A new approach in qualitative zoning of groundwater to assessment suitable irrigation water using fuzzy logic spatial modeling via GIS

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Abstract Water quality must be tested before it can be used for agricultural purposes since difficulties might arise in terms of increased soil salinity, decreased soil permeability, and decreased water absorption by plant roots; leading to reduced agricultural productivity. The aim of this study was to assessment suitable irrigation water based on a new approach in Asalem region, Iran. For reduce the uncertainty, fuzzy logic spatial modeling via GIS was applied. To receive these aims, four stages were performed. In stage 1, we calculate the values of nine conventional and effective parameters used for agricultural water quality classification upon analyzing the statistical quality data regarding various ions existing in 15 sample wells dug in 2015. In stage 2, interpolate these parameters by kriging method via ArcGIS software. In stage 3, parameter standardization with fuzzy membership function were done. And in stage 4, for Aggregation parameters, several fuzzy overlay operations were used. Finally, to identify the best operation, the correlations between the fuzzy membership and operation maps were used. Results showed that the "GAMMA 0.9" with six high correlation above 80%, is the best overly operation in our study area. According to the best operation map, only west and northwest parts of the study area have "good" to "excellent" groundwater quality for irrigation water and in other parts, the quality is within "poor" to "fair".

Key words Qualitative zoning, Irrigation water, Fuzzy logic spatial modeling, GIS, Asalem

1. Introduction

Groundwater is the most important agricultural water resource in Iran and many other countries with a similar climate. In addition, the lower probability of groundwater pollution compared to other water resources has led to abundant use of this resource even in areas where there is no surface water shortage (Singh, 2016). Natural purification of water during its downward movement into the ground improves ground water quality, thus creating in most cases a clean and colorless water resource (Babiker et al., 2007) . Nevertheless, changes in groundwater quality and its increased salinity pose as major risks for agricultural development (Mohebbi Tafreshi et al., 2014). Water quality is important in agriculture because low quality water adversely affects soil and plants due to the existing physical and chemical impurities in the same, sometimes further affected by environmental factors. Water used in agriculture can affect soil which, in turn, change both the quality and quantity of agricultural produce (Azimi et al., 2014). As elimination of groundwater pollution is a very costly and time-consuming process, and as, by the time pollution is detected, it is almost impossible to elimination, the best solution would be to determine beforehand groundwater quality and take measures to prevent pollution and low quality conditions in these waters (Mir Arabi et al., 2011). Conceptually, water quality refers to those properties of a water resource that affect its suitability for specific uses (Rhoades and Merrill, 1976). Waters used for irrigation purposes are, to a great extent, qualitatively affected by the type and amount of their dissolved salts. Though salts are found in relatively low levels in agricultural soils, they can increase due to the dissolution of certain rocks, including carbonate and evaporite rocks (Ravikumar and Somashekar, 2010). For this reason, using various parameters for simultaneously detecting several dissolved ions in soils has led to classification methods for determining suitably of groundwater for agricultural purposes. Based on the selected parameter(s), each method can rank the groundwater quality. Some of these parameters and their related classification methods are: sodium percentage (Na%), Sodium Adsorption Ratio , Residual Sodium Carbonate (RSC), Electrical Conductivity (EC), Magnesium Ratio (MR), Potential Soil Salinity (PS), general soil classification or Kelly's ratios, pH, Corrosivity Rate (CR). Numerous studies attempted to examining or zoning groundwater quality for agriculture purposes by considering the relevant quality classification parameters (Bashir et al., 2013; Kumarasamy et al., 2014; Naseem et al., 2010; Oladeji et al., 2012; Parimala renganayaki and Elango, 2013; Ravikumar et al., 2015; Sheikhy Narany et al., 2014; Venkateswaran and Vediappan, 2013).

According to uncertainty in qualitative classifications, it is necessary to use a suitable method that solves this problem, and fuzzy logic can do it. Fuzzy logic is based on fuzzy set theory proposed by Zadeh (1965). Fuzzy logic is used extensively in poorly definable engineering applications. According to fuzzy logic theory, membership sets may not complete, and each member has a degree of membership of zero to one, and unlike Boolean logic (Classic), in fuzzy logic no confirmation exists that could be based on, an area completely considered appropriate or inappropriate. Fuzzy modelling allows flexible standardization and aggregation by partial membership. Numerous studies attempted to use fuzzy modeling in development of water quality index and water quality assessment (Gharibi et al., 2012; Icaga, 2007; Liu and Zou, 2012; Scannapieco et al., 2012) or in the other proposes that are near to aim of our study (Akumu et al., 2015; Araya-Muñoz et al., 2007; Caniani et al., 2016; Chen and Paydar, 2012; Hellwig et al., 2017; Lewis et al., 2014; Zhang et al., 2017).

Despite all of these researches, there is no paper that used from described quality parameters together for assessment suitable irrigation water. Accordingly, this study provides a new approach for examine groundwater quality for irrigation water based on combining the conventional and effective parameters used for irrigation water quality classification according to fuzzy logic spatial modeling.

2. Study area

The studied area is located to the northwest of Gilan Province – a province in northern Iran - within Zone 39N at the geographical coordinates of 315054-326836.8 and 4166598.8-4186090.5 (in accordance with the UTM coordinate system). Mean annual precipitation and mean temperature in this region are 1150mm and 19°C respectively, thus placing this region in the humid climate zone (according to the De Martonne classification). Geologically, the greater part of the studied region consists of contemporary outcrops. Vast sections of the areas upstream of the studied region (to the west) comprise andesite volcanic rocks. In the southwestern parts, masses of metamorphic and sedimentary conglomerate outcrops can be observed (Fig. 1). Groundwater direction is consistent with the direction of the rivers in the area, namely, from the west of the studied area towards the east (Caspian Sea). Regarding land use, a vast area of the studied region is devoted to irrigated agriculture. Thick forests cover the land in the western parts, and rice farms are the main agricultural activity (Fig. 2).

