Egyptian Journal of Aquatic Biology & Fisheries
Zoology Department, Faculty of Science,
Ain Shams University, Cairo, Egypt.
ISSN 1110 – 6131
Vol. 29(1): 2879 – 2892 (2025)
www.ejabf.journals.ekb.eg

Evaluation of Surface Water Quality for Aquatic Life Using Artificial Intelligence Method

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ARTICLE INFO
Article History:
Received: Feb. 3, 2025
Accepted: Feb. 26, 2025
Online: Feb. 28, 2025

Keywords:
ANFIS,
NSFWQI,
Aquatic life,
Tigris River

ABSTRACT

Surface water is considered one of the most invaluable natural resources in the world, finding its application for many purposes. Water quality is affected by many natural changes and human activities; therefore, assessment of its suitability is of great importance. This study determined the suitability of Wadi Akab and the Tigris River waters for aquatic life using pH, temp., TDS, Tur., PO_4, NO_3, *F. coli*, and DO%. Samples were collected every two weeks and analyzed from 7 sites from June 2024 to December 2024 with 10 replicates. ANFIS artificial intelligence model was applied, and the results showed that Wadi Akab water is unsuitable for aquatic life, and it was classified as poor except for the first site, which was very poor due to the high level of most of the measured parameters and the low saturated oxygen concentration that did not exceed 20%. The performance of ANFIS was verified by applying the NSFWQI model and comparing it using the statistical criteria R^2, RMSE and MAPE and the results were 0.9, 3.86 and 6.85 respectively. These results confirmed the degree of convergence between the NSFWQI model and the ANFIS model. The ANFIS model can be used as an effective tool for estimating surface water quality indicators for aquatic life purposes in the study area and other areas with similar conditions.

INTRODUCTION

Rivers are major natural ecosystems consisting of assemblages of aquatic organisms and abiotic components. They provide important means of material transport, energy flow, and information diffusion in terrestrial and aquatic ecosystems; therefore, they play an essential ecological role. In addition, rivers carry immense importance **(Roshani-Sefidkouhi *et al.*, 2025)**.

Natural resources are a quintessential requirement for human development. They not only support the supply of food, production, and drinking water for human beings but also provide numerous ecosystem services, including flood control, energy generation, transportation, irrigation for agriculture, and recreation. However, due to rapid population growth and increasing human industrial and agricultural activities **(Abdel-Galil *et al.*, 2023; Al-Assaf *et al.*, 2024)**, rivers are continuously being disrupted by pressures exerted by human beings. For example, the construction of reservoirs, diversion of channels, discharge of numerous sewage and overfishing have destroyed the river structure, degraded water quality, reduced fish resources, disappeared species, soil erosion and other serious ecological and environmental problems. Therefore, the accurate assessment of the health status of the river ecosystem has become a hot issue in recent years **(Al-Mashhadany, 2021c; Haque *et al.*, 2024)**.

Aquatic life forms are among the core components of Earth's biodiversity and, in large measure, integral to the proper balance and functioning of the ecosystems. Aquatic life depends on water bodies to survive and procreate. Water pollution may directly occur through chemicals and wastes produced by human activities that enter the aquatic ecosystem, such as sewage. Therefore, water pollution has been listed as a significant threat to aquatic biodiversity, including habitat destruction and degradation, overexploitation, biological invasion, and climate change **(Al-Mashhadany, 2022; Ikram *et al.*, 2024)**.

Every year, approximately 300 to 400 million tons of pollutants are released into the world's aquatic systems, seriously threatening water pollution and posing a significant challenge for water quality control. This is aggravated by the fact that many countries continue to face the problem of severe river pollution, which negatively impacts aquatic and terrestrial ecosystems, apart from human populations. With the advancement of industrialization and modernization in these countries, these problems are continually worsening. Researchers around the globe are striving to come up with means of actively improving water-related applications. In recent years, much emphasis has been placed on designing and simulating optimal, low-cost, innovative models that could solve this problem **(Al-Mashhadany, 2021b; Chalane *et al.*, 2023)**.

