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A comparative study of fuzzy logic-based models for groundwater quality evaluation based on irrigation indices

Meysam VADIATI[1] ABEF, Deasy NALLEY[2] DEF, Jan ADAMOWSKI[3] ADE ✉, Mohammad NAKHAEI[4] CE, Asghar ASGHARI-MOGHADDAM[5] AEF

[1] orcid.org/0000-0003-0841-6919; Kharazmi University, Department of Applied Geology, Faculty of Earth Sciences, Tehran, Iran; McGill University, Department of Bioresource Engineering, Faculty of Agricultural and Environmental Sciences, Quebec, Canada; e-mail: Mey_vadiati@tabrizu.ac.ir
[2] orcid.org/0000-0003-3714-6110; McGill University, Department of Bioresource Engineering, Faculty of Agricultural and Environmental Sciences, Quebec, Canada; e-mail: deasynalley.mcgill@gmail.com
[3] orcid.org/0000-0002-1242-3364; McGill University, Department of Bioresource Engineering, Faculty of Agricultural and Environmental Sciences, Quebec, Canada; e-mail: jan.adamowski@mcgill.ca
[4] orcid.org/0000-0002-4823-5197; Kharazmi University, Department of Applied Geology, Faculty of Earth Sciences, Tehran, Iran; e-mail: nakhaei@khu.ac.ir
[5] orcid.org/0000-0002-5984-094X; University of Tabriz, Department of Earth Sciences, Faculty of Natural Science, Tabriz, Iran; e-mail: moghaddam@tabrizu.ac.ir

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Abstract

Groundwater quality modelling plays an important role in water resources management decision making processes. Accordingly, models must be developed to account for the inherent uncertainty that arises from the sample measurement stage through to the data interpretation stages. Artificial intelligence models, particularly fuzzy inference systems (FIS), have been shown to be effective in groundwater quality evaluation for complex aquifers. Applying fuzzy set theory to groundwater-quality related decision-making in an agricultural production context, the Mamdani, Sugeno, and Larsen fuzzy logic-based models (MFL, SFL, and LFL, respectively) were used to develop a series of new, generalized, rule-based fuzzy models for water quality evaluation using widely accepted irrigation indices. Rather than drawing upon physiochemical groundwater quality parameters, the present study employed widely accepted agricultural indices (e.g., irrigation criteria) when developing the MFL, SFL and LFL groundwater quality models. These newly-developed models, generated significantly more consistent results than the United States Soil Laboratory (USSL) diagram, addressed the inherent uncertainty in threshold data, and were effective in assessing groundwater quality for agricultural uses. The SFL model is recommended because it had the best performance in terms of accuracy when assessing groundwater quality using irrigation indices.

Key words: *fuzzy inference model, fuzzy rules, irrigation indices, Mamdani model, Sarab Plain*

INTRODUCTION

The potable, domestic, industrial and agricultural use of water resources have led to global concerns regarding the degradation of water quality [VADIATI *et al.* 2018]. The main causes of water quality problems include agriculture practices, expanding industries and tourism [GOETHALS, VOLK 2016]. Groundwater quality deterioration, and its effects on soil quality and farmland productivity, is also problematic. Particularly in semi-arid countries, population growth and rising water demands have led to the over-exploitation of surface and ground water resources. This rising demand has increased the need for groundwater quality assessment [BAIN *et al.* 2014]. In the Middle East, and especially in Iran, widespread groundwater distribution and consumption networks have been implemented to support agricultural activities [VAN DER GUN *et al.* 2007]. Accounting for roughly 94% of the nation's annual water usage, Iran's agricultural sector is the nation's biggest water resource stakeholder [ALIZADEH, KESHAVARZ 2005]. Given the potential effects of irrigation water on cultivated soils and crops, assessment and monitoring of water quality are important to decision-makers. Accordingly, the food and agriculture organization of the United Nations (FAO) has published water quality guidelines for the agriculture sector.

Compared to surface water, groundwater bears a greater quantity and variety of dissolved minerals, complicating the assessment of its quality, particularly due to varying crop tolerance for different minerals [ABBASI, ABBASI 2012]. Variation in groundwater quality is tied to a range of factors, including regional hydrogeology, geochemical processes, irrigation return flows, cation exchange and anthropogenic activities [GORGIJ, VADIATI 2014; VADIATI *et al.* 2013]. Groundwater is subject to the poorly understood process of hydrochemical evolution as it passes through different soil layers and geologic formations, and moves from recharge to discharge areas [SINGH *et al.* 2013].

Many diagrammatic and graphical techniques can serve to represent the hydrochemical characteristics of water destined for agricultural applications [DONEEN 1962; PIPER 1944; SCHOELLER 1962; STIFF 1951; USSL 1954; WILCOX 1955]. Given the lack of precision these diagrams provide, particularly for marginal samples, their interpretation can prove challenging. The widely-used United States Salinity Laboratory (USSL) water quality classification system for agricultural production applications, which draws solely on electrical conductivity (*EC*) and sodium adsorption ratio (*SAR*), and ignores other critical indices (e.g., magnesium adsorption ratio (*MAR*), soluble sodium percentage (*SSP*), Kelly's ratio (*KR*), residual sodium carbonate (*RSC*) and permeability index (*PI*)), is unsuited for water quality assessment. Water quality assessments and modelling involving multi-criteria decision-making processes that also consider qualitative and quantitative uncertainties and their transformation, figure among these strategies [WANG *et al.* 2016]. The fact that many samples may be classified within a single category obscures the interpretation of USSL results, complicating decision-making and highlighting the need for models that address these issues. Moreover, deterministic approaches and graphical techniques cannot account for uncertainty throughout the water quality assessment process. In this study, we propose to overcome these limitations in assessing water quality by: (i) using fuzzy logic (FL) and (ii) developing generalized models to evaluate groundwater quality using important irrigation indices.

Among the many discussions of water quality criteria selection for decision-making in the literature, a great number have noted the inability of deterministic approaches to monitor uncertainty throughout the entire decision-making process [DAHIYA *et al.* 2007]. Ambiguity and the absence of inherent certainty, differing standards and decision-making units, along with challenges regarding judgment, have led water resources research to explore fuzzy set theory and FL [BARDOSSY *et al.* 1995]. Considering water quality assessment to be a fuzzy concept involving many indicators and classes, comprehensive fuzzy evaluation methods have recently been widely developed and evaluated for their potential use in water quality assessment [DANGE, LAD 2017; WANG *et al.* 2014].

While studies have applied surface water quality criteria to groundwater quality evaluation for agricultural purposes, few studies have directly addressed groundwater quality. Similarly, while many studies have discussed the applications of FL in water resources evaluation, these have been largely limited to the assessment of water quality for potable uses [DAHIYA *et al.* 2007; HOSSEINI--MOGHARI *et al.* 2015; VADIATI *et al.* 2016]. Accordingly, further research on water quality assessment, particularly in the context of groundwater use for agricultural purposes, is necessary [ALAVI *et al.* 2010; MIRABBASI *et al.* 2008; OSTOVARI *et al.* 2015].

This study's novelty arises from its development of generalized rule-based fuzzy models for water quality evaluation using widely accepted irrigation indices. We attempt to fill previous gaps in water quality evaluation models by applying three types of FL models: Sugeno (SFL), Mamdani (MFL) and Larsen (LFL). While these three models normally achieve similar levels of accuracy, each has different strengths and weaknesses. In this study, they were used to develop new fuzzy inference system (FIS) models for agricultural applications. To deal with the inherent uncertainty in groundwater quality assessment, a comprehensive FL rule-based decision model was built based on expert knowledge.

STUDY METHODS

USSL-DIAGRAM FOR IRRIGATION WATER QUALITY EVALUATION

The USSL diagram [USSL 1954] (see: Fig. 1) is targeted to agricultural production, draws on two important physiochemical criteria (*SAR* and *EC*), and is a widely accepted system for water quality classification. The USSL diagram is divided into different salinity zones based on *EC*: low (<0.025 $S \cdot m^{-1}$), medium (0.025–0.075 $S \cdot m^{-1}$), high (0.075–0.225 $S \cdot m^{-1}$) and very high (0.225–0.500 $S \cdot m^{-1}$) [USSL 1954].

