

Original Article

EVALUATING POTABILITY OF GROUNDWATER USING AI-DRIVEN APPROACHES

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ABSTRACT

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Integrating artificial intelligence (AI) techniques into groundwater quality assessments is a pivotal step toward achieving water resource sustainability and ensuring its safety for human consumption. This is achieved by leveraging the advanced analytical capabilities of these technologies. Parameters such as pH, total dissolved solids (TDS), total alkalinity (T.A), chloride, sulfate (SO₄), phosphorus oxide (PO₄), Temperature (T), electrical conductivity (EC), turbidity (Tur), bicarbonate (HCO₃), total hardness (T.H), calcium hardness (Ca.H), magnesium hardness (Mg.H), sodium (Na), potassium (K), and dissolved oxygen were analyzed to assess groundwater quality in Duhok City, Iraq. Water Quality Index (WQI) and Adaptive Neuro-Fuzzy Inference System for Drinking (ANFIS-D) were employed in classifying water quality as excellent, good, poor, very poor, and unsuitable. It is beneficial to infer water quality for the individuals and decision-makers in the region. The WQI and ANFIS-D of the research area are between (37-50) (33-49), respectively. The overall WQI of the research area finds that the groundwater is safe and potable. The statistical metrics such as root mean square error (RMSE), mean bias error (MBE), and correlation coefficient (R) are used to check the validity of the ANFIS-D model. Studies show that the R value, MBE, and RMSE of the ANFIS-D model are (0.851, 2.9 and 3.81) respectively. Based on the results of these Statistical parameters, the ANFIS-D estimation model can predict the groundwater quality index of Duhok City with reasonable accuracy, which is useful and valuable for estimating the groundwater quality index.

Keywords: Nutrition, vitamin D, calcium, Cow milk, Breast milk.

1. INTRODUCTION

Groundwater is a critical source of fresh water for domestic, agricultural, and industrial use, especially in regions facing surface water scarcity. Its quality is a fundamental determinant of public health, ecological stability, and long-term economic development. However, groundwater systems are increasingly threatened by a combination of natural factors and human activities, including over-extraction, agricultural runoff, industrial waste, and the broader impacts of climate change. As groundwater contamination rises, so do the challenges of ensuring safe and sustainable water supplies for growing populations. (M. Al-Mashhadany, 2021; Al-Mashhadany, 2022; Ali *et al.*, 2024; Cobaner *et al.*, 2012; Palaniselvan *et al.*, 2024).

In the Duhok region of Iraq, groundwater has become an essential lifeline amid declining surface water availability, particularly due to the receding levels of the Duhok Dam. Prolonged droughts and increased demand have intensified the reliance on groundwater resources. This overdependence poses serious risks—not only to water quantity but also to water quality, making effective monitoring and management strategies more urgent than ever. Traditional methods of groundwater quality assessment, including laboratory analyses of physical, chemical, and biological parameters, remain important but are often time-consuming, expensive, and reactive rather than predictive. In contrast, modern computational tools have opened new frontiers in water resource management. Artificial intelligence (AI) techniques, in particular, have shown promise in enhancing the accuracy, speed, and adaptability of groundwater quality assessments. (M. H. S. Al-Mashhadany, 2021b; Brown *et al.*, 1972; Dehghan Rahimabadi *et al.*, 2024; El-Rawy *et al.*, 2023).

One such technique is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines the learning ability of neural networks with the decision-making capabilities of fuzzy logic. ANFIS excels in modeling complex, non-linear relationships between variables, making it especially suited for environmental systems where data uncertainty and variability are common. Recent studies have demonstrated its potential in predicting groundwater quality indices with high accuracy, offering a powerful complement or even alternative to traditional methods. (Al-Adhaileh *et al.*, 2022; Alshahri & Al-Mashhadany, 2025; Ibrahim *et al.*, 2023).

This study aims to evaluate the effectiveness of ANFIS in assessing groundwater quality in the Duhok region. By comparing ANFIS-based predictions with conventional analytical results, the research seeks to determine the model's accuracy, adaptability, and practical value in supporting sustainable groundwater management. Ultimately, the goal is to offer a decision-support tool that can aid policymakers and water authorities in ensuring safe, clean, and reliable groundwater for current and future generations. (Gautam *et al.*, 2024; Gholami *et al.*, 2022; Mohammed *et al.*, 2023).