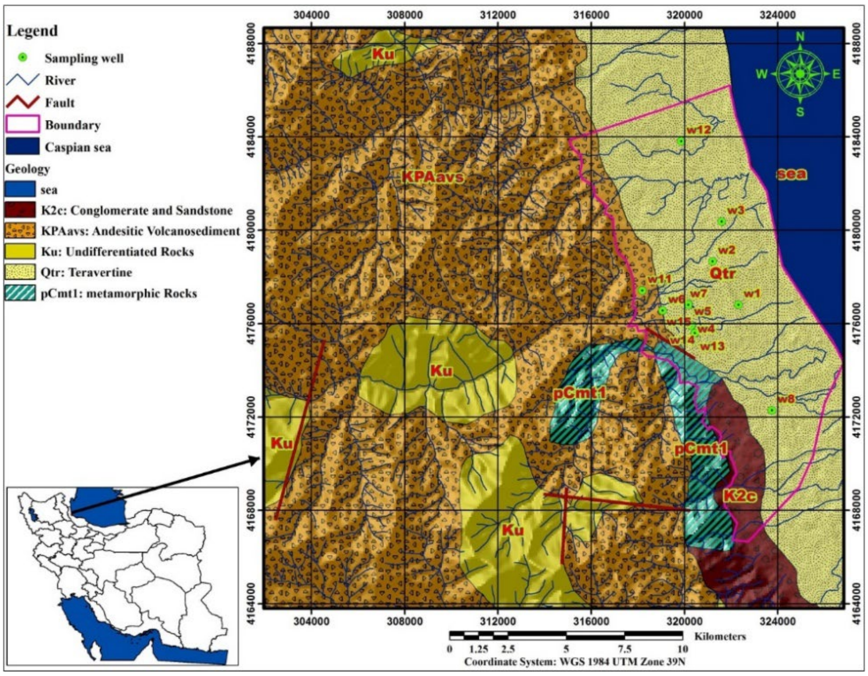

Figure 1 The Geology map of the study area

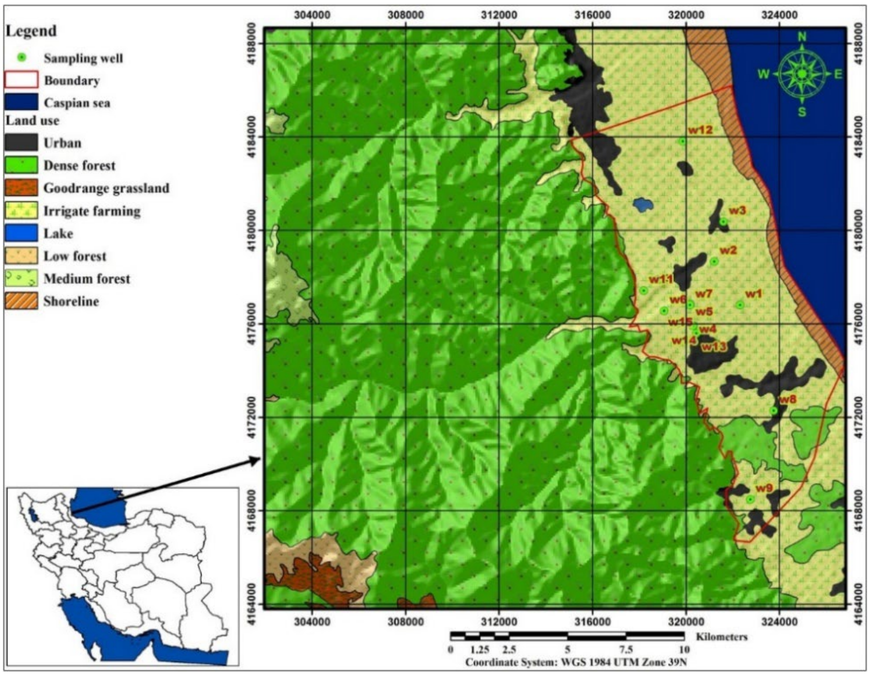

Figure 2 The land use map of the study area

2. Data collection and preparation

The qualitative statistics of 15 wells, prepared for 2015, were used for examining groundwater quality used for agricultural purposes in the studied area and calculating the classification parameters. These statistics included the values of the following parameters: Na, HCO_3, EC, CO_3, K, Mg, Ca, SO_4, Cl, and pH (Table 1). Immediately after being placed inside 250 cc polyethylene bottles, the samples were transferred to the laboratory for hydrochemical tests. The "Istek Model 915" apparatus was used to read the samples directly upon their arrival in the laboratory. Titration and flame photometry methods were used to measure the quantity of the main anions and cations in the samples. Table 1 lists the maximum, minimum, and mean values of the measured parameters for determining the quality of the studied well water samples (except for pH which a dimensionless parameter, all other parameters were measured in mg/l).

Table 1 statistical characteristic of the chemical components

Parameter	EC	pH	Ca	Mg	Na	K	HCO_3	CO_3	Cl	SO_4
Number of samples	15	15	15	15	15	15	15	15	15	15
Arithmetic mean	762.07	7.3	86.09	16.13	32	1.58	339.5	0	73.91	7.6
Standard Deviation	381.39	0.26	16.28	8.58	46.72	3.39	56.94	0	135.2	1.88
Variant Coefficient (%)	50.05	3.56	18.91	53.19	146	214.56	16.77	-	182.9	24.74
Maximum	1776	7.89	113.03	33.5	168	11.5	390.4	0	461	11
Minimum	435	6.91	56.1	3.3	0.26	0.11	206.2	0	10.6	5
Mode	510	7.11	96.1	14.5	17	0.28	366	0	10.6	8
Median	648	7.28	86.6	14.5	18	0.28	366	0	10.6	7
Range	1341	0.98	56.93	30.2	167.7	11.39	184.2	0	450.4	6
Skewness	1.81	0.78	-0.4	0.64	2.48	2.57	-1.24	0	2.2	0.6
Variance	145457	0.07	264.97	73.6	2183	11.49	3243	0	18270	3.54

3. Methodology

In this study, four stages were performed as follows:

3.1. Calculate irrigation water quality classification parameters

To examination the quality of groundwater for agriculture purpose we must examine the parameters that affect the quality of water for agricultural purposes. For example, salt content in soil is a great concern in waters used for agriculture. High concentrations of salt in water and soil adversely affect the quality of agricultural land. The total salt content in agricultural waters is usually determined by measuring soil Electrical Conductivity (EC) in µs/cm (Meybeck, 1987). Like other cations, sodium reacts with soil clays and substituting the Ca and Mg ions, decreases soil permeability and lowers soil quality. SAR is the best measure for assessing sodium hazard in soil because it measures the degree of Ca and Mg substitution by Na ions (Todd, 2006). Percent Sodium as another sodium hazard classification method is a parameter that used for agricultural waters. The Wilcox (1955) and Eaton (1950) methods are used for chemically classifying waters in terms of their Na%

parameter. Another parameter affecting agricultural water quality is residual sodium carbonate hazard. High levels of carbonate and bicarbonate ions increase soil RSC, whereas Ca and Mg ions reduce this parameter. Carbonate and bicarbonate ions react with Ca and Mg ions to form $MgCO_3$ and $MgCO_3$ sediments. As a result of this reaction, concentration of Ca and Mg ions are lowered below that of the Na ion, leading to an increase in the pH value (Richards, 1954). The ratio of the measured Na to the sum of the measured Ca and Mg in a soil sample is termed the Kelly Ratio (Kelley, 1951). Since increasing Na reduces soil permeability, a high KR can be used as an indicator of reduced permeability. KR can also be used as a measure for warning against increased water alkalinity (Handa, 1981). Increased levels of Mg in groundwater would increase the destructive effects of Na in soils with high levels of Mg (or if waters containing high levels of Mg are used). In fact, increased Mg levels would gradually decrease plant water absorption capacity due to increased cation exchange. MR is used as an index for assessing magnesium hazard in groundwater (Grattan, 1994). pH value is among the important parameters used for assessing agricultural water quality (Bashir et al., 2013). The suitable pH range for agricultural use is from 6.5 to 8.4 (Bauder, 2010). Corrosion is an electrolyte process occurring at metal surfaces, leading to destruction and perforation of metallic walls. This problem mostly occurs due to high salinity and encrustation (Ryznar, 1944) . In agricultural waters, CR is often used for assessing the quality of waters flowing in the transfer pipes to farmland. Potential Salinity is another criterion used for assessing groundwater quality for agricultural purposes in terms of dissolved salts. Lower levels of the water salinity increase gradually with each irrigation, thus exhibiting a cumulative effect; and higher levels of water salinity would lead to unacceptable levels of soil salinity in a shorter time. Doneen (1962) argued that even dissolved salinity could increase soil salinity, thus creating problems in agriculture. Potential salinity as chloride concentration plus half sulfate concentration. Table 2 shows all classification parameters that described in this section.

Table 2 Summary of water quality classification parameters for agriculture purpose

Parameter	Describe	Calculation method	Classification
EC	Electrical Conductivity	Field measurement	100-250 = Excellent 250-750 = Good 750-2250 = Fair >2250 = Poor
SAR	Sodium Adsorption Ratio	$SAR = \frac{Na^{+}}{\sqrt{\frac{Ca^{2+} + Mg^{2+}}{2}}}$	<10 = Excellent 10-18 = Good 18-26 = Fair >26 = Poor
Na%	Percent Sodium	$Na\% = \frac{(Na^{+} + K^{+})}{(Na^{+} + K^{+} + Mg^{+} + Ca^{+2})} \times 100$	<20 = Excellent 20-40 = Good 40-60 = Fair 60-80 = Poor >80 = Very Poor
RSC	Residual Sodium Carbonate	$RSC = (CO_3{}^{2-} + HCO_3{}^{-}) - (Ca^{2+} + Mg^{2+})$	<1.25 = Excellent 1.25-2.5 = Fair >2.5 = Unsuited
KR	Kelly Ratio	$KR = \frac{Na^{+}}{Ca^{2+} + Mg^{2+}}$	<1 = Suitable >1 = Unsuitable
MR	Magnesium Ratio	$MR = \frac{Mg^{2+}}{Ca^{2+} + Mg^{2+}} \times 100$	<50 = Suitable >50 = Unsuitable
pH	-	Field measurement	6.5 < pH < 8.5
CR	Corrosively Rate	$CR = \frac{\frac{Cl^{-}}{35.5} + 2\left(\frac{SO_4^{2-}}{96}\right)}{2\left(\frac{HCO_3^{-} + CO_3^{2-}}{100}\right)}$	<1 = Suitable >1 = Unsuitable
PS	Potential Salinity	$PS = Cl^{-} + \frac{SO_4^{2-}}{2}$	<0.5 = Excellent to good 0.5-2 = Good to Injurious >2 = Injurious to Unsuits

3.2. Interpolate parameters by kriging

Kriging is an estimate stochastic method based on weighted moving average that using known values to determine unknown values. This method is the best linear unbiased estimator (Webster and Oliver, 2001).

In kriging, the estimated value, z, at any point x_0 is given as follows:

$$Z^*(X_0) = \sum_{i-1}^{n} \lambda_i \, Z(Xi)$$

where, λ_i is the weight for the known value z at location x_i. The kriging weights of ordinary kriging fulfill the unbiasedness condition

$$\sum_{i-1}^{n} \lambda_i \; = 1$$

First an experimental semivariogram has to be calculated using the following equation.

$$\gamma^*(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(X_i) - Z(X_i + h)]^2$$

where γ^*(h) is the estimated value of the semivariance for lag class h; N(h) is the number of experimental pairs separated by a vector h of that lag class; z(x_i) and z(x_i + h) are values of variable z at x_i and x_i+ h, respectively.

When experimental semivariogram calculate, suitable theoretical models are fitted to them, and the best model is selected based on the least RSS value and used in the kriging procedure.

3.3. Parameters standardization with fuzzy membership function

Fuzzy logic provides an approach that allows expert semantic descriptions to be converted into a numerical spatial model to predict the location of something of interest. First step in Fuzzy suitability model is parameter standardization with fuzzy membership function. Fuzzy values were assigned by converting raw input values to a membership scale from 0 to 1 based on a transformation function defined by expert opinion. Values approaching 1 are more suitable and those approaching 0 are less suitable. Several fuzzy membership functions are available in fuzzy logic extension of ArcGIS version 10.1 software that produces a sigmoid shape of the membership, which is used commonly in many fuzzy logic applications (ESRI, 2012). Use and apply any of these functions are carried out according to the midpoint and spread parameters. Select the function to the fuzzification done with respect to the identity, importance and relationship of each criterion with the goal. In this study, the midpoint of each function selects according to parameter classification that described in table 3. In this preliminary analysis, for standardization the parameters, three fuzzy membership function were employed (Fig. 3) that describe in the following section:

Fuzzy Gaussian: This function is based on alter the initial data in raster according to normal function. Membership of other raster values decreased as we move from the midpoint in positive and negative directions. Gaussian function can be useful when membership is close to a certain amount.

