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Assessing salinity and sodicity hazards of ground water for irrigation purposes using fuzzy logic

Samad Abdi*, Ahmad Tajabadi Pour, Hosein Shirani, Mohsen Hamidpour, Hosein Shekofteh

Department of Soil Science, College of Agriculture, Vali-e-Asr University of Rafsanjan, Rafsnjan, Iran,
emails: sabdi1100@yahoo.com (S. Abdi), ahtajabadi@yahoo.com.au (A. Tajabadi Pour), shirani379@yahoo.com (H. Shirani), mohsen_hamidpour@yahoo.com (M. Hamidpour), hoseinshekofteh@yahoo.com (H. Shekofteh)

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ABSTRACT

In order to perform environmental management, precise classification and identification of groundwater quality is necessary. There are various uncertainties with traditional classification methods. In recent years fuzzy logic-based methods are widely used to control uncertainties in different environmental problems. Therefore, a fuzzy logic approach was developed to evaluate the groundwater quality of Rafsanjan plain in Iran. The plain is known for its intensive pistachio production, which has caused water table draw downs and depletion of groundwater resources. In this study three parts of FAO guideline for irrigation water quality assessment were combined by fuzzy logic to create a new method for assessing salinity and sodicity hazards of irrigation water. Salinity fuzzy inference system (FIS) was constructed with water electrical conductivity (EC) and total dissolved solids as inputs and infiltration; FIS (sodicity hazard) was constructed using sodium adsorption ratio and EC and then, these two FISs (salinity and sodicity) were combined to develop a new FIS that can be used to assess irrigation water quality. The results of the calculated FAO guideline and fuzzy logic approach have yielded good agreement. In order to evaluate models' validation, the available water quality data from 20 wells, from 2002 to 2010 in Rafsanjan plain aquifer were used. Results showed that water quality in this region is bad to medium in the view of salinity and sodicity hazards.

Keywords: FAO guideline; Fuzzy inference system; Infiltration; Irrigation

1. Introduction

Ground water is widely used for many purposes such as irrigation and livestock watering, public and domestic water supply systems, commercial, industrial, thermoelectric power production, and mining [1]. Ground water resources are continuously subjected to a dynamic state of change due to lithological characteristics and geo-climatic conditions. Human activities can upset this dynamic balance in the aquatic system [2]. These factors can change water quality spatially and temporally [3].

In order to formulate suitable guidelines and efficient implementation for water monitoring, quality assessment and enforcement of prescribed limits by different regulatory bodies, awareness of status, and changing trends in water quality are necessary [4].

*Corresponding author.

Various methods have been used for evaluation of irrigation water quality criteria and decision-making. The United States salinity laboratory staff [5] considers salinity and sodicity hazards together based upon electrical conductivity (EC) and sodium adsorption ratio (SAR) to assess irrigation water quality. The Food and Agriculture Organization of the United Nations (FAO) has released a guideline for interpretations of water quality for irrigation that considers salinity, sodicity, toxicity, and other problems of irrigation water. Artificial neural network (ANN) [6], adaptive neuro fuzzy inference system (ANFIS) [7], and so on are also used for irrigation quality assessment. But these deterministic approaches that compare water quality criteria with prescribed limits provided by different regulatory bodies do not consider uncertainties throughout the entire steps of experiment [8]. All studies related to water quality assessments consider two parameters such as SAR and EC; therefore, in order to improve applicability of these systems, it is good to incorporate more parameters, but, uncertainties do arise when more parameters are considered for classification [9]. Due to this problem in traditional approaches, new classification method is needed to consider imprecise, vague, and fuzzy information in assessing irrigation water quality [4]. A solution for avoiding the uncertainties that exist in water quality assessment is to introduce a degree of precaution, before applying a single value to irrigation water quality standards [10]. Fuzzy logic is a practical and useful tool in modeling complex systems. In this way, the human expertise plays an important role in the modeling process [11].

The fuzzy logic has been used to assess irrigation water quality by several researchers. Pauzi Abdullah et al. [12] developed a methodology based on fuzzy inference system (FIS) to assess water quality. In their method six inputs and one output were used to evaluate the Semenyih river quality in Malaysia. They compared their method with a conventional method, water quality index (WQI), and concluded that the FIS may successfully harmonize inherent discrepancies and interpret complex conditions. Muhammetoglu and Yardimci [13] developed a fuzzy logic approach to assess the groundwater pollution levels below agricultural fields of Kumluca plain of Turkey. In their study the results of the calculated water pollution index (WPI) and the monitoring study yielded good agreement. Mirabbasi et al. [14] converted United States Salinity Laboratory (USSL) diagram to a continuous form. They combined EC and SAR values by fuzzy logic to build a new diagram. In Iran, evaluation of irrigation water quality is based on FAO guideline. Guideline values given identify water potential problem based on possible restrictions in use related to (1) salinity, (2) rate of water infiltration into the soil, (3) specific ion toxicity, and (4) to some other miscellaneous effects. The FAO guideline (Table 2) has several problems such as, many points being located in each class of this diagram thus making determination and comparison of their quality very difficult. Also, where a water quality parameter is in the range of slight to moderate, more concern is required in the selection of plant species and precautions are needed to minimize salt injury. By fuzzy logic, one score is allocated to each sample and comparison is easy. The objectives of this study were to develop a new fuzzy method based on FAO guideline for assessing ground water quality in the view of salinity and sodicity hazards and resolving the problems of this guideline and finally evaluating the quality of ground water of Rafsanjan region in the northwestern part of Kerman province, Iran, using this new method.

