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Application of Artificial Neural Network and Geographical Information System Models to Predict and Evaluate the Quality of Diyala River Water, Iraq

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Abstract—This research discusses application Artificial Neural Network (ANN) and Geographical Information System (GIS) models on water quality of Diyala River using Water Quality Index (WQI). Fourteen water parameters were used for estimating WQI: pH, Temperature, Dissolved Oxygen, Orthophosphate, Nitrate, Calcium, Magnesium, Total Hardness, Sodium, Sulphate, Chloride, Total Dissolved Solids, Electrical Conductivity and Total Alkalinity. These parameters were provided from the Water Resources Ministryfrom seven stations along the river for the period 2011 to 2016. The results of WQI analysis revealed that Diyala River is good to poor at the north of Diyala province while it is poor to very polluted at the south of Baghdad City. The selected parameters were subjected to Kruskal-Wallis test for detecting factors contributing to the degradation of water quality and for eliminating independent variables that exhibit the highest contribution in p-value. The analysis of results revealed that ANN model was good in predicting the WQI. The confusion matrix for Artificial Neural Model (NNM) gave almost 96% for training, 85.7% for testing and 100% for holdout. In relation to GIS, six color maps of the river have been constructed to give clear images of the water quality along the river.

Keywords—Water quality index, Inverse distance weighted, Geographical information system, Artificial neural network, Diyala river.

1. Introduction

Water is considered one of the most important natural resources not only for a country or state but also for the entire human race. The increase in population and economic activities has led to intensive demand for large-scale freshwater suppliers for different competing end users. The decline in the quantity and quality of surface water resources is attributed to pollution of water and improper management of water resources [6]. The monitoring of water quality has the highest priority in the policy of environmental protection. The major purpose of this monitor is for controlling and minimizing the incidence of pollution problems, and for providing quality appropriate for water to serve various purposes like irrigation water, drinking water supply, etc. [5].

The prediction and assessment of water quality index (WQI) focuses mainly on water derived from rivers, groundwater, lakes, estuaries, tributaries and other large water bodies using Artificial Neural Network (ANN), Geographic Information System (GIS) and statistical analysis methods [13]. Developing intelligent computer tools and reducing a cost in evaluating condition of water quality is one of the biggest challenges facing today's research on water quality [11]. In this research, the development and optimization of the neural network and GIS based on their predictive and assessment performance are discussed. To complement, the Kruskal-Wallis test is also applied, which reduces the dimensions of large input data by explaining the relation amongst a large input data.

In several recent publications, successful applications of ANN as a water quality forecaster and GIS as a water quality evaluator can be seen in various fields of water resources. Among the research that have been published are; Nathan et al. 2017 used ten physio-chemical parameters to predict groundwater quality at Lawspet, Puducherry in India. The results revealed that the ANN model gives a high R2 in forecasting the CWQI in all Clusters 1, 2 and 3[15]. Nooriet al., 2017 correlated the results of BWQI with satellite image by GIS to obtain colored analytical maps for the Euphrates River in Al-Najaf City [14].

Broadly the objective of this research is to predict the changes in Diyala River condition using a Neural Network Model (NNM). In addition, GIS was used to evaluate the river water quality by making colorful analytical maps of the WQI that can be used by decision makers to give a clear image of water quality.

2. Material and Method

2.1 Description of Study Area

Diyala River is located between longitude (44° 30´E-45° 20´E) and latitude (33° 130´N- 35° 50´N), and passes through Diyala province north-eastern Baghdad. It is considered the most important tributary of the Tigris River and one of the main water resources sampling sites.

In Iraq [1]. It drains an area reaching 31,846 km2 lying across Iraqi-Iranian border, and the catchments of river are divided into four parts include: Derbendikhan, Upper Diyala, Middle Diyala and Lower Diyala, where the last one feeds the Tigris in the south part of Baghdad [8]. The river basin climatic conditions vary widely, in which the rainy season starts in November to April, with annual rainfall of 800 mm in the northern parts and reaches to 250 mm in the southern part. The rate of annual evaporation may be more than 2000 mm/year. These conditions have obvious effects on changing dry and wet years and thus on River water quality [4].

2.2 Data Collection

Water samples have been collected from seven stations along Diyala River near the Iraqi-Iranian borders at Jalawlaa City to the Bridge Diyala at Baghdad City, in order to evaluate the water Quality index of Diyala River and predict the conditions of the river. Locations of these stations have been described in **Table. 1** and shown in **Fig. 1**.The data utilized in this research was provided from Water Resources Ministry in Iraq for the period from 2011 to 2016. This data includes fourteen water parameters: pH value, Temperature (Temp.), Dissolved Oxygen (DO), Orthophosphate (PO_4^{-3}), Nitrate(NO_3^-), Calcium (Ca), Magnesium (Mg), Total Hardness (TH), sodium (Na), Sulphate (SO_4^{-2}), Chloride (Cl^-), Total Dissolved Solids (TDS), Electrical Conductivity (EC), and Total Alkalinity (TA).

