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Water quality studies using fuzzy-analytic hierarchical procedure method to identify their suitability for drinking, industry, and agriculture – a case study

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ABSTRACT

Given the importance of assessing water quality in arid and semi-arid regions, the purpose of this study is to investigate water quality in Kohgiluyeh and Boyer-Ahmad Province, Iran, using fuzzy-analytic hierarchical procedure (FAHP) and the geographic information system. To this end, various parameters counting on potassium, sodium, magnesium, calcium, chloride, and sulfate content as well as PH levels, total dissolved solids in water, sodium absorption ratio, and alkalinity levels were extracted for 35 wells in the study region. These parameters were fed as input data for assessing the quality of water in regards to different usages. Through geostatistic methods (inverse distance weighted), water quality zoning maps were procured for each respective parameter affecting water quality. Upon generation of the respective zoning maps, fuzzy membership functions were used to homogenize each layer so as to obtain fuzzy maps for different parameters. The AHP technique was ultimately employed to overlay the fuzzy maps and generate the final water quality zoning map of the study area. The Langelier saturation index (LSI), the metal index (MI), and the Ryznar stability index (RSI) were also incidentally used as the prime indicators for assessing water quality for both industrial and agricultural purposes. The results of the LSI index showed that most of the studied areas are in the sedimentation class that indicates high pollution. RSI values were obtained between 6 and 8 where the eastern regions had an RSI of less than 6, the southern regions had an RSI of 6 to 7 and the northern regions had an RSI of more than 7. The results also showed that LSI in the northern regions is greater than zero, which indicates a corrosive state, and in the eastern part it is equal to zero which is indicative of the neutral state. The MI zonation map showed that the areas in the south have values greater than 1 which shows the low quality of water in these areas in terms of drinking. Residual sodium carbonate levels in the southern regions with values higher than 2 meq/L indicate low water quality in these regions. Finally, the results of the fuzzy method showed that the areas located in the eastern parts of the region have a better quality than the northern and western regions. According to the results, it is clear that in areas where there is agriculture or urban lands, pollution is high.

Keywords: Water quality; Fuzzy method; Analytic hierarchical procedure method; Langelier saturation index; Metal index; Ryznar stability index.

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1. Introduction

The earth has indeed an abundance of water; however, only a small percentage can be virtually used as a source of drinking water. In light of this fact, water quality assessment has emerged as one of the most challenging tasks in various regions throughout the globe, particularly Iran. Fortunately, methods relying on geographic information systems (GIS) have succeeded in ameliorating the situation by means of providing tools for the discernment of spatial changes in water quality. Put differently, GIS is potentially among the most robust and efficient tools for spatial analysis of various sorts of data, with numerous features including analysis and representation of different data among other components. Studies show that incorporating GIS into readily available as well as newly emerged models could in fact open up new doors to assessment and evaluation of different phenomena, including water quality assessment. One of the highlights of GIS is the ability to employ geostatistical models, such as fuzzy and analytic hierarchical procedure (AHP), to generate zoning maps. Along these lines, a certain study on groundwater quality zoning in the Yazd-Ardakan plain, Iran, using geostatistical models (kriging, cokriging, and inverse distance weighted (IDW)) was indicative of the superiority of kriging and cokriging for obtaining groundwater quality zoning maps [1].

Numerous studies have recently been conducted on the topic of water quality [2] as well as a qualitative assessment of water resources for various agricultural purposes using fuzzy logic [3–5].

Ahmad [6] used the kriging method to investigate groundwater quality. The results showed that the kriging approach does indeed attain a rather acceptable accuracy in estimating different variables of water quality including TDS.

Gauss et al. [7] attempted to assess the arsenic content in groundwater resources of Bangladesh. They used discrete kriging as the primary method for estimating arsenic content and obtaining zoning maps. The results were speculative of significantly high arsenic content in the groundwater resources of the area which, if not attended to, would expose millions of individuals to mortal dangers.

Mehrjerdi et al. [1] used IDW, kriging, and cokriging to obtain groundwater quality maps for the Yazd-Arsanjan plain. The results indicated the high accuracy of the kringing approach in obtaining zoning maps for different water quality parameters.

Kholghi and Hosseini [8] sought to investigate the potency of simple kriging and ANFIS-based networks in the interpolation of groundwater levels in a free water table located to the north of Iran. Their results showed that the ANFIS model outperformed simple kriging in regards to estimating groundwater levels. Among other studies in the literature of water quality assessment and zoning are works by Sanches [9], Fetouani et al. [10], Alver [11], Thoradeniya et al. [12], Camacho-Cruz et al. [13].

One of the gravest and most suitable methods for water quality assessment in the GIS environment, among the vast body of proposed methods, is the fuzzy approach. Fuzzy logic was pioneered by Zadeh [14] as a novel and acceptable approach to developing complex and unknown systems in artificial intelligence, such as environmental indices [15]. Fuzzy logic seeks to extrapolate indices in such a fashion as to simulate human behavior and thought patterns. By this token, fuzzy information could be introduced as a means for preventing potential errors, ambiguities, and other probable complications [16].

Given the gravity of the impacts of water quality assessment, fuzzy logic, and analytic hierarchical processes could well be used to estimate water quality in the designated study region. A flowchart of the proposed methodology is depicted below.

2. Case study

The study area consists of the northern part of Kohgiluyeh and Boyer-Ahmad Province, Iran. The area is situated at 30°36′ – 30°54′ N and 50°25′ – 50°54′ E, as illustrated in Fig. 1. Taking into account the fact that the study region is primarily comprised of agricultural, industrial, and residential lands, water quality assessment would capably prove most significant in terms of locating suitable regions for supplying drinking water as well as water for industrial uses. The study region extends to approximately 823.55 km^2 in area, with elevation ranging from a minimum of 598 m to a peak of 2,465 m.

The prime parameters for drinking water quality include potassium, sodium, magnesium, calcium, chloride, and sulfate concentrations as well as PH level, total dissolved solids (TDS), sodium absorption ratio (SAR), and alkalinity. For assessment purposes, 35 sample points were randomly selected from the study area and the intended parameters were assessed. Table 1 lists the statistical figures for the respective parameters.

3. Materials and methods

Topographic maps with varying scales (1:25,000 and 1:50,000) were used to select the designated study area within the northern parts of Kohgiluyeh Boyer-Ahmad province. Field surveys were conducted for obtaining water samples, upon which concentrations of potassium, sodium, magnesium, calcium, chloride, and sulfate were measured for each sample as well as PH level, TDS, SAR, and alkalinity.

