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Evaluation and Mapping Water Wells Suitability for Irrigation Using GIS in Darb El-Arbaein, South Western Desert, Egypt

[1]El-Sayed Ewis Omran, [2]Ahmed Ghallab, [2]Salman Selmy and [3]Abd-Alla Gad

[1]Department of Soil and Water, Suez Canal University, Ismailia, Egypt
[2]Department of Soil and Water, Faculty of Agriculture, Assiut University, Assiut, Egypt
[3]Natonal Authority for Remote Sensing and Space Science, Cairo, Egypt

Abstract: The objective of this study was to propose a simple method to assess the water quality and to map their spatial variation in terms of suitability for irrigation in Darb El-Arbaein area. 36 surveyed wells with GPS data were used to assess and map the water quality. Multivariate Factor Analysis/Principal Component Analysis was used in order to develop a water quality index (WQI). The results of analyses had been used to map and predict models for water quality. The ordinary Kriging (OK) method was applied to produce the spatial patterns of water quality. Based on these results, the distribution pattern of water quality parameters such as EC, Cl^- and SAR were produced. The results showed that Circular semivariogram model was best fitted for chloride and Cd parameters where spherical model fitted best for Ni and Zn parameters. Stable semivariogram model was best fitted for Pb and SAR parameters while J-Bessel model fitted best for EC parameter. High salinity was due to high chloride concentration in the water. Three of the 36 water samples felt in the moderate WQI. Most of the samples (26) felt in the Doubtful WQI category. Seven samples felt in the higher WQI category. Water samples that felt in the low salinity hazard class and high WQI can be used for irrigation of most crops and the majority of soils. The WQI for the samples ranged from 47.9 to 88.6. The irrigation water quality index distribution maps delineated an area of 266.66ha were suitable for irrigation in village 3-4 and area of 382.35 ha were moderate suitability in village 1-2.

Key words: Darb El-Arbaein · GIS · Water quality · Kriging · Water quality index · Suitability

INTRODUCTION

Groundwater quality evaluation in the developing countries has become a critical issue due to fresh water scarcity. The quality of groundwater is equally important as that of quantity. Assessment of aquifers vulnerability to pollution is necessary for the feasibility and development analysis, planning management and land use decisions. Two major techniques for groundwater protection strategies are groundwater vulnerability assessment and groundwater quality mapping. Groundwater quality mapping is one of the major techniques which provide the information about the water suitability for irrigation. Water Quality Index (WQI) is a very useful and efficient method for assessing the suitability of water quality and for communicating the information on overall quality of water [1-4] to the concerned decision-makers. Many researches and projects have been conducted to assess water quality [5]. Shihab and Al-Rawi [6] and Al-Hussain [7] used WQI as a management tool for water quality of Tigris River within Mosul City for different uses. Debels, *et al*. [8] had used a modified water quality index that is composed of physicochemical parameters for evaluating the quality status of a river in Central Chile. Numaan [9] established irrigation WQI for Tigris River between Al-Sharqat and Alboajeel in Iraq. Bhatti and Latif [10] used water quality index to assess the water quality of Chenab River in Pakistan for irrigation use. Fulazzaky [11] assessed the status and the suitability of the Citarum River water in Malaysia for agriculture use. Meireles *et al*. [12] classified water quality in the Acarau Basin, in the North of the state of Ceara, Brazil for irrigation use.

Corresponding Author: El-Sayed Ewis Omran, Department of Soil and Water, Suez Canal University, Ismailia, Egypt.
E-mail: ee.omran@gmail.com.

Pollution of water has become a thing of health concern both in urban and rural areas [13]. Parameters that generally need to be considered for modeling WQI are for example EC, pH, B, Na^+, Cl^- and HCO_3^-. Specific properties in water Residual Sodium Carbonate (RSC) and SAR may be suitable or unsuitable for irrigation. The information on concentrations of some important heavy metals (Cu, Zn, Pb, Cr and Cd) are necessary to assess their suitability for irrigation. Many studies have successfully used interpolation techniques with the use of the ArcGIS Geostatistical tool [14, 15, 16]. The soil heavy metal concentrations (Cu, Zn, Pb, Cr and Cd) in paddy fields were estimated for the sites with no sampling data. Ordinary Kriging (OK) and lognormal Kriging were used to produce the spatial patterns of heavy metals and disjunctive Kriging was applied to quantify the probability of heavy metal concentrations higher than their guide values [17]. Geostatistical methods, Kriging and co-Kriging, were applied to estimate the sodium adsorption ratio (SAR) in a 3,375 ha agricultural field [18].

The knowledge of irrigation water quality is critical to understand what management changes are necessary for long-term and short-term productivity particularly for crops that are sensitive to changes in quality [19]. With an adequate database, GIS can be a powerful tool for assessing water quality, developing solutions for water resources problems and decision-making tool for agriculture development [20]. Despite the large number of studies regarding water quality index techniques, no complete assessment tool has been found in the literature that incorporates the crucial aspects of irrigating water quality analysis. Indexes based on specialist opinion and based on statistical methods have some degree of subjectivity, because they depend on the choice of variables upon which the major indicators of water quality are built. Thus generalization is not acceptable due to special characteristics of each water system. Simple but objective and interpretable methods that use the peculiar characteristics of water resources are necessary to simplify the analysis of water quality in the monitoring task.

The overall objective of the current study is “to propose a simple model to evaluate and map groundwater quality using Geostatistics in Darb El-Arbaein, South Western Desert, Egypt”. The purposes of this assessment are (1) to evaluate and monitor the status of groundwater quality and assess its suitability for irrigation, (2) to determine spatial distribution of groundwater quality parameters and (3) to generate groundwater quality map for the Darb El-Arbaein area. There is an urgent need to have a first-hand assessment of the groundwater quality in Darb El-Arbaein area which has special significance and needs great attention of all concerned since it is the main source of domestic, irrigated and drinking water supply.

