

# Assessment of groundwater quality using DEA and AHP: a case study in the Sereflikochisar region in Turkey

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**Abstract** This study investigated the spatial distribution of groundwater quality in Sereflikochisar Basin, in the Central Anatolian region of Turkey using different hydrochemical, statistical, and geostatistical methods. A total of 51 groundwater samples were collected from the observation wells in the study area to evaluate the characteristics of the groundwater quality. As a relatively simple and practical method, a groundwater quality index (GWQI) was developed to evaluate the overall groundwater quality. In this process, complex decision-making techniques such as analytic hierarchy process (AHP) and data envelopment analysis (DEA) were used. Based on these models, two new indices (A-GWQI and D-GWQI) were proposed. According to the D-GWQI score (from 0.6 to 1), water quality was classified in four categories as unsuitable (0.6–0.7), permissible (0.7–0.8), good (0.8–0.9), and excellent (0.9–1). The spatial distribution maps of the groundwater quality were created using the Kriging method. For each map, seven different semivariogram models were

tested and the best-fitted model was chosen based on their root mean square standardized error. These maps showed that the areas with high groundwater quality were in the eastern and southern parts of the study area where the D-GWQI scores were greater than 0.8. Depending on the distance from the Salt Lake, the characteristics of groundwater changed from NaCl to NaHCO<sub>3</sub> and CaHCO<sub>3</sub> facies. This study shows how to determine the spatial distribution of the groundwater quality and identify the impact of salt lakes on the groundwater quality in inland aquifers. The findings of this study can be applied to ensure the quality of groundwater used for drinking and irrigation purposes in the study area.

**Keywords** Groundwater quality · Analytic hierarchy process · Data envelopment analysis · Geostatistics · Turkey

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## Introduction

The rise in world population and industrial growth necessitates the continuous monitoring of fresh water resources. Groundwater is one of our most important sources of water for drinking and agricultural and industrial purposes; however, the quality of groundwater quality varies as a result of physical, chemical, and ecological changes. The use of low quality water sources for drinking and agricultural and industrial purposes may result in serious health problems and economic losses (Germolec et al. 1989). Since good water

quality is essential to a healthy ecosystem, assessment of groundwater is an important aspect of water resource management (Banerjee and Srivastava 2009). Furthermore, monitoring defined water quality parameters is a key activity in managing the environment. The standard quality for drinking water has been specified by the World Health Organization (WHO 2012) and European Union (EU 2014), which have provided the acceptable limits for the presence of various elements in groundwater. The large number of water quality parameters (Ojha et al. 2003) has led to the emergence of different quality classes for the same water sample. Therefore, to prevent any confusion in terms of water quality, water quality indices (WQI) have been developed by researchers such as Horton (1965), Pesce and Wunderlin (2000), Cude (2001), Liou et al. (2004); Nasiri et al. (2007), Banerjee and Srivastava (2009), and Abtahi et al. (2015).

A WQI is a system of ranking the quality of water in the environment by numerical means. First developed by Horton (1965), WQI has been widely used for describing the source water quality all over the world. A WQI is a dimensionless number that combines multiple water quality variables into a single number by normalizing values to subjective rating curves (Miller et al. 1986). It converts pollutant concentration data into sub-index values and then combines them into a single score (Cude 2001). In recent years, complex decision analysis techniques such as analytic hierarchy process (AHP) and data envelopment analysis (DEA) have been developed and used to evaluate the water quality and determine WQI (Banai-Kashani 1989; Soutter and Musy 1998; Kim and Hamm 1999; Jha et al. 2010; Pourghasemi et al. 2012; Do et al. 2013; Tirkey et al. 2013; Jeihouni et al. 2014).

The analysis of complex decisions involves the evaluation of activities using multiple criteria to determine the best alternative activity. Multicriteria decision-making (MCDM) tools can support decision-makers in this process (Saaty 1996; Yang et al. 2008; Üstün and Anagün 2015). MCDM provides the stakeholders to assess a list of alternatives by providing them with an evaluation of each decision alternative against individual criteria together with intercriteria information demonstrating the relative importance of different criteria (Saaty 1986; Banai 2010; Agarwal et al. 2013). This technique has been extensively employed in the evaluation of decisions particularly regarding disaster management (Üstün and Barbarosoglu 2015; Üstün 2015)

and environmental management (Üstün 2015; Cooper et al. 2000).

Although a number of methods are commonly used for organizing and analyzing complex decisions, MCDMs have rarely been comprehensively applied to water quality systems. Agarwal et al. (2013) developed a method for the delineation of groundwater potential zone in the Uttar Pradesh (India) using AHP and ANP. The researchers evaluated the following nine parameters: rainfall, geomorphology, soil, land use, geology, lineament, slope, drainage density, and groundwater depth. Similarly, Sener and Davraz 2013 used AHP and geographical information system (GIS) to identify groundwater quality. Shabbir and Ahmad (2015) used a similar method involving AHP to assess the vulnerability of the water resource in Rawalpindi and Islamabad. Kumar et al. (2014) applied multicriteria analysis to the GIS environment to create a map of potential groundwater zones.

