A GIS-Based Spatial Classification Technique to Identify the Groundwater Quality and Type Classes

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Abstract: Classification either quality or type based for groundwater can offer great advantages especially in regional groundwater management. It provides a short, quick processing, interpretation for a lot of complete hydrochemical data sets and concise presentation of the results. Traditional statistical classification methods which aim at defining natural groups of groundwater quality or types, do not take the spatial dimensional into consideration during the classification process. The main objective of this study is to introduce a GIS spatial clustering technique to the hydrochemical data in order to identify over geographical space the different homogenous groundwater quality and type classes present in the study area without the use of any prior knowledge. In this approach the multivariate tool available in the ARCGIS (ArcInfo) Spatial Analyst Toolbox was utilized. This approach was successfully applied to a set of 13 hydrochemical parameters determined in 45 groundwater sampling sites in the Nile Delta aquifer, located between longitudes 29° 59' 00" to 32° 00' 00" East and latitudes 30° 08'00" to 31° 12' 00" North in the Nile Delta region north Egypt. As a preprocessing stage, the parameters were modeled to produce representative surfaces of the concentration level in ppm to illustrate their spatial distributions in the study area. Unsupervised classification process which was evaluated by the Dendrogram, followed by supervised classification process that utilized the Maximum Likelihood classification algorithm was carried out. The results showed that the groundwater in the study area can be classified into homogenous seven groundwater quality classes and five groundwater types geochemically interpretable. Also, the results revealed reliable agreement between the groundwater quality and its type in the same class. This approach is believed to be an effective tool in understanding the spatial variability of measured parameters in the study area more easily by providing a visual representation in great details. It also assists policy and decision makers to report the state of the groundwater quality, and provide land managers with knowledge of the precise groundwater quality problems affecting the aquifer. This technique can also serve as a guide for assessment of the hydrogeochemical processes controlling groundwater. The study recommended reuses this classification approach at regular and suitable temporal resolution with different classification algorithms to investigate the spatial and temporal changes of the groundwater quality and type in same area and other different locations.

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1. Introduction

Water is called matrix of life because it is an essential part of all living systems and is the medium from which life evolved and in which life exists. In arid and semi-arid regions, groundwater is a significant part of the total water resources. The quality as well as the quantity of clean water supply is of vital significance for the welfare of humanity Polluted water is a source of many diseases for human beings (Mahmood *et al.*, 2011). One of the major problems encountered with groundwater chemistry evaluation is that there are large amounts of basic information regarding the groundwater quality in regional studies. The usefulness of water for particular purpose is determined by the water quality. In recent years, with increasing number of chemical, physical variables, the complexity and large variation of environmental datasets limit the usefulness of univariate statistical methods which are often difficult to interpret and draw meaningful conclusions, so the application of multivariate statistical methods is recommended.

Multivariate statistical analysis comprises a number of statistical methods or a set of algorithms that may be applied to several fields of empirical investigation. These methods of cluster analysis, discriminant analysis, principal component analysis (PCA) and factor analysis (FA) were used with remarkable success as a tool for interpretation of the complex datasets. In recent studies, the multivariate treatment of hydrochemical data was commonly used to characterize and evaluate surface and groundwater quality, and it was useful for evaluating the groundwater monitoring wells similarity and detecting temporal and spatial variations caused by natural and anthropogenic factors. These techniques also permitted identification of the possible factors that influence the groundwater systems and are responsible for the variations in groundwater quality, which thus offers a valuable tool for developing appropriate strategies for effective management of the water resources and also giving a better understanding of the physical and chemical properties of the groundwater system (Sanchez-Martos *et al.*, 2001; Subyani, and Al Ahmadi 2010; Ishaku *et al.*, 2011; Lalitha *et al.*, 2012; Cobbina *et al.*, 2012).

The above mentioned multivariate statistical methods can be considered as data reduction and non-spatial clustering techniques. Grouping or classification of hydrochemical measurements is the key element in these data analysis procedures. There are lots of non-spatial clustering techniques in various areas. However, spatial clustering techniques and software are not so common. Many previous studies concerned the characterization of groundwater faces utilized graphical representations of the major compositions of groundwater**.** These classical classification techniques such as Stiff and Piper diagrams only consider selected major water constituents in determining the groundwater type (Adomako *et al*., 2011; Kura *et al*., 2013;).

