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Development of Irrigation Water Quality Index Using Artificial Neural Network

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Abstract:

The data-driven Artificial Intelligence (AI) techniques revealed specific relevance for the treatment of nonlinear relations and predicting the behaviour of complex systems, as a promising application in hydrology and water quality problems. The goal of this study is to build a developed model to forecast the quality of irrigation water by estimating its Water Quality Index using Artificial Neural Network (ANN). The developed model is applied to predict a data-based Irrigation Water Quality Index (IWQI) for groundwater usability in a desert reach pilot area in Egypt. The raw data for the model were the results of the main ion-causing irrigation hazards: (Salinity & Infiltration rate& Specific Toxics and Miscellaneous effects) for seventy-seven groundwater samples. The effectiveness of the model was achieved through the standardized coefficient of input variables. Revealing that the developed ANN model has a high agreement between measured and calculated IWQI (R^2= 0.963, RMSE=0.0693) and becomes satisfactory verified for predicting the overall quality of groundwater in the research region, which is based on individual measurements rated according to their sensitivity. Moreover, the newly developed model can overcome the problem of missing some sample index parameters when one or more of the parameters are missing.

Keywords: Irrigation Water Quality Index, Prediction, Artificial Neural Network, regressions, groundwater.

1. Introduction

The use of a single measure to evaluate water quality is ineffective in expressing the total water quality for any one water body. One of the most efficient methods for combining measured quality parameters into meaningful values are Water Quality Indices (WQIs) that show the suitability of considered water resources for various uses in a simplified and logical format. The WQI is a dimensionless value accustomed to describing the overall status of water quality based on a set of variables and/or specific sub-indices that depict the composite

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integrative effects of the parameters on the status [1]. The use of the water quality index and conventional statistical methods for its determination are unsatisfactory due to the nonlinear relationships between water quality parameters and the multivariate nature of their temporal and spatial variations. Alternative, more pertinent methods must be substituted.

Many researchers discussed the water quality-related problems in irrigated agriculture such as Ayers and Westcot [2]; water quality problems in agriculture irrigated systems are subdivided into four categories. Firstly, High salinity causes a reduction of uptake water and a decrease in plant growth rate. Secondly, decreasing rate of water infiltration: caused by relatively high sodium or low calcium content, high sodium content tends to be adsorbed on soil and inters into a cation exchange reaction with calcium and magnesium reducing soil drainage and permeability. The restriction of irrigation due to high sodium content relative to calcium is estimated by the Sodium Adsorption Ratio Index (SAR) [3]. Thirdly, Specific ion toxicity is initiated by a high level of certain ions (e.g., Na, Cl, B) which may lead to crop damage and yield reduction. Fourthly, miscellaneous effects: caused by excessive nutrients which may reduce yield or degrade quality. The continuous usage of high HCO_3 water for irrigation may lead to the deposition of limes or calcite in soil reducing production and leading to increase in the soil SAR index and the potential for hydrogen.

In addition, several methods and variant parameters or indexes have been adopted to measure the restriction of irrigation water use under one or more of the indicated four groups of water quality problems. Single individual hydrochemical or physical parameters (Na^+, Cl^-, EC, TDS, pH, HCO_3, Mg, B..) or specific indexes (SAR, PI, KI, RSC, PS….) have been developed through the years to measure the irrigation water quality by comparison against classifying limits established as standard guidelines, among the most used is the FAO [4].

Water consumption in Egypt is increasing the country's growing population and rising standard of living and national programs for agricultural and industrial development. Egypt currently faces a water resource shortage which is expected to worsen over time. The agricultural sector is the largest water consumer, accounting for more than 85 % of Nile water consumption. A country plan is put to balance the fertile lands lost by fertilization, through the expansion of agricultural areas in the desert areas, securing groundwater resources sufficient in quantity and adequate in quality is critical due to water irrigation hazards such as: (Salinity & Infiltration rate& Specific Toxics and Miscellaneous effects). The present work is concerned with quality terms of groundwater resources evaluation by determining and predicting the Irrigation Water Quality Index. Artificial intelligence (AI) models are currently used to predict system behavior that current methods cannot discover [5]. Over the past decade, artificial intelligence models have made significant progress in various hydrologically and geologically related fields, such as hydraulic conductivity estimation, groundwater prediction, water quality estimation and distribution, and groundwater vulnerability [6]. In order to minimize the uncertainty in the parameter evaluation process, artificial intelligence techniques adapted to nonlinear processing have recently been applied to water quality estimation. In recent years, artificial intelligence machine learning models have been increasingly used in research on water quality forecasting, hydrological processes, and reservoir operation. [7-15].