Artificial intelligence (AI) is currently revolutionizing some areas of research. It has been applied in diverse fields of knowledge, such as chemistry, medicine, biology, the food and agriculture industry, arts, psychology, water quality monitoring, and many more. AI technologies, especially ANFIS, have revolutionized water quality monitoring by revolutionizing data evaluation analysis and interpretation. These innovations have improved the ability to extract meaningful information, identify patterns, and make accurate predictions using various statistical and mathematical techniques, more commonly known as algorithms, which form the underlying procedures in chemical and biological measurements **(Tiwari *et al.*, 2018; Kisi *et al.*, 2023; Jibrin *et al.*, 2024)**.

AI generally refers to the broader goal of simulating human behavior, while ANFIS refers to specific self-optimizing algorithms for data analysis. The literature has different classifications of water; however, this work will only consider surface water and wastewater. These two classes are the most common and well-known categories of water bodies used in daily life. They are paramount to human health, national economic development **(Mekawey *et al.*, 2023; Kuzibaev *et al.*, 2024)**, and environmental sustainability. Its application in water quality prediction has great potential to revolutionize methods and solve imminent challenges completely. ANFIS focuses on intelligent systems that adjust their behavior regarding new information applied during training. The idea with Anfis is to create an algorithm that could perform tasks and draw conclusions typically requiring human intelligence. On the other hand, ANFIS deals with intelligent systems that can change their behavior concerning new information given during the training phase **(Elsabagh *et al.*, 2024; Rashid *et al.*, 2024)**.

This study aimed to evaluate the suitability of the waters of Wadi Akab and the Tigris River for aquatic life by analyzing the physical, chemical and biological properties, as well as developing another method for evaluating water by applying the artificial intelligence model ANFIS and studying its efficiency.

MATERIALS AND METHODS

1. Method of study

Wadi Akab is one of the natural valleys that transport rainwater and floods in Iraq. It was exploited after the expansion of Mosul City to transport sewage water and heavy waste due to wrong and irresponsible individual practices that are directly dumped into the right bank of the Tigris River at the beginning of its entry into Mosul City without any significant treatment **(Al-Assaf *et al.*, 2024)**. This valley penetrates the industrial area and residential neighborhoods located in the western part of the right coast of Mosul City. It collects wastewater from the following areas: the Wadi Akab industry, the Alaisilah Alziraeiu Quarter, the Alaiqtisad Quarter, the Tamuwz Quarter, the Al-Rafai Quarter, and Hawi Al-Kanisa. The discharge rate of the valley was measured in the field and was around $125m^3$/ h. Seven sites were identified to collect samples, as shown in the satellite image. Fig. (1) shows a satellite image of the study area, while Table (1) shows the coordinates of the sites and their height above sea level.