2. Material and methods

2.1. Study area

The Rafsanjan plain in Kerman province, Iran, is known as one of the greatest pistachio production sites. The area of this region is 7,678 km^2. This area is located between longitudes 55˚59´38´´ E and latitudes 30˚24´24´´ N, with a 1,517 m elevation above sea level (Fig. 1). This region has mean annual precipitation less than 100 mm and mean annual potential evapotranspiration more than 3,000 mm. The soil moisture regime is aridic and temperature regime is thermic. Pistachio orchards in this region are irrigated with ground water through wells. Water quality has decreased due to excessive withdrawal of ground water. Therefore, it is important to pay attention to water quality for its management and application.

2.2. Data source

The available water quality data including EC, SAR and total dissolved solids (TDS) from 30 wells for 9 years of 2002–2010 for September of each year were used. These data were received from Kerman regional water company. Twenty of them were used to evaluate salinity, sodicity and quality of aquifer in this research. To show an overview of the qualitative data, the statistical parameters for 30 wells such as minimum value (Min), maximum value (Max), mean, and standard deviation (SD) for each parameter are calculated and given in Table 1.

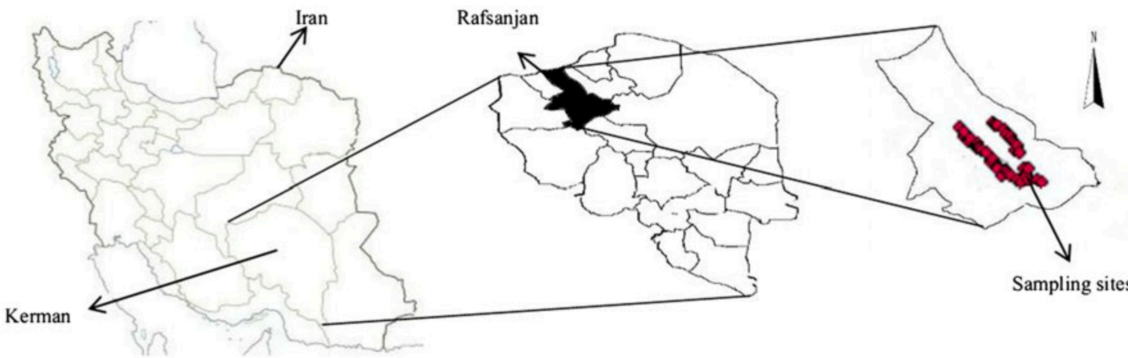

Fig. 1. Location of study area and sampling sites (Attribution information for part 1 is By Uwe Dedering (Own work) [CC BY-SA 3.0 (http://creativecommons.org/licenses/by-sa/3.0) or GFDL (http://www.gnu.org/copyleft/fdl.html)] for part 2 is By mjbmr (Own work – Geography Department, Kerman) [GFDL (http://www.gnu.org/copyleft/fdl.html) or CC BY-SA 4.0-3.0-2.5-2.0-1.0 (http://creativecommons.org/licenses/by-sa/4.0-3.0-2.5-2.0-1.0)]).

Table 1
Summary of basic statistical parameters

	EC (dS m^{-1})				SAR				TDS (mg l^{-1})			
Year	Max	Min	SD	Mean	Max	Min	SD	Mean	Max	Min	SD	Mean
2002	18.9	1.29	3.7	6.2	27.4	6.7	4.4	12.0	12,633	862	2,442.5	4,107.7
2003	17.5	1.30	3.2	5.9	18.5	5.8	3.1	10.9	11,698	880	2,184.2	3,924.6
2004	17.5	1.30	3.2	5.9	18.5	5.8	3.1	10.8	11,698	880	2,189.9	4,008.3
2005	19.6	1.30	4.0	6.4	34.4	6.6	5.0	12.2	12,721	810	2,556.9	4,107.6
2006	18.8	1.20	4.0	6.4	32.4	6.3	5.1	12.8	12,253	804	2,602.9	4,144.1
2007	18.0	1.20	3.8	6.3	26.0	6.7	4.8	12.3	12,000	787	2,558.5	4,141.1
2008	18.9	1.17	4.1	6.5	30.0	5.9	4.8	12.5	12,311	761	2,655.0	4,198.6
2009	21.1	1.30	4.7	7.1	33.7	5.9	4.7	11.9	13,715	854	3,029.8	4,589.8
2010	19.3	1.30	4.3	6.8	23.8	5.4	3.7	11.8	12,545	813	2,803.5	4,384.7

2.3. Fuzzy systems

Fuzzy theory is supported with fuzzy sets. The main research fields in fuzzy theory are fuzzy sets, fuzzy logic, and fuzzy measure. Fuzzy reasoning is applied to knowledge processing [15]. A fuzzy set is an extension of the traditional set theory. A fuzzy set describes the relationship between an uncertain quantity X and a membership function μ, which ranges between 0 and 1 [11]. The value 0 means that x is not a member of the fuzzy set; the value 1 means that x is fully a member of the fuzzy set and the values between 0 and 1 characterize fuzzy members that belong to the fuzzy set only partially [16]. If X is a collection of objects denoted generically by x, then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs:

$$\tilde{A} = \{x,\ \mu_{\tilde{A}}(x) \mid x \in X\} \tag{1}$$

$\mu(x)$ is called the membership function which maps X to the membership space M [17].

