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Artificial Neural Network Assessment of Groundwater Quality for Agricultural Use in Babylon City: An Evaluation of Salinity and Ionic Composition

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ABSTRACT

In recent years, the decline in the level of Iraq's rivers necessitated groundwater use for irrigation. A data set collected from 111 wells in the Nile region of Babylon City was analyzed in this research to assess whether or not the groundwater is suitable for irrigation. The studied parameters included electrical conductivity, pH, sulfate, chloride, magnesium, calcium, potassium, sodium, nitrate, bicarbonate, and Total Dissolved Solids (TDS). The quantification of water salinity was achieved through statistical analysis of the examined data, as well as the computation of the sodium adsorption ratio (SAR), magnesium adsorption ratio (MAR), and percentage of dissolved sodium (Na%). Statistical packages for the social sciences (SPSS) software were utilized to generate mathematical models that forecast the quality of groundwater suitable for irrigation, employing artificial intelligence in the form of neural networks. The obtained results indicated that a large proportion of samples fall into the undesirable category, and therefore the groundwater in this region is unsuitable for irrigation. In comparison, it was found that the predicted models have high accuracy and coefficients of determination up to 0.984 for TDS, 0.952 for SAR, 0.918 for Na%, and 0.933 for MAR, with a relative error of no more than 0.056.

1. INTRODUCTION

Recently, Iraq began to suffer from the deterioration of the water situation of the Tigris and Euphrates rivers due to the construction of dams at the headwaters with a decrease in water flows in addition to climate change [1-4]. These things have a negative impact in the short term, so the tendency to know the quality of groundwater available in Iraqi lands has become important to determine its suitability for human use [5]. Also, in many countries, groundwater is an important water source, as it is relied on as drinking water and as a source of water used in industry and irrigation [6, 7]. Also in rural areas, where rivers, dams, and canals are not available, groundwater is the main factor in irrigating crops, so its quality is important in those areas. A hydrogeochemical study of groundwater in the Nile region near Babylon City was conducted to analyze the dissolution and precipitation ratios of mineral phases along specific flow paths and assess the impact of surface water (Babylon stream) on the groundwater using hydrogeochemical mixing techniques [8]. Other researchers developed three-dimensional modeling for groundwater flow and experimental assessment for 19 wells in the vicinity southwest of the area under investigation. The laboratory tests revealed that the water is affected by various salinity concentrations and high salt ranges between 3,000 and 7,500 µS/cm [9]. A quantitative and qualitative evaluation, of the groundwater to the northwest of the studied area, on its appropriateness for irrigation and municipal applications was conducted by other scholars. Geographic Information System (GIS) and groundwater modeling and movement through the soil strata of the research regions were constructed utilizing GMS software. Additionally, laboratory experiments were performed for sampling groundwater from 24 wells for six months. A comparison of test findings with national and international standards indicates that the water parameters were within permissible limits [10].

Groundwater quality assessment of shallow aquifer hand-dug wells in rural localities of Ilorin Northcentral Nigeria [11]. Pollution can be defined as the presence of natural and unnatural substances in high concentrations that negatively affect the environment. Thus, groundwater pollution occurs when the concentrations of natural or unnatural substances exceed the permissible limit in this water in a way that poses a threat to living organisms, especially humans and plants [12]. Undoubtedly, groundwater is subject to pollution directly or indirectly in several ways, such as pollution by sewage pipes, improper sanitary landfills, fertilizers, industrial pollutants, mining, and various other pollutants [13]. Human activities including over-extraction of groundwater, the introduction of contaminants to aquifer recharge areas, and climate changes impact groundwater [14, 15] and as it is known, drinking contaminated water is a major cause of common diseases such as dysentery, cholera, typhoid, diarrhea, skin infection, polio, and guinea worm, etc. [14]. Remediation of polluted groundwater is difficult and expensive. Therefore, it is better to prevent or reduce sources of groundwater pollution, as this is a cheaper solution than reclaiming it [12]. Water resources interest many researchers in this field worldwide, as researchers use various scientific methods to study water quality to determine its suitability for human use [14].

