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Evaluation of Irrigation Water Quality Using Fuzzy Logic

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Abstract: In this study, the United States Salinity Laboratory diagram has been convert to the continuous form and then the concentration values of Electrical Conductivity (EC) and Sodium Adsorption Ratio (SAR) combined together by a Fuzzy Inference System (FIS). Finally, ground water quality of Sirjan plain aquifer in Iran has been classified for irrigation purpose by proposed methods. Results obtained from FIS showed 84% general agreement with the results from the USSL diagram evaluation. Results showed that water quality classification with proposed method is more precise in comparison with USSL diagram classification and it improved error effects in hydro chemical experiments.

Key words: USSL diagram, Fuzzy Inference System (FIS), water quality classification, Sirjan plain aquifer

INTRODUCTION

Suitability of water for various uses depends on type and concentration of dissolved minerals. Groundwater has more minerals concentration in comparison with surface water. All groundwater contains minerals carried from the ground earth. Type and concentration of minerals depend on the environment, movement and source of the groundwater. The degree and type of mineralization of groundwater determines its suitability for municipal, industrial, irrigation and other uses. In general, standards of water quality have been established for almost every water use. Several criteria for water quality requirements had been developed through the years, which serve as guidelines in determining the suitability of water for various uses. Subjects covered by the guidelines are bacterial content, physical characteristics; include color, taste, odor, turbidity, temperature and chemical constituents.

The US Public Health Service (1962) established standard for drinking water. The US Salinity Laboratory Staff (1954) and Wilcox (1955) established standards for irrigation water. Water quality classification methods utilize evaluation of water applicability for various uses. For this purpose, after performing the hydro chemical analysis on water samples and determining the amount of every ions and computing the required parameters, it could classify the water quality. Presentation of chemical analysis in graphical form makes evaluation of water quality simpler and quicker. Methods of representing the chemistry of water like Stiff diagram (Stiff, 1951), Schoeller diagram (Schoeller, 1962) and Wilcox diagram Wilcox (1948) have been used in many parts of the world to show the proportion of ionic concentration in individual samples. Each of these diagrams is used to determine the applicability of water for a certain purpose. For example, the Schoeller diagram applies for drinking water evaluation and the Stiff diagram uses to determine hardness of water. But it should notice that interpretation of diagram's results involves some limitations and ambiguities. Water quality diagrams contain quality classes which use crisp sets and the limits between different classes have inherent imprecision (Silvert, 2000). For this reason, water quality evaluation based only on diagrammatic classification may cause imprecise and indefinite results, as in this approach, a parameter which

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is close or far from the limit has equal importance for evaluation of concentration (Icaga, 2007). Also, when two water samples lie in a same class, it is not possible easily to determine that which of them has better quality. Specially, in cases that diagram classifies water quality conditions with respect to more than two ions or parameters, conditions become too difficult.

When a water sample lies near a class's border, separator boundary, because of water sampling and experimental errors, water quality may be determined with errors, so it lies in another class. To overcome these limitations and rating of various water quality samples in comparison with other samples, we can use Fuzzy Inference Systems (FIS) which provide a mathematical tool that can convert the complicated set of linguistic evaluation variables into an automatic evaluation strategy. Fuzzy logic is a mathematical discipline based on fuzzy set theory and expresses multiple levels process among [0] and [1] instead of two levels in classical mathematic.

The first concept of fuzzy logic was conceived by Zadeh (1965). Thereafter fuzzy set theory has been applied to a wide range of applications such as control, image processing, filter design, data clustering, pattern recognition and event classification. Classifications of uniform plant, soil and residue color images were conducted with FIS by Meyer (2004). Mazloumzadeh *et al*. (2008) used Mamdani Fuzzy Inference System (MFIS) as a decision support system to classify general purpose lifters in the date harvest industry. Grading results obtained from MFIS showed 85% agreement with the results from the human expert. Ocampo-Duque *et al*. (2006) used FIS to water quality evaluation in rivers and developed a water quality index. Jacquin and Shamseldin (2006) developed rainfall-runoff models using Takagi-Sugeno Fuzzy Inference Systems (TSFIS) to describe the non-linear relationship between rainfall as input and runoff as output to the real system. Muhammetoglu and Yardimci (2006) developed a fuzzy logic approach to assess the groundwater pollution levels below agricultural fields for Kumluca Plain of Turkey. Water Pollution Index values are calculated by Fuzzy Logic utilizing. Nasiri *et al*. (2007) proposed a fuzzy multiple-attribute decision support expert system to compute the water quality index and to provide an outline for the prioritization of alternative plans based on the amount of improvements in Water Pollution Index (WPI).

The main objective of the present research is to establish a fuzzy logic system to evaluate and classify irrigation water based on USSL diagram.

Evaluation of Water Quality for Irrigation Uses

Previously, many criteria established for evaluation and classification of irrigation water, for example Wilcox (1948) present an irrigation classification diagram on specific conductance and percent of sodium. Eaton (1950) recommended the concentration of residual sodium carbonate to determine suitability of water for irrigation purposes. Wilcox (1955) created a rating of irrigation water for various crops on the basis of the boron concentration of water. He also classified groundwater for irrigation purposes based on percent of sodium and EC. The US Salinity Laboratory Staff (1954) present an irrigation classification diagram on specific conductance and sodium adsorption ratio.

