Assessment of Irrigation Water Quality in Menzel Habib Aquifer System – A Combined Geochemical and Fuzzy Logic Approaches

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Assessment of irrigation water quality in Menzel Habib aquifer system – a combined geochemical and Fuzzy logic approaches

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Abstract

Groundwater is an important source for irrigation uses in many arid and semi-arid regions such as Menzel Habib area. In this work, the groundwater quality for irrigation water was investigated based on conventional indices notably Electrical Conductivity (EC), Sodium Absorption Ratio (SAR), Soluble Sodium Percentage (SSP), Magnesium Adsorption ratio (MAR), Kelly Ratio (KR) and Permeability index (PI). The water quality for irrigation was also evaluated by Simsek method. However, a proposal fuzzy logic model has been developed to avoid uncertainties associated to the classical methods. The results obtained on thirty-six groundwater samples, indicated that 3% of these samples are classified as “good” for irrigation, 3% are “good to permissible”, 33% “permissible”, 36% “permissible to unsuitable” and 25% with an “unsuitable” quality. The application of fuzzy logic approaches has more

reliable results with the definition of seven classes to evaluate the groundwater quality for agricultural irrigation.

Keywords Groundwater . quality indices . fuzzy logic . agricultural use . Tunisia.

1. Introduction

Water scarcity is a global issue of concern that affects all socioeconomic activities and threatens the sustainability of the natural resources. The development of agricultural lands, to provide food for the growing population, highly depends on the availability of irrigation water (Ghazaryan et al. 2020). Indeed, agriculture has become the main sector of water consumption (Kawo and Karuppannan 2018).

The consumption of low-quality water can promote serious diseases in the population, permanent damage to the ecosystem and economic losses (Schwarzenbach et al. 2010). Especially for countries located in arid and semi-arid climate zone, efficient management of water resources is crucial to prevent economic losses. Therefore, the sustainability of water resources is directly related to water quality protection (Kavurmacı and Karakuş 2020).

Groundwater is an important source of irrigation water all over the world, as well as in arid and semi-arid areas. Groundwater quality depends on various factors, natural and/or anthropogenic, such as hydrogeology, degree of mineral weathering, ion exchanges, evaporation, groundwater flow and human activities (e.g., Agoubi et al. 2012; Alabjah et al. 2018; Isawi et al. 2016; Kharroubi et al. 2012; Telahigue et al. 2018), as well as by climate change (e.g., Burri et al. 2019; D'Alessandro et al. 2020; Hu et al. 2019).

Evaluation of groundwater quality is an important tool to promote sustainable development of agricultural areas and to provide important water management data (Kavurmacı and Karakuş 2020). Therefore, it is useful to provide information on water quality, classification of water

for various purposes, assessment of groundwater potential, and investigation of different chemical processes (Al Maliki et al. 2020).

Numerous studies on water quality assessment have been developed with different techniques to evaluate water quality, essentially based on chemical relations, physical proprieties, and Water Quality Index (WQI) (e.g., Abd El-Aziz, 2017; Al Maliki et al. 2020; Ben Alaya et al. 2013; Ghazaryan et al. 2020; Pazand and Javanshir 2014; Prasad et al. 2019; Tian and Wu 2019). Different hydrochemical indices, such as Sodium Adsorption Ratio (SAR), Sodium percentage (Na%), Magnesium Hazard (MH), Residual Sodium Carbonate (RSC) and Permeability Index (PI) are applied to the assessment of groundwater quality for agricultural irrigation (Ghazarhyan et al. 2020; Beyene et al. 2019; Mirza et al. 2017; Safiur et al. 2017; Khan et al. 2015). Additionally, several studies used geostatistical approaches to investigate the suitability of water for irrigation purposes (El Bilali and Taleb 2020; Ghazarhyan et al. 2020; Jahin et al. 2020; Kavurmacı and Karakuş 2020; Sutadian et al. 2017).