In general, machine learning models produce more accurate IWQI predictions than other indicators. ANN techniques have relevance to investigate in several areas including prediction, classification, data compression, optimization, and uncertainty evaluation. The present work is devoted to the objective of an example of ANNs' computational capability in creating a model that can accurately predict IWQI and usability of the groundwater, the developed model is introduced to improve and optimize the water quality parameters in a multivariate nonlinear relation through a neural network that is utilized for predicting the overall quality of groundwater directly.

The developed model is applied to predict a data based IWQI for groundwater usability in a desert reach pilot area in mid-upper Egypt. For reducing the input variables of the ANN network in the developed model, sensitivity analysis as a mathematical tool is used to study how changes in a model's output can be ascribed to changes in its inputs, to find the most relevant and highly significant parameters for the prediction of IWQI, utilizing the standardized coefficient of input variables. The newly developed model can overcome the problem of missing some sample index parameters when one or more of the parameters are missing.

1. Description of the study area

The region under study lies in the western desert reaches of the Nile valley, to the west of El-Minia Governorate in mid-upper Egypt, Figure 1. Its climate is arid and water resources are limited to groundwater that is mainly used for irrigation so the total water quality must be taken into inconsideration to avoid causing irritation hazards: (Salinity & Infiltration rate& Specific Toxics and Miscellaneous effects). Groundwater exists in two main aquifers (Quaternary alluvium and Eocene limestone) in the desert fringes and limestone plateau of the study region [16].

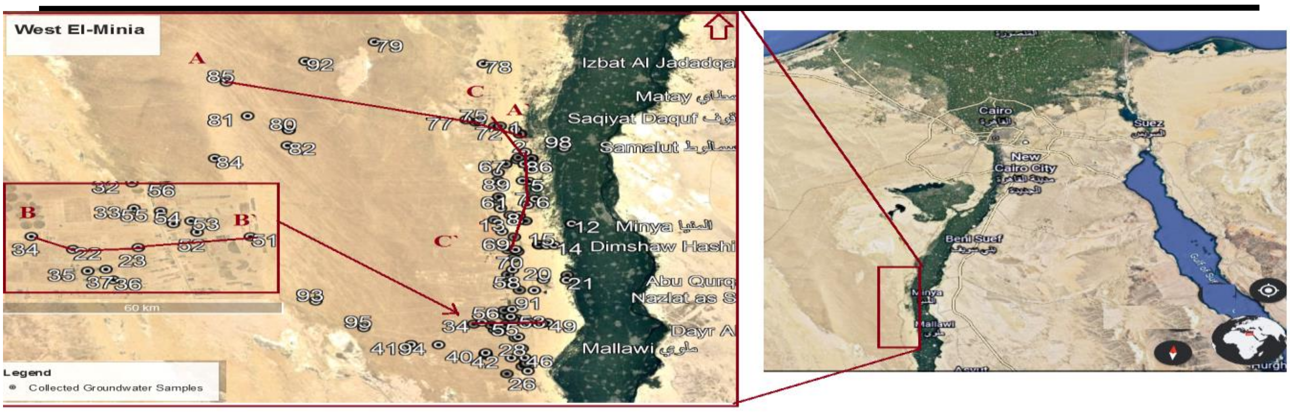

Figure 1. The location map for of the samples

2. Materials and Methods

2.1. Field and Laboratory Work

A field campaign has been conducted for tracing and following the major features that control the recharge and quality of the groundwater in the study area. Seventy-seven representative samples were gathered from the two aquifers with in-situ measurements of coordinates, EC, PH, and depth. The main ions (Ca, Na, Mg, Cl, K, SO_4 and HCO_3) have been determined according to [17]. The results are expressed in mg/l, epm/l, and epm%. The hydrochemical analysis has been conducted in the Central Laboratory of Isotope Hydrology, Egyptian Atomic Energy Authority.