Evaluation of water quality is necessary in planning, design and operation of irrigation systems to ensure that no deleterious salts or compounds occur in the irrigation water (Sangodoyin and Ogedengbe, 1991). The suitability of waters for irrigation should be evaluated on the basis of criteria indicative of their potentials to create soil conditions hazardous to crop growth or crop use. The extent to which chemical quality limits the suitability of water for irrigation depends on the nature, composition and drainage of the soil and subsoil; the amounts of water used and methods of application; the kinds of crops grown and the climate of the region, including the amounts and distribution of rainfall.

Generally, the suitability of water for irrigation is determined by its mineral constituents and type of the plant and soil to be irrigated. In order to classify irrigation water, some chemical characteristics should be enlightened. The characteristics of irrigation water that seems to be most important in determining its quality are:

- Total concentration of dissolved salts
- Relative proportion of sodium to other elements such as magnesium, calcium and potassium
- Concentration of boron or other elements that may be toxic
- Under some conditions, the bicarbonate concentration as related to the concentration of calcium plus magnesium

Besides the factors already discussed, many additional factors affect water suitability for irrigation. In this article we limit ourselves to salinity and sodium hazards associated with water use for irrigation. Due to interaction between different water quality's parameters, in order to classification of water quality should be considered combinations of these parameters.

USSL Diagram for Irrigation Water Quality Evaluation

One well-known diagram for classifying irrigation water was suggested by US Salinity Laboratory Staff (1954) that called as USSL diagram. The USSL diagram best explains the combined effect of sodium hazard and salinity hazard.

The Fig. 1 is a simple scatter chart of sodium hazard (SAR) on the Y-axis versus salinity hazard (EC) on the X-axis. The EC is plotted by default in a log scale. Water can be grouped into 16 classes. Waters are divided into four classes with respect to conductivity, the dividing points between classes being at 250, 750 and 2250 micromhos per centimeter. These classes' limits were selected in accordance with the relationship between the electrical conductivity of irrigation waters and the electrical conductivity of saturation extracts of soil.

The curves of Fig. 1 can be constructed by the use of the following empirical equations (US Salinity Laboratory Staff, 1954):

$$\text{Upper curve: } S = 43.75-8.87 (\log C) \quad (1)$$

$$\text{Middle curve: } S = 31.31-6.66 (\log C) \quad (2)$$

$$\text{Lower curve: } S = 18.87-4.44 (\log C) \quad (3)$$

where, S, C and Log are abbreviation of Sodium Adsorption Ratio (SAR), Electrical Conductivity (EC), in micromhos per centimeter and logarithm to base 10, respectively.

These equations plot as straight lines on rectangular coordinate paper when log C is used.

Using the SAR and the EC value as coordinates, locate the corresponding point on the diagram. The position of the point determines the quality classification of the water. The significance and interpretation of the quality class ratings on the diagram are summarized as:

For purposes of determination and classification, the total concentration of soluble salts (salinity hazard) in irrigation water can be adequately expressed in terms of specific conductance. Based on the EC, irrigation water can be classified into four categories; include:

Low-salinity water (C_1) can be used for irrigation with most crops on most soils with little likelihood that soil salinity will develop. Some leaching is required, but this occurs under normal irrigation practices except in soils of extremely low permeability.

Medium-salinity water (C_2) can be used if a moderate amount of leaching occurs. Plants with moderate salt- tolerance can be grown in most cases without special practices for salinity control.

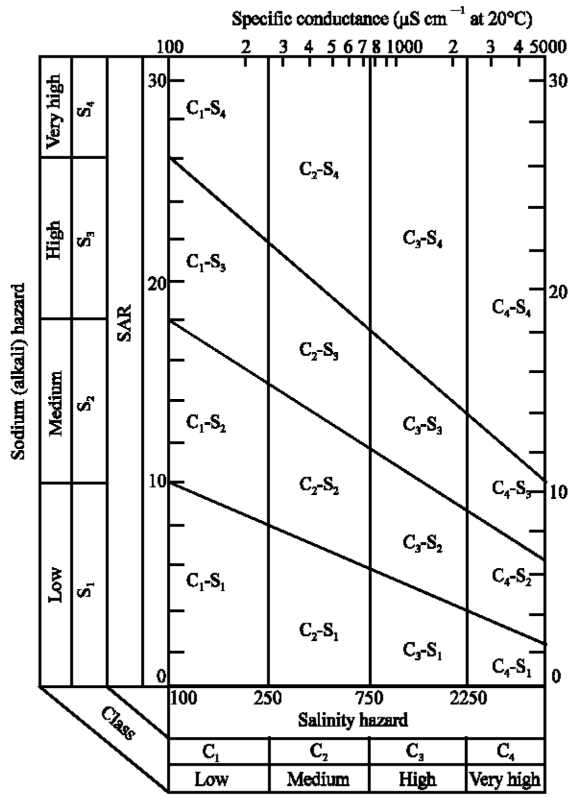

Fig.1: USSL diagram for classification of irrigation waters (US Salinity Laboratory Staff, 1954)

High-salinity water (C_3) cannot be used on soils with restricted drainage. Even with adequate drainage, special management for salinity control may be required and plants with good salt tolerance should be selected.