Chlorine was measured through standard $AgNO_3$ titration (Mohr method). The pH measurements of water samples were carried out *in-situ*, using a portable pH meter (model PCD650). Calcium was measured titrimetrically, using standard ethylenediaminetetraacetic acid. The concentration of other heavy metals was measured by inductively coupled plasma-mass-spectrometry. The accuracy and precision of the measurements were checked by the use of reference materials and appropriate replicates.

The proposed methodology consisted of five stages as following:

- Procuring water samples and further laboratory analysis
- Using IDW to obtain zoning maps for different parameters
- Water quality assessment for industrial use considering Langelier saturation index (LSI), metal index (MI), and Ryznar stability index (RSI) indices

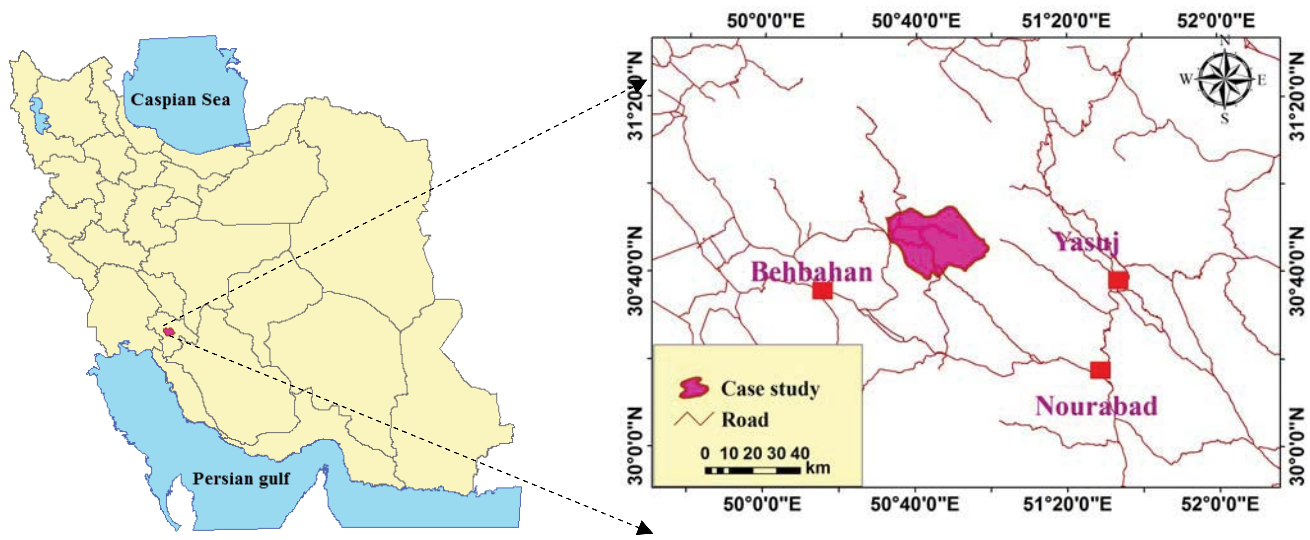

Fig. 1. Location of the study area.

Table 1
Statistical characteristics of each of the parameters affecting the determination of drinking water quality

Parameter	Minimum	Maximum	Average	STDVE
Ca, mg/L	64.87	84.42	72.85	5.9
Cl, mg/L	10.13	25	19.34	5.8
Na, mg/L	23.55	39.69	31.4	5.41
pH	7.18	8.1	7.57	0.21
Alkalinity, mg/L	38.24	95.72	57.90	22.33
Mg, mg/L	2.27	25.14	16.17	7.11
SO_4, mg/L	1.13	106.9	47.11	39.38
K, mg/L	0.731	1.21	0.94	0.16
TDS, mg/L	35.15	772	537.39	233.57

- Water quality assessment for agricultural use using the RSC index
- Drinking water quality assessment using fuzzy and AHP approach

A detailed explanation of each stage is presented below.

3.1. IDW method

The IDW technique was used to obtain zoning maps for each parameter affecting water quality. IDW is a conventional geostatistical model used to generate zoning maps and interpolate different coordinates extracted from a specific region. Stated differently, during the course of generating the zoning map based on the obtained coordinate points, it is assumed that the effects of one point on its counterpart varies for each point, such that when attempting to estimate unknown points (unmeasured coordinates), those closest to the target have a more significant effect compared to points situated farther away. In other words, the shorter the distance from the origin, the lower the effects of the corresponding parameter. The following equation can be used in ArcGIS to obtain zoning maps of different parameters using the sample points obtained a priori [17].

$$\hat{z}(x_0) = \frac{\sum_{i=1}^{n} z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \tag{1}$$

In this equation, $\hat{z}(x_0)$ is the estimated amount of variable z, $z(x_i)$ is the value for the measured sample at point x_i, d_{ij} is the distance between points i and j, and r is a regulatory coefficient for obtaining weight based on distance [17].

3.2. Industry quality water

Environmental Protection Agency (EPA) standards, in conjunction with other globally accredited standards, state that any source of drinking water must not be corrosive. Accordingly, the most common factors used to assess the drinkability of water resources, hinging on corrosivity and sedimentation, include LSI, MI, and RSI. Corrosivity is a measure of how aggressive the water is. It measures how much metal content (materials inside corrosive pipelines) enters the water as a result of dissolution. High rates of corrosivity can cause cavities within the pipes and at times increase the negative pressure potential of pollutants entering the pipeline. Sedimentation, on the other hand, is the process by which residues gradually form within a pipe, increasing the inner diameter of pipes and thereby reducing flow. The LSI and the RSI indices measure the corrosivity and sedimentation of water by virtually measuring the difference in real water pH levels and the pHs levels of carbonate calcium satiated water. By this token, in order to assess the quality of groundwater in the study area, pHs and pHeg values for each parameter were calculated and sedimentation and corrosivity were measured accordingly.