3. Methodology

3.1 Water Quality Index (WQI)

Water quality index is a tool used to determine water quality condition, where it requires knowledge of basic principles and concepts of water and also related issues. WQI considers the most efficient tools for communicating information on the water quality to citizens of the concerned and policy makers so that it is able to facilitate complex environmental data [17]. The concept of WQI is based on the principle of colleting water quality parameters and comparing it with respective regulatory standards for producing a single number that express the overall water quality at a specific site.

3.1.1. Arithmetic method to determine WQI

Arithmetic method means the relative significance of each factor in the overall water quality and it depends on the permissible standards for drinking water quality recommended by the Iraqi standard organization (ISO). Factors that have high permissible limits are considered less harmful and have low weighting [2]. The overall water quality index was calculated using the following equation:

$$WQI = \sum_{n-1}^{n} q_n w_n \Big/ \sum_{n-1}^{n} w_n \qquad (1)$$

Where: n = total number of the water quality parameters, q_n=the scale of quality rating for each parameter and W_n = unit weight for the n^{th} parameter, this value ranges from (0-1).

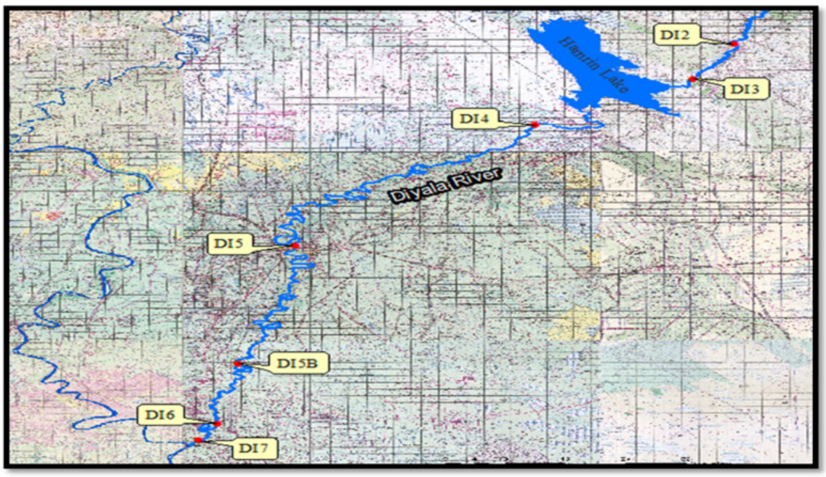

Figure 1: Map of Diyala River illustrates the Sampling sites.

Table 1: Description of the monitoring stations along Diyala River.

Station	Location	Coordinates		Distance to next station (km)	Accumulated Distance (km)
		East	North		
DI2	Jalawlah station- before Jalawlah Bridge	45° 9' 19.70"	34° 17' 9.01"	0	0
DI3	Saadiyah station- before inter to Hamren Dam	45° 6' 28.85"	34° 11' 29.11"	14.9	14.9
DI4	Muqudadia station- after Diyala Dam	44° 55' 12.62"	34° 4' 24.52"	35.4	50.3
DI5	Baqubah station at Iron Bridge	44° 37' 57.42"	33° 45' 20.66"	60.7	111
DI5B	9 Nissan pumping station	44° 33' 53.52"	33° 26' 8.31"	47.9	158.9
DI6	100 meters south of the Rustomiya sewer station	44° 31' 6.38"	33° 15' 34.06"	26.6	185.5
DI7	south of Baghdad City- after Diyala Bridge	44° 30' 47.36"	33°13'46.25"	6	191.5

3.1.2 Classification of water quality

Any source of water can be classified into different classes referring useful uses to which can be put to it. The classes are based on the allowable limits of relevant water quality parameters or set of standards developed by various authorities. Water quality of the region can be determined according to how it's suitability for useful use. The study of the region case was classified according to arithmetic weighted method for specifications of drinking water as shown in **Table. 2.**

3.2. Artificial Neural Network (ANN) Model

Neural networks (NNs) are used to predict outcome data through input data in a manner that simulates the operating system of the human nervous system. The basic benefit of NNs is that they don't use any mathematical model, because they can learn from data set and determine patterns in a series data of input and output without providing previous assumptions about of their type and interrelations [7]. Generally, the model is able to simulate non-linear (i.e. dynamic or static) behaviors within the assessment process and able to handle ordinal outputs like condition classes [16]. In the case of water quality modeling, the relationship between independent variables (water quality parameters) and dependent variable (water quality index) are studied through learning from past data of a river water quality. Then, the gained knowledge from a past data is stored in the NNs to predict the river's condition [22].

