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Application of Adaptive Neuro-Fuzzy Inference System to Estimate the Groundwater Quality Index in Telkaif, Iraq

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ABSTRACT

In this study, an innovative application of the ANFIS artificial neural network is presented to predict the water quality index based on physicochemical parameters for groundwater in the Telkaif District, Iraq. Samples of water were collected from 16 wells located in the Telkaif district for nine months, from January to September 2024. Measured parameters include total dissolved solids (TDS), magnesium, calcium, sodium, sulfate, and dissolved oxygen. The spatial distribution pattern of all measured parameters is prepared, indicating that most of the parameters are high in the central region of the study area. The groundwater quality index is estimated using ANFIS, and the results show that one well is excellent, 3 wells are good, one is marginal, 2 are moderate, and 9 are poor. The validity of the ANFIS model is confirmed using the Canadian model, which shows (very good R and R^2) values, while the RMSE value is (good) (0.97, 0.93, and 8%), respectively. The ANFIS model can be relied upon to assess the quality of drinking water due to its time-saving, ease of application, and accuracy of results.

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تطبيق نظام الاستدلال العصبي الضبابي التكيفي (ANFIS) لتقدير مؤشر جودة المياه الجوفية في تلكيف، العراق

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الملخص

في هذه الدراسة تم تقديم تطبيق مبتكر لشبكة ANFIS العصبية الاصطناعية للتنبؤ بمؤشر جودة المياه بناءً على المعايير الفيزيائية والكيميائية للمياه الجوفية في قضاء تلكيف، العراق. تم جمع عينات المياه من 16 بئرًا تقع في قضاء تلكيف لمدة تسعة أشهر، من يناير إلى سبتمبر 2024. تضمنت المعايير المقاسة المواد الصلبة الذائبة الكلية (TDS) والمغنيسيوم والكالسيوم والصوديوم والكبريتات والأكسجين المذاب (DO). تم إعداد نمط التوزيع المكاني لجميع المعايير المقاسة وأشار إلى أن معظم المعايير كانت مرتفعة في المنطقة الوسطى من منطقة الدراسة. تم تقدير مؤشر جودة المياه الجوفية باستخدام ANFIS، وأظهرت النتائج أن بئرًا واحدًا كان ممتازًا و 3 آبار كانت جيدة وواحداً كان هامشياً و 2 كانا متوسطين و 9 كانوا سيئين. تم التأكد من صحة نموذج ANFIS باستخدام النموذج الكندي، والذي أظهر قيم R و R2 (جيدة جدًا)، بينما كانت قيمة RMSE (جيدة) (0.79 و 0.93 و 8٪) على التوالي. يمكن الاعتماد على نموذج ANFIS لتقييم جودة مياه الشرب بسبب توفيره للوقت وسهولة تطبيقه ودقة النتائج.

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Introduction

Among all natural systems, water resources have been the most exploited since humans first inhabited the earth. Intensive agricultural practices, urbanization, industrialization, and other developmental activities result in the pollution of Earth's natural water systems. Several physicochemical parameters normally describe the quality of groundwater. The variations of these parameters are normally high as a result of differences in pollution nature, seasonal variations, and the extraction of groundwater (Al-Mashhadany, 2021; Jalal et al., 2024). Therefore, it is necessary to monitor the water quality levels for the assessment of pollution levels and associated risks to the environment. The Groundwater Quality Index is an indispensable parameter in assessing and managing groundwater. It is one of the most essential tools in communicating information on water quality to interested citizens and decision-makers (Al-Mashhadany, 2022, Al-hamdany et al., 2024).

Modelling groundwater water quality often includes physicochemical water quality variables. Both physical and chemical variables synergistically impact water quality in interaction with other environmental variables that may produce unpredictable results in relation to the water quality. There are mostly just a few water quality variables that have conventionally been used to assess groundwater health, including dissolved oxygen, total dissolved solids, calcium, magnesium, sodium, and sulfate. Another widely used index is the water quality index obtained by complicated numerical formulae (Nikoo et al., 2011; Muslim et al., 2024). It involves the application of various water quality variables in computation and their comparison with a standard value for better understanding by nonscientific people, such as policymakers. The water quality index can be assigned classes like good, bad, and worst depending on the levels set by the monitoring bodies of the study region; the values obtained numerically are usually still reduced. This accordingly stipulates why water quality research is significant in the determination, monitoring, and maintenance of the quality of groundwater. Consequently, the number of scientific methodologies aimed at accessing, managing, and understanding water quality data has significantly increased (Oğuz and Ertuğrul, 2023; Saleh et al., 2024).

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a neuro-fuzzy system that works on a feedforward network to identify fuzzy decision rules with effectiveness in a particular task. Using a set of input/output, the ANFIS constructs a fuzzy inference system, whose membership function parameters are adjusted by the back-propagation algorithm alone or by a hybrid learning method combining the back-propagation algorithm with LMS (Sharifi, et al. 2021). Makes it possible for fuzzy systems to learn from the data they are intended to model. ANFIS also provides a means for the fuzzy modelling process to learn. Knowledge is derived from the dataset, which in turn drives the generation of membership function parameters that optimize performance for the task at hand. The ANFIS is capable of simulating and analyzing the mapping relationship between the input and output data by using a hybrid learning algorithm, which is intended for optimizing the parameters of a specified FIS(Tiwari et al., 2018; Singh et al., 2021).