2.4. Fuzzy inference system (FIS)

FIS is a practical tool which can be used in solving complicated set of linguistic variables [14]. Mamdani and Sugeno are two common FIS that are different in

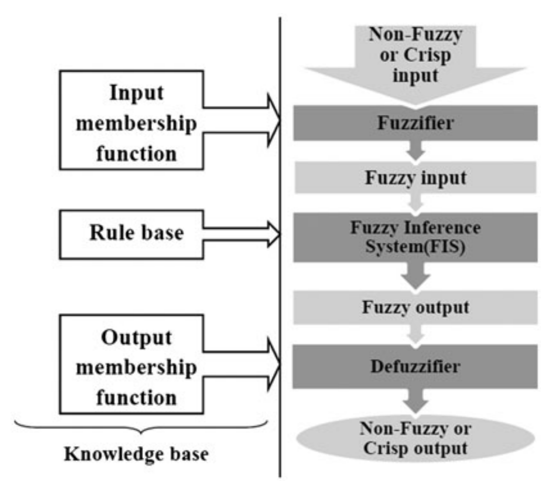

Fig. 2. Basic architecture of a FIS.

specifications of the consequent part of their rules. In Mamdani FIS, the rule consequence is defined by fuzzy sets [18] and in Sugeno FIS the conclusion of a fuzzy rule is a weighted linear combination of the crisp inputs [19]. In this research Mamdani fuzzy inference system model was used to assess the salinity and sodicity hazards of groundwater for irrigation purposes. Mamdani fuzzy rules have the following structure:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z \text{ is } C \tag{2}$$

Basically, a FIS is constituted by a group of four main elements: knowledge base, fuzzifier, fuzzy inference engine, and defuzzifier, as shown in Fig. 2. The knowledge base includes the expert information in the form of linguistic rules. This part is constituted of two components: a database, which determines the membership functions of the fuzzy sets that are used in the fuzzy rules; a rule base is composed of a series of linguistic rules that are joined by a specific operator. The fuzzifier has the responsibility of transforming the crisp inputs into degree of membership function. Inference system (Engine) makes inference using a reasoning method. Defuzzifier transforms the fuzzy results of the previous part (engine) into a crisp output by means of a defuzzification method [20].

2.5. Fuzzification

The fuzzification is done using membership functions (MF). A membership function provides a measure of the degree of similarity of an element to a fuzzy set [10]. For each input and output variable selected, two or more MF can be defined, normally three but can be more. There are different shapes of MF; triangular, trapezoidal, piecewise-linear, Gaussian, bell-shaped, etc. Triangle and trapezoid MF are widely used in decision-making. However, in this research using trial and error, the Gaussian MF had the best results. A Gaussian MF is specified by two parameters c (center), σ (width) and is given by following expression:

Table 2
FAO guideline for interpretations of water quality for irrigation [23]

Potential irrigation problem			Units	Degree of restriction on use		
				None	Slight to moderate	Severe
Salinity (affects crop water availability)						
	EC_w (or)		dS m^{-1}	<0.7	0.7–3.0	>3.0
	TDS		mg l^{-1}	<450	450–2,000	>2,000
Infiltration (affects infiltration rate of water into the soil. Evaluate using EC_w and SAR together)						
SAR	0–3	and EC_w		>0.7	0.7–0.2	<0.2
	3–6			>1.2	1.2–0.3	<0.3
	6–12			>1.9	1.9–0.5	<0.5
	12–20			>2.9	2.9–1.3	<1.3
	20–40			>5.0	5.0–2.9	<2.9
Specific ion toxicity (affects sensitive crops)						
	Sodium (Na)					
	Surface irrigation		SAR	<3	3–9	>9
	Sprinkler irrigation		mel^{-1}	<3	>3	
	Chloride (Cl)					
	Surface irrigation		mel^{-1}	<4	4–10	>10
	Sprinkler irrigation		mel^{-1}	<3	>3	
	Boron (B)		mg l^{-1}	<0.7	0.7–3.0	>3.0
	Trace Elements					
Miscellaneous effects (affects susceptible crops)						
	Nitrogen (NO_3-N)		mg l^{-1}	<5	5–30	>30
	Bicarbonate (HCO_3)					
	(Overhead sprinkling only)		mel^{-1}	<1.5	1.5–8.5	>8.5
	pH				Normal range 6.5–8.4	

$$\mu_{\bar{A}(x)} = \exp\left(-\frac{(c-x)^2}{2\sigma^2}\right) \quad (3)$$

where the parameter c has a distance from the origin and σ parameter is the width of the curve [21].

2.6. Determination of MF

Several methods are existing for membership function determination such as direct rating, set valued statistics, polling, and reverse rating [22]. Artificial neural network and genetics algorithm are also used to generate membership function automatically. Mirabbasi et al. [14] determined MF for EC and SAR by direct rating based on USSL diagram. Priya [9] determined MF for four significant parameters using direct rating based on USSL classification system for SAR and EC and Indian standards for chloride and sulfate.

In this research Gaussian MF for EC, SAR, and TDS were determined by direct rating based on FAO guideline for assessing irrigation water quality (Table 2). This guideline considers the long-term effect of irrigation water quality on crop production and soil physicochemical properties. Based on this guideline, water quality problems are categorized in salinity, soil permeability, toxicity, and miscellaneous effects. This guideline has been used to evaluate groundwater and other types of water such as surface water, drainage water, sewage effluent, and wastewater successfully [23]. In order to determine MF for salinity and infiltration FISs, three parts of this guideline, which are marked by dotted line borders in Table 2, were used. MF were assigned for EC, TDS, and SAR. In order to assess the salinity of irrigation water, a Mamdani FIS (salinity FIS) was developed with EC and TDS as inputs and for assessing the infiltration problem of irrigation water, other Mamdani FIS (infiltration FIS) was also developed with EC and SAR. According to expert knowledge and FAO guideline, in salinity FIS