MATERIALS AND METHODS

Study Area: Darb El-Arbaein, a historic desert track running between Sudan and Egypt and passing El-Kharga Oasis to Assuit, area is geographically located between 30° 21´ 57" – 31° 27´ 24" E and 23° 40´ 32" - 24° 40´ 29" N, in South Western Desert, Egypt. The average rainfall is 1 mm, temperature 16.2-32.5°C and the humidity 37%. The area is considered one of the horizontal expansions in the Western Desert which aims at establishing a link between the South Valley Project and Al-Kharga Oasis. The ongoing project aims at reclamation of 4830 h (11500 fed.) and digging 85 wells of depth ranging between 150 and 500 m. Groundwater is the only available source of water in the area, so the assessment of agricultural potentiality in Darb El-Arbaein area requires water resources evaluation. The general geology and geomorphology of the area under study are outlined in the geology of Egypt [21] which is a desertic plateau with vast flat extensions of rocky deep closed in depressions (Figure 1). The greatest altitude is attained in the extreme south western corner where the general plateau character is disturbed by the great mountain Gebel Uweinat. The study area which consists of four villages (1, 2, 3 and 4) having an area around 5723h (13626 fed.). The area of villages 1 and 2 is equal to 1933 h. (4603 fed.), however; villages 3 and 4 have an area equal to 3790 h. (9023 fed.).

Figure (2) shows the distribution of wells at the site of the study in four villages by their names. There are five wells in the village (1), eight wells in village (2), eleven wells in the village (3) and twelve wells in the village (4).

Overall the Proposed Methodology: The flow chart of the methodology adopted for groundwater quality mapping using water quality data in the GIS environment is shown in Figure 3. The study was carried out with the help of four major components: input from remote sensing data, topographic sheets, groundwater quality data and data collected during field visits. In order to evaluate the quality of groundwater in Darb El-Arbaein area for irrigation, 36 surveyed wells with GPS data were used to produce the evaluation map.

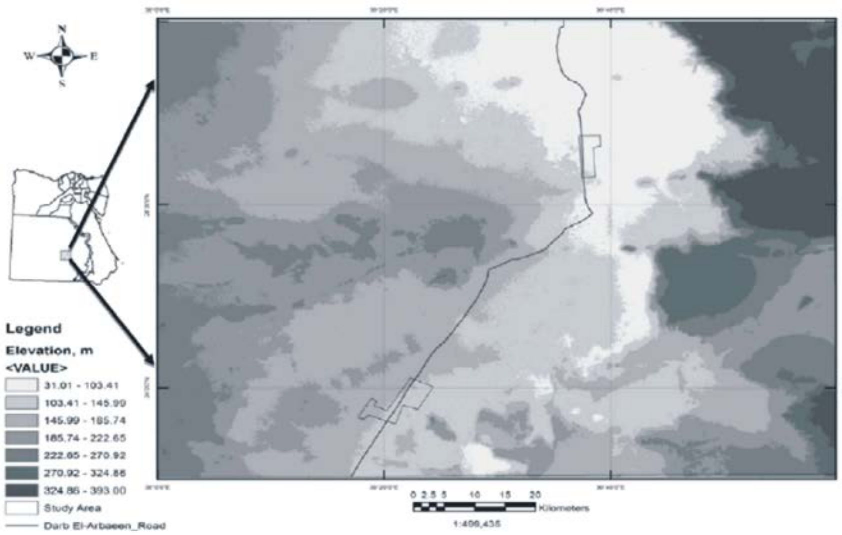
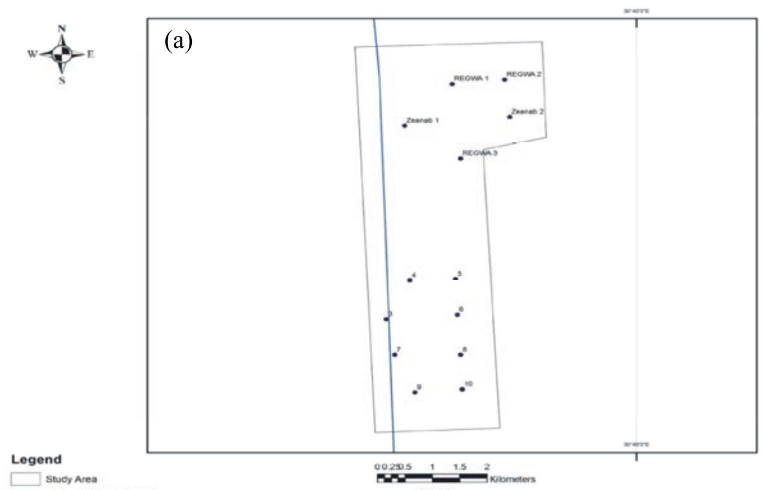


Fig. 1: Location map of the study area in relation to Egypt.



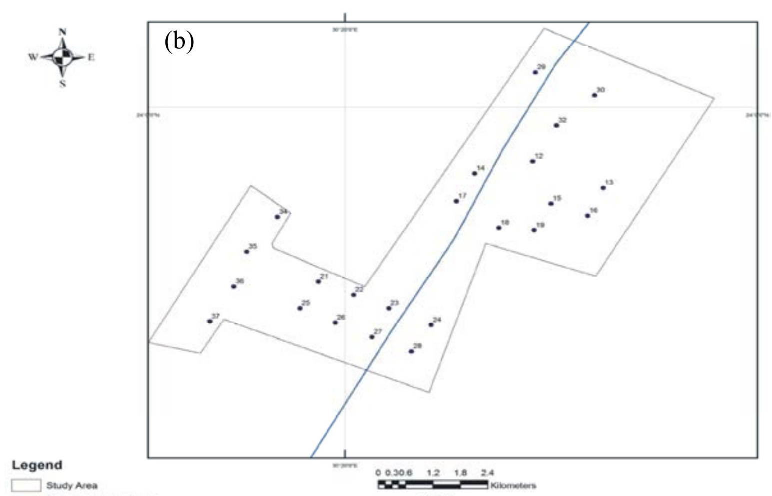


Fig. 2: Location of wells: (a) villages 1 and 2 (b) villages 3 and 4.