The use of the ANFIS index to assess groundwater quality for drinking aims to leverage the capabilities of artificial intelligence to analyze complex and overlapping parameters that affect water quality. ANFIS combines the features of neural networks and fuzzy systems, making it a powerful tool for predicting water quality based on various input data. By providing a clear and accurate assessment of water quality, ANFIS helps water resource management agencies make informed decisions about groundwater use(Yaseen et al. 2018, Aghel et al., 2019).

Materials and Methods

Description of the study area

The Telkaif District lies in the North East of Iraq. It belongs to the Nineveh Governorate, occupying an area of 1244 km^2, located between 36.41175 - 36.71381 E and 36.41175 - 36.71381 N. Telkaif District is surrounded by Dohuk to the north, Erbil to the east, and Mosul to the south. The maximum temperature in Telkaif District during the hottest summer day is about 51 °C, while the minimum on the coldest winter night reaches –3 °C. Average annual precipitation is about 150 mm. Table 1 shows the coordinates of the well sites, and Figure 1 shows the location of the study area within the Telkaif district (Al-Mashhadany, 2021).

Table 1: Coordinates and depth of the studied wells.

Well	E	N	Depth (m)
1	43.20761	36.44563	14.0
2	42.98004	36.42293	17.0
3	43.10933	36.48304	33.0
4	43.02707	36.54123	20.0
5	43.02985	36.41175	50.0
6	43.23772	36.67006	180.0
7	42.93063	36.57815	80.0
8	43.06895	36.65043	130.0
9	43.10982	36.63141	250.0
10	43.10807	36.60583	120.0
11	43.11276	36.71381	160.0
12	43.17267	36.62857	200.0

13	42.76948	36.54257	46.0
14	43.15685	36.43200	22.0
15	42.82117	36.51273	47.0
16	43.00633	36.53132	150.0

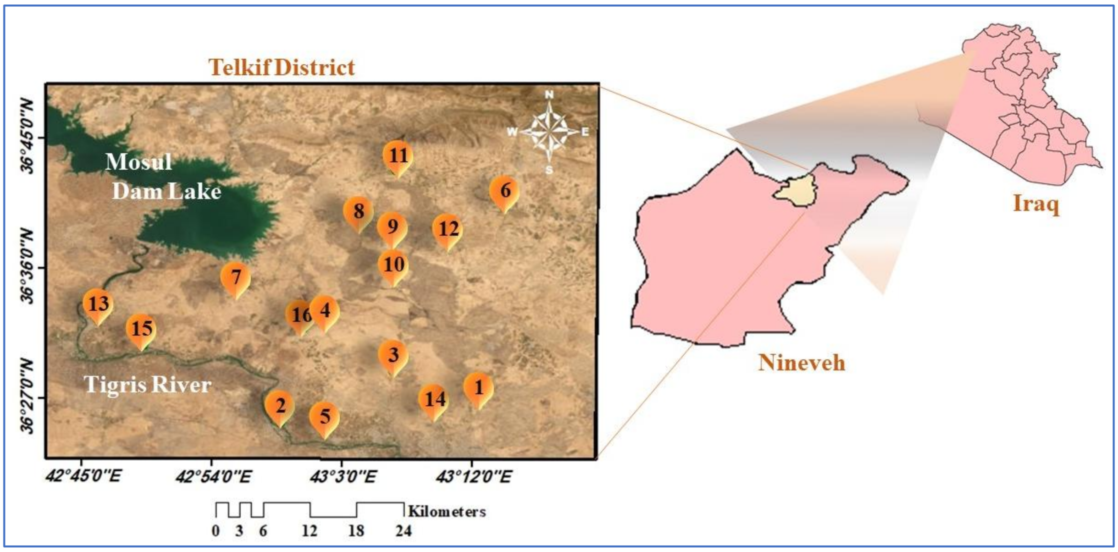


Fig.1. Study area.

Collection and analysis of samples

A total of 144 water samples from well water resources were collected from 16 villages in Telkaif District for the period from January to September 2024. All the villages are coded (1–16). All the samples were collected into polyethylene bottles and then moved at a temperature below 4 °C to water and wastewater laboratories. The parameters are considered as (total dissolved solids, magnesium, calcium, sodium, sulfate ions, and dissolved oxygen (DO). All the water samples were analyzed using standard methods for the analysis of groundwater (Rice et al. 2017).

CCME (Canadian Council of Ministers of Environment)

This analysis is based on the Canadian water quality. The first extended Quality Index, designed by the Canadian Council of Ministers of Environment, had three criteria defined as failed parameters: failed tests and failed amounts that did not meet the set standard limit, which were expressed as scope, frequency and amplitude, abbreviated as E_1, E_2, and E_3 respectively; hence this index categorized the values from the equations below into values between (0 – 100) as follows:

$$\boldsymbol{Scope = E_1 = \frac{Number\ of\ failed\ variables}{Total\ variables} \times 100}$$

$$\boldsymbol{Frequency = E_2 = \frac{Number\ of\ failed\ tests}{Total\ tests} \times 100}$$

$$\boldsymbol{Amplitude = E_3 = \frac{NSE}{0.01\ NSE + 0.01}}$$

Where: E_1 is the frequency of standard violations, E_2 is the non-conforming times, and E_3 is the intensity of a standard violation.