IRRIGATION INDICES

The suitability of groundwater for irrigation is influenced by such factors as soil type, soil drainage, salt tolerance and crop type [MICHAEL 2008]. Among the most frequently used water quality evaluation criteria are the *SAR*, *MAR*, *EC*, *SSP*, *KR*, *RSC* and *PI*. *SAR* represents the alkalinity hazard to crops [RAGHUNATH 1987]; excessive sodium in water can stunt plant growth and deteriorate soil structure through the dispersion of clay particles, hardening of soil, surface crusting and the alteration of soil hydraulic conductivity [RAMESH, ELANGO 2012; SUAREZ *et al.* 2006]. Since high levels of sodium can reduce soil per-

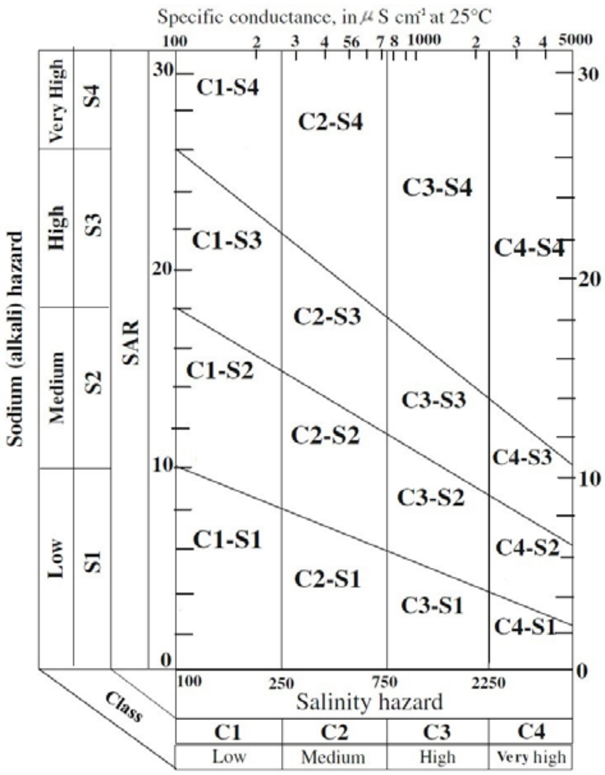


Fig. 1. USSL diagram classes for evaluation of irrigation waters; source: USSL [1954]

meability, the *SSP* is important in groundwater quality evaluation for irrigation purposes. Irrigation water *RSC* assesses water acceptability for irrigation purposes [HOWARI *et al.* 2005], and correlates with the adsorption of sodium to the soil [EATON 1950]. Accordingly, for irrigation purposes, water is not suitable when *RSC* > 2.5 mmol Na dm^{-3}, and is deemed harmful when *RSC* > 5 mmol Na dm^{-3}. DONEEN [1962] assessed irrigation water quality using the *PI* because long-term irrigation can affect soil permeability. A high magnesium ratio in irrigation groundwater decreases soil quality and crop yield [GOWD 2005]. PALIWAL [1972] introduced the *MAR* index as a measure of magnesium hazard, where *MAR* > 50 and *MAR* < 50 indicate whether groundwater is unsafe or safe for irrigation purposes, respectively. The *KR* is based on the ratio of measured sodium to calcium and magnesium [KELLEY 1940], where *KR* < 1.0 and *KR* > 1.0 indicate suitable and unsuitable water for irrigation, respectively. *EC* reflects the dissolved constituents present in groundwater and when elevated, reduces the absorption of nutrients and water from the soil and increases soil solution osmotic pressure [MARGHADE *et al.* 2011].

FUZZY INFERENCE SYSTEM (FIS)

The concept of FL, proposed by ZADEH [1965], has been applied in many fields of science and technology. FISs normally consist of three main steps: 1) fuzzification, 2) fuzzy rule base, and 3) defuzzification. One of the main advantages of FIS is that it can address various kinds of uncertainty.

The fuzzy sets assign a domain for the interval [0, 1]:

$$A = \{(x_1, \mu_A(x)) | x \in X\}, \quad o \leq \mu_A(x) = 1 \qquad (1)$$

Where: $\mu_A(x)$ is the membership function (MF) of x in A.

A fuzzy set's level of fuzziness is determined through the selection of its MF's membership values (ranging from 0 to 1) and shape (e.g., trapezoidal, triangular, etc.) [KUSKO 1993]. Qualitative aspects of expert knowledge are transferred as "if-then" rules [ZADEH 1965]. Since fuzzy inference rule-based systems can address different types of uncertainty and vagueness that influence results, FISs are helpful in decision-making regarding water management [LERMONTOV *et al.* 2009]. A FIS includes significant elements, such as MFs, logical operations and fuzzy rules [ZADEH 1965]. The aggregation of separate rules is accomplished by means of a conjunctive and/or disjunctive system, such that logical outputs are subsequently extracted for all rules. In the conjunctive and disjunctive systems, rules are connected by "and" and "or" connectives, respectively [ROSS 2012].

FUZZIFICATION

Different types of MFs, both linear and nonlinear, are involved in the construction of the fuzzification process. The MF of a trapezoidal fuzzy set is calculated as [ROSS 2012]:

$$f(x; a, b, c, d) = \begin{Bmatrix} 0 \;\; x < \frac{a}{d} < x \;\; \frac{(a-x)}{(a-b)} \;\; a \leq x \leq b \\ b \leq x \leq c \;\; \frac{(d-x)}{(d-c)} \;\; c \leq x \leq d \end{Bmatrix} \qquad (2)$$

Where *a*, *b*, *c* and *d* are constants.

FUZZY RULE BASE

The rule base, known as fuzzy "if-then" rules, is included in linguistic terms prepared by experts or by extractions from the data set. Every rule consists of a mathematical methodology that transfers expert knowledge into fuzzy "if-then" rules. The fuzzy rules are comprised of two parts; the antecedent (the "if" part) and the consequent (the "then" part) [WANG *et al.* 2009].

DEFUZZIFICATION

The procedure of converting a fuzzy output into a crisp value is called defuzzification. Frequently used defuzzification operators include the centroid of area (COA), calculated as:

$$Y^*_{COA} = \frac{\int_Y \;\; \mu_A(Y) Y dY}{\int_Y \;\; \mu_A(Y) dY} \qquad (3)$$

Where: Y^*_{COA} is the fuzzy output converted into a crisp value and $\mu_A(Y)$ is the aggregation of the output MF [WANG *et al.* 2009].

FUZZY LOGIC-BASED MODELS

The main advantages of FL-based models are their capability of handling both numerical and linguistic terms at the same time [VADIATI *et al.* 2016]. Additionally, the models are transparent with regards to the fuzzy system as they use "if-then" rules and MFs. As such, FL models are straightforward and can be used in many practical applications for modelling and control of complex systems. The many FIS models found in the literature can generate outputs that differ significantly. The most well-known FIS model types (e.g., Mamdani [MAMDANI, ASSILIAN 1975], Sugeno [TAKAGI, SUGENO 1985] and Larsen [LARSEN 1980]; MFL, SFL and LFL, respectively) follow an "if antecedence then consequence" pattern. While all fuzzy models share the same antecedence, consequence comes in different forms for different models. Further inter-model differences are based on their formulation of fuzzy "if-then" rules, aggregated rules and the defuzzification process. In zero or first-order SFL models, the output MFs are constant or linear, whereas the MFL and LFL *models'* outputs are fuzzy sets, which then require defuzzification.