The Irrigation Water Quality (IWQ) can be assessed by the combination of several parameters which are associated to specific irrigation concerns, such is: (i) salinity hazard, (ii) infiltration or permeability hazard, (iii) specific ion toxicity, and (iv) miscellaneous effects to sensitive crops (Simsek and Gunduz 2007). The IWQ method classifies the quality of water for irrigation into low, medium, or high suitability. Furthermore, the conventional hydrochemical and statistical approaches follow the Boolean logic which exact values will define the limits (boundaries) between different classification groups. So according to this, the traditional water quality indices values vary between 0 or 1 (e.g., good or bad), and consequently, for the same water sample, different water quality classes could be attributed with the application of previous indices; resulting an ambiguity for water quality classification (Icaga 2007).

To overcome the subjectivity and to incorporate environmental uncertainty in groundwater quality evaluation process, the application of Artificial Intelligence (AI) based computational

methods are highly recommended (e.g., Agoubi et al. 2018; Jha et al. 2020; Lu and Ma 2020; Meyers et al. 2017; Nadiri et al. 2019; Nadiri et al. 2017; Rajaei et al. 2019). Among various computational AI methods, Fuzzy Logic (FL) is extensively used to deal with complex water-related environmental problems (Agoubi et al. 2016; Jha et al. 2020; McKone and Deshpande 2005; Tafreshi et al. 2018), owing to its capability to deal with non-linearity and uncertainty of environmental systems (Tirupathi et al. 2019). In addition to this, FL serves as an effective tool for conveying the results to the public and beneficiaries in a much understandable linguistic format (Li et al. 2018). Nowadays, FL is extensively applied to groundwater quality assessment for different purposes and adequate management, usually combined with GIS and geostatistical tools (e.g., Jha et al. 2020; Ostovari et al. 2014; Pathak and Bhandary 2020; Shwetank et al. 2019).

Tunisia is facing the problem of water scarcity due to its arid and semi-arid climate. This region has a rather unstable climate with irregular rainfall quantity and spatial distribution leading to either periods of drought or intensive rainy periods which makes the groundwater resources quite fragile. The Menzel Habib region (southeastern Tunisia), is well known by groundwater potentiality and quality, and is mainly used to domestic purposes and agricultural activities. So, the assessment of groundwater quality is crucial for a sustainable and groundwater management in this region.

The main topic of this study is groundwater quality assessment from Menzel Habib aquifer system for irrigation purposes and includes the following objectives: i) application of different water quality indices; ii) application of Simsek method; iii) Comparison with Irrigation Water Quality Index (FIWQI) determined by Fuzzy Logic.

2. Materials and methods

2.1. Menzel Habib aquifer system

Menzel Habib aquifer system is located in southeastern Tunisia, between latitudes 34° and 34°20' N, and longitudes 9°15' and 9°58' E (Fig. 1a). The area is characterized by an arid climate and a complex geology, including formations from Triassic to Quaternary age. The aquifer system contains three different layers: the shallow aquifer is contained in plio-quaternary sandy-loam formation, with a depth varying from 10 m to 65 m, the Senonian aquifer, corresponding to the first deep aquifer, is logged in marl levels with limestone layer, and, finally, the Cenomanian-Turonian aquifer is in the limestone and marl-limestone formation (Fig. 1b, c).

Groundwater from Menzel Habib aquifer system is intended to agricultural activities and is mainly extracted from the shallow and Senonian aquifers because of the high salinity in the Cenomanian-Turonian groundwater level (Ben Cheikh et al. 2013). In this study, the groundwater quality assessment from shallow and the Senonian aquifers will be presented.

A total of thirty-six representative groundwater samples were extracted from the shallow aquifer (25 samples: P1 to P25) and deep aquifer (11 samples: G1 to G11) of Menzel Habib aquifer system, from water supply boreholes used for agricultural purposes (Fig. 1b). After a minimum of 15 minutes of pumping the boreholes, groundwater samples were collected and stored in polyethylene bottles. Immediately after sampling, Electrical Conductivity (EC), Total Dissolved Solids (TDS) and pH were measured “in situ” with a multi-parameter analyzer reference (C933 Multi-Parameter). Groundwater bottles were correctly conditioned and transported to the laboratory. On the laboratory, the water samples were filtered with a 0.45µm Millipore filter and bicarbonate (HCO_3) water content was determined through the titration method with hydrochloric acid. Selected major cations (Na, K, Ca, Mg) and anions (F, Cl, Br, SO_4) water contents were determined by ionic liquid chromatography Metrohm 850 Professional IC. The chemical data quality was checked through careful standardization; the ionic charge balance of each sample was within $\pm 5\%$ error. All the determinations were

obtained at the Integrated Laboratory of Water Sciences, Higher Institute of Water Sciences and Techniques of Gabès (Tunisia).