2.2. Irrigation Water Quality Index (IWOI) Calculations

The results of the analysis of the collected samples used to calculate the overall IWOI by using the method described in the work of [18]; it facilitates the evaluation of the total integrative hazard caused by the major four problems: (Salinity, Infiltration Rate, Specific Toxic Hazards, and Miscellaneous Effects). The following five water quality parameters have been selected and used to treat the indicated four problems in the calculated (IWQI): Electrical Conductivity (EC), SAR, Na^+, Cl^- and HCO_3 Each of the five parameters is a set that has a weight value (W_i) that represents how much it controls irrigation suitability in the overall index, Table (1) [18]. The class limits and amplitudes of the indicated classification parameters are given in Table (2) [1]. Equation (1) is used for calculating parameter limiting values quality index (q_i) and equation (2) is used for calculating the overall IWOI.

Table 1: Parameters Weights for the IWQI, [18]

Parameter	Weight (Wi)
EC	0.211
Na	0.204
HCO_3	0.202
Cl	0.194
SAR	0.180
TOTAL	1

Table 2: Limiting Values of Parameter for Quality Measurement (q_i) Calculation.

qi	**EC (µS/cm)**	**SAR (meq/l)** $^{1/2}$	**Na^+**	**Cl^-**	**HCO_3-**
			(meq/l)		
85-100	200 ≤ EC < 750	SAR < 3	2 ≤ Na < 3	Cl<4	1≤ HCO3 < 1.5
60-85	750 ≤ EC < 1500	3 ≤ SAR < 6	3 ≤ Na < 6	4< Cl<7	1.5≤ HCO3 < 4.5
35-60	1500≤ EC <3000	6 ≤ SAR < 12	6 ≤ Na < 9	7< Cl<10	4.5≤ HCO3 < 8.5
0-35	EC < 200 or EC ≥ 3000	SAR ≥ 12	Na < 2 orNa ≥ 9	Cl ≥ 10	HCO_3< 1 orHCO_3≥ 8.5

Table 3: Water Quality Index Characteristics

value of WQI	Quality of water	Extent of pollution
90-100	Excellent	Clean
70-90	Good	Slight pollution
50-70	Medium	Moderate pollution
25-50	Bad	Excess pollution
0-25	Very bad	Sever pollution

$$q_i = q_{imax} - [\frac{(x_{ij}-x_{inf})*q_{iamp}}{x_{amp}}] \quad (1)$$

Where : $q_{imax}$is the maximum value of q_i for the class; x_{ij} is the observed value for the parameter; x_{inf} is the corresponding value to the lower limit of the class to which the parameter belongs; $q_{iamp}$is class amplitude; x_{max} is class amplitude to which the parameter belongs. As stated in Table (2), each parameter weight used in the IWQI was taken from [18]. The W_i values were normalized to the point where their sum equals one.

$$\text{IWQI}= \sum_{\text{i}=1}^{\text{n}} q_i * W_i \qquad (2)$$

3.3 The New Developed Model

The Artificial Neural Network combines several modeling architectures, the most extensively used of them are the feed-forward neural network, Multi-Layer Perceptron (MLP) as back-propagation network math Works, Massachusetts, USA [19]. In this work, we used MATLAB computing environments for developing a new model that to predict IWQI in the study area. The developed model introduces a convenient measure of irrigation usability of groundwater based on combined water quality parameters, with an account of their nonlinear relations and multi-variation. Moreover, it is used to find the most relevant parameters in the prediction of IWQI, parameters regulating water quality to estimate the IWQI in the critical case by using a statically sensitive method. A neural network's neurons are a collection of consistent cells; each one is connected to the cells in the layer above it, but there are no links between the cells in the same layer [20]. Depending on the issue, the number of neurons in each layer may change. The initial data are presented in the input layer to be ready and fed for processing within the successive layers in the neural network; the output layer holds the response to the input. There are hidden layers between the input and output layers, one or more intermediate layers exist to allow these networks to represent and calculate complex associations between patterns. Each input is multiplied by its weight before being added to the total, which is then handled using a non-linear transfer function to generate a result in all hidden and output neurons. One of the most common transfer functions is the S-shaped sigmoid curve [21].