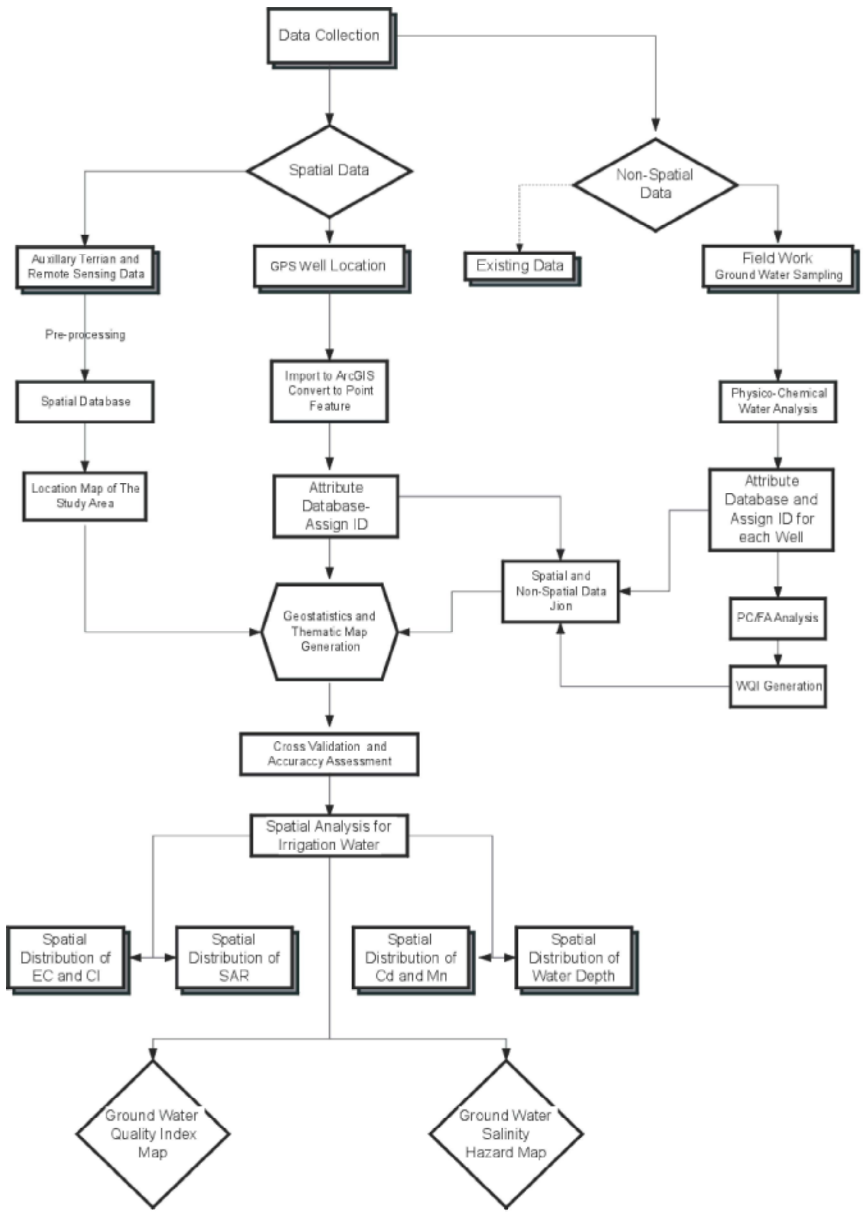


Fig. 3: Flow chart showing the methodology adopted for groundwater quality mapping.

The water samples were collected after 30 min of pumping to avoid stagnant and contaminated water. White plastic containers of 1 L capacity were rinsed out 3-4 times with sampling water. Then the containers were filled up to the brim and were immediately sealed to avoid exposure to air [22]. The groundwater samples have been analyzed for (pH, EC, Na^+, Ca^{++}, Mg^{++}, B, Cl^- and HCO_3^-) irrigation purposes. Sodium Adsorption Ratio (SAR), Soluble Sodium Percentage (SSP) and Residual Sodium Carbonate (RSC) were calculated on the basis of some standard equations. The concentrations of the heavy metals (Mn, Fe, Pb, Ni, Cd, Zn and Cu) were determined using atomic absorption spectrophotometer. Water quality maps were generated for different water properties and surfaces were interpolated using Kriging interpolation technique. A salinity hazard map was prepared to show regions with low, medium and high salinity hazards. Thus the final groundwater quality map for irrigation purpose was prepared by overlying the above mentioned grid data. Finally the study area was delineated into three classes on the basis of groundwater quality for irrigation purposes: suitable, moderate and unsuitable.

Proposed Water Quality Evaluation Model: The water quality evaluation model proposed in this study was developed in three steps. In the first step, principle component and factor model were developed. Parameters that contribute to most variability in irrigation water quality were identified using Principal Components and Factor Analysis (PC/FA) as described in SPSS (Statistical Package for the Social Sciences v.13). Indexes based on statistical techniques favor the recognition of the most characteristic indicators of the water under study. Factorial analysis allows the reduction of a great number of data obtained upon monitoring and permits the interpretation of these data and various constituents separately, as well as making it possible to find better various constituents separately [23] and to find a better selection of the relevant parameters for water quality classification [24, 25].

The correlation matrix was calculated based on the normalized data of the 13 parameters, evaluated for the sampling sites throughout the Darb El-Arbaein. Based on correlation matrix, a preliminary analysis of the representative parameters of water quality was performed. According to Helena *et al*. [26] only values above 0.5 should be considered; this rationale was used in this study. In order to identify the most significant interrelation of water quality parameters in Darb El-Arbaein area for each resulting factor of PC, a matrix rotation procedure was adopted using the Varimax method. This method minimizes the contribution of parameters with a lower significance in the factor such that the parameters will present loads close to one or zero, eliminating the intermediate values, which are difficult interpretation.

In the second step, water quality index WQI model is proposed. A definition of quality measurement values (Qi) and aggregation weights (Wi) was established. Values of (Qi) were estimated based on each parameter value shown in Table 1.

Water quality parameters were represented by a non-dimensional number; the higher the value, the better the water quality. Values of Qi were calculated using the following equation, based on the tolerance limits shown in table 1 and water quality results determined in laboratory:

$$QI = qimax - [(xij - xinf)*qiamp) / xamp] \quad (1)$$

where qimax is the maximum value of Qi for the class; xij is the observed value for the parameter; xinf is the corresponding value to the lower limit of the class to which the parameter belongs; qiamp is class amplitude; xamp is class amplitude to which the parameter belongs. In order to evaluate xamp, of the last class of each parameter, the upper limit was considered to be the highest value determined in the physical-chemical and chemical analysis of the water samples, then Wi values were normalized such that their sum equals one.

$$WI = \sum_{j=1}^{k} (F_j A_{ij}) / \sum_{j=1}^{k} \sum_{i=1}^{n} (F_j A_{ij}) \quad (2)$$

where Wi is the weight of the parameter for the WQI; F = component 1 autovalue; Aij is the explainability of parameter i by factor j; i is the number of physical-chemical and chemical parameters selected by the model, ranging from 1 to n; j is the number of factors selected in the model, varying from 1 to k.

