Evaluation and Mapping Groundwater Quality Using Geostatistics for Sustainable Land Management in Darb El-Arbaein Area, South of Western Desert, Egypt

Salman. A. H. Selmy[(1)], Ahmed.M. Ghallab[(1)], Abdallh. Gad[(2)] and El-Said. E. Omran[(3)]

[(1)]Dept.Soils & water, Fac.of Agric., Assiut Univ., Assiut. [(2)]National Authority for Remote Sensing and Space Science, Cairo. [(3)]Dept. Soils & water, Fac. of Agric., Suez Canal Univ., Ismailia.

Abstract: Assessing the vulnerability of aquifers is the first step toward careful management of groundwater resources.The groundwater quality has to be evaluated to avoid or, at least, to minimize impacts on agriculture. The main objective of this study was to sit up a simple method to assess the groundwater quality and to map their spatial variation in terms of suitability for irrigation in Darb El-Arbaein area and the complementary objective was to demonstrate the GIS capabilities in exploring the full value of environmental data through spatial analysis and visual display of geographic information.Thirty six surveyed wells represented four villages with GPS data were used to assess and map the groundwater quality. For calculating the Water Quality Index (WQI), 13 parameters (EC, pH, Cl^-, SAR, RSC, B, Zn, Cu, Fe, Mn, Pb, Ni and Cd) have been considered those. The results of analyses have been used to map and predict models for water quality. The data were imported into the GIS software and the different water quality maps were produced. The geostatistical analysis was used for exploratory data analysis. The results showed that the groundwater in the study area has pH values of 7 to 8 and EC values ranging from 642 to 2686 μScm^{-1}. The concentration of chlorides in most of the areas is high with a maximum of 570.86 ppm. The SAR values range from 1.83 to 8.47. The concentrations of heavy metals are lower than the permissible recommended limits. The high salinity was due to the high chloride concentration in the groundwater. The WQI of the studied samples ranges from 47.9 to 88.6; most of the samples (26 samples) fall in the Doubtful WQI category; three samples fall in the moderate WQI, and seven samples fall in the high WQI category. Groundwater samples that fall in the low salinity hazard class with high WQI can be used for the irrigation for most crops and the majority of soils. The present study demonstrated a high efficiency for GIS to analyze complex spatial data and groundwater quality mapping.

Key-words: GIS, Groundwater,Kriging, Semivariogram, Water quality index, Heavy metals, Suitability, Darb El-Arbaein.

1. 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 (Hu et al., 2005; Asadi et al., 2007; Lado et al., 2008; Buchanan and Triantafilis, 2009) to the concerned decision-makers. Many researches and projects have been conducted to assess water quality (Horton 1965). Shihab and Al-Rawi (1994) and Al-Hussain (1998) used WQI as a management tool for water quality of Tigris River within Mosul city for different uses. Debels, et al., (2005) has used a modified water quality index that is composed of physicochemical parameters for evaluating the quality status of a river in Central Chile. Numaan (2008) established irrigation WQI for Tigris River between Al-Sharqat and Alboajeel in Iraq. Bhatti and Latif (2009) used water quality index to assess the water quality of Chenab River in Pakistan for irrigation use. Fulazzaky (2009) assessed the status and the suitability of the Citarum River water in Malaysia for agriculture use. Meireles et al., (2010) classify water quality in the Acarau Basin, in the North of were applied to estimate the sodium adsorption ratio (SAR) in a 3,375 ha agricultural field (Pozdnyakova and Zhang, 1999).

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 (Ramakrishnaiah et al., 2009). 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 (Arsalan, 2004). 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 irrigational 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 inter- the state of Ceara, Brazil for irrigation use.

Pollution of water has become a thing of health concern both in urban and rural areas (Orebiyi et al., 2010). 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 (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) is necessary to assess their suitability for irrigation. Many studies have been successfully used interpolation techniques with the use of the ArcGIS Geostatistical tool (He and Jia, 2004; Kumar, et al., 2007; Woo et al., 2009). 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 (Liu, et al., 2005). Geostatistical methods, Kriging and co-Kriging, fall was 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 11500 feddans and digging 85 wells of depth 150-500 meters. 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 (Said, 1961) 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, 4) has an area around 5723.18 h (13626.16 fed.). The area of villages 1-2 is equal to 1933.45 h. (4603.45 fed.), however; villages 3-4 have an area equal to 3789.73 h. (9023.16 fed.).

pretable 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 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.

2. Materials and Methods

2.1 Study Area

Darb El-Arbaein area is located in South Western Desert of Egypt between 30° 21´ 56.7″ – 31° 27´ 24.1″ E and 23° 40´ 31.6″ - 24° 40´ - 28.5″ N,. The average rain-