Very high salinity water (C_4) is not suitable for irrigation under ordinary conditions, but may be used occasionally under very special circumstances. The soils must be permeable, drainage must be adequate, irrigation water must be applied in excess to provide considerable leaching and very salt-tolerant crops should be selected.

Classification of irrigation waters with respect to SAR is based primarily on the effect of exchangeable sodium on the physical condition of the soil. However, Sodium-sensitive plants may suffer injury as a result of sodium accumulation in plant tissues when exchangeable sodium values are lower than those effective in causing deterioration of the physical condition of the soil.

The Sodium Adsorption Ratio (SAR), which was calculated for the water samples based on the formula provided by the US Salinity Laboratory Staff (1954) as follows:

$$\mathrm{SAR} = \frac{\left(\mathrm{Na}^{+}\right)}{\sqrt{\frac{1}{2}\left[\left(\mathrm{Ca}^{2+}\right)+\left(\mathrm{Mg}^{2+}\right)\right]}} \tag{4}$$

where, ion concentrations (in parentheses) are expressed in milli equivalents per liter. The USSL diagram based on SAR divided to four categories included:

Table 1: Water samples quality results using USSL diagram for 20 discharge wells in the study area

	1997			1998			1999			2000			2001		
No.	EC	SAR	Class	EC	SAR	Class	EC	SAR	Class	EC	SAR	Class	EC	SAR	Class
1	858	4.39	C_3-S_1	914	8.22	C_3-S_2	915	7.50	C_3-S_2	920	5.06	C_3-S_1	909	7.02	C_3-S_2
2	1860	6.48	C_3-S_2	2190	7.37	C_3-S_2	1971	8.33	C_3-S_2	1990	5.98	C_3-S_2	1923	7.22	C_3-S_2
3	1188	4.74	C_3-S_1	1237	5.86	C_3-S_2	1234	5.62	C_3-S_2	1200	4.55	C_3-S_1	1075	4.41	C_3-S_1
4	1682	4.14	C_3-S_1	1657	4.66	C_3-S_1	1942	4.56	C_3-S_2	2600	3.83	C_4-S_2	2870	4.39	C_4-S_2
5	4730	11.21	C_4-S_3	4850	8.59	C_4-S_3	4740	10.62	C_4-S_3	4700	8.28	C_4-S_3	4850	9.24	C_4-S_3
6	1466	4.23	C_3-S_1	1529	5.36	C_3-S_2	1546	4.67	C_3-S_1	1800	5.84	C_3-S_2	3490	3.95	C_4-S_2
7	2520	6.35	C_4-S_2	2370	5.39	C_4-S_2	2390	7.11	C_4-S_2	2400	6.67	C_4-S_2	2420	7.51	C_4-S_2
8	600	2.66	C_2-S_1	509	2.55	C_2-S_1	497	2.77	C_2-S_1	500	1.76	C_2-S_1	517	1.95	C_2-S_1
9	1270	5.54	C_3-S_1	1263	6.00	C_3-S_2	992	7.61	C_3-S_2	950	5.47	C_3-S_1	978	6.08	C_3-S_2
10	1329	5.06	C_3-S_1	1538	8.01	C_3-S_2	1244	5.03	C_3-S_1	1150	4.37	C_3-S_1	1135	5.38	C_3-S_1
11	1176	4.87	C_3-S_1	1147	5.02	C_3-S_1	1270	5.93	C_3-S_2	1190	4.85	C_3-S_1	1138	5.35	C_3-S_1
12	502	1.79	C_2-S_1	511	1.60	C_2-S_1	524	1.73	C_2-S_1	500	2.06	C_2-S_1	505	1.66	C_2-S_1
13	2310	8.34	C_4-S_2	2260	10.21	C_4-S_3	2190	7.55	C_3-S_2	2330	7.43	C_4-S_2	2380	7.80	C_4-S_2
14	1700	5.28	C_3-S_2	1664	2.32	C_3-S_1	1622	5.53	C_3-S_2	1230	5.19	C_3-S_1	1335	5.56	C_3-S_2
15	1247	5.72	C_3-S_1	1226	6.69	C_3-S_2	1045	4.91	C_3-S_1	1300	7.08	C_3-S_2	1278	6.57	C_3-S_2
16	2600	5.83	C_4-S_2	2530	7.24	C_4-S_2	2530	6.40	C_4-S_2	2400	6.84	C_4-S_2	2328	5.88	C_4-S_2
17	1439	3.85	C_3-S_1	1392	5.24	C_3-S_2	1392	3.79	C_3-S_1	1190	3.62	C_3-S_1	1084	2.40	C_3-S_1
18	1738	6.57	C_3-S_2	1735	6.42	C_3-S_2	1808	6.92	C_3-S_2	1700	6.98	C_3-S_2	1838	7.56	C_3-S_2
19	4240	11.38	C_4-S_3	4140	10.68	C_4-S_3	4570	13.63	C_4-S_4	4200	11.92	C_4-S_4	4710	15.90	C_4-S_4
20	1151	5.66	C_3-S_1	1168	5.58	C_3-S_1	1190	6.36	C_3-S_2	1300	6.32	C_3-S_2	1750	5.33	C_3-S_2

Low-sodium water (S_1) can be used for irrigation on almost all soils with little danger of the development of harmful levels of exchangeable sodium. However sodium-sensitive crops such as stone fruit trees and avocados may accumulate injurious concentrations of sodium.