The developed model's input parameters are the EC, Na, Cl, HCO_3 and SAR values of 77 groundwater samples, and the output is IWQI value. The developed model divided the variables for training and testing ANN network using the stepwise regression method. The training set comprised 70% of the total number of samples, while the test and evaluation sets comprised the remaining 30%. In ANNs modeling, the important indicators are determined the optimal number of neurons and training iterations in the hidden layers but there is no precise algorithm for determining the optimal number of neurons in the hidden layer, so most of them are determined by trial and error [22]. The network is a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons. The network architecture consists of one input layer, two hidden layers, and one output layer. The number of neurons determined for the hidden layers is 14 and 7 respectively. A total of 77 datasets are imported from an Excel file. In order to create an output, five classes based on the water quality standard are selected as the target variable, and five parameters that have been established for the samples are used in the input selection. Seventy percent of the 77 samples are used to train the ANN model, fifteen percent to validate it, and fifteen percent to test it. The input layer and output layer nodes in the ANN design are fixed at 5 and 1, respectively. The design (5-14-7-1) in this network, shown in figure 2.

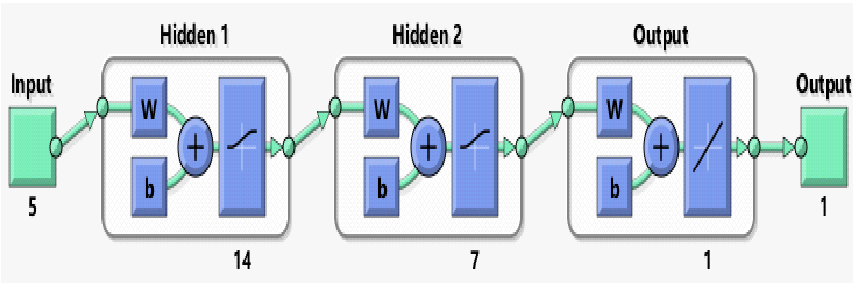

Figure 2. Structure of the ANN

3.3.1. Sensitivity Analysis tool

For reducing the input variables of the ANN network in the developed model, sensitivity analysis as a mathematical tool is used to study how changes in a model's output can be ascribed to changes in its inputs, to find the most relevant and highly significant parameters for the prediction of IWQI, utilizing the Standardized coefficient of input variables. Three scenarios have been produced as a result of this work; the first scenario is built to predict the IWQI using all of the examined factors as input variables. The other scenarios are built using sensitivity analysis to decrease the number of inputs and choose the essential parameters regulating water quality.

3.3.2. Performance Measurement

The performance results of the developed model are evaluated by monitoring the error between the model's predicted output and the measured dataset of IWQI. The error decreases for the dataset with the appropriate number of hidden neurons. Performance measurement through two approaches:

- **Root Mean Square Error (RMSE)**

RMSE is gritty through equation 3 which is always positive, with zero being the ideal case.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(IWQI_p^i - IWQI_A^i\right)^2}{n}} \qquad (3)$$

Where: $IWQI_A^i$ is the actual output, $IWQI_p^i$ is the predicted output, and n is the number of data sets.

- **Multiple determination coefficients (R^2)**

R^2 is determined through equation 4 which is always positive, with one being the ideal case.

$$R^2 = \frac{\sum_{i=1}^{n}\left(IWQI_l^{i-} - IWQI_A^i\right)^2}{\sum_{i=1}^{n}\left(IWQI_p^i - IWQI_A^i\right)^2} \qquad (4)$$

Where: $IWQI_l^{i-}$ is the water quality index value for the i- is the observation received from the model. The higher the Multiple determination coefficients R^2 and the lower the RMSE, the better quality of the generated network.

3. Results and Discussion

3.1. The Result of Irrigation Water Quality Index (IWOI) calculations

The descriptive statistic values (mean, standard deviation, minimum, maximum, coefficient of variation) of the results of the chemical analysis of the collected samples are given in Table (4). The variation coefficients are significantly high for the indicated parameters (EC, TDS, Na, Cl, HCO_3, SO_4, and SAR) and show a big difference among them, this supports the non-homogeneity and non-linearity of salinity and water quality of the study samples and renders using the new developed model as machine learning approach for predicted the water quality justifiable.