Despite the rapid development of computer technology, Geographic Information Systems (GIS) and the increased number of statistical applications of water quality over recent years, relatively few studies have considered a GIS-based approach for multivariate data analysis. Some studies have attempted to apply both multivariate analysis and GIS techniques in environmental studies; however GIS techniques have only been used for visualization purposes in these studies. Geostatistical techniques have been given special attention because they incorporate the spatial autocorrelation concept explicitly in the modeling process and facilitate to assess the prediction quality (Balakrishnan, 2011; Narmatha *et al*., 2011; Sahebjalal, 2012**;** EL Hammoumi *et al*., 2013).

From this point of view it might be beneficial to investigate how spatial multivariate analysis integrated with GIS technology for the spatial assessment of groundwater quality to inform relevant stakeholders on steps required to sustain this fragile natural resource. This study aims to introduce a GIS spatial clustering technique based on the clustering concepts that used in pattern recognition, image processing and information retrieval to the hydrochemical data in order to identify the different groundwater quality classes present in the study area without the use of any prior knowledge. In this approach the multivariate tool available in the ARCGIS (ArcInfo) Spatial Analyst Toolbox was utilized.

2. Study Area and Data

2.1. Study Area Description

The study area lies between longitudes 29° 59' 00" to 32° 00' 00" East and latitudes 30° 08'00" to 31° 12' 00" North in the Nile Delta region north Egypt as shown in Figure 1.

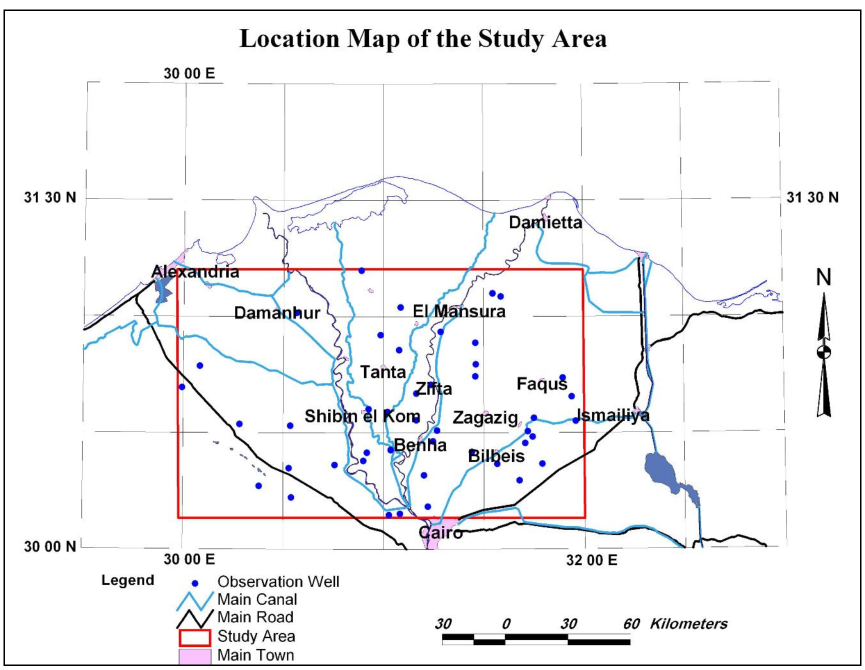

Figure 1. Location Map of the Study Area

The climate is less arid compared to the rest of Egypt and the rainfall is in excess of 150 mm/y along parts of coastal zone, decrease rapidly southwards to less than 25 mm/y in the vicinity of Cairo city. The annual minimum and maximum temperatures vary from about 13^{o}C to about 28^{o}C. On the basis of landuse it includes the traditionally cultivated land areas, the newly reclaimed areas as well as the scattered urbanized areas. Industrial activities are mainly in urbanized areas**.** The ground elevation varies from near sea level in the north to 5.5 m above mean sea level (AMSL) in the southern portion. The average groundwater level ranges from 1.3 m to 3.65 m AMSL. Extensive man made drainage systems are found which are particularly noticeable in the traditionally cultivated land areas and have been extended to some of the newly reclaimed areas, which allow for conveyance of the agriculture drainage water directly to the Mediterranean Sea or to its peripheral lakes (RIGW, 1992).