Mean and standard deviation were also obtained for each value. The calculations are as follows:

$$\mathrm{LSI} = \mathrm{pH} - \mathrm{pHs} \tag{2}$$

$$\mathrm{RSI} = 2\mathrm{pHs} - \mathrm{pH} \tag{3}$$

$$\mathrm{pHs} = 9.3 + A + B - C + D \tag{4}$$

$$A = \frac{\log 10\ \mathrm{TDS} - 1}{10} \tag{5}$$

$$B = -13.12 \times \log 10°\mathrm{C} + 273 + 34.55 \tag{6}$$

$$C = \log 10\left[\mathrm{Ca}^{2+}\ \text{as}\ \mathrm{CaCO_3}\right] - 0.4 \tag{7}$$

$$D = \log 10\left[\text{alkalinity as}\ \mathrm{CaCO_3}\right] \tag{8}$$

SI values lower than zero indicate corrosive waters, while values above zero show sedimentation. An SI value of zero indicates a zero (none) tendency toward sedimentation or corrosiveness.

The MI index was also used to evaluate water quality. This index can be calculated using the following equation based on the WHO standard [18]:

$$\mathrm{MI} = \sum_{i=1}^{N} \frac{C_i}{\left(\mathrm{MCA}\right)_i} \tag{9}$$

where C_i is the target density, i is the ith target element in the sample, and $(\mathrm{MAC})_i$ is the maximum density allowed for the target element.

MI values of lower than one are an indication of drinking quality water, while values above one show that the water is not drinkable. MI = 0 indicates the threshold value.

3.3. Agricultural water quality

Sodium (Na) concentrations and electroconductivity are commonly used to assess the quality of water for agricultural use. Sodium is the most abundant alkaline metal, primarily found in ignite (porphyry) and evaporate stones. Similar to other cations, sodium binds with and reacts to clay found in soil and substitutes for the calcium and magnesium ions in clay, reducing the permeability of the soil. The sodium absorption ratio (SAR), which is a measure of the rate calcium and magnesium ions are substituted with sodium ions, is the chief index for estimating sodium risk. SAR can be obtained as follows (density values are expressed in milliequivalents per liter):

$$\mathrm{SAR} = \frac{\mathrm{Na}^{+}}{\sqrt{\left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+}\right)/2}} \tag{10}$$

Sodium percentage (Na%) is another parameter for estimating the sodium content in water, which is commonly used alongside electro-conductivity to assess the quality of water for agricultural use. Na% can be obtained using the equation below:

$$\%\mathrm{Na} = \frac{\left(\mathrm{Na}^{+} + \mathrm{K}^{+}\right) \times 100}{\left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+} + \mathrm{Na}^{+} + \mathrm{K}^{+}\right)} \tag{11}$$

In addition to SAR and Na%, residual sodium carbonate (RSC) – both carbonates and bicarbonates – also affect the appropriateness of water for irrigation purposes. Excess carbonate and bicarbonate sodium alter the characteristics of soil, such as dissolved organic matter in soils. RSC can be calculated as follows:

$$\mathrm{RSC} = \left(\mathrm{Co}_3^{2-} + \mathrm{HCO}_3^{-}\right) - \left(\mathrm{Ca}^{2+} + \mathrm{Mg}^{2+}\right) \tag{12}$$

The corresponding RSC values for samples used in this study are listed in the Table. RSC values lower than 1.25 meq/L indicate good water quality; values between 1.25 and 2 meq/L signal suspicious water; and values higher than 2 meq/L show inappropriateness of water for irrigation.

3.4. Drinking water quality using the fuzzy method and AHP method

Ultimately, AHP and fuzzy methods were utilized to obtain the final zoning maps for each parameter. A detailed explanation of the application follows:

3.4.1. Fuzzy method

Lotfizadeh defines fuzzy as a class of objects with a continuous membership degree obtained from the membership function. This function assigns a value between 0 and 1 to each object. The concept of the membership function is crucial to the fuzzy set theory, where all information on a fuzzy set is defined through its membership function. All applications and issues related to the fuzzy set theory are also solved and analyzed in terms of the corresponding membership function for that set. The membership function shows the fuzziness of a fuzzy set. Virtually, any function which defines the degree of membership of an element in a specific set can be called a membership function.

Membership functions in fuzzy models are defined as shown in Eq. (13) [19]:

$$A = \left\{x, \mu_A(x)\ \text{for each}\ x\ \varepsilon\ X...\right\} \tag{13}$$

where μ_A is the membership function that shows the membership degree of element x in set A, and ranges between values 0 and 1.

3.4.2. AHP method

AHP is amongst the most popular techniques in multi-criteria decision making, introduced by Saaty in the 1970s. AHP proves most helpful in situations where the number of criteria and options are multiple. The criteria could be either qualitative or quantitative. AHP basically hinges on hidden pairwise comparisons. The method works by initially prompting the decision-maker to procure a hierarchical decision tree, which consists of the indices and decision items. A series of pairwise comparisons are then performed and weights are assigned to different factors relative to the target item (option). Finally, AHP combines the different pairwise comparison matrices obtained during the course of running the method and outputs the most optimal decision.

AHP was used in this study to obtain water quality zoning maps for identifying suitable locations for drinking water supply. The weight parameter is central to relating different factors affecting water quality. As the effects of the parameters used tend to differ, a weighted version of the AHP method was used. AHP facilitates the process of allocating weights to different parameters and is primarily based on pairwise comparisons between the involved parameters. Each parameter is assigned a value between 1 and 9 based on the significance it has on water quality and supply (Table 2).

Put differently, the significance of each parameter relative to other parameters can be obtained using the pairwise comparison matrix and Eqs. (14) and (15).

$$a_{ij} = a_{ik} \cdot a_{kj} \tag{14}$$

$$a_{ij} = \frac{1}{a_{ji}} \tag{15}$$

where i, j, and k are the indices of the matrix.

Eqs. (14) and (15) assign a value of 1–9 to each parameter affecting water quality. These values are then incorporated into the pairwise comparison matrix and a value between 0 and 1 is allotted to each parameter.

Ultimately, the following equation is used to prepare a water quality map of the target region. According to this equation, the weights assigned to each parameter are multiplied by the corresponding values in the fuzzy map in order to obtain the final water quality zoning map.

$$\mu_A = \sum_{j=1}^{k} W_j \times \mu_{A(x)} \qquad x\varepsilon X \tag{16}$$

$$\sum_{j=1}^{k} W_j = 1 \qquad W_j > 0 \tag{17}$$

A close inspection of the equation above shows that the weights assigned to each parameter range between 0 and 1, with the total sum of weights equal to 1. Fig. 2 illustrates the different steps for estimating drinking water quality using the fuzzy approach.

