 to 53 m, covering seasonal variations. Groundwater sampling sites (Table-1) were chosen to capture the variability in hydrogeological settings and land-use patterns across the study area. Samples were collected in pre-cleaned polyethene bottles in accordance with standard sampling protocols to minimise the risk of contamination.

Table-1: Geological coordinates of Sampling Locations

| Id | Sampling location | Mandal | Latitude(N) | Longitude(E) |
|---|---|---|---|---|
| S1 | Alamanda | Jami | 17°59′46.1″ | 83°14′27.9″ |
| S2 | Attada | Jami | 18°04′10.3″ | 83°18′45.6″ |
| S3 | Bheemasingi | Jami | 18°02′49.3″ | 83°17′35″ |
| S4 | Chinthada | Jami | 18°04′17.1″ | 83°11′32″ |
| S5 | Jami | Jami | 18°03′08.2″ | 83°15′54.8″ |
| S6 | Thandrangi | Jami | 18°05′30.6″ | 83°14′01.5″ |
| S7 | Venne | Jami | 18°05′20.8″ | 83°16′27.5″ |
| S8 | Athava | Vepada | 17°59′52″ | 83°06′17″ |
| S9 | Kondagangupudi | Vepada | 18°04′09″ | 83°04′21″ |
| S10 | Sompuram | Vepada | 18°02′19″ | 83°07′59″ |
| S11 | Vavilapadu | Vepada | 17°59′26″ | 83°01′20″ |
| S12 | Vepada | Vepada | 18°0′05″ | 83°04′51″ |
| S13 | Bheemali | L. Kota | 17°58′40.3″ | 83°13′42.5″ |
| S14 | Kallempudi | L. Kota | 18° 03′13.9″ | 83°10′32.6″ |
| S15 | L. Kota | L. Kota | 18°01′16.1″ | 83°09′24.9″ |

| | | | | |
|---|---|---|---|---|
| S16 | Pothampeta | L. Kota | 17°58′38″ | 83°05′56″ |
| S17 | Thamarapalli | L. Kota | 17°56′17.2″ | 83°08′19.23″ |
| S18 | Denderu | Kothavalasa | 17°51′46.9″ | 83°09′39.3″ |
| S19 | Devada | Kothavalasa | 17°55′29.8″ | 83°08′42.1″ |
| S20 | Ganisettipalem | Kothavalasa | 17°52′06.7″ | 83°09′52.1″ |
| S21 | Gulivindada | Kothavalasa | 17°52′19.1″ | 83°09′36.5″ |
| S22 | Kothavalasa | Kothavalasa | 17°53′33.2″ | 83°11′33.2″ |
| S23 | Relli | Kothavalasa | 17°53′28.4″ | 83°13′26.1″ |
| S24 | Tummikapalli | Kothavalasa | 17°54′44.8″ | 83°10′49.4″ |

**Physicochemical Analysis**

All groundwater samples were analyzed for fifteen physicochemical parameters, including pH, electrical conductivity (EC), total dissolved solids (TDS), total hardness (TH), TA, calcium ($Ca^{2+}$), magnesium ($Mg^{2+}$), sodium ($Na^{+}$), potassium ($K^{+}$), chlorides ($Cl^{-}$), sulfates ($SO_4^{2-}$), nitrates ($NO_3^{-}$), fluoride ($F^{-}$) carbonate ($CO_3^{2-}$)and bicarbonates ($HCO_3^{-}$). The analysis was carried out following standard methods prescribed by the American Public Health Association (APHA-2017).[18] Appropriate analytical techniques such as titrimetry, spectrophotometry, and flame photometry were employed. Quality control measures, including calibration of instruments and use of standard solutions, were maintained throughout the analysis to ensure data accuracy.

**Weighted Arithmetic Water Quality Index Calculation**

The WA-WQI method was used to evaluate the overall fitness of groundwater for drinking purposes. Under this approach, the WQI is determined through a series of equations (Eq.-1 to Eq.-4) that combine multiple water quality variables into a single representative index for assessment.