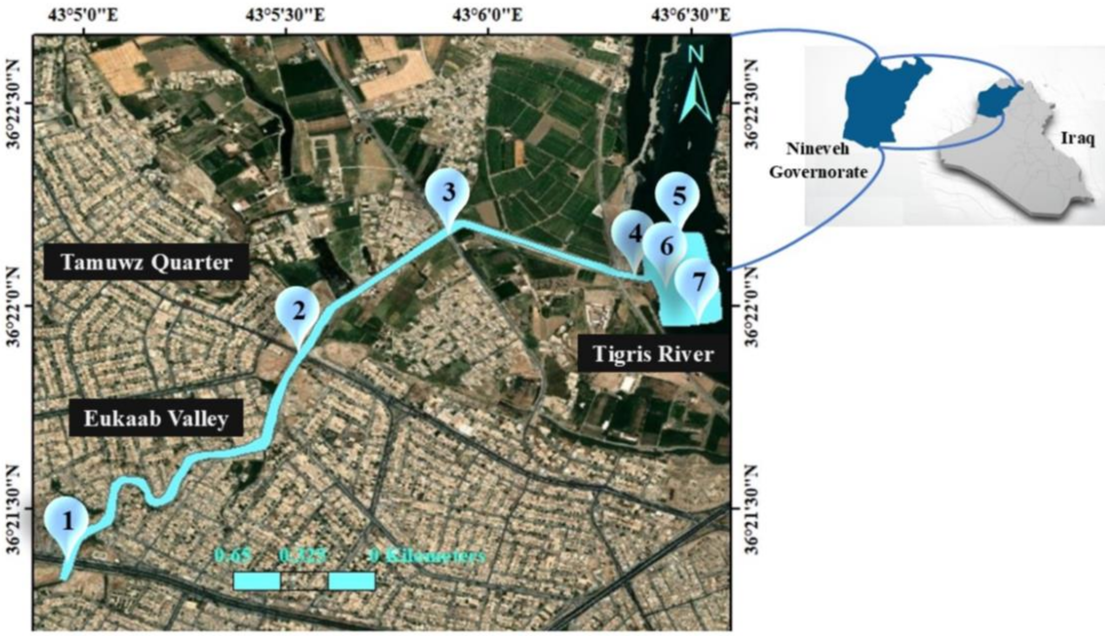

Fig. 1. Satellite image of sample collection sites for the study area

Table 1. Coordinates and altitude of the studied sites

Site	E	N	Altitude (m)	
1	43.08271	36.35569	264	Wadi Akab
2	43.09214	36.36439	242	Wadi Akab
3	43.09807	36.3696	226	Wadi Akab
4	43.10507	36.36803	220	Wadi Akab
5	43.10688	36.36873	217	Tigris River
6	43.10673	36.36784	216	Tigris River
7	43.10736	36.36703	214	Tigris River

2. Data collection

Water quality data were collected from 7 sites, four from wastewater and three from the Tigris River from June to December 2024. Samples were taken every 15 days (Water depth 0.3 - 1m), and water quality parameters including DO%, TDS, T and pH were measured in the field, while phosphate, nitrate, turbidity and *F. coli* were measured in the laboratory according to the methods given in the Standard Method Book **(Baird *et al.*, 2017)**.

3. National sanitation foundation water quality index (NSFWQI)

The quality of surface water was determined using the National Foundation Water Quality Index (NSFWQI), one of the most widely used models worldwide for its accuracy in assessing water quality. The parameters (DO%, temp., TDS, pH, NO_3, PO_4, Tur. and *F. coli*) were used, and the above criteria were calculated by applying the following equation **(Prabagar *et al.*, 2023)**:

NSFWQI= $\sum_{i=1}^{n} Wi * Qi$=

Where:

Wi: The relative importance of the attribute, as shown in Table (2)

Qi: The quality of each characteristic is represented and obtained from special curves and ranges between (0-100). Table (3) shows the classification of water quality for aquatic life based on the NSFWQI model **(Mirzaei *et al.*, 2016; Mekawey *et al.*, 2023; Ketabi *et al.*, 2024)**.

Table 2. Parameters and weights used to calculate NSFWQI

Parameter	Unit	Standard	Weight (Wi)
pH	-	6.5-8.5	0.12
Temp	C	15-25	0.10
DO%	%	50-100	0.19
TDS	mg/L	500	0.10
NO_3	mg/L	1	0.12
PO_4	mg/L	0.03	0.12
Tur.	NTU	>10	0.10
F. Coli.	Cell/100mL	0-100	0.15
Σ			1

Table 3. Water quality classification for aquatic life based on the NSFWQI model

The index limit	Water quality
90-100	Excellent
70-89	Good
50-69	Moderate
25-49	Bad
0-24	Very Bad

4. Adaptive neuro-fuzzy inference system (ANFIS) modeling

The ANFIS model is being trained by using the previous datasets which include measurements of DO%, T, TDS, pH, NO_3, PO_4, Tur. and F. Coli. This structure consists of five distinct layers:

a. Input node of layer 1: Each node represents one input parameter in this layer. These nodes send signals to the nodes in layer 2. The proposed fuzzy sets for the input variables include all membership functions: very bad, bad, moderate, good and excellent. To find the output at the input node, formula (1) was utilized **(Frincu, 2024; Jibrin *et al.*, 2024)**:

$O_i^1 = f_i^1(net_i^1) = net_i^1$……… Formula (1)

Layer 2: the nodes of this layer are the linguistic labels for the input variables; they define membership functions for each input parameter. Generalized bell-shaped membership is the function that represents each variable in a fuzzy set. Neuron j, from this layer has an output expressed as given as: Formula (2):

$O_j^2 = f_j^2(net_2^2) = \frac{1}{1+(\frac{x-c_j}{a_j})^{2bj}}$.......... Formula (2)

Where, the parameters aj, bj and cj define the shape of the jth membership function. The parameter cj locates the center of the curve while parameter bj is positive more often.

c. Layer 3-rule layer, which includes a multiplication to obtain the firing strength value of the rule in each node. Layer 3 consists of 2187 nodes. Each node will receive eight inputs to create a fuzzy rule for all variables. One may calculate the output of kth-order neuron by using: (3) and (4):

$O_k^3 = f_k^3(net_k^3) = net_k^3$……..(3)

$net_k^3 = \Pi_j W w_{jk}^3 y_j^3$…………(4)

Where, y_j^3 is jth input to the node layer three and w_{jk}^3 is assumed to be unity.

d. Layer 4 - output membership function: the fuzzy sets utilized by the following fuzzy inference rules are defined by neurons in this layer. A linked fuzzy rule neuron feeds its inputs to an output membership neuron, which combines these applying the fuzzy operation union. The output from neuron m may be written as: Formula (5, 6):

$O_m^4 = f_m^4(ne_{km}^{\ 4}) = \max(net_{km}^4)$………. Formula (5)

$net_{km}^4 = O_k^3 W_{km}$………. Formula (6)

Where, $W_{km}$is the output action of the mth output associated with the k*th* rule.

e. Layer 5 is a defuzzification layer; that is where by sum-product composition (Formula 7, 8), the de-fuzzified result or crisp value is determined. The result of the weighted average of the centers of all membership functions' outputs **(Kuzibaev *et al.*, 2024; Tyokighir *et al.*, 2024)**.

$O_o = f_0^5(net_0^5) = net_0^5$……..(7)

$net_0^5 = \frac{\sum_m O_m^4 a_{cm} b_{cm}}{\sum_m O_m^4 b_{cm}}$……..(8)

Fig. (2) shows the five layers and inputs.

