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Analysis of groundwater quality for drinking purposes using combined artificial neural networks and fuzzy logic approaches

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ABSTRACT

The anticipation of groundwater quality under the influence of urban and agricultural expansions is an essential issue in environmental problems. Several different chemical and physical parameters affect groundwater quality for drinking purposes. Therefore, the purpose of this study is to comparatively analyze three different prediction approaches to assess groundwater quality for drinking purposes. One of these approaches is multiple linear regression (MLR), while the others are fuzzy inference systems (FIS), including clustering (Model I), and artificial neural network (ANN) model with FIS, including clustering (Model II). In the assessment approaches, clustering analysis is done with the self-organizing map (SOM) methodology, FIS is applied as Mamdani fuzzy system, and ANNs are implemented as feed-forward neural networks. All results of the prediction approaches were compared with the laboratory results. A total of fourteen different chemical and physical parameters were used as inputs for all methods. The results of this study demonstrated that the Model II method developed by the combination of SOM, FIS, and neural networks can be used as an alternative approach for evaluating groundwater quality for drinking purposes as compared with the MLR method, which is a well-known approach.

Keywords: Drinking water; Groundwater; Fuzzy inference system; Artificial neural networks; Decision-making

1. Introduction

Groundwater is an important natural resource that is crucial for human life; in fact, groundwater resources are primarily used for drinking, irrigation, livestock, and consumption. Groundwater resources are being utilized for drinking and agricultural production in many parts of the world. There has been a gradual increase in the demand for freshwater resources due to social and economic development. As a result of meeting this increasing demand, the use of groundwater resources as a source of fresh water has increased over a short time. The total abstractable groundwater in Turkey was approximately 14 billion m^3 in 2014. Fresh groundwater abstraction for municipal water supply networks was 2,408,620 thousand m^3/y in Turkey in 2014 as compared to 2,133,032 m^3/y in 1994 [1]. This pattern shows that groundwater use has been increasing day by day, which assesses quality significant in Turkey.

Natural and human-induced chemicals can be found in groundwater; therefore, its quality may be affected by many different chemical and physical factors. These may be caused by contamination sources, such as agricultural and industrial activities.

Dissolved chemicals and contaminants are transported to the subsurface from disposal sites by groundwater flow; therefore, the water quality of wells is worsened due to the contaminated groundwater [2]. Many studies have been carried out to investigate and understand the chemical and physical properties of groundwater in the Goksu Delta. The over-usage of groundwater may lead to a critical issue which is seawater intrusion problems [2,3]. The levels of

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Cl^-, Na^+, and electrical conductivity (EC) are greater in the Goksu Delta, which can increase soil salinity and limit water use for different purposes [4]. Also, nitrogen compounds, phosphate, and organochlorine pesticide parameters, which generally originate from agricultural activity and fertilizers, are found at high levels in the Delta, thereby causing the deterioration of irrigation water quality [2,5]. However, it has been reported that dissolved nutrient distributions (such as inorganic phosphate (DIP), inorganic nitrogen (DIN), inorganic carbon (DIC), total dissolved organic carbon (DOC), and alkalinity), which are used to characterize groundwater, were low and currently posed no or little risk in the Delta [6]. Also, some trace element contents in the Goksu Delta are reported to show excess concentrations of Fe, Ni, Mn, Mo, and Cu at some locations, leading to decreased quality of potential drinking water [7]. However, Seckin et al. [8] reported that uses of groundwater for irrigation and human consumption are suitable in terms of trace elements except for B, Ba, and Fe. The results demonstrate that several parameters are reported to affect the groundwater quality in the Goksu Delta.

In recent decades, the applications of artificial intelligence techniques have recognized an optimal use of investigating and evaluating the multifaceted environmental problems [9,10] including the prediction of drought and rainfall [11], real-time prediction of flood events [12], estimation of the spatial variability of groundwater level [13] along with wind and wave predictions [14]. Groundwater quality-related studies based on artificial intelligence techniques are one of the subjects of this phenomenon that has been recently and frequently studied. Srinivas et al. [15] analyzed the use of groundwater resources in domestic usage and irrigation purposes. They used the fuzzy inference rules to interpolate the concentration of hydrochemical parameters for the intended use of water. The results of water quality for both drinking and irrigation purposes using the artificial neural network (ANNs) demonstrate that the region's groundwater wells are in unfavorable conditions. Wagh et al. [16] used adaptive ANNs models to predict the nitrate concentration in groundwater. Their results showed that adaptive neural networks demonstrated acceptable performance in the prediction of water contaminants. Chanapathi et al. [17] implemented the conjunctive use of groundwater resources through the centroid defuzzification method in selected Asian cities. Their results showed that the use of the fuzzy-based system can replace other conventional methods for groundwater management. Chaudhary [18] used the Mamdani fuzzy model for the evaluation and suitability assessment of groundwater for drinking. The overall water quality for the Haridwar city, India was estimated four classes and suggest confidence level. Lee et al. [19] used the combination of a self-organizing map (SOM) and the fuzzy C-means (FCM) models to interpret the urban groundwater quality in Seoul, South Korea. The cooperative use of SOM and the FCM clustering was developed to determine the hydrochemical groups and identify their distributions. Azimi et al. [20] evaluated the annual quality of drinking water and its relationship with the occurrence of droughts in Iran plain aquifer by using the combination of fuzzy ANN, radial basis function, and probabilistic neural network (PNN) methods. ANNs indicate that there is a decline in groundwater quality in most of the aquifers in the country due to unsuitable conditions. However, few studies have been conducted on decision-making in the Delta. One such study has focused on determining the quality regarding the similarities of quality factors obtained from the fuzzy clustering approach for numerous groundwater sources [21].