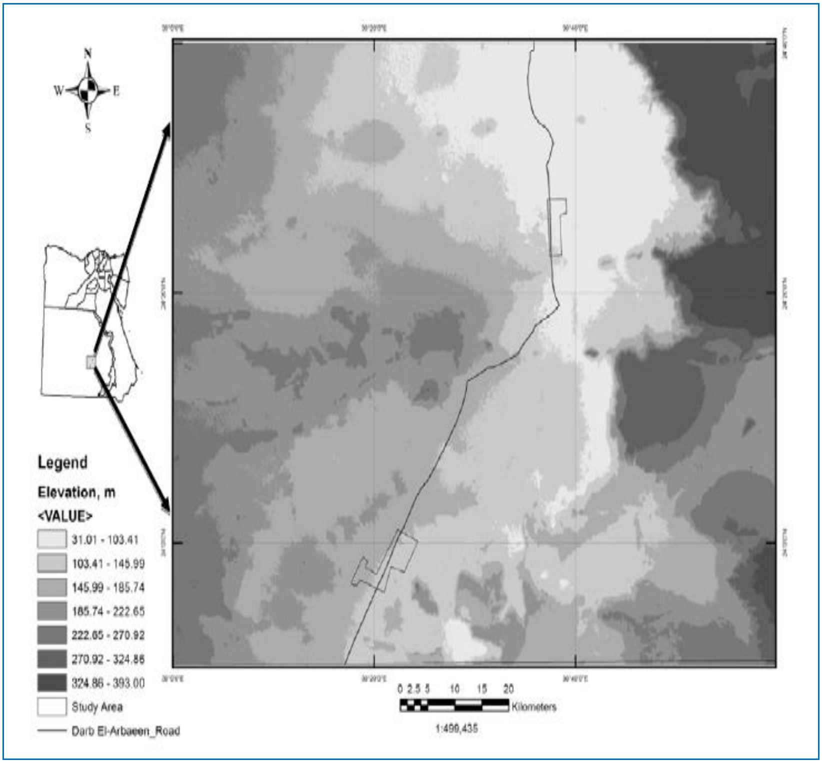
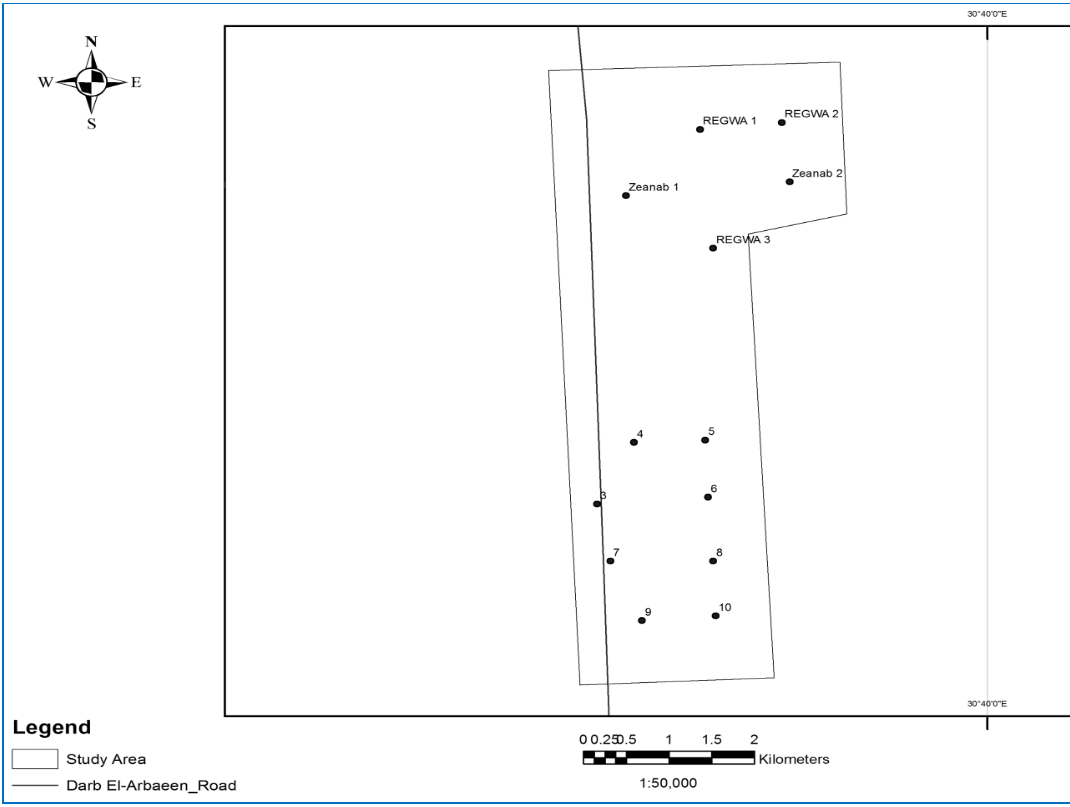


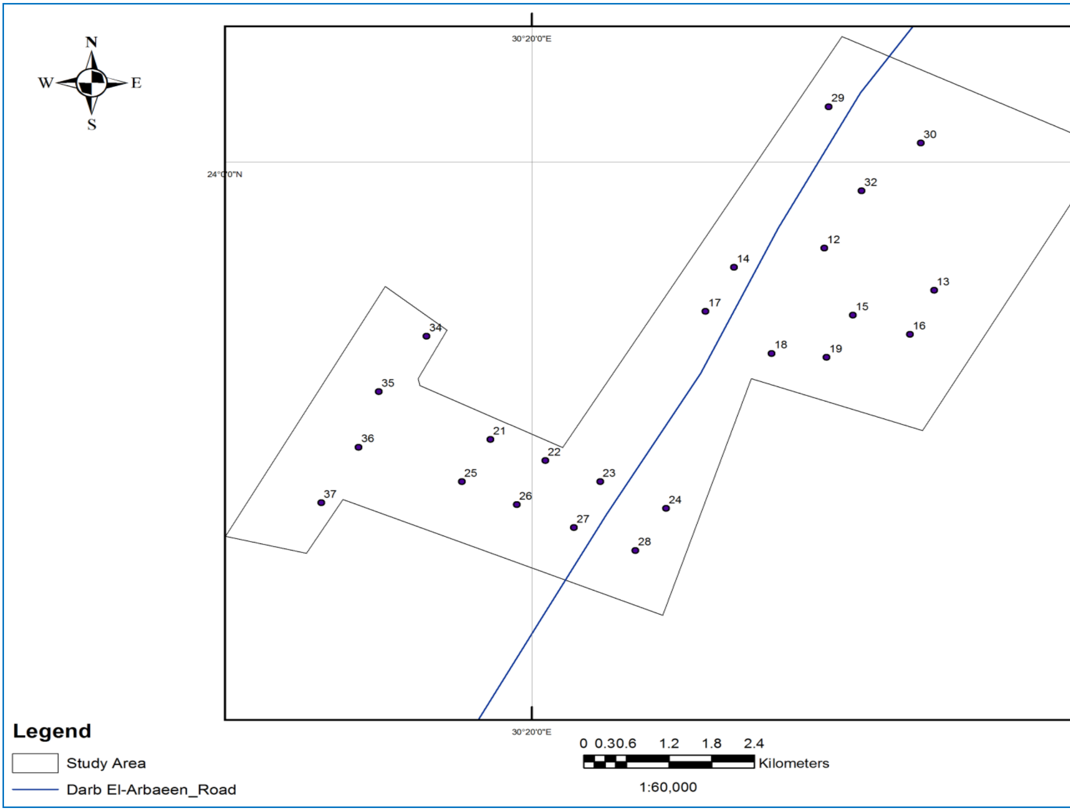
Fig. (1): Location map of the study area in relation to Egypt.