Among the studies on water resources in general and groundwater in particular are the studies [11, 16-26] and many others. Using statistical techniques and methods with multiple variables is preferable to simplify large-scale arithmetic operations and explain the relationship between multiple variables, such as cluster analysis and factor analysis [27]. Also, artificial neural networks are a modern mathematical method widely used to predict water quality because they save effort and time and give high-accuracy results [28]. Mokarram [29] conducted a study in 2016 on groundwater in northern Shiraz, and using multi-layer regression, the strongest correlation was between total dissolved solids and chloride, as the determination coefficient was 0.97 [29]. Ismail et al. [27] conducted a study in 2020 of the Zubair and Safwan regions of Basra City in southern Iraq using artificial neural networks to classify wells' groundwater based on the physical and chemical properties of the samples. The obtained model has proven good performance and efficiency [30]. Also, in 2020, The Artificial Neural Network (ANN) method was applied to estimate groundwater table in Madhya Pradesh by study [31]. Al-Waeli et al. [28] used artificial neural networks to predict groundwater salinity, where the model was reached between the independent variable and the dependent variable with a high percentage of coefficient of determination that ranged between 0.96-0.97 with very little relative error [28]. Also, Dawood et al. [32] conducted a study in Basra Governorate in 2022 to assess and predict groundwater quality, as it was found for them that in the studied area the groundwater quality ranges from poor to unsuitable for drinking according to the water quality index method [32].

Despite the importance of groundwater quality evaluation for assessing its validity for irrigation, there is a lack of studies dealing with that in the Nile region of Babylon City. The current research was undertaken to verify the validity of irrigation groundwater for the Nile region located in the city of Babylon, by collecting samples from wells distributed in this region. The statistical package for the social sciences (SPSS) software was used for statistical analysis and prediction of groundwater quality and suitability for irrigation uses utilizing ANN models. ANN model can be used to predict important water quality parameters accurately with a relatively small error [33]. The results show that a large proportion of the samples fall into the undesirable category, and therefore the groundwater in this region is unsuitable for irrigation.

2. MATERIAL AND METHOD

2.1 Study area

Babylon City is one of the ancient governorates of Iraq. The area of study has (44°2'42.245"E; 45°2'2.964"E) longitude and (32°25'55.287"N; 33°7'34.229"N) Latitude, is situated away from Baghdad (the capital of Iraq), about 100 km to the south [5]. Since the Nile area is agricultural, herbicides, fertilizers, and pesticides that are used in agricultural processes can seep into groundwater, causing contamination of well water. This becomes more significant in rainy seasons. In addition, the variation in temperature, precipitation, and humidity during the year have a great influence on the water quality of the wells since they play a big role in the recharging rates of the wells as well as the dilution of contaminants' concentration in the groundwater. In this study, the samples of groundwater were taken from 111 wells located in the Nile region. Three groundwater samples were taken from each well, and each sample was tested for the following parameters: electrical conductivity, pH, sulfate, chloride, magnesium, calcium, potassium, sodium, nitrate, bicarbonate, and total dissolved solids. Figure 1 shows the location of the studied wells.

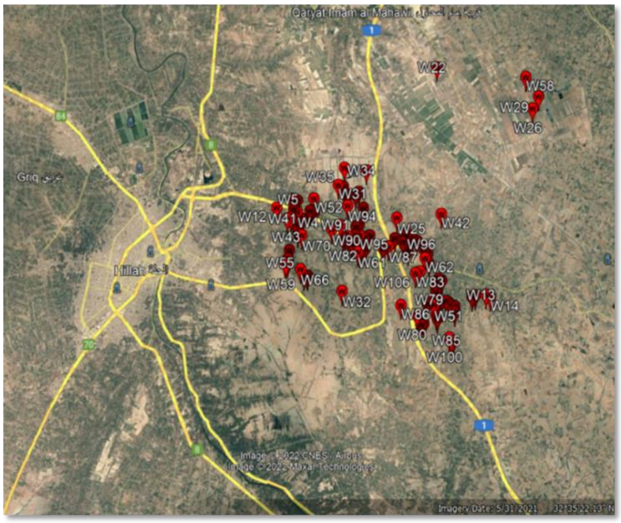

Figure 1. Wells distribution in the Nile region

2.2 Sampling description

To achieve the goal of the research, Groundwater samples were collected from 111 wells that are well distributed in the Nile region within Babylon City. The 111 sampling wells were strategically placed within the study region to map the regional distribution of water quality. Three samples were taken from each well using a sterile 1-liter glass bottle. The depths of these wells range from 12 to 15 meters. These samples were collected during (April, May, and June) 2019. The parameters measured are pH, electrical conductivity, sulfate, chloride, magnesium, calcium, potassium, sodium, nitrate, bicarbonate, and total dissolved solids. On-site, samples were examined for pH, TDS, and EC using a portable water-resistant Tracer POCKETESTER (Code: 1766, LaMotte, Taiwan), which was calibrated according to the instructions and manual of the manufacturing company; while other parameters were examined in the laboratory.