Fuzzy Small: This function is used when small input values have higher membership value. The membership values less than the midpoint increased in this function and has been high suitability.

Fuzzy Linear: This function between the minimum and maximum values defined by the user establishes a linear relationship. The values that are less than the minimum value, zero awarded and values greater than the maximum value, 1 awarded.

3.4. Aggregation parameters with fuzzy overlay operations

After the standardization each of the parameters, to determine the suitable irrigation water, we should combine all quality parameters that are involved. For this reason, fuzzy operators are used in the fuzzy inference network. Five major operator who used in the fuzzy inference network to combine the parameters (Fig. 3) are described in the following section:

Fuzzy OR: This operation is equal to the union set, which extract the maximum degree of membership and the maximum combined uses. If you use this operation between two membership functions, the maximum value of membership function is selected.

Fuzzy AND: This operation is equal to the intersection set, which extract the minimum degree of membership. This means that between all the membership functions, the minimum values (weight) per pixel were extracted and put in the final map (ESRI, 2012).

Fuzzy PRODUCT: In this operation, all membership functions are multiplied together. This cause a lower suitability value than any of single input and in the final map the pixel value tends to 0. As a result, fewer pixels are in excellent class. For this reason, this operator applies high sensitivity to the location (ESRI, 2012).

Fuzzy SUM: This function linearly combines the inputs, so the combined evidence is more important. For this reason, unlike "Fuzzy PRODUCT", in the final map, the pixel value tends to 1. As a result, more pixels are in excellent class. For this reason, this operator applies low sensitivity to the location (ESRI, 2012).

Fuzzy GAMMA: This overlay function multiplies the "Fuzzy SUM" by the "Fuzzy PRODUCT" to the power of gamma (Lewis et al., 2014). When gamma tending to 1, it is closer to the "Fuzzy SUM" and whereas gamma tending to 0, it is closer to the "Fuzzy PRODUCT" (Bonham-Carter, 2014). According to Lewis et al. (2014) research, "increasing the value of gamma (γ), the frequency of higher suitability values increases and the frequency of lower suitability values decrease."

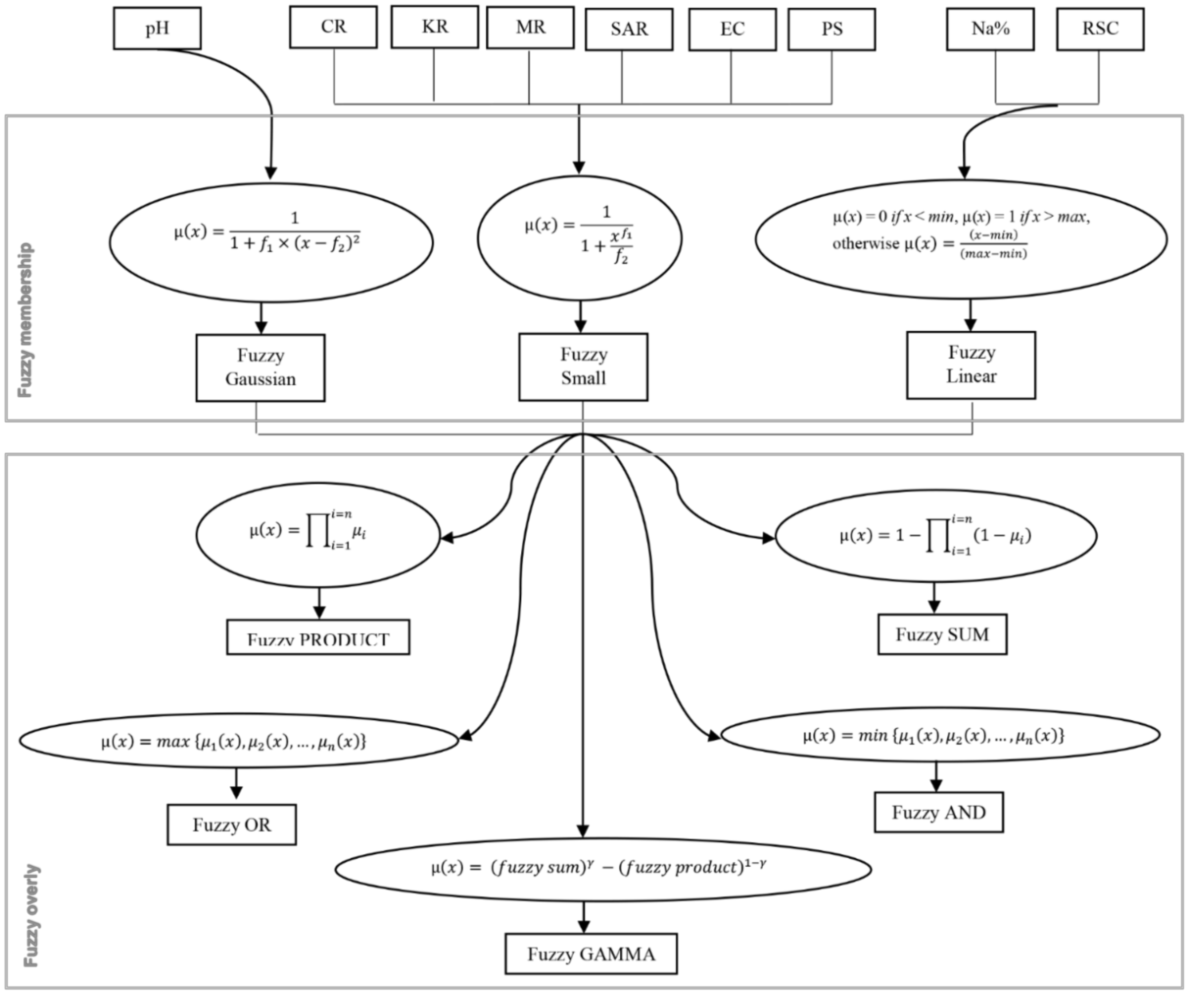

Figure 3 Fuzzy suitability model for irrigation water quality classification. In this figure, RSC, Na%, MR, KR, PS, SAR, CR, EC and pH are irrigation water quality classification parameters, user inputs f_1 is the spread and f_2 is the midpoint, min and max are user inputs, μ_1, μ_2, μ_n represent membership pixels values in the relevant layer, μi is the pixels' membership value in i factor and γ is power of gamma and input by user.