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) and twenty-three wells in the villages (3, 4).



30°40'0"E
N
W
E
S
REGWA 1
REGWA 2
Zeanab 1
Zeanab 2
REGWA 3
4
5
3
6
7
8
9
10
30°40'0"E
Legend
Study Area
Darb El-Arbaeen_Road
0 0.25 0.5 1 1.5 2
Kilometers
1:50,000

(a)



(b)

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

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. The water samples were collected after 30 min of pumping to avoid stagnant and

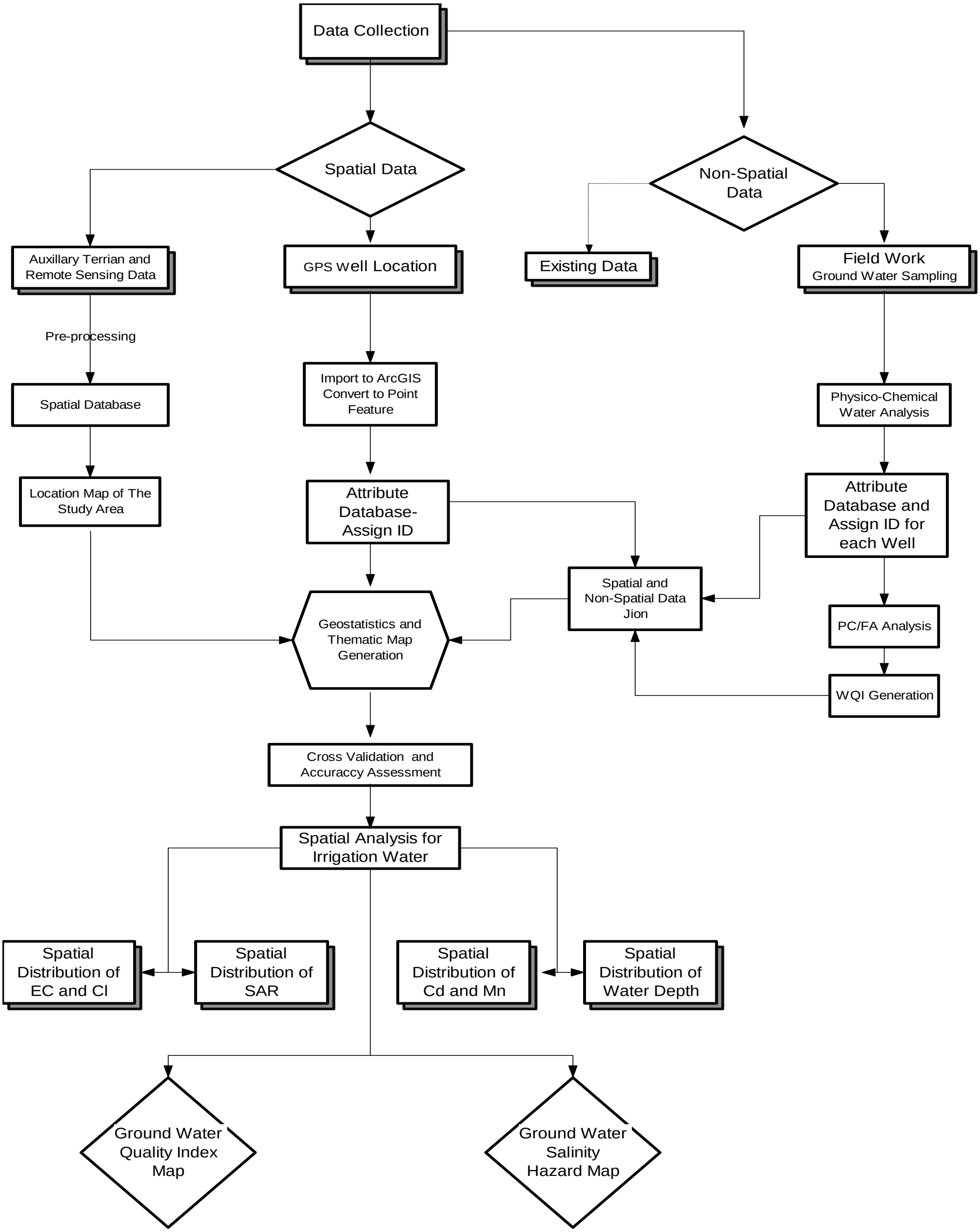
2.2 Overall the Proposed Methodology

The methodology adopted for groundwater quality mapping using water quality data in the GIS environment is shown in Figure 3. The study had been carried out with the help of four major components: input from remote sensing data, topographic tic containers of 1 L ca area was delineated into three classes on the basis of groundwater quality for irrigation purposes: suitable, moderate, and unsuitable.