2.3 The validity of groundwater for irrigation purposes

Na%, SAR, and MAR are crucial water quality parameters that assess the suitability of water for agricultural purposes as they offer valuable information about the possible threats of soil erosion, decreased permeability, and overall effects on crop yield [34, 35].

2.3.1 The percentage of dissolved sodium (Na%)

Irrigation water containing high saline concentrations negatively affects the growth of crops, as the increased concentration of dissolved sodium salts changes with calcium or magnesium salts, which causes problems in soil permeability in addition to swelling and dispersion of minerals in clay and others. Where the excessive concentration of sodium causes damage to soil in terms of permeability, structure, and ventilation in addition to its effect on crops, and polluting groundwater due to its ability to exchange with magnesium and calcium ions, the percentage of dissolved sodium could be computed using the following equation [15]. Where Ca, Na, K, and Mg concentrations are denoted in milli-equivalents per liter (meq/L).

$$Na\% = 100 \times \frac{K + Na}{K + Na + Mg + Ca} \tag{1}$$

2.3.2 Sodium adsorption ratio (SAR)

Sodium expresses the alkalinity of water, so it is necessary to know its percentage in irrigation water due to its danger to crops and soil, and it is expressed by the percentage of sodium absorption, which is calculated from the following equation [24]. Where Ca, Na, and Mg concentrations are denoted in milli-equivalents per liter (meq/L).

$$SA = \frac{Na}{\sqrt[2]{\frac{Mg + Ca}{2}}} \tag{2}$$

2.3.3 Magnesium adsorption ratio (MAR)

The presence of magnesium in groundwater is determined as a percentage that depends on the magnesium and calcium ions in its calculation as shown in Eq. (3), which includes two classifications only, where the ratio is acceptable if the result is less than 50. Otherwise, it is not acceptable [6]. Where Ca and Mg concentrations are denoted in milli-equivalents per liter (meq/L).

$$MAR = \frac{Mg}{Mg + Ca} \times 100 \tag{3}$$

3. ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial Neural Networks are mathematical algorithms inspired by the human brain. Artificial neural networks provide high accuracy in data analysis and prediction. ANN has the ability to produce output with reasonable accuracy if it has gone through an effective learning phase [36]. As in the human brain, these networks consist of a set of interconnected neural networks that are used to communicate with each other, which contain three layers: the input, the output, and the hidden layer. The data to be analyzed is received in the input layer, and the necessary calculations are performed in the hidden layer by multiplying the entered value by its corresponding weight, and it also works on processing this data in a trial-and-error manner, according to the required accuracy of the model [28, 37]. In this study, to predict groundwater quality for irrigation based on neural networks, physical and chemical parameters of wells were used as the independent variable while TDS, SAR, MAR, and Na percentage were used as dependent variables as shown in Figure 2.