4. Results

4.1. LSI, RSI, and MI indices to determine water pollution by industry

Based on the LSI values obtained for the study region, the sample wells can be classified into three categories of corrosive, sedimentation, and moderate, with the

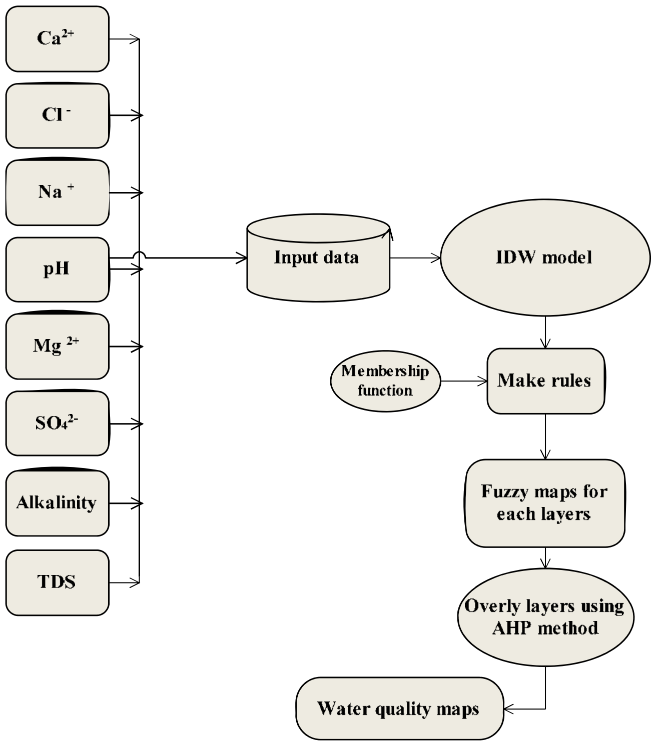

Fig. 2. Model implementation steps to determine water quality from a drinking and industrial point of view.

Table 2
Fundamental scale for paired comparison

Numerical value	Descriptive value	Description
1	Poor	Equal importance
2	Poor	–
3	Almost average	One factor is slightly more preferable than the other
4	Medium	–
5	Higher importance than another	One factor is preferable to another
6	Strong	–
7	Very strong	One element is more important than another
8	Very very strong	–
9	Quite preferable	One element is much more important than another
Interaction (two-way)	When parameter *i* is compared to *j* and has one of the above values, parameter *j* has a reciprocal value of *i*	

majority of wells falling within the sedimentation category. The corresponding LSI values are shown in Table 3.

Water quality zoning maps for industrial use were also obtained for different parameters (pH, TDS, pHs, alkalinity, and Ca) using IDW in GIS environment. The spatial maps for each parameter are depicted in Fig. 3. Based on the final results, pH values tend to vary within the ranges of 7.25–8.09, with the lowest values occurring toward the northwestern sectors and the highest values observed in the southern as well as central regions. The highest TDS value was observed in the eastern sections of the study area while the lowest were seen towards the northern parts as well as a small segment of the western regions. The results also indicated a higher alkalinity and concentration of calcium within the central areas compared to the remaining regions. Finally, Eq. (4) was employed to measure the pHs levels and obtain pHs zoning maps. The results are indicative of a higher pHs value in the southern, western, and northwestern regions, respectively.

The various zoning map layers were eventually overlaid in order to obtain maps for the three parameters of LSI, RSI, and MI. The maps are shown in Fig. 4.

As is evident from Fig. 4, RSI values range from 6 to 8, with values lower than 6 indicating a state of sedimentation in the eastern regions of the study area. RSI values between 6 and 7 exhibit a neutral state, found in the southern regions and RSI values above 7 convey a state of corrosion, primarily found in the northern and northwestern parts as well as certain western regions of the study area.

Based on the quantities shown in Fig. 4, LSI values lower than zero indicate a state of sedimentation, mostly found in the central regions, while LSI values higher than zero exhibit a state of corrosion, primarily in the northern, northwestern, and certain western regions of the area. LSI = 0, which shows a

Table 3
Langelier index (LSI) and RSC values

Code	Ca (mg/L)	Alkalinity	pH	PHs	PH–PHs	LSI	TDS	RSC	LST	MI
1	70.85	40.63	7.64	7.54	0.1	Sedimentation	746.3542	4.031473	–1.9	2.44
2	76.82	87.11	7.37	6.73	0.64	Sedimentation	605.15	0.08281	–1.6	0.02
3	64.87	41.53	7.35	7.54	–0.19	Corrosive	423.4496	0.647743	–1.49	0.02
4	65.25	43.47	7.41	7.41	0	Moderate	35.15	0.646	–1.51	1.58
5	79.35	89.98	7.61	6.96	0.66	Sedimentation	625.1	0.08554	–1.61	0.02
6	84.42	95.72	8.1	7.4	0.7	Sedimentation	665	0.091	–1.68	0.02
7	69.52	39.87	7.49	7.4	0.09	Sedimentation	732.3501	3.955829	–1.8	2.40
8	75.7	51.47	7.43	7.62	–0.2	Corrosive	534.6	0.6039	–1.47	0.01
9	78.51	89.02	7.53	6.88	0.65	Sedimentation	618.45	0.08463	–1.61	0.02
10	65.42	41.89	7.41	7.61	–0.2	Corrosive	433.62	0.6633	–1.5	0.02
11	82.31	93.33	7.9	7.22	0.68	Sedimentation	35.77086	0.65741	–1.53	1.61
12	68.15	39.09	7.35	7.25	0.09	Sedimentation	717.96	3.8781	–1.7	2.35
13	80.08	90.8	7.68	7.02	0.66	Sedimentation	630.8456	0.086326	–1.62	0.02
14	74.55	50.69	7.31	7.51	–0.2	Corrosive	526.5	0.59475	–1.32	0.01
15	66.96	44.62	7.61	7.61	0	Moderate	36.075	0.663	–1.56	1.62
16	68.68	45.76	7.8	7.8	0	Moderate	37	0.68	–1.59	1.66
17	68.88	39.51	7.43	7.33	0.09	Sedimentation	725.68	3.9198	–1.76	2.38
18	72.55	41.61	7.82	7.72	0.1	Sedimentation	764.28	4.1283	–1.95	2.50
19	71.45	40.98	7.7	7.61	0.1	Sedimentation	617.785	0.084539	–1.61	0.02
20	66.4	44.24	7.54	7.54	0	Moderate	648.375	0.088725	–1.65	0.02
21	68.08	39.05	7.34	7.25	0.09	Sedimentation	717.188	3.87393	–1.7	2.35
22	78.43	88.92	7.52	6.87	0.65	Sedimentation	752.7	4.06575	–1.95	2.46
23	67.1	42.96	7.6	7.8	–0.2	Corrosive	438	0.67	–1.51	0.02
24	73.28	42.03	7.9	7.8	0.1	Sedimentation	772	4.17	–2.1	2.53
25	66.43	42.53	7.52	7.72	–0.2	Corrosive	427.05	0.65325	–1.5	0.02
26	67.99	45.3	7.72	7.72	0	Moderate	36.63	0.6732	–1.58	1.65
27	73.92	50.26	7.25	7.44	–0.19	Corrosive	522.0612	0.589736	–1.3	0.01
28	76.46	51.99	7.5	7.7	–0.2	Corrosive	540	0.61	–1.49	0.01
29	81.62	92.54	7.83	7.15	0.68	Sedimentation	631.75	0.08645	–1.63	0.02
30	83.58	94.76	8.02	7.33	0.69	Sedimentation	658.35	0.09009	–1.68	0.02
31	69.62	39.93	7.51	7.41	0.1	Sedimentation	702.52	3.7947	–1.7	2.30
32	80.2	90.93	7.7	7.03	0.67	Sedimentation	642.9087	0.087977	–1.65	0.02
33	66.68	38.25	7.19	7.1	0.09	Sedimentation	733.4	3.9615	–1.83	2.40