2. METHODS AND MATERIALS

Method of study:

The city of Duhok is located in northern Iraq within the Kurdistan Region, at latitude 36.8667° north latitude and 42.9876° east longitude (Khaled *et al.*, 2023). The city is encircled by mountains and rugged terrain that form part of the Zagros Mountains. Mount Begova lies to the northwest, and Mount Matin is located to the east

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of Duhok. They are sources of groundwater and springs because of rainfall and snowfall. Duhok's geological composition is characterized by its diversity of sedimentary and metamorphic rocks, with complex geological structures influenced by tectonic movements over the ages. Environmental challenges include overexploitation of groundwater, which may lead to a decline in water levels in some areas. Urban sprawl and the expansion of agricultural activities affect the replenishment of groundwater. Overall, Duhok has a rich geology that contributes to the availability of groundwater, but sustainable management is essential to ensure its sustainability for future generations (Table 1) (M. H. S. Al-Mashhadany, 2021a).

Table 1: Coordinates and elevation of wells in the study area.

Well no.	E	N	Altitude (m)
1	43.01697	36.83927	658
2	43.05706	36.83544	687
3	42.91441	36.89461	607
4	42.86113	36.85699	468
5	42.91942	36.84945	483
6	42.95394	36.88211	635
7	43.00227	36.86796	555
8	43.06021	36.85627	701
9	43.08078	36.83318	711
10	43.0833	36.83226	708

Data Collection:

Groundwater samples were collected from ten wells between September 2024 and February 2025 at one sample every 15 days from the experimental site according to the standard guidelines of the American Public Health Association (APHA, 2017). The sampling points were assigned using a global positioning system (GPS), as shown in Fig.1. The sampling was achieved through the application of an on-site electric pump. Sterile one-liter volume high-density polyethylene (HDPE) sample bottles were aseptically sterilized to avoid any direct contamination and related shift in groundwater properties. The sample was refrigerated in a field icebox and transported to the University of Zakho, College of Science, Environmental Sciences department. ten groundwater quality parameters were analyzed using standard test methods (APHA 2017) in the lab, with the exception of unstable parameters. Hydrogen ion concentration, dissolved oxygen, and total dissolved solids (TDS) were analyzed in the

field with a portable device (pH meter, DO meter, and TDS meter) HI 99301 EC/TDS Meter (Hanna Instruments) HI 9146 Dissolved Oxygen Meter (Hanna Instruments). Alkalinity (T.A.) and chloride ion were analyzed by titration. Sulfate (SO_4) was analyzed by turbidity and phosphate (PO_4) was analyzed by ammonium molybdate colorimetric assay (Adams, 2017; Rice *et al.*, 2012).

The water quality index (WQI):

WQI has been computed on the basis of drinking water. The standard reference has been adopted from World Health Organization (WHO, 2017). Weighted arithmetic method has been employed to find out the Water Quality Index, initially introduced by Horton (1965) and later modified by Brown *et al.* (1972). The weighted arithmetic water quality index (WQI) formula is given below (Najafi Saleh *et al.*, 2020):

$$WQI = \sum_{i=1}^n W_i Q_i / \sum_{i=1}^n W_i \quad (1)$$

Where n = number of variables or parameters.
 W_i = unit weight for the i th parameter.
 Q_i = quality rating (sub-index) of the i th water quality parameter.

$$W_i = K / S_n \quad (2)$$

Where, W_i = weight for i th parameter, S_n = standard value for i th parameters, K = constant of proportionality, The value of K is assumed to be '1' here and is calculated with the help of the following equation:

$$K = 1 / \sum \left(\frac{1}{S_n} \right) \quad (3)$$

Brown *et al.* (1972) (Brown *et al.*, 1972) The value of the sub-index or quality rating (Q_i) is obtained from the following formula:

$$Q_i = 100[(V_o - V_i) / (S_n - V_i)] \quad (4)$$

where V_o = i th parameter value as recorded at a specific sampling location,
 V_i = pure water ideal i th parameter value, S_n = standard allowable value of i th parameter.

In the Table 2 shows the classification of the model (M. H. S. Al-Mashhadany, 2021a, 2021b).