2.3 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 an interpretation of the various constituents separately and making it possible to find a better various constituents separately (Hair et al., 2005).

contaminated water. White plaspacity 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 (APHA, 1998). The containers were labeled for identification and brought to the laboratory. 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



Data Collection
Spatial Data
Non-Spatial Data
Auxillary Terrian and Remote Sensing Data
GPS well Location
Existing Data
Field Work Ground Water Sampling
Pre-processing
Spatial Database
Import to ArcGIS Convert to Point Feature
Physico-Chemical Water Analysis
Location Map of The Study Area
Attribute Database-Assign ID
Attribute Database and Assign ID for each Well
Spatial and Non-Spatial Data Jion
Geostatistics and Thematic Map Generation
PC/FA Analysis
WQI Generation
Cross Validation and Accuraccy Assessment
Spatial Analysis for Irrigation Water
Spatial Distribution of EC and Cl
Spatial Distribution of SAR
Spatial Distribution of Cd and Mn
Spatial Distribution of Water Depth
Ground Water Quality Index Map
Ground Water Salinity Hazard Map

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

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 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.

Various constituents separately making it possible to find a better selection of the relevant parameters for water quality classification (Simeonov et al., 2003; Wunderlin et al., 2001). 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., (2000) 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

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

Qi	EC, μScm^{-1}	SAR	Na^+	Cl^-	$HCO3^-$
			$Meql^{-1}$		
85-100	200≤EC<750	SAR <3	2 ≤ Na < 3	Cl^-< 4	1≤ HCO3 <1.5
60-85	750 ≤EC<1500	3≤ SAR <6	3 ≤ Na <6	4 ≤ Cl^- <7	1.5≤ HCO3 <4.5
35-60	1500≤EC<3000	6≤ SAR <12	6 ≤ Na <9	7 ≤ Cl^- <10	4.5≤ HCO3 <8.5
0-35	EC<200 or EC≥3000	SAR ≥ 12	Na <2 or Na ≥ 9	Cl^- ≥ 10	HCO3 <1 or HCO3≥ 8.5

The criteria established by Ayers and Westcot (1999)

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

…………..… Eq. 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:

$$IWQI = \sum_{i=1}^{n} QiWi$$

……………………………… Eq. 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. Division in classes based

Water quality parameters were represented by a non-dimensional number; the higher the value, the better the quality water. 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] ………. Eq. 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.

well as toxicity to plants as observed in the classifications presented by Bernardo (1995). Restrictions to water use classes were characterized as shown in Table (2).

on the proposed water quality index which was based on existent water quality indexes, and classes were defined considering the risk of salinity problems, soil water infiltration reduction, as

Table (2): Water quality index characteristics.

WQI	Water Use Restrictions
$85 \leq 100$	No restriction (Excellent)
$70 \leq 85$	Low restriction (Good)
$55 \leq 70$	Moderate restriction (Poor)
$40 \leq 55$	High restrictions (Very poor)
$0 \leq 40$	Severe restrictions (Unsuitable for irrigation)

ditions 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 many authors (Isaaks and Srivastava, 1989; Stein, 1999; Yamamoto, 2000; Gringarten and Deutsch, 2001; Omran 2011). 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 (Isaaks and Srivastava, 1989).

Geostatistical analysis is the first to fully explore the data in which the histogram, normality, trend of

In the third step, the water quality data (attribute) is linked to the sampling location (spatial) in ArcGIS and maps showing spatial distribution are prepared to easily identify the variation in concentrations of the groundwater parameters at various locations of the study area. Different water quality maps are 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 (ESRI, 2008). 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 conshould be as small as possible (this is useful when comparing models), and the root-mean square standardized error should be close to 1 (Johnston et al., 2001).

3. Results and Discussions

3.1 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 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 was 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 -7.1 to -1.86 (Table data, semivariogram cloud and cross covariance cloud of the raw data were observed (Sarangi et al., 2005). Kriging methods work best if the data is approximately normally distributed (Johnston et al., 2001). Transformations were used to make the data normally distributed and satisfy the assumption of equal variability for the data. In ArcGIS Geostatistial Analyst, the histogram and normal QQPlots were used to see what transformations are needed to make the data more normally distributed. For each water quality parameter, an analysis trend had been made. Directional influences (anisotropy) are critical to the accurate estimation of water quality surface. 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 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).

3.2 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 indicated an optimum value of 0.82, considered as indicating that the factorial model may be applied without restrictions. A similar result was found by

3). Analyses of samples of groundwater in the area however reveal that heavy metals pollution of groundwater is low. The variations in the distribution of the

Parameters	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
Depth to Well	316.00	214.00	530.00	13792.00	383.11	107.28	-0.42	-1.43
Elevation	83.00	82.00	165.00	4747.00	131.86	25.12	-0.67	-0.99
EC	2044.00	642.00	2686.00	59645.00	1656.81	540.32	-0.46	-0.59
pH	1.14	6.99	8.13	271.55	7.54	0.31	0.01	-0.70
SAR	6.64	1.83	8.47	198.28	5.51	1.82	-0.60	-0.54
RSC	5.24	-7.10	-1.86	-145.52	-4.04	1.56	-0.26	-1.04
Cl^-	446.76	124.10	570.86	12385.18	344.03	115.68	-0.24	-0.62
B	0.17	0.02	0.18	3.34	0.09	0.05	-0.47	-1.34
Fe	0.19	0.00	0.19	2.60	0.07	0.06	0.72	-0.21
Mn	0.27	0.00	0.27	1.35	0.04	0.06	2.25	5.40
Cu	0.12	0.00	0.12	1.37	0.04	0.03	0.49	-0.32
Zn	0.07	0.00	0.07	1.34	0.04	0.02	-0.10	-0.42
Cd	0.001	0.00	0.001	0.07	0.002	0.003	2.34	5.62
Pb	0.24	0.00	0.24	2.62	0.07	0.07	0.78	-0.06
Ni	0.17	0.00	0.17	0.58	0.02	0.04	2.65	7.53

Table (3): Descriptive statistics of water quality parameters of groundwater samples.