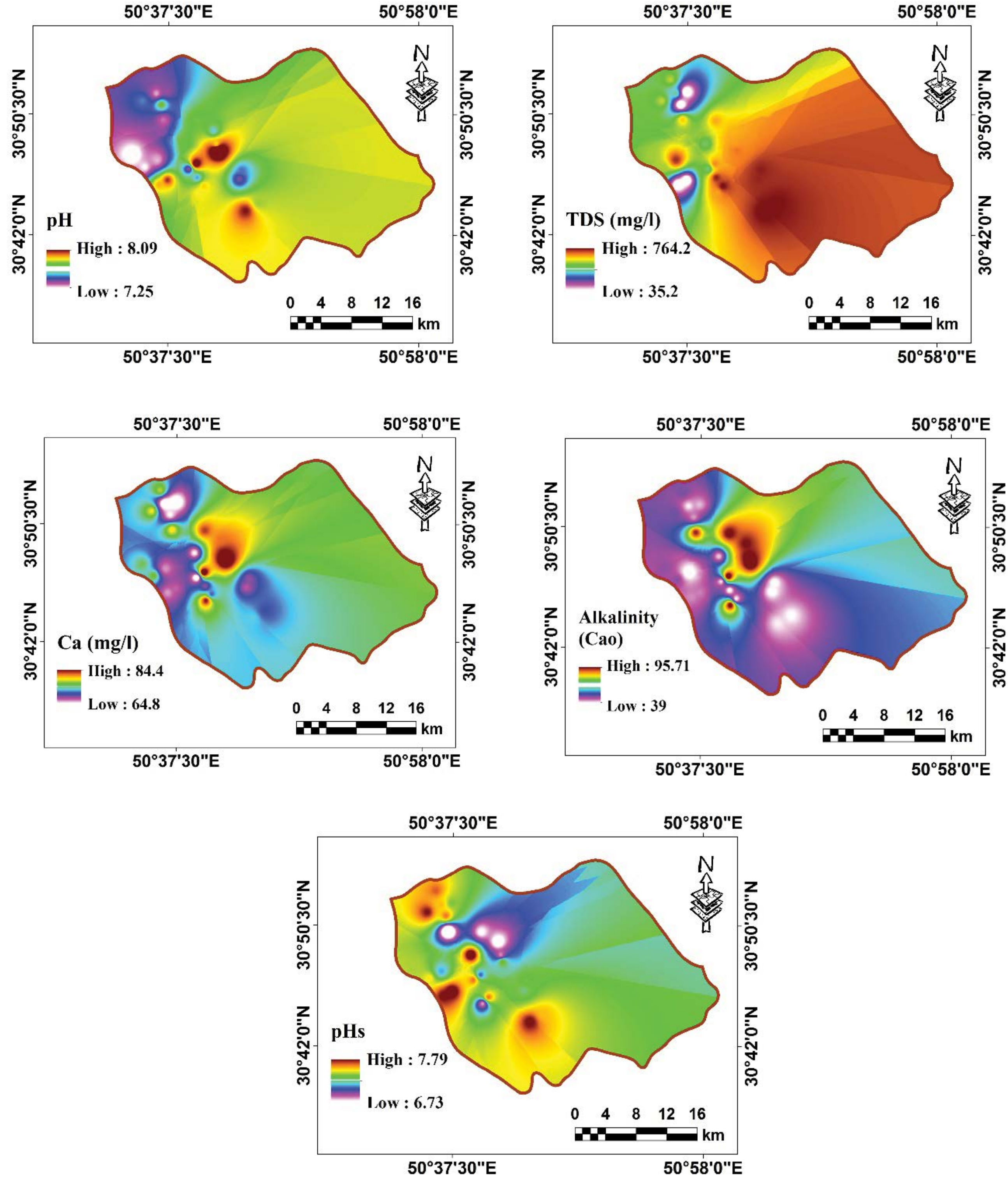

Fig. 3. Interpolation maps of each element using the IDW method.