This parameter is calculated through excursion analysis. Excursion can be described as a number that designates how often a specific parameter has crossed its standard limit. It is the sum of excursions divided by the total number of tests done.

The test amount shall not exceed the guideline = excursion. $= \left(\frac{\boldsymbol{amount\ of\ faield\ test}}{\boldsymbol{guidline}}\right)$-1

The test amount shall not be less than the guide excursion.

$$\left(\frac{\boldsymbol{guidline}}{\boldsymbol{amount\ of\ faield\ test}}\right)\text{-1}$$

$$\boldsymbol{NSE} = \frac{\sum \boldsymbol{excursion}}{\boldsymbol{total\ tests}}$$

Finally, the index is obtained from the Scope, Frequency, Amplitude and NSE. The scaling factor of (1.732) has been incorporated to define the index in terms of a range between (0 and 100). Table 2 shows how the CCME water quality index scale is classified.

$$\boldsymbol{CCME = 100 - \frac{\sqrt{E_1^2 + E_2^2 + E_3^2}}{1.732}}$$

Table 2: Water quality index scale classification based on the CCME quantity.

Rating	CCME Values
Poor	0-44
Marginal	45-59
Fair	60-79
Good	80-94
Excellent	95-100

Adaptive Neuro-Fuzzy Logic

The ANFIS is a neuro-fuzzy system that provides neural learning using fuzzy-typed numbers generated from a set of input and output data. The embedded adaptation function in ANFIS renders the neuro-fuzzy capability in this machine learning system. Additionally, the structure of the neuro-fuzzy system resembles that of a multi-layer neural network. Generally, a neuro-fuzzy system has an input and an output layer, in addition to three hidden layers dedicated to the membership function representation, fuzzy rules, normalized rule strengths, and defuzzification. This study is an attempt to develop an ANFIS with the aim of classifying groundwater quality for drinking purposes. The proposed ANFIS model consists of six inputs and one output. A normal ANFIS model consists of five layers, with all the layers having some predefined functions, which preprocess the input through fuzzy logic rules and neural network adaptation (Azad et al. 2018; Al-Sulttani et al., 2021).

Layer 1: Fuzzification Layer

Each node in this layer calculates membership grades for each input with respect to a membership function (MF) like Gaussian or bell-shaped functions.

The membership degree is the degree of membership in fuzzy sets, e.g., Poor and Good.

Layer 2: Rule Layer

Each node represents a fuzzy rule and operates in order to combine membership values. This layer computes the firing strength of each rule, essentially how strongly each rule is activated.

Layer 3: Normalization Layer

The strength of each rule is normalized for each node by dividing every strength by the sum of all the strengths.

The normalized values are used as weights to scale the influence of each rule.

Layer 4 Resulting Layer (Defuzzification)

In Sugeno-type ANFIS, the consequent part is a linear function of the inputs.

Each node computes its output as the product of its normalized firing strength with a linear combination of the inputs.

Output Layer Layer 5

This node puts together the outputs of Layer 4 to produce the final output.

ANFIS uses weighted averaging, summing all rule outputs to obtain a crisp result. The training process is iterative, adjusting membership function parameters to minimize the error between predicted and target outputs.

In general, ANFIS combines the strengths of both neural networks—learning and adaptability—and fuzzy systems—handling uncertainty and interpretability—so the technique could find its place as a rather versatile and powerful one within soft computing, as presented in Figure 2 (Al-Adhaileh et al., 2021; Barzegar et al., 2023).