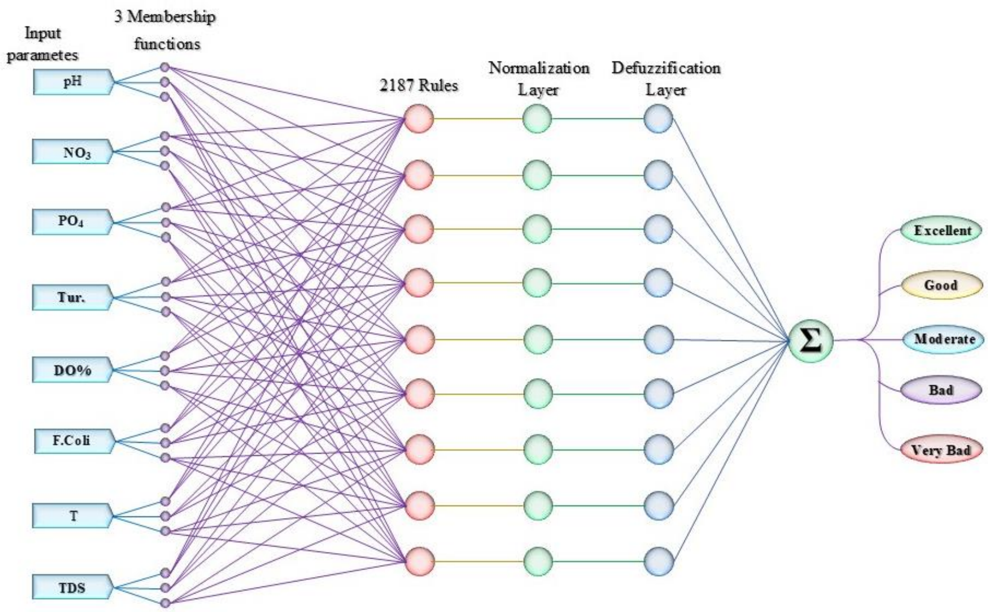

Fig. 2. ANFIS topology for predicting water quality for aquatic life

5. Performance evaluation

This paper considers the performance of the prediction with respect to both accuracy and speed. The challenge is defining the parameters of ANFIS, like the number of inputs, the type and number of membership functions, and the rules applied to the system, while there exists an acceptable tradeoff between the bounds of accuracy and those of speed. In addition, the performances of the prediction will be quantified by the following statistical standards that have also been used in previous papers: root mean square error (RMSE), mean absolute percent error (MAPE), and coefficient of determination (R^2). Where, y'_i describes the predicted values, y_i is the observed values;$\bar{y}_i$ is the average of the observed set, and m is the number of the observed set.

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y'_i - y_i)^2}$$

$$\mathrm{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\frac{|y'_i - y_i|}{|y_i|} \times 100$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - y'_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y}_i)^2}$$

RMSE and MAPE values are positive values. In case of perfect predictions, the value of RMSE and MAPE will be near to zero. R^2 also takes positive value in between zero and one; a value close to one demonstrates the most accurate predictions **(Kisi *et al.*, 2019)**.

RESULTS AND DISCUSSION

The pH values ranged between 7-7.6 and the lowest was at site No. (1) (Table 4). All measured valley water samples were within the standard limits for aquatic life, while the nitrate values ranged between 5.88mg/ L at site No. (4) and the highest at site No. (2) where it reached 13.53mg/ L, and all measured values were higher than the standard limits for aquatic life. There is an inverse relationship between pH and NO_3 (Pearson coefficient -0.79) along the valley path as a result of the activity of anaerobic bacteria, where NO_3 is reduced to N_2 gas as it consumes hydrogen ions (H^+) present in the water, which leads to an increase in pH add reference **(Al-Mashhadany, 2022)**.

$$NO_3^- + 6H^+ \rightarrow 0.5N_2 + 3H_2O$$

Table 4. Measurement results for the measured parameters of the Wadi Akab and the Tigris River water sites

Parameters		Site No.						
		1	2	3	4	5	6	7
pH	Min	7	7.3	7.4	7.3	7.5	7.6	7.7
	Max	7.6	7.6	7.6	7.6	8.1	8.1	8.2
	Mean	7.5	7.4	7.5	7.5	7.8	7.8	7.9
	SD	0.2	0.1	0.1	0.1	0.2	0.1	0.1
DO%	Min	5	4	4	3	72	65	73
	Max	20	18	18	18	84	82	87
	Mean	10	9	9	9	79	75	78
	SD	5.0	5.2	5.5	5.8	4.3	5.7	4.6
T	Min	17.5	18.2	18.2	17.9	14.7	14.7	14.8
	Max	29.5	29.9	33.8	33.7	22.6	23.9	23
	Mean	24.1	25.8	26.6	26.1	20.4	21	20.4
	SD	4.2	4.2	5.1	5.2	2.3	2.7	2.2
Tur	Min	2.8	5	3.5	5.3	0.12	3	0.7
	Max	66.9	352	50.2	39.1	5.2	19.9	33.7
	Mean	20.9	58.9	21	18.8	3	9.6	12.2
	SD	21.6	104.4	15.4	10.8	4.8	6.1	12
TDS	Min	470	372	380	379	180	215	191
	Max	1029	511	482	581	278	280	222
	Mean	735	429	427	445	217	248	210
	SD	190	37	39	77	24	27	9
NO_3	Min	6.8	8.84	6.78	5.88	4.02	4.07	3.92
	Max	17.32	20.65	15.01	12.61	10.61	10.69	10.51
	Mean	12.55	13.53	11.18	10.57	8.73	9.14	8.72
	SD	3.01	3.29	2.07	1.82	1.86	1.92	1.82
PO_4	Min	0.81	0.71	0.74	0.67	0.37	0.47	0.33
	Max	5.22	2.57	1.95	1.48	0.72	0.98	0.72
	Mean	2.68	1.12	1.08	0.96	0.55	0.66	0.55
	SD	1.44	0.59	0.43	0.31	0.11	0.15	0.14
F. Coli.	Min	300	300	300	300	0.3	0	0.3
	Max	110000	24000	110000	110000	110	1100	110
	Mean	27544	3878	18456	46178	35	281	39
	SD	46972	7644	35331	49671	45	471	54