Table 2: Water quality classification according to arithmetic method [20].

No.	Water Quality Index Level	Water quality classification
1	0-25	Excellent
2	26-50	Good
3	51-75	Poor
4	76-100	polluted
5	More than 100	Very polluted

3.2.1. Model structure

In general, the neural network is system composed of a collection of nodes called "neurons or nervous cells" connected with each other on the form of a network **[15]** as shown in **Fig.2**. The connection weights (CWs) are used to attach the connections between nervous cells and determined by reducing the error between the actual output and the predicted output value using the observed data. The nervous cells have a specific input signal with a value of 1 and have a bias weight linked to this signal [3].

The relationship between input and output signals in a neural network can be written as below:

$$Y = f(\sum_{i=1}^{k} X_i W_i) \qquad (2)$$

Where: Y= the output signal, X_i= the input signal, K= the number of input signals, W_i= the connection weights, and f = the activation function.

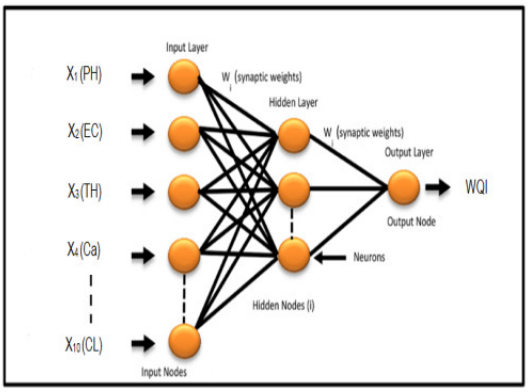

Figure 2: Architecture of an ANN model [17].

3.2.2 Activation functions

It works to link values of nodes in the succeeding layer to weighted sums of nodes in the preceding layer. In this study, automatic architecture used the hyperbolic tangent function for the hidden layer neurons and used the softmax function for output layer neurons [9]. The nonlinear relationship between the input (independent) and output (dependent) data can be written as follows:

$$C = \sum_{i=1}^{n} X_i W_i + W_0 \quad (3)$$

$$H_i = \tan h\,(C) \quad (4)$$

$$Y_i = \frac{e^{H_k}}{\sum_j e^{H_j}} \quad (5)$$

Here: n =the number of the input, W_0=bias weight, H_i=the output of the hidden nodes, Y_j=the output of the output nodes and H_k=the input for Y_j.

3.3 Geographical Information System (GIS) Model

Geographical Information System is a set of software that allows for creating, visualizing and analyzing geospatial data. Geospatial data refers to information about the geographic location including the geographic coordinate, like a latitude or longitude value. While spatial data includes geographic data, map data, GIS data, location data and spatial geometry data [18], so that these data can be analyzed and integrate for deriving useful outputs and modeling.

GIS techniques have been developed to facilitate the integration and analysis of large amounts of multidisciplinary data, whether spatial or non-spatial within the same geographic reference. The spatial analysis of GIS can allow interpolation of water quality index at unknown location through known values for creating a continuous surface helps to understand the water quality condition scenarios of the study area [19]. Hence, tools of the spatial analysis are used to re-classify water quality index into a various categories and each category is specified with a unique number. The spatial distribution model has been adopted for creating analytical maps for water quality index. The Inverse Distance Weighted (IDW) interpolation method was used in this research to obtain thematic maps. This method does not extrapolate beyond the maximum and minimum values, and it gives accurate results on the observation area.

4. Results

4.1. Calculation of WQI

A sample of WQI calculations at station DI7 south of Baghdad City is shown in **Table.3** for the year 2016. Calculations of annual average WQI for each station on Diyala River for the period 2011 to 2016 are represented in **Table.4**.From the tables it is noticed that there is deterioration in the water quality of Diyala River when it enters Baghdad City. The river water at DI2 to DI5 stations were classified from good to poor for drinking purpose, while in DI5B to DI7 stations it was classified from poor to unsuitable for drinking.