Medium-sodium water (S_2) will present an appreciable sodium hazard in certain fine-textured soils having high cation-exchange capacity under low leaching conditions, unless gypsum is present in the soil. This water may be used on coarse-textured or organic soils with good permeability.

High-sodium water (S_3) may produce harmful levels of exchangeable sodium in most soils and will require special soil management.

Very high sodium water (S_4) is generally unsatisfactory for irrigation unless special action is taken, such as addition of gypsum to soil (Lyerly and Longenecker, 1957). Whereas USSL diagram classify irrigation water based on EC and SAR.

We used EC and SAR data of 20 discharge wells in Sirjan plain aquifer for 5 years to develop model (Table 1). The groundwater sampling and chemical analysis was done by Iranian Ministry of Power, Kerman Office (Anonymous, 2003).

Fuzzy Inference System (FIS)

FIS can be particularly suited to models that relationship between variables in environments that are either ill-defined or very complex. Mamdani and Sugeno are two types of FIS and have been formulated in fuzzy logic toolbox of MATLAB software. The most important facility of fuzzy logic toolbox is creating and editing FIS within the framework of the software (Math Works, 2004).

The main idea of the Mamdani method is to describe the process states by linguistic variables and to use these variables as inputs to control rules. In FIS model (Fig. 2), fuzzifier performs a mapping that transfers the input data into linguistic variables and the range of these data forms the fuzzy sets. It is an interface between the real world parameters and the fuzzy system and transforms the output set to crisp (non-fuzzy). The fuzzy inference engine uses the defined rules and it develops fuzzy outputs from the inputs. Defuzzifier maps the fuzzy output variables to the real world variables that can be used to control a real world application. The deffuzification process is a reverse of fuzzification.

The Knowledge Base in FIS model, includes the information given by the expert in the form of linguistic variables (fuzzy if-then rules), composed of two components, the first is Data Base that

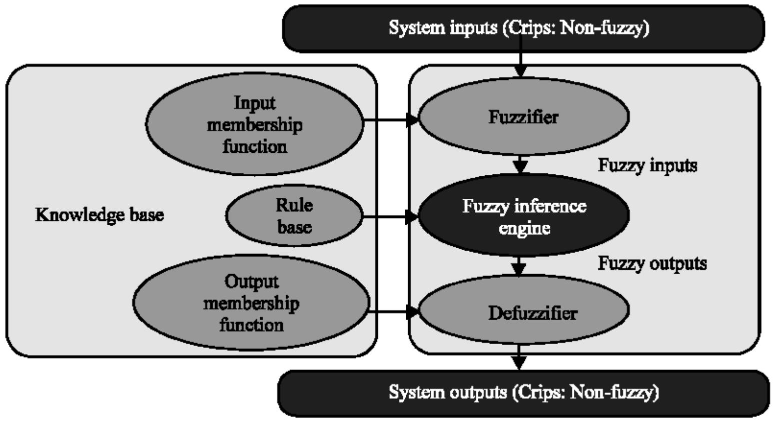

Fig. 2: Block diagram of a fuzzy inference system

contains the linguistic term sets considered in the linguistic rules and the input-output membership functions defining the semantics of the linguistic label. The second component is a Rule Base that comprised of a collection of linguistic rules that are joined by the operator. A wide description of FIS can be found in Ross (2004).

In this research the FIS in fuzzy logic toolbox version 7.0 of MATLAB was selected to evaluate and classify the available groundwater quality samples for irrigation purpose. Two inputs and one output FIS were used to evaluate and classify the irrigation water quality samples in the Sirjan plain aquifer in Iran. Based on considered membership functions for inputs, the FIS has $4\times4 = 16$ rules. In the applied system: intersection, union, aggregation, implication and defuzzification are considered MIN, MAX, SUM, PROD and CENTROID, respectively.

Determination of Membership Functions

Many researchers have investigated more rational techniques for determining membership functions. Turksen (1991) reviewed the various methods and research into the acquisition of membership functions and introduced four different approaches to determine membership functions: direct rating, set valued statistics, polling and reverse rating. The automatic generation of membership functions (particularly neural networks and genetic algorithms) covers a wide variety of different approaches (Park *et al*., 1994).

In this research direct rating based on USSL diagram limits were used to develop the membership functions. In the beginning, the membership functions of EC and SAR determined according to Fig. 1 approximately, then the best membership functions determined by trial and error for 100 irrigation water samples, results from fuzzy system compared with USSL diagram results to obtain the best membership functions.