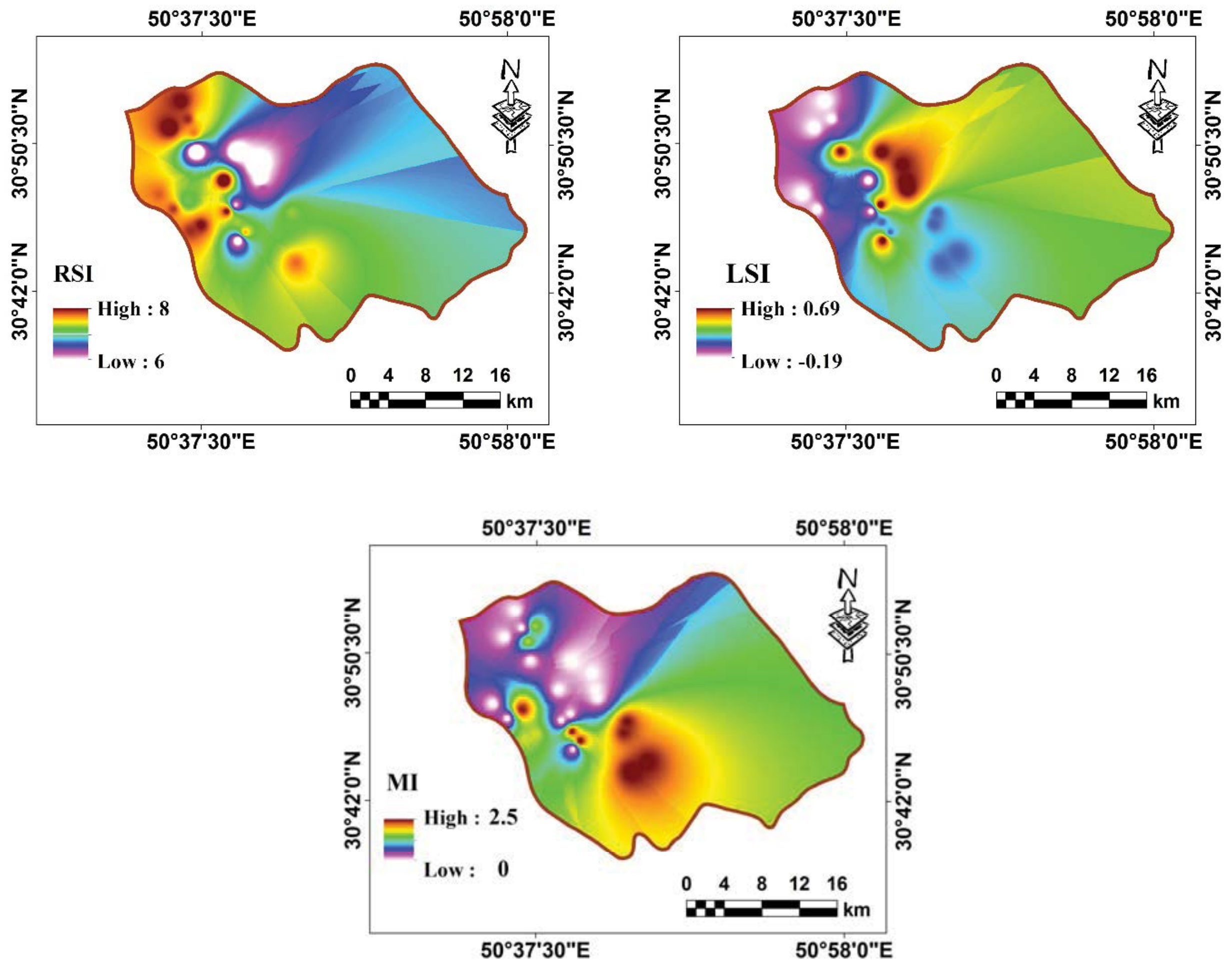

Fig. 4. Interpolation map of the LSI and RSI indices.

neutral state, was observed in the eastern regions of the study area.

The MI zoning map indicates that areas located to the south of the study region have an MI value of higher than 1, indicating low drinking water quality.

4.2. Agricultural water quality using RSC index

Water quality assessment for agricultural use was carried out using the Na%, SAR, and RSC indices. Table 4 lists the measured values for 33 water samples. According to Ravi Kumar and Somashekar [20], RSC values less than 1.25 meq/L indicate good water quality while values above 2 meq/L show inappropriateness of water for irrigation purposes. The majority of samples (more than 23) had an RSC value of less than 1.25 meq/L and are therefore suitable for irrigation.

RSC zoning maps were then procured using IDW as shown in Fig. 5. It can be observed that the northern and northwestern regions with an RSC of less than 1.25 meq/L are suitable for irrigation whereas areas located in the southern parts with an RSC value of above 2 meq/L are unsuitable for irrigation.

4.3. Determination of drinking water quality using the fuzzy method and AHP

IDW was also employed in ArcGIS environment in order to obtain drinking water quality zoning maps based on the following parameters: TDS, pH, Cl, SO_4, Ca, Mg, Na, and K. The maps are illustrated in Fig. 6. It is evident from this Fig. 6., that calcium, magnesium, and potassium concentrations as well as pH and TDS are higher in the southern parts whereas the remaining parameters (SO_4, Cl, and Na) are highest in the northern and northwestern areas.

Membership functions were also used for different parameters and AHP method was used to assign weights to different layers of maps and overlay them to obtain the final fuzzy maps for each parameter according to national drinking water standards (Table 5). A pairwise comparison of figures listed in Table 5 shows that pH and Ca have the highest significance (weight of 0.2) while *K* has the lowest significance (weight of 0.07).

The final fuzzy map is shown in Fig. 7. It can be seen that fuzzy values higher than 0.75 indicate inappropriate quality while values less than 0.75 exhibits good and great drinking water quality. Thus, areas located in the

Table 4
Values of water quality parameters for irrigation

Code	X	Y	SAR	Na%	RSC	Code	X	Y	SAR	Na%	RSC
1	475,950	3,400,610	1.073126	25.02027	4.031473	18	474,260	3,399,570	1.0989	25.6212	4.1283
2	463,520	3,411,410	2.1112	36.1179	0.08281	19	468,790	3,402,770	2.15528	36.87201	0.084539
3	462,596	3,414,826	1.208475	29.06141	0.647743	20	467,760	3,405,680	2.262	38.69775	0.088725
4	463,996	3,415,019	1.387	33.782	0.646	21	462,680	3,406,140	1.03119	24.04252	3.87393
5	467,890	3,411,280	2.1808	37.3086	0.08554	22	468,790	3,402,770	1.08225	25.233	4.06575
6	470,634	3,407,405	2.32	39.69	0.091	23	466,520	3,408,277	1.25	30.06	0.67
7	473,774	3,404,851	1.05299	24.5508	3.955829	24	468,035	3,401,929	1.11	25.88	4.17
8	461,924	3,416,636	1.3662	29.9574	0.6039	25	466,818	3,405,010	1.21875	29.3085	0.65325
9	470,067	3,409,950	2.1576	36.9117	0.08463	26	462,961	3,402,984	1.4454	35.2044	0.6732
10	466,818	3,405,010	1.2375	29.7594	0.6633	27	459,560	3,406,795	1.334156	29.25476	0.589736
11	467,760	3,405,680	1.411499	34.3787	0.65741	28	460,803	3,413,870	1.38	30.26	0.61
12	462,600	3,406,200	1.0323	24.0684	3.8781	29	470,416	3,408,278	2.204	37.7055	0.08645
13	468,035	3,401,929	2.200845	37.65152	0.086326	30	470,634	3,407,405	2.2968	39.2931	0.09009
14	461,087	3,405,254	1.3455	29.5035	0.59475	31	467,936	3,403,861	1.0101	23.5508	3.7947
15	463,250	3,413,390	1.4235	34.671	0.663	32	470,416	3,408,278	2.24293	38.3715	0.087977
16	464,040	3,403,550	1.46	35.56	0.68	33	467,936	3,403,861	1.0545	24.586	3.9615
17	473,448	3,403,689	1.0434	24.3272	3.9198						