This study investigated the groundwater quality of aquifers in the Sereflikochisar Basin (SB) in the Central Anatolian region of Turkey using physical and chemical data and statistical methods. Freshwater aquifers in SB are contaminated by the Salt Lake, which provides 60 % of the salt demand in Turkey. Salinisation of groundwater is one of the main processes influencing the groundwater chemistry (Kazmann 1972; Freeze and Cherry 1979; Hussain et al. 2015; Kohfahl et al. 2015). Salinisation of freshwater resources is a significant problem in SB. The main purpose of this research was to develop a model to predict the groundwater vulnerability and determine optimum locations based on high water quality. For the assessment of the groundwater quality, 51 water samples were collected from different irrigation wells in the area and evaluated in terms of vulnerability using AHP and AHP-DEA. A groundwater quality index (GWQI) was developed with a combination of parameters that affected the water quality. The final groundwater quality map of the region was created using the Kriging method and the recommended AHP and hybrid AHP-DEA models. Based on the results, two new groundwater quality indices were proposed (A-GWQI and D-GWQI). The findings of this study can be applied to ensure the quality of groundwater used for drinking and irrigation purposes in the study area. This will reduce the risks of people contracting

diseases after coming into contact with contaminated groundwater. Furthermore, the use of clean water for crop irrigation will decrease economic losses due to poor harvests.

## Materials and methods

### The study area and sampling

The study area is located at Sereflikochisar (Ankara district) in the Central Anatolian part of Turkey, between 33° 23' and 33° 37' E longitude and 39° 03' and 38° 45' N latitude (Fig. 1). The average altitude of the study area is 1050 m and its coverage is 550 km<sup>2</sup>. The mean temperature of the area is 12.4 °C and the mean annual rainfall is 360 mm. The study area is topographically flat. In terms of geomorphology, it is surrounded with high hills extending on the west and east. There is not a significant river network, except episodic streams, in the study area. The most significant water structure is Salt Lake, the second largest and the shallowest lake in Turkey. SB is one of the most significant agricultural areas of the region. As irrigated agriculture is performed on the plain, groundwater is widely used. There are more than 250 water wells for drinking water and irrigation. The depth of these wells varies between 30 and 150 m. The main flow rate of these wells varies between 2 and 12 L/s. The salinisation of groundwater is among the most important problems of the region.

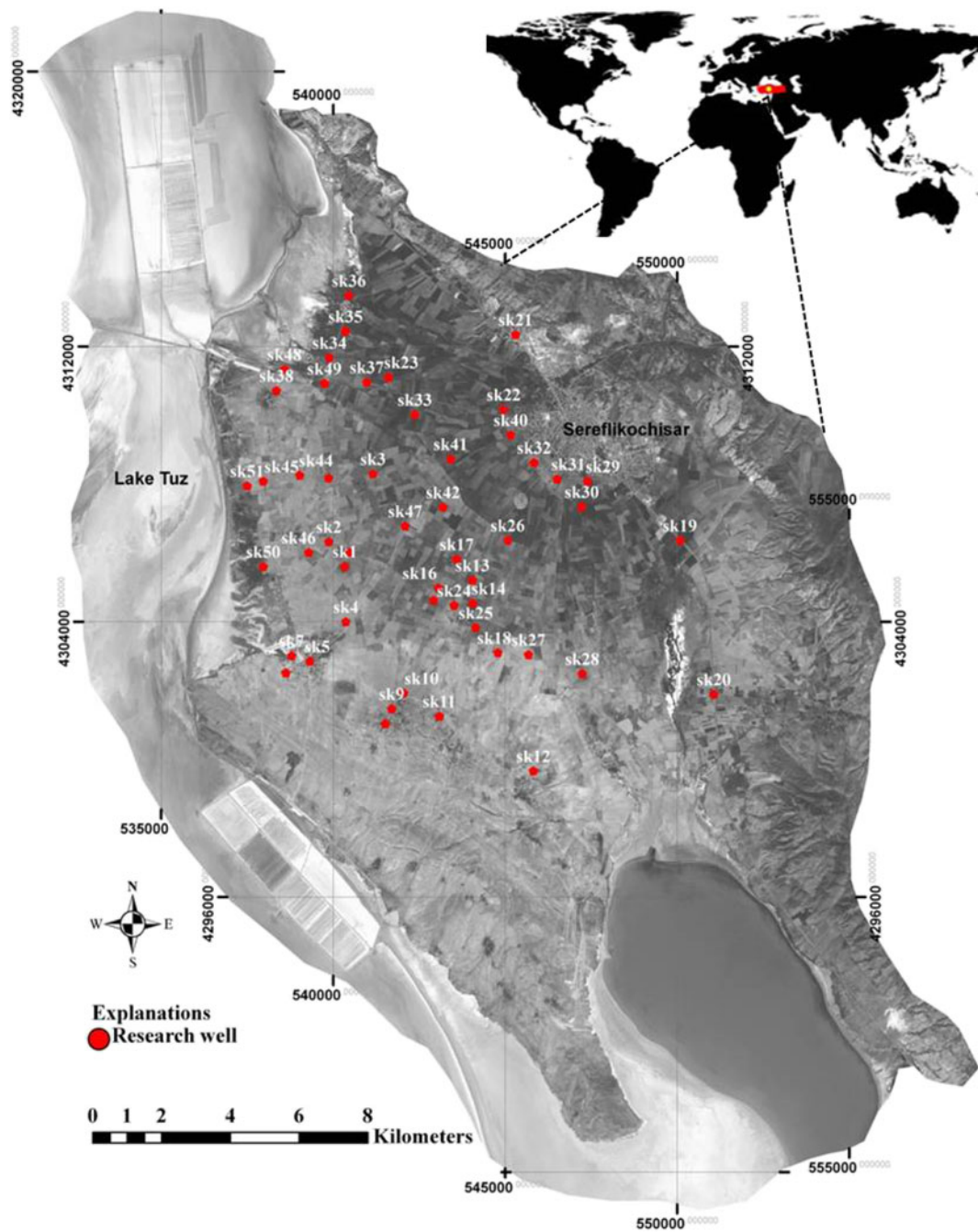
Water samples were collected from 51 different irrigation wells as shown in Supplementary Table 1. Sampling was carried out in May 2012. The water samples (with and without acid) were placed in 1-L polyethylene double-lidded bottles. HNO<sub>3</sub> was added to the samples to minimize the interaction of the heavy metal content of water samples until the analysis was completed. The samples without acid were used for the anion and cation analysis. The analysis of water samples were conducted at the Chemistry Laboratory in Technical Research and Quality Control Department of General Directorate of State Hydraulic Works. The anion values, such as sulfate, phosphate, nitrate, nitrite, fluoride, chloride, and bromide, of the water samples were measured with a Dionex Ics-1000 ion chromatography device. Chemical cation analyses were undertaken with an Agilent 7500a ICP MS device. Apart from sampling periods, the physical and chemical parameters such as water level, pH, temperature, electrical