4.2. Statistical Analysis

The Kruskal-Wallis test was performed for the analysis on the water quality dataset using the SPSS software package and used to detect factors contributing to the degradation of water quality. The results of Kruskal-Wallis test performed on the water quality data are summarized in **Table. 5**. The results showed that water quality index condition is affected by the following parameters: pH, DO, PO_4^{-3}, Ca, Mg, TH, Na, SO_4^{-2}, Cl, TDS, EC and TA. These standards can be considered responsible for the deterioration of water quality in Diyala River. Meanwhile, it was found that Temperature and Nitrate have the highest contribution in p-value ($P > 0.05$) (i.e. the significance level is 0.05, the corresponding confidence level is 95% thus, the greater the p-value the lower the confidence level). Moreover, the parameters that affect the water quality will be used for developing of the prediction model (i.e. NNM).

Table 3: WQI Calculations for the DI7 station during the year 2016.

2016	value	Si	Wi	qi	wi*qi	WQI
pH	7.73	7.5	0.1333	103.1	13.74	
Temp.	14	15	0.0667	93.33	6.222	
DO	3.55	7.25	0.1379	48.97	6.754	
PO_4^{-3}	1.63	1	1	163	163	
NO_3^-	2.723	50	0.02	5.445	0.109	
Ca	145.3	50	0.02	290.6	5.812	
Mg	63.69	50	0.02	127.4	2.548	141.5
TH	630.5	500	0.002	126.1	0.252	
Na	147.5	200	0.005	73.75	0.369	
SO_4^{-2}	671.5	250	0.004	268.6	1.074	
Cl^-	198.8	250	0.004	79.5	0.318	
TDS	1258	1000	0.001	125.8	0.126	
EC	2260	2000	0.0005	113	0.056	
TA	229	500	0.002	45.8	0.092	
SUM			1.4164		200.5	

Table 4: The average annual WQI for each station during the period 2011 to 2016.

Station	2011	2012	2013	2014	2015	2016
DI2	35.42	36.42	41.88	38.29	39.94	39.94
DI3	36.68	36.46	43.56	37.89	38.84	38.84
DI4	37.52	38.14	43.74	39.75	37.59	37.59
DI5	44.72	44.49	54.37	48.15	45.49	39.02
DI5B	222	52.74	54.62	55.29	67.49	53.6
DI6	263.4	271.9	118.6	134.4	169.7	108.1
DI7	277.5	298.6	177.7	169.7	161.7	141.5

Table 5: Results of the Kruskal-Wallis test on water quality data.

Parameter	Kruskal-Wallis test statistic, K#	Degree of Freedom, df	Probability, p-value*
pH	10.292	3	0.016*
Temp.	4.239	3	0.237
PO_4^{-3}	32.292	3	0.000*
DO	13.192	3	0.004*
NO_3^-	6.91	3	0.075
Ca	18.15	3	0.000*
TH	30.203	3	0.000*
Na	30.628	3	0.000*
Mg	29.972	3	0.000*
Cl^-	29.988	3	0.000*
SO_4^{-2}	30.787	3	0.000*
EC	29.806	3	0.000*
TDS	25.621	3	0.000*
TA	28.365	3	0.000*

statistically significant at 5% level if K $\geq \chi^2_{0.05:3} = 7.82$, * Statistically significant at 5% level if p-value≤0.05.

4.3 Neural Network Model (NNM)

The available dataset for this network contain to 42 records corresponding to stations located along Diyala River during the years. Approximately 59% of the data were assigned to train, 17% to tests, and 24% to holdout samples in this model. Moreover, all values of the scale input are rescaled according to equation (6) using a normalized method to improve network training.

$$X_i = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

Where: x= indicate the original data, X_{max} and X_{min} are the maximum and minimum values of the original data respectively.

4.3.1 Training of NNDM

In this study, the training of NNM has been used for calculating the model structure (i.e. the numbers of hidden neurons and the weights of network). For the numbers of hidden neurons, automatic architecture selection has chosen four neurons in the hidden layer. The type of training used to estimate the network weights is batch because it suitable for small datasets whereas, the optimization algorithm is calculated by the scaled conjugate gradient. The network weights are listed in **Table 6** that can use to predict the condition of water quality according to equations (3), (4) and (5).

4.3.2 Independent Variable Importance

The importance of each predictor (independent variable) was computed in determining the neural network according to the combined training and testing samples [17]. **Fig.3** shows that variables PO_4^{-3}, SO_4^{-2}, Cl^-, Mg, TH, and DO, Na, EC and pH have the greatest effect on how the network classifies the riverfollowed by Ca, TDS and TA. The importance of independent variable is a measure of the amount change in value and predicting the network model for different values of the independent variable. Whereas, normalized importance represents the values of independent variable importance divided by the largest importance values and expressed as percentages [9].

4.3.3 Model Performance Evaluation

For testing or assessing the model performance accuracy, the error of model (i.e. the difference between the predicted output and the observed targets) must be quantified [21]. The model performance becomes low, when the model error is high. In this research, the confusion matrix was used for evaluating performance of the model because it contains information about observed and predicted classifications done by a classification NNM technology [23].