The water quality index was calculated as:

$$IWQI = \sum_{i=1}^{n} QiWi \quad (3)$$

WQI is dimensionless parameter ranging from 0 to 100; Qi is the quality of the ith parameter, a number from 0 to 100, function of its concentration or measurement; Wi is the normalized weight of the ith parameter, function of its importance in explaining the global variability in water quality.

Table 1: Parameter limiting values for quality measurement (Qi) calculation

Qi	EC, μScm^{-1}	SAR	Na^+	Cl^-	HCO_3^-
			----------Meql^{-1}----------		
85-100	200 ≤ EC□750	SAR □ 3	2 ≤ Na □ 3	Cl^- □ 4	1≤ HCO_3 □ 1.5
60-85	750 ≤ EC□1500	3≤ SAR □ 6	3 ≤ Na □ 6	4 ≤ Cl^- □ 7	1.5≤ HCO_3 □ 4.5
35-60	1500 ≤EC□3000	6≤ SAR □ 12	6 ≤ Na □ 9	7 ≤ Cl^- □10	4.5≤ HCO_3 □ 8.5
0-35	EC □ 200 or	SAR ≥ 12	Na □ 2 or	Cl^- ≥ 10	HCO_3 □ 1 or
	EC≥ 3000		Na ≥ 9		HCO_3≥ 8.5

The criteria established by Ayers and Westcot [41]

Table 2: Water quality classes

Water Quality Class	WQI	Water Use Restriction
Excellent	$85 \leq 100$	No
Good	$70 \leq 85$	Low
Poor	$55 \leq 70$	Moderate
Very poor	$40 \leq 55$	High
Unsuitable for irrigation	$0 \leq 40$	Severe

Division in classes based on the proposed water quality index was based on existent water quality indexes and classes were defined considering the risk of salinity problems, soil water infiltration reduction, as well as toxicity to plants as observed in the classifications presented by Bernardo [23]. Restrictions to water use classes were characterized as shown in Table (2).

In the third step, the water quality data (attribute) were linked to the sampling location (spatial) in ArcGIS and maps showing spatial distribution were prepared to easily identify the variation in concentrations of the groundwater parameters at various locations of the study area. Different water quality maps were produced using point data like pH, EC, SAR, Cl and B by ArcMap GIS software. Geostatistical analyses were performed using the Geostatistical analyst extension available in ESRI ArcMap v 10 [28]. Kriging differs from other methods (such as IDW), in which the weight function is no longer arbitrary, being calculated from the parameters of the fitted semivariogram model under the conditions of unbiasedness and minimized estimation variance for the interpolation. Thus, Kriging is regarded as a best linear unbiased estimation (BLUE). A more detailed explanation of the method is given by Isaaks and Srivastava, [29] Stein [40], Yamamoto [30], Gringarten and Deutsch [31] and Omran [32]. Out of different Kriging techniques, the ordinary Kriging (OK) method was used in the present study because of its simplicity and prediction accuracy in comparison to other Kriging methods [29].

Geostatistical analysis was applied first to fully explore the data in which the histogram, normality, trend of data, semivariogram cloud and cross covariance cloud of the raw data were observed [33]. Kriging methods work best if the data is approximately normally distributed [34]. Transformations were used to make the data normally distributed and satisfy the assumption of equal variability for the data. In Arc GIS Geostatistial Analyst, the histogram and normal QQPlots were used to see what transformations were needed to make the data more normally distributed. For each water quality parameter, an analysis trend was made. Directional influences (anisotropy) are critical to the accurate estimation of surface water quality. The directional search tool was used to remove the directional influences from the groundwater quality data. In this study, the semivariogram models were tested for each parameter data set. Prediction performances were assessed by cross validation. Cross validation allows determination of which model provides the best predictions. For a model that provides accurate predictions, the standardized mean error should be close to 0, the root-mean-square error and average standard error should be as small as possible (this is useful when comparing models) and the root-mean square standardized error should be close to 1 [34].

RESULTS AND DISCUSSIONS

Overall Statistical Evaluation: Table 3 shows the summary of the statistical evaluation of laboratory analyses conducted on the samples. The pH of the groundwater samples around the area were within a range of 7-8. The overall EC values varied between 642 and 2686 μScm^{-1}. EC was lowest for a sample collected from village 1 (sample 3) while the highest occurred in a sample from a village 4 (sample 32). The chloride concentration of the groundwater samples were within a wide range of 124.1 – 570.9 ppm. The concentration of chloride in most of the areas is high with the maximum 570.86 ppm at village 2 (sample 9). The range of SAR values in the water samples were 1.83-8.47, that the highest SAR value related to village 4 (sample 32) and the lowest value related to village 1 (sample 3). Based on RSC criterion all groundwater samples were ranging from -7.1 to -1.86 (Table 3). Analyses of samples of groundwater in the area however revealed that heavy metals pollution of groundwater was low. The variations in the distribution of the investigated heavy metals (Cu, Fe, Pb, Mn, Ni, Cd and Zn) in the study area were small and were within the maximum permissible range (Table 3).

Principal Component and Factorial Model: Table 4 shows the correlation matrix for the analyzed parameters. High correlations (above 0.9) were observed between EC and SAR and Cl^-. Kaiser-Meyer-Olkin (KMO) adequacy test for coefficient magnitude comparison resulted in an optimum value of 0.82, indicating that the factorial model may be applied without restrictions. A similar result was found by Parinet *et al*. [35] in an evaluation of water quality in tropical lake systems, with a KMO value of 0.85, which was considered adequate for the study.

