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Estimation of irrigation water quality index in a semi-arid environment using data-driven approach

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ABSTRACT

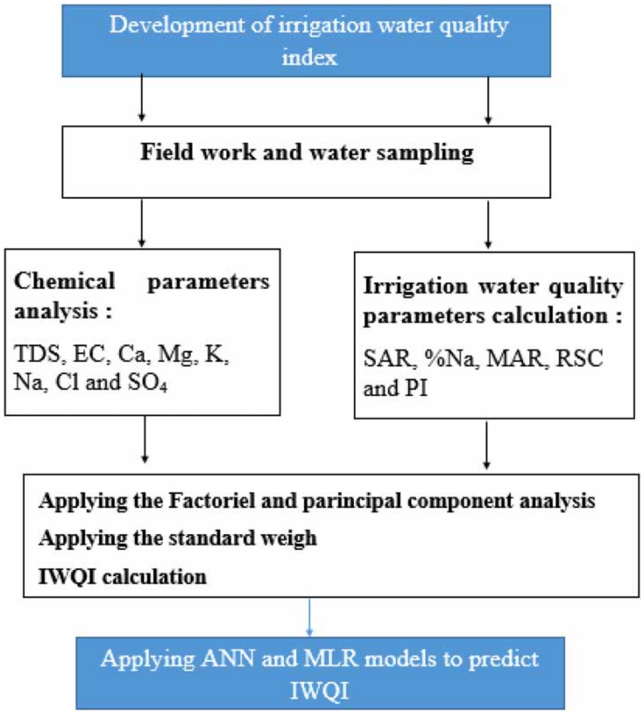
The primary objective of this study was to calculate and assess the irrigation water quality index. Furthermore, an effective method for predicting IWQI using artificial neural network (ANN) and multiple linear regression (MLR) models was proposed. The accuracy performance of each model was evaluated at the end of this paper. According to the calculated index based on 49 groundwater samples, the Sidi El Hani aquifer was of good and sufficient quality. Moreover, both the ANN and MLR models performed well in terms of actual and predicted water quality. The ANN model, on the other hand, demonstrated the highest prediction accuracy. The results of this model also revealed that the predicted and computed values were close, with determination coefficients R^2, RMSE, and MAE of about 0.95, 1.02, and 0.90, respectively. As a result, the proposed ANN model in this study was consistent and sufficient. These findings will help to guide irrigation water management decisions for the study aquifer in the future. The proposed ANN model can also be used to estimate the irrigation water index of other semi-arid aquifers, but accuracy is dependent on proper training techniques and selection parameters.

Key words: artificial neural network, irrigation water quality index, multiple linear regression, salinization, Sidi El Hani aquifer

HIGHLIGHTS

- Assessment of irrigation water quality (IWQI) index in a semi arid-environment.
- Prediction of IWQI using ANN model.
- Prediction of IWQI using MLR model.
- Effectiveness of a machine learning tool (ANN) in accurately predicitng of IWQI.
- Developing an accurate model may be valuable to manage the irrigation water quality.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Groundwater is an important component in many regions and locations around the world, and it plays an important role in the long-term development of various sectors. Unfortunately, groundwater quality has been severely degraded and threatened in recent decades as a result of a variety of factors such as rapid population growth, industrial and agricultural expansion, and climate change. These factors, in fact, reduce and destroy the value of aquifers as a source of water (Vaux 2011; Houéménou *et al.* 2020). Therefore, groundwater sustainability has become a major concern; the challenge is to protect these resources for future generations while also meeting the needs of many economic sectors, particularly agricultural systems (Elgettafi *et al.* 2013; Abdel-Fatteh *et al.* 2020).

Agriculture is the primary consumer of hydric resources worldwide, accounting for approximately 60% of available hydric resources, primarily in developed countries. Groundwater supplies, on the other hand, account for more than 90% of accessible resources in developing countries (Aliyu *et al.* 2017; Velasco-Muñoz *et al.* 2018). As a result, considering the quality of these resources for irrigation purposes is critical. The primary water quality concern in most irrigation situations is salinity content as well as soluble salt compositions (Zaman *et al.* 2018; Malakar *et al.* 2019; Mirzavand *et al.* 2020). A high salinity level can have a negative impact on crop yield, soil physical conditions, fertility requirements, and irrigation system performance (Adimalla 2018; Ramadan *et al.* 2019). Therefore, improving water quality is critical to ensuring the production of high-quality crops as well as the preservation of soil quality.

The sustainability of irrigation water quality is a growing field of study around the world. Indeed, various types of research have been carried out to thoroughly develop hydrochemical indices for evaluating irrigation water quality. Edmunds *et al.* (2003), for example, used geochemical and statistical approaches to define baseline concentrations to investigate groundwater's natural baseline quality. Li *et al.* (2013) used standard methods to assess groundwater quality in Pengyang county, China, including irrigation coefficient, sodium adsorption ratio (SAR), total alkalinity, and total dissolved solids (TDS). They also refined the approach for order preference by comparing it to the ideal solution model for full evaluation. Furthermore, many studies used a statistical technique to assess water quality. This method was crucial in assessing groundwater contamination and locating pollution sources. Venkatramanan *et al.* (2016) used statistical methods to identify the characteristics and variables influencing groundwater pollution in Miryang, Korea. The findings revealed that groundwater was impacted by salty water and nitrate pollution. Ettaib *et al.* (2017) analyzed the water quality of the Medjerda River using hydrographic techniques and the PHREEQC geochemical software, and its suitability for irrigation was determined based on its electrical conductivity (EC), SAR, and salt content. The study found that some points fell into the excellent to good and good to permissible irrigation water categories. The remaining ones, on the other hand, were labeled as questionable to unsuitable for irrigation, limiting river water use to plants. All of these techniques are incapable of producing generated data. As a result, significant efforts have been made to develop a water quality index (WQI). Karbassi *et al.* (2011), for example, created a WQI for the Gorganrood River based on a variety of river conditions and features, including geographical, hydrological, discharge rate, and pollution sources. Additionally, Singh *et al.* (2020) evaluated and studied the water quality of the Bharalu river using yearly datasets for its suitability for irrigation using the suggested entropy weighted for spatiotemporal variability. Furthermore, Parvez & Inayathulla (2020) developed a WQI for the upper Cauvery, Karnataka, India, by measuring five water quality parameters: pH, nitrates, chloride, EC, and fluoride.