conductivity (EC), total dissolved solids (TDS), and salinity were measured in the field every month. A WTW-LT 330 brand portable conductivity meter (SCT), Orion brand “pH meter,” and YSI-055 “oxygen meter” were used to measure physical parameter values. The hydrogeological data was interpreted in accordance with WHO (2012) and EU (2014) standards. Spot satellite images and related software were used in the evaluation phase. After compiling in a suitable format, data input was undertaken, and groundwater quality maps of region were created with Kriging interpolation method statistical technique.

### Establishment of GWQI

The main purpose of this research was to develop a relatively simple and practical method for the assessment of groundwater vulnerability using the recommended AHP and AHP-DEA models. AHP is an MCDM tool used to derive relative priority scales of absolute numbers from individual judgments (Saaty 2005). The assessment of groundwater resource vulnerability with AHP involves the establishment of a GWQI, the construction of the decision matrix and single permutation of layer. The GWQI is computed to reduce the large amount of water quality data to a mere numerical value that expresses the overall water quality at a certain location and time based on several water quality parameters. This index transforms a large number of water quality data into a single number. It integrates complex data and generates a score that describes the water quality status, which makes it easier for decision-makers to determine the quality and identify possible uses of any water body.

The GWQI of the study area comprised of 19 parameters classified under four categories of factors causing vulnerability as follows: (i) Group 1, (ii) Group 2 (iii) Group 3, and (iv) Group 4 (Fig. 2). Group 1 includes basic physicochemical parameters in relation to the water's natural structure such as temperature, pH, electrical conductivity, turbidity, and total hardness. Group 2 is primarily based on inorganic chemical parameters which greatly affect the water's natural structure such as chloride, sodium, sulfate, and alkalinity. Group 3 consists of parameters concerning toxic substances such as arsenic, chromium, nickel, manganese, and iron. Group 4 contains parameters concerning substances undesirable in excessive amounts such as nitrate, total nitrogen, ammonium, and total organic carbon.



**Fig. 1** Location of the sampling points and general view of the study area on Landsat-5 TM (natural color) image data

These parameters were chosen considering the actual conditions of the study area, the complexity of the problem, and the environmental quality and stability as well as for easy acquisition of data and relatively easy quantization of quantitative indices. Water quality depends on the local geology and ecosystem. The greater

part of the soluble constituents in groundwater comes from soluble minerals in rocks. Local conditions can result in variations in the selected parameters. Table 1 presents the data interval of each index.

Water quality status in Table 1 have been classified as excellent, good, poor, or unsuitable according to the

**Table 1** The ranges of suitability classes for AHP

Parameters	Unit	Excellent	Good	Poor	Unsuitable
T	(°C)	0–10			
pH	–	6.5–8.5	>8.5	<6.5	–
EC	(µS/cm)	<250	250–1000	1000–2250	>2250
Th	(mg/L)	<150	150–500	500–1000	>1000
Tu	(NTU)	<5	5–25	25–50	>50
Cl <sup>-</sup>	(mg/L)	<30	30–250	250–600	>600
Na <sup>+</sup>	(mg/L)	<125	125–250	250–1000	>1000
SO <sub>4</sub> <sup>2-</sup>	(mg/L)	<200	200–400	400–1000	>1000
Alk	(mg/L)	<250	250–500	500–1000	>1000
SAR	–	<10	10–18	18–26	>26
As	(mg/L)	<0.01	0.01–0.05	0.05–0.1	>0.1
Cr	(mg/L)	<0.02	0.02–0.05	0.05–0.2	>0.2
Mn	(mg/L)	<0.05	0.05–0.5	0.5–3	>3
Fe	(mg/L)	<0.3	0.3–1	1–5	>5
Ni	(mg/L)	<0.02	0.02–0.05	0.05–0.2	>0.2
TOC	(mg/L)	<5	5–8	8–12	>12
TN	(mg/L)	<0.5	0.5–2	2–5	>5
Nt	(mg/L)	<5	5–10	10–20	5–20
Amm	(mg/L)	<0.02	0.02–0.1	0.1–1	>1

