A Novel GIS-Based Approach to Assessment Suitable Irrigation Water Using a fuzzy-Multi Indices Method in Astaneh-Kuchesfahan Plain, Iran

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Abstract

Increasing soil salinity decreased soil permeability and reduced water absorption by plant roots leading to reduced agricultural productivity. For this reason, water quality must be tested before it can be used for agricultural purposes. Accordingly, the currentresearch aimed to assess suitable irrigation water (IW)using a new GIS-basedapproach in Astaneh-Kuchesfahan plain, Iran.Fuzzy logic (FL) via GISwas used to reduce the uncertainty. Four steps were performed to receive this aim. In step 1, the values of nine indices used for agricultural water quality classification were calculated based on chemical analysis of 19 water samples in wet and dry seasons.In step 2, these indices were interpolated via ArcGIS 10.8 software. In the following, fuzzy membership functions (FMF) were used for the standardization of parameters in step 3. Finally, in step 4, foraggregation of the indices, several fuzzy overlay operations were used. Eventually, to identify the most accurate overlay operation,the correlations between the fuzzy memberships and operation maps were used.The results showed that the sum of absolute values for correlations (SAVC) in the dry season is higher than in the wet season.The results also showed that the "GAMMA 0.9" and"GAMMA 0.95"withthe highest SAVCare the bestoverlay operations in dry and wet seasons, respectively. According to the best operation maps, only a small southeast area has"good" groundwater quality for IWin both dry and wet seasons.

Introduction

Groundwater is the essential agricultural water resource in Iran and many other countries with a similar climate (Kheirkhah Zarkesh et al. 2012). Besides, the lower probability of groundwater pollution than other water resources has led to the great use of this resource even in areas with no surface water shortage (Mohebbi Tafreshi et al. 2019; Singh 2016). Natural purification of water during its downward movement into the ground improves groundwater quality, thus creating, in most cases, a clean and colorless water resource (Babiker et al. 2007). Water quality is vital 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 (Mohebbi Tafreshi and Mohebbi Tafreshi 2020). Conceptually, water quality refers to the water resource's properties that affect its suitability for specific uses (Rhoades and Merrill 1976).

To a great extent, waters used for irrigation purposes, qualitatively affected by the type and amount of their dissolved salts (Nakhaei et al. 2019). Though salts are found in relatively low agricultural soils, they can increase due to the dissolution of certain rocks, including carbonate and evaporite rocks (Ravikumar and Somashekar 2010). Thus, using various indices for simultaneously detecting several dissolved ions in soils has led to classification methods for determining groundwater suitable for agricultural purposes. Accordingly, based on the selected parameter, each method can rank the groundwater quality (Ostovari et al. 2015). Some of these indices and their related classification methods are sodium percentage (Na%), Electrical Conductivity (EC), Sodium Adsorption Ratio (SAR), Magnesium Ratio (MR), Residual Sodium Carbonate (RSC), Potential Soil Salinity (Ghanbarian et al. 2015), general soil classification or Kelly's ratios (Kelley 1951), pH, and Corrosion Rate (CR). Numerous studies attempted to examining or zoning groundwater quality for agriculture purposes by considering the relevant quality classification indices (Abera et al. 2021; Adimalla et al. 2020; Kumari and Rai 2020; Mortazavi Chamchali et al. 2021; Singh et al. 2020; Yurtseven and Randhir 2020).

In the recent decade, the applications of geographic information system (GIS) have increased in many studies all around the world (Hamzaoui-Azaza et al. 2020; Hasan and Rai 2020; Moghimi Kandlousy et al. 2016; Mohebbi Tafreshi and Mohebbi Tafreshi 2017; Muniz et al. 2020; Zhou et al. 2020). In some of these studies, a GIS-based multi indices method were used in combining with commonly used and well-known techniques such as AHP (Ghosh et al. 2020; Mega and Khechana 2021; Mohebbi Tafreshi and Mohebbi Tafreshi 2021; Saha and Paul 2021), ANP (Ahmadee 2018; Mokarram et al. 2019), TOPSIS (Gorgij et al. 2019; Liu et al. 2019; Moghimi Kandlousy et al. 2018; Seifi and Soroush 2019), and the hybrid form of WQI (Adimalla and Taloor 2020; El Mountassir et al. 2020; Fang et al. 2020; Singh et al. 2018).

Performing the qualitative classifications is always accompanied by uncertainty. Therefore, it is vital to use an applicable method that fixes this shortcoming, and FL can do it. This method is based on the fuzzy set theory presented by Zadeh (1965). It is used extensively in poorly definable engineering applications and allows flexible standardization and aggregation by partial membership. Several works worldwide used fuzzy modeling in water quality assessment based on developing water quality indices (Gholami et al. 2017; Jha et al. 2020; Kisi et al. 2019; Vadiati et al. 2019) or in the other purposes that are near to aim of our study (Akumu et al. 2015; Azimi et al. 2018; Hellwig et al. 2017; Lee et al. 2019).

Since the hybrid form of indices methods in combination with FL (Adimalla 2020; Haider et al. 2017; Jalalkamali and Jalalkamali 2018; Mohebbi Tafreshi et al. 2021a; Selvaraj et al. 2020; Zhang et al. 2021) are more efficient and accurate in comparison with the non-hybrid methods (Mohebbi Tafreshi et al. 2020b), this form of the fuzzy-multi indices was used. Using these hybrid techniques is beneficial because they can work as a widely used estimator to handle more complicated cases better than using one method (Mohebbi Tafreshi et al. 2020a).

Assessing literature shows that there has been no research (or limited researches) that used together from described quality indices for the assessment of suitable IW. Accordingly, this study aims to provide a novel GIS-based approach to assessing suitable IW using a fuzzy-multi indices method.

Study area

The study area (375000-430000N and 4100000-4150000E) is located in the 39N zone of the UTM coordinate system, in the north of Gilan province, Iran (Fig. 1). The maximum average long-term annual rainfall in the study area is about 1300 mm (Rahnama et al. 2020). The southern parts comprise

volcanic rocks, masses of metamorphic and sedimentary conglomerate outcrops (Fig. 2). The aquifer's constituent materials are deltaic and alluvial sediments of the Sefidrood River which the grain particles are large and create better conditions in terms of quantity and quality in the southern parts (Arezooman omidi langrudi et al. 2015; Rahnama et al. 2020). The rivers and groundwater direction in the area is the same; from the south towards the north (Caspian Sea).

Regarding land use, a vast area of the studied region is devoted to irrigated agriculture. Thick forests cover the land in the southern parts. Peanut orchards and rice farms are the main agricultural activity (Fig. 3).

Data collection and preparation

To calculating the irrigation indices, the qualitative parameters from 19 sampling wells in the wet (September) and dry (February) seasons of 2017 were performed in the study area. The parameters such as pH, total dissolved solids (TDS), and electrical conductivity (EC) were measured with a multiprobe. The samples were analyzed at the Chemistry Laboratory of Gilan Regional Water Authority (GRWA). The quantity of the samples' main anions and cations was measured using flame photometry and titration methods. Table 1 lists the statistical analysis of the measured parameters for determining the water samples' quality in dry and wet seasons. Except for EC (micromhos/cm) and pH (which is a dimensionless parameter), all other parameters were measured in meq/l).