$$WQI=\frac{\sum Q_i W_i}{\sum W_i} \tag{1}$$

The quality rating scale (Qi) for each parameter is calculated by using this expression:

$$Q_i=100\left(\frac{V_i\text{-}V_o}{S_i\text{-}V_o}\right) \tag{2}$$

Where $V_i$ represents the measured concentration of the $i^{th}$ parameter in the water sample, $V_o$ denotes its ideal concentration in pure water. For most parameters, $V_o$=0, except for pH, where the ideal value is 7.0 $S_i$ indicates the standard permissible value of the $i^{th}$ parameter. The unit weight ($W_i$) assigned to each water quality parameter is determined using the following expression:

$$W_i=\frac{K}{S_i} \tag{3}$$

Where *K* is a proportionality constant, which can itself be obtained from the following equation:

$$K=\frac{1}{\sum\left(\frac{1}{S_i}\right)} \tag{4}$$

The overall WQI was calculated using the standard guideline values prescribed by WHO and BIS.[19-20] Based on the obtained WQI values, groundwater quality for drinking purposes was grouped into five classes: excellent (0–25), good (26–50), poor (51–75), very poor (76–100), and unsuitable (>100). This approach simplifies the interpretation of complex hydrochemical data into a single numerical value. The yearly average WQI values are presented in Table-2.

Table-2: WQI Values and Their Ranking

| Sample ID | Yearly Average WQI Values | | | Average WQI Values | WQI ranking |
|---|---|---|---|---|---|
| | Year1 | Year2 | Year3 | | |
| S1 | 63.70 | 65.63 | 65.39 | 64.91 | Poor |
| S2 | 40.37 | 42.29 | 42.05 | 41.57 | Good |
| S3 | 40.73 | 42.66 | 42.42 | 41.94 | Good |
| S4 | 44.63 | 46.56 | 46.31 | 45.83 | Good |
| S5 | 40.50 | 42.42 | 42.18 | 41.70 | Good |
| S6 | 29.59 | 31.52 | 31.28 | 30.79 | Good |

| | | | | | |
|---|---|---|---|---|---|
| S7 | 46.33 | 48.26 | 48.02 | 47.53 | Good |
| S8 | 133.72 | 135.65 | 135.41 | 134.93 | Unsuitable |
| S9 | 35.15 | 37.08 | 36.84 | 36.35 | Good |
| S10 | 66.20 | 68.12 | 67.88 | 67.40 | Poor |
| S11 | 66.57 | 68.50 | 68.26 | 67.77 | Poor |
| S12 | 65.27 | 67.20 | 66.96 | 66.47 | Poor |
| S13 | 35.12 | 37.05 | 36.81 | 36.33 | Good |
| S14 | 74.33 | 76.26 | 76.02 | 75.54 | Very Poor |
| S15 | 29.42 | 31.35 | 31.11 | 30.63 | Good |
| S16 | 43.02 | 44.95 | 44.70 | 44.22 | Good |
| S17 | 37.74 | 39.67 | 39.43 | 38.95 | Good |
| S18 | 38.00 | 39.93 | 39.69 | 39.21 | Good |
| S19 | 55.08 | 57.01 | 56.77 | 56.29 | Poor |
| S20 | 58.88 | 60.80 | 60.56 | 60.08 | Poor |
| S21 | 37.23 | 39.16 | 38.92 | 38.44 | Good |
| S22 | 50.60 | 52.53 | 52.29 | 51.80 | Poor |
| S23 | 36.65 | 38.57 | 38.33 | 37.85 | Good |
| S24 | 118.72 | 120.65 | 120.41 | 119.93 | Unsuitable |

## ANN Modelling for Prediction of WQI

A feedforward backpropagation Artificial Neural Network (ANN) was implemented in MATLAB to estimate the Water Quality Index (WQI). The selected optimal network structure (Fig.-2) included 15 input neurons representing the chosen physicochemical variables, one hidden layer containing 5 neurons with a sigmoid activation function, and a single output neuron with a linear activation function. In total, the network contained 86 adjustable parameters, including weights and biases. The dataset was randomly divided using MATLAB's default divider and function into training, validation, and testing subsets in an approximate ratio of 70%, 15%, and 15%, respectively. Out of the full dataset, 720 samples were allocated for training cum validation together, while 144 separate samples were retained to independently evaluate model performance. Before model training, all input variables were scaled using Min–Max normalization to enhance convergence behaviour and overall computational efficiency. The Levenberg–Marquardt algorithm was employed for training due to its fast convergence and suitability for nonlinear problems. The number of hidden neurons was determined through iterative testing within the range of 3 to 10 neurons, based on validation error minimisation. The selected 15–5–1 architecture demonstrated optimal performance with minimal generalisation error and reduced risk of overfitting, as the number of training samples exceeded the number of model parameters.