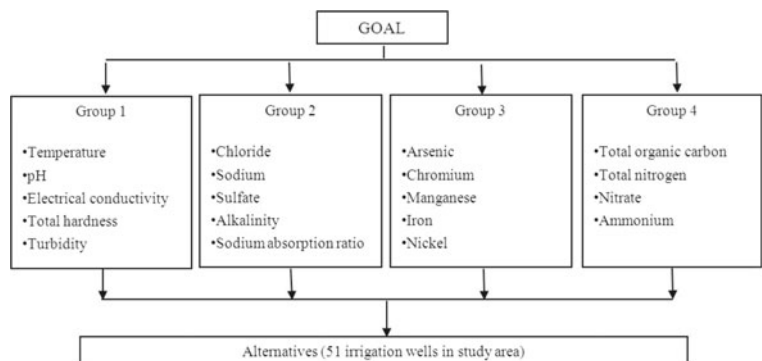
T temperature, EC electrical conductivite, Th total hardness, Tu turbidity, Alk alkalinity, SAR sodium adsorption ratio, TOC total organic carbon, TN total nitrogen, Amn ammonium, Nt nitrate

concentration of pollutant present. The quality rating scale for each parameter has been divided into the four classes by assigning a numerical value to each of the boundaries between the classes. The values for the boundary between the classes of excellent and unsuitable status have been established through water quality standards developed by the World Health Organization (WHO), European Union (EU), and Turkish Water Pollution Control Regulation (WPCR). Guidelines must be appropriate for national, regional, and local

circumstances, which require adaptation to environmental, social, economic, and cultural circumstances.

The concentration of toxic substances such as As, Cr, Mn, Fe and Ni in water samples changed between 0.023 and 0.001, 0.11 and 0.002, 2.97 and 0.001, 2.69 and 0.003, and 0.36 and 0.001 mg/L, respectively. These parameters may damage the ecosystem if their values are in higher concentrations than the safe limits set by the WHO and other regulatory bodies. In drinking

**Fig. 2** AHP hierarchy of the problem



water, the international standards for As, Cr, Mn, Fe, and Ni are 0.01, 0.05, 0.1, 0.3, and 0.02 mg/L, respectively. The classification of these parameters and class intervals in this study have been determined by regulations developed by WHO (2012), EU (2014), and WPCR (2004).

The data intervals of the parameters, such as electrical conductivity, alkalinity, and sodium adsorption ratio have been classified considering the US Salinity Laboratory. Moreover, the data interval of the parameters, such as temperature, turbidity, pH, sodium, sulfate, total organic carbon, total nitrogen, ammonium, and nitrate have been determined by regulations developed by WPCR (2004).

WHO (2012) recommends that hardness of ideal drinking water should be under 500 mg/L or lower. In this study, hardness levels between 150 and 500 mg/L have been considered as “good.” Up to 1000 mg/L is usually “poor.” The acceptable range of chloride for drinking water should be under 250 mg/L according to WHO (2012), EU (2014), and WPCR (2004). In this study, chloride levels between 30 and 250 mg/L have been considered as “good” according to WPCR (2004).

The classes of “excellent” and “good” given in Table 1 fulfill the international standards and do not exceed the limit values permitted in these standards. Conversely, the classes of “poor” and “unsuitable” do not fulfill the international standards.

#### Pairwise comparisons and determination of priorities

Fifteen academicians with expertise in water quality were asked to provide information in the form of pairwise comparisons, in which the main criteria are compared with each other, and then the subcriteria are evaluated against each other. In this study, water samples from 51 irrigation wells were compared using the subcriteria. For each judgment, each expert was asked in

his/her opinion, which of two criteria they considered more important and how much, using Tables 1 and 2. A score of 1 demonstrates equal importance between the two criteria and a score of 9 represents the extreme importance of one criterion compared to another. In this study, the AHP hierarchy consisted of 4 main criteria, 19 subcriteria, and 51 alternatives (irrigation wells).

For each pairwise comparison, average judgment is calculated using the geometric mean of experts' judgments. All diagonal entries are equal to 1 presenting the comparison of one criterion to itself. Applying the geometric mean of each expert's query, the corresponding comparison of one criterion to another is entered into the matrix. All comparisons are made using Table 2. For example, if criterion A is preferred to criterion B with the strength of preference of “3,” then the comparison of criterion B with criterion A is “1/3.” The principle eigenvector of matrix is established and the priorities of criteria are determined. Then, the inconsistency of the matrix is calculated. The inconsistency ratio shows the legal consistency of the experts' judgments to ensure that the participants followed a logical thought process during pairwise comparisons. For fair comparison, this ratio must be lower than 0.1 (Saaty 2005).

#### The AHP-DEA model

DEA is a linear programming model for evaluating the performance of decision-making units (DMUs). This method is extensively used in performance evaluation and benchmarking in many organizations (Banker et al. 1984; Charnes et al. 1994; Berg 2010; Üstün and Barbarosoglu 2015). Therefore, it is also called “balanced benchmarking” by Sherman and Zhu (2013).