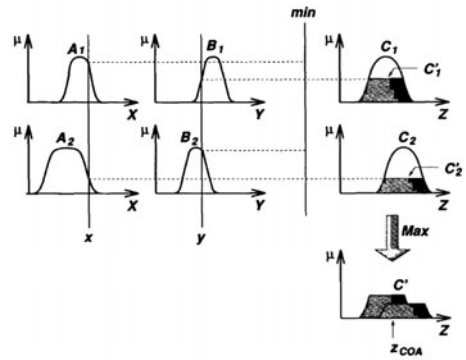

Fig. 3. Graphical technique of Mamdani (Max–Min) inference.

three classes for EC (dS m^{-1}) including low (0–3.8), medium (0.9–6), and high (3.2–9) were determined. For TDS (mg l^{-1}), classes of low (0–750), medium (450–2,500), and high (1,500–5,000) were determined. Three output MF of this FIS including bad (0–0.49), medium (0.22–0.75), and good (0.55–1) refer to degree of water salinity goodness (Fig. 4).

In infiltration FIS, five classes for SAR including very low (0–4.9), low (2.6–6.9), medium (5.4–12), high (8–25), and very high (16–40) were considered to design MF. For EC input in this FIS, 3 classes including low (0–3.8), medium (0.9–6), and high (3.2–9) were considered. Three output MF for this FIS including bad (0–0.49), medium (0.22–0.85), and good (0.55–1) refer to degree of water infiltration goodness (Fig. 5).

2.7. Rule definition

A fuzzy rule-based system is characterized by a collection of linguistic statements through which experts apply their knowledge about the classification system [24]. After the input and output variables and MF are determined, the rule base in the form of IF < antecedents > THEN < conclusions > rules which

Table 3
Fuzzy rules designed for the salinity FIS based on FAO guideline

1	If EC is low and TDS is low then salinity is good
2	If EC is low and TDS is medium then salinity is good
3	If EC is low and TDS is high then salinity is bad
4	If EC is medium and TDS is low then salinity is medium
5	If EC is medium and TDS is medium then salinity is medium
6	If EC is medium and TDS is high then salinity is bad
7	If EC is high and TDS is low then salinity is bad
8	If EC is high and TDS is medium then salinity is bad
9	If EC is high and TDS is high then salinity is bad

Table 4
Some of the fuzzy rules designed for the infiltration FIS based on FAO guideline

1	If SAR is very low and EC is low then infiltration is good
2	If SAR is very low and EC is medium then infiltration is good
3	If SAR is very low and EC is high then infiltration is good
4	If SAR is low and EC is low then infiltration is good
5	If SAR is low and EC is medium then infiltration is good
6	If SAR is low and EC is high then infiltration is good
7	If SAR is medium and EC is low then infiltration is medium
8	If SAR is medium and EC is medium then infiltration is medium
9	If SAR is medium and EC is high then infiltration is good
10	If SAR is high and EC is low then infiltration is bad
11	If SAR is high and EC is medium then infiltration is medium
12	If SAR is high and EC is high then infiltration is good
13	If SAR is very high and EC is low then infiltration is bad
14	If SAR is very high and EC is medium then infiltration is bad
15	If SAR is very high and EC is high then infiltration is good