2.2. Irrigation water quality parameters

Different and combined Irrigation Water Quality Indices (IWQI) to groundwater quality assessment for irrigation purposes were applied on the Menzel Habib aquifer system. The assessment of water quality for irrigation purposes is conditioned by several parameters and indices that are fixed by many organizations and agencies. In this research, Electrical Conductivity (EC), Sodium Adsorption Ratio (SAR), Soluble Sodium Percentage (SSP), Magnesium Adsorption Ratio (MAR), Permeability index (PI) and Kelly Ratio (KR) were considered. Indeed, groundwater salinity hazard is an important quality indicator for agricultural irrigation, as high salinization renders the soil saline that affects the salt intake capacity of the crops through the roots (El Bilali and Taleb 2020).

Water salinity is generally evaluated using EC ($\mu\text{S}/\text{cm}$) or TDS (mg/L), according to the FAO guidelines (Ayers and Westcot 1994). In a water with TDS $< 400 \text{ mg}/\text{L}$ there is no restriction in the respective application, while if TDS varies from $400 - 2000 \text{ mg}/\text{L}$ there is a slight to moderate restriction and a water TDS $> 2000 \text{ mg}/\text{L}$, the degree of restriction will be severe. For sodium hazard assessment, there are several parameters commonly applied in the evaluation of the suitability of water for irrigation purposes, such are SAR and SSP (El Bilali and Taleb 2020).

The SAR index is obtained by Equation [1]. The high SAR value degrades soil texture by reducing the hydraulic conductivity and, therefore it decreases the irrigation performance. However, water is considered unsuitable when the SAR is higher than 10, according to FAO

145 guidelines (Bilali and Taleb 2020). The indices SSP, MAR, PR and KR are presenting on the
146 equations [2] to [4].

147 Sodium Adsorption Ratio (SAR) is computed using equation (Richards 1954):

148
$$SAR = \frac{Na}{\sqrt{\frac{Ca+Mg}{2}}} \quad [1]$$

149 Soluble Sodium Percentage (SSP) is calculated according to equation (Kopittke et al. 2006):

150
$$SSP = \frac{Na}{Ca+Mg+Na} \times 100 \quad [2]$$

151 Magnesium Adsorption Ratio (MAR) or Magnesium Hazard is calculated according to
152 equation (Raghunath 1990):

153
$$MAR = \frac{Mg}{Ca+Mg} \quad [3]$$

154 Permeability index (PI), in %, is defined as water suitability for irrigation index and is
155 determined using equation:

156
$$PI = \frac{Na + \sqrt{HCO_3}}{Ca+Mg+Na} \times 100 \quad [4]$$

157 While Kelly Ratio (KR) is obtained using equation (Kelly 1963):

158
$$KR = \frac{Na}{Ca+Mg} \quad [5]$$

159 All ion contents were expressed in meq/L.

160

161 **3. Irrigation Water Quality Index**

162 One of the main purposes of this study is to develop a groundwater quality index to be applied
163 on agricultural irrigation. The water quality index is a system that could incorporate different

parameters of a water source as a single number and was firstly developed by Horton (1965). There are different water quality indexes developed with distinct methods and selected parameters (Kavurmacı and Karakuş 2020).