Table 3: Descriptive statistics of water quality parameters of groundwater samples

Parameters	Range	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
Depth to Well	316.00	214.00	530.00	383.11	107.28	-0.42	-1.43
Elevation	83.00	82.00	165.00	131.86	25.12	-0.67	-0.99
EC	2044.00	642.00	2686.00	1656.81	540.32	-0.46	-0.59
pH	1.14	6.99	8.13	7.54	0.31	0.01	-0.70
SAR	6.64	1.83	8.47	5.51	1.82	-0.60	-0.54
RSC	5.24	-7.10	-1.86	-4.04	1.56	-0.26	-1.04
Cl^-	446.76	124.10	570.86	344.03	115.68	-0.24	-0.62
B	0.17	0.02	0.18	0.09	0.05	-0.47	-1.34
Fe	0.19	0.00	0.19	0.07	0.06	0.72	-0.21
Mn	0.27	0.00	0.27	0.04	0.06	2.25	5.40
Cu	0.12	0.00	0.12	0.04	0.03	0.49	-0.32
Zn	0.07	0.00	0.07	0.04	0.02	-0.10	-0.42
Cd	0.001	0.00	0.001	0.002	0.003	2.34	5.62
Pb	0.24	0.00	0.24	0.07	0.07	0.78	-0.06
Ni	0.17	0.00	0.17	0.02	0.04	2.65	7.53

All units except pH, SAR, RSC and EC are in ppm. Depth to Well and Elevation, m; SD= Std. Deviation

Table 4: Correlation matrix for the analyzed parameters.

Parameters	Elevation	Depth to Well	EC	pH	SAR	RSC	Cl	B	Fe	Mn	Cu	Zn	Cd	Pb	Ni
Elevation	1														
Depth to Well	0.803	1													
EC	0.697	0.725	1												
pH	0.597	0.601	0.45	1											
SAR	0.761	0.773	0.955	0.496	1										
RSC	-0.226	-0.322	-0.780	-0.143	-0.594	1									
Cl	0.478	0.499	0.94	0.304	0.836	-0.883	1								
B	0.895	0.895	0.717	0.658	0.817	-0.199	0.487	1							
Fe	0.423	0.32	0.194	0.089	0.158	-0.154	0.042	0.238	1						
Mn	-0.589	-0.628	-0.67	-0.256	-0.679	0.387	-0.6	-0.672	-0.009	1					
Cu	0.559	0.626	0.432	0.265	0.544	-0.026	0.253	0.583	0.102	-0.238	1				
Zn	0.067	0.13	0.158	0.031	0.089	-0.276	0.077	0.006	0.501	0.151	-0.161	1			
Cd	-0.192	-0.091	-0.223	-0.184	-0.352	-0.053	-0.194	-0.247	0.178	-0.028	-0.403	0.341	1		
Pb	0.285	0.258	0.236	0.056	0.298	-0.051	0.138	0.258	0.076	-0.167	0.118	0.51	0.118	1	
Ni	-0.155	-0.042	0.075	-0.152	0.034	-0.265	0.128	-0.162	0.341	0.043	-0.161	0.229	0.099	0.203	1

Table 5: Factorial loads for the observed parameters

	Factorial Loads Matrix			
Parameters	F1	F2	F3	F4
EC	0.9666	0.1866	-0.1303	0.0068
pH	0.5579	-0.2983	0.0767	-0.0226
SAR	0.9710	-0.0364	-0.0636	0.0481
RSC	-0.6320	-0.6985	0.2836	-0.0091
Cl	0.8392	0.3776	-0.3457	-0.0165
Na	0.9781	0.1065	-0.0580	0.0474
K	-0.7883	0.4831	-0.3159	-0.0163
Mg	0.5395	0.5618	-0.2283	0.0896
HCO_3	0.8209	-0.4469	0.2306	-0.0632
Fe	0.2529	0.2356	0.6348	0.3909
Mn	-0.7149	0.0775	0.1227	0.4571
Cu	0.5380	-0.5113	0.0334	0.3242
Zn	0.1442	0.5101	0.6947	-0.0016
Cd	-0.2484	0.4213	0.3839	-0.6110
Pb	0.2884	0.0929	0.5945	-0.2261
Ni	0.0179	0.5396	0.2458	0.4044
Variance %	47.0300	15.5120	10.7250	6.0170
Cumulative %	47.0300	62.5410	73.2660	79.2840

Extraction Method: Principal Component Analysis

Table 6: Weights for the WQI parameters

Parameters	EC	SAR	Na	Cl	HCO_3	Total
Wi	0.24117	0.24227	0.20941	0.24406	0.06309	1.000

Table 7: Groundwater Quality Index (WQI)

Location	Sample No.	Well No.	WQI	Water Quality	Location	Sample No.	Well No.	WQI	Water Quality
Village (1)	1	R 1	53.48	Very poor	Village (3)	19	19	44.04	Very poor
	2	R 2	75.29	Good		20	29	60.65	Poor
	3	Z 1	75.21	Good		21	30	54.92	Very poor
	4	Z 2	74.16	Good		22	32	53.37	Very poor
	5	R 3	81.98	Good	Village (4)	23	17	48.42	Very poor
Village (2)	6	3	49.13	Very poor		24	18	45.53	Very poor
	7	4	88.60	Excellent		25	21	45.84	Very poor
	8	5	50.71	Very poor		26	22	44.75	Very poor
	9	6	47.93	Very poor		27	23	43.88	Very poor
	10	7	65.90	Poor		28	24	40.64	Very poor
	11	8	85.42	Excellent		29	25	45.18	Very poor
	12	9	68.42	Poor		30	26	43.22	Very poor
	13	10	70.40	Good		31	27	41.40	Very poor
Village (3)	14	12	51.14	Very poor		32	28	38.87	Unsuitable for irrigation
	15	13	45.38	Very poor		33	34	50.86	Very poor
	16	14	49.89	Very poor		34	35	46.15	Very poor
	17	15	46.01	Very poor		35	36	46.31	Very poor
	18	16	43.27	Very poor		36	37	45.44	Very poor

R= REGWA, Z= Zeanab

Table 5 shows the application of principal component analysis to describe dispersion of original parameters which implied in a four component model, explaining 77.393% of total variance, diluted in fifteen dimensions. This result is in agreement with the works of Helena *et al*. [26], Prado *et al*. [36] and Simeonov *et al*. [24] in which the two to three first generated components explain a great part of the variation of original data (60 to 90%). In many cases, allowing the use of these components to describe the entire data system without significant loss of information.