There was no effect of the acidity function of the valley water on the Tigris River, while the effect of nitrate concentration was an increase of 5%.

The is an inverse relationship between temp. and DO% for the measured water samples (Pearson coefficient -0.964), as shown in Table (5). Studies also confirmed that the amount of DO in water decreases with increasing temperature **(Al-Mashhadany, 2021a)**; the rates ranged between 24.1 - 26.6°C and 3-20% for temp, and DO percentage, respectively. The dissolved oxygen percentage increases in autumn and winter due to the decrease in temperature compared to summer. In contrast to the Tigris River samples, all values of saturated oxygen percentage were suitable for aquatic life.

Table 5. Pearson's correlation coefficient for parameters, NSFWQI and ANFIS

Param.	pH	NO3	PO4	Tur.	T	TDS	F. Coli.	DO%	ANFIS	NSFWQI
pH										
NO_3	-0.915									
PO_4	-0.574	0.686								
Tur.	-0.889	0.923	0.535							
T	-0.941	0.773	0.405	0.866						
TDS	-0.762	0.787	0.958	0.691	0.638					
F. Coli.	-0.598	0.346	0.476	0.436	0.673	0.656				
DO%	0.971	-0.866	-0.622	-0.902	-0.964	-0.812	-0.713			
ANFIS	0.927	-0.912	-0.807	-0.882	-0.847	-0.930	-0.654	0.950		
NSFWQI	0.957	-0.887	-0.699	-0.909	-0.930	-0.867	-0.712	0.993	0.978	

The turbidity values of Wadi Akab water ranged between 2.8 - 352NTU and were at their highest at site two and the lowest at the site (1). As for fecal bacteria, their values ranged between 300 - 110000 x 10^{-4}. There is a positive relationship between turbidity and F. coli bacteria, with a Pearson coefficient of 0.436. The reason is that the causes of turbidity in sewage water are organic materials and thus provide a suitable environment for the growth of *F. Coli*. Bacteria.

The increase of phosphate in wastewater leads to the phenomenon of eutrophication, which causes the growth of phytoplankton to a large extent and affects the quality of water for aquatic life. The phosphate concentrations in wastewater ranged between 0.67 - 5.22mg/ L (Table 4). All measured values were not within the water quality for aquatic life and were all higher than 0.03mg/ L. As for TDS concentrations, the rates varied between 427 - 735mg/ L, and 30% of the measured samples of valley water were not within the standard limits for aquatic life. As for the Tigris River, all values were within the standard limits for aquatic life.

The spatial distribution of the waters of Wadi Akab and the Tigris River shows the effect of the river water on the Tigris River, as it shows that the values of the DO% ratio were low along the course of the valley. At the same time, the *F. coli* bacteria had the highest numbers at site No. 4 (Fig. 3).