4. Result and Discussion

4.1. Calculate irrigation water parameters

Based on the results obtained from Table 1 and according to Table 2, the water quality classification parameters for irrigation water were calculated and listed in Table 3. As shows in Table 3, the quality of all samples was classified as excellent for agricultural purposes in terms of the following parameters: MR, SAR, Na% (except for w1 and w8), RSC, pH, KR (except for w8), CR (except for w1 and w8), and PS (except for w1 and w8).

Table 3 The important parameters which determine the irrigation water quality of the study area

Sample	RSC	Na%	MR	KR	PS	SAR	C.R	EC	pH
w1	-1.80	39.91	35.78	0.66	6.47	2.62	1.53	1290	7.19
w2	0.40	7.13	5.97	0.08	0.35	0.23	0.11	510	7.31
w3	0.49	14.39	31.91	0.17	0.38	0.5	0.12	510	7.28
w4	0.20	11.46	19.18	0.13	0.36	0.45	0.09	685	7.16
w5	0.48	17.27	20.10	0.21	0.42	0.01	0.12	878	7.21
w6	0.38	11.98	17.33	0.13	0.38	0.46	0.10	645	7.11
w7	0.19	17.89	30.11	0.22	0.37	0.61	0.14	480	7.45
w8	-0.01	55.83	20.09	1.21	7.63	4.21	1.80	1285	6.98
w9	0.59	16.84	21.58	0.20	0.37	0.66	0.10	645	7.12
w10	0.27	6.84	16.17	0.07	0.38	0.25	0.09	648	7.42
w11	0.37	14.02	35.94	0.16	0.41	0.54	0.11	657	7.45
w12	0.39	11.02	20.09	0.12	0.61	0.43	0.14	690	7.38

w13	0.08	14.49	35.61	0.17	0.35	0.59	0.08	685	7.11
w14	-0.11	9.88	13.20	0.07	0.37	0.2	0.13	490	7.71
w15	-0.63	8.44	12.65	0.09	0.86	0.24	0.37	435	7.89

4.2. Interpolate calculated irrigation water parameters

Fig. 4 shows the interpolated maps of irrigation water parameters. As it can be seen, in most parameters revealing high levels of anomalies in south and center parts. These high anomalies can be attributed to the metamorphic conglomerate as well as sediment structures at the upstream of groundwater streams (east to west) since the salts existing in these structures have entered the groundwater streams due to erosion, thus increasing groundwater salinity. Furthermore, it might cause duo to be located in the urban zone.