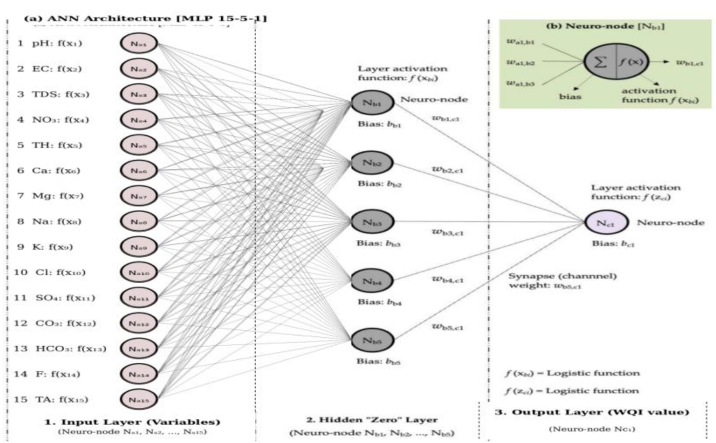


Fig.-2:Architecture of the Feed-Forward Back-Propagation ANN model (15–5–1) used for WQI Prediction

## ANN Model Evaluation

The ANN model performance was evaluated using the coefficient of determination ($R^2$), root mean square error (RMSE), mean absolute error (MAE), and bias. The mathematical expressions for these statistical measures are provided in Eqs.-5 to 8.

Coefficient of Determination

$$R^2 = 1 - [\Sigma(Oi - Pi)^2 / \Sigma(Oi - \bar{O})^2] \quad (5)$$

Root Mean Square Error

$$RMSE = \sqrt{[(1/n)\, \Sigma(Oi - Pi)^2]} \quad (6)$$

Mean Absolute Error

$$MAE = (1/n)\, \Sigma|Oi - Pi| \quad (7)$$

Mean Bias Error

$$MBE = (1/n)\, \Sigma\, (Pi - Oi) \quad (8)$$

Where Oi = observed WQI; Pi = predicted WQI; $\bar{O}$ = mean observed WQI; n = number of samples

## RESULTS AND DISCUSSION

### Groundwater Quality Status

The Water Quality Index (WQI) was computed for all 864 groundwater samples from 24 sampling locations (S1–S24) over three consecutive years (November 2018 and October 2021) to evaluate the overall groundwater quality status of the study area. WQI values (from Table-2) indicate the status of groundwater samples quality ranges from good to unsuitable for drinking. Approximately: 58.33% – Good, 29.17% – Poor, 4.17%- Very poor and 8.33% – Unsuitable. The comparison between experimentally determined and ANN-predicted WQI values demonstrates strong agreement across all sampling locations, indicating the robustness of the developed model. The ANN effectively captures both central tendency (mean) and variability (standard deviation) of WQI videTable-3, confirming its ability to model complex hydrochemical interactions. Minor deviations observed in a few samples can be attributed to inherent variability in groundwater chemistry and nonlinear parameter interactions.

Table- 3: Experimented and ANN-predicted WQI Ranges (testing period)