A typical rule base in MFL has the form, R^i = if x is A_i and y is B_i then z is C_i i = 1, 2, …, n then $R^i = (A_i \cap B_i) \rightarrow C_i$ is defined by $\mu_{R_i} = \mu_{(A_i \text{ and } B_i \rightarrow C_i)}(x, y, z)$. A typical rule base in LMF, R^i = if x is A_i and y is B_i then z is C_i i = 1, 2, …, n then $R^i = (A_i \cap B_i) \rightarrow C_i$ is defined by $\mu_{R_i} = \mu_{(A_i \cap B_i \rightarrow C_i)}(x, y, z)$. In SFL, the rule structure is based on if Input $1 = x_0$ and Input $2 = y_0$, then $z = px_0 + qy_0 + r$. For a zero-order Sugeno model, the output level is a constant ($p = q = 0$) [TAKAGI, SUGENO 1985]. A graphical illustration of the MFL, LFL and SFL models are shown in Figure 2.

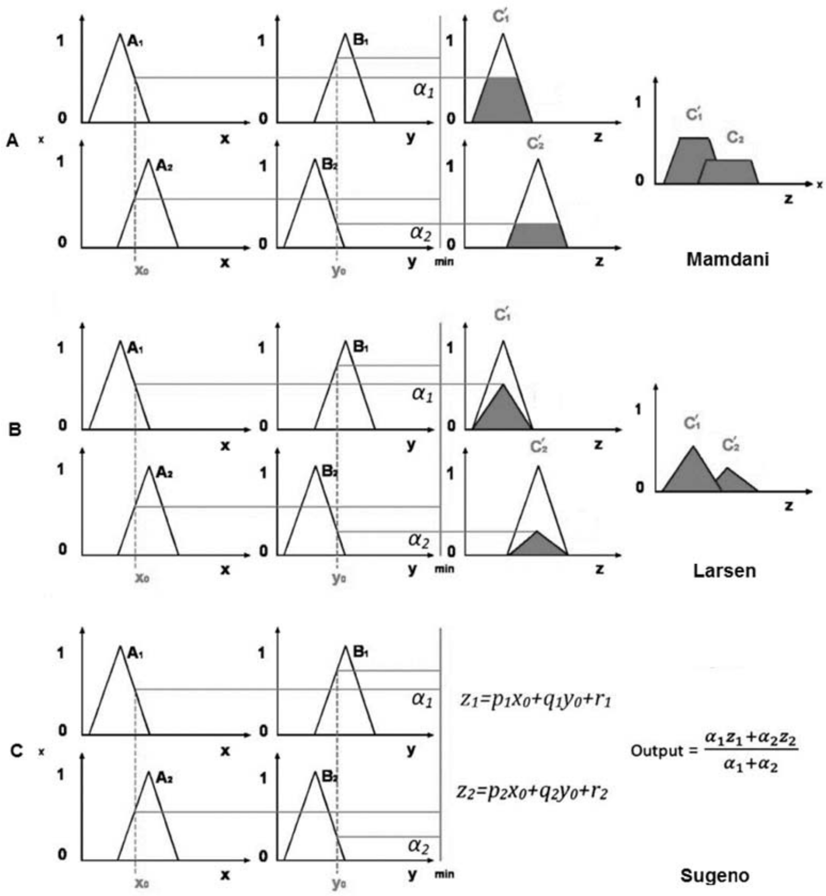


Fig. 2. Graphical diagrams of fuzzy logic models: a) of Mamdani, b) of Larsen, c) Sugeno; source: own elaboration based on MAMDANI and ASSILIAN [1975], LARSEN [1980] and TAKAGI and SUGENO [1985]

STUDY AREA AND DATA

The Sarab Plain is located in northwestern Iran. The Sabalan Mountain, situated in the northern part of the study area, has the respective highest and lowest elevations of 4850 m and 1660 m a.s.l. The study area has an average annual rainfall of 343 mm and an average annual temperature of 7.9°C. The Sarab alluvial aquifer originates from the weathering of the Sabalan and Bozqoush mountain ranges. The main outcrops in the Sarab plain consist of: andesite, dacite, basalt, evaporate sediments, conglomerate, siltstone, and marl, which may have an impact on groundwater quality. The groundwater level fluctuation in the unconfined Sarab aquifer is due mostly to precipitation, river recharge, irrigation return flows to groundwater and intensive groundwater withdraw [VADIATI *et al.* 2016]. The hydrochemical composition of groundwater in the Sarab Plain is strongly controlled by geology, hydrogeology and evaporation minerals within Miocene sediment formations. The verification of FL methods is improved through the use of general data. Therefore, hydrogeological uncertainty and the intensive impact of agricultural activities in the Sarab Plain made this study area an ideal candidate to check the applicability of FL models with respect to regional and seasonal variability of groundwater quality.

Increasing demand for water supplies at new farms has led to excessive deep well drilling and the subsequent over-extraction of groundwater in the plain. As a result, deterioration of groundwater quality has recently become a major concern. To assess groundwater quality, a total of 49 well samples were collected in the wet season, specifically April 2015, and their hydrochemical parameters analysed based on standard procedures outlined by the American Public Health Association [APHA, AWEF 1998]. The physical parameters (*EC*, pH and temperature) were measured in situ and hydrochemical, physiochemical and ion balance error analysis was carried out in a laboratory at the University of Tabriz, Iran. The sampling sites and water resources map of the Sarab Plain is presented in Figure 3.

MODEL DEVELOPMENT

The main aim of the present study was to explore FL rule-based decision models based on important irrigation indices with the aim of replacing conventional classification diagrams that have parameter selection insufficiencies. The general process used to develop a fuzzy rule-based model for agricultural purposes is presented in Figure 4. The procedure begins with the selection of sampling locations and groundwater quality indices. This is followed by

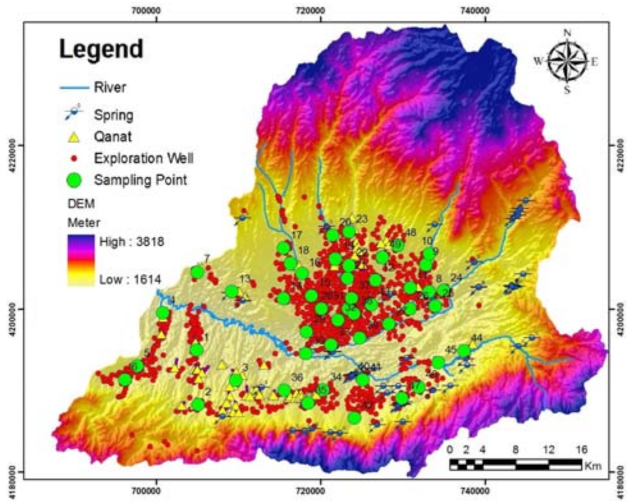


Fig. 3. The sampling sites and water resources map of the Sarab Plain, Iran; source: own elaboration

the development of the fuzzy model by the fuzzification of groundwater quality parameters, the use of expert knowledge and datasets, and then the development of the MFL, SFL and LFL.

Since water quality degradation can be caused by various environmental factors acting simultaneously, indices most appropriate to local environments and most relevant to the quality of groundwater should be selected. Selecting a suitable number of relevant indices is also necessary to define the main concerns of management and to facilitate efficient restoration and conservation efforts for water resources.