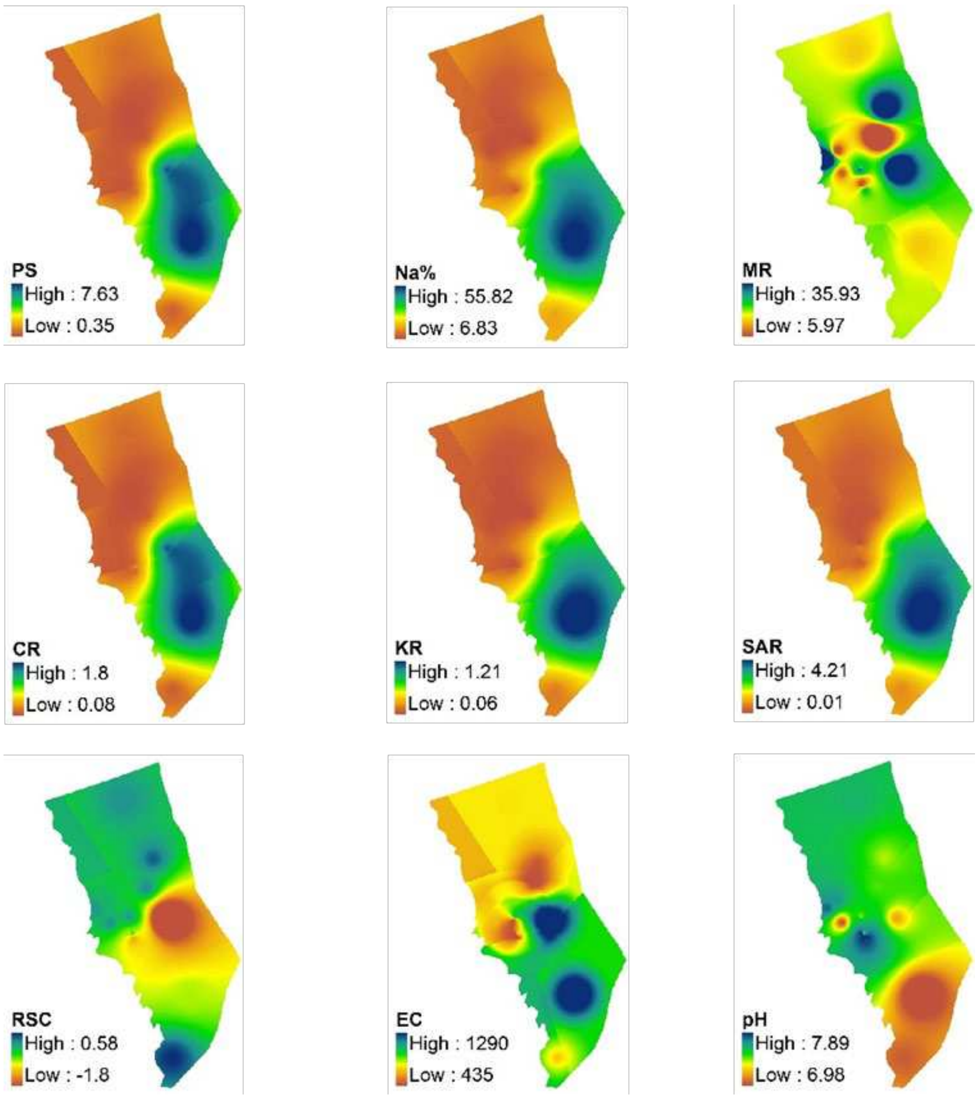

Figure 4 Interpolate irrigation water parameters by kriging method

4.3. Parameters standardization

Fig. 5 shows the standardized suitability according to fuzzy memberships. Because the RSC parameter has negative values, and the "Fuzzy Small" function doesn't able to calculate these type values, we don’t use this function for this parameter. Considering that in the CR, KR, MR, EC, SAR and PS parameters, low quantities have a higher proportion and quality and are more suitable in irrigation, the "Small" function was used to fuzzy standardize. In the pH parameter, due to the suitability of 6.5 to 8.5 period and select 7.5 as midpoint, the "Gaussian" function was used. Based on Table 2, classification values of Na% ranked linearly and distance of each quality class to the next class is fixed. For this reason, the "Linear" function was used for this parameter. Furthermore, according to that the smaller quantities are a better fit in this parameter, decrease form of this function was used to fuzzy standardize.

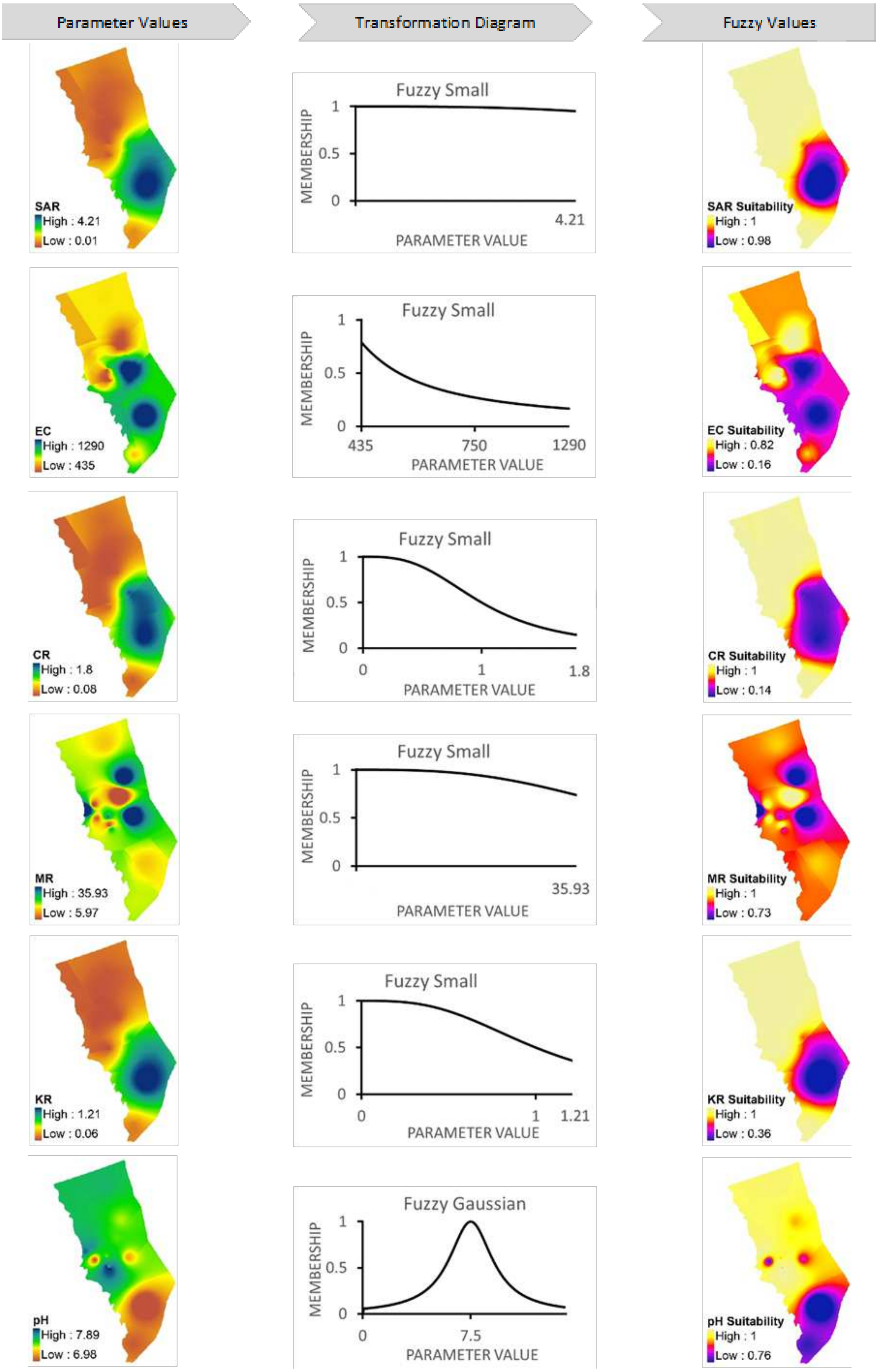

Figure 5 The standardized suitability according to fuzzy memberships for SAR, EC, CR, MR, KR and pH parameter