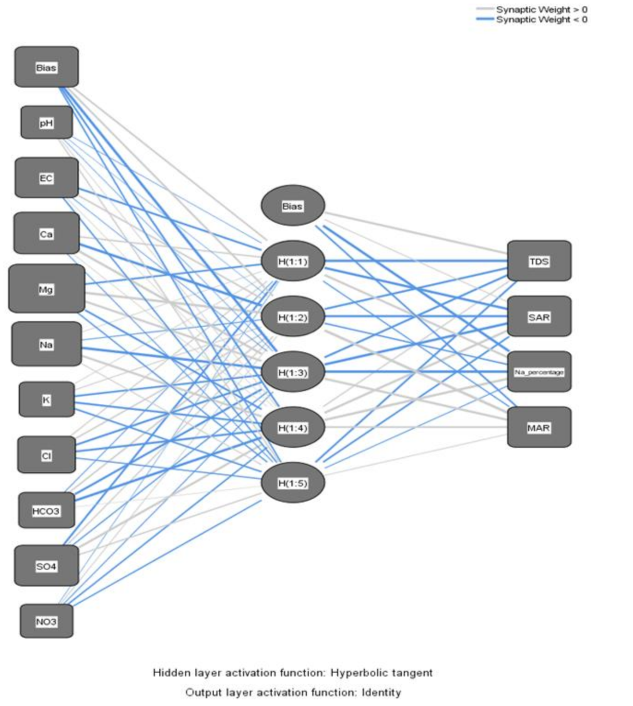

Figure 2. Network architecture for predictive models

These layers consisted of the input, hidden, and output layers. The input and hidden layers used tan-sigmoidal activation functions to cover the whole input value range, whereas the output layer used linear activation functions to display the result values. Hidden layer had 5 neurons. By training the model several times, the best result of the ANN model is adopted depending on the value of the coefficient of determination (R^2) and the mean square error (MSE). One crucial aspect of creating a soft-computing model is gathering the database relevant to the problem being studied. Normalization was achieved by using max-min normalization of both input and output datasets before training the ANN model to ensure a stable analysis. Normalizing the datasets ensures that all processing parameters are weighted equally. All inputs and outputs in the study were normalized to a scale from zero to one. The normalization of input and output parameters was conducted as described in the study [38]:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4}$$

where, x_n represents the normalized value of a specific parameter, while x represents the actual parameter value. x_{max} and x_{min} denote the maximum and minimum values of the database for this parameter, respectively.

4. RESULTS AND DISCUSSION

4.1 Statistical analysis of groundwater

SPSS software was used to obtain the descriptive statistical analysis of the physical and chemical parameters mentioned in Table 1, showing that there is a discrepancy between the standard deviation and the mean of the studied parameters, and this indicates that the parameters exceeded the upper permissible limits as a result of the fact that the area is semi-remote and that the drains in it are old and dilapidated, which negatively affected the quality of the groundwater there.

Table 1. Descriptive statistics of groundwater data for wells in the Nile region

Water Quality Parameter	Units	N	Minimum	Maximum	Mean	Std. Deviation
		Descriptive Statistics				
pH	-	111	7.11	7.61	7.20	.074
EC	μS/cm	111	`1353	29200	6617.69	4553.32
TDS	mg/L	111	970	18900	4356.75	2986
Ca	mg/L	111	39	1122	375.56	220.58
Mg	mg/L	111	22	790	192.78	122.13
Na	mg/L	111	79	4000	622.94	556.32
K	mg/L	111	2	310	53.40	54.84
Cl	mg/L	111	3.50	2900	835.71	526.59
HCO_3	mg/L	111	27	2260	452.21	306.88
SO_4	mg/L	111	220	10000	1463.57	1371.03
NO_3	mg/L	111	0.10	6	1.77	0.908

4.2 Groundwater quality for irrigation

Irrigation water quality greatly affects crop production as the high concentration of salts in water affects the growth of crops and soil. This is due to the accumulation of salts in the root zone, which affects the permeability of the soil as a result of increased sodium or calcium leaching [6]. The necessary indicators for the quality of irrigation water were calculated, as Table 2 shows the percentage of soluble sodium, the proportions of samples were determined according to their suitability for cultivation from excellent to unsuitable, and it was noted that a high percentage of them amounted to 79% that fell within the permitted or acceptable category for irrigation and the remaining ranged between good, doubtful and unsuitable. Also, Table 3 represents the rate of sodium adsorption, and it turns out that 67% of the samples are classified as unsuitable, while all samples were permissible in terms of magnesium adsorption rate as shown in Table 4. According to the results, it was found that the groundwater in the Nile region is not suitable for irrigation because of the high percentage of salt, and it is not preferred to use for irrigation because it negatively affects the soil and the growth of crops. Irrigation water quality greatly affects crop production as the high concentration of salts in water affects the growth of crops and soil. This is due to the accumulation of salts in the root zone, which affects the permeability of the soil as a result of increased sodium or calcium leaching [6]. The necessary indicators for the quality of irrigation water were calculated, as Table 2 shows the percentage of soluble sodium, the proportions of samples were determined according to their suitability for cultivation from excellent to unsuitable, and it was noted that a high percentage of them amounted to 79% that fell within the permitted or acceptable category for irrigation and the remaining ranged between good, doubtful and unsuitable. Also, Table 3 represents the rate of sodium adsorption, and it turns out that 67% of the samples are classified as unsuitable, while all samples were permissible in terms of magnesium adsorption rate as shown in Table 4. According to the results, it was found that the groundwater in the Nile region is not suitable for irrigation because of the high percentage of salt, and it is not preferred to use for irrigation because it negatively affects the soil and the growth of crops.