IWQI, in particular, is a useful synthetic tool for arranging datasets. This index combines a number of physical and chemical variables, with a single number representing the level of water quality derived from a large number of water parameters (Mufeed *et al.* 2021). This method makes it very easy for planners to assess the quality and potential hazards of a water type based on a variety of factors (Muniz *et al.* 2020). Furthermore, IWQI allows for the evaluation and comparison of various water samples to avoid the negative impact on soil and plants (Abbasnia *et al.* 2018). The estimation of IWQI aids in lowering the cost of drilling wells for agricultural purposes in areas with high salinization of groundwater. As a result, it distinguishes between excellent groundwater areas for irrigation and those that are not (Maliki *et al.* 2020). Horton (1965) proposed the first modern IWQI, which sparked several types of research around the world. Among these studies, however, the calculation of IWQI varied from one researcher to the next. Meireles *et al.* (2010), for example, used multivariate statistical analysis to create a new IWQI tailored to the Brazilian context. This index considered five variables: EC, sodium, chloride, bicarbonate, and sodium adsorption ratio. Simsek & Gunduz (2007) also used a new GIS-integrated tool to evaluate irrigation water quality in relation to soil and crop problems. This index considered five hazard categories: salinity, infiltration and permeability, specific ion toxicity, trace element toxicity, and miscellaneous impact on sensitive crops. Furthermore, Misaghi *et al.* (2017) used a national sanitation foundation water quality index (NSFWQI) to evaluate irrigation water quality requirements (Ghezel Ozan River, Iran), which included seven chemical parameters: EC, sodium, chloride, pH, bicarbonate, sodium adsorption ratio, and TDS.

Recently, the intelligent approach has been widely used for assessing water quality in several research studies owing to its relevance to find a solution to a complex problem and to underline the relationship between input and output data. The intelligent approach is made up of several models, the most common of which are artificial neural networks (ANNs), which can adapt to any intermittent change. Abbaa *et al.* (2017), for example, used a combination of multilinear regression, ANN, and adaptive neuro-fuzzy interference system tools to forecast the dissolved oxygen concentration downstream of Agra city. Similarly, Khudair *et al.* (2018) assessed groundwater quality for drinking purposes in Baghdad using an ANN model. Furthermore, Alves *et al.* (2018) proposed a new alternative approach to determining the water quality index that combines ultra-visible spectrophotometry with an ANN. This combined approach may enable the prediction of WQI in areas where there is no infrastructure to assess WQI using traditional methods and to monitor water in real-time. Several studies have demonstrated the reliability of ANN in comparison to other tools; however, the ability of ANN approaches to predict IWQI has not been compared to conventional regression methods such as MLR.

In a similar context, the shallow Sidi El Hani aquifer, located in a semi-arid region of central-eastern Tunisia, is the primary source of water for irrigation. Nonetheless, over the past few decades, the measured salinity of this aquifer has risen from 6 g/l to 8 g/l, potentially leading to a reduction in agricultural production and, as a result, an economic downturn in the medium term. M'nassri *et al.* (2016) conducted a previous study in which they assessed the level of physical and chemical parameters in the investigated aquifer and mapped them using a GIS tool to evaluate their spatial distribution. In comparison to previous studies, none has presented data on IWQI and their prediction using ANN and MLR models. Hence, the purpose of this paper is to calculate the IWQI to assess the Sidi El Hani aquifer for irrigation purposes, using the methodology proposed by Meireles *et al.* (2010). In addition, we propose a method for predicting IWQI using ANN and multiple linear regression (MLR) models. The accuracy of predicted and computed IWQI values is then assessed using these two models. The findings will be useful as a biased technique for monitoring and predicting water quality change, allowing for better water resource management, planning, and decision-making regarding available resources, particularly in arid and semi-arid regions.

2. MATERIALS AND METHODS

2.1. Study area description

The Ouled Chamkeh plain is located in the Mahdia region, between the latitudes of 10°10′ and 10°25′ east and 10°12′ and 35° 35′ north (Figure 1). This plain has a total area of 346 km^2. The study area is bounded to the north and northeast by the sabkha of Sidi El Hani, to the east by the wadi Cherita, to the south by the sabkha of Cherita and the Ktitr Mountain, and to the west by the El Guessat Mountain. The research area has a mean annual precipitation of 270 mm and an evapotranspiration rate of 1,500 mm/year, making it a semi-arid region (INM 2016). Mio-Plio-Quaternary sediments cover the investigated area. These formations' lithstratigraphic sequence is as follows: (i) Holocene deposits of clays, sands, silts, and evaporates; (ii) Pleistocene deposits of sand, halite hard limestone, silts, and soft white limestone with a thickness of about 120 m; and (iii) Mio-Pleistocene deposits of sand with an interlayered 50 m thickness. (Tagorti *et al.* 2013; M'nassri *et al.* 2019a). The shallow aquifer of Sidi El Hani is the main source of water in this area. The depth of this aquifer ranges from 3 m at the eastern of the area up to 26 m in the centre. The groundwater flow direction is from the west to the sabkha Sidi El Hani in the north-east and to the sabkha Cherita in the south (M'nassri *et al.* 2019b). The study area's economy is primarily based on agricultural activities, with more than 70% of the total area under cultivation. The main crops cultivated are olives and cereals.