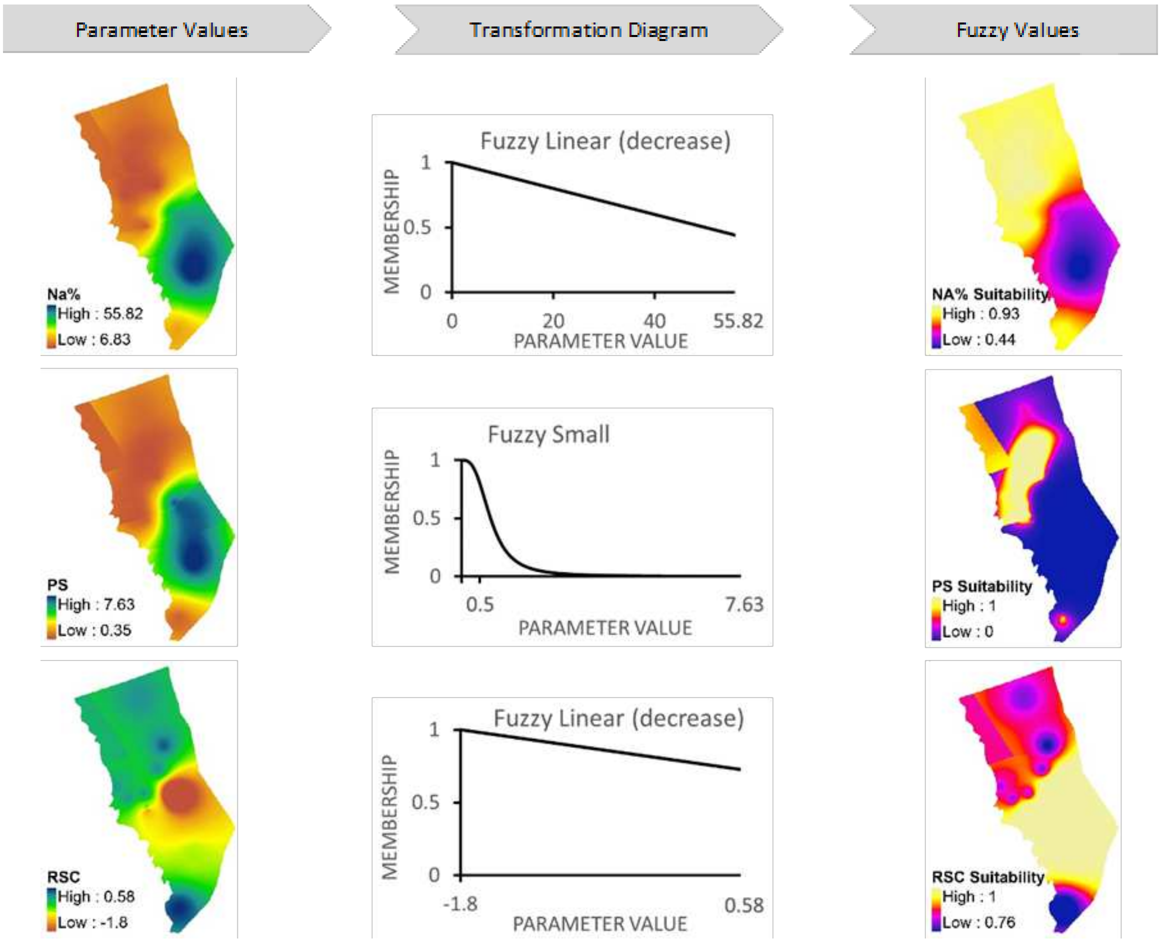

Figure 6 The standardized suitability according to fuzzy memberships for Na%, PS and RSC parameter

4.4. Aggregation parameters

As it can be seen in Fig. 7, the "OR" and the "SUM" overly function considers the maximum degree of membership that shows these operations are comparatively liberal suitability operations. Unlike these functions, the "PRODUCT" and the "AND" overly functions select the minimum degree of membership. Nonetheless, the "PRODUCT" is more restrictive than the "AND" function because multiplication standardized parameters with less than one value have lower values than the value of anyone standardized parameter (Lewis et al., 2014). According to Fig. 7, in "GAMMA" overly function with an increase in "γ" value (the power of gamma), the frequency of higher suitability values increases. In contrast to our results, some authors (Araya-Muñoz et al., 2007) argue that in values above 0.7, giving more weight to the lowest components tends to decline. However, Lewis et al. (2014) research confirming our results.

4.5. Identify the best operation to use as selected overly operation

In this study to identify the best overly method, the correlations between the fuzzy membership and operation maps were used. For this purpose, the "Band collection statistics" tool in ArcGIS software was used. According to the result that shows in Table 4, the "GAMMA 0.9" method with six high correlation above 80%, is the best overly operation in this research. After this method, the "GAMMA 0.8" (with five high correlation above 80%) and the "GAMMA 0.7"(with four high correlation above 80%), methods are suitable respectively.