As stated previously, assessing groundwater quality for drinking purposes is quite a difficult process because of the different numbers of influenced parameters that exist. In addition, this process should be performed by an expert, and it becomes very complex to determine the qualities within a comparative number of wells. The purpose of this study is to propose a new methodology to handle the effects of different chemical and physical parameters together in the drinking quality of groundwater. This study proposes a combined methodology with fuzzy logic and ANNs. In this method, the influenced parameters are expressed by fuzzy logic regarding the degree of importance, and the rules are created by considering these degrees. The proposed approach was evaluated in the Goksu Delta, which is a valuable wetland of Mersin City, Turkey.

2. Materials

2.1. Study area

Coastal wetlands are important areas due to the presence of fertile farmlands, various irrigation and agricultural activities, freshwater sources, and their unique floral and faunal characteristics. However, groundwater from coastal aquifers suffers from numerous threats such as unplanned exploitation, excessive groundwater extraction, saltwater intrusion, coastal building, and dense populatıon. So, this more vulnerable area is adversely affected by natural or anthropogenic activities that may lead to freshwater scarcity. Therefore, it is important to predict the water quality of groundwater resources in coastal aquifers and make predictions about how the water quality in this region will change according to which parameters in the future.

Aiming to develop a prediction model, Goksu Delta was chosen as the data collection area in this study. Goksu Delta is an important nature reserve and one of the most important natural coastal wetlands in the Mediterranean Region in terms of Turkey's ecological, cultural, and social values. The Goksu Delta was included in the 1994 statute of the Convention on Wetlands of International Importance (Ramsar), especially as a waterfowl habitat that aims to ensure the sustainable use of these areas. Considering the bird species that are hosted in the past, this area is classified as a class "A" wetland (waterfowl wetlands hosting more than 25,000 species according to the Ramsar Convention).

2.2. Climate and agriculture

A Mediterranean climate is dominant in the region of Goksu Delta. Summer is hot and arid, and winter is rainy and mild. The monthly average temperature and monthly total precipitation data have been collected from the Silifke Meteorology Directorate Turkish Meteorological Archiving System database via a formal request. The collected data indicated that Station 17330, which is located at the center of the city, has the most appropriate data for Silifke. The meteorological data of Silifke indicated that the annual average temperature was 20.89°C, the total annual precipitation was 606.8 mm, and the average annual relative humidity was 55.5% in 2012.

Agriculture is the most important occupation in the Goksu Delta. The Silifke Plain is divided into two regions (east and west) by the Goksu River. Soil structure and climate, which have a role in the determination of agricultural potential, cause the diversification of production patterns and an increase in the amount of production. These features allow for the growth of various agricultural products. This constitution of the Goksu Delta creates a very rich agricultural structure, allowing for the growth of warm climate crops, such as wheat and barley on one hand, and peanuts, citrus fruits, and turmeric vegetables on the other [22].

2.3. Geological and hydrogeological settings

A detailed discussion on the general geology and hydrogeological description of the Delta plain has been previously reported in a study [21]. The Delta is characterized by a complex hydrogeological structure that is based on alluvial formations with gravel, sand, silt, clay, and sandy clay. This situation allows for significant water storage in an otherwise water-scarce area. The area shows large differences in lithology and grain size, both vertically and in cross-section. Therefore, the hydraulic properties of these sediments display transitional characteristics horizontally and vertically at short distances. The region also contains several coastal aquifers that are in contact with these structures. Alluvial aquifers of the region were under severe saltwater intrusion, which significantly altered the freshwater/seawater interface as a result of excessive pumping [3,8].

2.4. Groundwater sampling and analysis

The 24 wells located over the Goksu Delta constitute the samples of this study as depicted in Fig. 1. Samples were collected monthly between May 2012 and April 2013. The parameters measured for evaluating groundwater quality are shown in Fig. 2.

At each sampling station, the temperature (T; °C), pH, and EC (µS cm^{-1}) of the water samples were measured in the field using the WTW pH340 and 2510-A Orion instruments. The amount of total dissolved solids (TDS) was determined by filtering the samples through Whatman (0.45 µm) filter paper, followed by evaporation for 24 h at 150°C in preconditioned and preweighed crucibles.