Based on Fig. 1, membership functions were assigned to two variables inputs as shown in Fig. 3 and 4. In Fig. 3, classes of Low (0-9), Mid (2-17), High (6-25) and Very high (11-35), refer to Good, Medium, Bad and Very bad values of SAR, respectively. Also, in Fig. 4, classes of Low (0-350), Mid (200-900), High (600-3000) and Very high (1650-5000), refer to Good, Medium, Bad and Very bad values of EC, respectively. The output membership functions of Fig. 5 were chosen for water quality evaluation. In figure, classes of Very bad (0-0.3), Bad (0.15-0.45), Medium (0.3-0.7), Good (0.55-0.85) and Very good (0.7-1), refer to Very bad, Bad, Medium, Good and Very good values of water quality evaluation, respectively.

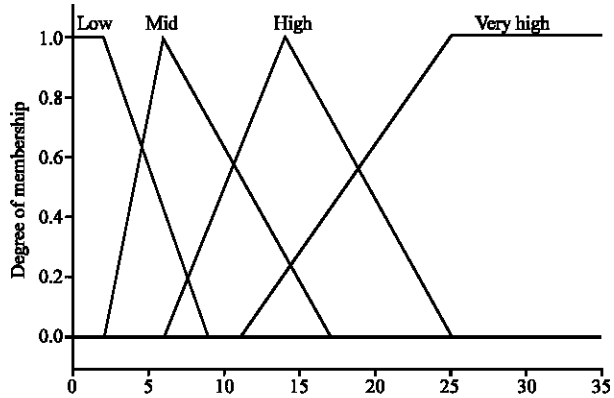

Fig. 3: SAR membership functions

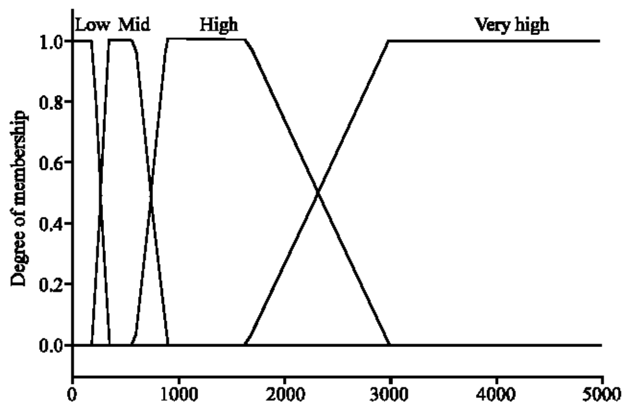

Fig. 4: EC membership functions

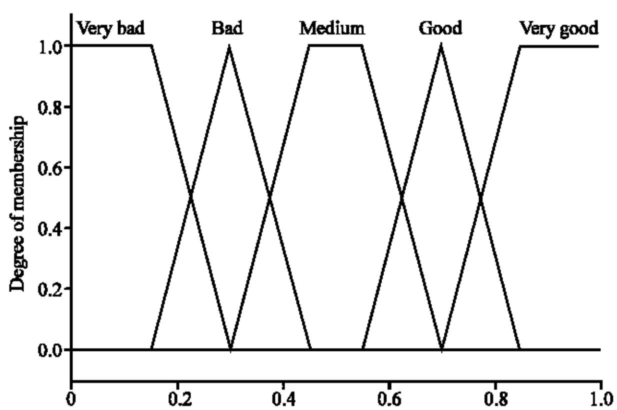

Fig. 5: Irrigation water quality evaluation output membership functions

Table 2: Developed Fuzzy rules

EC/SAR	Low	Mid	High	Very high
Low	Very good	Good	Medium	Bad
Mid	Good	Good	Bad	Bad
High	Medium	Medium	Very bad	Very bad
Very high	Bad	Bad	Very bad	Very bad

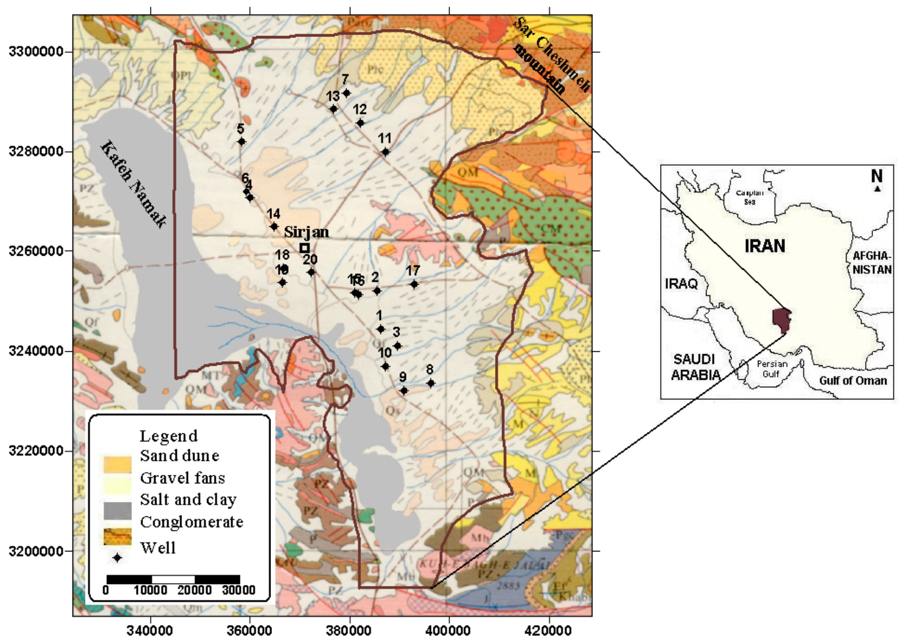

Fig. 6: Sampling sites in the studied area (Sirjan watershed location)

Fuzzy Rules Determination

In a fuzzy inference system the experts represent their knowledge concerning the classification of the water quality in the form of rules. The set of rules using expert knowledge for the presented model are given in Table 2. A sample of the rule definition is:

If SAR is Low and EC is Mid then quality of irrigation water is Good;
Also, if SAR is High and EC is Low then quality of irrigation water is Medium.