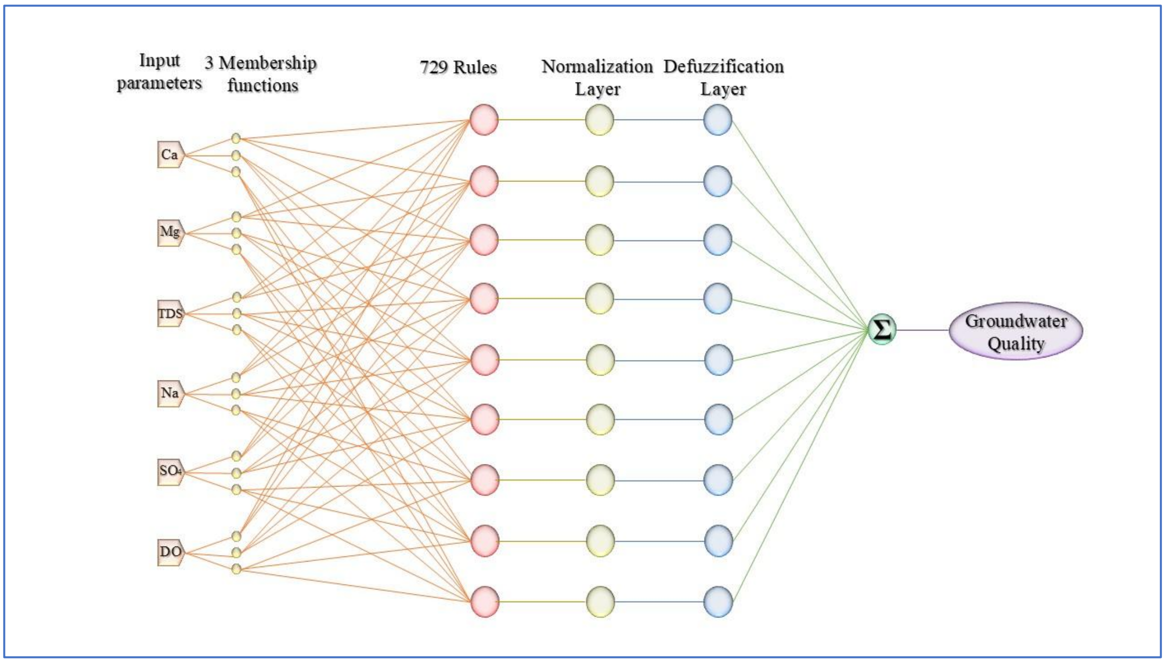


Fig. 2. ANFIS model structure.

It is worth mentioning that for the construction of fuzzy numbers, we tried four types of membership functions: bell-shaped, Gaussian, trapezoidal, and triangular. Consequently, after many trials, the trapezoidal-shaped distributed membership function had the lowest relative error compared with the others. The ANFIS module is trained after a predefined number of training epochs or until a predefined number of minimal errors is reached. Due to time constraints, fewer iterations are used in this investigation than in Figure 3 (Khan and Chai, 2017).

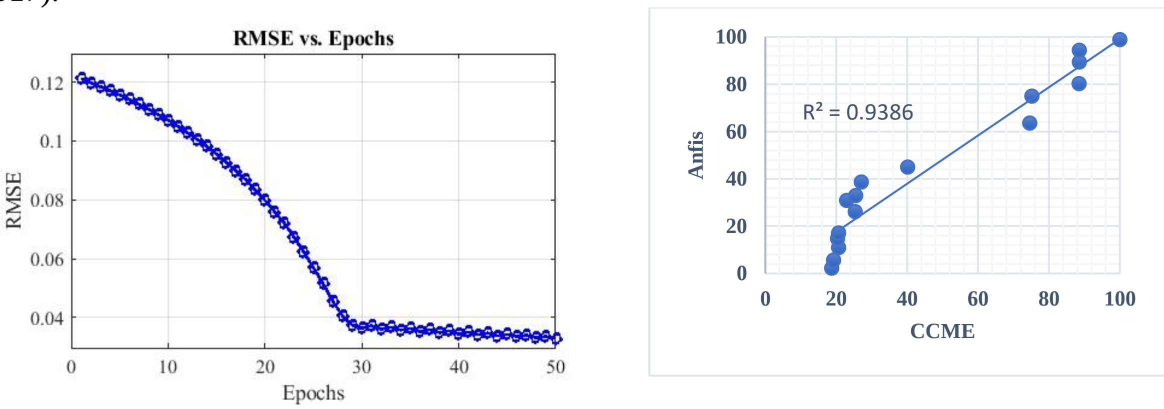


Fig. 3. Variation of RMSE for ANFIS module during training and cross-validation.

Results and Discussion

The TDS results show that the average value ranges between 148 and 3725 mg/l. This difference is due to the nature of the geological units through which the water flows.

Groundwater moving through evaporation-rich layers has a very high percentage of dissolved solids. The figure (6) shows the spatial distribution with 49% of the area of the Telkaif district within the standard specifications for drinking (Cotruvo, 2017).

The subject of dissolved oxygen concentration in aquatic systems is one of the important criteria for determining the quality of water, the degree of its pollution, and its role in mitigating the development of detrimental substances and adverse odors. The results of this study and the data given in Table 3 show that the concentration of dissolved oxygen is between (0.80-8.0) ppm, and 85% of the measured water samples exceeded the permissible limits for drinking. The reason for this decline is the lack of friction with the atmospheric air and also, the comparative increase in the temperature of the water within the wells will lead to an increase in the activity of microorganisms and so decrease the amount of dissolved oxygen in the water, which will establish anaerobic environments, altering the pathways of reactions, and form disagreeable odors and products harmful to the aquatic ecosystem as shown in the following equations (Al-Mashhadany, 2021):

$$2(CH_2O) + SO_4^{=} \xrightarrow{Anoxic\ Bact.} 2CO_2 + 2H_2O + S^{=}$$

$$\boldsymbol{S^{=} + 2H^{+} \rightarrow H_2S}$$

High levels of sulfate (more than 400 ppm) would tend to produce harmful effects on consumers, such as a purgative effect, irritation of the gastrointestinal tract, and a human body catharsis system with excess magnesium ions in the groundwater. 57% of the total samples are above the WHO threshold. At the same time, the spatial distribution shows that 42% of the area of the Telkaif district is over the standard drinking limits (Cotruvo, 2017).