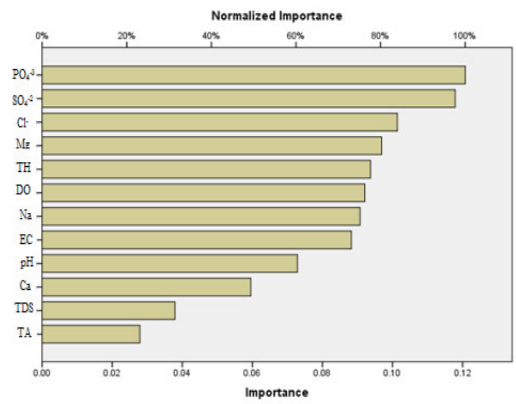

Figure 3: Independent Variable Importance's.

Table 6: Appreciation of hidden and output weights.

Predictor		Predicted							
		Hidden Layer 1				**Output Layer**			
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	WQI=2	WQI=3	WQI=4	WQI=5
Input Layer	(Bias)	-1.316	1.583	.904	-.452				
	pH	-.555	-1.616	-.604	.149				
	DO	-3.381	.905	-.613	.111				
	PO_4^{-3}	3.155	-.261	.247	-.171				
	Ca	-.200	-1.506	.420	-.058				
	TA	.716	-.554	-.105	.377				
	EC	.803	-1.653	-.422	.232				
	Cl^-	.313	-2.245	-.685	-.186				
	Na	.293	-2.932	.124	-.239				
	TDS	.484	-.973	.192	-.379				
	SO_4^{-2}	1.120	-2.505	-.823	.162				
	Mg	.942	-1.963	-.367	-.240				
	TH	-.534	-2.791	.297	-.325				
Hidden Layer 1	(Bias)					2.084	-1.547	-1.404	.654
	H(1:1)					-3.125	-1.087	-1.064	4.643
	H(1:2)					3.580	-2.037	-1.030	-.744
	H(1:3)					1.602	-.620	-.055	.133
	H(1:4)					-.390	-.329	-.342	-.112

4.3.3.1 Confusion matrix

When comparing an observed target with predicted output, one will always observe one of four situations: (a) true negative (TN) when the correct model predicts the river condition (i.e. water quality in polluted condition), (b) true positive (TP) when the correct model predicts the river condition (i.e. water quality in good condition), (c) false negative (FN) when the incorrect model predicts a water quality actually in polluted condition as in a positive case, and (d) false positive (FP) when the incorrect model predicts a water quality actually in good condition as in a negative case. In this research, the confusion matrix for n = 4 are shown in **Table.7**, and the overall predict rate (OPR) was calculated using the following equation:

$$OPR = \frac{TP_{22}+TP_{33}+TN_{44}+TN_{55}}{O_2+O_3+O_4+O_5} \quad (7)$$

Where: TP_{22}, TP_{33}, TN_{44} and TN_{55} mean the number of stations during six years which were observed and correctly predicted in condition 2, 3, 4 and 5. O_2, O_3, O_4 and O_5 represent the total stations during six years which were observed in condition 2, 3, 4 and 5 while condition 1 was not found because the river has no excellent water quality.**Table. 8** is the confusion matrix for NNM, which showed almost 96% overall prediction rate for training, 85.7% for testing and 100% for holdout. This results indicate that the NNM has great potential to simulate and predict the WQI as well as the high overall prediction rate could be attributed to it is inherent ability for modeling complex processes.

4.4. Using the GIS software for building the colored model

The results of WQI have been linked with ArcGIS 9.3 software to obtain that layers represent the nature of spatial distribution of WQI in the form of colored maps showing pollution zones in the Diyala river water. Analysis has helped to identify the appropriate zones of water quality for drinking purposes. **Figs.4** to **9** show the GIS maps representing annual WQI of the Diyala River as maps during 2011-2016 between the selected stations. The colored ramp indicator has been used in the GIS maps based on maximum and minimum value of WQI.

Table 7: Confusion matrix.

		Predicted condition				Total
		2 good	3 Poor	4 Polluted	5 Very polluted	
Observed condition	2 good	TP_{22}	FP_{32}	FP_{42}	FP_{52}	O_2
	3 Poor	FP_{23}	TP_{33}	FP_{43}	FP_{53}	O_3
	4 polluted	FN_{24}	FN_{34}	TN_{44}	FN_{54}	O_4
	5 Very polluted	FN_{25}	FN_{35}	FN_{45}	TN_{55}	O_5
	Total	P_2	P_3	P_4	P_5	

Table 8: Prediction efficiencies during the training, testing and holdout of the NNM.