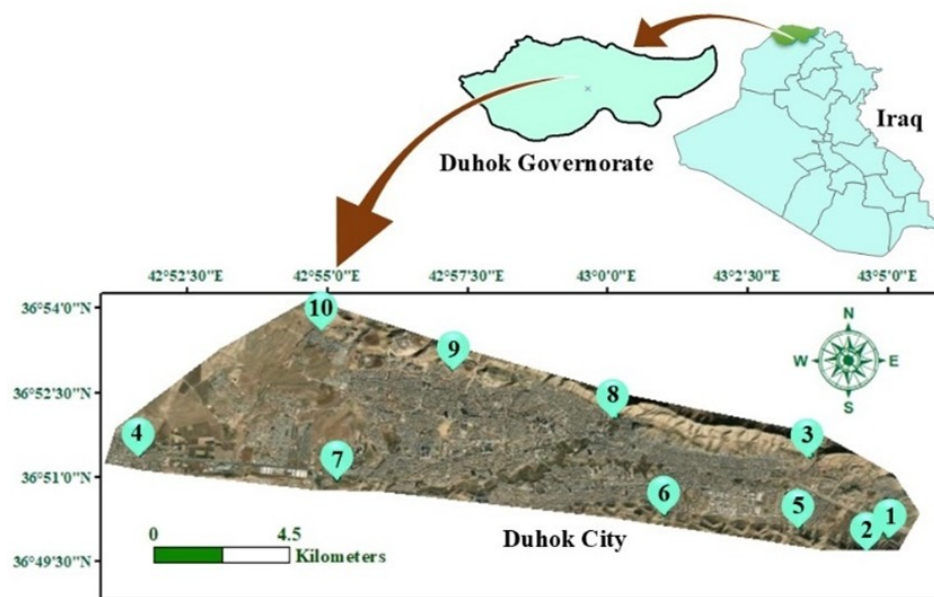


Figure 1: Location map of the study area showing Duhok City within Duhok Governorate, northern Iraq, and the distribution of the ten sampling sites.

Table 2: Classification of water quality based on the importance of WQI.

Rating Class	WQI
>100	Unsuitable
76–100	Very Poor
51–75	Poor
26–50	Good
0–25	Excellent

Adaptive Neuro-Fuzzy Inference System (ANFIS) modeling:

Five hundred thirty-nine records of the total 700 records were used in training the ANFIS model. The remaining data were used for testing and validating the models as required. In attaining the consistency of the model, all data sets were first normalized between the range 0 to 1 and then converted back to original values after simulation Using the formula suggested by Doğan (2008) (Cobaner *et al.*, 2012):

$$X_{norm} = \left[X - \frac{X_{min}}{X_{max}} - X_{min} \right] \times 0.8 + 0.1 \quad (5)$$

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is an intelligent system that leverages the capability of Artificial Neural Networks (ANNs) to learn and the capability of Fuzzy Inference Systems (FIS) to reason. ANFIS was employed in this study to learn the input-output mapping of a given experimental data via MATLAB (Wan Mohtar *et al.*, 2018).

The following Figure (2) illustrates the ANFIS model output before training. As can be seen, obviously, the predicted outputs (small red dots) are far away from the actual data values (light blue markers).

The Figure (2) shows the system performance after completing the training process. A significant improvement is observed, where the

ANFIS predications (red stars) track the real data (blue circles) very closely. An apparent and significant enhancement in accuracy is observed with training, as the model output closely overlaps actual data values. This verifies that the models have effectively learned the input-output nonlinear relationship. The visually reduced error indicates successful learning and good predictive accuracy by the trained ANFIS model. ANFIS has demonstrated itself as being able to approximate complex relationships with training and has offered stable performance in modelling the dynamics of the dataset.

Data sets used in the testing of the neural network component. The chosen Water Quality Index (WQI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) were compared on the basis of three statistical parameters: determination coefficient (R), root mean square error (RMSE), and mean bias errors (MBE), as follows (Gautam *et al.*, 2024; Mohammed H. Sabry Al-Mashhadany & Al-Saffawi, 2025):

$$R = \frac{\sum(\bar{O} - O_i)(\bar{P} - P_i)}{\sum\sqrt{(\bar{O} - O_i)^2} \sum\sqrt{(\bar{P} - P_i)^2}} \quad (6)$$

$$RMSE = [N^{-1} \sum_{i=1}^N (p_i - O_i)^2]^{0.5} \quad (7)$$

$$MBE = \frac{1}{N} \sum_{i=1}^N (O_i - P_i) \quad (8)$$

Where N is number of observations, P_i is estimated values (through the WQI and ANFIS), O_i is observed data $P_{\perp}^-$ and $O_{\perp}^-$ are average values of P_i and O_i , respectively Figure 3 illustrates a diagram illustrating ANFIS steps which are made up of five layers (Input parameter, Membership functions, Rules, Normalization Layer and Defuzzification Layer).