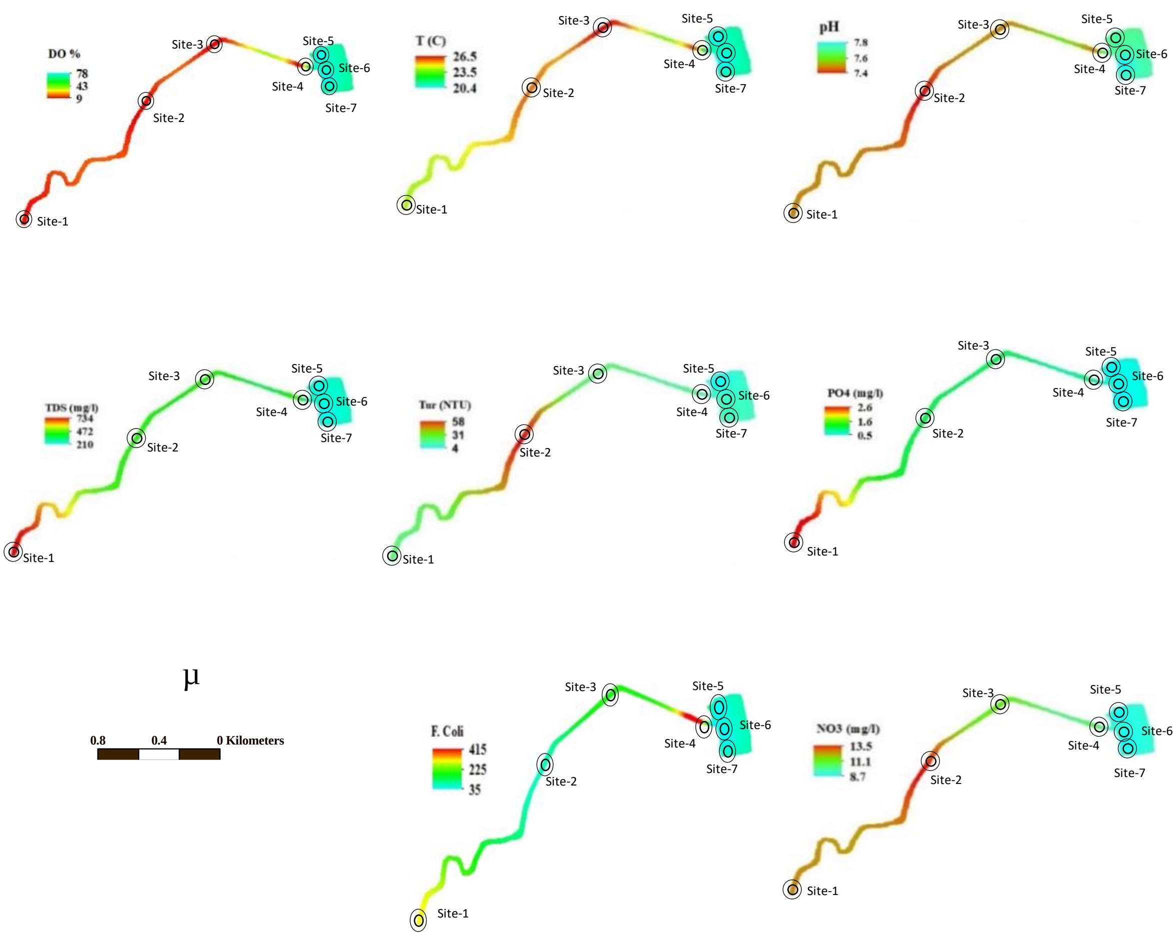

Fig. 3. Spatial distribution of chemical and biological parameters of the waters of the Akab Valley and the Tigris River

The ANFIS results in Table (6) indicate that all the valley water sites were unsuitable for aquatic life and were of a bad and very bad type. The reason is the high parameters measured at the standard limits for aquatic life in addition to the lack of DO% in the valley water, as the values approached zero, while the water of the Tigris River was of moderate water quality for aquatic life due to the high oxygen saturation in the water, which ranged between (75 - 79).

Table 6. ANFIS and ANFIS model results

Site No.	NSFWQI	Water quality	ANFIS	Water quality
1	29.9	Bad	21.2	Very Bad
2	32.8	Bad	29.5	Bad
3	34.0	Bad	33.8	Bad
4	33.4	Bad	33.6	Bad
5	59.0	Moderate	59.8	Moderate
6	55.4	Moderate	51.5	Moderate
7	56.6	Moderate	57.9	Moderate

The water quality assessment of aquatic life for the NSFWQI model and the artificial intelligence ANFIS were identical in classification in most study sites (2, 3, 4, 5, 6 and 7). However, the difference was in site No. 1, where the NSFWQI classification was Bad, while ANFIS was Very Bad. This indicates that ANFIS is more sensitive at low values, which leads to a more conservative classification. We also found that ANFIS is more adaptive to the data, which makes it more accurate in predicting water quality, especially the limit values. NSFWQI is based on static equations, so it may be less accurate in cases where dynamic analysis is required.