Sample	Observed	Predicted				
		2	3	4	5	Percent Correct
Training	2	15	0	0	0	100.0%
	3	0	3	0	0	100.0%
	4	0	1	0	0	0.0%
	5	0	0	0	6	100.0%
	Overall Percent	60.0%	16.0%	0.0%	24.0%	96.0%
Testing	2	3	0	0	0	100.0%
	3	1	1	0	0	50.0%
	4	0	0	0	0	0.0%
	5	0	0	0	2	100.0%
	Overall Percent	57.1%	14.3%	0.0%	28.6%	85.7%
Holdout	2	5	0	0	0	100.0%
	3	0	0	0	0	0.0%
	4	0	0	0	0	0.0%
	5	0	0	0	5	100.0%
	Overall Percent	50.0%	0.0%	0.0%	50.0%	100.0%

Dependent Variable: WQI

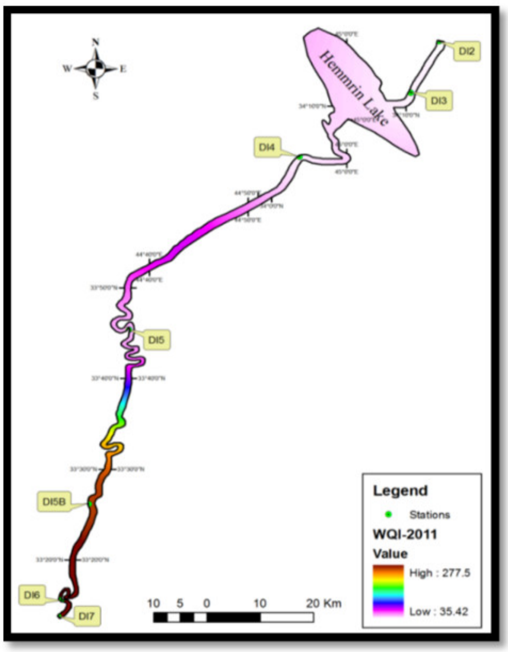

Figure 4: GIS Map for WQI variation in Diyala River in 2011.

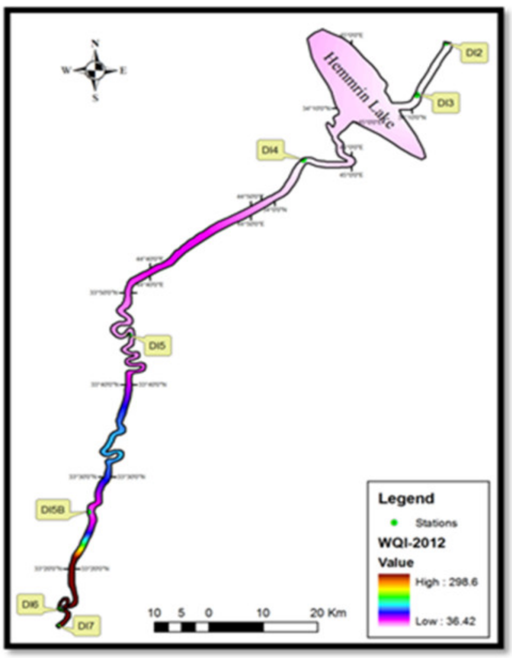

Figure 5: GIS Map for WQI variation in Diyala River in 2012.

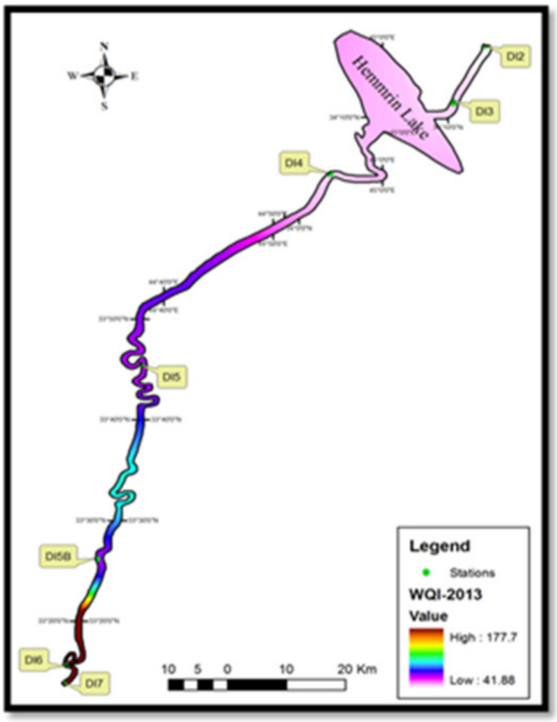

Figure 6: GIS Map for WQI variation in Diyala River in 2013.