2.2. Sample collection and laboratory analysis

During the field studies conducted in March 2015, 49 groundwater samples were collected (Figure 2). A multi-parameter portable quality meter was used to measure hydrogen ion activity (pH), temperature (T), and EC *in situ*. The samples were then kept at a temperature below 4 degrees Celsius until they were analyzed in the laboratory. The chemical analyses were carried out in accordance with the American Association of Public Health's standard methods (APHA 1995). Atomic absorption spectrometry was used to determine the concentrations of sodium and potassium. The titrimetric method was used to measure calcium and magnesium. The Mohr method was used to dose chloride concentrations. Titration with H_2SO_4 was used to determine bicarbonates. Colorimetric analysis was used to determine sulfate concentrations. TDS were determined by evaporating a pre-filtered sample until it was dry. The charge balance error for the samples was within the acceptable limit of 5% (Freeze & Cherry 1979), confirming the results' accuracy. Furthermore, using the Equations (1)–(5) shown in Table 1, a set of fundamental parameters characterizing irrigation water quality, including SAR, percent Na, MAR, RSC, and PI, were

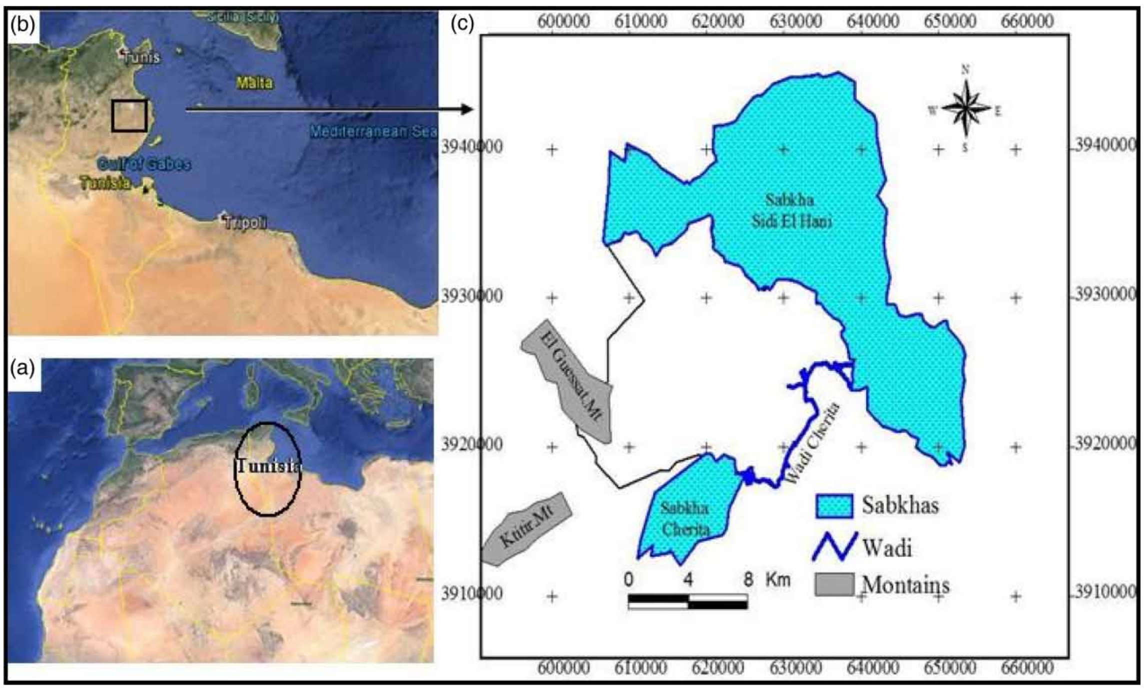


Figure 1 | Location of the study area.