Table (4): Descriptive statistic values of the results of chemical analysis of the collected samples

Variable	Minimum	Maximum	Mean	Std. Deviation	coefficient of variation
EC	241.56	6880.00	1943.1482	1478.33600	0.76
Na	0.86	53.04	10.9063	10.02883	0.92
Mg	0.40	12.00	4.4462	2.84237	0.64
Ca	0.50	16.00	3.4848	3.23485	0.93
Cl	0.76	48.28	11.2704	10.61741	0.94
SO4	0.42	33.04	4.0245	6.22244	1.55
HCO3	0.90	6.39	3.3815	0.91148	0.27

The results data of the selected five water quality parameters (EC, Na, Cl, HCO_3, and SAR) have been used to calculate the IWQI for the sampled groundwater using the methodology described in the work of [23]. The calculated values of the water quality index vary in the range from 17.21 to 90.17 as shown in Fig 3. Comparing the IWQI values of the collected samples with the classifying limits indicated in Table (3), the suitability of using the water for irrigation is determined. The samples under study can be classified into five categories of irrigation use suitability as follow: Excellent for 1.12 % of the samples, good for 52.81%, moderate for 7.87 % &bad for 24.72 %& very bad for 10.11%.

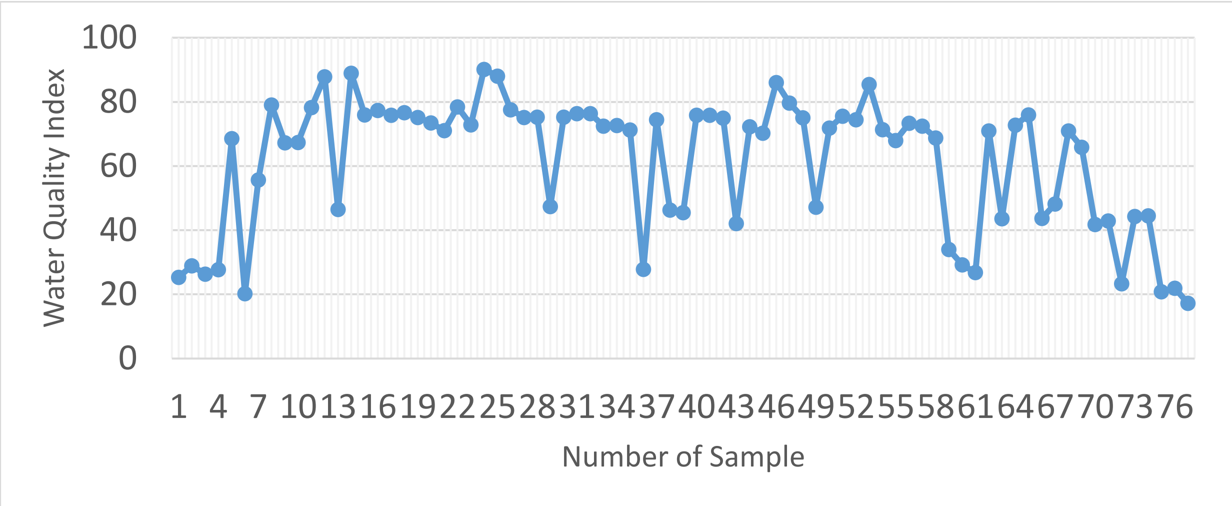

Figure 3. Water Quality Index values

3.2. The New Developed Model (Artificial Neural Network) Results

During the training and testing processes of the developed model, excellent results are obtained. Following the training phase, the testing phase is carried out on the selected dataset of with predefined IWQI variable parameters. Figure 3 shows the regression plot of the developed model to predict IWQI during the training and testing stages. The regression plot is used to assess the relationship between predicted and calculated (observed) IWQI values. The observed IWQI data is represented by the target (x-axis) values, and the predicted IWQI data is represented by the output (y-axis) values obtained using the ANN model. As shown in Fig.4, the predicted values are getting closer to the target values. The performance and results demonstrated that the developed model produces 0.9849 accuracy during the training process and 0.98093 accuracy during the validation process, using the above-defined dataset for input and the desired targeted output. The results generated during the testing phase, on the other hand, are 0.96131, and the overall accuracy achieved by the developed system is also 0.98131, indicating that R > 0.95 for each case, which is characteristic of a great fit of the network.