The numerical differences between the two methods are very small, indicating that ANFIS can tradition the performance of NSFWQI but in a more advanced and data-adaptive way (Fig. 4).

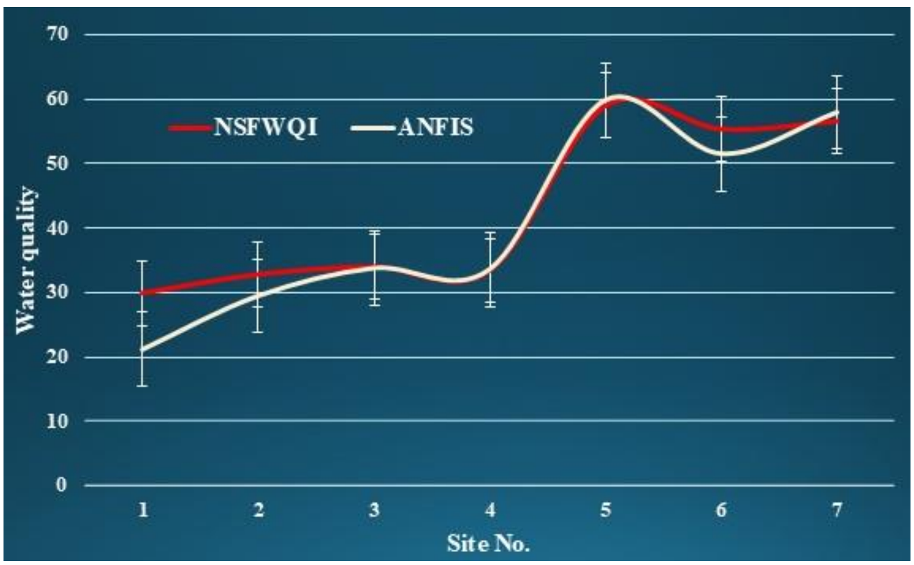

Fig. 4. Comparison of measured and predicted NSFWQI by ANFIS

The RMSE, MAPE and R^2 between ANFIS and NSFWQI were calculated, and the results obtained were 3.86, 6.85 and 0.9, respectively. MAPE is used to measure the accuracy of evaluating the performance of predictive models; the lower the MAPE value, the more accurate the model. The MAPE value indicates a relatively low mean prediction error, and the RMSE value was relatively small, indicating that ANFIS is very close to NSFWQI in assessing water quality for aquatic life. Also, the R^2 value was close to one, which means that the ANFIS model provides accurate performance in interpreting the data.

CONCLUSION

In this study, the suitability of surface water for aquatic life purposes was evaluated using eight different water quality indices; in addition, ANFIS models were developed and compared with NSFWQI, using three different statistical parameters (R^2, RMSE and

MAPE) to compare the performance of ANFIS model with NSFWQI. The results of the statistical parameters were very good and showed a convergence between them. Spatial distribution maps were prepared using GIS to evaluate the aquatic life purposes of the waters of the Wadi Akab and the Tigris River, and according to the spatial distribution maps, it was shown that the Tigris River is suitable for aquatic life.

RECOMMENDATIONS

1. The requirement to reduce sources of pollution, especially affecting dissolved oxygen and toxic substances.
2. Employment of treatment mechanisms of wastewater before discharging it in water bodies (Tigris River).
3. Conducting constant water quality monitoring by artificial intelligence systems (such as ANFIS) for sustainability of water animals.
4. Utilization of public awareness programs of residents in areas around to reduce anthropogenic activities that affect water quality.
5. Implementation of the ANFIS model as a real tool to quantify the water quality in other similar locations.
6. Developing and refining intelligent models such as ANFIS and NSFWQI for making predictions more precise and better decision-making.

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