If there are  $n$  DMUs, each with  $m$  inputs and  $s$  outputs, the efficiency score of the DMU  $o$  is obtained by solving the model proposed by Charnes et al. (1978). In this study, the decision-making units were 51

**Table 2** Saaty's 1–9 scale for AHP preference index

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one over another
5	Strong importance	Experience and judgment strongly favor one over another
7	Very strong importance	Activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	Importance of one over another affirmed on the highest possible order

observation wells in SB and inputs of the AHP-DEA model were the four main criteria explained above.

$$\text{Max } \theta_0(v, u) = \sum_{r=1}^s u_r y_{ro}, \tag{1}$$

s.t.

$$\sum_{i=1}^m v_i x_{io} = 1, \tag{2}$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \geq 0, \quad (j = 1, 2, \dots, n) \tag{3}$$

$$u_r, v_i \geq 0, \tag{4}$$

where,

- $\theta_0$  Efficiency score of decision making unit “o”
- $n$  number of DMUs
- $s$  number of outputs
- $m$  number of inputs
- $o$  1, 2, …, n;  $j = 1, 2, \dots, n$
- $i$  1, 2, …, m;  $r = 1, 2, \dots, s$
- $x_{ij}$  amount of input  $i$  utilized by DMU  $j$
- $y_{rj}$  amount of output  $r$  produced by DMU  $j$
- $u_r$  weight given to output  $r$
- $v_i$  weight given to input  $i$

The AHP and AHP-DEA models given above were run  $n$  times and the relative efficiency scores of all the DMUs were calculated. In the model, each DMU takes input and output weights that maximize its efficiency score. A DMU is considered efficient when its efficiency score is one. (Üstün 2015; Üstün and Anagün 2015).

Geostatistical approach (ordinary Kriging method)

In this study, the groundwater quality maps were constructed using the results obtained from the AHP and AHP-DEA models. The spatial distribution of the groundwater quality was modeled on a Geostatistical Analyst tool that allowed for the investigation of spatial autocorrelation and the interpolation of attribute values at unsampled locations. This assessment was performed on the physical and chemical analysis data obtained from the 51 wells. The spatial distribution of the groundwater quality was mapped using the results of the AHP

and AHP-DEA models and the Ordinary Kriging method.

The Kriging method is an advanced geostatistical procedure that generates an estimated surface from a scattered set of points with  $z$ -values (Esri 2015). It is considered a deterministic interpolation method since it is directly based on the surrounding measured values or on specified mathematical formulas that determine the smoothness of the resulting surface (Esri 2015). It is proved to be an effective methodological approximation in problems related to the estimation of groundwater quality (Goovaerts et al. 2005; Stigter et al. 2006; Chica-Olmo et al. 2014). The general formula for Kriging is defined as follows (Esri 2015):

$$Z(x_0) = \sum_{i=1}^N \lambda_i Z(x_i), \tag{5}$$

where  $Z(x_i)$  is the measured value at the location,  $\lambda_i$  is an unknown weight for the measured value at the location,  $x_0$  is predicted value at location  $x_0$ , and  $N$  is the number of measured values.

The Kriging method uses a variogram to express the spatial variation. It is a key step between spatial description and spatial prediction (Aldworth 1998). The main application of Geostatistics is the prediction of attribute values at unsampled locations (Chiles and Delfiner 1999). The variogram  $\gamma(h)$  is defined as (Oliver 1990)

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^n [Z(x_i) - Z(x_i + h)]^2, \tag{6}$$

where  $\gamma(h)$  = estimated value of the semivariance for lag  $h$ ;  $n(h)$  is the number of experimental pairs separated by vector  $h$ ;  $z(x_i)$  and  $z(x_i + h)$  is the sample value at two points separated by the distance interval  $h$ .

In this study, semivariograms were fitted with various theoretical models such as spherical, exponential, Gaussian, and linear to obtain the most accurate estimations. Variable lag sizes were used for spatial autocorrelation in groundwater quality maps to be captured well, especially at short distances. Of the seven semivariogram models obtained to describe the spatial autocorrelation, the exponential model gave the minimum standard error and therefore was chosen as the best-fit model to create the groundwater quality maps.

Differences between the estimated and observed values are summarized using the cross-validation statistics. The root mean square standardized error value ( $R^2$ )

is used as the error indicator to inspect the prediction quality in cross-validation. The root mean square standardized error should be close to 1 (Esri 2015). The  $R^2$  is the square root of the average squared distance of a data point from the fitted line calculated with the following equation:

$$R^2 = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad (7)$$

where  $\hat{y}_i$  and  $y_i$  are the measured and estimated arsenic levels, respectively, of the  $i$  data point and  $n$  is the total number of data points.

## Results and discussion

### Hydrogeochemical evaluation

Alluvium from the quaternary period covers a large part in the study area. Aquifer parameters, including hydraulic conductivity ( $K$ ), transmissivity ( $T$ ), storativity ( $S$ ), average velocity ( $V$ ), and porosity ( $n$ ), were calculated from pumping tests in four observation wells (30 m deep) in the alluvium. Some hydrogeological properties of the alluvium aquifer are determined as  $K=0.04$  cm/s,  $T=0.014$  m<sup>2</sup>/s,  $S=5 \times 10^{-4}$ , and  $V=5.5 \times 10^{-5}$  m/s in this study.