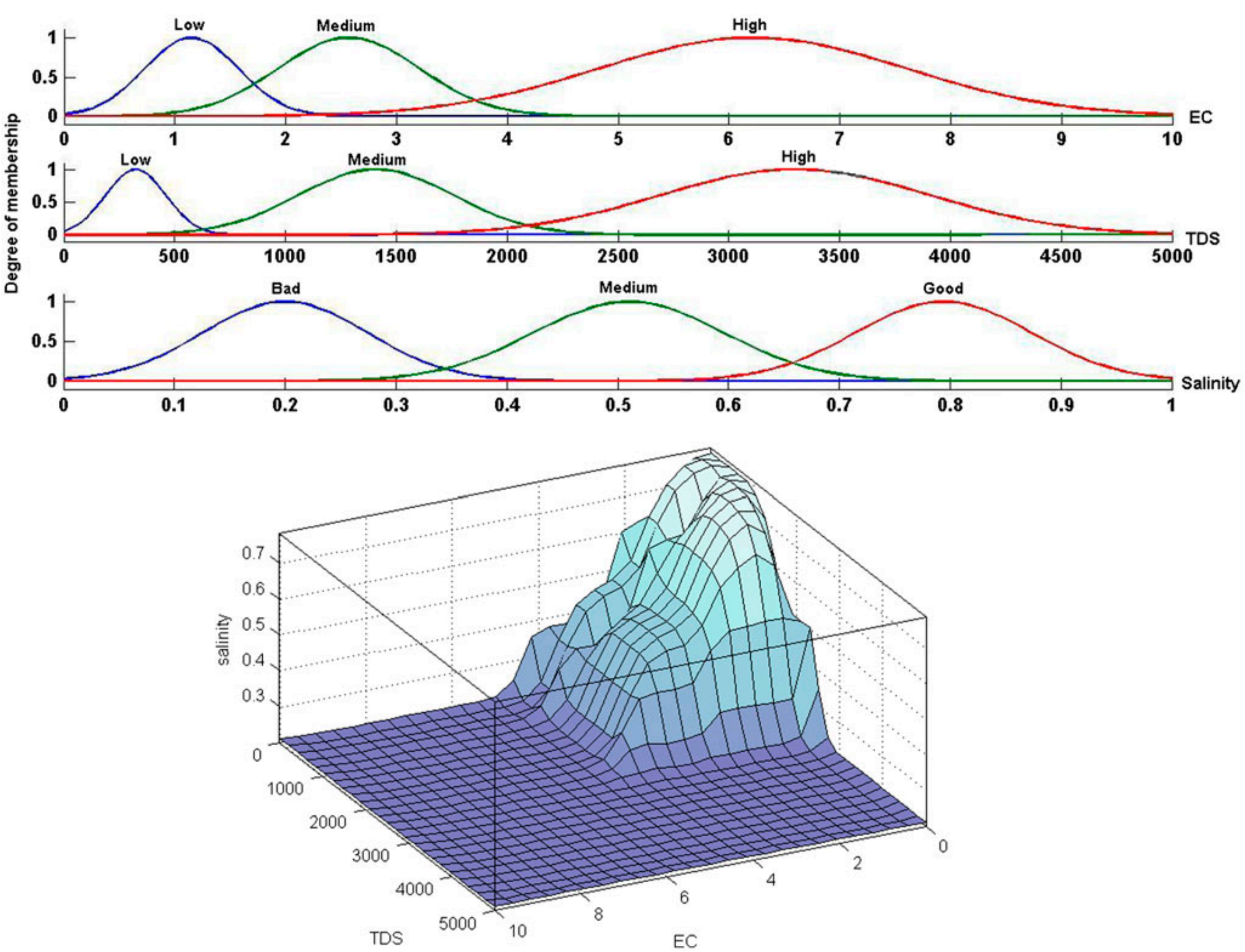

Fig. 4. MF and fuzzy surface for salinity FIS.

are easily implemented by fuzzy conditional statements must be designed [25]. These rules are responsible for transforming the input variables into a single output that determines the risk of operational problems. Output variable must be defined with MF. A single number given by the antecedent is used as an input for the implication process, and the output is a fuzzy set. Implication is implemented for each rule. In order to make a decision, the rules must be combined in some manner because decisions are based on the testing of all of the rules in a FIS. Next step is aggregation process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Finally, the aggregate output fuzzy set is used as input for the defuzzification process and the output is a single number [12] (Fig. 3).

If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. Many fuzzy operators have been suggested for all types of fuzzy decisions. These suggestions vary with respect to the generality or adaptability of the operators and to the degree to which and how they are justified. Following Zadeh's definition [11], the "AND" operator is described by the intersection of the two fuzzy sets, which is given as the minimum of both of the MF:

$$\mu_c(x) = \min(\mu_A(x),\ \mu_B(x)) \tag{4}$$

For the "OR" operator, the union of both the fuzzy sets defined as the maximum of both MF is taken:

$$\mu_c(x) = \max(\mu_A(x),\ \mu_B(x)) \tag{5}$$

Inputs of salinity FIS have 3 × 3 = 9 rules. Connective in these rules was AND (Table 3). A sample of rule is given below:

If EC is low and TDS is low then salinity is good.