The change in weight was used to determine the dissolved salts. Alkalinity was analyzed by titration (CO_3^{2-}, HCO_3^-), using the alkalinity (2320)/titration S.2-35 Standard Methods. For ion analysis, nitric acid was added to each

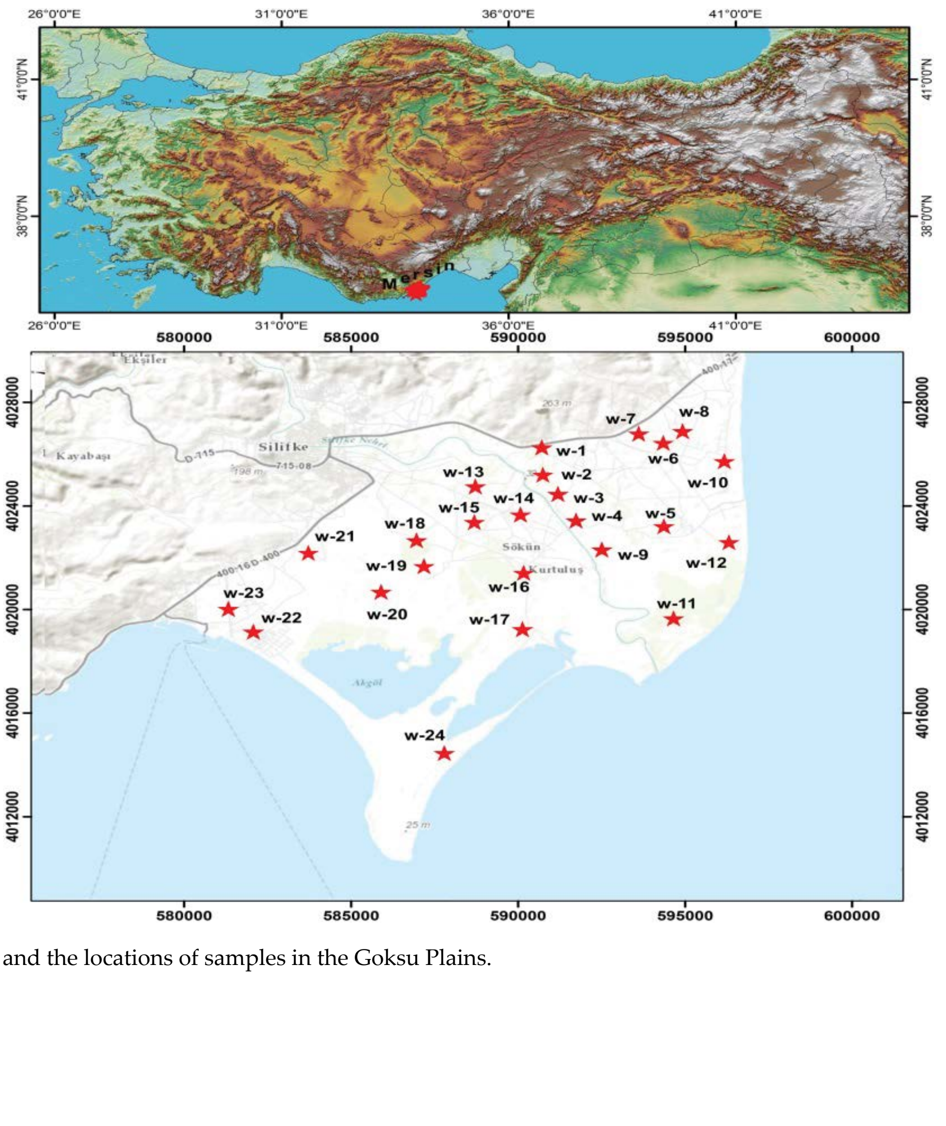

Fig. 1. Sample sites and the locations of samples in the Goksu Plains.

water sample to ensure a pH of greater than 2. The bottles were tightly capped to prevent the intrusion of atmospheric CO_2. All samples were transported to the Environmental Chemistry Laboratory of Cukurova University and stored in the refrigerator at 4°C until further analysis. All major cations, that is, Ca^{2+}, Mg^{2+}, Na^+, K^+, Si, and Ba were analyzed using a Perkin Elmer highly sensitive inductively coupled plasma spectrometer, and anion concentrations, that is, SO_4^{2-}, NO_3^-, and Cl^- were measured using the process of ion chromatography, following the APHA [23].

The results of the 288 samples taken from 24 wells are summarized in Table 1. According to Table 1, all the parameters except for temperature, pH, NO_3^-, Ba, and Si levels had shown significant variability in the study area. This, in turn, made the current drinking water quality to these parameters difficult to analyze and evaluate. Therefore, the use of other methods is beneficial to overcome this variability.

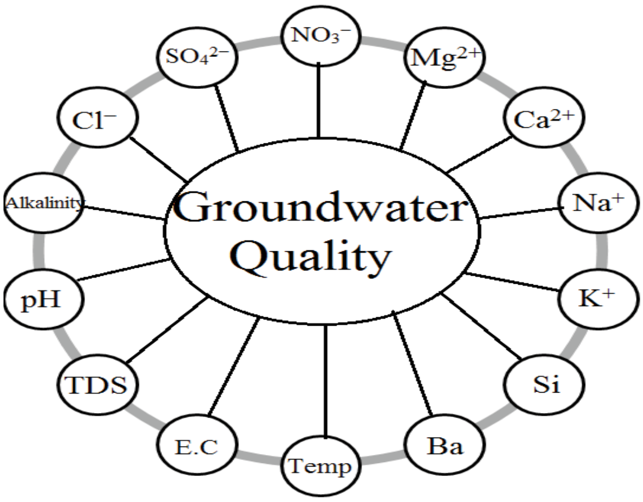

Fig. 2. Evaluation parameters of groundwater quality.