Table 1
statistical characteristic of the chemical components in wet and dry seasons

WET SEASON										
Parameter	EC	PH	Ca	Mg	Na	K	HCO_3	CO_3	Cl	SO_4
Arithmetic mean	1207.2	7.36	6.61	1.7	3.6	0.19	6.14	0	3.91	1.96
Standard Deviation	277.74	0.12	1.61	0.72	1.51	0.25	0.98	0	1.7	1
Variant Coefficient (%)	23.01	1.63	24.36	42.35	41.94	131.58	15.96	-	43.48	51.02
Maximum	1531	7.57	8.5	3.42	5.57	1.06	7.56	0	5.9	3.99
Minimum	550	7.1	2.43	0.9	0.67	0.03	3.69	0	0.35	0.27
Mode	-	7.43	8.1	1	4.56	0.09	5.76	0	4.1	-
Median	1279	7.4	6.68	1.51	4.13	0.09	6.3	0	4.6	2.2
Range	981	0.47	6.07	2.52	4.9	1.03	3.87	0	5.55	3.72
Skewness	-0.88	-0.44	-1.02	1.33	-1.01	2.81	-0.79	0	-1.09	-0.04
Variance	77139	0.01	2.61	0.52	2.29	0.06	0.95	0	2.89	1
DRY SEASON										
Parameter	EC	PH	Ca	Mg	Na	K	HCO_3	CO_3	Cl	SO_4
Arithmetic mean	906.68	7.62	3.46	1.78	3.71	0.06	3.34	0	4.28	1.35
Standard Deviation	300.67	0.32	1.22	0.71	1.63	0.03	0.7	0	1.91	0.91
Variant Coefficient (%)	33.16	4.2	35.26	39.89	43.94	50	20.96	-	44.63	67.41
Maximum	1430	8.02	6.84	2.84	6.26	0.11	4.5	0	7	2.98
Minimum	326	6.92	1.57	0.35	0.63	0.01	2.07	0	0.4	0.15
Mode	983	7.53	-	-	3.61	0.03	3.24	0	-	2.21
Median	975	7.61	3.59	1.82	3.62	0.07	3.32	0	4.45	1.44
Range	1104	1.1	5.27	2.49	5.63	0.1	2.43	0	6.6	2.83
Skewness	-0.53	-0.62	0.9	-0.59	-0.39	-0.14	-0.1	0	-0.64	0.23
Variance	90405	0.1	1.49	0.5	2.65	0	0.49	0	3.66	0.83

Methodology

To achieve the aim of this study, several steps were applied as follows:

Calculate and classification of irrigation water quality indices

To assessing the groundwater quality for agricultural purposes, we must use the indices that examine water quality for this purpose. For example, salt content in soil is an excellent 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 IWs is usually determined by measuring soil electrical conductivity (EC) in micromhos/cm (Meybeck 1987). Like other cations, sodium reacts with soil clays, and substituting the Ca and Mg ions decrease soil permeability and lower 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 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 the residual sodium carbonate hazard. High levels of carbonate and bicarbonate ions increase soil RSC, whereas Ca and Mg ions reduce this index. Carbonate and bicarbonate ions react with Ca and Mg ions to form $MgCO_3$ and $CaCO_3$ sediments. As a result of this reaction, the 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 measured Na's ratio 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 identified as an indicator of reduced permeability. KR can also be used as a measure for warning against increased water alkalinity (Handa 1981). Increased Mg levels in groundwater would increase Na's destructive effects in soils with high Mg levels (or if waters containing high Mg levels are used). Increased Mg levels would gradually decrease plant water absorption capacity due to increased cation exchange. MR is used as an index for assessing magnesium hazards in groundwater (Grattan 1994). pH value is among the important parameters used for evaluating agricultural water quality (Bashir et al. 2013). The suitable pH range for irrigation use is from 6.5 to 8.4 (Bauder 2010). Corrosion is an electrolyte process occurring at metal surfaces, leading to the destruction and perforation of metallic walls. This problem mainly 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 evaluating 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 (1975) argued that even dissolved Salinity could increase soil salinity, thus creating agriculture problems. Potential Salinity as chloride concentration plus half sulfate concentration. Table 2 shows classifications of indices and parameters described in this section.

Table 2 Summary ofwater 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	$SAR = \frac{Na^{+}}{\frac{Ca^{2+} + Mg^{2+}}{2}}$	<10 = Excellent 10-18 = Good 18-26 = Fair >26 = Poor
Na%	Soluble sodium percentage	$Na\% = \frac{Na^{+} + K^{+}}{Na^{+} + K^{+} + Mg^{+} + Ca^{+2}} \times 100$	<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	$CR = \frac{\frac{Cl^{-}}{35.5} + 2\frac{SO_4^{2-}}{96}}{2\frac{HCO_3^{-} + CO_3^{2-}}{100}}$	<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

Indices standardization with fuzzy membership functions

The first step in the Fuzzy model is the standardization of the parameters with FMFs. According to fuzzy set theory, a range of values between 0 and 1 can express a set's members' value. A fuzzy set refers to a cluster whose membership of all its members, unlike double (Boolean) and triple logics, is not entirely straightforward and whose elements belong relatively to a setting that is between 0 and 1. The fuzzy method evaluates each layer's membership in terms of its value. It considers the higher value points in the map, the appropriate location, and the lower value points as inappropriate points. Thus, a value of 0 means no full membership, and a value of 1 means full membership of the group members. Other collection members can also receive values between 0 and 1, depending on the degree of certainty of their membership in the collection and to themselves. Version 10 and above of ArcGIS software have several FMFs available in FL extension which is commonly used in many FL applications (Raines et al. 2010). Usage of any of the functions to the fuzzification concerns each criterion's identity, importance, and relationship with the goal. The application of any of these

functions is according to the midpoint and spread indices. In this study, each function's midpoint selects according to parameter classification shown in Fig. 4. For standardization of the indices, three FMFs were employed that describes in the following section:

Fuzzy Gaussian: This function sets the input values as a normal distribution between zero and one. To execute this function, a numeric value called midpoint must normalize the input data between zero and one by taking the midpoint value normalizing the larger and smaller values to one and zero asymmetrically, respectively (Nakhaei et al. 2021; Raines et al. 2010).

Fuzzy Small: It is another fuzzy function that attempts to normalize input data. In this way, it needs a numeric value called midpoint that considers the median value or midpoint in the normal distribution diagram 0.5 and sets the values less than the midpoint to one and the values above the midpoint to zero (Raines et al. 2010).

Fuzzy Linear: This function sets the primary data linearly between zero and one (Nakhaei et al. 2021). The value of zero is allocated for the minimum data, and the value of one is assigned for the maximum data. In this function, two minimum and maximum values are required (Rahnama et al. 2020).

Aggregation indices with fuzzy overlay operations

In this step, the factors that were fuzzified are used, and the fuzzy overlap is applied. This step is located in the ArcGIS software inside the Fuzzy Overlay tool. The essential fuzzy rules used in this step include AND, OR, PRODUCT, SUM, and GAMMA. These fuzzy overlay operations (Fig. 5) will be explained as below:

Fuzzy AND: The operator's output will be the minimum so that it will select the least value among several layers that are overlaid on top of each other. That is, it extracts the minimum membership degree (Zadeh 1965).

Fuzzy OR: This operator operates precisely the opposite of the AND operator and selects the maximum membership among the fuzzy member's inputs (Zadeh 1965).

Fuzzy PRODUCT: The fuzzy membership values combined with this operator tend to be very small due to its multiplication properties. Because in this operator, several fuzzy inputs between zero and one are multiplied by each other (Zadeh 1965).

Fuzzy SUM: The output of this operator is utterly opposed to the PRODUCT operator. This operator's result is always greater than or equal to the largest value of the fuzzy membership. Therefore, this operator has an incremental mode (Zadeh 1965).

Fuzzy GAMMA: This operator is defined in terms of multiplies the "Fuzzy SUM" to the "Fuzzy PRODUCT" in the power of gamma (γ) (Lewis et al. 2014). When γ is selected as 1, the output will be the same as the "Fuzzy SUM", but when this parameter is selected as 0, the composition will be the product of the same "Fuzzy PRODUCT" (Bonham-Carter 2014).

Result And Discussion

Calculation of the irrigation indices

Based on the results obtained from Table 1 and according to Table 2, the water quality classification indices for irrigation were calculated from major groundwater ions (Fig. 6) and listed in Table 3. As shown in Table 3, the quality of indices for agriculture purposes was classified as excellent in the following indices: MR (except w6 in the dry season), SAR, Na% (just w16 and w18 in dry and w7, w15, and w19 in wet seasons), RSC, pH, KR (except w4 and w13 in the dry season), and CR (just w16 and w18 in dry and w7, w15, and w18 in wet seasons). Accordingly, w18 has the best, and w4 and w13 have the worst quality for irrigation purposes among other sample wells in dry and wet seasons, respectively.