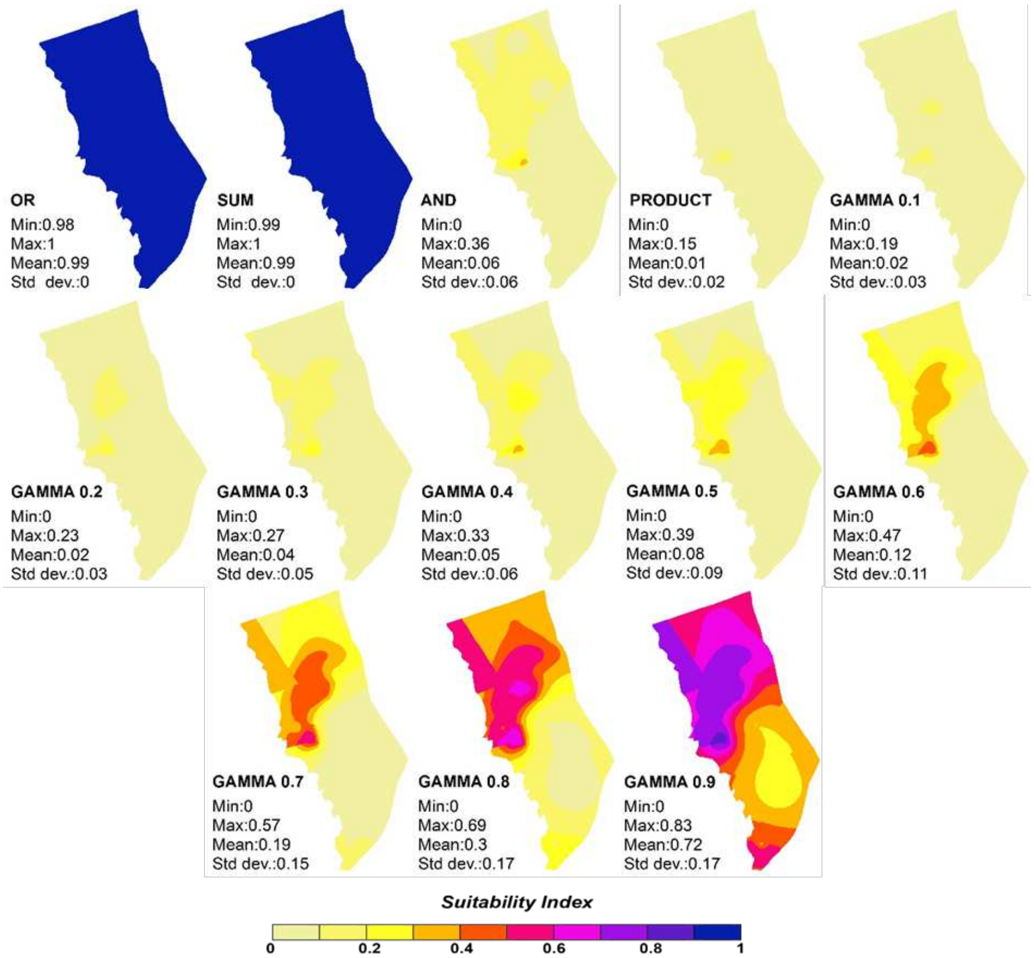

Figure 7 The fuzzy overlay function maps. The "OR" and "SUM" operations are highest suitability and the "PROUCT" is lowest.

Table 4 The correlation between the "Fuzzy membership" and "Fuzzy overly" rasters. In this table, the "Fuzzy Na%", the "Fuzzy SAR", the "Fuzzy PS", the "Fuzzy pH", the "Fuzzy RSC", the "Fuzzy EC", the "Fuzzy KR", the "Fuzzy MR" and the "Fuzzy CR" are fuzzy membership raster form of the parameters and the "SUM", AND", OR, PRODUCT", the "GAMMA0.1", the "GAMMA0.2", the "GAMMA0.3", the "GAMMA0.4", the "GAMMA0.5", the "GAMMA0.6", the "GAMMA0.7", the "GAMMA0.8" and the "GAMMA0.9" are fuzzy overly raster form of them. The values are the correlation between the "Fuzzy membership" and "Fuzzy overly" rasters, and the values that have been marked with "*" and underline, are the high correlations above 80%.

Overly vs. membership	Fuzzy Na%	Fuzzy SAR	Fuzzy PS	Fuzzy pH	Fuzzy RSC	Fuzzy EC	Fuzzy KR	Fuzzy MR	Fuzzy CR
Fuzzy SUM	0.49	0.70	0.20	0.62	0.12	0.45	0.60	-0.12	0.47
Fuzzy AND	0.82*	0.62	0.76	0.54	0.27	0.76	0.69	0.14	0.76
Fuzzy OR	0.91*	0.99*	0.46	0.65	0.41	0.71	0.97*	-0.01	0.90*
Fuzzy PRODUCT	0.59	0.40	0.93*	0.36	0.09	0.63	0.45	0.13	0.51
Fuzzy Gamma 0.1	0.62	0.42	0.94*	0.38	0.11	0.65	0.48	0.13	0.53
Fuzzy Gamma 0.2	0.65	0.45	0.95*	0.40	0.13	0.67	0.51	0.12	0.57
Fuzzy Gamma 0.3	0.69	0.48	0.95*	0.42	0.16	0.70	0.54	0.12	0.60
Fuzzy Gamma 0.4	0.73	0.52	0.95*	0.45	0.19	0.73	0.58	0.12	0.65
Fuzzy Gamma 0.5	0.77	0.56	0.95*	0.48	0.23	0.76	0.63	0.11	0.69
Fuzzy Gamma 0.6	0.82*	0.61	0.93*	0.51	0.28	0.79	0.68	0.11	0.75
Fuzzy Gamma 0.7	0.87*	0.67	0.91*	0.54	0.33	0.82*	0.74	0.11	0.80*
Fuzzy Gamma 0.8	0.91*	0.73	0.87*	0.58	0.39	0.85*	0.80*	0.11	0.86*
Fuzzy Gamma 0.9	0.95*	0.80*	0.81*	0.61	0.44	0.87*	0.86*	0.11	0.91*

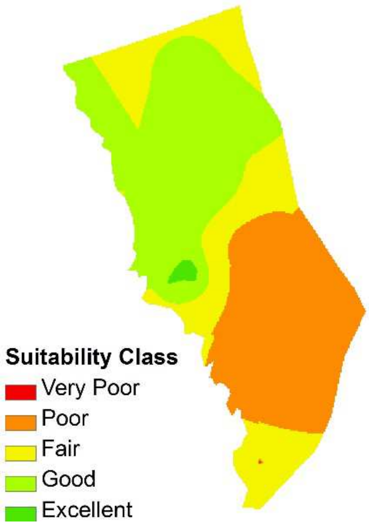

Fig 8 The suitability class of ground water quality for irrigation water purposes

5. Conclusion

The results obtained by analyzing the effective parameters on irrigation water quality showed that the quality of the groundwater samples taken from the studied area could be classified as fair to suitable for agricultural purposes.

In fuzzy logic spatial modeling, to fuzzy standardize, the "Small" (for the CR, KR, MR, EC, SAR and PS parameters), decrease form of the "Linear" (for Na% and RSC) and the "Gaussian" functions (for the pH parameter) were used. In aggregation parameters stage, we used from the "OR", the "AND", the "PRODUCT", the "SUM" and the "GAMMA" (with various values) overly functions. According to the results of this stage, the "OR" and "SUM" operations were highest suitability and the "PROUCT" was lowest. Finally, based on correlations between the fuzzy membership and operation maps, the "GAMMA 0.9", the "GAMMA 0.8" and the "GAMMA 0.7" methods are most suitable overly operation respectively. Based on results of the best overly operation in this work, unlike groundwater in center and south, the west and northwest parts of the study area have "good" to "excellent" groundwater quality for irrigation water purposes.

The model developed in this work that based on using GIS, fuzzy logic spatial model and irrigation water parameter, is a new approach to qualitative zoning of groundwater for agriculture proposes methods, and it extends the existing methods of this field in terms of groundwater management.

Conflict of interest

No conflict of interest.

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