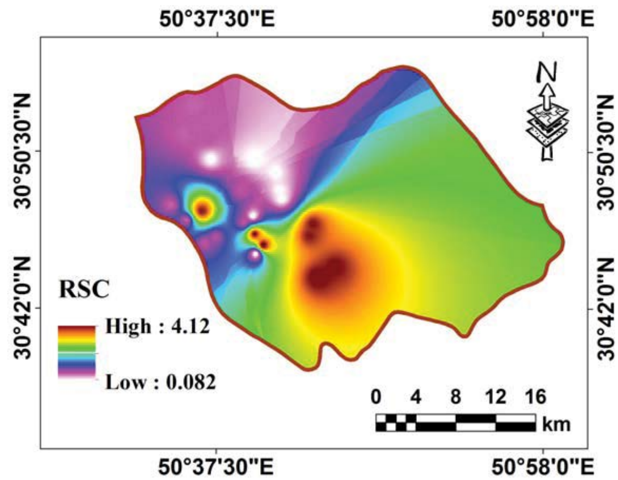

Fig. 5. Water quality map for irrigation.

eastern parts of the study area are better suited for drinking water supply compared to the northern and western regions.

Eventually, in order to evaluate the effectiveness of different parameters in estimating water quality, 15 sample points with known water quality were selected as shown in Fig. 8. A glance at Table 6 shows that areas with agricultural and urban lands (points 8, 9, and 10) correspond to a high rate of pollution, an outcome consistent with the results obtained from different models. According to Table 6, reductions in LSI, MI, and RSC as well as increases in RSI and fuzzy-AHP indicate an increase in water quality, which is consistent with the results obtained by the proposed models in agricultural and urban regions.

Table 5
Drinking Water Quality Standards (WHO) and weight of each parameter using AHP method

Parameter	Limit (mg/L)	Weight
Ca	200	0.2
Cl	200	0.1
Mg	150	0.15
K	12	0.07
Na	200	0.08
SO_4	200	0.1
TDS	500	0.1
pH	7.5	0.2

Studies have proven the aptness of fuzzy models in estimating water quality [5,21,22] as well as the appropriateness of employing LSI, MI, and RSI as complementary means for locating polluted areas in terms of industrial uses [23–25].

5. Conclusion

This study sought to generate groundwater quality zoning maps for the northern regions of Kohgiluyeh Boyer-Ahmad province, Iran, through the application of geostatistical models in GIS environment. For this purpose, a diverse body of parameters were employed including potassium, sodium, magnesium, calcium, chloride, and sulfate concentrations as well as pH levels, TDS in water, SAR, and alkalinity. The parameters were measured for a total of 35 sample wells within the study area. GIS and AHP were incorporated along with fuzzy membership functions for estimating groundwater quality in the study region.