Table 3
The important parameters and indices which determine the IW quality of the study area in wet and dry seasons

DRY SEASON									
Sample	RSC	Na%	MR	KR	PS	SAR	CR	EC	pH
W1	-1.30	33.29	31.83	0.48	3.45	1.59	1.24	829	7.08
W2	-2.91	42.05	32.35	0.72	6.86	2.70	2.48	1234	6.92
W3	-2.67	37.78	34.53	0.59	5.45	2.07	2.40	983	7.97
W4	-0.61	55	48.07	1.20	6.03	3.57	2.25	983	7.47
W5	-3.11	42.34	33.74	0.72	6.02	2.44	3.53	994	7.96
W6	-0.76	46.39	62.88	0.85	4.05	2.48	1.69	784	7.45
W7	-0.61	41.93	29.75	0.71	4.20	2.26	1.34	896	8.02
W8	-2.92	38.7	40.71	0.62	6.28	2.19	2.82	1050	7.70
W9	-2.70	37.74	42.48	0.59	5.32	2.06	2.36	975	7.48
W10	-1.47	38.29	42.59	0.61	3.80	1.80	1.95	706	7.53
W11	-1.51	42.98	31.73	0.74	4.62	2.40	1.90	911	7.98
W12	-1.26	40.55	40.22	0.68	3.88	2.03	1.78	764	8.01
W13	-2.44	53.4	27.03	1.13	7.80	3.76	3.77	1211	7.88
W14	-3.73	43	15.56	0.75	8.38	3.00	2.91	1430	7.81
W15	-3.69	47.42	29.31	0.90	7.69	3.16	4.70	1198	7.61
W16	-0.50	19.94	13.62	0.25	0.92	0.56	0.71	326	7.69
W17	-3.69	41.42	40.98	0.70	7.11	2.59	3.32	1173	7.53
W18	0.09	19.69	18.63	0.24	0.51	0.58	0.25	375	7.55
W19	-0.36	36.68	23.81	0.57	1.76	1.27	1.20	405	7.17
WET SEASON									
Sample	RSC	Na%	MR	KR	PS	SAR	CR	EC	pH
W1	0.51	42.23	18.55	0.72	3.13	2.36	0.78	936	7.57
W2	-3.36	32.74	13.38	0.48	6.31	2.04	1.70	1360	7.28
W3	-2.90	30.33	18.59	0.42	5.61	1.74	1.49	1239	7.44
W4	-1.07	41.27	19.67	0.69	6.04	2.65	1.36	1256	7.25
W5	-2.97	32.01	15.34	0.46	6.12	2.01	1.45	1382	7.43
W6	-0.63	36.75	28.57	0.57	3.78	2.03	1.00	988	7.33
W7	-1.09	14.66	13.21	0.11	1.84	0.45	0.45	877	7.45
W8	-3.15	30.77	18.58	0.44	6.59	2.00	1.37	1517	7.10
W9	-2.97	27.62	35.19	0.37	5.35	1.64	1.24	1335	7.15
W10	-3.24	39.03	16.61	0.61	6.90	2.61	1.89	1480	7.34
W11	-3.47	29.91	23.32	0.42	6.59	1.96	1.38	1531	7.26
W12	-2.34	31.08	13.46	0.44	5.25	1.91	1.16	1355	7.45
W13	-3.13	34.29	16.97	0.51	6.67	2.22	1.63	1433	7.43
W14	-2.34	31.91	18.18	0.46	5.47	2.05	1.15	1469	7.25
W15	-0.18	12.97	13.92	0.11	0.74	0.41	0.19	805	7.43
W16	-1.33	34.17	14.29	0.44	3.40	1.57	1.11	945	7.28
W17	-3.29	38.07	27.10	0.60	6.63	2.41	2.22	1279	7.41

DRY SEASON									
W18	-0.18	30.89	37.21	0.17	1.09	0.48	0.54	550	7.40
W19	-4.14	15.70	33.13	0.18	5.41	0.82	1.36	1200	7.50

Interpolation of calculated irrigation indices

Figure 7 shows the prepared maps of the irrigation indices by interpolation. Accordingly, medium to high anomalies was revealed in the center to north parts in most indices. It can be related to the groundwater flow's direction (south to north) and leaching of the main ions from the sediment structures upstream of groundwater streams. Furthermore, it might have been caused due to the higher density of urban areas and agricultural lands in the center to northern parts of the plain. As can be seen, the trend of index changes in the wet and dry seasons is different for some indices. This case is well visible in the central and northern regions. As can be seen, in the dry season, the maximum rates of CR, EC, KR, Na%, PS, and SAR are observed in the northeastern regions. However, in the wet season, precisely the opposite of the dry season, these indices' minimum rate is observed in described areas. It can be related to changes in the leaching rates and groundwater flow rates and ion exchanges between ions in the dry and wet seasons.

Indices standardization

Figures 8 and 9 show the fuzzy standardized IW indices according to fuzzy memberships. Because the RSC parameter has negative values, and the "Fuzzy Small" function cannot calculate these type values, the "Linear" function was used for this parameter. Considering that in the CR, KR, MR, EC, SAR, and PS indices, low values are more suitable in irrigation, the "Small" function was used to fuzzy standardize. Due to the suitability values between 6.5 to 8.5 as the appropriate range in the pH parameter, the "Gaussian" function was used. In this regard, value 7.5 was selected as the midpoint. Based on Table 2, classification values of Na% ranked linearly, and the distance of each quality class to the next class is fixed. For this reason, the "Linear" function was used for this parameter. Furthermore, because the smaller values are better suited to this index, this function's decreased form was used to fuzzy standardize.

Aggregation indices

As shown in Fig. 10, in the "SUM" and the "OR" overly operations, the highest values of membership were selected that indicates they are expander operations. On the contrary, in the "PRODUCT" and the "AND" overly operations, the lowest membership's values were selected. This means they are restrictive operations. However, the "PRODUCT" is more restrictive than the "AND" function because the multiplication of the standardized indices less than one has lower values than the value of the standardized parameters (Lewis et al. 2014).

Figure 11 showed that in the "GAMMA" overlay operation, an increase in "γ" value caused the higher accuracy. In contrast to our results, some authors (Araya-Muñoz et al. 2017) believe that "γ" values above 0.7 cause to decline in the accuracy. However, our results were confirmed by the research of Lewis et al. (2014), Mohebbi Tafreshi et al. (2018), Mohebbi Tafreshi et al. (2021b), Mortazavi Chamchali and Ghazifard (2019), and Mortazavi Chamchali and Ghazifard (2020). These researches were indicated that "GAMMA 0.8" and "GAMMA 0.9" are more accurate than other overlay operations.

Identify the most accurate operation

To specify the most accurate overlay operation, the correlations between the fuzzy membership and operation maps were used. For this purpose, the "Band collection statistics" tool in ArcGIS software was used.

Despite the relatively good correlation of most membership functions with overlapping operators, the lowest correlation is F-pH and F-MR in both dry and wet seasons (Table 4). However, contrary to the better trend of correlations in the dry season, for these two parameters, the correlation values are higher in the wet season.

Table 4
The correlation between the "Fuzzy membership" and "Fuzzy overlay" raster maps. 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 indices and the "SUM", AND", OR, PRODUCT", the "GAMMA 0.1", the "GAMMA 0.2", the "GAMMA 0.3", the "GAMMA 0.4", the "GAMMA 0.5", the "GAMMA 0.6", the "GAMMA 0.7", the "GAMMA 0.8", the "GAMMA 0.9", the "GAMMA 0.95" and the "GAMMA 0.99" are fuzzy overlay raster form. The values are the correlation between the "Fuzzy membership" and "Fuzzy overlay" raster maps, and the values that have been marked with an underline, are the highest value amount in each category.