Study Area

The case study relates to fuzzy water quality classification with the available water quality data from 20 discharge wells for five years in Sirjan plain aquifer.

Sirjan watershed, with an area of about 8027 km^2, is located in Kerman province, south-eastern part of Iran (Fig. 6). The region has a semi-arid climate, with maximum temperature about 27.8°C in July and minimum temperature 4.3°C in January. The average potential evaporation is 3250 mm per annum. The humidity in the Sirjan station ranges from a minimum of 27% to a maximum of 48%. The average annual precipitation is 156 mm. Elevation ranges from a maximum of 3813 to 1650 m at the flood plains. The main recharge source of this aquifer is precipitation in Sar Cheshmeh mountain ranges that after infiltration, from northeastern recharges this plain.

RESULTS AND DISCUSSION

In this research ground water quality of Sirjan plain aquifer evaluate with emphasis on irrigation purposes by both fuzzy logic and traditional USSL diagram. We used the available water quality data from 20 discharge wells for five years of 1997-2001. The data which were used include EC and SAR water samples for September of each year (Table 1). In the method, membership functions of the irrigation water quality parameters and fuzzy rule bases were defined and then fuzzy logic toolbox of MATLAB 7 package was used. The outputs of model present a water quality ranking according to suitability for irrigation purposes. Table 3 shows the fuzzy score of each irrigation water sample from defuzzification process.

Model's Validation

Evaluation of agreement between the FIS obtained outputs and the expert knowledge is an important phase in FIS construction. It means that the system must give appropriate respond to the different conditions that can be presented.

Comparison between results of USSL diagram and MFIS in Table 4 showed that the MFIS method could rank water quality samples, with 84% general agreement apart from samples that lie in class's borders. Also the difference between water quality samples, which lied in a same class, distinct by MFIS method. In the MFIS method, according to SAR and EC of each water sample, a score assigned to be between [0, 1]. Whatever fuzzy score of sample become greater, which the quality for irrigation purpose will be better. For example overview of Table 4 shows ground water quality sample of wells No. 1, 3, 4, 6 and 9 for 1997, lie in C_3-S_1 class (Medium), but the difference between these quality samples is not clear and all of these samples based on USSL diagram have a same importance. But MFIS goes further and gives values of 100, 81, 87, 93 and 67% to the Medium class; so, this system can rank the results. Also the sample of well No. 1 has the higher quality and the sample of well No. 9 has the lower quality in comparison with other samples.

To evaluate irrigation water quality variations from a source during a time period, it could plot fuzzy score of sample versus time. Figure 7 indicates the water quality scores of some wells in Sirjan plain aquifer during years 1997-2001. For instance, all samples of well No. 5 according to USSL diagram (Fig. 1) lie in C_4-S_3 class, but based on MFIS results water quality of this well vary periodically during years 1997-2001. Also all samples of well No. 20 during years 1999-2001 according to USSL diagram lie in C_3-S_2 class, but based on MFIS results water quality of this well increase during that period.

A way to visualize the relationship between input variables and their contribution to the output variable is through fuzzy surfaces. The fuzzy surface is a graphical user interface (GUI) tool that lets examining the output surface of a FIS. Figure 8 allows watching the possible combinations of two input variables and the output in a three dimensional view.

Table 3: Defuzzification results of the FIS for 20 wells water quality evaluation

	Well No.									
Year	1	2	3	4	5	6	7	8	9	10
1997	0.468	0.324	0.420	0.428	0.114	0.434	0.263	0.7	0.396	0.410
1998	0.270	0.243	0.380	0.420	0.120	0.390	0.301	0.7	0.363	0.283
1999	0.311	0.219	0.383	0.367	0.114	0.422	0.240	0.7	0.306	0.411
2000	0.410	0.334	0.425	0.286	0.125	0.361	0.261	0.7	0.398	0.430
2001	0.337	0.273	0.428	0.224	0.114	0.221	0.219	0.7	0.380	0.401
	11	12	13	14	15	16	17	18	19	20
1997	0.416	0.7	0.186	0.394	0.392	0.256	0.445	0.323	0.114	0.393
1998	0.414	0.7	0.151	0.486	0.353	0.224	0.405	0.340	0.114	0.395
1999	0.380	0.7	0.234	0.396	0.414	0.260	0.447	0.300	0.114	0.367
2000	0.417	0.7	0.229	0.406	0.334	0.253	0.452	0.323	0.114	0.369
2001	0.410	0.7	0.207	0.392	0.358	0.302	0.488	0.268	0.114	0.381