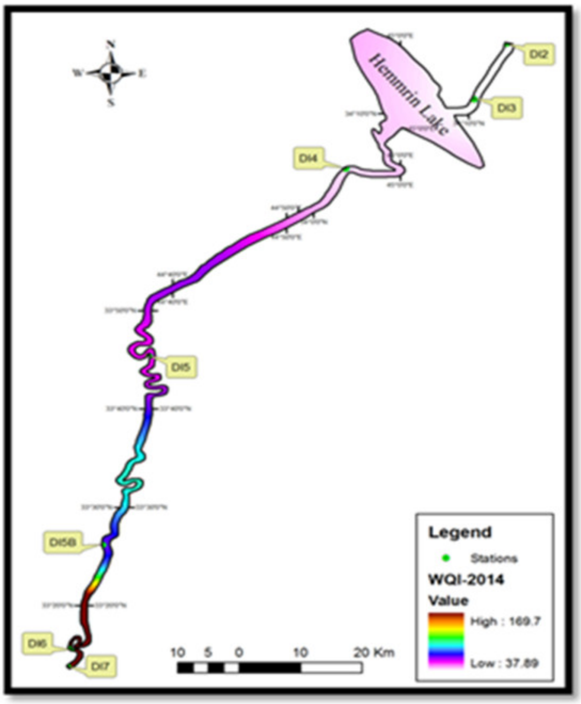

Figure 7: GIS Map for WQI variation in Diyala River in 2014.

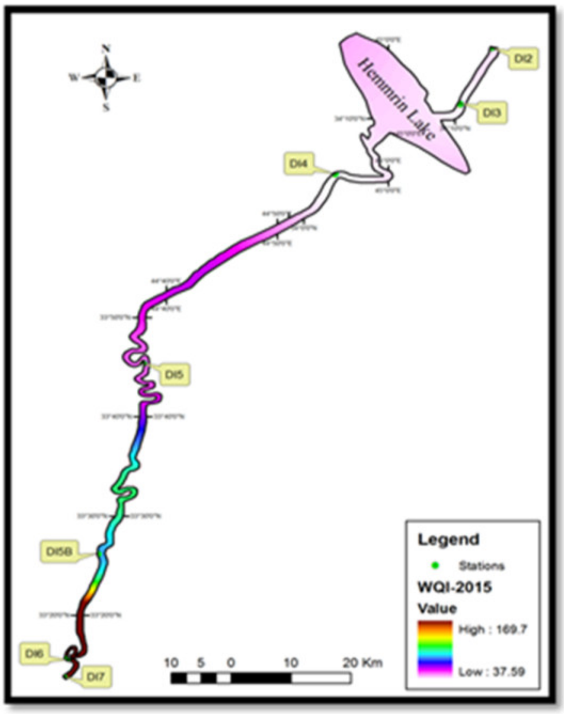

Figure 8: GIS Map for WQI variation in Diyala River in 2015.

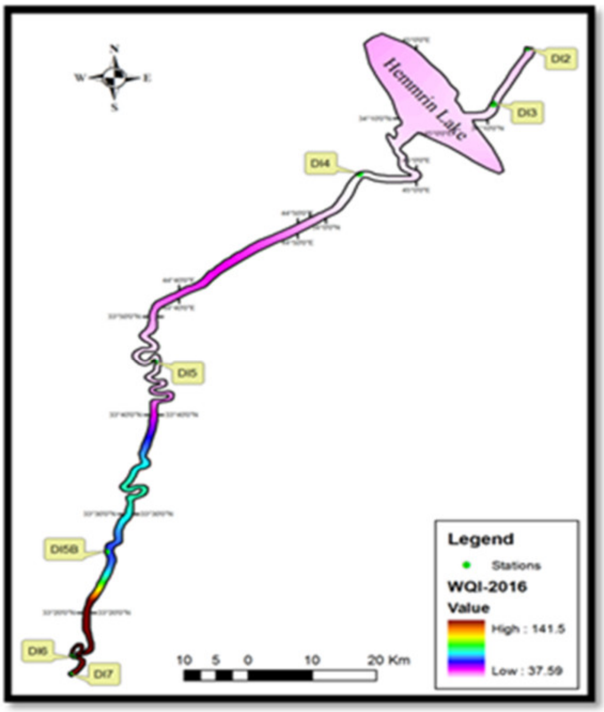

Figure 9: GIS Map for WQI variation in Diyala River in 2016.