The IWQI is calculated by the linear combination of four groups of water quality parameters adapted from the IWQ developed by Simsek and Gunduz (2007). This index is assessed to determine the suitability of the water for irrigation and classifies the water quality into low, medium, or high suitability for irrigation. The first group is the *salinity hazard* which will be represented by groundwater electrical conductivity (EC) (Table 1). The second group corresponds to *infiltration and permeability hazard* which is determined using a combination between EC and SAR as a single parameter (Table 2). In the third group, water chloride content and SAR are used to quantify the *specific ion toxicity* (Table 1). Finally, the fourth group is represented by *miscellaneous effects to sensitive crops* based on bicarbonate (HCO_3^-) water content and pH values (Table 1). All these groups are assigned by weights from the highest (4) to the lowest (1) according to the relevance of the group on irrigation water quality assessment. Thus, the salinity hazard is considered as the highest priority factor (4), while the miscellaneous effect to sensitive crops as the lowest factor in IWQI assessment (1). The remained two groups, corresponding to infiltration and permeability hazard and specific ion toxicity have the weights of 3 and 2, respectively. Indeed, the IWQI is calculated as following [6]:

$$IWQI = \sum_{i=1}^4 G_i \quad [6]$$

Where i is an incremental index and G_i is the contribution of each one of the four considered groups. Each G_i is calculated according to the equation [7]:

$$G_i = \frac{w_i}{k} \sum r_j \quad [7]$$

With w_i as the weight of each group, k is the number of parameters included in each group and r_j is the rating of each parameter.

Although the weight factors could present some differences for different geographical settings, with distinct soil conditions and different crop patterns, it is considered that the relevance for each one could be used in regular agricultural patterns and as a general water quality assessment tool (Simsek and Gunduz 2007). The suitability of water for irrigation is indicated by a numerical value of IWQI index and the groundwater will be classified into three levels corresponding to: low (IWQI < 22), medium (IWQI: 22-37) and high (IWQI > 37) suitability for irrigation (Table 3).

2.4. Fuzzy Logic

The real quantitative questions are proposed to be resolved using mathematical methodologies, bellowing deterministic methods These methods are reinforced by classical logic, which uses crisp sets. However, the different environmental uncertainties are not statistical and enforce the possibility of probability (Harris 2000). These uncertainties could be minimized using fuzzy logic (Shwetank et al. 2019). Fuzzy Logic was firstly introduced by Zadeh (1965) as a tool to consider uncertainties in measured quantities or to deal with reasoning, which is imprecise rather than exact (Baghel and Sharma 2013). It is also called multi-valued logic, and is used to resolve multifaceted problems, corresponding to imprecise and vague data (Mujumdar and Sasikumar 2002). The functions of classical logic discriminate members and non-members of a set by assigning them crisp values such as 1 and 0, or true and false, respectively. Otherwise, functions of fuzzy logic (membership functions) discriminate members and non-members of a set by assigning them degrees of membership. The degree of membership, corresponding to a value attributed to each element, indicates the

211 membership score of the elements (Shwetank et al. 2019). So, this methodology confers a
212 very appreciable flexibility and will be possible to consider inaccuracies and uncertainties.

213 The fuzzy logic is based on fuzzy set and the variable to be modeled is considered as a
214 linguistic variable (Zadeh 1971), and is characterized by a quadruplet (X, T(x), U, F(x)),
215 where X is the name of the variable (e.g., water flow, ion concentration), T(x) the set of
216 corresponding linguistic values (labels) (e.g., Low, Medium, High), U is the physical domain
217 associated with the considered variable. F(x) is a semantic function (membership function)
218 that associates a fuzzy meaning to any set T(x) (Driankov et al. 1993, Nakoula 1997). In
219 general, the construction of a fuzzy model follows the syntax: If (premise) Then (Conclusion).
220 So, a fuzzy rule can be written as the form: If X is A Then Y is B.