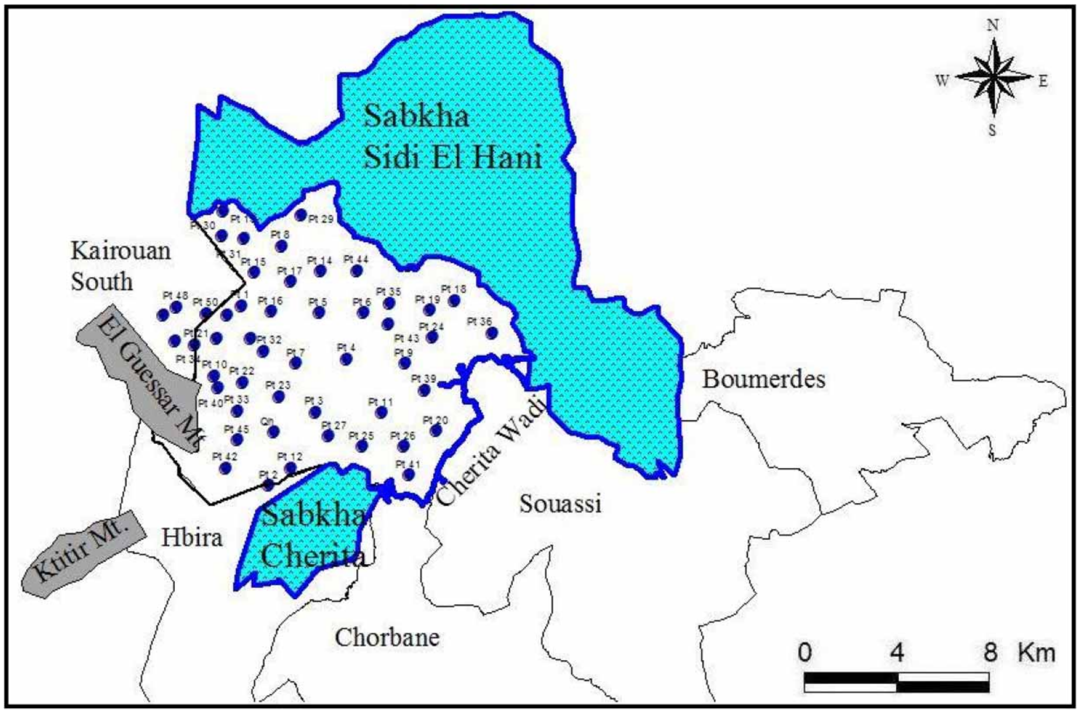


Figure 2 | Location of water samples.

Table 1 | Calculated water quality parameter based on measured parameters

Quality parameter	Formula adopted	Reference
Sodium adsorption ratio	$SAR = \frac{Na}{\sqrt{\frac{Ca+Mg}{2}}}$ (1)	Richards (1954)
Percentage of sodium	$\%Na = \frac{Na+K}{Na+K+Ca+Mg} \times 100$ (2)	Eaton (1950)
Magnesium adsorption ratio	$\mathrm{MAR} = \frac{\mathrm{Mg}}{\mathrm{Mg}+\mathrm{Ca}} * 100$ (3)	Raghaunth (1989)
Residual sodium carbonate	$\mathrm{RSC} = [(\mathrm{HCO_3} - \mathrm{CO_3}) - (\mathrm{Ca} + \mathrm{Mg})]$ (4)	Raghaunth (1989)
permeability index	$\mathrm{PI} = \frac{\mathrm{Na} + \sqrt{\mathrm{HCO_3}}}{\mathrm{Ca}+\mathrm{Mg}+\mathrm{Na}} \times 100$ (5)	Doneen (1964)

calculated based on measured parameters. SAR and percent Na values that are too high reduce soil hydraulic conductivity and irrigation efficiency. If the SAR and percent Na are both greater than 10 meq/L and 80 percent, the water is deemed unfit for irrigation. The MAR ratio (Equation (3)) emphasizes the importance of magnesium for soil and plant health. It is considered an essential component when the MAR is less than 50. The RSC also emphasizes the abundance of carbonates and bicarbonates. These elements can have an effect on soil fertility when the RSC exceeds 1.5 meq/l. The PI was calculated using Equation (5). As a result, three classes were maintained. Good irrigation water suitability is defined as Classes I and II, with a maximum of 75%. Class III, on the other hand, includes points with a PI of less than 25% and water unfit for irrigation (M'nassri *et al.* 2018).

2.3. Computation of IWQI

The IWQI was a critical parameter for determining the impact of various water parameters on water quality and thus the suitability of the water for irrigation purposes (Shabbir & Ahmad 2015; Darvishi *et al.* 2016; Adimalla 2018). The IWQI was divided into five categories: (i) excellent, (ii) very good, (iii) good, (iv) satisfactory, and (v) inappropriate (Table 2). It was computed in four stages (Abbasnia *et al.* 2018; Asadi *et al.* 2020; Yildiz & Karakus 2020). To begin, principal component and factor analysis (PC/FA) was used to identify the parameters that contribute to the variability of water irrigation. In this regard, the principal component chosen should have an eigenvalue greater than one (Jiang *et al.* 2009). These variables are determined by these factors, and the large dataset is reduced for easy interpretation. The Kaiser-Meyer-Olkin index (KMO), which should be greater than 0.5, and the Bartlett sphericity test were used to determine the adequacy of the selected factors (Kaiser 1960). Second, using Equation (6), the weight values (w_i) were normalized and their final sums equaled one (Meireles *et al.* 2010).

$$w_i = \frac{\sum_{j=1}^{k} F_j A_{ij}}{\sum_{j=1}^{k}\sum_{i=1}^{n} F_j A_{ij}} \tag{6}$$

where w_i is the parameter's weight, F is the component 1 autovalue, A_{ij} is the explainability of parameter I by factor j, i is the number of physical-chemical parameters chosen by the model, ranging from 1 to n, and j is the number of factors chosen in the model, ranging from 1 to k. The water quality measurement parameter value (q_i) was then calculated using Equation (7).

$$q_i = q_{max} - \left(\frac{(X_{ij} - X_{inf}) \times q_{iamp}}{X_{iamp}}\right) \tag{7}$$

where q_{max} is the maximum value of q_i for the class, X_{ij} is the observed value, X_{inf} is the lower limit of the class to which the parameter belongs, q_{iamp} is the class amplitude, and X_{iamp} is the class amplitude to which the parameter belongs. The X_{amp} of the final class of each parameter was calculated by taking the highest value of physicochemical sample analyses as the upper limit. Finally, Equation (8) was used to calculate the IWQI.

$$IWQI = \sum_{i=1}^{n} q_i\, w_i \tag{8}$$

where IWQI is a dimensionless parameter ranging from 0 to 100, q_i is a measurement parameter ranging from 0 to 100, and w_i is the normalized weight of the i^{th} parameter.

2.4. ANN model

The ANN application created connections between inputs and outputs. The artificial neurons received weighted inputs through the neural structure, combined them, and then used the nonlinear operation to produce the output in the second step (Ehteshami *et al.* 2016; Foddis *et al.* 2019). The ANN is commonly referred to as a multi-layer perceptron (MLP), which can be either feedforward or feedback (Çelik *et al.* 2016). Different algorithms are used to train the MLP, the most popular of which is the back propagation algorithm (Qaderi & Babanejad 2017).