Table 4: Evaluation results of MFIS and USSL diagram expert for 20 discharge wells water in irrigation purpose

Well No.	Year	USSL class	output score	Fuzzy evaluation (Fig. 5)	USSL diagram expert evaluation	Agreement of Evaluations (%)
1	1997	C_3-S_1	0.468	100% in Medium	Medium	100
	1998	C_3-S_2	0.270	82% in Bad and 18% in Very bad	Bad	82
	1999	C_3-S_2	0.311	94% in Bad and 6% in Very bad	Bad	94
	2000	C_3-S_1	0.410	23% in Bad and 77% in Medium	Medium	77
	2001	C_3-S_2	0.337	86% in Bad and 14% in Medium	Bad	86
2	1997	C_3-S_2	0.324	87% in Bad and 13% in Medium	Bad	87
	1998	C_3-S_2	0.243	60% in Bad and 40% in Very bad	Bad	60
	1999	C_3-S_2	0.219	49% in Bad and 51% in Very bad	Bad	49
	2000	C_3-S_2	0.334	89% in Bad and 11% in Medium	Bad	89
	2001	C_3-S_2	0.273	83% in Bad and 17% in Very bad	Bad	84
3	1997	C_3-S_1	0.420	19% in Bad and 81% in Medium	Medium	81
	1998	C_3-S_2	0.380	47% in Bad and 53% in Medium	Bad	47
	1999	C_3-S_2	0.383	46% in Bad and 54% in Medium	Bad	46
	2000	C_3-S_1	0.425	16% in Bad and 84% in Medium	Medium	84
	2001	C_3-S_1	0.428	13% in Bad and 87% in Medium	Medium	87
4	1997	C_3-S_1	0.428	13% in Bad and 87% in Medium	Medium	87
	1998	C_3-S_1	0.420	19% in Bad and 81% in Medium	Medium	81
	1999	C_3-S_2	0.367	49% in Bad and 51% in Medium	Bad Boundary	49
	2000	C_4-S_2	0.286	93% in Bad and 7% in Very bad	Bad	93
	2001	C_4-S_2	0.224	54% in Bad and 46% in Very bad	Bad	54
5	1997	C_4-S_3	0.114	100% in Very bad	Very bad	100
	1998	C_4-S_3	0.120	100% in Very bad	Very bad	100
	1999	C_4-S_3	0.114	100% in Very bad	Very bad	100
	2000	C_4-S_3	0.125	100% in Very bad	Very bad	100
	2001	C_4-S_3	0.114	100% in Very bad	Very bad	100
6	1997	C_3-S_1	0.434	7% in Bad and 93% in Medium	Medium	93
	1998	C_3-S_2	0.390	42% in Bad and 58% in Medium	Bad	42
	1999	C_3-S_1	0.422	17% in Bad and 83% in Medium	Medium	83
	2000	C_3-S_2	0.361	61% in Bad and 39% in Medium	Bad	61
	2001	C_4-S_2	0.221	50% in Bad and 50% in Very bad	Bad	50
7	1997	C_4-S_2	0.263	68% in Bad and 32% in Very bad	Bad	68
	1998	C_4-S_2	0.301	99% in Bad and 1% in Very bad	Bad	99
	1999	C_4-S_2	0.240	58% in Bad and 42% in Very bad	Bad	58
	2000	C_4-S_2	0.261	66% in Bad and 34% in Very bad	Bad	66
	2001	C_4-S_2	0.219	48% in Bad and 52% in Very bad	Bad	48
8	1997	C_2-S_1	0.700	100% in Good	Good	100
	1998	C_2-S_1	0.700	100% in Good	Good	100
	1999	C_2-S_1	0.700	100% in Good	Good	100
	2000	C_2-S_1	0.700	100% in Good	Good	100
	2001	C_2-S_1	0.700	100% in Good	Good	100
9	1997	C_3-S_1	0.396	33% in Bad and 67% in Medium	Mid	67
.	1998	C_3-S_2	0.363	53% in Bad and 47% in Medium	Bad	53
.	1999	C_3-S_2	0.306	98% in Bad and 2% in Very bad	Bad	98
.	2000	C_3-S_1	0.398	32% in Bad and 68% in Medium	Medium	68
	2001	C_3-S_2	0.380	46% in Bad and 54% in Medium	Bad	46
20	1997	C_3-S_1	0.393	31% in Bad and 69% in Medium	Medium	69
	1998	C_3-S_1	0.395	30% in Bad and 70% in Medium	Medium	70
	1999	C_3-S_2	0.367	58% in Bad and 42% in Medium	Bad	58
	2000	C_3-S_2	0.369	56% in Bad and 44% in Medium	Bad	56
	2001	C_3-S_2	0.381	46% in Bad and 54% in Medium	Bad	46
The average conformity between MFIS and USSL diagram evaluation without boundary values						84

The MFIS method improves greatly the effects of inherent imprecision due to separation between different classes in USSL diagram. Also this method could modify the effect of hydro chemical analysis errors, especially when water quality samples lie adjacent to class's borders. Because such samples may lie in wrong class if a small error percentage occur in chemical experiments. If the MFIS method implements, the effect of experimental errors is not significant in final evaluation of water quality. For instance, the water quality of well No. 14 for years 2000 and 2001 due to small change in SAR and EC lie in different USSL classes of C_3-S_1 (Medium) and C_3-S_2 (Bad), respectively (Table 1). Whereas these