DRY SEASON										
Overlay vs. membership	F-CR	F-EC	F-KR	F-MR	F-Na%	F-pH	F-PS	F-RSC	F-SAR	SAVC
AND	0.580	0.570	0.113	0.111	0.323	0.042	0.892	-0.177	0.079	2.888
OR	0.301	0.228	0.696	-0.067	0.643	0.113	0.053	-0.488	0.812	3.401
PRODUCT	0.374	0.387	0.066	0.065	0.203	0.028	0.989	-0.109	0.045	2.268
SUM	0.003	0.003	0.042	0.016	0.027	-0.001	0.001	-0.014	0.036	0.143
GAMMA 0.1	0.413	0.435	0.075	0.073	0.227	0.030	0.988	-0.120	0.051	2.411
GAMMA 0.2	0.459	0.491	0.085	0.083	0.255	0.032	0.979	-0.134	0.058	2.576
GAMMA 0.3	0.515	0.556	0.098	0.097	0.290	0.034	0.960	-0.152	0.067	2.770
GAMMA 0.4	0.582	0.631	0.116	0.114	0.334	0.037	0.928	-0.176	0.080	2.998
GAMMA 0.5	0.663	0.716	0.140	0.139	0.391	0.041	0.878	-0.209	0.099	3.276
GAMMA 0.6	0.759	0.806	0.178	0.175	0.466	0.048	0.804	-0.261	0.130	3.628
GAMMA 0.7	0.865	0.891	0.240	0.226	0.568	0.059	0.700	-0.348	0.187	4.083
GAMMA 0.8	0.948	0.931	0.338	0.277	0.692	0.074	0.557	-0.492	0.292	4.601
GAMMA 0.9	0.936	0.860	0.464	0.277	0.793	0.083	0.383	-0.681	0.456	4.934
GAMMA 0.95	0.876	0.777	0.520	0.241	0.811	0.081	0.300	-0.766	0.546	4.919
GAMMA 0.99	0.809	0.695	0.556	0.196	0.807	0.077	0.241	-0.817	0.611	4.807
WET SEASON										
Overlay vs. membership	F-CR	F-EC	F-KR	F-MR	F-Na%	F-pH	F-PS	F-RSC	F-SAR	SAVC
AND	0.586	0.835	0.215	-0.067	0.493	0.154	0.527	-0.388	0.298	3.563
OR	0.578	0.388	0.507	-0.205	0.653	0.236	0.156	-0.234	0.815	3.771
PRODUCT	0.305	0.420	0.113	0.013	0.319	0.086	0.984	-0.222	0.151	2.611
SUM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000
GAMMA 0.1	0.330	0.447	0.122	0.013	0.341	0.092	0.984	-0.238	0.164	2.733
GAMMA 0.2	0.362	0.479	0.134	0.014	0.369	0.101	0.980	-0.259	0.181	2.878
GAMMA 0.3	0.403	0.515	0.149	0.015	0.403	0.111	0.970	-0.285	0.202	3.054
GAMMA 0.4	0.457	0.556	0.168	0.018	0.446	0.126	0.951	-0.318	0.230	3.270
GAMMA a 0.5	0.527	0.604	0.191	0.023	0.497	0.145	0.919	-0.364	0.266	3.536
GAMMA 0.6	0.617	0.655	0.216	0.032	0.555	0.172	0.868	-0.425	0.314	3.856
GAMMA 0.7	0.727	0.706	0.238	0.045	0.613	0.210	0.790	-0.507	0.372	4.209
GAMMA 0.8	0.840	0.742	0.248	0.061	0.652	0.260	0.684	-0.607	0.433	4.526
GAMMA 0.9	0.927	0.747	0.234	0.075	0.651	0.314	0.556	-0.706	0.482	4.692
GAMMA 0.95	0.951	0.736	0.218	0.080	0.632	0.339	0.491	-0.748	0.497	4.692
GAMMA 0.99	0.960	0.720	0.202	0.082	0.610	0.358	0.442	-0.775	0.504	4.653

After calculating the correlations, the SAVC of each overlay method was obtained. Accordingly, a higher SAVC amount shows the more accurate "overlay operation".

Based on the result shown in Table 4, the "GAMMA 0.9" and "GAMMA 0.95" methods with the highest SAVC are the best overlay operation in dry and wet seasons, respectively. In the following, the "GAMMA 0.95" and the "GAMMA 0.99 in the dry season, and the "GAMMA 0.9" and the "GAMMA 0.99 in

the wet season are next ranking, respectively. Comparing the results obtained in dry and wet seasons shows that the rate of adaptation of operators in the dry season is higher than in the wet season.

Conclusion

Astaneh-Kuchesfahan plain, located in the central part of Gilan province, is one of the crucial hubs of special and unique agricultural products in Iran, including rice and peanuts. Consequently, it is very significant to assess groundwater quality for irrigating these products. Accordingly, in the current study, a new hybrid approach that uses GIS-based FL and a comprehensive model that includes most water quality assessment indices for irrigation have been developed. For this purpose, nine indices that are widely using for IW quality assessment were employed. This method was obtained in four steps. 1. The calculation of irrigation indices; 2. Fuzzy standardization indices to scaling; 3. Aggregation standardized indices; 4. Identify the best overlay operation.

Based on the results obtained from the calculation of irrigation indices for each well, all sampling wells have excellent quality in RSC, SAR, and pH in both wet and dry seasons. Moreover, this has also happened for MR (except W6 that has very poor quality in the dry season) and KR (except W4 and W13 that have very poor quality in the dry season). On the other hand, PS with 84.21% in both wet and dry seasons and CR with 89.47% and 78.95% in dry and wet seasons have the worst quality, respectively. In terms of Na%, 31.58% and 73.68% of wells have good quality in dry and wet seasons, respectively. In this regard, 10.53% and 15.79% of wells have excellent quality. Eventually, in terms of EC, 78.94% and 94.74% of wells have good quality in dry and wet seasons, respectively. Accordingly, 21.06% in the dry season and 5.26% in the wet season have good quality.

For fuzzy standardization, the "Small" (for the CR, KR, MR, EC, SAR, and PS indices), decrease form of the "Linear" (for Na% and RSC), and the "Gaussian" fuzzy memberships (for the pH parameter) were used. In the aggregation indices step, the "OR", the "AND", the "PRODUCT", the "SUM", and the "GAMMA" (with various values) fuzzy overlay functions were used.

The correlation between the "Fuzzy membership" and "Fuzzy overlay" raster maps showed that GAMMA 0.8 for F-CR and F-EC, OR for F-KR, F-pH, and F-SAR, GAMMA 0.9 for F-MR, GAMMA 0.95 for F-Na%, PRODUCT for F-PS, and GAMMA 0.99 for F-RSC have the highest correlation in the dry season. In this regard, GAMMA 0.99 for F-CR, F-pH, and F-RSC, OR for F-KR, F-MR, F-Na%, and F-SAR, AND for F-EC, GAMMA 0.99 for F-pH, and PRODUCT for F-PS have the highest correlation in the wet season. Despite these results, the overall accuracy based on SAVC showed that GAMMA 0.9 and GAMMA 0.95 are the most accurate overlay function in dry and wet seasons, respectively.

From the regional assessment of water quality for irrigation purposes viewpoint and according to best overlay function, in the dry season, 93.15%, 5.91%, 0.86%, and 0.08% of the study area have very poor, poor, moderate, and good quality, respectively. Accordingly, in the wet season, 85%, 14.2%, and 0.8% of the study area have poor, medium, and good quality, respectively.

Water quality for irrigation purposes in the Astana-Kuchesfahan plain is very poor to poor, and poor to moderate in dry and wet seasons, respectively. According to the best overlay map, the dry season was found to have higher accuracy than the wet season.

The approach used in this research can provide a more comprehensive view based on more agricultural parameters and indices and make it easier to decide on water quality for irrigation purposes.

Declarations

Ethical Approval

The manuscript is not submitted to any other journal for simultaneous consideration. The work is original and not published elsewhere.

Consent to Participate

Not applicable

Consent to Publish

Not applicable

Competing interests

The authors declare no competing interests.

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Contributions

Conceptualization, methodology: G. Mohebbi Tafreshi and A. Mohebbi Tafreshi; software, validation, formal analysis, investigation: A. Mohebbi Tafreshi; writing: G. Mohebbi Tafreshi and A. Mohebbi Tafreshi; visualization; G. Mohebbi Tafreshi; supervision: G. Mohebbi Tafreshi.All authors read and approved the final manuscript.

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Conflict of interest

The authors declare that they have no conflict of interest.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