| S. No. | Sample ID | Experimented WQI | | | | ANN Predicted WQI | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Range | | Mean | Standard Deviation | Range | | Mean | Standard Deviation |
| | | Min | Max | | | Min | Max | | |
| 1 | S1 | 61.37 | 73.78 | 65.50 | 4.97 | 61.41 | 73.69 | 66.11 | 5.55 |
| 2 | S2 | 35.06 | 47.21 | 40.31 | 4.83 | 33.83 | 47.44 | 39.66 | 5.29 |
| 3 | S3 | 35.73 | 59.34 | 45.39 | 8.70 | 35.42 | 59.31 | 44.98 | 8.83 |
| 4 | S4 | 41.35 | 53.85 | 46.04 | 5.78 | 41.87 | 53.23 | 45.79 | 5.33 |
| 5 | S5 | 39.24 | 45.76 | 42.02 | 2.52 | 39.22 | 45.56 | 41.92 | 2.47 |
| 6 | S6 | 28.06 | 37.92 | 31.91 | 4.39 | 28.23 | 38.01 | 31.93 | 4.41 |
| 7 | S7 | 43.87 | 53.57 | 47.98 | 4.28 | 43.24 | 53.28 | 47.69 | 4.38 |
| 8 | S8 | 127.59 | 143.23 | 133.84 | 6.81 | 127.40 | 142.59 | 133.54 | 6.66 |
| 9 | S9 | 32.21 | 41.97 | 36.04 | 4.17 | 31.30 | 42.08 | 35.74 | 4.55 |
| 10 | S10 | 61.60 | 76.46 | 67.92 | 6.11 | 61.56 | 75.98 | 67.78 | 5.76 |
| 11 | S11 | 62.83 | 73.80 | 68.02 | 4.52 | 62.41 | 73.20 | 67.64 | 4.77 |
| 12 | S12 | 54.71 | 76.62 | 67.03 | 9.10 | 54.92 | 76.38 | 66.29 | 9.82 |
| 13 | S13 | 31.56 | 42.86 | 36.11 | 5.28 | 30.28 | 43.10 | 36.15 | 5.49 |
| 14 | S14 | 68.20 | 85.42 | 74.45 | 7.06 | 67.83 | 84.07 | 73.92 | 6.87 |
| 15 | S15 | 26.27 | 35.33 | 30.28 | 3.57 | 25.86 | 34.79 | 30.29 | 3.95 |
| 16 | S16 | 39.71 | 53.21 | 44.30 | 5.85 | 39.30 | 52.21 | 44.10 | 5.62 |
| 17 | S17 | 32.03 | 46.65 | 39.32 | 5.67 | 31.91 | 46.49 | 38.80 | 5.72 |
| 18 | S18 | 31.41 | 44.33 | 38.91 | 4.83 | 30.60 | 44.57 | 38.74 | 5.12 |
| 19 | S19 | 50.19 | 63.43 | 56.04 | 5.88 | 49.43 | 63.40 | 55.11 | 5.86 |
| 20 | S20 | 56.73 | 65.35 | 59.90 | 2.88 | 56.75 | 65.64 | 59.69 | 3.06 |
| 21 | S21 | 29.82 | 46.56 | 38.96 | 6.46 | 28.55 | 46.64 | 38.45 | 6.96 |
| 22 | S22 | 42.99 | 57.68 | 50.16 | 5.89 | 42.72 | 56.82 | 49.97 | 5.93 |
| 23 | S23 | 32.76 | 44.24 | 36.62 | 5.44 | 32.02 | 42.70 | 36.15 | 4.98 |
| 24 | S24 | 115.13 | 125.75 | 120.68 | 3.50 | 115.02 | 125.05 | 120.39 | 3.35 |

The high predictive performance ($R^2$= 0.999) along with low error metrics (RMSE = 0.7940, MAE = 0.5098 and Bias = -0.2870) highlights the superiority of ANN over conventional descriptive approaches such as WQI alone. These results add to the existing body of knowledge by showing that data-driven

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models can substantially improve the prediction of groundwater quality in hard-rock aquifer systems, particularly in areas where conventional monitoring is constrained. The ANN model exhibited high predictive capability across all 24 sampling sites. The Regression coefficient (R) values for training, validation, and testing subsets ranged from 0.9226–1.0000, 0.9087–0.9987, and 0.8457–0.9990, respectively (Table-4), with overall R values between 0.9250 and 0.9985. Slightly lower testing R at certain locations (S15, S10 and S2) indicates site-specific hydrochemical variability, but the model maintained excellent generalisation performance across the study area.

Table-4: Sample-wise Regression Coefficient (R) Values for ANN Model

| Sample ID | Training | Validation | Testing | All |
|---|---|---|---|---|
| S1 | 0.9641 | 0.9975 | 0.9985 | 0.9684 |
| S2 | 1.0000 | 0.9720 | 0.9023 | 0.9815 |
| S3 | 0.9980 | 0.9916 | 0.9927 | 0.9985 |
| S4 | 0.9761 | 0.9905 | 0.9958 | 0.9950 |
| S5 | 0.9951 | 0.9671 | 0.9761 | 0.9838 |
| S6 | 0.9835 | 0.9870 | 0.9305 | 0.9573 |
| S7 | 0.9819 | 0.9947 | 0.9889 | 0.9811 |
| S8 | 0.9226 | 0.9987 | 0.9960 | 0.9543 |
| S9 | 0.9600 | 0.9972 | 0.9927 | 0.9732 |
| S10 | 0.9907 | 0.9985 | 0.9038 | 0.9867 |
| S11 | 0.9952 | 0.9873 | 0.9609 | 0.9773 |
| S12 | 0.9436 | 0.9987 | 0.9640 | 0.9598 |
| S13 | 1.0000 | 0.9087 | 0.9971 | 0.9648 |
| S14 | 0.9994 | 0.9164 | 0.9154 | 0.9617 |
| S15 | 0.9465 | 0.9905 | 0.8457 | 0.9260 |
| S16 | 0.9998 | 0.9793 | 0.9744 | 0.9824 |
| S17 | 0.9808 | 0.9494 | 0.9424 | 0.9660 |
| S18 | 0.9618 | 0.9587 | 0.9730 | 0.9555 |
| S19 | 0.9947 | 0.9721 | 0.9313 | 0.9738 |
| S20 | 0.9945 | 0.9519 | 0.9583 | 0.9498 |
| S21 | 0.9262 | 0.9780 | 0.9365 | 0.9250 |
| S22 | 0.9772 | 0.9871 | 0.9107 | 0.9644 |
| S23 | 0.9611 | 0.9893 | 0.9410 | 0.9627 |
| S24 | 0.9974 | 0.9969 | 0.9990 | 0.9968 |