The ANN was used in this study to forecast IWQI values in 49 wells. The physicochemical parameters with a high load in the first component obtained from AF/ACP analysis were the neural network's final input and were used to predict IWQI.

Table 2 | The range and type of irrigation water for IWQI (Zahedi 2017)

IWQI range	Water type
85 – 100	Excellent
70–85	Very good
55–70	Good
40–55	Satisfactory
0–40	Unsuitable

This study's MLP had only one hidden layer, which was a universal approximation for MLP (Cybenko 1989). Following the selection of appropriate explanatory variables for the IWQI variation, the database was divided into two groups: 70% of the data (34 samples) were used for training, and 30% (15 samples) were used for testing. In the second step, all of the input data should be normalized using Equation (9) to improve the ANN model's performance. Various training sets were run until the target error between forecasted and measured output values was minimized.

$$\mathrm{X_{nor}} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{9}$$

where X and X_{nor} denote original and normalized values, respectively, and X_{max} and X_{min} denote minimum and maximum value in the series.

2.5. MLR model

In this study, regression modeling is used to identify and quantify the importance of each variable on the independent variable based on AF/ACP results. The MLR established a linear relationship between the dependent variables, which were predicted, and the independent variables, which were referred to as predictors (Abyaneh 2014; Chen & Liu 2015). MLR was used to identify the least significant variables to eliminate heavy multicollinearity (Abbaa *et al.* 2017). The best MLR model, as expressed by Equation (10), was distinguished by a low sum square error between observed and predicted parameters.

$$\mathrm{Y = b_0 + b_1X_1 + b_2X_2 + \ldots b_iX_i} \tag{10}$$

where X_1 denotes the value of i^{th} predictor, b_0 represents the regression constant, and b_i denotes the coefficient of the i^{th} predictor.

In the final stage of this framework, the ANN results were compared to those of the MLR model to assess the prediction model's accuracy. As a result, statistical indices such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were calculated using Equations (11)–(13), respectively. The SPSS (Statistical Package for the Social Sciences version 20) software was used for all modeling and statistical analysis processes in this research paper.

$$R^2 = 1 - \frac{\sum (X_0 - X_t)^2}{\sum (X_t)^2} \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (X_0 - X_t)^2} \tag{12}$$

$$\mathrm{MAE} = \frac{\sum |X_0 - X_t|}{n} \tag{13}$$

where X_0 and X_t denote the predicted and observed values and n represents the total number of observed data.

The flow chart below depicts the methodology used to develop the IWQI, ANN, and MLR models (Figure 3).

3. RESULTS AND DISCUSSION

3.1. Physical and chemical characteristics of irrigation water

Table 3 shows the minimum, maximum, mean, and standard deviation of TDS, EC, pH, major ions (Ca^{2+}, Mg^{2+}, Na^+, K^+, HCO_3^-, Cl^-, and SO_4^{2-}), and qualitative parameters like SAR, percent Na, MAR, RSC, and PI for all 49 samples. In this study, the ions concentration and calculated parameters are compared to the Food and Agriculture Organization's (FAO) criterion for agricultural purposes proposed by Ayers & Westcot (1994) and the classification proposed by the University of California (Doneen 1964). TDS levels in this study range from 2,400.0 to 8,410.0 mg/l, with a mean and standard deviation of around 4,280.0 and 1,493.0 mg/l, respectively. According to FAO guidelines, because all of the samples have TDS values greater than 2,000 mg/l, the water is subject to severe restrictions on its use in irrigation. Likewise, EC ranges from 3.75 to 12.00 mS/cm, with a mean of 6.10 mS/cm. All of the samples are classified as severe (>3 mS/cm). The use of this irrigation water may result in serious problems such as high soil salt levels, which can interfere with plant water absorption and have a serious negative

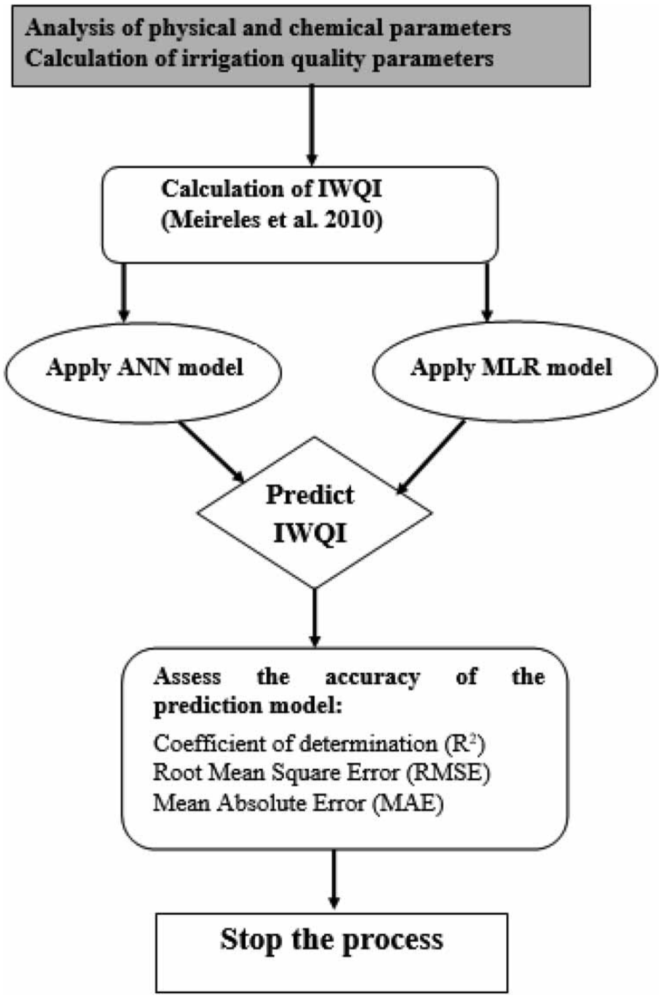


Figure 3 | Flow chart architecture of the methodology that was adopted to predict IWQI.