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

Parinet et al. (2004) in an evaluation of water quality in tropical lake systems, with a KMO value of 0.85, considered adequate for the study. 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., (2000), Prado et al., (2002) and Simeonov et al. (2003) 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.

Table (4): Correlation matrix for the analyzed parameters.

Elevation	Depth to Well	EC	pH	SAR	RSC	Cl	B	Fe	Mn	Cu	Zn	Cd
1												
0.803	1											
0.697	0.725	1										
0.597	0.601	0.45	1									
0.761	0.773	0.955	0.496	1								
-0.226	-0.322	-0.780	-0.143	-0.594	1							
0.478	0.499	0.94	0.304	0.836	-0.883	1						
0.895	0.895	0.717	0.658	0.817	-0.199	0.487	1					
0.423	0.32	0.194	0.089	0.158	-0.154	0.042	0.238	1				
-0.589	-0.628	-0.67	-0.256	-0.679	0.387	-0.6	-0.672	-0.009	1			
0.559	0.626	0.432	0.265	0.544	-0.026	0.253	0.583	0.102	-0.238	1		
0.067	0.13	0.158	0.031	0.089	-0.276	0.077	0.006	0.501	0.151	-0.161	1	
-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
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
-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

factorial loads and communalities after transformation are presented in Table 5. The first Factor explains 43.371% of total variance in the data, whereas the second and third factor explains 15.366% and 11.510%, respectively. In the first Factor/Component, parameters such as elevation, depth of wells, EC, SAR, Cl^-, B and Mn present a load above 0.70, indicating the most common composition of the observed parameters. In the second Factor/Component, parameters Zn and Ni show high factorial loads of 0.774 and 0.625 respectively. The fourth Factor/Component showed Cd as the element with the load (0.644).

Selection of this four component model used the criterion described by Norusis (1990) considering only those components with a variance that has an autovalue above one. Any component must explain a variance above that presented by a single variable. This criterion is observed by Mendiguchia et al., (2004) 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

Table (5): Factorial loads for the observed parameters.

Parameters	**Factorial Loads Matrix**			
	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
HCO3	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 %	47.030	15.512	10.725	6.017
Cumulative %	47.030	62.541	73.266	79.284

Extraction Method: Principal Component Analysis.

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.

3.3 WQI Development

In order to develop the proposed WQI, the folling parameters EC, Cl, Na, HCO**3** and SAR parameters were used. These carry the major factorial load (above 0.82 from table 5), that is, define the best water quality. Henceforth, the weight of each parameter was

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	81.	Good	**Village (4)**	23	17	48.	Very

		3	98					42	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

for using this water in irrigation at long term are required especially because the soils texture is heavy and the climate is hot.

Overall, the results in table 7 indicate that villages 1-2 are generally have Good water quality, however villages 3-4 have a Very poor water quality. Restrictions effect, K-Bessel, J-Bessel, and stable) were tested for each parameter data set. Prediction performances were assessed by cross validation, which examines 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 range is from 0.006153 to -0.000346 and the RMSS range is from 0.9642 to 0.9788. In this case, for the EC parameter the best fit is the J-Bessel model (SME -0.000346) and Circular model for Cl^- with a 0.005528 standardized mean error. It is closest to zero, and the 0.9788 RMSS value is closest to 1. When the average estimated prediction standard errors are close to the root-mean-square prediction errors from cross-validation, then you can be confident that the prediction standard errors are appropriate (Johnston et al., 2001).

3.4 Spatial and Interpolation Analysis of Groundwater Quality Variation

Water samples have been taken from 36 wells in the study area. The data has been checked by a histogram tool and normal QQPlots to see if it shows a normal distribution pattern. Normal QQPlots provide an indication of univariate normality. If the data is asymmetric (i.e., far from normal), the points will 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 show normal distributions, however, only the pH, B, and Zn parameters do not show normal distribution. For this parameter, a log transformation has 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 is no global trend for all parameters. In this study, the semivariogram models (circular, spherical, tetraspherical, pentaspherical,exponential, gaussian, rational quadratic, hole

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

Models	Prediction Errors									
	Mean		Root-Mean-Square		Average Standard Error		Mean Standard-ized		Root-Mean-Square Stand-ardized	
	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

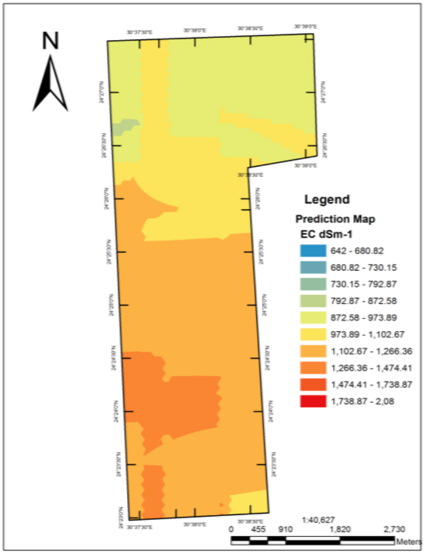
and their prediction error values for each parameter. Table 9 also shows that for different parameters different models may give better results. For water quality parameters, RMSS range from 0.945 to 1.2452.