3. Basic principles of AI methods used in this study

3.1. Fuzzy inference system

In classical mathematics, most parameters and structures on models are implied as certain, which means it is assumed that the values are known absolutely [24]. Despite this certainty in assumption, in fuzzy sets, membership in a set is permitted as partially known [25]. In other words, in fuzzy sets, crisp valued variables are represented by membership functions and linguistic terms. A typical membership triangular function is depicted in Fig. 3a. Crisp variables (denoted as x) have membership values regarding membership values.

A fuzzy inference system (FIS) can deal with linguistic and numerical information. The system has four basic parts: rules, fuzzifier, inference engine, and defuzzifier as depicted in Fig. 4 [26].

When the input value has entered the system as a crisp number, the crisp number is fuzzified by using membership functions. The crisp numbers need to be fuzzified to be processed with fuzzy algebra. Fig. 3b shows the fuzzification process of the crisp number X_1. The X_1 is fuzzified as membership value a. After fuzzification, the fuzzified inputs are evaluated with the user-defined decision rules for the inference operation. The fuzzy output regarding these rules and inputs is acquired, and finally, it is defuzzified to calculate the crisp output value. The defuzzification process converts a fuzzified output to a crisp value to output's membership functions. Different methods can be applied to this process. Because of its wide use, the centroid method is applied for defuzzification in this study as shown in Eq. (1) [27].

$$Z^* = \int \frac{\mu_c(z) z d_z}{\mu_c(z) d_z} \tag{1}$$

Table 1
Descriptive for chemical, physical parameters, and drinking water quality values

	Minimum	Maximum	Mean	Standard deviation
Temperature	14.80	37.50	21.45	2.5852
EC	143.10	51,400.00	2,621.28	6,102.96
pH	6.64	9.05	7.83	0.3574
NO_3^-	9.87	19.93	12.55	1.1577
Na^+	10.41	6,205.50	341.48	831.339
Cl^-	41.55	11,964.50	578.54	1,584.534
K^+	0.99	415.45	18.89	50.2585
TDS	109.50	38,801.30	1,556.66	4,383.261
Mg^{2+}	2.64	1,110.90	66.82	139.939
Ca^{2+}	10.85	496.30	72.03	63.228
SO_4^{2-}	79.75	1,210.82	227.80	189.02
Alkalinity	68.05	5,415.90	456.87	699.61
Ba	0.01	6.36	0.38	0.6506
Si	0.00	6.17	2.44	1.059
Drinking water quality	10	96	52.41	24.17

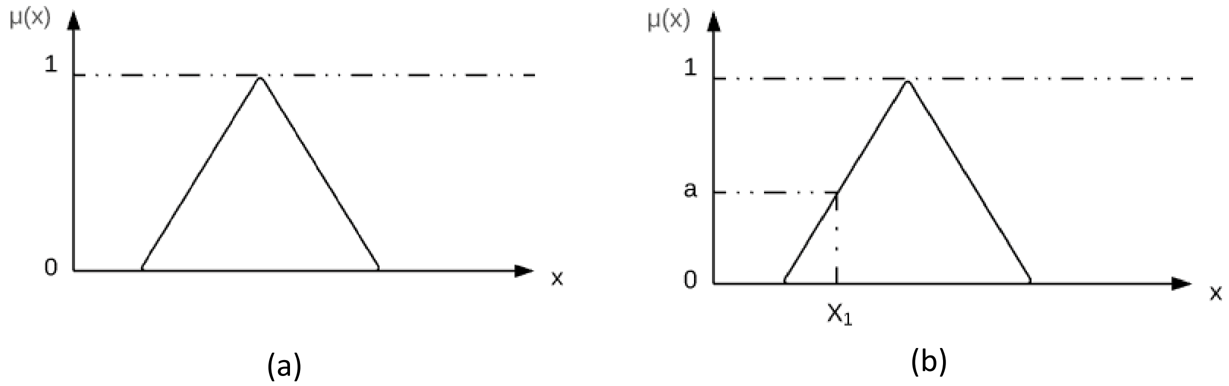

Fig. 3. An example triangular membership functions.

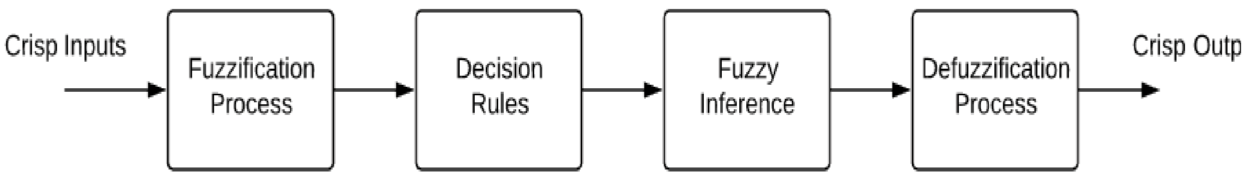

Fig. 4. Basic elements of FIS.