Selection of this four component model used the criterion described by Norusis [37] considering only those components with a variance that has an auto-value above one. Any component must explain a variance above that presented by a single variable. This criterion is observed by Mendiguchia *et al*. [36] upon evaluation of water quality in the Guadalquivir River in the South of Spain, where through PC three hidrochemical factors were identified with variances above unity and explaining 79.1% of total variance of the data.

Table 5 presents a factorial loads for the observed parameters. A matrix rotation was performed and data for factorial loads and communalities after transformation are presented in table 5. The first Factor explains 47.030% of total variance in the data, whereas the second and third factors explain 15.512% and 10.725%, respectively. In the first Factor/Component, parameters such as EC, SAR, Cl^-, Na, HCO_3 and Mn present a load above 0.70, indicating the most common composition of the observed parameters. In the second Factor/Component, parameters Mg and Ni show high factorial loads of 0.5618 and 0.5396 respectively. The third Factor/Component showed Fe and Pb as the elements with the load 0.6348 and 0.5945 respectively.

WQI Development: In order to develop the proposed WQI, EC, Cl, Na, HCO3 and SAR parameters were used. These carry the major factorial load (above 0.82 from Table 5) and define best water quality. Henceforth, the weight of each parameter was based on the variance of the first factor (Table 6), associated to the explainability of each parameter, in relation to this factor. The normalized weights, Wi, computed through Equation 2, are listed in table 6. The suitability index which calculated based on equation 3 is shown in Table 7.

Overall, the results in Table 7 indicated that villages 1-2 are generally have Good water quality, however villages 3-4 have a Very poor water quality. Restrictions for using this water in irrigation at long term are required especially because the soil texture is heavy and the climate is hot.

Table 8: Cross validation results of EC and Cl^- parameters.

	Prediction Errors									
	Mean		Root-Mean-Square		Average Standard Error		Mean Standardized		Root-Mean-Square Standardized	
Models	EC	Cl^-	EC	Cl^-	EC	Cl^-	EC	Cl^-	EC	Cl^-
Circular (Cl)	2.8311	0.2810	331.711	96.730	343.976	97.070	0.00553	0.00001	0.9679	1.006
Spherical	2.8075	0.5185	331.250	94.960	343.476	96.900	0.00549	0.0024	0.9685	0.983
Tetraspherical	2.7862	1.6871	330.965	95.270	343.168	96.990	0.00544	0.014	0.9684	0.985
Pentaspherical	2.7841	1.0608	330.811	95.410	343.003	97.049	0.00545	0.013	0.9685	0.985
Exponential	2.9911	1.5944	328.131	96.375	341.106	97.327	0.00609	0.013	0.9675	0.990
Gaussian	-0.2096	1.7452	324.440	95.762	334.378	96.699	-0.00268	0.0147	0.9772	0.992
Rational Quadratic	2.4740	1.6371	329.068	96.402	338.294	97.613	0.00478	0.013	0.9772	0.989
Hole Effect	-0.6005	1.5360	322.291	94.020	332.479	96.75	-0.00350	0.012	0.9775	0.970
K-Bessel	2.9260	1.7198	327.299	95.911	341.621	96.759	0.00615	0.014	0.9642	0.990
J-Bessel (EC)	0.6290	1.4001	323.982	93.697	333.446	96.973	-0.00035	0.011	0.9788	0.969
Stable	2.9880	1.7452	327.052	95.762	341.423	96.699	0.00630	0.0147	0.9643	0.992

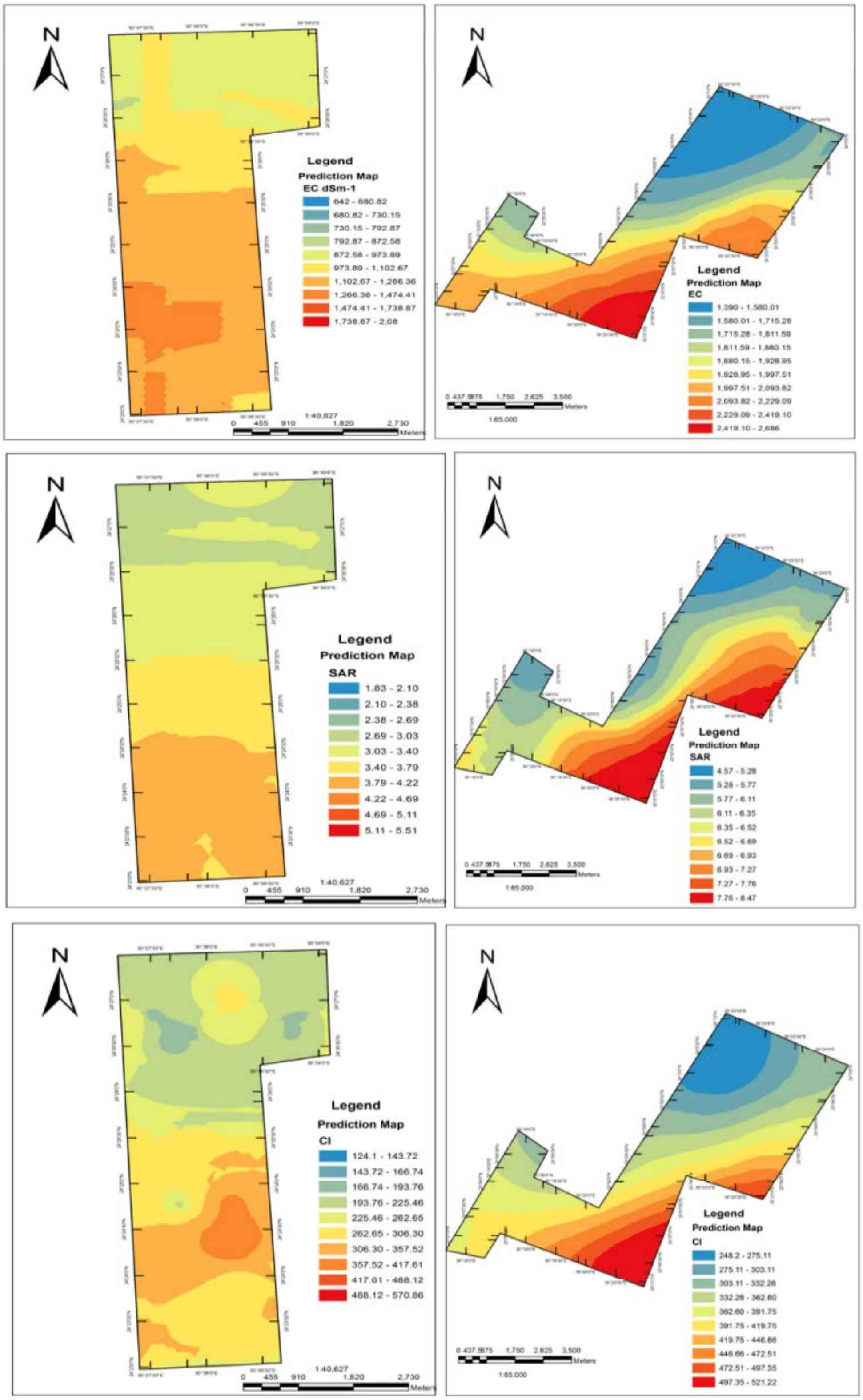
Table 9: Fitted parameters of the variogram model for groundwater quality