Fuzzy-logic models based on measured data have been receiving more attention than traditional fuzzy models, which in general, merely use linguistic rules. The MFL, SFL and LFL models developed in this research can provide groundwater quality assessment for agricultural purposes. This study selected a number of irrigation water indices relevant to water quality (e.g., *EC*, *SAR*, *SSP*, *RSC*, *PI*, *MAR* and *KR*) as input parameters in the development of the FIS models. More specifically, these indices were used to develop the generalized fuzzy models based on the prescribed ranges of each parameter. The structure of the proposed fuzzy models is depicted in Figure 5. The process was executed using MATLAB [MathWorks 2014]. The FISs transfer of expert judgment was expressed as "if-then" rules. In the "if" part, the model input parameters

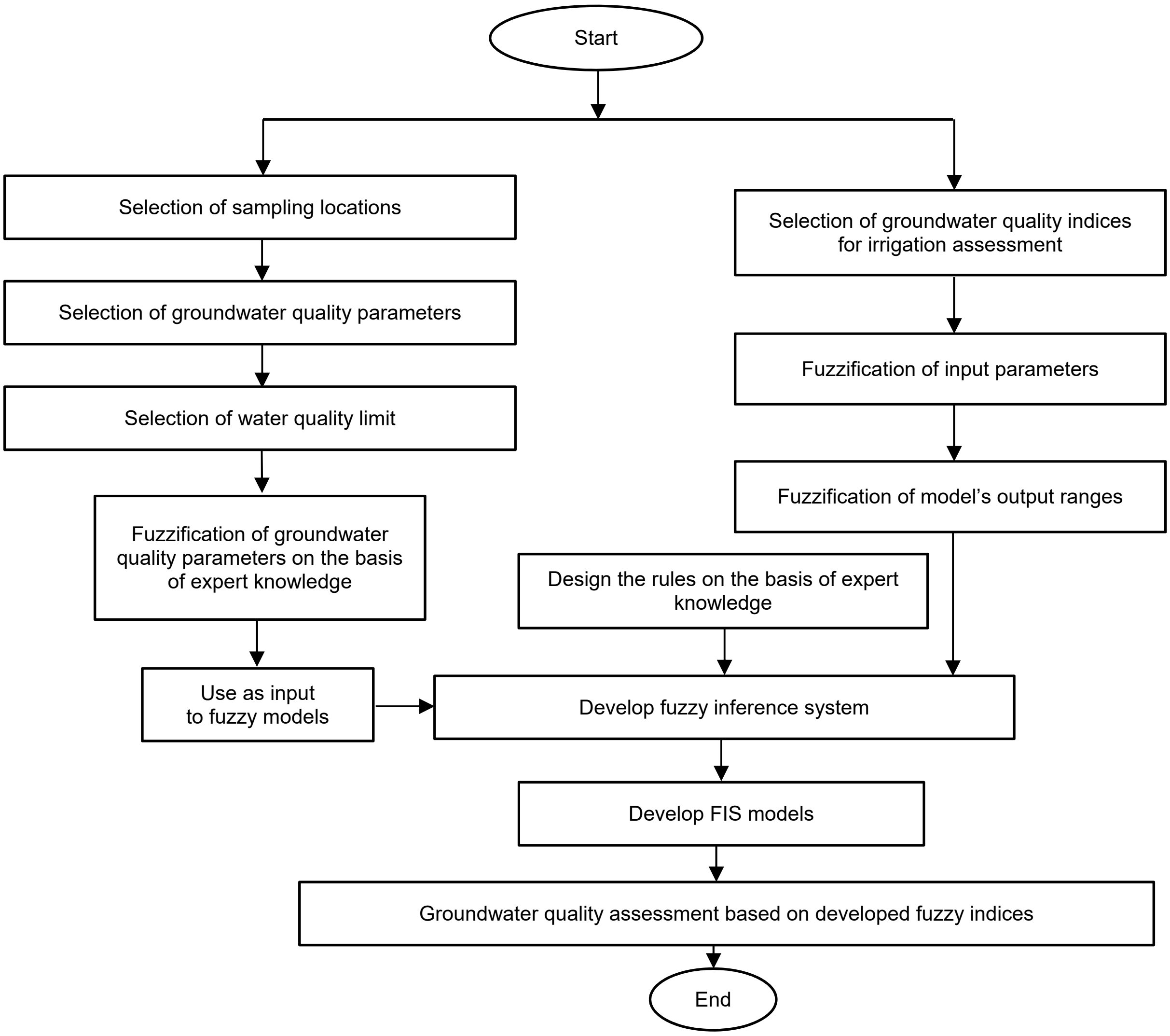


Fig. 4. The general process to develop the fuzzy inference system (FIS) models; source: own elaboration

SAR, *SSP*, *RSC*, *PI*, *MAR*, *KR*, and *EC*, were each categorized into three linguistic terms: "low", "moderate", and "high". In the consequent "then" part, the model outputs were categorized as "desirable", "acceptable", and "unacceptable".

Appropriate methods for evaluating FL models depend strongly on the number of their fuzzy sets. Several MF shapes can exist, however, simple "trapezoid" MFs work well [BARUA *et al.* 2013]. In the present study, triangular and trapezoidal MFs were used according to the nature of the hydrochemical parameters and information available from past studies and research. Moreover, to achieve an ideal FIS, the type of MFs were selected according to a trial and error process and inputs from expert knowledge. For example, Figure 6 shows the MF of the *SSP* input parameter.

Fuzzy sets determine each input MF, thereby defining fuzzy sets in terms of degrees of membership, ranging from 0 to 1. Table 1 shows the parameter MFs used in the inference fuzzy model in this study. The rules for the model were constructed based on information drawn from the effects of physicochemical input parameters on soil and crop quality. The number of rules in the fuzzy inference model depends on input parameters and linguistic terms. Generally, the weight of every rule is a number between 0 and 1, and rule weights were set at 1 in the present study.

After the fuzzy rules are determined, the structure of the FL model must be designed. Using an implication process, the previously-developed rules served to transform the input MFs into a single MF defined as the output variable. The outputs of every rule were separately aggregated

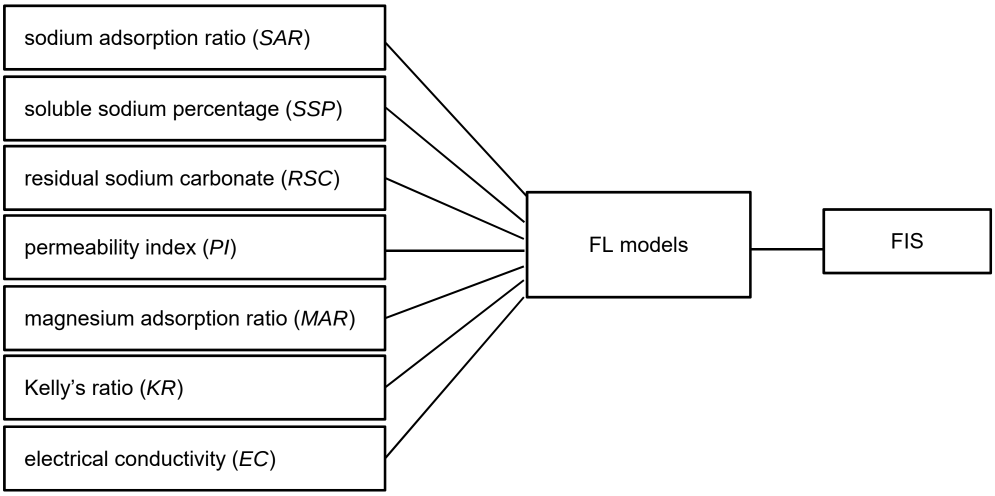


Fig. 5. A schematic illustration of the fuzzy inference (FIS) models used in this study; source: own elaboration electrical conductivity (*EC*), sodium adsorption ratio (*SAR*), magnesium adsorption ratio (*MAR*), soluble sodium percentage (*SSP*), Kelly's ratio (*KR*), residual sodium carbonate (*RSC*), permeability index (*PI*), fuzzy logic (FL), fuzzy inference system (FIS); source: own elaboration

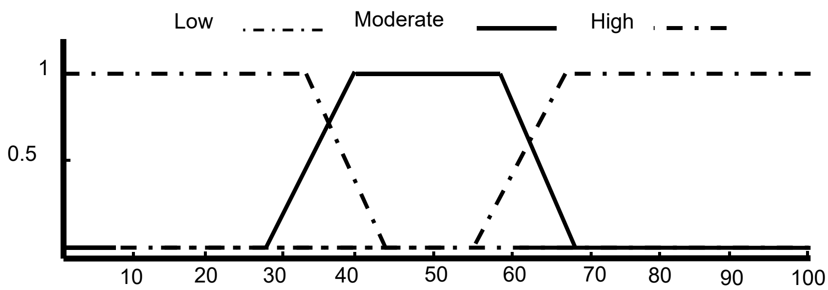


Fig. 6. Membership function of the soluble sodium percentage (*SSP*); source: own elaboration

Table 1. The parameter membership functions used in inference fuzzy models

Input model	High			Moderate				Low		
	c = d	b	a	d	c	b	a	d	c	a = b
Sodium adsorption ratio	50	14	10	13	10	7	3	7	4	0
Soluble sodium percentage	100	67	55	67	57	42	28	42	35	0
Residual sodium carbonate	9	2.8	2	3.5	2.5	1.25	0.5	1.5	0.5	–13.1
Permeability index	100	62	50	62	56	42	33	44	36	0
Magnesium adsorption ratio	100	63	55	66	58	44	36	42	35	0
Kelley's ratio	9	0.9	0.65	0.9	0.65	0. 5	0.3	0. 5	0.35	0
Electrical conductivity	4000	3400	2800	3500	3000	780	600	800	695	0

Explanations: a, b, c, and d = membership function parameters.
Source: own study.

into a single fuzzy set, which was then used as the input for the defuzzification procedure. For the implication, the “min” and “product” operators were used in MFL and LFL models, respectively. For both the MFL and LFL techniques, the COA defuzzification method, a well-known and widely used technique, was used to obtain the crisp output values [HELLENDOORN, THOMAS 1993].