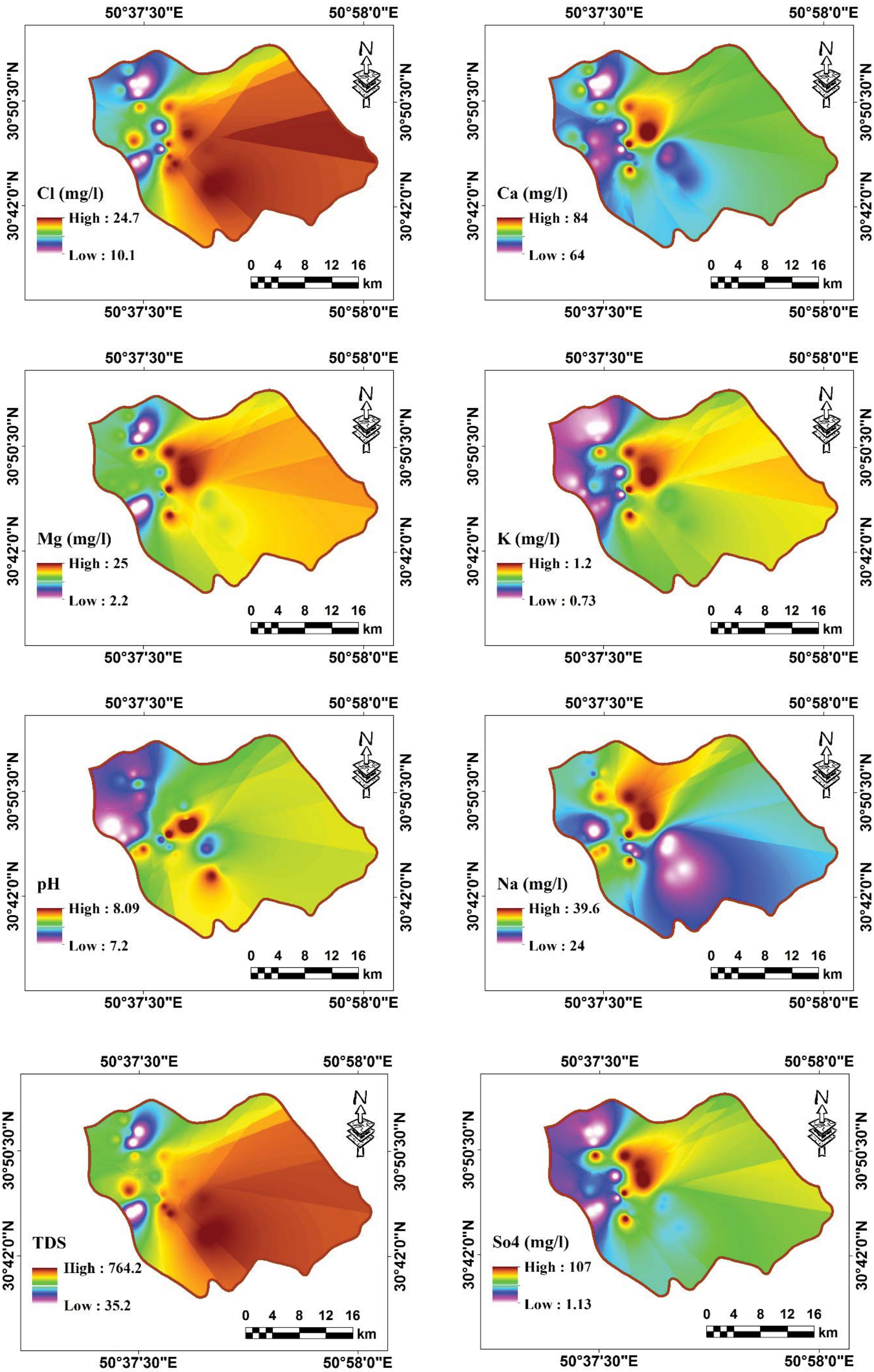

Fig. 6. Fuzzy map of each of the effective parameters in determining water quality in terms of drinking.

Table 6
Values of each model

Number	LSI	RSI	MI	RSC	Fuzzy–AHP	Quality
1	–0.16	8	0	0.8	0.92	Good
2	–0.1	7.5	0	3	0.8	Good
3	0.03	7.8	0.1	0.04	0.93	Good
4	0.17	8	0.1	0.054	0.92	Good
5	0.6	6	0.2	0.2	0.55	Moderate
6	0.1	7	0.11	2	0.53	Moderate
7	0.2	7.2	2.5	3.8	0.51	Weak
8	0.4	7.8	2.4	4	0.5	Weak
9	0.5	6.9	2.3	4.1	0.5	Weak
10	0.6	6	2.5	4.1	0.48	Weak
11	0.3	6.5	1	3	0.47	Good
12	0.1	5.5	1.2	3.1	0.49	Good
13	0	5.2	1.1	3	0.48	Good
14	0	7	1.3	3.2	0.48	Good
15	0	5.6	1.8	2.9	0.49	Good

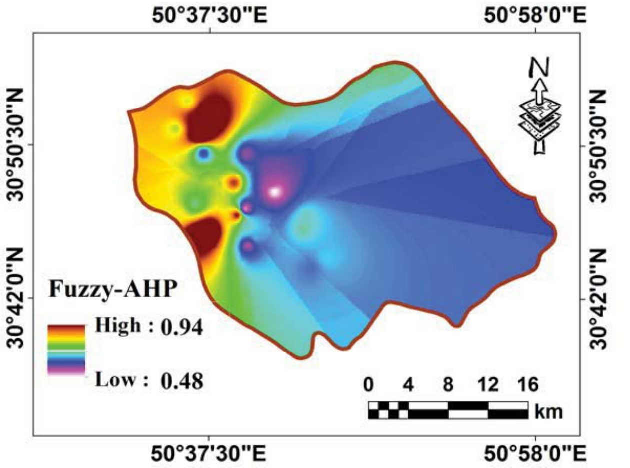

Fig. 7. Final fuzzy water quality map by fuzzy method and AHP.

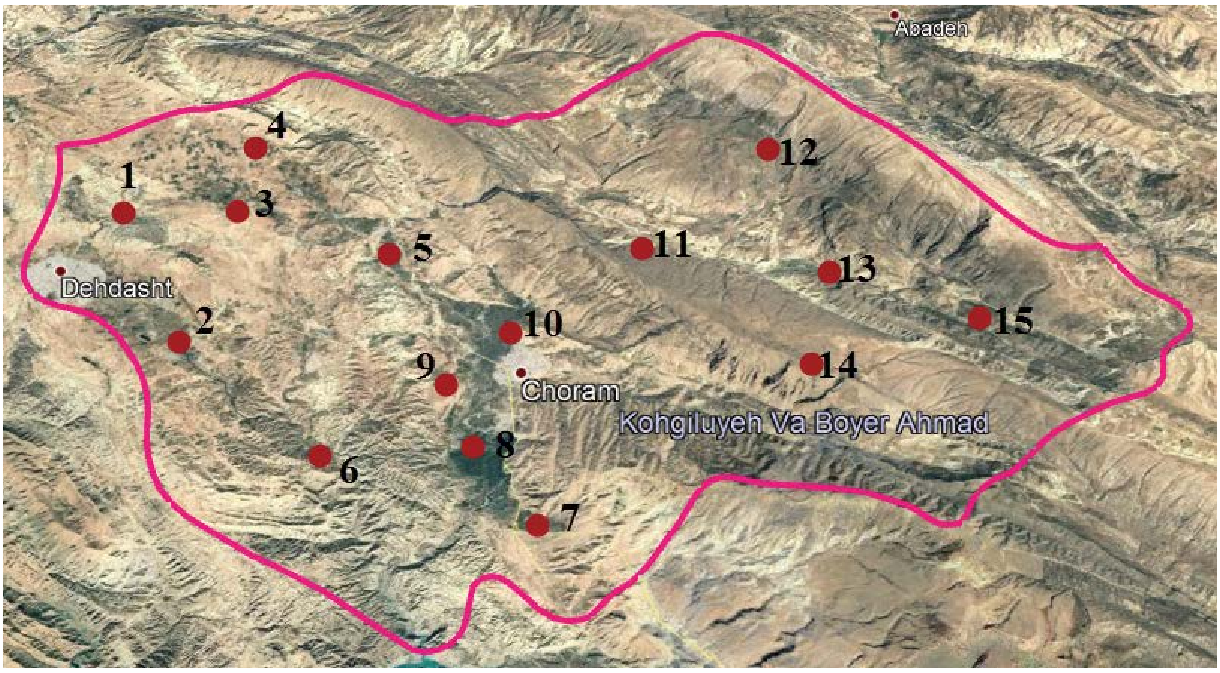

Fig. 8. Position of the sample points.

The LSI, MI, and RSI factors were also employed along with the RSC index for the assessment of water quality for industrial and agricultural purposes, respectively. The findings suggest that areas consisting of agricultural or urban lands are categorized as low water quality according to five different models. This is most likely due to the use of chemical fertilizers and pesticides as well as the ingress of industrial pollutants and wastewaters into water wells, which increases the overall water pollution in the area, rendering the water unsuitable for different purposes.

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