High levels of sodium in drinking water can have negative health effects, especially if they exceed acceptable levels, such as high blood pressure, kidney problems, and fluid retention. It is demonstrated that the sodium content (32%) of the samples collected in the study area is within acceptable parameter levels according to WHO norms. The cause of the comparably high sodium concentrations originates from the dissolution process and weathering of rocks containing sodium salts as water goes through them. The spatial distribution shows that 56% of the area of the Telkaif district is outside the standard drinking limits (Koufman and Johnston, 2012).

The calcium concentration in the study area ranges from 24 to 720 mg/l, and the calcium concentration in 29 groundwater samples is within the standard limits for drinking; on the other hand, the calcium concentration in 115 groundwater samples is above the permissible limit (Table 3). The high calcium concentration is a result of the interaction between rocks and water in limestone terrain. The magnesium concentration in the study area is found to vary between 24 mg/l and 429 mg/l in the study area; altogether, 37 samples have a value higher than 75 mg/l, which is within the acceptable limit according to WHO. This is due to the high concentrations of magnesium in the groundwater and dolomite rocks. The spatial distribution of calcium and magnesium shows that 8% and 7.6% of the area in the Telkaif district are within the standard specifications for drinking respectively (Chycki et al., 2018, Verma et al., 2020).

Table 3: Chemical measurement values of groundwater in the Telkaif district.

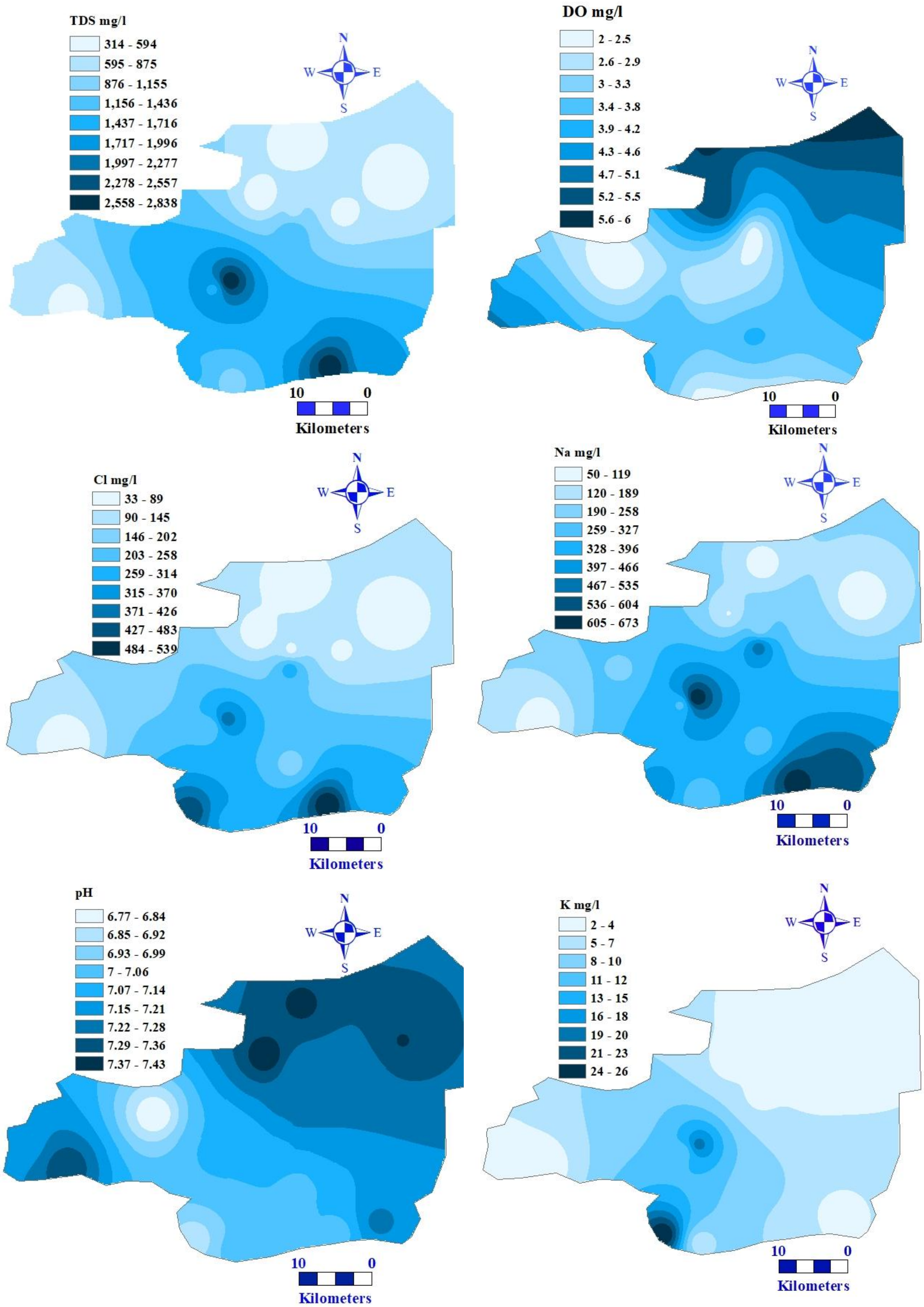
Well		DO	TDS	Ca	Mg	Na	SO_4
1	min	1.6	1233	80	215	480	574
	max	4.8	2580	240	390	910	1128
	mean	3.3	1771	149	293	643	896
	SD	1.1	448	44	65	154	201
2	min	1.6	1221	112	127	310	263
	max	5.6	1894	344	332	930	926
	mean	3.7	1459	216	221	439	521
	SD	1.7	214	74	61	194	194
3	min	1.2	1335	480	107	160	995
	max	5.6	1814	720	264	560	4869
	mean	3.9	1629	609	169	314	1671