RESULTS

EVALUATION OF GROUNDWATER QUALITY USING THE USSL DIAGRAM

The USSL classification diagram (Fig. 7) of groundwater classifies water samples into several categories, e.g., C1–S1, C2–S1, C3–S1, C3–S2, C4–S2 and C4–S4. Twenty-four samples were in the C2–S1 class, meaning that they posed no hazard of sodium exchange in soils for agricultural use. Twenty samples were in the C3–S1 class, meaning that there was little hazard of sodium exchange. One sample was in the C1–S1 class, indicating that the water had a low saline level and was acceptable in each type of soil for agricultural use. One sample was placed in each of the C3–S2 and C4–S2 classes, which represented high and very high salinity water, respectively, and both required specific soil management for agricultural use. The remaining two samples were classified as C4–S4, indicating that the water was highly saline and unacceptable for agricultural use.

The spatial distribution of groundwater samples in the Sarab Plain, as classified by the USSL classification diagram, showed that samples in the C2–S1 class were found largely in the east where the aquifer is recharged from streams (Fig. 8). Samples in the moderate water quality C3–S1 class were found mainly in the middle section of the study area, where groundwater quality deteriorates due to the dissolution of gypsum and mineral salts from Miocene formations, cation exchange and urban wastewater. The sample in the C4–S2 class was located in the northern portions of the Sarab Plain, where salinity and *SAR* increased as a result of aquifer recharge from the saline water of the Talkheh Rud River [ASADOLLAHFARDI *et al.* 2011].

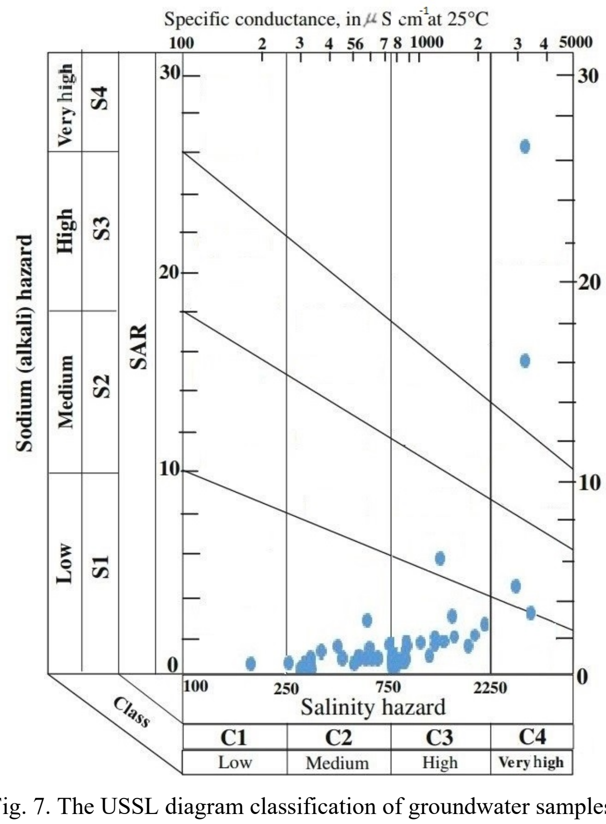


Fig. 7. The USSL diagram classification of groundwater samples from the Sarab Plain; source: own study

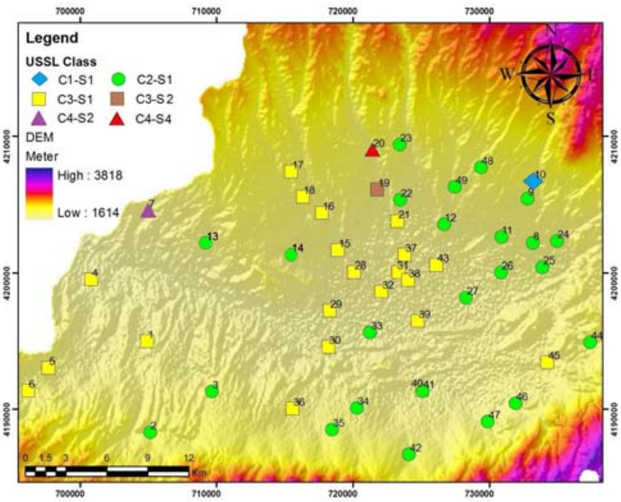


Fig. 8. Spatial USSL classification diagram of groundwater samples in the Sarab Plain, Iran; source: own study