3.2. Self-organizing maps

The SOM is a technique that represents the input values with various features. This means that this method is novel for observing the semantic relations with a self-organization process [28]. In the SOM clustering approach, the relations of features are mapped with competitive learning. This makes SOM different from other ANN techniques. In other words, training of the SOM occurs through unsupervised learning and the clusters are formed by similarities regarding features.

3.3. Neural networks

The neural networks (NNs) are inspired by the biological neural systems and try to simulate the systems of a human brain. In the NNs approach, inputs are mapped to outputs by using different layers. Multilayer NNs are formed with additional hidden layers that separate inputs and output layers. The feed-forward neural networks are a special type of multilayer NNs which are directed from input to output by connecting the successive layers [29]. A typical multilayer feed-forward NN architecture is depicted in Fig. 5.

Each connection depicted in Fig. 5 has to be weighed by different values. To achieve the best-fitted model regarding the dataset, the NN model has to be trained. There are many different training algorithms are presented in the literature. This study applies the Levenberg–Marquardt learning algorithm [30] to the NN.

4. Structure and parameters of developed AI models and multiple linear regression

In this study, the groundwater quality for drinking purposes was assessed by the combination of the FIS, SOMs, and NNs systems. In the FIS model, after determining the details of membership functions, fuzzy decision rules were formed using the experimental results and experimental experiences of the authors. One of the authors had conducted some doctoral studies on water quality analysis. During her studies spanning for eight years, including doctoral studies in this field, she conducted various physical and chemical water quality analyses on approximately 1,250 samples taken from 55 different wells in various regions. Two different models named as Model I and Model II, respectively, were proposed as a combination of FIS, SOMs, and NNs.

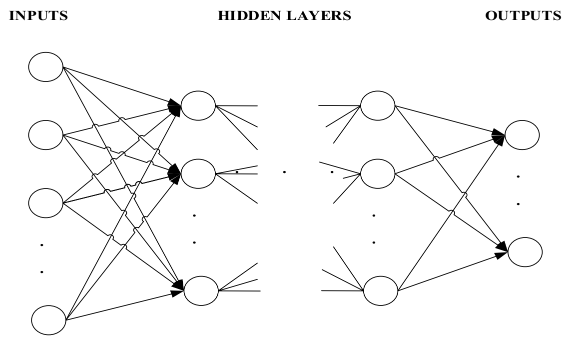

Fig. 5. Multilayer feed-forward NNs model.

4.1. Model I (SOMs + FIS)

In Model I, SOMs and FIS was used as an integrated approach. In this approach, first, the methodology of SOMs was applied to the input parameters to cluster the relative parameters that similarly affect the water quality. The results taken from the Goksu Delta groundwater were used in the clustering application. According to the results of the clustering application, the input parameters were clustered as *n* different clusters, with *n* denoting the number of clusters.

After the clustering stage, the second stage consisted of creating FIS models for each cluster. In other words, the drinking water quality was estimated regarding each cluster's own inputs' attributes. The general structure of Model I is shown in Fig. 6.

4.2. Model II (SOM + FL + ANN)

Model II works parallel to Model I during the clustering stage and FIS stage. The difference between Model II and Model I is the additional step composed by the NNs approach. The NN tool added to Model I uses the results of FIS in Model II. The outputs of FIS were used as input parameters by the ANN tool in Model II. The general structure of Model II is shown in Fig. 7.

In this model, outputs of all fuzzy models were fed to the final decision model. This multilayer approach provided weighting and fuzzified each cluster regarding their influence on the drinking water quality. In this way, a sensitive estimation of the drinking water quality could be made. The feed-forward NNs were applied by determining the drinking water quality.

4.3. Multiple linear regression analysis

Temperature, EC, pH, NO_3^-, Na^+, Cl^-, K^+, TDS, Mg^{2+}, Ca^{2+}, SO_4^{2-}, alkalinity, and Ba and Si contents were used as