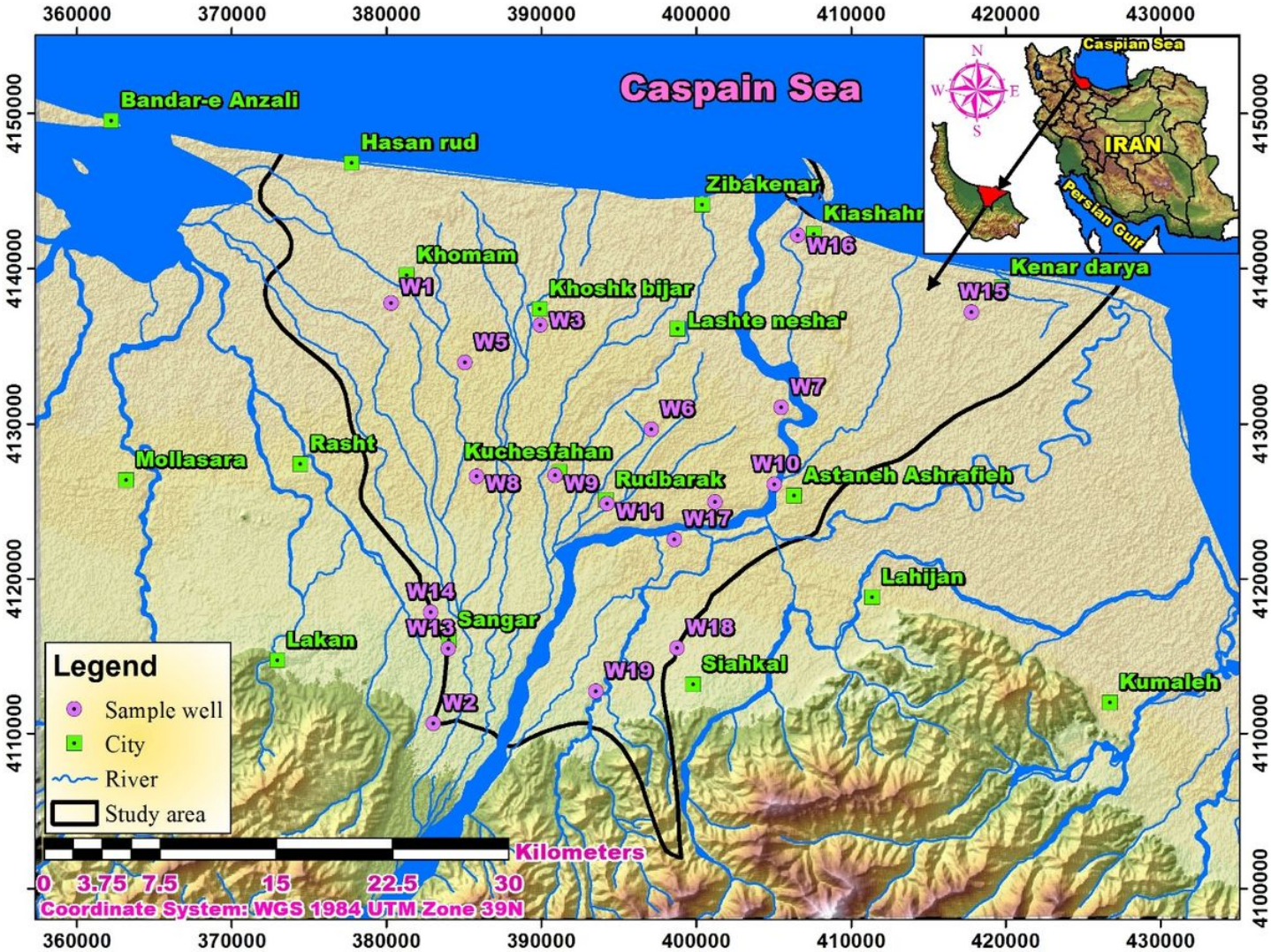

Figure 1

The location of the study area

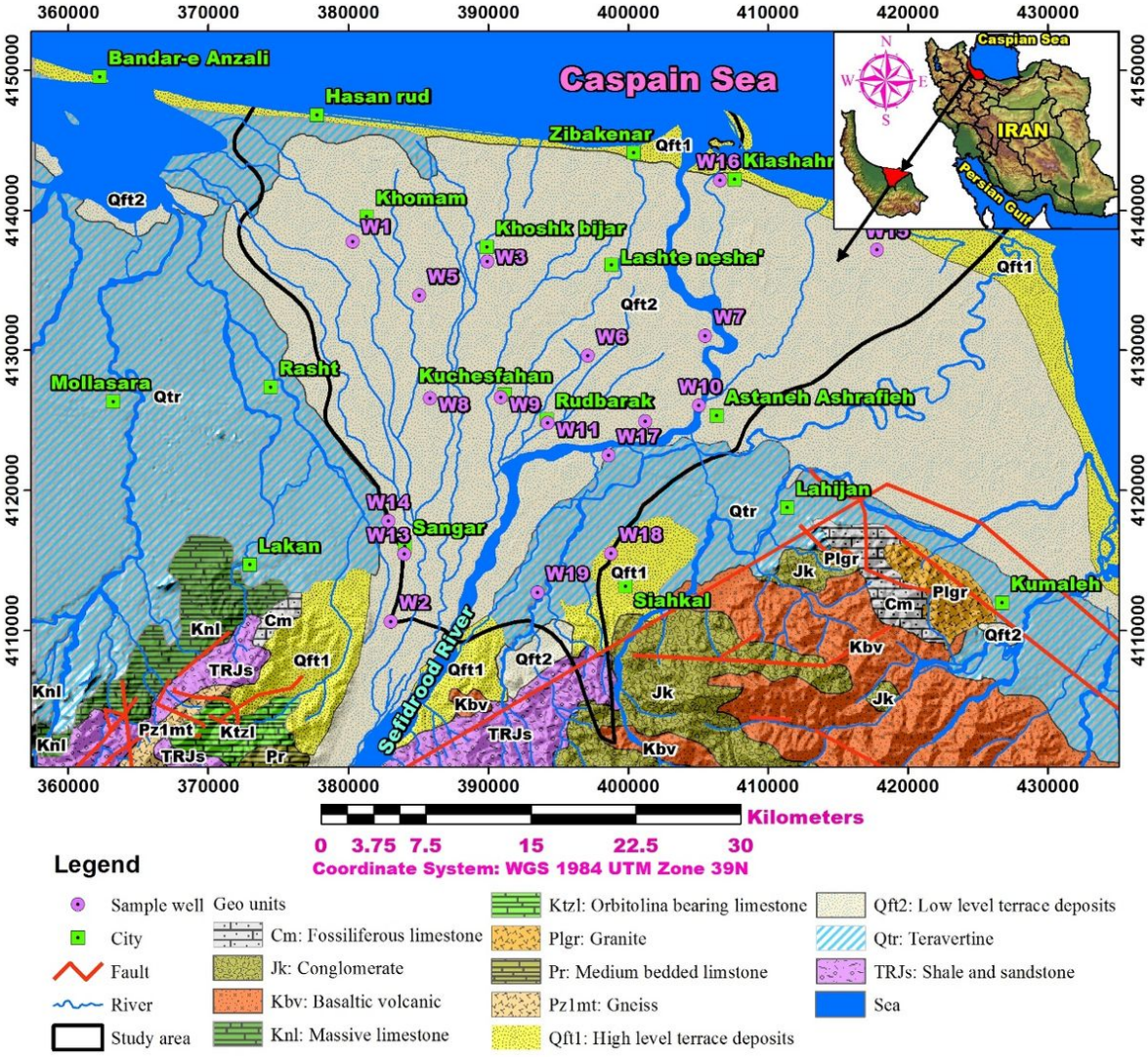

Figure 2

The Geologicalmap of the study area

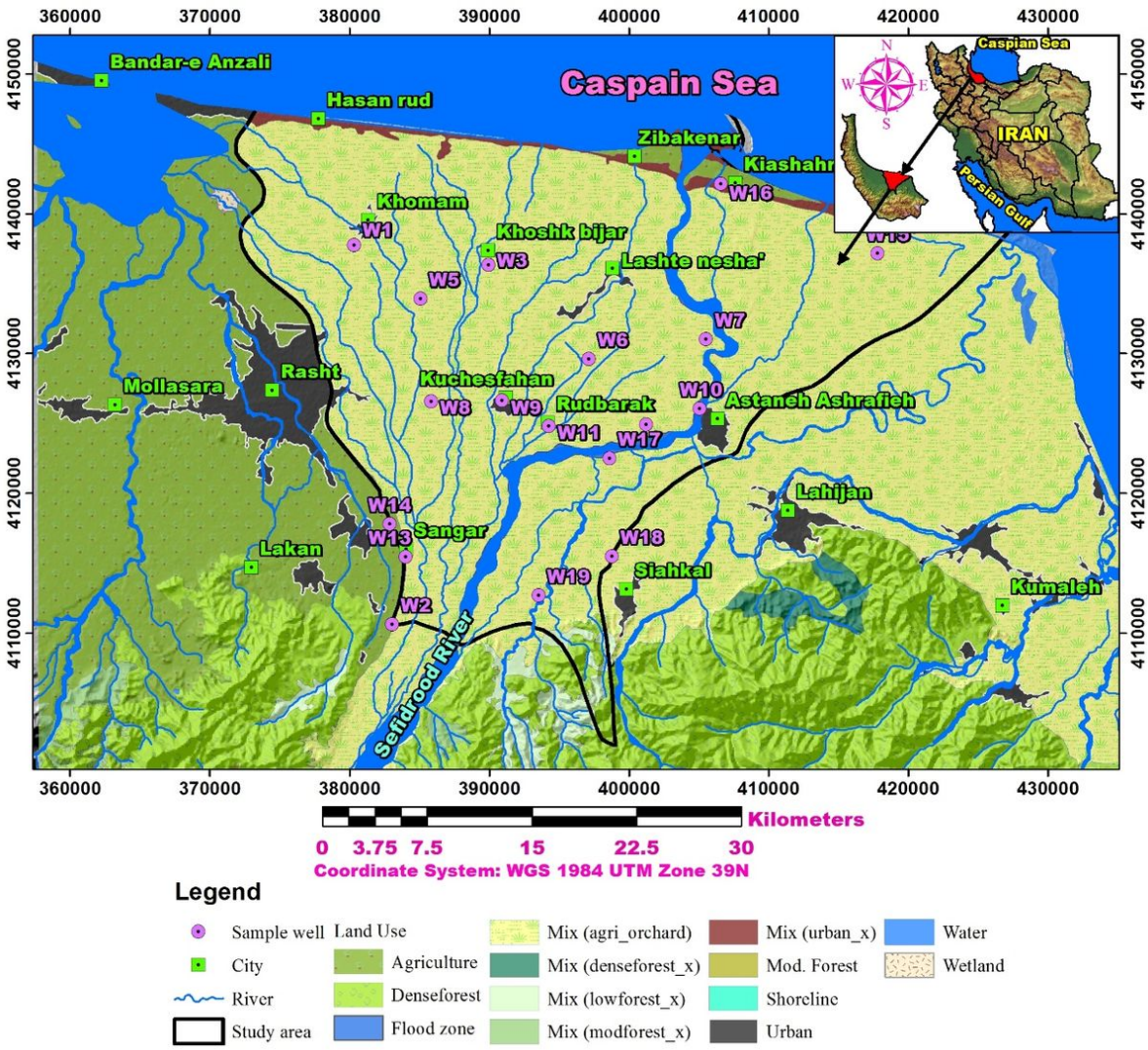

Figure 3

The land use map of the study area

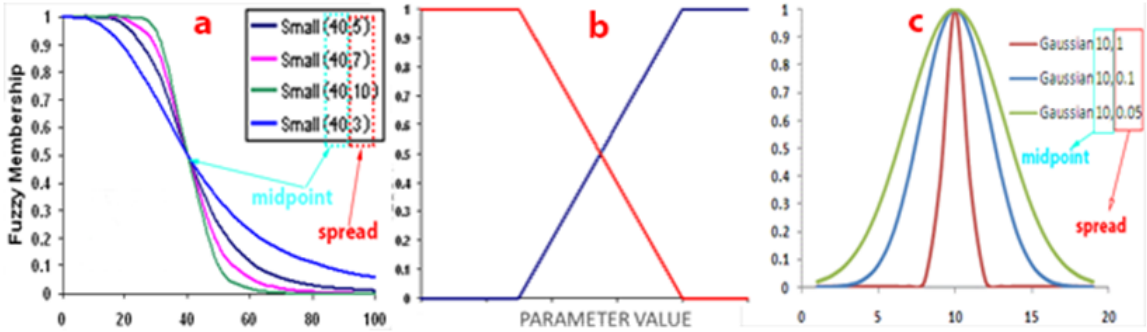

Figure 4

Fuzzy membershipsdiagrams; a: Small, b: Linear, c: Gaussian (Raines et al. 2010).