	SD	1.5	168	79	52	133	1224
4	min	1.3	2504	280	215	600	1009
	max	4.0	3020	640	429	760	2992
	mean	2.7	2840	524	357	672	1864
	SD	0.9	184	124	66	64	674
5	min	1.2	880	144	68	220	364
	max	4.8	1115	272	181	360	481
	mean	2.5	1032	210	127	280	421
	SD	1.3	96	44	42	46	46
6	min	2.0	308	40	39	20	14
	max	5.6	356	80	78	130	52
	mean	4.7	326	64	65	52	30
	SD	1.1	17	14	16	42	15
7	min	1.2	1320	400	39	210	775
	max	3.2	1690	720	185	370	5187
	mean	2.0	1561	630	108	260	1759
	SD	0.7	117	109	45	57	1316
8	min	2.0	148	24	39	60	11
	max	8.0	350	80	107	210	79
	mean	5.2	313	48	67	131	34
	SD	2.7	62	21	24	51	21
9	min	0.8	705	64	29	150	204
	max	6.4	935	208	205	340	870
	mean	2.4	818	126	132	228	489
	SD	1.7	89	48	65	56	178
10	min	1.6	1245	80	39	430	300
	max	4.0	1590	192	244	640	1195
	mean	2.3	1385	142	165	519	690
	SD	0.7	93	37	61	69	232
11	min	1.6	275	24	49	30	2
	max	7.6	368	80	98	170	16
	mean	4.6	315	49	75	97	11
	SD	1.7	37	21	18	50	5
12	min	1.6	351	40	44	110	9
	max	5.6	714	192	127	530	29
	mean	4.3	472	71	79	198	16
	SD	1.2	128	48	25	130	8
13	min	2.4	554	72	49	170	172
	max	5.1	753	192	117	200	366
	mean	4.3	666	161	86	187	285
	SD	1.0	70	39	22	9	64
14	min	0.8	1734	240	166	590	1098
	max	5.6	3725	512	429	820	5265
	mean	2.9	2770	397	347	659	2085
	SD	1.6	557	85	81	71	1268
15	min	1.6	415	96	24	40	137
	max	5.6	446	160	73	160	323
	mean	4.2	431	139	50	64	229
	SD	1.4	11	27	18	37	56
16	min	1.4	1079	368	102	240	1014
	max	5.6	1832	704	268	680	3610
	mean	3.5	1652	558	181	358	1682
	SD	1.7	229	132	54	131	769
Standard		5	1000	75	75	200	400

The Pearson correlation coefficient is used to determine the relationship between the parameters given in Table 3. The obtained results are listed in Table 4, which exhibits a positive correlation between TDS and Ca, Mg, Na, and SO_4, while DO is inversely correlated with TDS, Na, SO_4, Mg, and Ca. This is due to the effect of surface tension, as the ions resulting from the dissolution of salts reduce the areas in which oxygen can dissolve. The relationship between the ANFIS model and DO is positive and inversely correlated with TDS and the rest of the ions.

Table 4: Pearson correlation matrix of parameters.

	INFIS	Ca	Mg	TDS	Na	SO_4	DO
INFIS	1						
Ca	-0.676	1					
Mg	-0.718	0.431	1				
TDS	-0.834	0.659	0.822	1			
Na	-0.770	0.380	0.840	0.857	1		
SO_4	-0.643	0.691	0.512	0.709	0.502	1	
DO	0.485	-0.223	-0.186	-0.339	-0.289	-0.187	1