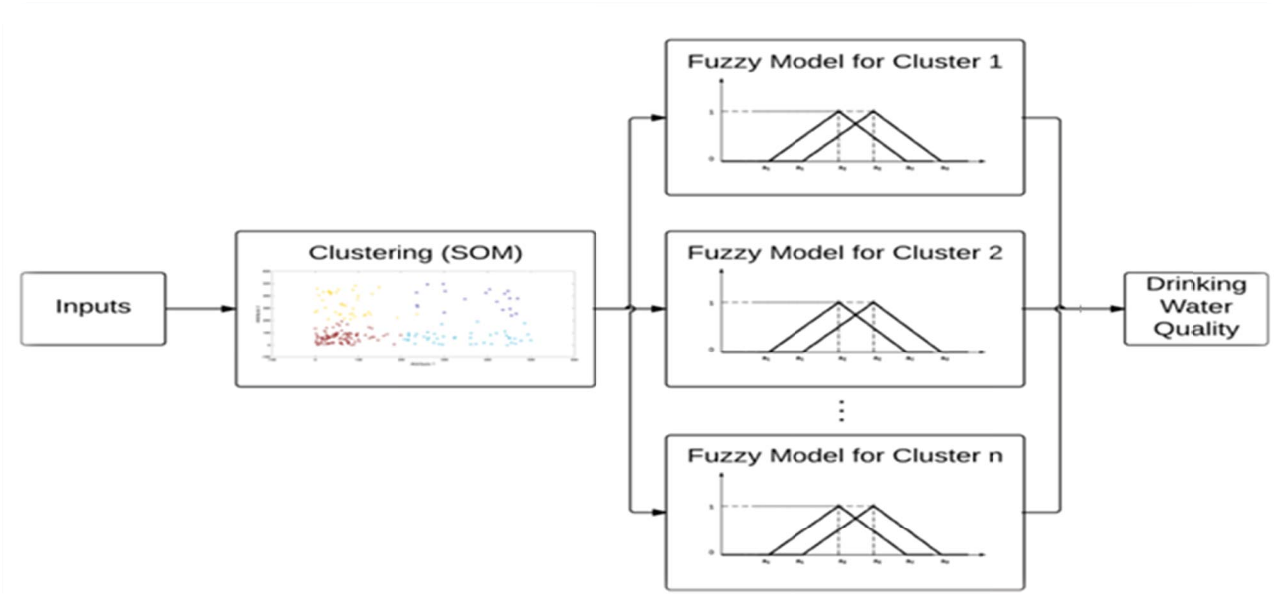

Fig. 6. General structure of Model I.

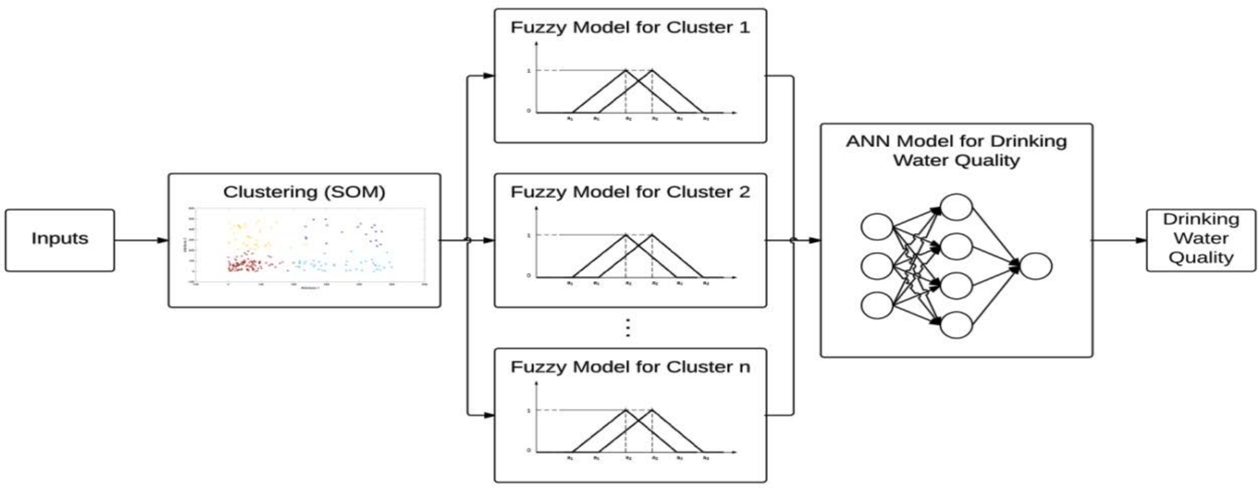

Fig. 7. General structure of Model II.

independent variables, and groundwater quality scores (GWQS) was used as dependent variables to make multiple linear regression (MLR) analysis. An empirical correlation was developed to predict GWQS by using 288 data samples collected from the area. Eq. (2) shows the MLR prepared to predict the GWQS of Goksu Delta.

$$\text{GWQS} = -0.51 \times \text{Temperature} + 12.49 \times \text{E.C} - 0.43 \times \text{pH} + 0.0002 \times NO_3^- - 0.05 \times Na^+ - 0.02 \times Cl^- + 1.01 \times K^+ + 0.0003 \times \text{TDS} + 0.10 \times Mg^{2+} - 0.08 \times Ca^{2+} + 0.01 \times SO_4^{2-} + 1.15 \times \text{Alkalinity} - 0.03 \times \text{Ba} - 5.38 \times \text{Si} \quad (2)$$

5. Results and discussions

The relationship between the input and output variables was established by using three approaches including two artificial intelligence models (Model I and Model II) and an MLR model. The predictability of the developed models was evaluated by using mean absolute error (MAE) statistics defined by Eq. (3).

$$\text{MAE} = \sum_{i=1}^{n} \frac{\left| y_i - \hat{y}_i \right|}{n} \quad (3)$$

Here, in this equation, y_i is the measured value, $\hat{y}_i$ is the predicted value and n is the number of data samples. The prediction accuracy is very important for a forecasting technique. For this reason, to more meaningfully interpret the prediction success of the models, both the monthly based results obtained from the wells and the results of each well were compared separately. Matching figures and correlation figures were drawn to observe the relationship between prediction models, MLR, and expert opinion results. Besides, MAE statistics were calculated to evaluate the prediction errors. Fig. 8 (monthly) and Fig. 9 (wells-based) show the matching figures of GWQS results obtained through different approaches and expert opinion results.