To improve clarity and interpretation, graphical representations such as regression plots of the S1 sample (Fig.-3) have been included to visually demonstrate the agreement between observed and predicted values. These figures complement the tabulated data without redundancy and provide intuitive insight into model performance.

The findings of the present study provide significant insight into the application of data-driven techniques for groundwater quality assessment. The excellent agreement between experimentally determined and ANN-predicted WQI values demonstrates the capability of the model to accurately capture complex nonlinear relationships among hydrochemical parameters.

This contributes to the existing body of knowledge by validating the effectiveness of Artificial Neural Networks as a reliable alternative to conventional statistical and index-based methods, which are often limited to descriptive analysis. Unlike traditional approaches, the integrated WQI–ANN framework introduces predictive capability, enabling proactive groundwater quality management. Furthermore, this study directly contributes to Sustainable Development Goal 6[15], which emphasises improving water quality and ensuring sustainable management of water resources and also extends current research by applying this methodology to a hard-rock aquifer system with limited monitoring infrastructure, a context that remains underrepresented in the literature. The results thus reinforce the growing evidence that intelligent modelling techniques can enhance the accuracy, efficiency, and applicability of water quality assessment, particularly in data-scarce regions.

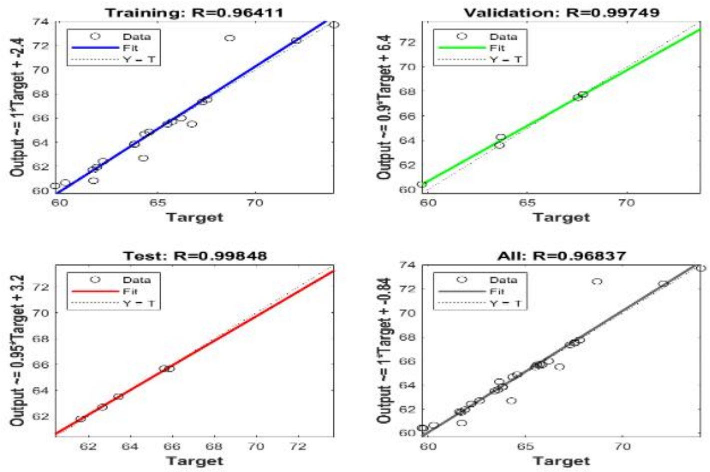


Fig.-3: ANN Model Regression Performance During Training, Validation and Testing Phases of Sample ID S1

## CONCLUSION

From theWQI analysis, the results indicate that the groundwater quality at sampling locations Athava (S8) and Thummikapalli (S24) is unsuitable for drinking, while Kallempudi (S14) is classified as very poor, and Alamanda (S1), Sompuram (S10), Vavilapadu (S11), Vepada (S12), Devada (S19), Ganisettipalem (S20), and Kothavalasa (S22) are categorised as poor**.** The present study successfully developed an integrated WQI–ANN model for the accurate prediction of groundwater quality in the southwestern region of Vizianagaram District. The ANN model demonstrated excellent predictive performance, effectively capturing complex nonlinear relationships among hydrochemical parameters. The strong correspondence between observed and predicted WQI values confirms the model's reliability and practical applicability. The study highlights that the proposed approach can serve as a rapid, cost-effective, and efficient decision-support tool for groundwater quality assessment, particularly in hard-rock aquifer regions with limited monitoring infrastructure. The integration of ANN with WQI overcomes the limitations of conventional descriptive methods by enabling predictive capability. This research contributes to achieving Sustainable Development Goal 6[15] by promoting improved water quality monitoring and ensuring the availability of safe drinking water for sustainable groundwater management. It aids policymakers and water resource managers in making informed decisions to safeguard public health.