Table 3 | Summary statistics of physical, chemical and qualitative parameters

Parameter	Min.	Max.	Mean	S.D*	FAO usual range in irrigation water
TDS (mg/l)	2,400.0	8,410.00	4,280.00	1,493.00	<2,000
EC (mS/cm)	3.75	12.00	6.10	1.96	<0–3
pH	6.88	8.50	7.70	1.96	–
Ca^{2+} (meq/l)	7.50	35.00	16.45	5.59	<20
Mg^{2+} (meq/l)	5.00	38.00	17.00	8.49	<5
K^{+} (meq/l)	0.36	1.80	0.66	0.28	<0.05
HCO_3^- (meq/l)	2.00	8.00	5.00	1.80	<10
Na^{+} (meq/l)	17.86	63.56	36.29	11.92	<40
Cl^{-} (meq/l)	20.46	75.12	39.48	13.01	<30
SO_4^{2-} (meq/l)	13.28	57.00	28.75	9.45	<20
SAR	5.03	16.41	8.24	2.89	–
%Na	31.85	72.00	49.98	8.78	–
MAR	25.00	73.53	47.67	12.35	–
RSC	−64.00	−14.00	−29.50	11.52	–
PI	33.33	74.45	52.11	8.96	–

impact on plant growth (Kumar & Shrivastava 2015). Furthermore, pH values range from 6.88 to 8.50, indicating neutral to slightly alkaline water, and all samples fall within the FAO's normal range of pH values (Ayres and Westcot).

The calcium content of the groundwater in the study area ranges from 7.50 to 35.00 meq/l, with a mean of 16.45 and a standard deviation of 5.59 meq/l. Furthermore, magnesium values range from 5.00 to 35.00 meq/l, with a mean value of 16.45 meq/l. These chemical parameters are primarily associated with the weathering of carbonate minerals such as calcite and dolomite, as well as chemical fertilizer leakage (M'nassri *et al.* 2019a; Aminiyan & Aminiyan 2020). According to FAO guidelines, the calcium levels in the groundwater samples are within an acceptable range (40 meq/l), making them suitable for irrigation (Ayers & Westcot 1994). The magnesium content in all samples, however, exceeds the FAO value limit of 5 meq/l. The potassium and bicarbonates concentrations range from 0.36 to 1.80 meq/l and from 2.00 to 8.00 meq/l, respectively. The maximum concentration of K^+ is above the FAO recommended value (<0.05 meq/l). The K contents in groundwater have probably originated from agriculture fertilizers (Bekkoussa *et al.* 2013). Nevertheless, as per the FAO standard guideline for HCO_3^- (Ayers & Westcot 1994), all samples fall within the recommended permissible values for irrigation purposes (<10 meq/l).

As noted in Table 3, Na and Cl concentrations range from 17.86 to 63.56 meq/l and 20.46 to 75.12 meq/l, respectively. Previous studies (M'nassri *et al.* 2018, 2019a, 2019b) revealed that Cl and Na are the dominant ions in the groundwater of the studied area. They have several origins such as rock weathering and irrigation return flow. The usual levels of Cl and Na in irrigation water range from 0 to 30 and 0–40 meq/l, respectively (Ayers & Westcot 1994). In our study, nearly 80% of the samples exceed the permissible range for Cl; however, 37% of the samples have Na concentrations above 40 meq/l. It is acknowledged that the increase in Cl concentrations in irrigation water may affect crop growth and reduce productivity. As for Na contents, high levels lead to Na-soil exchange and, hence, generate soil dispersion as well as permeability reduction (Holgate *et al.* 2011). Table 3 also indicates that sulphate concentrations vary between 13.28 and 57.00 meq/l, with a mean value of 28.75 meq/l. Almost 85% of groundwater samples exceed the recommended range of sulphate for irrigation water (Ayers & Westcot 1994). High SO_4^{2-} contents in irrigation water may generate soil saturation with gypsum and, thus, clog the pores. These changes may affect the physical characteristics of the soil such as permeability and aeration (Prapadopoulos 1984).

Table 3 also reports the qualitative parameters of the irrigation water. SAR computed values range from 5.03 to 16.41, with a mean and standard deviation of approximately 8.24 and 2.89, respectively. M'nassri *et al.* (2016) revealed that all the samples have a SAR value ranging between 0 and 18 categorized them as 'excellent' and 'good' classes for irrigation. As per % Na, the calculated values vary between 31.85 and 72.00. A higher percentage of Na (>60%) can lead to soil physical properties deterioration (Palanisamy *et al.* 2020). In turn, MAR values range from 25.00 to 73.53. The permissible limit of MAR for irrigation water is 50 (Doneen 1964). In our studied area, 59% of the samples have a MAR value above 50 and, thus they are unsuitable for irrigation. The RSC and PI computed values range from −64.00 to −14.00 and 33.33 to 74.45, respectively. In terms of their MAR values, all the samples are appropriate for irrigation.