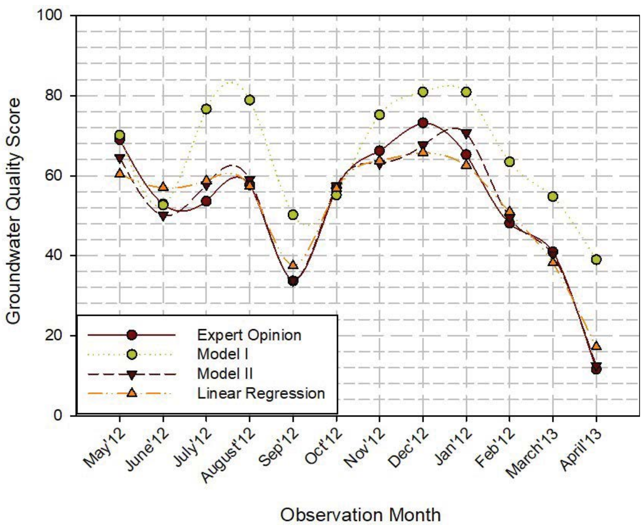

Fig. 8. Matching figure of GWQS results found by different approaches (monthly).

In addition to the matching figures provided in Figs. 8 and 9, MAE values between the results of each estimation approach and expert opinion results are given in Table 2 (monthly) and Table 3 (well based), respectively, to evaluate the predictability of the models.

The results derived from Tables 2 and 3 show that the proposed Model II for predicting GWQS has a high predictive capability for both monthly based and water well-based results rather than Model I with lower prediction errors. Model II also pointed out a better performance than MLR. Fig. 10 (monthly) and Fig. 11 (water well-based) show the correlations of the expert opinion results with the results obtained from MLR, Model I, and Model II. As it can be seen from the figures, the expert opinion results and Model II results have the best correlations as compared with the prediction abilities of other approaches both in monthly based and water well-based results.

The correlations provided in Figs. 10 and 11 support the MAE values and matching figures provided in Tables 2

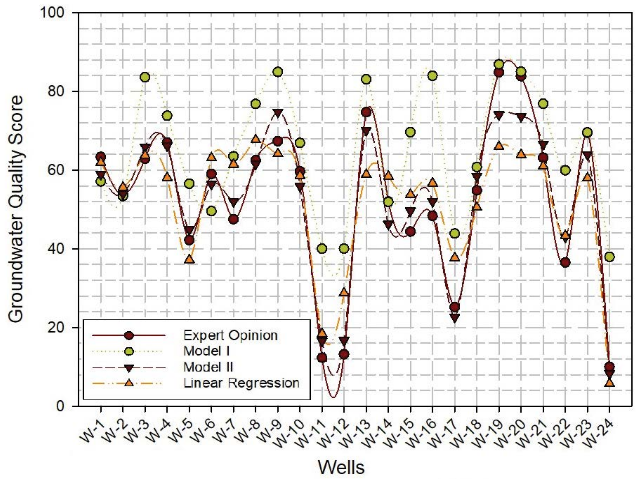

Fig. 9. Matching figure of GWQS results of each well found by different approaches.

Table 2
MAE values between each estimation approach and expert opinion (monthly)

Months	Exp-MLR	Exp-MODEL I	Exp-MODEL II
May'12	1,298,109	1,280,635	946,386
June'12	8,041,159	1,198,238	6,811,696
July'12	1,044,106	2,303,021	8,767,736
August'12	9,264,312	2,399,074	7,037,107
Sep'12	1,036,759	177,187	5,397,271
Oct'12	1,076,801	1,136,303	485,914
Nov'12	1,642,758	1,182,805	8,926,495
Dec'12	1,424,934	1,247,437	8,516,206
Jan'12	7,050,238	182,662	7,496,348
Feb'12	654,714	17,494	8,087,348
March'13	1,395,505	1,936,658	7,967,218
April'13	1,289,258	27,375	3,019,038

Table 3
MAE values between each estimation approach and expert opinion (well based)

Wells	Exp-MLR	Exp-MODEL I	Exp-MODEL II	Wells	Exp-MLR	Exp-MODEL I	Exp-MODEL II
W-1	6,550,167	1,099,217	6,167,235	W-13	1,941,201	1,462,053	1,276,048
W-2	4,136,893	9,294,102	5,333,023	W-14	1,194,543	1,467,066	8,290,369
W-3	9,818,524	2,075,721	720,772	W-15	110,636	2,530,321	1,032,775
W-4	100,993	1,236,083	6,392,055	W-16	8,429,328	3,562,065	7,682,159
W-5	7,554,487	1,675,982	6,098,598	W-17	131,807	1,867,758	4,695,945
W-6	9,247,995	1,176,806	4,696,716	W-18	1,228,803	10,958	5,021,563
W-7	1,395,504	1,663,912	6,784,855	W-19	1,890,012	701,699	1,106,813
W-8	8,564,884	1,862,104	5,908,917	W-20	1,993,379	6,327,697	111,235
W-9	6,009,045	1,991,571	7,579,917	W-21	8,091,431	1,661,669	7,412,778
W-10	3,601,987	1,122,868	7,402,942	W-22	9,492,292	2,375,932	8,771,755
W-11	9,921,758	2,766,667	6,801,106	W-23	1,798,834	1,106,649	9,133,331
W-12	1,673,855	2,683,333	4,337,198	W-24	9,046,612	2,791,667	1,700,879