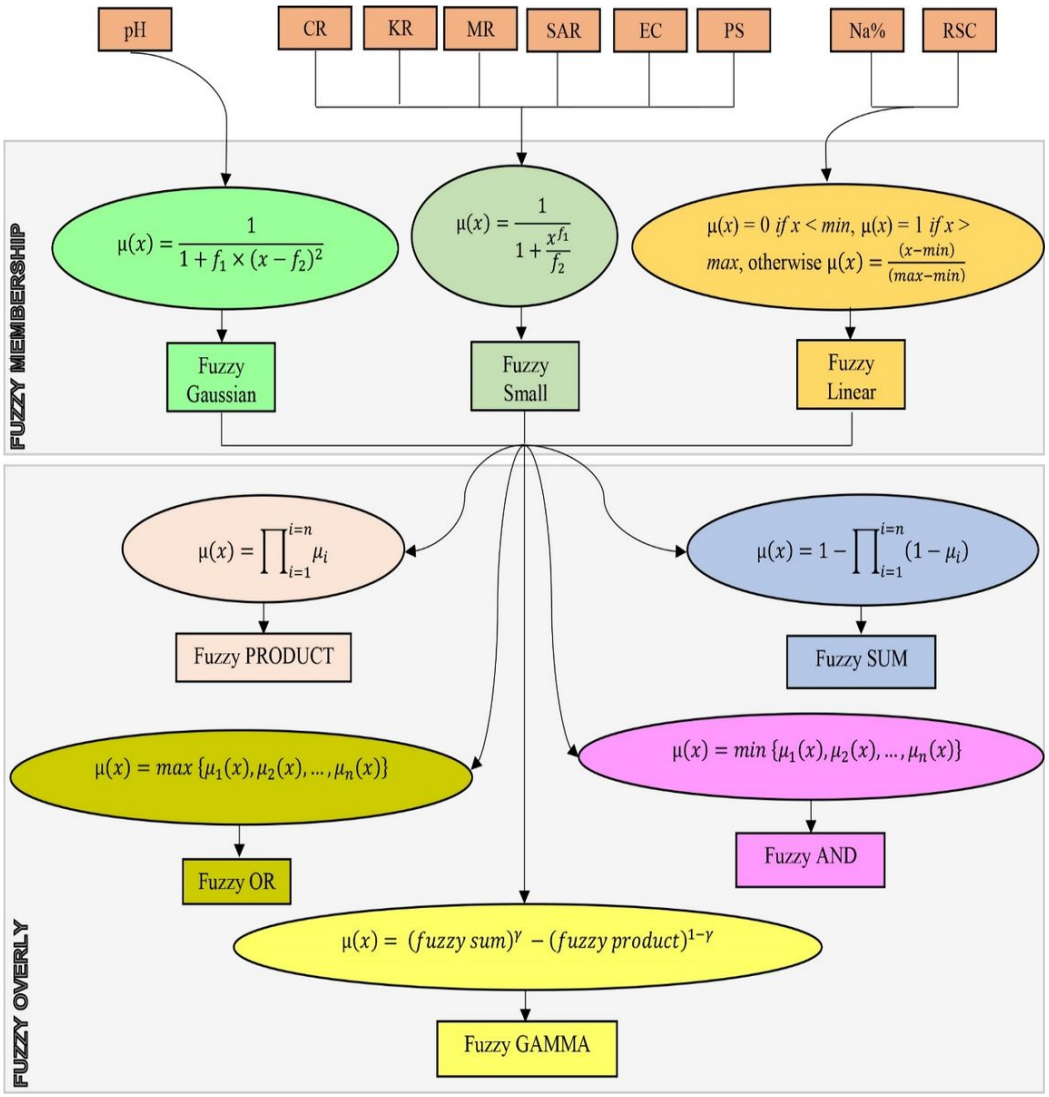

Figure 5

Fuzzy suitability model for IW quality classification. In this figure, RSC, Na%,MR, KR, PS, SAR, CR, EC, and pH areIW quality indices, user inputs f_1 is the spread andf_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 the power of gamma and input by the user.