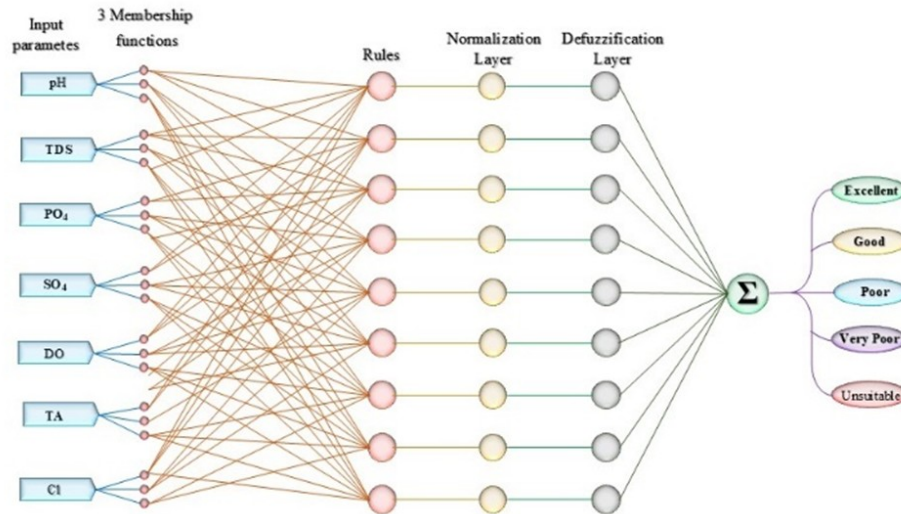
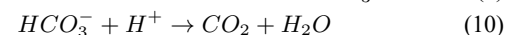
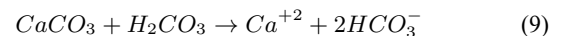


Figure 2: ANFIS-D groundwater assessment scheme.

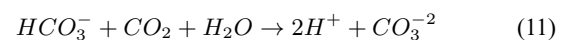
3. RESULTS AND DISCUSSION

The pH function is the fundamental function to determine the quality of drinking water. The acceptable pH of drinking water is 6.5 to 8.5, as per the World Health Organization (WHO) guidelines. The pH readings ranged between (7.7 - 8.2), and all readings were within the acceptable limits, while the total alkalinity readings were all above the acceptable limits for drinking since their values ranged between (224 - 334) mg/L. The relationship between pH and total alkalinity was inversely proportional with a correlation coefficient value (-0.650), as shown in Table 4, and the spatial distribution patterns reflect this (Fig.

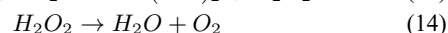
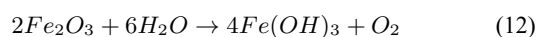
4). The high concentration of CO_2 dissolved in water is due to geological interaction, as shown in the following rates (Page *et al.*, 2014; Trivedi *et al.*, 2023).



When basicity increases, bicarbonates react with carbon dioxide in water to form hydrogen ions (H^+), lowering PH.



Dissolved oxygen is an important indicator of groundwater quality, affecting taste, odor, and chemical reactions. The dissolved oxygen values in groundwater ranged between (2.5-10.6) mg/L and (6.5-7.9) mg/L, with 82% of the total samples being within the permissible drinking limits. The source of dissolved oxygen in groundwater is due to geological reactions occurring in the groundwater aquifer, such as the reactions of iron oxides with water and calcium oxide with water (WO *et al.*, 2025).



In this study, chloride levels ranged from 0.0 to 50 mg/L, which is within the acceptable range (250 mg/L). High chloride levels in groundwater pose a risk to human health, as chlorine plays an important role in fluid and acid balance in the body, and excess levels can lead to disturbances in bodily functions.

The phosphate ranged between (0.001-0.135) mg/L, and all samples were within the acceptable for potable use. Phosphate is low

in groundwater due to the fact that it reacts with Minerals and salts present in rocks and soil form precipitates and are not retained in solution. Most importantly, phosphate combines with calcium ions to form insoluble calcium phosphate (e.g., apatite), which precipitates and dissuades it from being dissolved in water. It can also be adsorbed onto the surface of clay particles, a process that makes it stay in the soil rather than in water. The spatial distribution shows a high concentration of phosphate in groundwater in the northwestern part of the study area (Najafi Saleh *et al.*, 2020; Palaniselvan *et al.*, 2024).