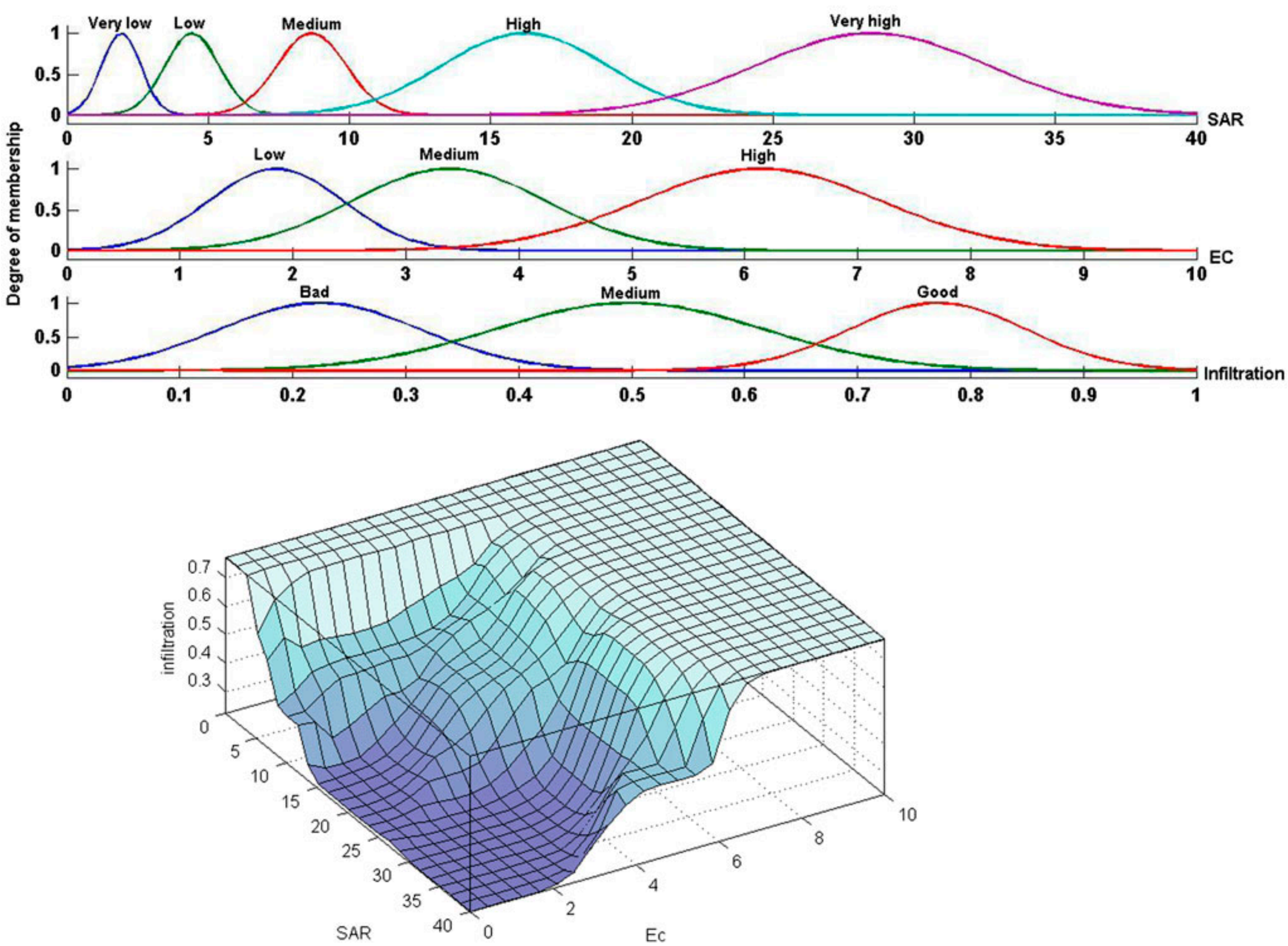

Fig. 5. MF and fuzzy surface for infiltration FIS.

Infiltration FIS based on MF, for its inputs has $3 \times 5 = 15$ rules (Table 4). Connective in these rules was AND. A sample of rule for this FIS is given below:

If SAR is very low and EC is high then infiltration is good.

In both FISs (salinity and infiltration) for intersection, union, aggregation, implication, and difuzzification, MIN, MAX, SUM, PROD, and CENTROID are considered respectively.

In order to visualize the relationship between input variables and their effects on output variables, fuzzy surface can be used (Figs. 4 and 5).

By combining two mentioned FISs (salinity and infiltration), another FIS (quality FIS) was created. Using this third FIS, irrigation water quality from the view of salinity and infiltration restrictions can be assessed. MF and fuzzy surface of this Mamdani FIS is given in Fig. 6. The outputs of salinity and infiltration FISs are considered as inputs for quality FIS. MF for quality output based on expert knowledge are defined as: bad (0–0.49), medium (0.22–0.75), and good (0.55–1). Defined rules for this FIS are given in Table 5. The schematic illustration of this fuzzy model is given in Fig. 7.

In order to test the salinity and infiltration FISs, 9 points were selected in various classes from Table 2 (FAO guideline) and applied to two mentioned FISs. As can be seen from Table 6, a good agreement exists between FAO guideline and fuzzy results.

3. Results and discussion

To evaluate the ground water quality of the Rafsanjan region by two obtained FIS from the view of

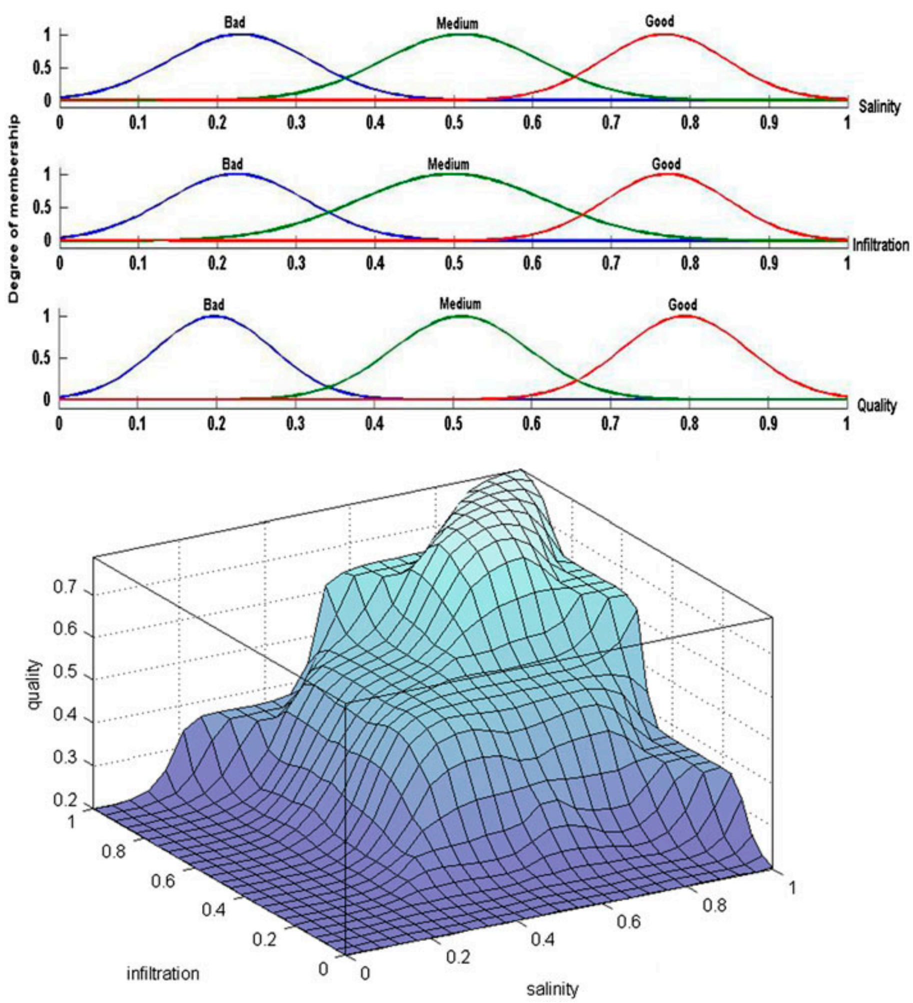

Fig. 6. MF and fuzzy surface for quality FIS.