The results of analyses for water samples that were taken from wells are given in Supplementary Table 1. Physical and chemical parameter values vary between the following values: temperature ( $T$ ) 14.1–21.9 °C, pH 6.2–8.3, electrical conductivity (EC) 516–295,000  $\mu$ S/cm, and total dissolved solid (TDS) 422–333,803 mg/L. Some of groundwater contains TDS of up to 1000 mg/L. On the basis of TDS classification (Fetter 2001), the groundwater in the region may be characterized as brackish water type according to the TDS value. The concentration of the major ions, such as  $\text{Cl}^-$ ,  $\text{Na}^+$ ,  $\text{SO}_4^{2-}$ ,  $\text{HCO}_3^-$ ,  $\text{Ca}^{2+}$ , and  $\text{Mg}^{2+}$  in groundwater samples changed between 81.2 and 3480.4, 28.5 and 1688.2, 49.2 and 1759.3, 129.3 and 2557, 42.1 and 459.3, and 2.6 and 477.2 mg/L, respectively. The main reason for the high ion concentrations is the Salt Lake which is recharged by shallow groundwater flow systems with a high salt content, throughout fracture system with various sizes. The highest ion values are observed in the groundwater flow system close to the Salt Lake. The

order of the relative abundances of cations and anions as measured in the basin are  $(\text{Na}^+ + \text{K}^+) > \text{Mg}^{2+} > \text{Ca}^{2+} / \text{Cl}^- > \text{HCO}_3^- > \text{SO}_4^{2-}$ . The dominant ions in groundwater are  $\text{Cl}^-$  and  $\text{Na}^+$ . The high  $\text{Na}^+$  and  $\text{Cl}^-$  and excessive total mineralization values in the groundwater may reflect that the main water resources have deep and long-term cycle systems. In terms of hydrochemistry, water samples have NaCl, NaHCO<sub>3</sub>, CaHCO<sub>3</sub>, CaSO<sub>4</sub>, MgCl, MgHCO<sub>3</sub>, and MgSO<sub>4</sub> water facie feature. As distance increases away from the Salt Lake, facies of water chemistry changes in the order of NaCl—NaHCO<sub>3</sub>—CaHCO<sub>3</sub>. As a result of NaCl and CaHCO<sub>3</sub> types of water mixing at different rates, there are many water facies of different types in the region.

The ion abundances have remained the same for many sampling points throughout the sampling period, but the ion arrays of some of the sampling points have changed resulting from different climatic conditions. Reduction of chlorine values in wells (SK4, SK30, SK46, SK51) in dry periods can be explained by the dilution of groundwater aquifers with a younger/freshwater. Facie changes in the groundwater usually reflect seasonal changes in the cation ordering in terms of the concentration. For example, during the rainy season, significant amounts of  $\text{Ca}^{2+}$ ,  $\text{Mg}^{2+}$ , and  $\text{SO}_4^{2-}$  ions dissolve in the water with more ratios than the during dry season. The dominant ion type was  $\text{Na}^+$ ,  $\text{Cl}^-$ , and  $\text{HCO}_3^-$  during all seasons.

Evaluating the groundwater quality based on the results of AHP and AHP-DEA

The evaluation was performed in three main stages. The first stage involved the implementation of the standard AHP method. A well-designed questionnaire was administered to 15 experts who were asked to rank the 51 irrigation wells in SB, Ankara/Turkey. As shown in Fig. 2, the experts compared these irrigation wells (alternatives) according to the 4 criteria and 19 subcriteria given in Table 1. The experts took part in group decision-making and discussion about pairwise comparisons and reviews. Then, the relative weights from pairwise comparisons of the AHP hierarchy were calculated taking the principal right eigenvector of relevant matrix. The results of this study were found consistent since the inconsistency ratio of all pairwise comparisons was less than 0.1.

Supplementary Table 2 presents the final results obtained with the AHP model. The first column



shows alternatives or DMUs (observation well) in the study area. The next four columns present the final weights of each observation well in terms of the four main criteria, and the last column demonstrates the final weights of alternatives. In this paper, this value is called the A-GWQI index, which shows the water quality of the related DMUs. Then, the groundwater quality map of the study area was constructed using the values on the last column and the Kriging method. According to the results of AHP, the well with the highest quality of water was found to be sk40, which had an A-GWQI index value of 0.028115 and the lowest quality of water was observed in sk51 with an A-GWQI index value of 0.009917. Supplementary Table 2 presents the water

quality index of other decision-making units, and Fig. 3 shows the related maps.

The second stage of evaluation in the study was the implementation of the AHP-DEA model, which resulted in a different water quality index and groundwater quality map. DEA is a data-oriented technique and uses mathematical programming approaches and models to evaluate the performance of DMUs (Üstün 2015). In this study, the AHP and DEA approaches were combined to construct a hybrid model. DMUs refer to the 51 irrigation wells being evaluated in the study area. The values obtained from the AHP implementation in the first stage were used as the inputs of the AHP-DEA model according to the same four criteria ( $\theta$ ,  $\gamma$ ,  $\beta$ ,