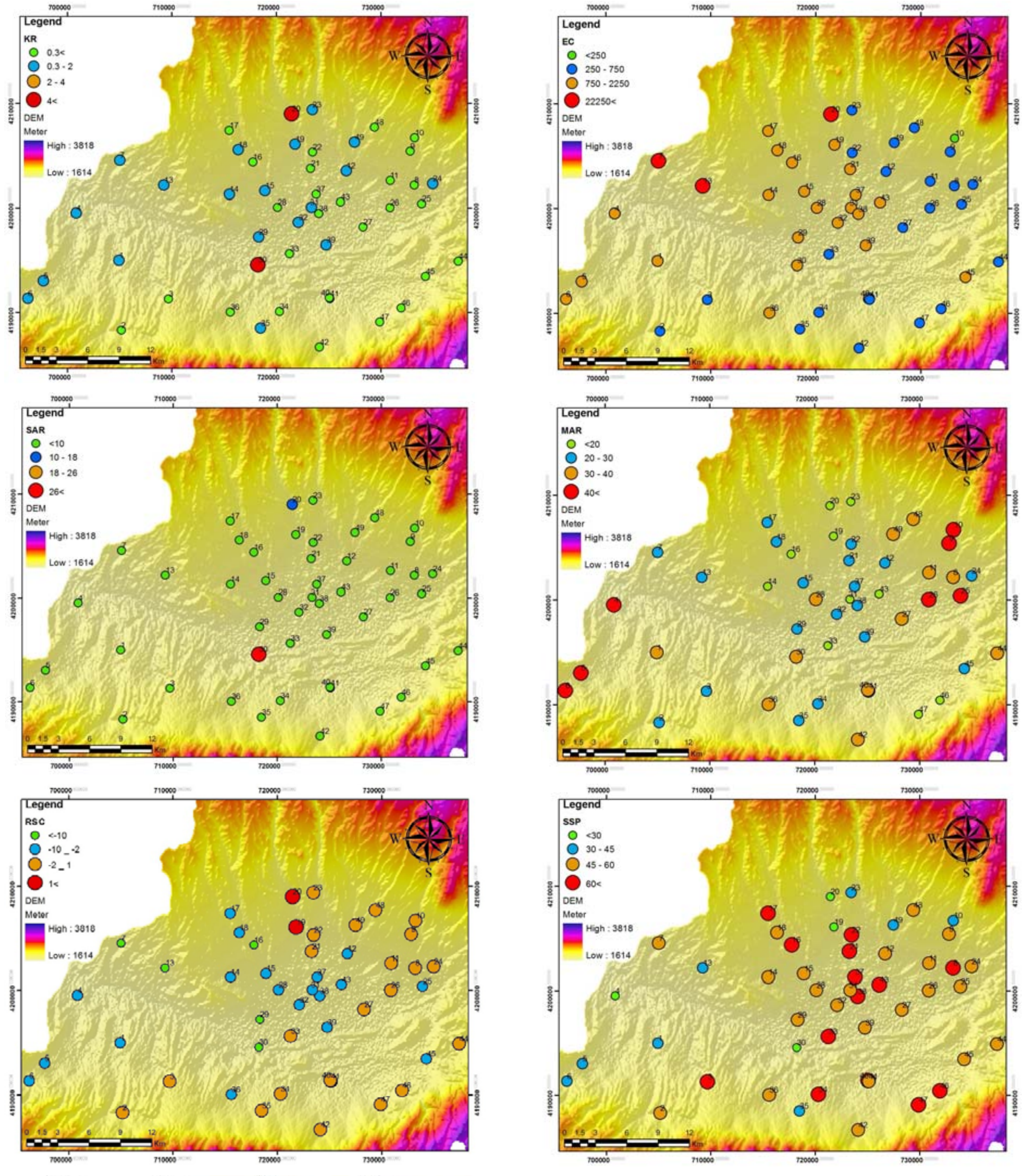
IRRIGATION INDICES

The key indices, *SAR*, *PI*, *KR*, *MAR*, *RSC*, *SSP* and *EC* were used to determine the water quality for agricultural purposes. In the study area samples, *KR* ranged between 0.03 and 7.6, and *PI* between 29.4 and 92.1. A summary of irrigation indices of groundwater samples from the Sarab Plain is shown in Table 2. A plot of the spatial variation of irrigation indices in the Sarab Plain (Fig. 9) shows a complex pattern, precluding simple conclusions being drawn regarding the varying behaviour of each index. For example, higher values of *EC*, *SSP* and *MAR* were apparent in the northern/northwestern, central, and North-East/South-West parts of the Sarab Plain, respectively. In contrast, the distribution of *PI* was found to be highly variable.

Table 2. Summary of irrigation indices in groundwater of the Sarab Plain

Statistic	*SSP*	*RSC*	*PI*	*MAR*	*KR*	*EC*	*SAR*
Minimum	7.5	–13.1	29.4	9.5	0.03	185	0.08
Maximum	75.9	8.2	91.2	51.1	7.6	3400	27.2
Mean	53.0	–0.9	55.3	28.7	0.6	952	2.6
Standard deviation	12.9	3.6	14.4	10.1	1.2	750	6.9

Explanations: *SSP* = soluble sodium percentage, *RSC* = residual sodium carbonate, *PI* = permeability index, *MAR* = magnesium adsorption ratio, *KR* = Kelly’s ratio, *EC* = electrical conductivity, *SAR* = sodium adsorption ratio. All ion concentration of the parameters were expressed in mg·dm^{-3}.
Source: own study.



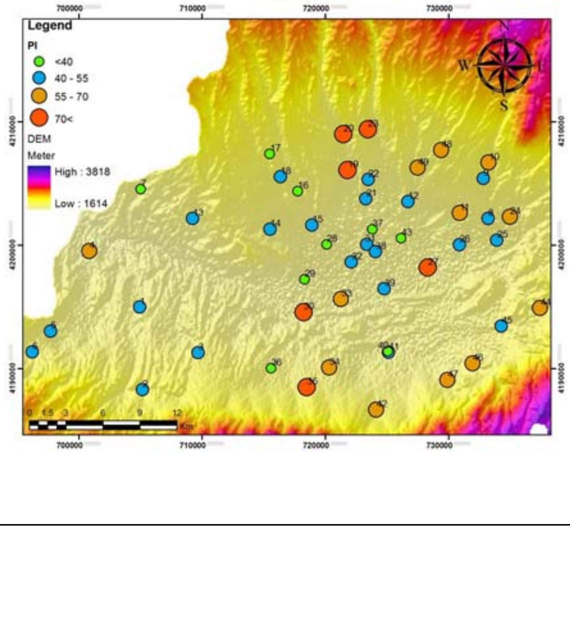


Fig. 9. Spatial variation of irrigation indices in groundwater of the Sarab Plain, Iran; *KR* = Kelly's ratio, *EC* = electrical conductivity, *SAR* = sodium adsorption ratio, *MAR* = magnesium adsorption ratio, *SSP* = soluble sodium percentage, *RSC* = residual sodium carbonate, *PI* = permeability index; source: own study

RESULTS OF THE FUZZY INFERENCE SYSTEM MODELS

The comparison of groundwater quality classes using the proposed FL methods and the USSL diagram (Tab. 3) shows that, for sample number 1, for example, input parameters of *SAR* = 2, *SSP* = 47.5, *KR* = 0.5, *MAR* = 31.6, *RSC* = –2.1, PI = 51.3 and *EC* = 1510 $\mu S \cdot cm^{-1}$, led to the sample being classified as "acceptable" by the FL approaches (MFL, LFL and SFL), and to fall within the C3–S1 category of the USSL classification. Many samples were situated on the border between the USSL C2–S1 and C3–S1 categories (Fig. 7). Therefore, the inherent uncertainty in various steps of groundwater quality assessment,

Table 3. Comparison of groundwater quality classes using fuzzy logic and USSL class