The TDS levels in the groundwater varied from (144-572) mg/L, and all the samples were less than the allowable drinking level. Low TDS is due to the fact that the groundwater flows through low-solubility rock environments, along with its ongoing renewal and lack of contamination. High sulfates in potable water can lead to diarrhea among children and adults and nausea and gastrointestinal disturbances. Sulfate concentrations of groundwater ranged from (185-614) mg/L, and 86% of the groundwater samples were safe for drinking. Spatial variation of sulfates showed maximum concentration in the north-central and southwestern parts of the study area (Singh & Noori, 2022; Uddin *et al.*, 2024; Wan Mohtar *et al.*, 2018).

Table 3: Calculated water quality parameters for area wells (mg/L).

Parameters		pH	DO	TDS	T.A	Cl	SO ₄	PO ₄
1	Min	7.80	5.9	171	280	0.0	234	0.00
	Max	8.29	9.7	306	420	20.0	392	0.09
	Mean	8.03	7.6	235	334	5.0	335	0.03
	SD	0.17	1.4	50	56	7.1	56	0.03
2	Min	8.03	5.7	166	220	0.0	244	0.00
	Max	8.30	10.0	281	360	20.0	399	0.06
	Mean	8.16	7.5	193	256	8.0	350	0.03
	SD	0.10	1.6	33	43	6.3	48	0.02
3	Min	7.90	2.5	173	160	0.0	212	0.00
	Max	8.23	10.0	366	340	20.0	588	0.14
	Mean	8.06	6.7	220	224	8.0	359	0.05
	SD	0.11	2.7	75	51	7.9	98	0.04
4	Min	7.65	4.1	171	180	0.0	269	0.00
	Max	8.27	9.8	379	340	20.0	494	0.05
	Mean	8.07	7.0	217	226	15.0	388	0.03
	SD	0.17	1.9	78	44	7.1	64	0.02
5	Min	7.51	4.8	187	160	0.0	185	0.00
	Max	8.24	9.7	288	360	10.0	421	0.06
	Mean	7.80	7.0	267	310	6.0	348	0.03
	SD	0.27	1.8	29	71	5.2	70	0.02
6	Min	7.46	3.5	184	240	0.0	209	0.00
	Max	8.20	9.3	286	360	20.0	470	0.05
	Mean	7.70	6.5	267	324	5.0	330	0.03
	SD	0.24	1.9	29	34	7.1	90	0.02
7	Min	7.40	3.6	349	220	10.0	234	0.00
	Max	8.04	9.5	572	340	50.0	480	0.08
	Mean	7.81	7.0	399	288	16.0	398	0.03
	SD	0.18	2.4	64	36	12.6	73	0.02
8	Min	7.60	4.5	180	160	0.0	271	0.00
	Max	8.18	9.9	323	340	20.0	389	0.09
	Mean	8.00	7.0	226	232	9.0	341	0.03
	SD	0.18	2.3	64	54	7.4	47	0.03
9	Min	7.72	3.7	172	180	0.0	207	0.00
	Max	8.34	9.9	385	360	10.0	614	0.06
	Mean	8.00	6.7	249	262	5.0	386	0.03
	SD	0.21	2.4	89	55	5.3	102	0.02
10	Min	7.83	4.4	172	200	0.0	221	0.00
	Max	8.17	10.6	232	280	20.0	399	0.07
	Mean	8.06	7.9	186	232	7.0	333	0.03
	SD	0.10	2.0	17	27	8.2	62	0.02
Standard Reference (eg: WHO)		6.5–8.5	5	1000	150	250	400	10