3.2. IWQI assessment

In the current study, The FA/ACP was applied to 49 samples and 15 variables, including TDS, CE, pH, Ca^{2+}, Mg^{2+}, Na^+, K^+, HCO_3^-, Cl^-, SO_4^{2-}, SAR, %Na, MAR, RSC, and PI. The KMO adequacy test and the Bartlett sphericity test indicate that the value are greater than 0.5 and lower than 0.001, respectively. Hence, the performed factorial model is adequate for this study. Based on the eigenvalue, which should be greater than 1, four factors are selected (Table 4). The first factor, C1, expressed more than 35.58% of the total variance. The second factor, C2, has a variance of 27.57%. However, C3 and C4 factors have a variance of 11.15% and 9.63%, respectively. It should also be noted that the cumulative variance of the load factors is 83.94%.

As indicated in Table 5, C1, which represents the important factor affecting water quality, is strongly correlated with Cl-, TDS, EC, SO_4^{2-}, Mg^{2+}, Na^+, and MAR as follow: Cl^- (0.87), TDS (0.86), CE (0.83), SO_4^{2-} (0.81), Mg^{2+} (0.79), Na^+ (0.75), and MAR (0.60). The C1 factor is introduced as the 'salinity' component. The second factor has a strong correlation with %Na, Na^+, SAR, and PI. C2 is considered a 'sodicity' component. The factor C3 has a significant loading value with Ca^{2+} (0.82), but C4 has a correlation with pH (0.69) and HCO_3^- (0.82). All of these variables are unrelated to C1. The C3 and C4 factors are considered as 'alkalinity' components.

In the current research, the computation of the IWQI is based on the parameters that have a good load in the first component such as Cl^-, TDS, EC, SO_4^{2-}, Mg^{2+}, Na^+, and MAR. C1 is considered as the most significant component that explains the global variability in irrigation water quality. The limiting values of the physicochemical parameters considered

Table 4 | Percentage of selected components

Selected component	Without rotation			Rotation of component		
	Eigenvalue	% total of variance	% of cumulative variance	Eigenvalue	% total of variance	% of cumulative variance
C1	5.51	36.73	36.73	5.33	35.58	35.58
C2	4.31	28.79	65.52	4.13	27.57	63.16
C3	1.64	10.94	76.47	1.67	11.15	74.31
C4	1.12	7.47	83.94	1.44	9.63	83.94

Table 5 | Component loads for the physicochemical parameters

Parameters	Component loads matrix			
	C1	C2	C3	C4
TDS (g/l)	0.86	0.14	0.04	0.20
CE (mS/cm)	0.83	0.23	0.14	0.19
pH	0.33	0.02	−0.06	0.69
Ca^{2+} (meq/l)	0.33	−0.39	0.82	0.03
Mg^{2+} (meq/l)	0.79	−0.51	−0.27	0.06
Na^{+} (meq/l)	0.75	0.89	0.12	0.16
K^{+} (meq/l)	0.22	0.04	0.32	0.15
HCO_3^{-} (meq/l)	−0.08	0.22	0.20	0.82
Cl^{-} (meq/l)	0.87	0.14	−0.01	0.19
SO_4^{2-} (meq/l)	0.81	−0.10	0.27	−0.23
SAR	0.37	0.89	0.07	0.13
%Na	0.02	0.98	−0.02	0.08
MAR	0.60	−0.31	−0.77	0.04
RSC	−0.76	0.45	−0.17	0.06
PI	−0.05	0.78	−0.03	0.12

in the calculation of IWQI are determined on the basis of the FAO's recommended usual range in irrigation water (Ayers & Westcot 1994) and of the classification proposed by the University of California (Doneen 1964). Furthermore, the weight values are estimated based on the variance of the first component related to its explainability towards each parameter. The normalized weight values are presented in Table 6.

Table 6 | Calculated relative weight of each parameter

Parameter	Weight
Cl	0.158
TDS	0.156
CE	0.151
SO_4^{2-}	0.146
Mg^{2+}	0.142
Na^{+}	0.135
MAR	0.112
Total	**1.000**

The IWQI computed values range from 19.29 to 55.41. About 40% of samples fell to a good category, and the rest of the samples are satisfactory. The last class can be used for coarse-textured soils that are characterized by high permeability (Abbasnia *et al.* 2018). In addition, the water can be applied only for plants with high salinity tolerance and with special salinity control practice, except for water with low Na, Cl, and HCO_3 values (Yildiz & Karakus 2020).

3.3. ANN and MLR analysis and modeling

In the development of the ANN model, several different ANN architectures, weights, and parameters are explored until the error between modelled and measured output values dataset was minimized. In this study, a model with three neurons in the hidden layer shows the best results. Consequently, the network architecture selected is composed of seven input layers, a hidden layer that contains three neurons, and an output layer with one neuron. The final trained weights and biases of a random train with the optimum parameters are illustrated in Table 7.

The IWQI predicted results using the ANN model reveal a good fit between them and the observed values. Table 8 shows that R^2 values are found to be very close to one; nevertheless, the RMSE and MAE results are close to zero, with values of 1.02 and 0.90, respectively, indicating the performance training of the ANN model. Furthermore, as noted for the MLR model, the obtained results were expressed by Equation (14). The performance criteria values of the MLR model, shown in Table 7, reveal that R^2 is found to be 0.81. Additionally, MSE and MAE values are in the range of 1.20 and 1.63, respectively.

$$\mathrm{Y} = 6.269 + 0.60Cl + 1.09TDS + 3.04EC - 0.80Mg + 1.71Na + 0.44SO4 + 1.36MAR \quad (14)$$

Additionally, the relationships between observed values and computed values generated from the ANN and MLR models, shown in Figure 4(a) and 4(b), indicate that several points lie on or close to the straight line. The R^2 value is found to be 0.928 in the ANN model prediction; however, it is in the range of 0.818 in the MLR model prediction.