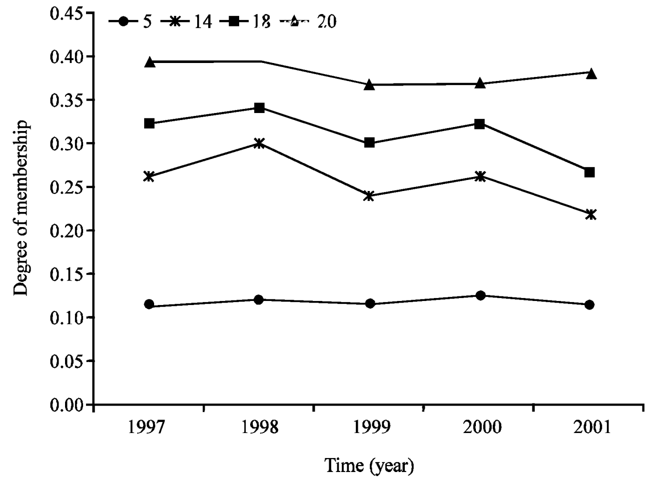

Fig. 7: The variation of ground water quality for wells No. 5, 14, 18 and 20 in Sirjan plain aquifer during 1997-2001

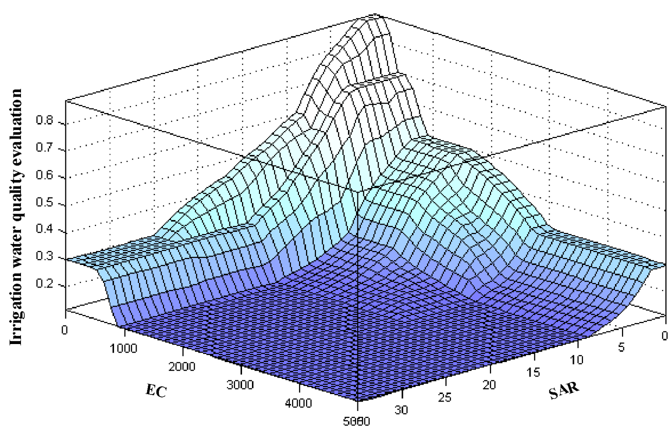

Fig. 8: Fuzzy surface: SAR and EC versus irrigation water quality evaluation

water quality samples haven't considerable difference practically. According to MFIS results, the fuzzy score of these samples are 0.406 (73% belong to Medium class) and 0.392 (68% belong to Medium class) for years 2000 and 2001, respectively (Table 3) and it is clear that the difference between two samples is not considerable. So water quality evaluation with MFIS is more exact than USSL diagram classification.

In the USSL method, evaluation of border values, between two classes, is one of the classification limits, however with application of proposed method, this value classify very well. For example, the water quality of well No. 6 for years 1999 according to USSL diagram lie on the class's border of C_3-S_1 (Medium) and C_3-S_2 (Bad) exactly (Table 4); but according to MFIS method, this sample is 49% in Bad class and 51% in Medium class. Hence this water quality sample is closer to Medium class i.e., C_3-S_1. When two border values lie in different class, their fuzzy score is near together but according to USSL diagram these samples differ each other absolutely.

Another advantage of MFIS method is when two border values lie in different classes. In this phase, their fuzzy score is near together but according to USSL diagram these samples differs from each other absolutely.

CONCLUSION

Groundwater quality diagrams classify the water quality in separated classes. The limits between different classes have inherent imprecision. Due to inherent imprecision, difficulties always exist in water quality evaluation and considerable uncertainties are involved in the process of defining water quality for specific usage. Field data also provide many uncertainties. Especially, in the phases that water quality samples have border values, these uncertainties affected water quality evaluation.

Groundwater quality diagrams define the water quality in linguistic terms whereas a fuzzy logic is based on approach that provides fuzzy scores for different linguistic terms. In fuzzy logic approach, water quality samples can be classified as Very bad, Bad, Medium, Good or Very good but with different fuzzy score.

In this study, a new approach using MFIS has been used to evaluate and classify ground water quality for irrigation uses.

Ground water quality of Sirjan plain aquifer in Iran is evaluated by both MFIS method and traditional USSL diagram.

The comparison between results of MFIS and USSL classification diagram showed 84% agreement. The results showed that the MFIS method could rank water quality samples which are in same class in USSL diagram. It showed that, water quality evaluation with MFIS is more exact than USSL diagram classification and it provides a better representation of water quality condition. Also MFIS could improve effects of probable errors and uncertainties in field data and hydro chemical analysis.

The use of linguistic terms and mathematical relationships in the MFIS gives more adequate evaluation results. Selection of membership functions in terms of shape and boundary has a significant effect on the evaluation and classification results of the irrigation waters samples. Selection of the right membership function forms and boundaries greatly depend on USSL diagram and human expert knowledge. To find the best evaluation results input and output levels and rules must be tested precisely.

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