221 The modeling of an input/output system by fuzzy logic is carried out in three essential phases:
222 (i) Fuzzification which transforms the modeled value X into a fuzzy set. This process will
223 allow to model the system inputs as a curve function - membership functions (MFs) - and to
224 delimit the fuzzy sets, which could have different shapes (e.g., triangular, trapezoidal)
225 (Bouchon-Meunier 1995). Trapezoidal MFs were adopted as in other several studies (e.g.,
226 Jaiswal and Ballal 2020; Kosko, 1993; Shwetank et al. 2019), and could be written according
227 to the equation:

$$f(x, a, b, c, d) = \begin{cases} 0 & x < a \text{ or } d < x \\ \frac{a-x}{a-b} & a \leq x \leq b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x \leq d \end{cases}$$

228 Where x is the variable to be fuzzified, a, b, c and d are the linguistic variables used to divide
229 the parameters into classes (Fig. 2).

230 (ii) Inference engine which produces fuzzy output resulting from fuzzy input using fuzzy
231 rules. At the presentation of each input, according to the fuzzy inference rules, the degree of

belonging to a given subset is determined. These rules are constructed using logic operator such as AND to support minimum, OR to support maximum and NOT to support without.

(iii) Defuzzification, which is the last step, transforms the fuzzy set resulting from the inference into a numerical output value (crisp), and can be performed by several methods such as centroid, bisector, middle or maximum. The center of gravity technique or centroid defuzzification is applied in this research.

The Fuzzy Inference System (FIS) is developed using fuzzy logic toolbox of MATLAB software to classify groundwater for irrigation using Mamdani approach. The structure of the proposed fuzzy model is shown in Fig 3. The inputs are the different traditional irrigation water indices - EC, SAR, SSP, MAR, PI, KR – and the output will be the fuzzy irrigation water quality index – FIWQI -.

3. Results and discussions

3.1. Groundwater geochemistry and water quality indices

The minimum, maximum, average, and standard deviation of Menzel Habib aquifer groundwater physio-chemical parameters is presented in Table 4. Indeed, the concentration of chemical elements vary from: 879 to 2876.4 mg/L for SO_4 , 489.6 to 3265 mg/L for Cl, 318.6 to 2064.6 mg/L for Na, 176.3 to 894.7 mg/L for Ca, 109.9 to 341.6 mg/L for Mg, 66.6 to 188.6 mg/L for HCO_3 and 18.27 to 53.01 mg/L for K. However, the water content in Br and F is very low. Thus, a spatial variation is observed for the samples. The abundance of groundwater major ions has the following order: $\text{SO}_4 > \text{Cl} > \text{HCO}_3 > \text{Br} > \text{F}$ for anions, and $\text{Na} > \text{Ca} > \text{Mg} > \text{K}$ for cations (Fig. 4).

The origin of major ions may be detected by different saturation indices of different minerals as a function of the ionic strength (Fig. 5). Thus, the saturation indices for halite, gypsum and

anhydrite are negative (Fig. 5a, Fig. 5b., Fig. 5c). However, they are positive for calcite and dolomite (Fig. 5d, Fig. 5f). Indeed, the dissolution of evaporites, dissolution/precipitation of carbonates constitute the main sources of major elements (Bahir et al. 2018; Mejri et al. 2018; Sunkari et al. 2021). Some points are characterized by a release of Ca and adsorption of Na, while others are characterized by release of Na and adsorption of Ca (Fig. 5f). This variability suggests that cationic exchange and inverse cationic exchange with soil and aquifer materials could be the main source of major ions (Abid et al. 2009; Kammoun et al. 2018).

The combination of the ions and physical parameters will promote the calculation of different water quality indices. These indices are classified into 4 classes: excellent, good, permissible, and unsuitable.

The SAR groundwater quality parameter from Menzel Habib groundwater varies from 4.08 to 19.3 which reflect that 36% of groundwater samples have an excellent quality and 64% with a good quality. The SSP groundwater parameter is an important parameter to assess the suitability of water to irrigation where an excess of sodium can affect the growth of plant. In the present study, the values are between 35.78% and 71.53%. Additionally, the SSP allows to detect that 17% of the samples are of good quality, and 83% are permissible and, consequently, deemed for irrigation.

The KR groundwater quality parameter varies from 0.56 to 2.47 (Table 4), allowing that 25% of groundwater samples have an excellent quality, 11% are of good quality and, 14% permissible. Otherwise, 50% of groundwater samples are unsuitable for irrigation purposes. The obtained results indicate that Menzel Habib groundwater is polluted by alkali hazard, according to defined criteria (Karanth 1987).