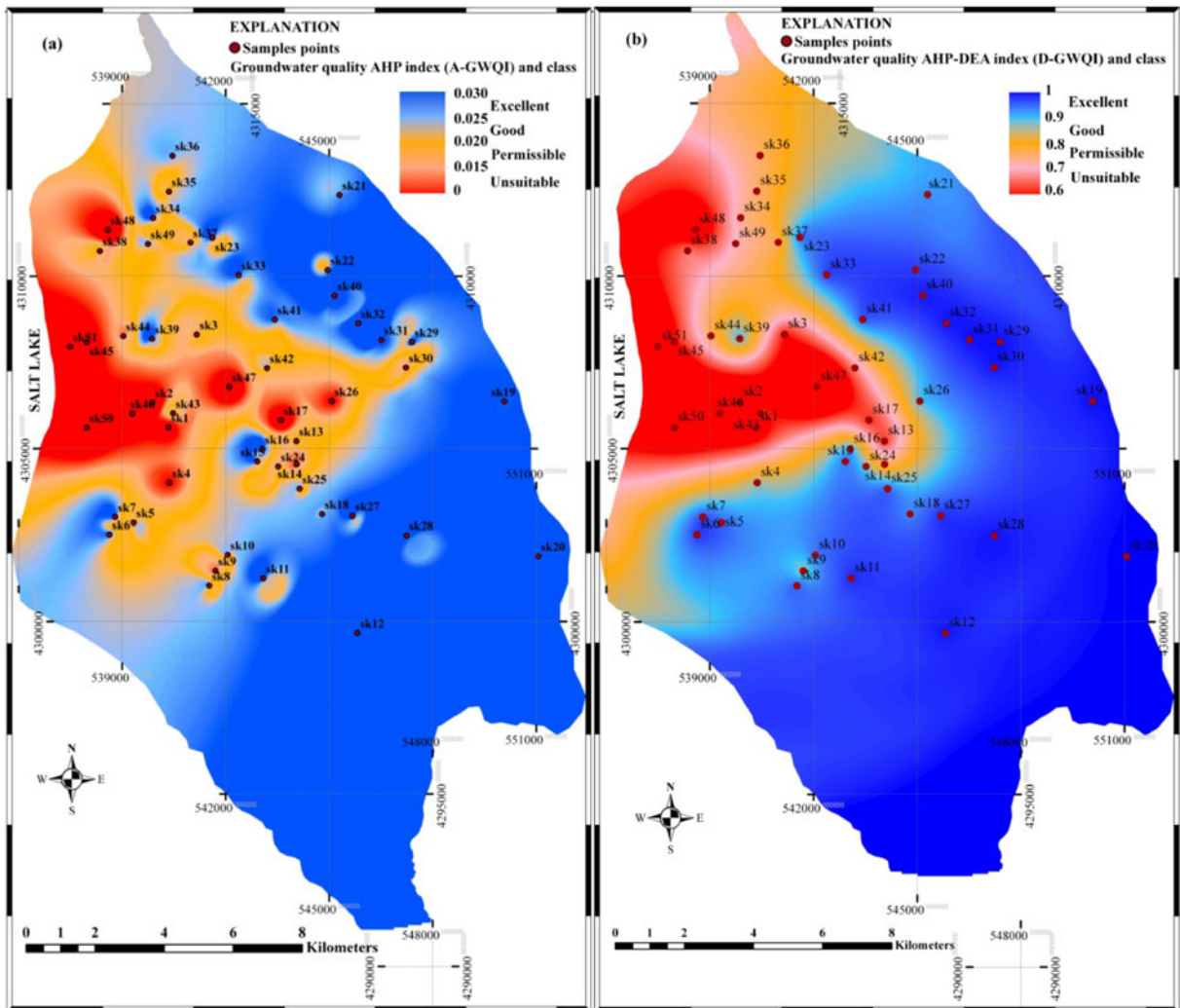


Fig. 3 The spatial distribution maps of the groundwater quality based on AHP index (a) and AHP-DEA index (b)

and  $\mu$ ) (Supplementary Table 2). Since all observation wells were assumed to produce the same amount of water, for each DMU, the output of the model was taken as 1. The inputs of the AHP-DEA model were defined as follows:

$\theta$ : 1/(Group 1 criteria weights obtained from the AHP model)

$\gamma$ : 1/(Group 2 criteria weights which is obtained from AHP model)

$\beta$ : 1/(Group 3 criteria weights which is obtained from AHP model)

$\mu$ : 1/(Group 4 criteria weights which is obtained from AHP model)

After the model construction, the solution was obtained on the Deafrontier software. Using this model, the efficiency score of each DMU was calculated as explained in the “Materials and methods” section. The efficiency score is evaluated on a scale of 0–1, where a value of 1 indicates that the DMU is relatively efficient, and a value less than 1 indicates that the DMU is inefficient (Cooper et al. 2000). In this study, this value represented the GWQI index, which showed the water quality of the corresponding DMUs. Table 3 illustrates the results of the AHP-DEA model. According to these

results, there were 19 relatively efficient DMUs with a D-GWQI index value of 1. The other observation wells were considered inefficient since their D-GWQI index was lower than 1.