TDS mg/l
314 - 594
595 - 875
876 - 1,155
1,156 - 1,436
1,437 - 1,716
1,717 - 1,996
1,997 - 2,277
2,278 - 2,557
2,558 - 2,838
N
W
E
S
10
0
Kilometers
DO mg/l
2 - 2.5
2.6 - 2.9
3 - 3.3
3.4 - 3.8
3.9 - 4.2
4.3 - 4.6
4.7 - 5.1
5.2 - 5.5
5.6 - 6
N
W
E
S
10
0
Kilometers
Cl mg/l
33 - 89
90 - 145
146 - 202
203 - 258
259 - 314
315 - 370
371 - 426
427 - 483
484 - 539
N
W
E
S
10
0
Kilometers
Na mg/l
50 - 119
120 - 189
190 - 258
259 - 327
328 - 396
397 - 466
467 - 535
536 - 604
605 - 673
N
W
E
S
10
0
Kilometers
pH
6.77 - 6.84
6.85 - 6.92
6.93 - 6.99
7 - 7.06
7.07 - 7.14
7.15 - 7.21
7.22 - 7.28
7.29 - 7.36
7.37 - 7.43
N
W
E
S
10
0
Kilometers
K mg/l
2 - 4
5 - 7
8 - 10
11 - 12
13 - 15
16 - 18
19 - 20
21 - 23
24 - 26
N
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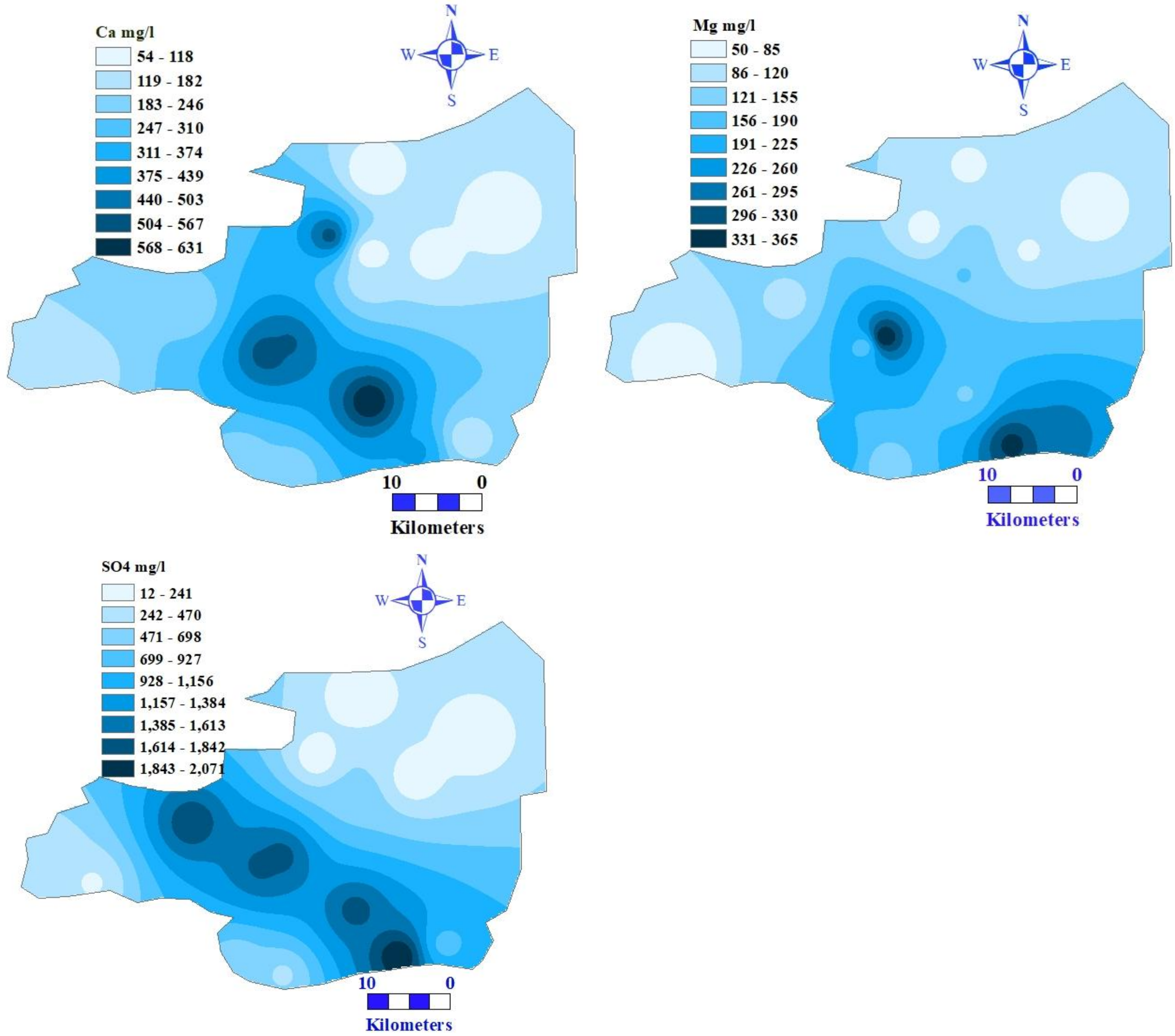

Fig. 4. Spatial distribution of measured values in the study area.

The ANFIS model values range between poor and excellent, and wells No. (1, 2, 3, 4, 5, 7, 10, 14, and 16) are due to most of the criteria being higher than the standard limits allowed for drinking, while wells No. 6, 8, 11, and 12 are between excellent and good (Table 5 and Figure 4) because most of the parameters are within the standard limits for drinking. Figure (6) shows the spatial distribution of Makhmur district using the ANFIS model that the best place for drinking water quality is in the northern areas of the district, and their percentage is 8% of the district's area.

To verify the validity of the ANFIS model, it is compared with the CCME model. R and R^2 are shown to be 0.97 and 0.93, respectively, which are very good values, while the RMSE value is 8%, which is good due to the variation in the well value in the study area.

Table 5: ANFIS and CCME values for the study area wells.