Indeed, the groundwater quality indices - SAR, KR, and SSP - may assess the deteriorating effect of Na contents in water and suggest that groundwater water from Menzel Habib aquifer

is unsuitable for irrigation purposes. Additionally, the Ca concentration is lower than Na concentration for almost groundwater samples. Consequently, it doesn't counter the dispersing effect of water sodium content (Fig. 5f) and thus enhancing the cationic exchange and the inverse cationic exchange (Tanvir Rahman et al. 2017).

The PI groundwater quality parameter indicates the suitability of groundwater for irrigation purposes. The soil permeability is affected by soil sodium, calcium, magnesium, and bicarbonate contents. PI values from Menzel Habib groundwater range between 38.47% and 72.74% (Table 4). As a result, two water classes are detected: 64% of the samples are considered of good quality and 36% are permissible for irrigation purposes.

The MAR water quality indices is also used to characterize groundwater quality for irrigation concerning the excess of magnesium over calcium water content. The obtained values from Menzel Habib groundwater fall in the range of 34.19% to 56.01% (Table 4). The use of MAR water quality parameter allows to classify 92% of the samples which were belonged to the category of suitable for irrigation ($MAR < 50\%$). However, 8% of the groundwater samples obtained scores exceeding the allowed standard ($MAR > 50\%$) resulting in deleterious impacts upon crop yield and increased soil alkalinity. The continuous application of these water sources will pose adverse risks, requiring interventional strategies to be in satisfactory conditions (Paliwal, 1972). Furthermore, Ca and Mg ions are incapable of identical behavior in soil systems, whereby Mg will negatively impact soil structure in highly saline and predominantly sodium-dense water. Generally, high Mg water contents will result in a highly exchangeable Na (Fig. 5f) in the irrigated soils (FAO 2008). This situation could adversely affect soil quality and lead to poor agricultural yield.

Otherwise, SAR parameter can be combined with EC under USSS (United States Salinity Laboratory) classification in diagram of Richards (Fig. 6). This classification considers a low ($EC < 250 \mu S/cm$), moderate ($250 < EC < 750 \mu S/cm$), high ($750 < EC < 2250 \mu S/cm$), very

high ($2250 < EC < 5000 \mu S/cm$) and extremely high ($EC > 5000 \mu S/cm$) water salinity values assigned to the classes C1, C2, C3, C4 and C5, respectively. While S1, S2 and S3 fields are considered according to SAR classes as low, medium, and high, respectively. Groundwater from Menzel Habib aquifer system is distributed as three groundwater samples in C4S2, nine are classified as C5S2, one as C4S3, five as C5S3 and the other ones contain a SAR ratio higher than 10, with an extremely high salinity (Fig. 6). According to the obtained results, most groundwater samples from Menzel Habib should not be used under normal conditions (e.g., without drainage network, plant non-tolerant for salinity; Ayers and Westcot 1994; FAO 1997), however, could be applied in areas with permeable soil and containing tolerant salinity crops. The other groundwater samples, with $EC > 10000 \mu S/cm$ and $SAR > 10$, are considered as harmful for irrigation purpose.

3.2. IWQI assessment

The four hazard groups are determined and combined to calculate IWQI and then to assess the groundwater quality irrigation purposes according to Equation 6. The IWQI index will consider three classes of groundwater suitability for irrigation purposes as: low ($IWQI < 22$), moderate ($22 < IWQI < 37$) and high suitability ($IWQI > 37$).

Groundwater samples from Menzel Habib aquifer system present a calculated IWQI lower than 22, and, consequently, are included in a low suitability category. The application of groundwater from the aquifer system on irrigation purpose requires a prior treatment considering some restriction and adequate caution. The low groundwater quality could be associated to the high groundwater EC values as a consequence of a high groundwater salinity. As a result, a low rating is attributed for the groundwater salinity hazard group. Otherwise, groundwater samples also present a high sodium and chloride contents which

could affect soil structure and permeability, as well as plants nutrition. Sodium and chloride water contents are relevant to the soil permeability assessment and to the infiltration hazard and specific ion toxicity relatively to groundwater quality. Indeed, these groundwater samples with high sodium and chloride concentration obtain a low score and are assigned by low ratings for the infiltration and permeability hazards and salinity hazard groups.