The data presented in Tables 2-4 indicate that groundwater in the area being studied is unsuitable for agricultural purposes by 2% due to Na% values exceeding 80% and by 67% due to SAR values exceeding 26%, while the MAR values were all smaller than 50%, meaning that the unsuitability of groundwater for agriculture was not due to MAR values.

Table 2. Groundwater classification based on the values of soluble sodium percentage [15]

Rang of Na%	Classes	Percentage of Samples
<20	Excellent	0
20-40	Good	11%
40-60	Permissible	79%
60-80	Doubtful	8%
>80	Unsuitable	2%

Table 3. Groundwater classification based on the values of SAR [15]

SAR	Classes	Percentage of Samples
<10	Excellent	1%
10-18	Good	13%
18-26	Permissible	19%
>26	Unsuitable	67%

Table 4. Groundwater classification based on the values of MAR [6]

MAR	Classes	Percentage of Samples
<50	Permissible	100%
>50	Unsuitable	0

High levels of sodium in irrigation water can degrade soil structure by causing dispersion, resulting in decreased water penetration and increased soil erosion. Soils with high SAR values are susceptible to dispersion, decreased permeability, and reduced water infiltration, leading to negative impacts on plant growth. SAR is valuable for determining whether irrigation water is appropriate for use on soils prone to sodium-induced structural issues. High levels of magnesium in irrigation water can similarly harm soil structure and permeability, albeit to a lesser degree than salt. MAR aids in comprehending the possible impacts of magnesium on soil structure and the entire soil-plant system. So, each of Na%, SAR, and MAR has an effect of water suitability for irrigation due to its effect on the soil or plant or both of them.

4.3 Artificial neural network

4.3.1 Model prediction

Artificial neural networks were used to develop prediction models for groundwater based on the value of TDS, SAR, Na%, and MAR as reliable variables as shown in Figures 3-6 using SPSS software. The model was then trained, tested, and validated using the actual as input parameters and the measured TDS, SAR, MAR, and Na percentage amount as output. Diverse artificial neural network architectures were assessed using varying input parameters. According to the results, the search became stable after 3200 iterations since the goal functions could only handle a maximum of 5000 iterations.

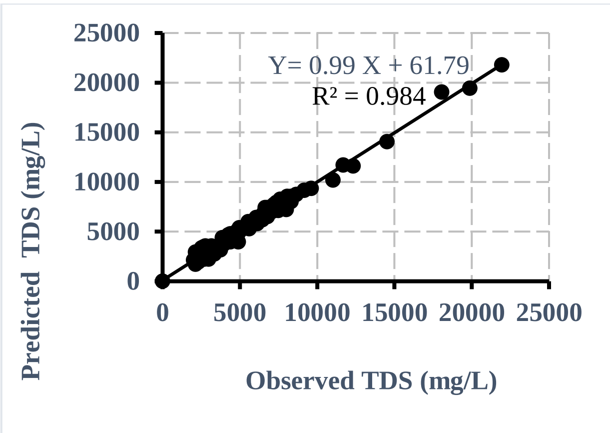

Figure 3. Predicted versus the observed values of TDS

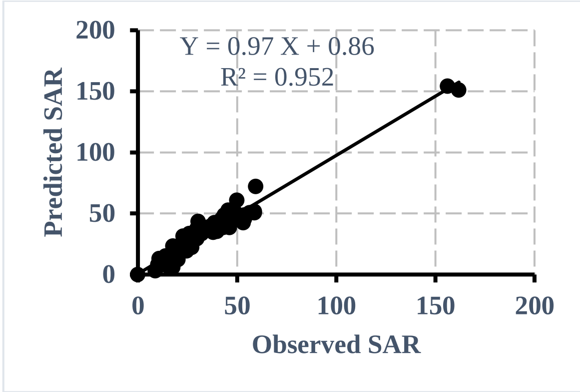

Figure 4. Predicted versus the observed values of SAR

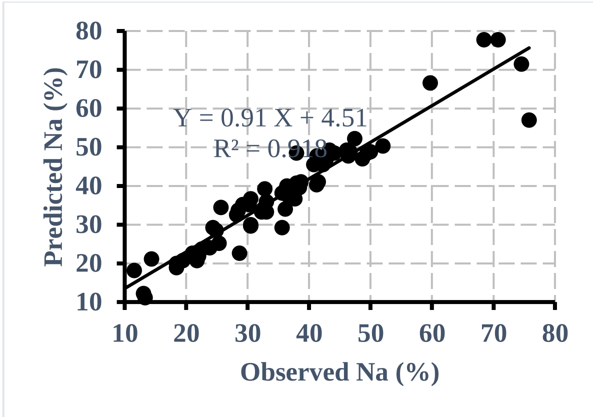

Figure 5. Predicted versus the observed values of Na (%)