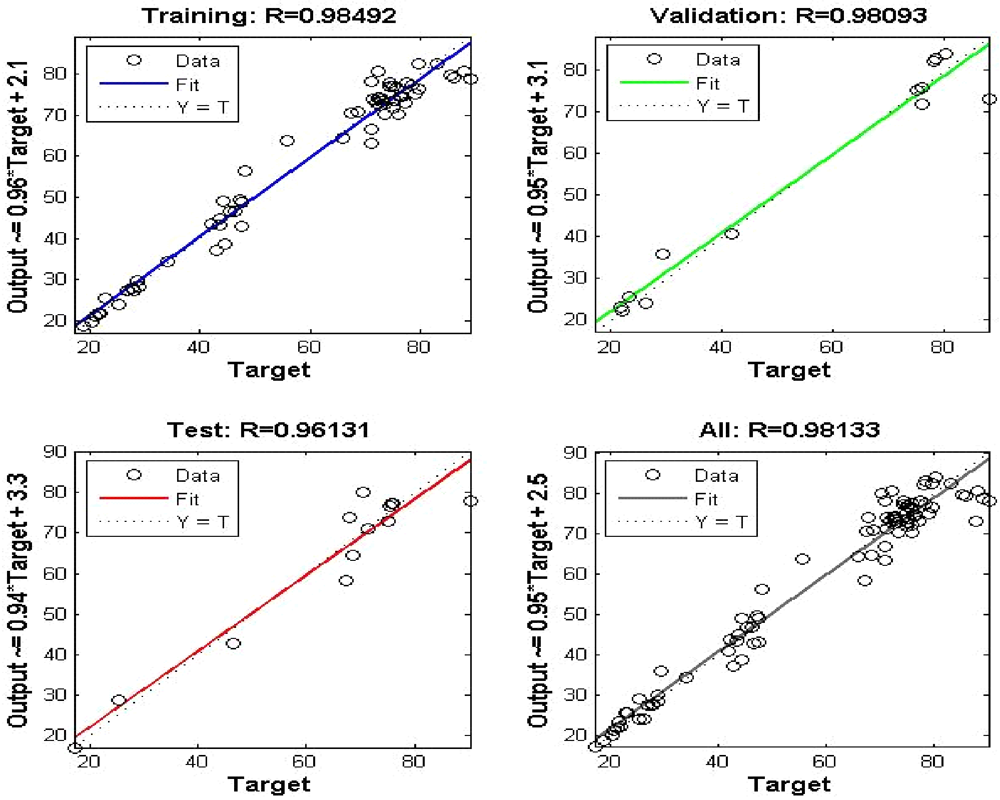

Figure 4. The neural network performance based on the training, validation and testing dataset for the prediction of IWQI with all input variables.

3.3. The results of relative significance (sensitive) of WQI parameters

Three times the developed model is applied to determine the relative significance of the five input parameters used for predicting the IWQI. In Neural network, it is useful for identifying the less important variables that should be removed or unnoticed in subsequent studies, furthermore to the most important variables [24, 25]. Since it helps in determining the most relevant parameters for water monitoring, protection, and remediation. This information is highly helpful for decision-making and efficient management. It is found that the HCO_3 has the least parameter effect on the IWQI calculation as shown in table (5). has a high regression coefficient (R=0.98) that is acceptable for predicting irrigation water quality.

Table (5) The performance of ANN models

ANN model	Excluded Parameter	RMSE	R^2
1st Model	------	0.0693	0.9630
2nd Model	HCO_3	0.0651	0.9674
3rd Model	HCO_3-SAR	0.5610	0.8630

To further validate the result, the performances of the models are evaluated using various statistical criteria, RMSE, and R^2 in Table 5. The results show that the model with four parameters (2ndmodel) which excludes HCO_3, has a mean square error equal to 0.0651 slightly better than the first model with five parameters (RMSE= 0.0693). After proving that the model's quality is slightly improved by eliminating the HCO_3variable, one more variable (SAR) is eliminated in the 3rd model. Compared to the original model, the 3rd model which eliminates two parameters ($HCO_3$and SAR) shows an R^2 value equal to 0.8630 slightly lower than that of 1st model R^2 equal to 0.9630 and for the 2nd model R^2 equal to 0.9674, this indicates that eliminating two input parameters from the original five ones slightly affect the performance. The new developed model results and the sensitivity analysis proved that the less important variables that affect IWQI are HCO_3 and SAR. which means that it can calculate IWQI by the newly developed model without using the data of HCO_3 and SAR , which can reduce the cost of measurements of water quality parameters and calculations.