3.3. Irrigation water quality index by fuzzy logic

Considering groundwater quality indices obtained from Menzel Habib aquifer system will be crucial to attend adequate decisions on groundwater management of this region. Then, there is an overlap and ambiguity in making the decision regarding water quality for some samples. More precisely, on the area, there are some groundwater samples with values on the range limits, which could correspond to a more than one decision regarding to groundwater quality irrigation purposes. Hence, the suitability of Menzel Habib groundwater for irrigation was developed using fuzzy logic methodologies.

The groundwater quality indices, such as SAR, EC, SSP, MAR, PI, and KR, are considered as the inputs. The inputs are represented and resulted membership functions are constructed (Fig. 7). The resulted FIWQI has a score ranging between 0 and 1 (Fig. 8) and represents the output of defuzzification result for the studied groundwater samples.

Further, fuzzy logic has clearly improved groundwater classification by considering new water quality classes (Excellent to good, good to permissible, permissible to unsuitable) (Table 6) compared with the classification generated by the Richards diagram and IWQI adapted from Simsek and Gunduz method. As a result, 3% of groundwater samples from Menzel Habib system are classified as “good quality”, 3% as “good to permissible quality”, and 33% as “permissible quality” for irrigation purposes. About, 36% of total groundwater

samples are classified as “permissible to unsuitable quality” for irrigation, while 25% are with an “unsuitable quality”. The developed fuzzy index superiority over the diagram of Richards classification and the IWQI is particularly relevant in groundwater samples of similar quality, promoting a more consistent decision, particularly on groundwater samples with threshold values between two different classes. Overall, under USSL classification and the IWQI, 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 groundwater quality classes, thus allowing for more reliable information about groundwater quality.

4. Conclusion

The classification of groundwater quality for irrigation purposes applying combined conventional water quality indices and the method of Simsek and Gunduz has been improved on the Menzel Habib aquifer system, considering a groundwater distribution into different quality classes according to water composition and features. The IWQI calculated to groundwater from Menzel Habib aquifer suggests a low suitability for irrigation purposes.

A Fuzzy Inference System index (FIS) is proposed considering the incorporation of conventional water quality indices in a global one. The developed model has been validated with satisfactory results on groundwater samples for Menzel Habib aquifer system. The obtained FIS system is more adequate to Menzel Habib aquifer area than USSL system, or the conventional water quality indices and proposed Irrigation Water Quality Index. Thus, the FIS result will be more relevant on the groundwater classification for irrigation purpose. Furthermore, this methodology will avoid the uncertainties associated in decision making by adding new sub-classes (excellent to good, good to permissible, permissible to unsuitable).

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Data availability

Geochemical data were generated at the Applied Hydrosciences Laboratory, Higher Institute of Water Sciences and Techniques of Gabès, Tunisia. Derived data supporting the findings of this study are available from the corresponding author on request.

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598

Figures

Figure 1

Menzel Habib area: (a) Geographical location; (b) Simplified geological map of the aquifer system, including the spatial distribution of groundwater samples from Plio-quaternary well and Senonian borehole, and CT3-CT1 cross section; (c) Cross section from CT3-CT1 (Ben Cheikh et al. 2012)

Figure 2

Illustration of trapezoidal of fuzzy membership function

Figure 3

Structure of fuzzy model

Figure 4

Groundwater samples plotted in Pie diagram

Figure 5

Ionic Strength versus: (a) Halite SI, (b) Anhydrite SI, (c) Gypsum SI, (d) Dolomite SI, (e) Calcite SI; (f) Ca+Mg-(HCO₃+SO₄) versus Na+K-Cl

Figure 7

Inputs membership functions

Figure 8

FIWQI classification of groundwater from Menzel Habib aquifer system