		Prediction Errors				
Parameters	Models	Mean	Root Mean Square	Average Standard Error	Mean Standardized	Root Mean Square Standardized
EC	J-Bessel	0.6290	323.98	333.45	-0.00034	0.9790
pH*	Rational Quadratic	0.0030	0.2580	0.2540	0.00584	1.0060
SAR	Stable	0.0058	1.0647	1.3280	0.00381	1.0647
Cl	Circular	0.2810	97.070	96.738	0.00001	1.0057
B *	Gaussian	0.0015	0.0147	0.0254	-0.04580	1.2452
Zn*	Spherical	-0.0002	0.0139	0.0143	-0.02108	0.9825
Mn	Stable	0.00001	0.0088	0.0093	-0.00140	0.9517
Cd	Circular	-0.0005	0.0119	0.0107	-0.02750	1.0930
Pb	Stable	-0.0021	0.0720	0.0760	-0.02630	0.9450
Ni	Spherical	-0.0000	0.0381	0.0396	-0.00230	0.9640

*Using logarithm to normalize data.

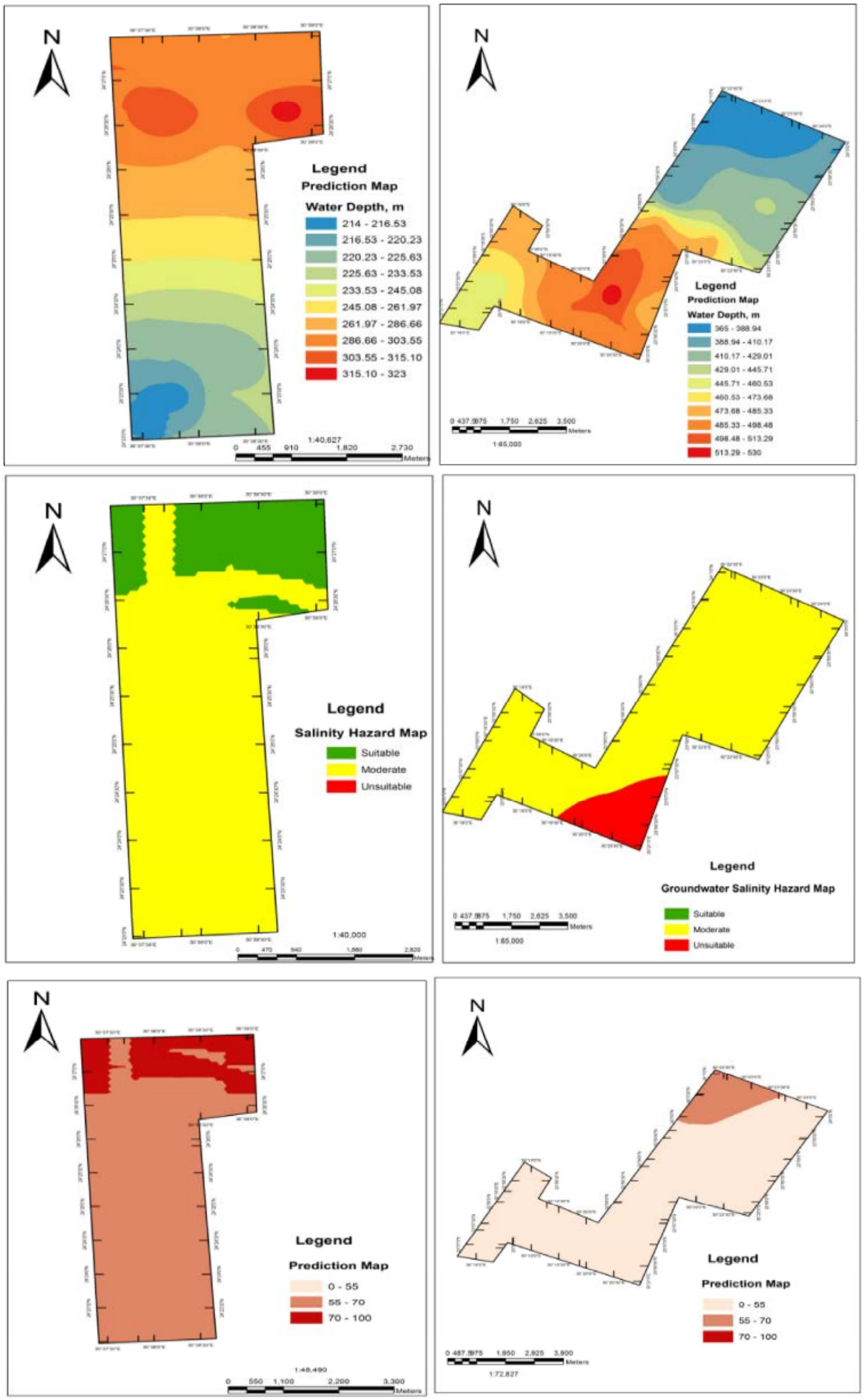
Spatial and Interpolation Analysis of Groundwater Quality Variation: Water samples were taken from 36 wells in the study area. The data had been checked by a histogram tool and normal QQPlots to confirm if they could show a normal distribution pattern. Normal QQPlots provide an indication of univariate normality. If the data is asymmetric (i.e., far from normal), the points would deviate from the line. Histogram and normal QQPlot analysis were applied for each water quality parameter. It was determined that electrical conductivity, chloride, Mn, Cd, Pb, Ni and SAR concentrations showed normal distributions, however, only the pH, B and Zn parameters did not show normal distribution. For this parameter, a log transformation had been applied to make the distribution closer to normal. For each water quality parameter, an analysis trend was made and it was determined that there was no global trend for all parameters. In this study, the semivariogram models (circular, spherical, tetraspherical, pentaspherical, exponential, gaussian, rational quadratic, hole effect, K-Bessel, J-Bessel and stable) were tested for each parameter data set. Prediction performances were assessed by cross validation, which examined the accuracy of the generated surfaces.