Table 5
Fuzzy rules designed for the quality FIS based on salinity and infiltration FISs

1	If salinity is bad and infiltration is bad then quality of irrigation water is bad
2	If salinity is bad and infiltration is medium then quality of irrigation water is bad
3	If salinity is bad and infiltration is good then quality of irrigation water is bad
4	If salinity is medium and infiltration is bad then quality of irrigation water is bad
5	If salinity is medium and infiltration is medium then quality of irrigation water is medium
6	If salinity is medium and infiltration is good then quality of irrigation water is medium
7	If salinity is good and infiltration is bad then quality of irrigation water is bad
8	If salinity is good and infiltration is medium then quality of irrigation water is medium
9	If salinity is good and infiltration is good then quality of irrigation water is good

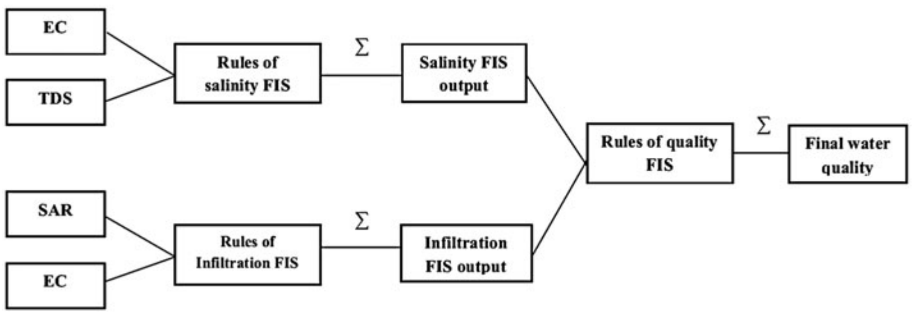

Fig. 7. The schematic illustration of quality FIS.

salinity and infiltration restrictions, available data from 20 wells for 9 years of 2002–2010 were used. These data were EC, SAR, and TDS. The outputs of fuzzy models (salinity FIS and infiltration FIS) represent a water quality score in the view of salinity and infiltration restrictions for irrigation purposes (Tables 7 and 8). When the fuzzy scores are greater, the salinity and sodicity quality are better. As can be seen from Tables 7 and 8, most of ground water samples have the salinity scores of bad to medium and can create salinity problems for crops. Although in the view of sodicity problem (Table 8), most of the samples have medium to good infiltration scores, and do not have any restriction for soil. The salinity score for well no. 18 is greater than the other wells so this well has lower salinity hazard for crops. Most of the samples have low quality from the view of salinity and can restrict the plant growth.

Salinity and sodicity have inverse relationship; this relation can be seen by comparing Tables 7 and 8. An increase of water salinity is shown to have a positive

Table 6
Evaluation of the agreement between FAO guideline and two used FISs (salinity and infiltration)

Salinity				Infiltration			
EC	TDS	FAO guideline	Salinity FIS results	SAR	EC	FAO guideline	Infiltration FIS results
0.1	150	No restriction	0.754 (Good)	1	0.5	No restriction	0.770 (Good)
0.3	250	No restriction	0.766 (Good)	30	5	No restriction	0.632 (Good)
0.5	350	No restriction	0.773 (Good)	15	6	No restriction	0.763 (Good)
0.9	500	Medium restriction	0.772 (Medium)	10	0.9	Medium restriction	0.443 (Medium)
1.5	1,000	Medium restriction	0.734 (Medium)	5	2	Medium restriction	0.762 (Medium)
2.5	1,500	Medium restriction	0.636 (Medium)	10	3.5	Medium restriction	0.515 (Medium)
3.5	2,500	Sever restriction	0.218 (Bad)	15	0.1	Sever restriction	0.239 (Bad)
4.5	3,500	Sever restriction	0.201 (Bad)	10	0.4	Sever restriction	0.388 (Bad)
5.5	4,500	Sever restriction	0.200 (Bad)	12	1.1	Sever restriction	0.282 (Bad)

Table 7
The salinity scores for 20 wells

Year	Well no. 1	2	3	4	5	6	7	8	9	10
2002	0.201	0.687	0.480	0.500	0.500	0.336	0.201	0.227	0.215	0.304
2003	0.201	0.687	0.472	0.500	0.359	0.383	0.202	0.251	0.222	0.264
2004	0.201	0.687	0.472	0.500	0.359	0.383	0.202	0.251	0.222	0.264
2005	0.200	0.684	0.449	0.334	0.500	0.359	0.202	0.272	0.237	0.500
2006	0.200	0.681	0.443	0.334	0.500	0.378	0.206	0.327	0.253	0.500
2007	0.200	0.681	0.413	0.387	0.500	0.405	0.229	0.354	0.286	0.500
2008	0.200	0.698	0.393	0.374	0.500	0.429	0.245	0.349	0.286	0.500
2009	0.200	0.645	0.402	0.451	0.500	0.500	0.286	0.444	0.291	0.500
2010	0.200	0.660	0.379	0.398	0.500	0.497	0.295	0.458	0.290	0.500

Year	11	12	13	14	15	16	17	18	19	20
2002	0.205	0.200	0.203	0.201	0.202	0.201	0.201	0.739	0.201	0.203
2003	0.205	0.200	0.203	0.201	0.202	0.200	0.200	0.739	0.201	0.203
2004	0.205	0.200	0.203	0.201	0.202	0.200	0.200	0.739	0.201	0.203
2005	0.205	0.200	0.202	0.201	0.200	0.200	0.200	0.735	0.201	0.203
2006	0.208	0.200	0.206	0.201	0.200	0.200	0.200	0.735	0.590	0.201
2007	0.208	0.200	0.205	0.201	0.200	0.200	0.200	0.734	0.218	0.201
2008	0.211	0.200	0.201	0.201	0.200	0.200	0.200	0.734	0.210	0.201
2009	0.247	0.200	0.200	0.201	0.201	0.200	0.200	0.734	0.205	0.201
2010	0.248	0.200	0.200	0.200	0.200	0.200	0.200	0.734	0.271	0.201