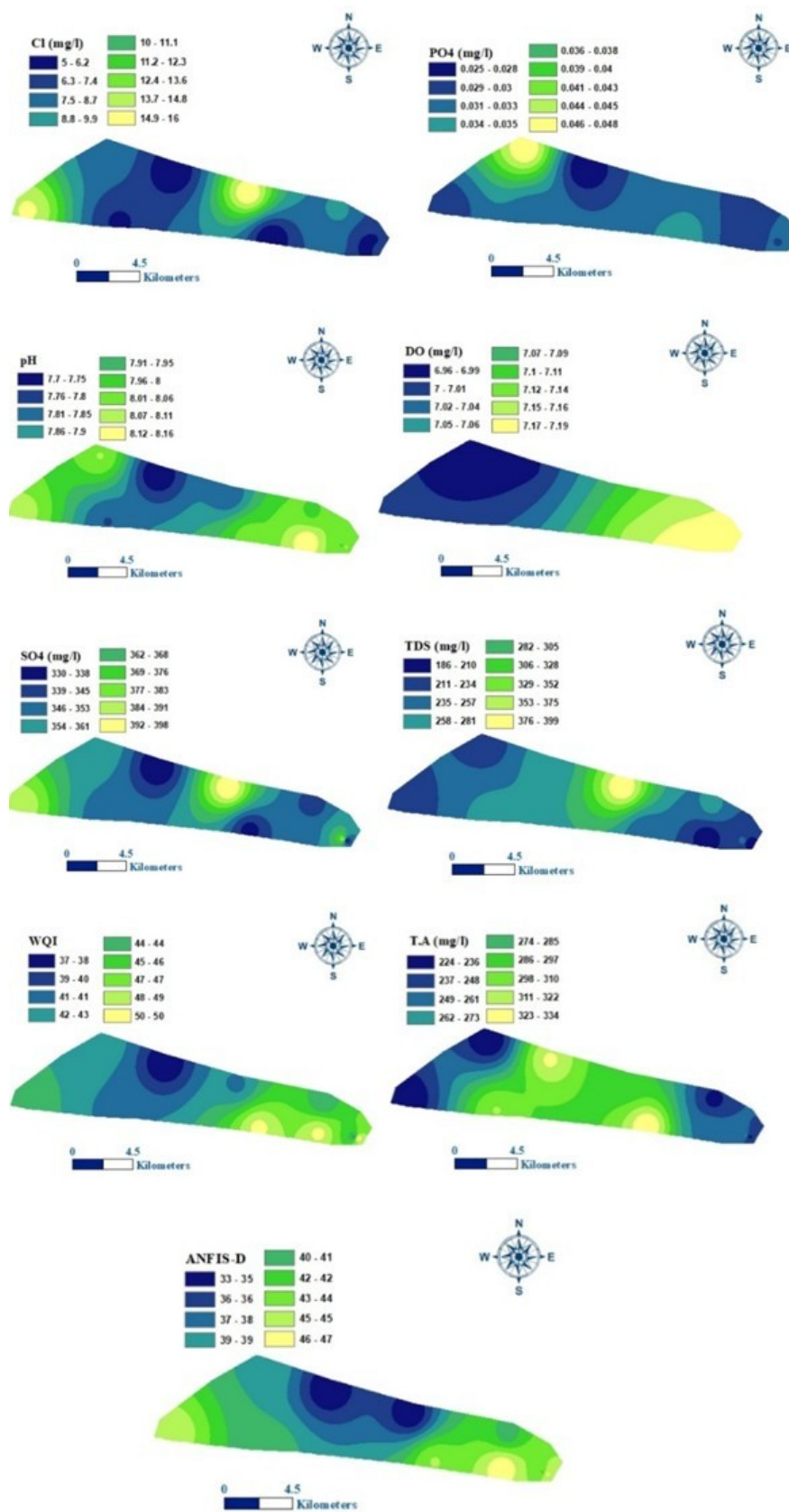


Figure 3: Spatial distribution of chemical parameters of the groundwater.

Table 4: Pearson's correlation coefficient for parameters.

Parameters	pH	DO	TDS	T.A	Cl	SO ₄	PO ₄	WQI	ANFIS-D
pH	1								
DO	0.531	1							
TDS	-0.682	-0.392	1						
T.A	-0.650	-0.074	0.383	1					
Cl	0.046	-0.041	0.463	-0.373	1				
SO ₄	0.034	-0.339	0.471	-0.268	0.699	1			
PO ₄	0.315	-0.006	-0.148	-0.270	-0.052	-0.003	1		
WQI	0.783	0.933	-0.573	-0.239	-0.080	-0.253	0.119	1	
ANFIS-D	0.854	0.706	-0.805	-0.396	-0.150	-0.166	0.020	0.860	1

WQI and ANFIS-D values ranged from (37-50) to (33-47) respectively Table 5, and were of good quality. This is because most of the criteria were within the standard limits for using groundwater for drinking, except for the total alkalinity, which was higher than the standards permitted for drinking. The spatial patterns of WQI and ANFIS-D distribution show that the drinking water classification converges in space in the study area such that the best sites are found in the north-central part (Mount Bekova). In comparison, the water quality decreases gradually towards the edges of the study area (Figure 3).