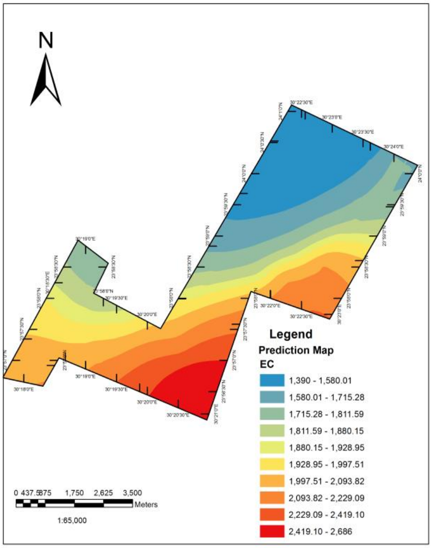
After applying different models for each water quality parameter examined in this study, the error was calculated using cross validation and models giving best results were determined. Table 9 shows the most suitable models

Table (9): Fitted parameters of the variogram model for groundwater quality.
*Using logarithm to normalize data.

Parameters	Models	Prediction Errors				
		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

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 generated from the surface map developed from the cross validation process.

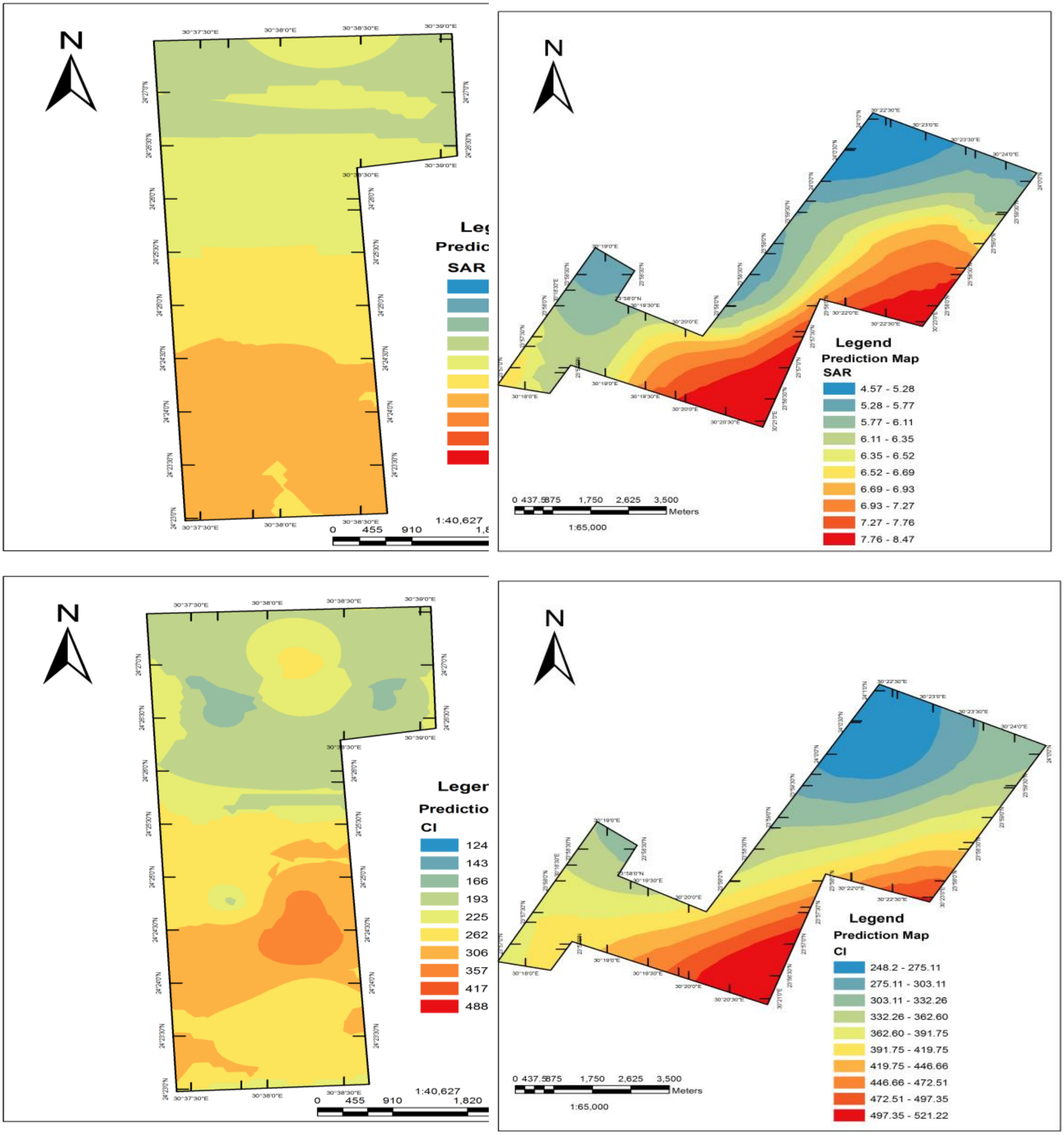




ed. Three of the groundwater samples fall in the moderate WQI. Most of the samples (26) fall in the Doubtful WQI category. Seven samples fall in the higher WQI category. Groundwater samples that fall in the low salinity hazard class and high WQI can be used in irrigation for most crops and the majority of soils.