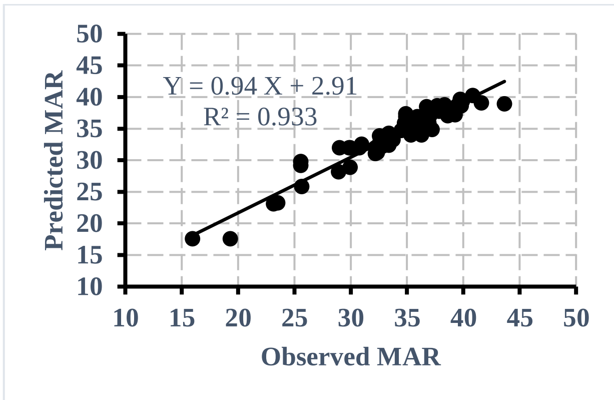

Figure 6. Predicted versus observed values of MAR

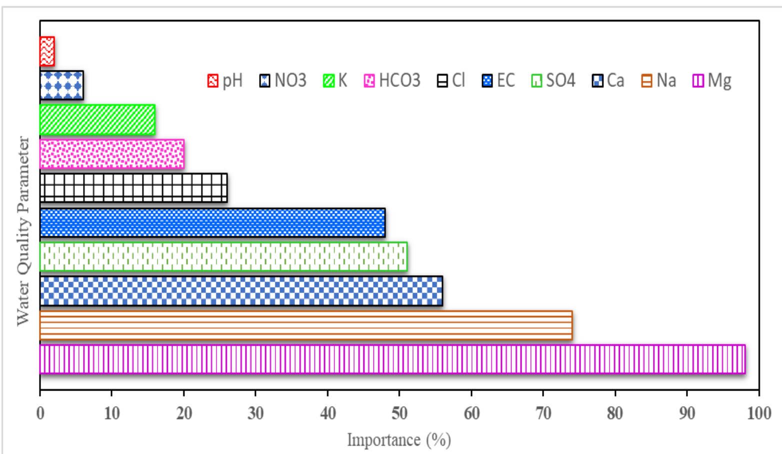

Figure 7. The importance of the independent variable diagram

The models obtained had high accuracy and low relative error; where the value of the coefficient of determination (R^2) was 0.984 for TDS, 0.952 for SAR, 0.918 for Na%, and 0.933 for MAR. Also, the estimated relative error was equal to 0.013, 0.034, 0.043, and 0.056 for TDS, SAR, Na%, and MAR respectively. So, from the results shown, it appears that these models are highly reliable.

4.3.2 Importance of the independent variables

The importance of the independent variables lies in measuring the variance of the model while predicting the output values. Figure 7 shows that Mg has the greatest influence on the method adopted in the prediction models, followed by Na, Ca, SO_4, EC, Cl, HCO_3, K, NO_3, and pH.

5. CONCLUSIONS

The Nile area is considered an agricultural area, so the quality of its groundwater is important for the growth of crops. The necessary indicators for irrigation water were studied, and the evaluation of the results showed that 2% of the samples fell into the undesirable category due to the exceedance of Na% values the 80%, and 67% of the samples fell into the undesirable category due to the exceedance of SAR values, the 26%. That means the undesirability of the groundwater for irrigation is due to the predominance of unsuitable SAR values, so this water is not suitable for irrigation. The future groundwater quality was also predicted using artificial neural networks, where a high determination coefficient value was reached with low relative error rates for the developed models. As a result, these models show a high prediction efficiency, and it was found that magnesium and sodium are found to be the most influential factors in predicting the model. Further refining the ANN models, exploring mitigation strategies for soil affected by poor-quality water, or investigating alternative water sources for irrigation are recommended for future research.

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NOMENCLATURE

Abbreviations

ANN	Artificial neural network
ANNs	Artificial neural networks
EC (μS/cm)	Electrical conductivity
MAR	Magnesium adsorption ratio

Meq.	Milli-equivalents
MSE	Mean square error
pH	Potential of hydrogen
SAR	Sodium adsorption ratio
SPSS	Statistical package for the social sciences
TDS (mg/L)	Total dissolved solids