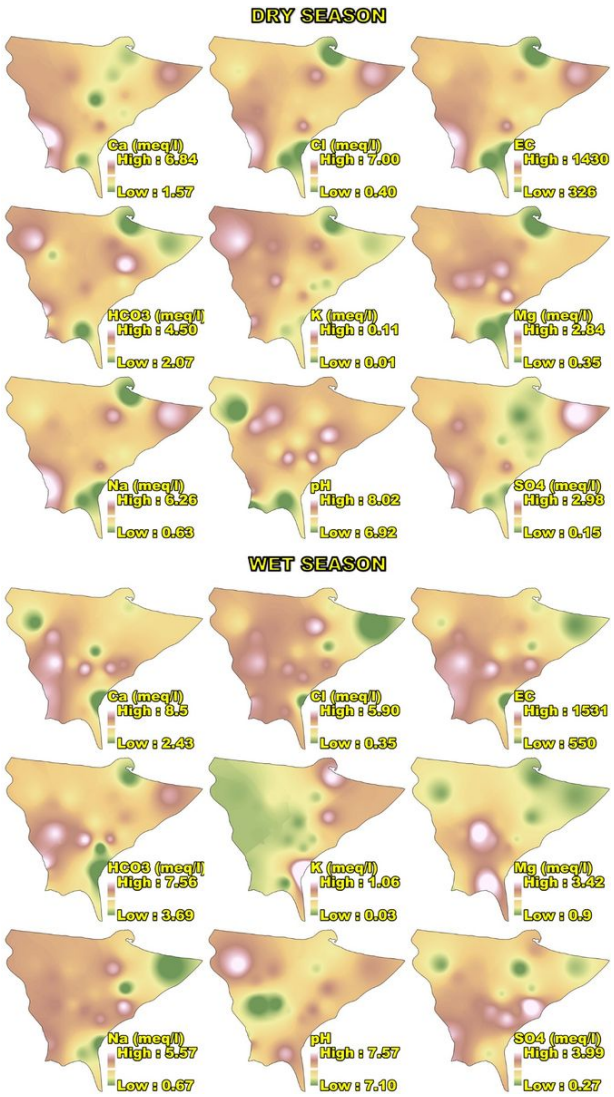

Figure 6

Interpolated maps of the concentration of significant groundwater ions in dry and wet seasons

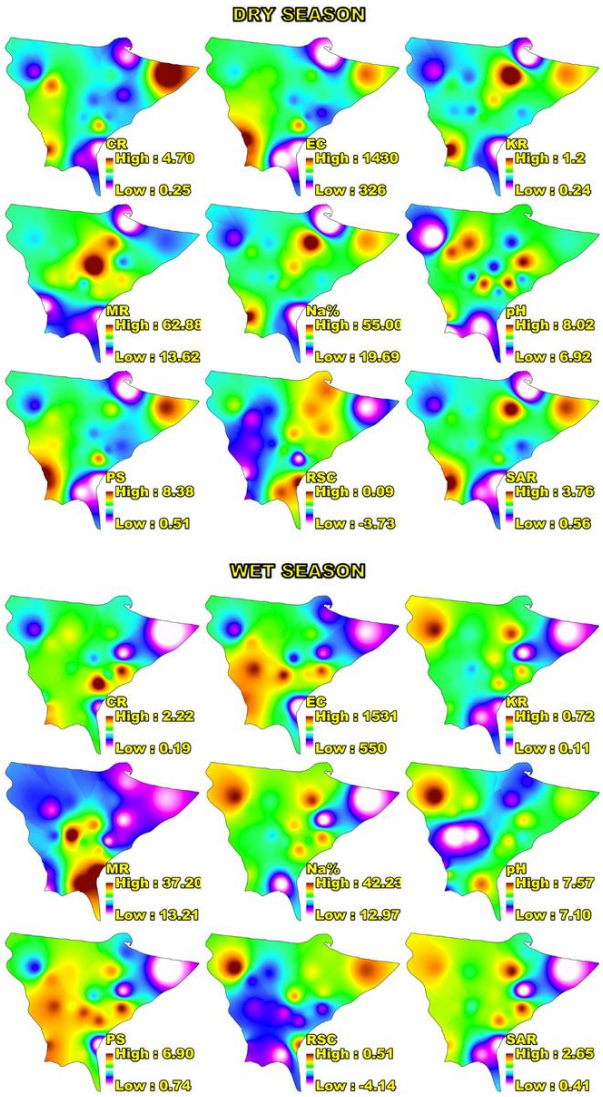

Figure 7

The interpolatedIWindices in dry and wet seasons

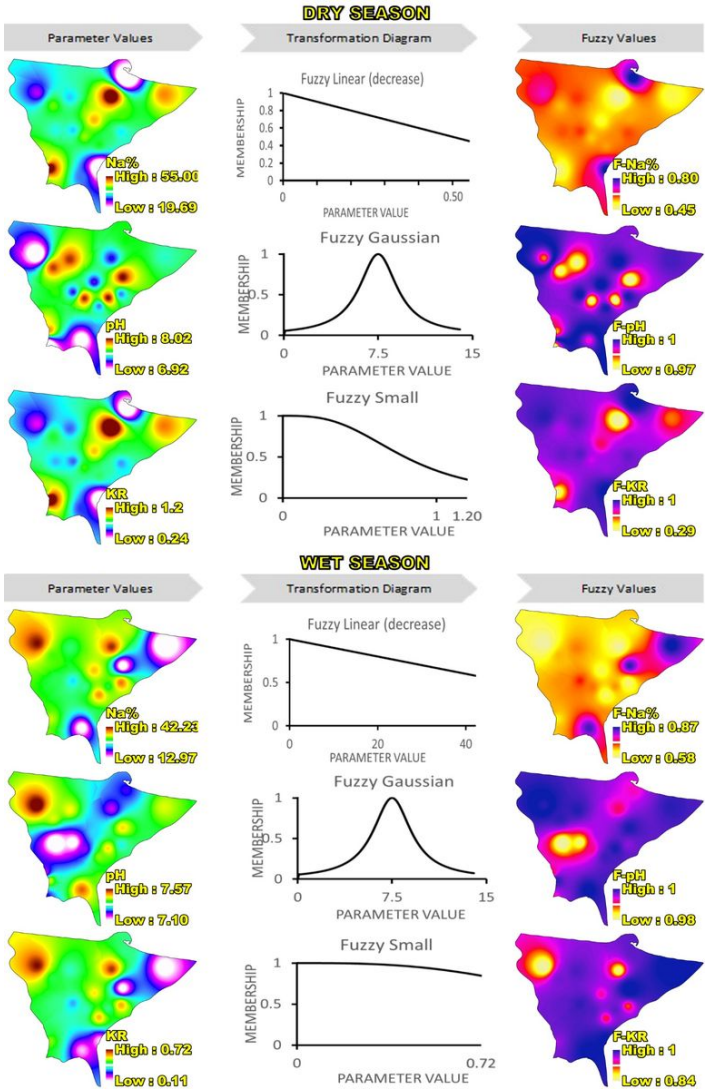

Figure 8

The procedure of fuzzy standardization using fuzzy "Linear", "Gaussian", and "Small" membership functions