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## CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

## AUTHOR CONTRIBUTIONS

The present work is related to *SDG-6: Clean Water and Sanitation.* All the authors contributed significantly to this manuscript, participated in reviewing/editing and approved the final draft for publication. The research profile of the authors can be verified from their ORCID ids, given below:

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## REFERENCES

1. Sanidhya Dadia, Harsh Patel, Keval H. Jodhani, Nitesh Gupta, Dhruvesh Patel, Punyawi Jamjareegulgarn, Sudhir Kumar Singh and Upaka Rathnayake, *Scientific Reports*, **15**, 8769(2025), https://doi.org/10.1038/s41598-025-92053-1
2. R.M. Brown, N.I. McClelland, R.A. Deininger and M.F. O'Connor, *Indicators of Environmental Quality*, Springer, Boston, 173(1972), https://doi.org/10.1007/978-1-4684-1698-5_15
3. C. Singaraja, *Applied Water Science*, **7**, 2157(2017), https://doi.org/10.1007/s13201-017-0594-5
4. Prince Kumar, Soumya Sucharita Singha and Sudhakar Singha, *Environmental Earth Sciences*, **85**, 96(2026), https://doi.org/10.1007/s12665-025-12793-1
5. E.M. García-del-Toro, M.I. Mas-López, L.F. Mateo and M.Á. Quijano, *Applied Water Science*, **15**, 247(2025), https://doi.org/10.1007/s13201-025-02605-z
6. V. Muthukumaran and V. Vinoth Kumar, *International Journal of Information Technology, Research and Applications*, **1(1)**, 33(2022), https://doi.org/10.59461/ijitra.v1i1.12
7. S. Maiti, S. Gupta and P.K. Gupta, *Water, Air, and Soil Pollution*, **235**, 664(2024), https://doi.org/10.1007/s11270-024-07459-w
8. H.K. Basim, M.M. Jasimb and A.S. Alsaqqar, *Civil Engineering Journal*, **4(12)**, 2959(2018), https://doi.org/10.28991/cej-03091212
9. H.R. Maier and G.C. Dandy, *Environmental Modelling and Software*, **15**, 101(2000), https://doi.org/10.1016/S1364-8152(99)00007-9
10. M. Ghadai, D.P. Satapathy, S. Krishnasamy, M. Ramalingam, G.P. Sreelal and B. Dhilipkumar, *Global NEST Journal*, **24(4)**, 562(2022), https://doi.org/10.30955/gnj.004414
11. A.V.L.N.S.H. Hariharan and B. Lakshmi, *International Journal of Pharmaceutical and Biological Sciences*, **1(2)**, 8(2011)
12. K. Krishna Kumar, *Journal of Indian Water Works Association*, **XXXXIV(2)**,125(2012)
13. N. Appala Raju, K. Harikrishna, P. Satyanarayana, P. Suneetha and S. Sachi Devi, *International Journal of Science and Environmental Technology*, **3(1)**, 148(2014)
14. G.V.S.R. Pavan Kumar, T.V.N. Partha Sarathi and K. Srinivasa Rao, *Journal of Indian Chemical Society*, **94(4)**, 1(2017)
15. United Nations, *The Sustainable Development Goals Report 2023: Special Edition*, United Nations Department of Economic and Social Affairs (UN DESA), New York, USA(2023), https://unstats.un.org/sdgs/report/2023/
16. Milica Vranešević, Maja Meseldžija, Jasna Grabić, Radoš Zemunac and Zuzana Boukalova, *Frontiers in Agronomy*, **7**, 1580338(2025), https://doi.org/10.3389/fagro.2025.1580338
17. Mohammad Hamza, Syed Daniyal Ali, Muhammad Fahim Aslam, Muhammad Rashid, Hafiz Kamran Jalil Abbasi and Saif Haider, *Cleaner Waste Systems*, **12**, 100351(2025), https://doi.org/10.1016/j.clwas.2025.100351
18. APHA, AWWA and WEF, *Standard Methods for the Examination of Water and Wastewater*, 23rd edn., American Public Health Association, Washington, DC(2017)
19. World Health Organisation (WHO), *Guidelines for Drinking-Water Quality*, 4th edn., World Health Organisation, Geneva(2017)
20. BIS, *Indian Standard Drinking Water Specification IS 10500*, Bureau of Indian Standards, New Delhi(2012)

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