Table 8
The infiltration scores for 20 wells

Year	Well no. 1	2	3	4	5	6	7	8	9	10
2002	0.761	0.525	0.771	0.771	0.771	0.771	0.768	0.771	0.771	0.771
2003	0.758	0.630	0.770	0.771	0.771	0.771	0.769	0.771	0.771	0.771
2004	0.758	0.630	0.771	0.771	0.771	0.771	0.769	0.771	0.771	0.771
2005	0.758	0.543	0.771	0.771	0.771	0.771	0.770	0.771	0.771	0.771
2006	0.764	0.542	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771
2007	0.761	0.524	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771
2008	0.762	0.506	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771
2009	0.769	0.496	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771
2010	0.764	0.692	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771

Year	11	12	13	14	15	16	17	18	19	20
2002	0.770	0.722	0.771	0.579	0.771	0.569	0.638	0.499	0.619	0.524
2003	0.770	0.701	0.770	0.556	0.724	0.657	0.653	0.486	0.606	0.529
2004	0.771	0.701	0.770	0.556	0.724	0.656	0.652	0.485	0.605	0.529
2005	0.771	0.724	0.770	0.601	0.718	0.690	0.613	0.486	0.606	0.546
2006	0.771	0.685	0.771	0.588	0.748	0.728	0.663	0.594	0.481	0.547
2007	0.771	0.702	0.771	0.570	0.749	0.716	0.609	0.250	0.521	0.559
2008	0.771	0.682	0.766	0.558	0.747	0.728	0.672	0.255	0.568	0.585
2009	0.771	0.740	0.763	0.620	0.768	0.749	0.738	0.671	0.567	0.605
2010	0.771	0.696	0.752	0.709	0.761	0.755	0.747	0.738	0.531	0.576

Table 9
The quality scores for 20 wells from the view of salinity and infiltration restrictions

Year	Well no. 1	2	3	4	5	6	7	8	9	10
2002	0.203	0.510	0.500	0.505	0.50	0.314	0.203	0.209	0.206	0.268
2003	0.203	0.556	0.497	0.505	0.359	0.405	0.203	0.220	0.208	0.229
2004	0.203	0.555	0.497	0.505	0.359	0.405	0.203	0.220	0.208	0.229
2005	0.203	0.513	0.483	0.311	0.505	0.360	0.203	0.236	0.213	0.505
2006	0.203	0.513	0.478	0.311	0.505	0.396	0.204	0.300	0.221	0.505
2007	0.203	0.510	0.449	0.413	0.506	0.439	0.210	0.350	0.250	0.505
2008	0.203	0.506	0.422	0.390	0.505	0.464	0.216	0.339	0.250	0.505
2009	0.203	0.503	0.434	0.484	0.505	0.505	0.250	0.479	0.254	0.505
2010	0.203	0.595	0.398	0.430	0.505	0.505	0.258	0.489	0.254	0.505
	11	12	13	14	15	16	17	18	19	20
2002	0.204	0.204	0.203	0.204	0.204	0.204	0.205	0.506	0.205	0.204
2003	0.204	0.204	0.204	0.204	0.204	0.205	0.205	0.503	0.205	0.204
2004	0.204	0.204	0.204	0.204	0.204	0.205	0.205	0.503	0.205	0.204
2005	0.204	0.203	0.203	0.205	0.203	0.204	0.205	0.503	0.205	0.204
2006	0.204	0.204	0.204	0.205	0.203	0.203	0.205	0.532	0.499	0.204
2007	0.204	0.204	0.204	0.204	0.203	0.203	0.205	0.256	0.205	0.204
2008	0.205	0.204	0.203	0.204	0.203	0.203	0.205	0.258	0.206	0.205
2009	0.217	0.203	0.203	0.205	0.203	0.203	0.203	0.636	0.205	0.205
2010	0.218	0.204	0.203	0.204	0.203	0.203	0.203	0.720	0.222	0.204

consequence on the sodicity effect. Sodicity has less impact at higher electrolyte concentrations at any particular level [26]. According to Table 9, the water quality scores for irrigation purposes are in the range of bad to medium.

The samples of well nos. 2, 3, 4, 5, 6, and 18 have medium quality from the view of salinity and sodicity hazards and other samples have bad quality. The quality of water samples during 2002–2010 has no considerable difference. This region has experienced a severe drought in recent years so that excessive withdrawal of groundwater can cause serious problem for pistachio orchards.

4. Conclusion

Salinity and SAR of irrigation water have an interactive effect on soil physical properties. When SAR increases, soil aggregates tend to become more dispersed and soil permeability to air and water will decrease. So that classification methods must consider these criteria. Evaluating the salinity and sodicity hazards of ground water using FAO guideline has several problems. This guideline shows salinity and sodicity as linguistic terms and many points are located in each class of guideline. In order to evaluate ground water as quantitative term, fuzzy logic can be used. In this study, fuzzy logic was used to combine three parts of FAO guideline to evaluate ground water quality. A good agreement existed between fuzzy results and this guideline. This method can be used as a practical and useful tool for ground water evaluation. The quality of the Rafsanjan aquifer was evaluated using this new method and results showed that water samples have medium to bad quality. Modern irrigation techniques and mixing high-quality water with poor-quality ones in the area are necessary to prevent the reduction of the water quality. Other parts of FAO guideline can be modeled by fuzzy logic to create a new method for evaluating other aspects of irrigation quality such as toxicity hazard.

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