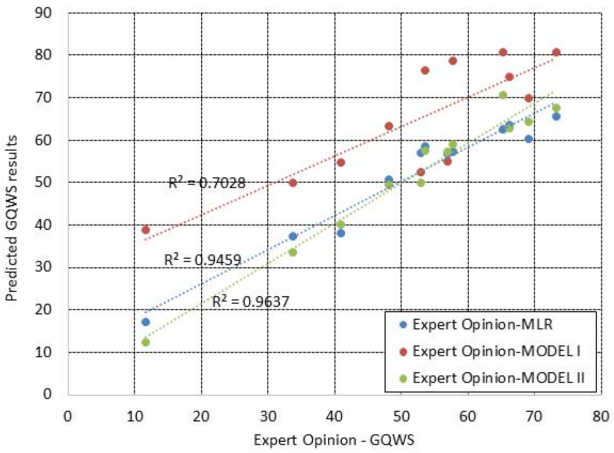

Fig. 10. Correlations of Model I, Model II and MLR with expert opinion (monthly).

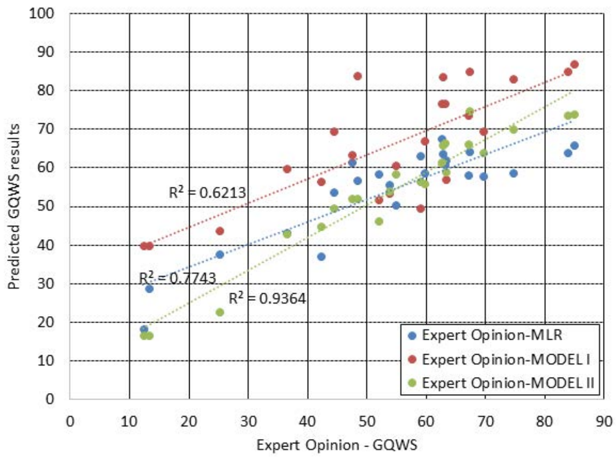

Fig. 11. Correlations of Model I, Model II and MLR with expert opinion (water well-based).

and 3 and Figs. 8 and 9, respectively. All results indicate that MODEL II is the best approach for the estimation of the GWQS. According to the MAE values provided in Table 3, the best predicted well is W-24 for Model II. When the wells from W-1 to W-12 were compared with the results of Model II, it is observed that nearly similar MAEs were calculated.

Demirel et al. [7] pointed out that the fertilizers, heavy metals, and other pollutants are transported to the river water by the irrigation return flow in up site areas in the Delta. This situation may be due to the main drainage line in the upsite region, which is constructed to be rearranged in the Delta flow into Akgöl and Paradeniz. Sediments and chemical wastes from agricultural areas are carried to these lakes via drainage channels [31]. Also, agricultural activities are nonpoint source polluters of water quality, and almost all of the wells may have been equally affected. These circumstances assess drinking quality a challenging task; however, the proposed method primarily overcame these difficulties and deduced this pattern in the Delta. Just as with coastal groundwater in various parts of the world, the Goksu Delta is also facing the threat of seawater intrusions [4,8]. As expected from this point of view, W-24 is the closest well to the Mediterranean Sea, and it was most affected by seawater intrusion. Although this condition exists, the proposed method and linear regression have made accurate predictions of drinking water quality. Additionally, well W-17 is the nearest to the Paradeniz, which contains high salt concentrations and had quite reliable predictions with the proposed method. The hydrochemical analyses indicated that nitrogen is an important contamination parameter in the Delta [6,32,33]. Among the other wells, wells W-19 and W-20 were especially affected by the anthropogenic activities in the Delta area due to agricultural activity and sewage. Therefore, these wells have slightly higher error values. Wells W-13 and W-14 are closer to the Goksu River than wells W-15 and W-16, which are near the Mediterranean Sea. This position of wells may help to dilute salinity, EC, and other quality parameters in wells W-13 and W-14. However, these parameters are concentrated in wells W-15 and W-16 near the sea. Therefore, assessing the groundwater quality may be more difficult in these wells as it can be understood from the errors. Finally, our results are consistent when compared with the studies that analyzed the physical and chemical properties present in the region [2,8,33].

6. Conclusion

The measurement of groundwater quality is a complex process due to various factors such as hydrogeology, geology, biology, and land-use practices. The Goksu Delta, which is an economically and ecologically important area, has a lot of groundwater resources. Additionally, this valuable Delta is protected by national and international treaties. In this research study, two different prediction methods and an MLR method were studied to assess the groundwater quality of the Goksu Delta for drinking purposes by examining the physical and chemical water quality parameters. The combination of FIS + SOMs + NNs techniques employed in this study provided an efficient way of analyzing the hydrochemical dataset (288 cases and 14 variables) from the Goksu Delta area. The results of this study are promising and suggest that the combination of these techniques can be successfully applied in the characterization of groundwater drinking quality. The results demonstrate that Model II (SOM + FL + ANN) can better reflect the continuous change in water chemistry variability in groundwater quality in the study area.

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