Table 8 lists cross validation results to examine the validity of the fitting models and parameters of semivariograms for EC and Cl^- parameters. All of the water quality parameters were assessed by cross validation and given EC and Cl^- parameters as an example. For the EC sample, the standardized mean ranged from 0.006153 to -0.000346 and the RMSS ranged from 0.9642 to 0.9788. In this case, for the EC parameter the best fit was the J-Bessel model (SME -0.000346) and Circular model for Cl^- with a 0.005528 standardized mean error. It was close to zero and the 0.9788 RMSS value is close to 1. When the average estimated prediction standard errors were close to the root-mean-square prediction errors from cross-validation, then it could be confident that the prediction standard errors were appropriate [34].



Village 1 and 2 Village 3 and 4

Fig. 4: Spatial distributions of EC, SAR and Cl^-.



Village 1 and 2 Village 3 and 4

Fig. 5: Water depth, groundwater salinity hazard map and WQI map of Darb El-Arbaein

After applying different models for each water quality parameter examined in this study, the error was calculated using cross validation and models giving best results were determined. Table 9 shows the most suitable models and their prediction error values for each parameter. Table 9 also shows that for different parameters different models may give better results. For water quality parameters, RMSS range from 0.945 to 1.2452.

Figure 4 shows the spatial distribution of different parameters (e.g., EC, pH, SAR, Cl) in the study area and some selected parameters (e.g., EC, SAR and water Cl^-) which have F1 and F4 factorial loads. The groundwater quality prediction maps showing the concentration distribution were generated from the surface map developed from the cross validation process.

Groundwater Quality Mapping for Agricultural Purposes: The groundwater quality maps for agricultural purposes are shown in Figure 5. The whole area was divided into three classes on the basis of EC. The quality of water for irrigation purposes depended on the salinity classified into suitable, moderate and unsuitable. Also, the map of WQI was presented. Three of the groundwater samples felt in the moderate WQI. Most of the samples (26) felt in the Doubtful WQI category. Seven samples felt in the higher WQI category. Groundwater samples that felt in the low salinity hazard class and high WQI can be used for irrigation of most crops and the majority of soils.

Figure 5 shows the suitability index map calculated in Table 7. Suitability index was calculated to determine the suitability of water for irrigation purpose. Suitability index values revealed that the groundwater in the study area were “Suitable” quality with the suitability index range between 85-100 (2 wells were Excellent water quality) and therefore can be used for irrigation usage. Most of the samples were Very poor (25 wells) with suitability index ranged between 40-55. One sample (well no. 32) was “unsuitable” quality and could be used for irrigation purposes. Five wells were Good quality and three wells were Poor quality. Overall, most of village 1 wells were Good quality which can be used for irrigation with Low restriction except well no. 1 which was Very poor quality. Village 2 wells were Very poor quality with high restrictions for irrigation except wells no. 7 and 11 were Excellent quality which can be used for irrigation with No restriction. The villages 3 and 4 wells were Very poor quality which can be used for irrigation with High restrictions.

The map of (Figure 5) villages 3-4 showed that 382.35 ha (10.09%) of area felt in the moderate category however, much of the area (3407.38 ha) had unsuitable water quality. For the villages 1-2, the corresponding area of suitable category were 266.66 ha (13.79%) however, moderate category were 1666.79 ha. The observed low Suitability Index of the groundwater quality was due to the desert location and lack of deficiency water and rainfall, dug of deep and semi-deep well was increased. Groundwater resources degradation is an issue of significant societal and environmental concern in Darb El-Arbaein area. In order to prevent groundwater pollution before it occurs and avoid the future need for costly remediation efforts, GIS can be used to assess the groundwater pollution potential. It is also helpful for public to understand the quality of water as well as being a useful tool in many ways in the field of water quality management [39]

CONCLUSIONS

The present paper proposed a simple model to assess and map groundwater suitability for irrigation purpose in Darb El-Arbaein area. Factor/Principal Component Analysis permitted the description of parameters involved in the processes that defined water quality in the Darb El-Arbaein through a four component model, the components of which explained 79.28% of total data variance, previously diluted in thirteen dimensions. Ordinary kriging method was used for preparation of thematic maps of groundwater quality parameters such as electrical conductivity, sodium adsorption ratio, chloride and heavy metals. Circular semivariogram model was best fitted for chloride and Cd parameters where spherical model fitted best for Ni and Zn parameters. Stable semivariogram model was best fitted for Pb and SAR parameters where J-Bessel model fitted best for EC parameter. High salinity was due to high chloride concentration in the groundwater. The map of villages 1 and 2 indicated the presence of about 13.79%) of the study area suitable groundwater for irrigation. However, in villages 3 and 4, 10.09% of the area felt in the moderate category for irrigation purposes. The groundwater quality index was devised to analyze the combined impact of different quality parameters on irrigation purposes. The Irrigation Water Quality (IWQ) index developed and proposed in this study provides an easy-to-use tool that could help analyze the overall quality of irrigation water. Overall, the proposed index incorporates EC parameter to represent salinity limitation; SAR and EC to represent permeability limitation; sodium, chloride, boron and trace elements to represent specific ion toxicity, HCO_3 and pH to represent effects to sensitive crops.

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