5. Discussion

The analysis results of the annual average WQI classified that the Diyala River is good to poor at stations (DI2, DI3, DI4 and DI5) while it was poor to very polluted at Baghdad City (DI5B, DI6 and DI7). The maximum value of WQI reached 299 at DI7 (south of Baghdad City before the confluence of Diyala River with Tigris River) in 2012 while the minimum value of WQI reached 35.42 at DI2 (north of Diyala province at the beginning of the river after the Iraqi-Iranian borders) in 2011.

The water parameters values that cause high WQI and responsible for water quality deterioration are pH, Dissolved Oxygen, Orthophosphate, Calcium, Magnesium, Total Hardness, sodium, Sulphate, Chloride, Total Dissolved Solids, Electrical Conductivity, and Total Alkalinity in the flowing water that was noticed from the Kruskal-Wallis test.

Moreover, the main parameter that causes deterioration in water quality results is the high concentrations of Orthophosphate (PO_4^{-3}). PO_4^{-3} forms are produced from natural sources, partially treated and untreated sewage, runoff from agricultural sites, and application of some lawn fertilizers. It also stimulates the growth of plankton and aquatic plants which provide food for larger organisms, including zooplankton, fish, etc. [24].

Another parameter which had an influence in water quality deterioration was Sulfates (SO_4^{-2}).Sulfates are a combination of oxygen and sulfur and arrive to river water from anhydrite and gypsum or from the oxidation of sulfuric compounds resulting from the sewage water, industrial discharges and groundwater[12]. Sulfate minerals can cause a bitter taste in water so that it can have a laxative effect on humans when existing permissible limits [10].

In general, the upstream of Diyala River is not heavily polluted. The most polluted area in the river is located downstream of Khan Bani Saad city because of the discharge of pollutants from the Rustmiyah stations south of Baghdad, as sewage is directly discharged into the river.

6. Conclusions

The results of WQI analysis revealed that the Diyala River was good to poor at the north of Diyala province while it was poor to very pollute at the south of Baghdad City. The maximum value of WQI reached 299 at DI7 in 2012 while the minimum value reached 35.42 at DI2 in 2011.

The neural network model was developed, tested and evaluated in this research as an assessment tool using water quality dataset for determining the water quality condition. The ANN gave high accurate results to predict the condition of water quality index.According to NNM, the most effective factors that had high influence on the model werePO_4^{-3}, SO_4^{-2}, Cl^-, Mg, TH, DO, Na, EC, pH, Ca, TDS, TA respectively.

In this research, the GIS technique helps to link the calculated WQI and convert them into colorful and simplified maps. It also represents the reliable picture of water quality that can be used in general without showinglarge amounts of data.

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تطبيق نماذج الشبكة العصبية الاصطناعية ونظم المعلومات الجغرافيه للتنبؤ وتقييم نوعيه مياة نهر ديالى، العراق

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الخلاصة – يناقش هذا البحث تطبيق نماذج الشبكة العصبية الاصطناعية ونظم المعلومات الجغرافية على نوعية مياه نهر ديالى باستخدام مؤشرنوعيةالمياه. أربعة عشر معلمة مائية استخدمت لحساب WQI تشمل: درجة الحموضة ، درجة الحرارة ، الأكسجين الذائب ،الفوسفات ،النترات ،الكالسيوم ،المغنيسيوم ،الصلابة الكلية ،الصوديوم ،الكبريتات ،الكلوريد ،المواد الصلبة الذائبة الكلية ،الموصلية الكهربائية والقلوية الكلية. تم جمع هذه المعلماتمن وزارة الموارد المائيه من سبع محطات على طول النهر للفترة من 2011 إلى 2016. أظهرت نتائج تحليل WQI أن نهر ديالى جيد الى رديئ في شمال محافظة ديالى في حين أنه رديئ إلى ملوث جدًا في جنوب مدينة بغداد. وقد خضعت المعايير المختارة الى اختبار Kruskal-Wallis لاكتشاف العوامل التي تسهم في تدهور نوعيه المياه والقضاء على المتغيرات المستقلة التي تظهر أعلى مساهمة في قيمة ال p. كشف تحليل النتائج أن ANN كان جيدًا في التنبؤ بمؤشر WQI. أعطت مصفوفة الارتباك ل NNM ما يقرب من 96 ٪ للتدريب ، و 85.7 ٪ للاختبار و 100 ٪ للتقييم. وفيما يتعلق بنظام المعلومات الجغرافية، تم بناء ستة خرائط ملونة للنهر لإعطاء صور واضحة لنوعية المياه على طول النهر.

الكلمات الرئيسية – مؤشرنوعية المياه، المسافة العكسية المرجحة، نظم المعلومات الجغرافيه، الشبكة العصبية الاصطناعية، نهر ديالى.