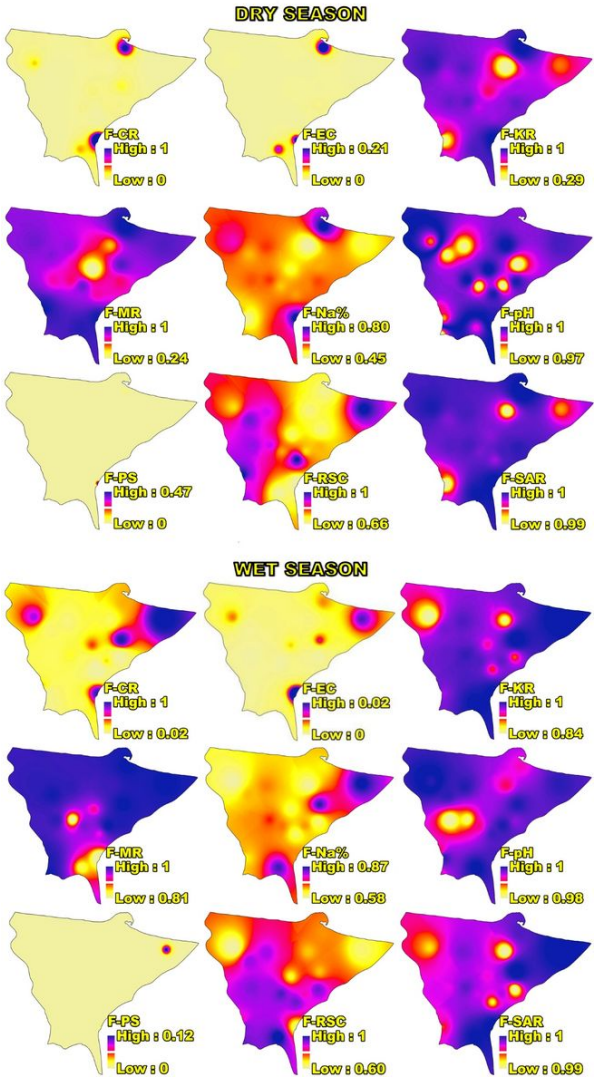

Figure 9

Fuzzy standardizedIWindices in dry and wet seasons

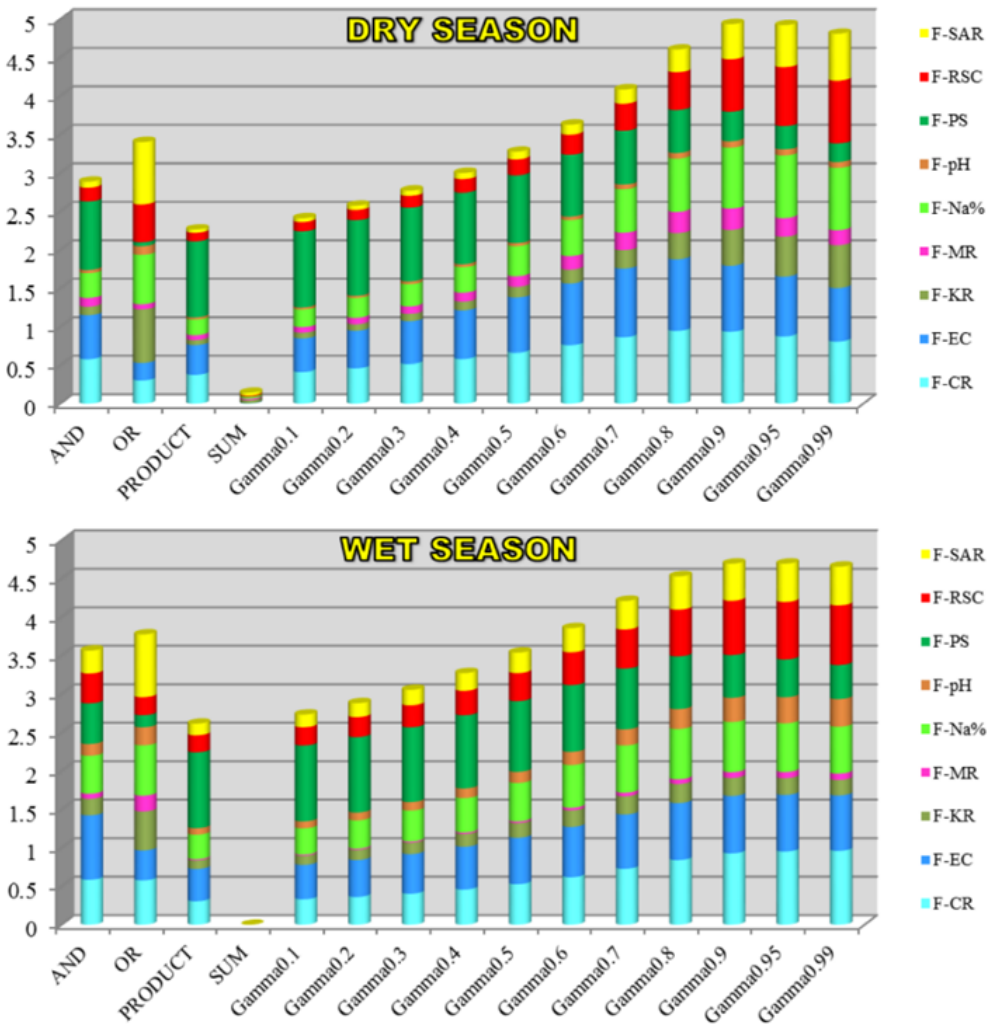

Figure 10

Identifying the most accurate operation according to SAVC in dry and wet seasons

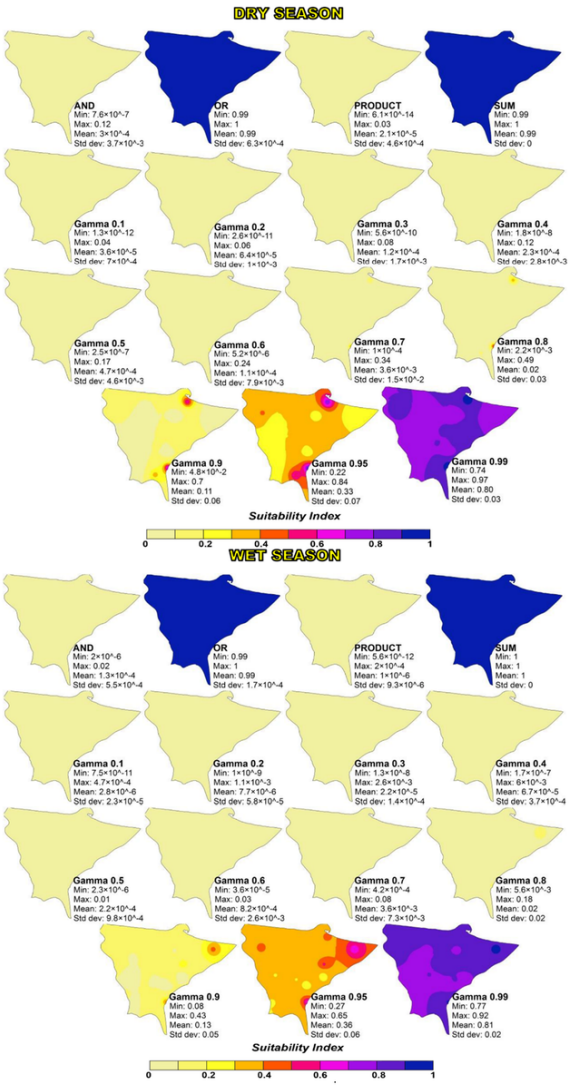

Figure 11

Thefuzzy overlay function maps indry and wet seasons

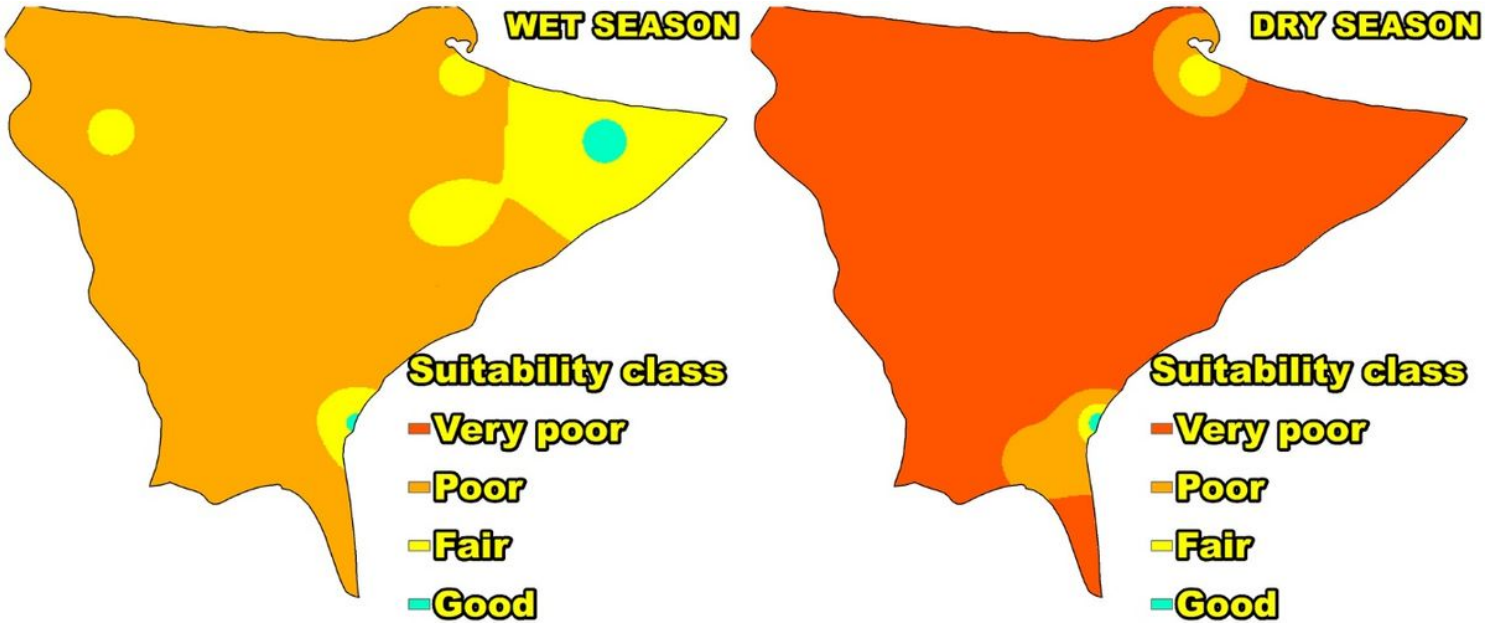

Figure 12