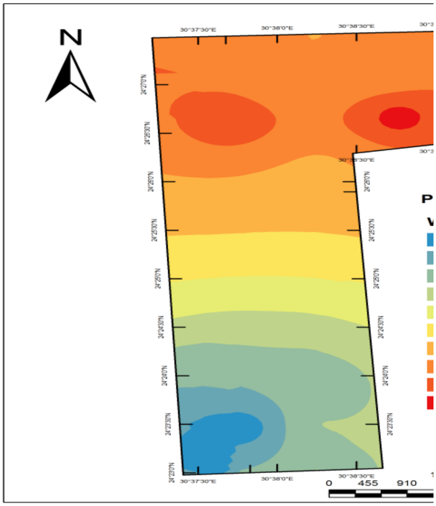
3.5 Groundwater Quality Mapping for Agricultural Purposes

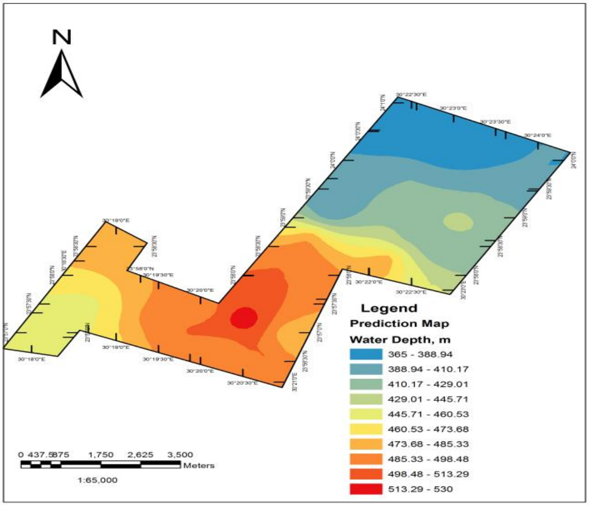
The groundwater quality maps for agricultural purposes are shown in Figure 5. The whole area is divided into three classes on the basis of EC. The quality of water for irrigation purposes depends on the salinity classified into suitable, moderate, and low. Also, the map of WQI is present-

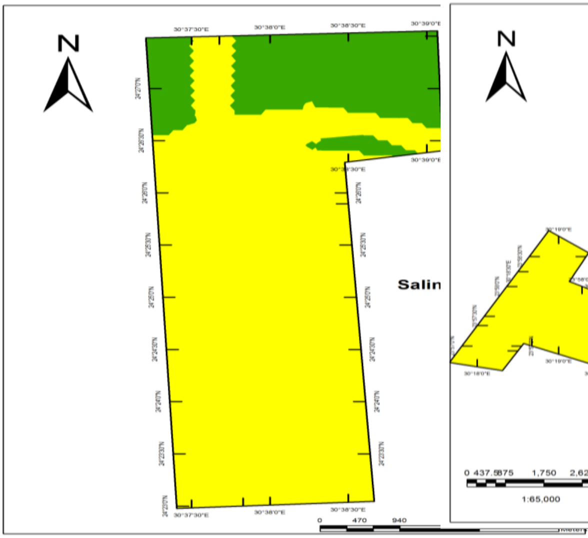


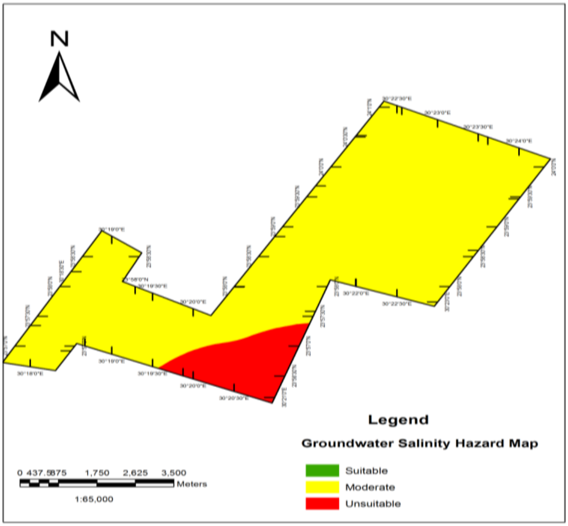
Village 1-2 **Village 3-4**

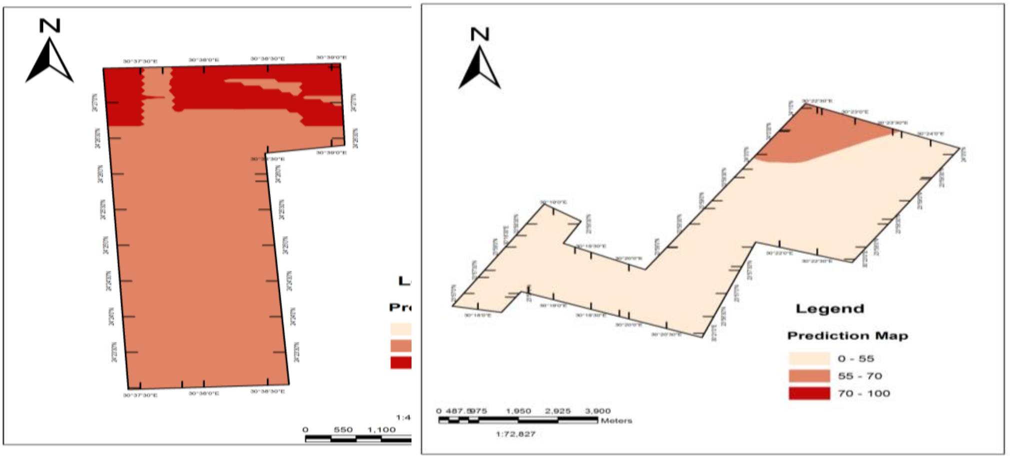
Fig. (4): Spatial distributions of EC, SAR and Cl^-.