4. Conclusion

The climate of the area under study is arid and the water resources are limited to groundwater that is mainly used for irrigation so the total water quality must be taken in consideration to avoid the causing irrigation hazards: (Salinity & Infiltration rate& Specific Toxics and Miscellaneous effects). In this research, a new model is developed to predict the quality of irrigation water of the study area though predicting its IWQI. Artificial Neural Network is created to develop the new developed model depending on the parameters of seventy-seven samples from the area of study which are the water quality parameters of the groundwater usability.

The new developed model predicted IWQI produced encouraging results for evaluating the suitability of irrigation water and classifying its quality grades. An ANN is constructed with the optimized number of hidden neurons and high values of performance parameters RMSE and R^2 for the training, validation, and testing stage. The obtained performance results provided a high correlation between actual and predicted values and can be used as a reference to manage the water quality and assessment the levels of groundwater pollution in the study area, it can also contribute to monitoring, protection or treatment plans. As a result of the conducted work, a verified, validated, and tested IWQI has been developed using ANN, it is highly advantageous compared to the conventionally determined ones, as it tackled the non-linearity and multivariate nature of water quality processes and helps for assessing the quality of groundwater without deepening in accounting physical processes, it is convenient for water quality monitoring and irrigation use evaluation in the study area which is allocated within the national agricultural development plan. The newly developed model results and the sensitivity analysis proved that the less important variables that affects IWQI are HCO_3 and SAR. this means that it can calculate IWQI by the newly developed model without using the data of HCO_3 and SAR , that can reduce the cost of measurements of water quality parameters and calculations. So, some parameters can be excluded without a great effect the accuracy of water quality monitoring and evaluation. Reducing the input parameters numbers is a challenge for IWQI prediction process.

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الملخص العربى

تطوير مؤشر جودة مياه الري باستخدام الشبكة العصبية الاصطناعية

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هيئة الطاقة الذرية المصرية

كشفت تقنيات الذكاء الاصطناعي المستندة إلى البيانات (AI) عن أهمية خاصة لمعالجة العلاقات غير الخطية والتنبؤ بسلوك الأنظمة المعقدة ، وقد شهدت هذه التقنيات نشاطًا كبيرًا في العصر السابق وتظهر تطبيقات واعدة في مشاكل الهيدرولوجيا وجودة المياه. الهدف من هذه الدراسة هو بناء نموذج مطور للتنبؤ بجودة مياه الري من خلال تقدير مؤشر جودة المياه الخاص بها. يتم استخدام الشبكة العصبية الاصطناعية (ANN) لإنشاء النموذج المطور الجديد. يعتمد النموذج بدقة على معلمات ANN التي يتم ضبطها وفقًا لمعايير جودة المياه لقابلية استخدام المياه الجوفية. يتم تطبيق النموذج المطور للتنبؤ بمؤشر جودة مياه الري المستند إلى البيانات (IWQI) لاستخدام المياه الجوفية في منطقة تجريبية تصل الصحراء في وسط الصعيد. تم تحديد IWQI مركب شامل يأخذ في الاعتبار نوعية المياه الإجمالية التي تسبب مخاطر الري: (معدل الملوحة والتسلل والسموم المحددة والآثار المتنوعة). كانت البيانات الأولية للنموذج هي نتائج التحليل الأيوني الرئيسي لسبعة وسبعين عينة من المياه الجوفية. لتقليل متغيرات الإدخال لشبكة ANN في النموذج المطور ، يتم استخدام تحليل الحساسية كأداة رياضية لدراسة كيف يمكن أن تُعزى التغييرات في مخرجات النموذج إلى التغييرات في مدخلاته ، للعثور على المعلمات الأكثر صلة والأكثر أهمية بالنسبة لـ التنبؤ بـ IWQI ، باستخدام المعامل القياسي لمتغيرات الإدخال. جذر متوسط مربع الخطأ (RMSE) ومعامل الانحدار (R2) هما مقياسان إحصائيان يستخدمان لتقييم فعالية النموذج. يُظهر نموذج ANN المطوّر توافقًا كبيرًا بين IWQI المقاسة والمحسوبة (R2 = 0.963، RMSE = 0.0693) ويصبح مُرضيًا تم التحقق منه للتنبؤ بالجودة الإجمالية للمياه الجوفية في منطقة البحث ، والتي تعتمد على القياسات الفردية المصنفة وفقًا لحساسيتها. علاوة على ذلك ، يمكن للنموذج المطور الجديد التغلب على مشكلة فقدان بعض معلمات مؤشر العينة عند فقدان واحد أو أكثر من المعلمات.