The performance of WQI and ANFIS-D models was compared. According to cross-validation criteria, generally, the ANDIS-D model performed well. The RMSE, R, and MBE values (3.81), (0.851), and (2.9), respectively, were in the range of very good to acceptable. The Figure 4 shows a clear convergence between real Water Quality Index (WQI) values and predicted values by the ANFIS-D model, depicting the model's accuracy in prediction. There are some discrepancies between the values, most significantly in wells 5, 6, and 7, where values drop abruptly prior to starting to rise once more in the direction of well 10. The adaptive neuro-fuzzy model (ANFIS-D) follows the general trend of the drinking water quality index with slight differences, indicating the ability of the model in estimating the actual data to a satisfactory degree. There is a large difference between the ANFIS output and the original data, meaning that the system is not yet learned the association between the input and output parameters. The model is still operating in default mode here, and default rules and parameters are utilized without having been set or optimized beforehand (Mohammed *et al.*, 2023). This indicates the weak predictive capability of the system prior to training. This apparent mistake indicates that the model needs additional training to accurately capture the relations within the data and generate useful predications.

Table 5: WQI and ANFIS model results.

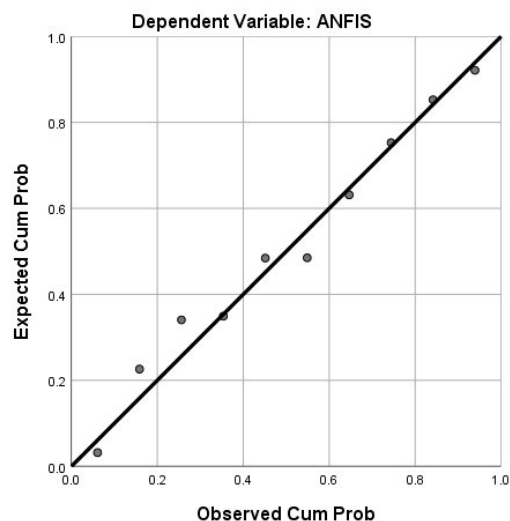
Well No.	WQI	ANFIS-D
1	49	44
2	49	47
3	42	39
4	44	45
5	41	40
6	37	33
7	41	33
8	43	40
9	42	42
10	50	46

The pH, TDS, Cl, and PO₄ level of all the samples of measured groundwater were within the drinking water standard range. In addition to this, sulfate and DO were 86% and 82% in drinking water appropriate, respectively, which was also reflected by the WQI and ANFIS-D values since the quality of all well water samples was in the good class. ANFIS-D model can precisely replicate the Water Quality Index (WQI) and can therefore serve as a quality prediction model for water in any well. Figure 4 shows a close agreement between the measured WQI values and those predicted by the ANFIS-D model, supporting the model's ability to estimate groundwater quality.

4. CONCLUSION

This concluded the study of alterations in growth, biochemical, and urinary mineral excretion parameters in the groups. Breastfed infants

revealed the most promising anthropometric and biochemical consequences, which indicated optimal nutritional composition and high bioavailability of nutrients in human milk. This demonstrated that breastfeeding can be used as the gold standard for infant nutrition. However, when breastfeeding is not feasible, the NAN Pro formula can be used as a suitable alternative, but the unmodified cow milk in infants should not be used during early infancy due to its negative effects on growth and mineral absorption.

**Figure 4:** Comparison between measured WQI (blue bars) and predicted WQI using the ANFIS-D model (orange bars) across 10 sampling points.**Normal P-P Plot of Regression Standardized Residual****Figure 5:** Standard P-P diagram of regression standardized residuals Dependent Variable (ANFIS-D).

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Ethical Statment:

The Ethical Committee of the College of Science, University of Zakho, Kurdistan Region approved the current experiment.

Conflict of Interests:

The authors declare that they have no conflicts of interest related to the publication or funding of this manuscript.

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Author Contributions:

V.N.Y, M.H.M., and N.M.A. participated equally in Data Collection, Laboratory Analysis, Literature Review, Design of the Project, Data Analysis, Writing Review, & Editing.

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