N
0 455 910


N
Legend
Prediction Map
Water Depth, m
365 - 388.94
388.94 - 410.17
410.17 - 429.01
429.01 - 445.71
445.71 - 460.53
460.53 - 473.68
473.68 - 485.33
485.33 - 498.48
498.48 - 513.29
513.29 - 530
0 437.5875 1,750 2,625 3,500
Meters
1:65,000


N
0 470 940


N
Legend
Groundwater Salinity Hazard Map
Suitable
Moderate
Unsuitable
0 437.5875 1,750 2,625 3,500
Meters
1:65,000



WQI

Village 1-2 **Village 3-4**

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

Good quality and three wells are Poor quality. Overall, most of village 1 wells are Good quality which can be used for irrigation with Low restriction except well no. one which is very poor quality. Village 2 wells are Very poor quality with high restrictions for irrigation except wells no. 7 and 11 are Excellent quality which can be used for irrigation with No restriction. The villages 3 and 4 wells are Very poor quality which can be used for irrigation with High restrictions.

The map of (Figure 5) villages 3-4 has shown that 382.35ha (10.09%) of area falls in the

Figure 5 shows the suitability index map calculated in table 7. Suitability index is 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 are Excellent water quality) and therefore can be used for irrigation usage. Most of the samples are very poor (25 wells) with suitability index range between 40-55. One sample (well no. 32) is “unsuitable” quality and cannot be used for irrigation purposes. Five wells are processes that define water quality in the Darb El-Arbaein through a four component model, the components of which explain 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 1-2 indicates the presence of about 13.79% of the study area suitable groundwater for irrigation. However, in villages 3-4, 10.09% of the area falls 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 moderate category however, much of the area (3407.38ha) have unsuitable water quality. For the villages 1-2, the corresponding area of suitable category is 266.66ha (13.79%) however, moderate category is 1666.79ha. The observed low Suitability Index of the groundwater quality is because of the desert location and due to lack of deficiency water and rainfall, dug of deep and semi-deep well is 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 (Yisa and Jimoh, 2010).

4. Conclusions

The present paper proposes 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

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
.

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

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تقييم و رسم خرائط نوعية المياه الجوفية باستخدام طرق الاحصاء الجيولوجى للإدارة المستدامة للأراضي فى منطقة درب الأربعين - جنوب الصحراء الغربية – مصر

سلمان عبدالله حسن سلمي[١] , أحمد غلاب محمد[١] , عبدالله جاد عبدالله[٢] و السيد عويس عمران[٣]

[١]قسم الأراضى والمياه - كلية الزراعة - جامعة اسيوط – اسيوط. [٢]الهيئة القومية للاستشعار عن بعد و علوم الفضاء –القاهرة. [٣]قسم الأراضى والمياه - كلية الزراعة - جامعة قناة السويس – الاسماعيلية.

يعتبر تقييم مدى صلاحية المياه الجوفية هي الخطوة الأولى نحو إدارة سليمة ومستدامة لموارد المياه الجوفية والتربة. وللحد من الآثار المترتبة للرى بهذه المياه على الزراعة كان الهدف الرئيسى من هذه الدراسة هو اقتراح طريقة بسيطة لتقييم نوعية المياه الجوفية و رسم خرائط التباين المكاني من حيث مدى ملاءمتها لأغراض الري في منطقة درب الاربعين. كما كان الهدف التكميلى لهذه الدراسة هو اظهار امكانيات نظم المعلومات الجغرافية في استكشاف القيمة الكاملة للبيانات البيئية من خلال التحليل المكان والعرض المرئي للمعلومات الجغرافية. باستخدام بيانات نظام تحديد المواقع تم تجميع عينات مياه من ست وثلاثون بئر تمثل اربع قرى وذلك لتقييم واعداد خرائط نوعية المياه الجوفية. و لحساب مدلول جودة المياه فقد اخذ فى الاعتبار١٣ مقياس هى الاملاح , درجة الحموضة , الكلوريد , النسبة الادمصاصية للصوديوم , الكربونات المتبقية , البورون , الزنك , النحاس, الحديد , المنجنيز, الرصاص والكادميوم. كما تم استخدام نتائج التحليلات لرسم خرائط التنبؤ بنوعية وجودة المياه. وقد تم ادخال البيانات المختلفة في برامج نظم المعلومات الجغرافية، وأنتجت خرائط نوعية المياه المختلفة. كما تم استخدام طرق الاحصاء الجيولوجى لتحليل البيانات. أظهرت النتائج أن المياه الجوفية في منطقة الدراسة لها درجة حموضة تتراوح من ٧ الى ٨ , تركيز أملاح من ٦٤٢ الى ٢٦٦٨ ميكروسيمنز /سم , كما كان تركيز الكلوريد في معظم المناطق مرتفعا ليصل الى ٥٧٠.٨٦ جزء في المليون كحد اقصى. وكان ارتفاع الملوحة راجع الى ارتفاع تركيز الكلوريد فى المياه الجوفية. و تراوحت قيم SAR من ١.٨٣ الى ٨.٤ , و كانت تركيزات المعادن الثقيلة أقل من الحدود المسموح بها.تراوحت قيم مدلول نوعية المياه الجوفية من ٤٧.٩ الى ٨٨.٦ , كما وجد ان معظم العينات (٢٦ عينة) تقع فى المرتبة ذات نوعية المياه

المنخفضــة الجــودة , ثــلاث عينــات فقــط ذات نوعيــة ميــاه متوســطة الجــودة و ســبع عينــات تنــدرج تحــت الميــاه العاليــة الجــودة. ان عينــات الميــاه الجوفيــة المنخفضــة الملوحــة أو العاليــة الجــودة يمكــن اســتخدامها لــرى معظــم المحاصــيل فــى غالبيــة الأراضــى. كمــا أثبتــت هــذه الدراســة أيضــا كفــاءة عاليــة لــنظم المعلومــات الجغرافيــة لتحليــل البيانــات المكانيــة المعقــدة ورســم خــرائط جــودة المياه الجوفية.