Well	ANFIS	Water quality	CCME	Water quality
1	30.9	Poor	23	Poor
2	32.9	Poor	26	Poor
3	10.9	Poor	21	Poor
4	2.21	Poor	19	Poor
5	38.6	Poor	27	Poor
6	89.4	Good	89	Good
7	14.7	Poor	20	Poor
8	98.9	Excellent	100	Excellent
9	44.9	Marginal	40	Poor
10	26.1	Poor	25	Poor
11	94.3	Good	89	Good
12	80.3	Good	89	Good
13	63.6	Fair	75	Fair

14	5.6	Poor	19	Poor
15	75	Fair	75	Fair
16	17.1	Poor	21	Poor

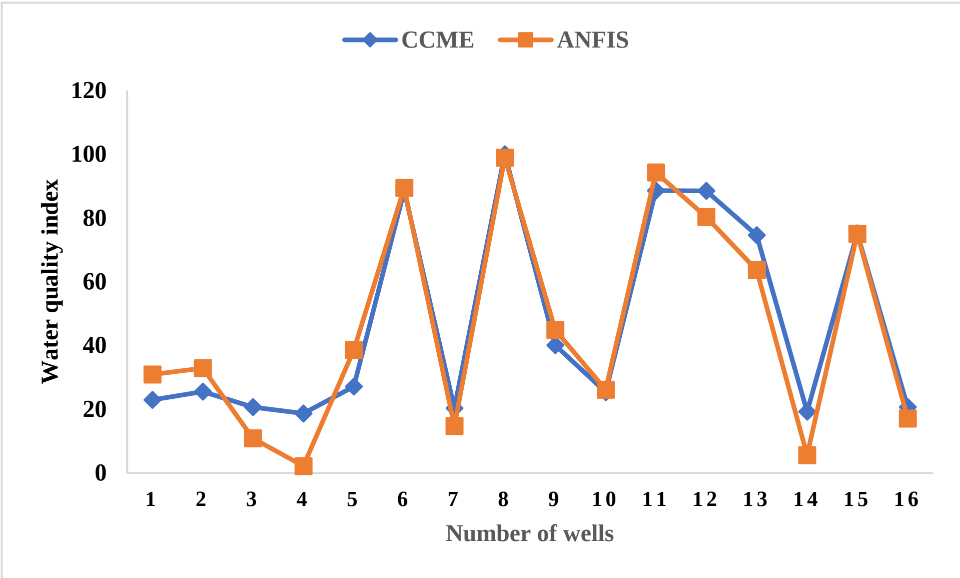

Fig.5. Comparison of measured and predicted WQI by ANFIS.

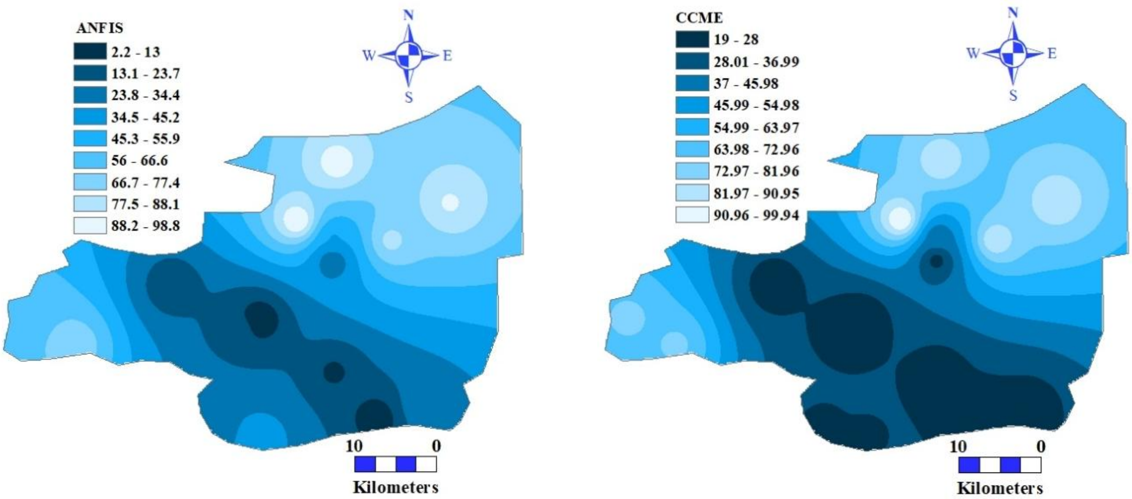

Fig.6. Spatial distribution for CCME and ANFIS values in the study area

Conclusions

The study results indicate that the percentages of calcium, magnesium, TDS, sodium, sulfate, and DO concentrations have increased, respectively, to 80%, 74%, 54%, 59%, 57% and 85% of the total well water samples above the permissible drinking limits. The results of the ANFIS model for classifying drinking water quality show that: 9 wells are poor, 2 are fair, one is marginal, 3 are good, and one is excellent. The spatial distribution of the ANFIS shows that the best possibilities for drinking well water are in the northern part of the study area. The ANFIS model is verified using the Canadian model for the same values of well water, and the values of R and R^2 are very good, while the RMSE values are good. The ANFIS model can be a good alternative to traditional models for evaluating drinking water quality from wells, as it reduces time, cost, effort, and sometimes computational errors.

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

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