No.	Crisp values of input parameters							Decision-making based on fuzzy logic-based models			USSL class
	SAR	*SSP*	*KR*	*MAR*	*RSC*	*PI*	*EC*	Mamdani model (MFL)	Larsen model (LFL)	Sugeno model (SFL)	
1	2.0	47.5	0.5	31.6	–2.1	51.3	1 510	acceptable	acceptable	acceptable	C3–S1
2	0.8	59.0	0.2	27.8	–1.2	48.5	580	desirable	desirable	desirable	C2–S1
3	0.5	64.6	0.2	25.0	–0.9	48.4	510	desirable	desirable	desirable	C2–S1
4	3.2	29.0	0.7	51.1	–3.9	55.5	1 460	acceptable	acceptable	acceptable	C3–S1
5	1.7	38.0	0.4	46.1	–2.3	51.8	1 020	acceptable	acceptable	acceptable	C3–S1
6	1.5	37.5	0.4	50.0	–2.2	47.1	880	acceptable	acceptable	acceptable	C3–S1
7	3.5	51.4	0.5	25.6	–19.7	38.9	3 400	unacceptable	unacceptable	unacceptable	C4–S2
8	0.1	62.1	0.0	36.8	–0.6	53.3	290	desirable	desirable	desirable	C2–S1
9	0.2	57.4	0.1	40.5	–0.8	51.3	325	desirable	desirable	desirable	C2–S1
10	0.3	46.6	0.1	48.1	–0.6	62.1	185	desirable	desirable	desirable	C1–S1
11	0.3	59.2	0.1	33.3	–0.3	62.5	290	desirable	desirable	desirable	C2–S1
12	1.5	51.7	0.4	26.4	–2.1	53.8	740	acceptable	acceptable	desirable	C2–S1
13	5.2	38.3	0.9	27.6	–12.7	53.8	3 000	desirable	desirable	desirable	C2–S1
14	2.8	54.0	0.5	19.5	–7.4	45.9	2 130	desirable	desirable	desirable	C2–S1
15	2.0	53.0	0.5	23.0	–6.0	44.6	1 200	acceptable	acceptable	acceptable	C3–S1
16	1.5	66.2	0.3	16.3	–12.6	29.4	1 765	acceptable	acceptable	acceptable	C3–S1
17	0.6	69.3	0.2	20.5	–5.0	31.0	847	acceptable	acceptable	acceptable	C3–S1
18	1.8	54.9	0.4	24.1	–6.1	42.7	1 330	acceptable	acceptable	acceptable	C3–S1
19	6.1	30.7	1.9	17.7	2.9	85.2	1 300	unacceptable	unacceptable	unacceptable	C3–S2
20	15.6	20.0	4.2	16.3	7.1	91.2	3 230	unacceptable	unacceptable	unacceptable	C4–S4
21	0.9	63.2	0.2	23.0	–1.4	47.5	760	desirable	acceptable	acceptable	C3–S1
22	0.8	64.3	0.3	20.1	–0.8	53.3	660	desirable	desirable	desirable	C2–S1
23	2.8	42.2	1.3	13.1	0.9	89.2	584	acceptable	acceptable	desirable	C2–S1
24	1.3	50.4	0.4	28.8	–0.6	60.9	600	desirable	desirable	desirable	C2–S1
25	0.8	48.8	0.2	40.7	–2.1	46.6	620	desirable	desirable	desirable	C2–S1
26	0.2	49.9	0.1	46.7	–1.0	46.8	310	desirable	desirable	desirable	C2–S1
27	0.5	52.8	0.2	36.4	0.0	70.2	254	desirable	desirable	desirable	C2–S1
28	1.0	56.7	0.2	31.0	–4.7	37.0	1 130	acceptable	acceptable	acceptable	C3–S1
29	2.1	56.6	0.4	23.1	–12.5	36.1	1 900	acceptable	acceptable	acceptable	C3–S1
30	47.2	7.5	7.7	36.0	–14.2	89.8	3 400	unacceptable	unacceptable	unacceptable	C4–S4
31	1.8	55.1	0.5	18.0	–2.6	54.7	870	acceptable	acceptable	acceptable	C3–S1
32	1.8	52.5	0.4	28.7	–5.2	43.2	1 350	acceptable	acceptable	acceptable	C3–S1
33	0.8	69.6	0.3	9.5	–0.6	59.7	450	desirable	desirable	desirable	C2–S1
34	0.4	61.6	0.2	28.4	–0.1	64.5	310	desirable	desirable	desirable	C2–S1
35	1.1	48.1	0.5	29.9	0.0	71.4	360	desirable	desirable	desirable	C2–S1
36	0.9	58.0	0.2	30.3	–3.6	38.6	835	acceptable	acceptable	acceptable	C3–S1
37	0.6	63.0	0.1	28.1	–2.5	39.4	800	acceptable	acceptable	acceptable	C3–S1
38	0.8	63.4	0.2	24.0	–2.5	41.1	870	acceptable	acceptable	acceptable	C3–S1
39	1.6	53.7	0.4	27.0	–6.1	41.3	1 200	acceptable	acceptable	acceptable	C3–S1
40	0.3	62.5	0.1	33.0	–1.7	36.6	760	acceptable	desirable	acceptable	C3–S1
41	0.5	55.3	0.2	34.8	–0.7	55.0	320	desirable	desirable	desirable	C2–S1
42	0.4	53.7	0.1	38.5	–0.6	56.0	300	desirable	desirable	desirable	C2–S1
43	0.7	75.9	0.2	11.2	–2.6	39.5	800	acceptable	acceptable	acceptable	C3–S1
44	0.9	54.5	0.3	31.8	–0.2	57.7	540	desirable	desirable	desirable	C2–S1
45	1.3	56.1	0.3	26.0	–2.8	46.1	860	acceptable	acceptable	acceptable	C3–S1
46	0.5	68.1	0.2	17.1	–0.1	64.4	300	desirable	desirable	desirable	C2–S1
47	0.8	68.8	0.2	14.5	0.1	56.0	540	desirable	desirable	desirable	C2–S1
48	0.8	50.7	0.3	37.0	–0.6	59.1	320	desirable	desirable	desirable	C2–S1
49	1.4	43.6	0.5	36.2	–1.0	62.9	430	desirable	desirable	desirable	C2–S1

Explanations: *SAR* = sodium adsorption ratio, *SSP* = soluble sodium percentage, *KR* = Kelly's ratio, *MAR* = magnesium adsorption ratio, *RSC* = residual sodium carbonate, *PI* = permeability index, *EC* = electrical conductivity.
Source: own study.

from measurement to interpretation, likely affected the results of the USSL classification. Accordingly, the FISs that addressed these issues were an appropriate choice to evaluate groundwater quality.

The comparison between the FIS-based approaches and a deterministic evaluation is presented in Table 3. For samples 8 and 9, the *SAR*, *KR*, *RSC* and *EC* were in the low category, the *PI* was in the high category, *SSP* was between the moderate and high categories, and *MAR* between the low and moderate categories. The USSL diagram classified samples 8 and 9 in the 'no risk' C2–S1 class, while the MFL, LFL and SFL models placed them in the "desirable" category. Accordingly, based on both the USSL classification and the FL models, samples 8 and 9 were deemed desirable for irrigation purposes. The FL models classified samples 13 and 14 as "desirable" and samples 16 and 17 as "acceptable", while the USSL classification categorized all those four samples as C3–S1 class. Based on the fuzzy models, samples 19 and 20 were classified as "unacceptable", whereas the USSL classification categorized them as C3–S2 and C4–S4, respectively. For both samples, the *SSP* and *MAR* criteria were placed in the low category, *EC* was in the moderate category, and *PI* and *KR* were in the high category. The *SAR* and *RSC* were placed in the moderate and high category for samples number 19 and 20, respectively. The MFL, LFL and SFL models placed sample 21 in the "desirable", "acceptable" and "acceptable" categories, respectively, while the USSL diagram categorized it as C3–S1. The USSL diagram classified sample 22 in the C2–S1 class while the FL models placed sample 22 in the "desirable" category.

The developed fuzzy models' superiority over the USSL classification was best revealed in samples of similar quality, as fuzzy models make a more consistent decision, especially with respect to threshold values between two different classes. The results of the MFL method showed that the number of groundwater samples categorized as "desirable", "acceptable" and "unacceptable" were 24, 21 and 4 (Tab. 3). The results obtained from the LFL model were comparable with those of the MFL model. Based on the SFL model, 25, 20 and 4 samples, respectively, were categorized as "desirable", "acceptable" and "unacceptable." Overall, in the USSL classification, the decision-making was based on crisp values, while the FIS drew flexible boundaries using linguistic terms with respect to threshold values between two different classes, thus allowing for more reliable information about groundwater quality. Generally, it can be concluded that the FL models developed in the present study were able to cover intrinsic uncertainty, were flexible enough to include more criteria or indices compared to traditional classification diagrams and were able to accommodate human and instrumental errors.

DISCUSSION

When studying the indices separately, it is easy to classify and understand groundwater quality. However, when different indices are studied together, it becomes difficult to assess overall groundwater quality. The fuzzy inference system (FIS) allows for the derivation of a comprehensive conclusion of groundwater quality evolution. There is a good agreement between the fuzzy models and the USSL classification results. It can be concluded that the Mamdani, Sugeno, and Larsen fuzzy logic-based models (MFL, SFL and LFL, respectively) confirmed the USSL classification, but the models provided a more consistent decision of water quality due to the incorporation of various irrigation indices, especially in marginal samples.

The results of the present study confirmed the findings of MIRABBASI *et al.* [2008], who proposed an irrigation water quality model based on a FIS, and compared its performance to that of the USSL diagram. While showing an 84% agreement with the USSL method, the proposed model proved to be significantly more accurate. Using an adaptive network-based fuzzy inference system (ANFIS), which compared *EC–SAR* values with the USSL diagram to evaluate irrigation water quality, ALAVI *et al.* [2010] showed the ANFIS model to be a reliable substitute for the traditional USSL diagram method. Similarly, OSTOVARI *et al.* [2015] employed a Mamdani FIS with a similar *EC–SAR* and USSL diagram comparison to evaluate groundwater quality, for irrigation purposes, in the Marvdasht alluvial aquifer. The authors showed that in 81% of cases, the FIS categorized water samples into the same classes as the USSL diagram. Nonetheless, many key groundwater quality criteria (e.g., *PI*, *KR*, *MAR*, *RSC*, *SSP*) were not included. Their accuracy was gauged against a crisp classification method (USSL diagram), and previously reported artificial intelligence techniques (e.g., FL and ANFIS) that based their irrigation water quality evaluations solely on *SAR* and *EC*, omitting many other criteria important in groundwater quality evaluation and classification.