#### Assessment of spatial distribution of groundwater quality

The last stage in the study was to assess the spatial distribution of groundwater quality using data obtained by the AHP and AHP-DEA models. The root mean square standardized errors of the groundwater quality maps for AHP and AHP-DEA were 0.91 and 0.94, respectively. The results of cross-validation showed that the chosen model and its parameters were adequate. Figure 3 presents the spatial distributions of groundwater quality in the study area. The groundwater quality maps created using the data from AHP and AHP-DEA displayed a similar distribution. In this study, the GWQI index of the zones in both maps was classified as (i) excellent when the water quality was protected with a virtual absence of threat or impairment, (ii) good when the water quality was protected with only a minor degree of threat or impairment, (iii) permissible when the water quality was usually protected but occasionally threatened or impaired, and (vi) unsuitable when the water

**Table 3** D-GWQI values generated using AHP-DEA model for each observation well

DMU	D-GWQI	DMU	D-GWQI	DMU	D-GWQI
sk40	1.000	sk25	1.000	sk37	0.821
sk31	1.000	sk30	1.000	sk49	0.821
sk12	1.000	sk23	0.999	sk43	0.820
sk16	1.000	sk22	0.986	sk38	0.818
sk28	1.000	sk10	0.977	sk14	0.815
sk32	1.000	sk5	0.972	sk45	0.796
sk39	1.000	sk15	0.970	sk42	0.793
sk11	1.000	sk21	0.956	sk17	0.734
sk20	1.000	sk26	0.954	sk13	0.716
sk7	1.000	sk18	0.945	sk3	0.715
sk27	1.000	sk24	0.933	sk50	0.650
sk29	1.000	sk4	0.933	sk1	0.647
sk19	1.000	sk9	0.875	sk48	0.637
sk33	1.000	sk44	0.851	sk46	0.633
sk6	1.000	sk36	0.845	sk2	0.602
sk41	1.000	sk34	0.844	sk47	0.544
sk8	1.000	sk35	0.844	sk51	0.479

quality was almost always threatened or impaired. The AHP A-GWQI values ranged from 0.015 to 0.030 (Table 4). Therefore, the groundwater quality was considered unsuitable in the western and central zones where A-GWQI is <0.015 and excellent in the north-eastern, eastern, and southern zones where A-GWQI is >0.25. As the distance from the lake increased, the groundwater quality decreased. Groundwater quality maps form a convergent nap in the midst of the study area. In this area, the concentrations of Na<sup>+</sup> and Cl<sup>-</sup> ion in groundwater may be increased due to the dissolution of evaporite rocks and especially halite. Furthermore, the existence of highly permeable units or well-developed fault systems in this part causes salinisation in the wells.

The D-GWQI values ranged from 0.47 to 1. Groundwater quality was considered unsuitable when the D-GWQI index was lower than 0.7 as observed in the northwestern and western parts of the study area. As shown in Fig. 3, the groundwater quality in the eastern and southern parts of the study area was found excellent with a D-GWQI value of 1.

When the two maps were compared, the map generated using AHP was found to have a larger pollution area. The difference between the water quality maps can be explained attributed to the relationship between the criteria and unassociated parameters such as chlorine (Cl<sup>-</sup>), iron (Fe), nitrate, and turbidity values. Thus, the water quality map generated using AHP-DEA was considered to be more realistic. Therefore, AHP-DEA can be used as a more effective tool in creating water quality maps.

**Conclusions**

In this article, the groundwater quality of SB was evaluated using two methods: AHP and the hybrid AHP-DEA. Based on the results obtained from these models,

two water quality indices (A-GWQI and D-GWQI) were proposed. Moreover, the groundwater quality maps of the Sereflikochisar Basin were created using the Kriging method and these indices.

Based on D-GWQI, the drinking water source areas were classified as excellent (48.2 %), good (10.8 %), permissible (10.2 %), and unsuitable (30.8 %). The groundwater quality maps showed that high groundwater quality was observed in the eastern and southern parts of the study area where D-GWQI scores were greater than 0.8. 77.14 km<sup>2</sup> of the study area was found to have poor water quality while 169.37 km<sup>2</sup> had good water quality. Thirteen samples were not suitable for agricultural irrigation due to very high sodium and salinity levels. Furthermore, 17 samples were not potable because of their very high salinity and medium sodium levels.

Closer to the Salt Lake, NaCl facies were dominant in groundwater. Depending on the distance from the Salt Lake, the characteristics of groundwater changed from NaCl to NaHCO<sub>3</sub> and CaHCO<sub>3</sub> facies. As a result of mixing at different rates of NaCl and CaHCO<sub>3</sub> type, water facies improved different types of water facies such as NaHCO<sub>3</sub>, NaSO<sub>4</sub>, and CaCl, in the region. Generally, Cl<sup>-</sup>, Na<sup>+</sup>, and HCO<sub>3</sub><sup>-</sup> ions were more dominant. High Na<sup>+</sup> and Cl<sup>-</sup> values in groundwater may indicate deep and long-term cycle systems. Therefore, it can be concluded that there is a high concentration of ions in the Salt Lake, which negatively affects the quality of the groundwater. The brackish groundwater area (TDS > 1 g/l) extends to about 3 km inland from the Salt Lake.

The results of the study indicated that A-GWQI and D-GWQI are useful and reliable indices and can be used to determine the groundwater quality of any region. Furthermore, the hybrid AHP-DEA model may be one of the most optimal techniques to establish a GWQI. This method can be used to ensure the quality of groundwater used for drinking and irrigation purposes

**Table 4** Groundwater quality ranking criteria

A-GWQI range	D-GWQI range	Category rank	Interpretation
0.025–0.030	0.9–1	Excellent	Safe to use as drinking water
0.020–0.025	0.8–0.9	Good	Generally safe to use as drinking water
0.015–0.020	0.7–0.8	Permissible	Inconvenient to use as drinking water; however, for some pollutants there may be health concern
0–0.015	0.6–0.7	Unsuitable	Should not be used as drinking water

in the study area. This will also reduce the disease risks of people coming into contact with contaminated groundwater.

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