Table 7 | Final trained weights and biases in the control run

	Weights and biases in the input-hidden layers		
	N1-1	**N1-2**	**N1-3**
Cl	−1.45	0.27	−0.21
TDS	−0.62	−0.06	−0.01
EC	−0.54	0.78	−1.43
SO4	−0.78	−1.15	−0.21
Mg	−0.57	0.14	−0.70
Na	−1.96	−1.12	0.76
MAR	−0.61	−0.11	0.46
Bias	1.09	0.27	0.17
	Weights and biases in the hidden-output layer		
IWQI	−2.15	−0.94	2.66
Bias	− 0.39		

Table 8 | Criteria for assessing the predictive validity of the ANN and MLR models

Statistical criteria	ANN	MLR
R^2	0.92	0.81
RMSE	1.02	1.20
MAE	0.90	1.63

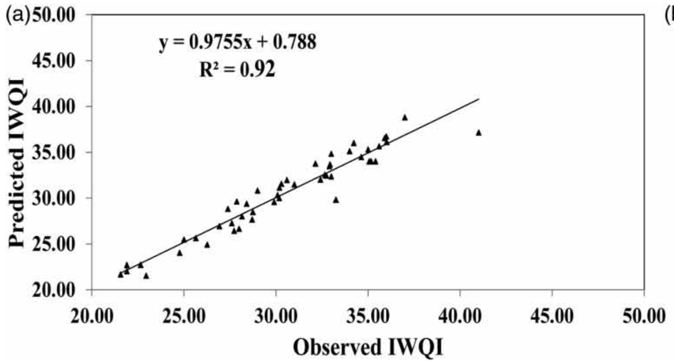


Figure 4 | Correlation between predicted and observed IWQI values with (a) the ANN model; (b) the MLR model.

On the other hand, the comparison between the IWQI observed values and the ANN and MLR prediction results for all samples is revealed in Figure 5. It is clear that the ANN predicted values of IWQI are nearer to the observed values compared to the MLR predicted values, thus suggesting the consistency and adequacy of the proposed ANN model. Based on these findings, the ANN modeling approach can be applied as a predictive tool to point up the most appropriate values of IQWI under various anthropogenic and natural factors affecting water quality and, hence, it is promising for modeling monthly water quality efficiency by integrating the time series analysis.

Based on these findings, the use of groundwater of the Sidi El Hani basin, which is mostly in the poor water class, for irrigation purposes is very hazardous for soil and plants. Indeed, the most significant salinization source in this region is agricultural activities. Therefore, potential measures should be implemented to avoid soluble salts leaching that threaten water quality. This situation should be performed by controlling the anthropogenic and natural factors that affect the water quality, such as soil characteristics, land use type, fertilizers, livestock number, and groundwater level. At this point, the developed ANN model promise for modeling monthly water quality efficiency by integrating the time series analysis of the factors distressing the irrigation water quality. This suggestion allows, thus, for better monitoring of salt leaching, and sustainable management of groundwater.

4. CONCLUSION

In arid and semi-arid regions, groundwater is commonly the only source of irrigation. Therefore, knowledge and assessment of the irrigation water quality index are helpful tools to manage water resources. The current study aims to determine the IWQI of Sidi El Hani aquifer, located in central-eastern Tunisia, and to predict this index, using the ANN and MLR models to highlight the most adequate predicted values. The sufficient model can be generalized to other regional territories that are dominated by an arid or semi-arid climate and thus contribute to the sustainable use and management of water resources.

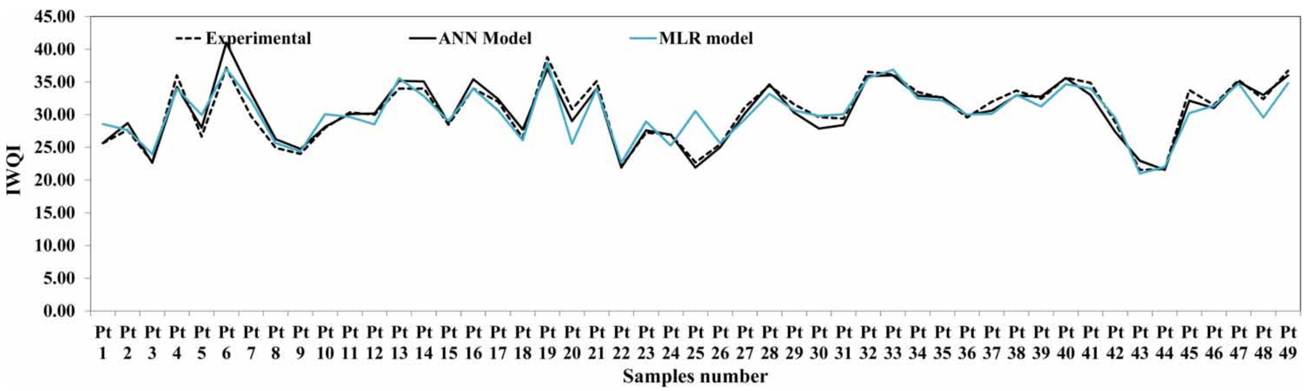


Figure 5 | Observed ANN and MLR results of IWQI for all samples.

Furthermore, the ANN modeling results show that the model has a good determination coefficient (R^2) that is equal to 0.92. The RMSE and MAE are also found to be 1.02 and 0.90, respectively. Additionally, the MLR model provides a satisfactory IWQI forecast. The statistical indicators such as R^2, RMSE, and MAE are about 0.81, 1.20, and 1.63, respectively. Nevertheless, the comparison between computed IWQI and predicted values, with the ANN and MLR models, shows that the ANN model seems to prove its prediction sufficiency. Thus, based on these results, more exhaustive monitoring and implemented management practice of groundwater in the Sidi El Hani aquifer are compulsory.

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ADDITIONAL INFORMATION

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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