The exacerbation of soil and water salinization through the intensive use of fertilizers and pesticides, heavy metal pollution, and the use of low-quality water and soil, requires the development of new indices and methodologies to address these critical issues. However, while the need for extensive models that consider the effects of water quality on both crops and soil is clear, one must keep in mind that improving a model's suitability by integrating more parameters also increases its uncertainties. There are many driving factors that can affect groundwater quality, including climate, hydrogeology and human activities. The hydrochemical parameters reveal the geological complexity of groundwater, and it was found that water-rock interactions and human activities have the most influence on groundwater quality [GÜLER *et al.* 2012; KOH *et al.* 2009]. Therefore, FIS is beneficial for groundwater quality evaluation in hydrogeologically complex regions such as the Sarab Plain. It can be argued that the fuzzy inference method is a suitable method for irrigation water quality assessment due to its integrated decision-making that is based on important irrigation indices. The spatial assessment of groundwater quality of the Sarab Plain using MFL, LFL and SFL models are shown in Figure 10, respectively. As can be seen, samples in the eastern part of the Sarab Plain were categorized as "desirable", and groundwater quality deteriorated in the western and central parts of the plain. Generally, the results showed that the FL models

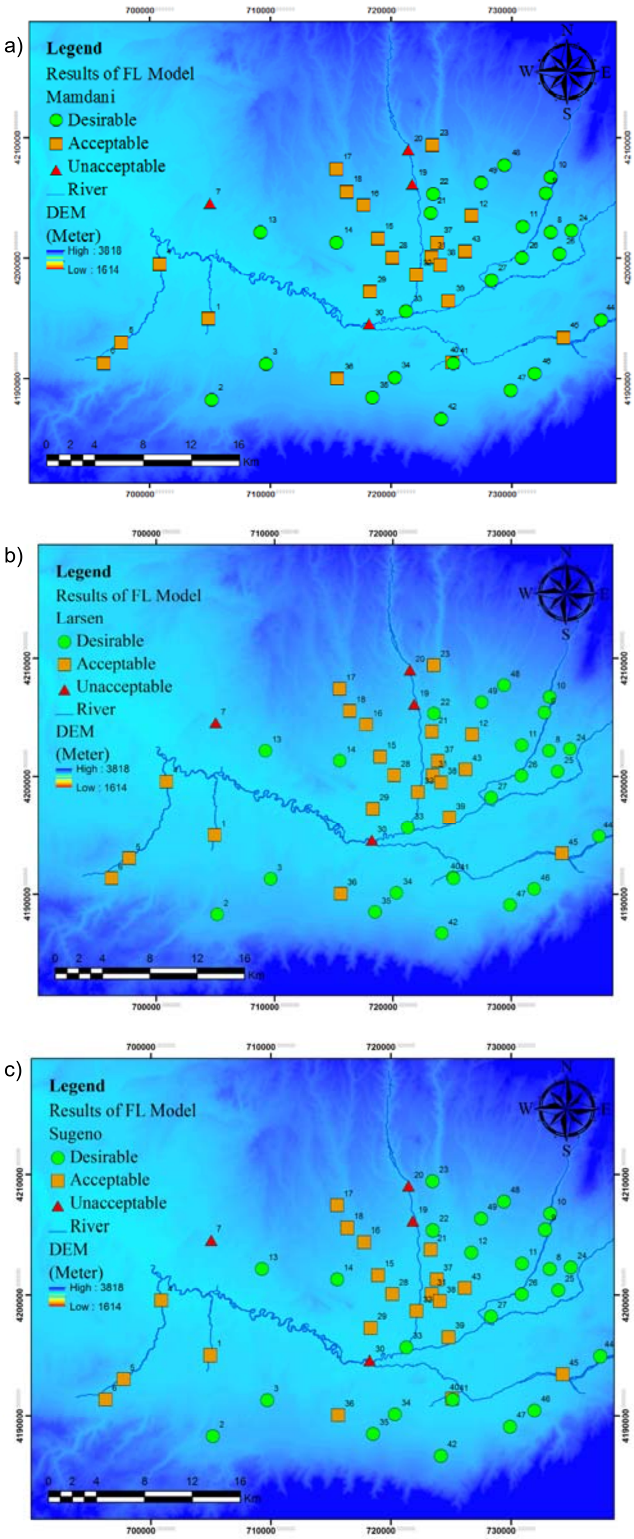


Fig. 10. Spatial assessment of groundwater quality of the Sarab Plain using some fuzzy logic models: a) Mamdani, b) Larsen, c) Sugeno; source: own study

developed in the present study assessed groundwater quality more precisely and logically than the USSL classification diagram (Fig. 8).

CONCLUSIONS

Due to the inherent uncertainty in water and soil environments, groundwater quality assessment for agricultural use is a challenging task. In this study, the Mamdani, Larsen and Sugeno fuzzy logic models (MFL, SFL and LFL, respectively) were used to determine water quality more precisely and to cover the inherent uncertainty in the assessment procedure. The present study applied the fuzzy assessment method in groundwater quality evaluation. The assessment of water quality using traditional methods, as well as its classification into “desirable”, “acceptable” and “unacceptable” categories based on water quality standards, were considered less appropriate since such methods overlooked the uncertainty of the sampling, analysis and interpretation steps. Using FL approaches, groundwater quality samples were categorized as “desirable,” “acceptable” or “unacceptable” on the basis of expert perception. The results showed that the SFL performed consistently better than the other FL models. The superiority of the developed fuzzy models is best revealed in samples of similar quality, which make a more consistent decision. The fuzzy inference method was shown to be a suitable method for irrigation water-quality assessment because of its integrated decision-making, which is based on important irrigation indices. This present study introduced a more trustworthy and flexible method for groundwater quality evaluation compared to traditional methods as the proposed model considered the uncertainty in the measurement and analytical process of hydrochemical data.

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Meysam VADIATI, Deasy NALLEY, Jan ADAMOWSKI, Mohammad NAKHAEI, Asghar ASGHARI-MOGHADDAM

Analiza porównawcza modeli opartych na logice rozmytej do oceny jakości wód podziemnych na podstawie wskaźników nawadniania

STRESZCZENIE

Modelowanie jakości wód podziemnych odgrywa ważną rolę w procesach podejmowania decyzji dotyczących zarządzania zasobami wodnymi. W związku z tym należy opracować modele uwzględniające naturalną niepewność, która pojawia się od etapu pomiaru próbki, aż do interpretacji danych. Wykazano, że modele sztucznej inteligencji, w szczególności systemy wnioskowania rozmytego (FIS), są skuteczne w ocenie jakości wód podziemnych w odniesieniu do złożonych warstw wodonośnych. Zastosowanie teorii zbiorów rozmytych do podejmowania decyzji związanych z jakością wód podziemnych w kontekście produkcji rolnej, modele oparte na logice rozmytej Mamdaniego, Sugeno i Larsena (odpowiednio MFL, SFL i LFL) zostały wykorzystane do opracowania serii nowych, uogólnionych modeli, opartych na regułach rozmytych, do oceny jakości wody z wykorzystaniem powszechnie akceptowanych wskaźników nawadniania. Zamiast czerpać z jakościowych parametrów fizykochemicznych wód gruntowych, w niniejszym badaniu zastosowano powszechnie przyjęte wskaźniki rolne (np. kryteria nawadniania) podczas opracowywania modeli jakości wód podziemnych MFL, SFL i LFL. Za pomocą tych nowo opracowanych modeli, wygenerowano znacznie bardziej spójne wyniki niż z zastosowaniem diagramu Amerykańskiego Laboratorium Gleby (USSL), uwzględniono nieodłączną niepewność danych progowych. Modele te były skuteczne w ocenie jakości wód podziemnych do zastosowań rolniczych. Model SFL jest zalecany, ponieważ miał najlepszą efektywność pod względem dokładności w ocenie jakości wód podziemnych z użyciem wskaźników nawadniania.

Słowa kluczowe: *model Mamdaniego, model wnioskowania rozmytego, reguły rozmyte, równanie Saraba, wskaźniki irygacyjne*