2.2 Hydrochemical Data and Laboratory Analyses

The hydrogeochemical data was obtained from the groundwater monitoring network in the Nile Delta Aquifer belongs to the Research Institute for Groundwater. The samples were collected in year 2009 from 45 observation wells at depth range from 40 to 50 m below the ground surface selected to represent the groundwater aquifer in the study area. The collected samples were analyzed in the central laboratory of the National Water Research Center (NWRC) for different physicochemical parameters, major cations major anions and trace metals such as pH, electrical conductivity (EC), Total Alkalinity, Total dissolved solids (TDS), ammonia, nitrate, sulfate, fluoride, chloride, sodium, calcium, magnesium, iron and zinc according to the standard methods.

3. Brief on Clustering

Cluster analysis is a type of Multivariate statistical methods. It is one of the important techniques in data mining and geographic knowledge discovery. Cluster analysis is the name given to an assortment of techniques designed to organize objects (observations) according to similar patterns, attributes, features, and other characteristics into natural groups called clusters to produce a concise representation of a system's behavior without explanation or interpretation. Objects within the same clusters are similar whereas objects in different clusters are dissimilar. Clustering of numerical data forms the basis of many classification and system modeling algorithms. Partitioning methods divide the data set into a number of groups predesignated by the user. Hierarchical cluster methods produce a hierarchy of clusters from small clusters of very similar items to large clusters that include more dissimilar items. Hierarchical methods usually produce a graphical output known as a dendrogram or tree that shows this hierarchical clustering structure. Some hierarchical methods are divisive; those progressively divide the one large cluster comprising all of the data into two smaller clusters and repeat this process until all clusters have been divided. Other hierarchical methods are agglomerative and work in the opposite direction by first finding the clusters of the most similar items and progressively adding less similar items until all items have been included into a single large cluster. Cluster analysis can be run in the Q-mode in which clusters of samples are sought or in the R-mode, where clusters of variables are desired. Hierarchical methods are particularly useful in that they are not limited to a pre-determined number of clusters and can display similarity of samples across a wide range of scales. Agglomerative hierarchical methods are particularly common in the natural sciences (Kaufman and Rousseeuw, 1990; Davis, 2002).

While clustering is one of the most important tasks in various areas, spatial clustering has also long been used as an important process in geographic analysis. The vast spatial data explosion caused by the GIS revolution, the computerization of key information sources and the availability of digital map information has greatly increased the opportunity and need for good spatial classification methods for both research and applied purposes. The principal problems in spatial data classification are outlined by large numbers of areas, large numbers of variables, non-normal variable distributions (most geographic data usually have very complex frequency distributions), non linear relationships, spatial dependency and systematic non random variations in spatial representation. For spatial clustering, it is important to be able to identify high-dimensional spatial clusters, which involves both the spatial dimensions and several non-spatial dimensions.

4. Methodology

To achieve the objectives of this paper the author went through the following procedure that can be summarized in the following steps as:

- Choosing the proper set of groundwater quality parameters.
- Preparing grid maps for the chosen chemical parameters as input for the classification procedure.
- Applying the proposed GIS based clustering approach based on the selected parameters to produce the final classified groundwater maps.

4.1 Choosing the Groundwater Quality Parameters

For the purpose of this research, the data of 45 observation wells that located in the study area have been chosen. The selected parameters encompass 13 hydrochemical variables as representatives for the most common chemical parameters. The physico-chemical parameters were represented by Bicarbonate (HCO_3) and Total Dissolved Solids (TDS). The major cations included Calcium (Ca), Potassium (K), Magnesium (mg) and Sodium (Na). In addition to Fluoride (F), Chloride (Cl), Nitrate (NO_3) and Sulfate (SO_4) were on behalf of the major anions. As well as the trace metals which covered by Copper (Cu), Iron (Fe) and Manganese (Mn). The selected parameters usually are the main factors that can easily define both of the groundwater quality and groundwater type.

4.2 Preparing the Grid Maps for Spatial Classification

The hydrochemical parameters were analyzed graphically by means of maps to illustrate their spatial distribution in the study area as shown in Figure 2. The measurements of the parameters were modeled to produce representative surfaces of the concentration levels in ppm for each variable within the study area. The Inverse Distance Weighting (IDW) modeling as one among of the spatial interpolating techniques which are built in the ARCGIS Spatial Analyst extension was utilized for this purpose. This IDW method uses a defined or selected set of sample points for estimating the output grid cell value. It determines the cell values using a linearly weighted combination of a set of sample points and controls the significance of known points upon the interpolated values based upon their distance from the output point. Thus, GIS enables us to look into the cause and effect relationship with visual presentation. On the other hand, the raster based GIS structure was selected because of its calculation capability in and integrating layers in the GIS classification approach.

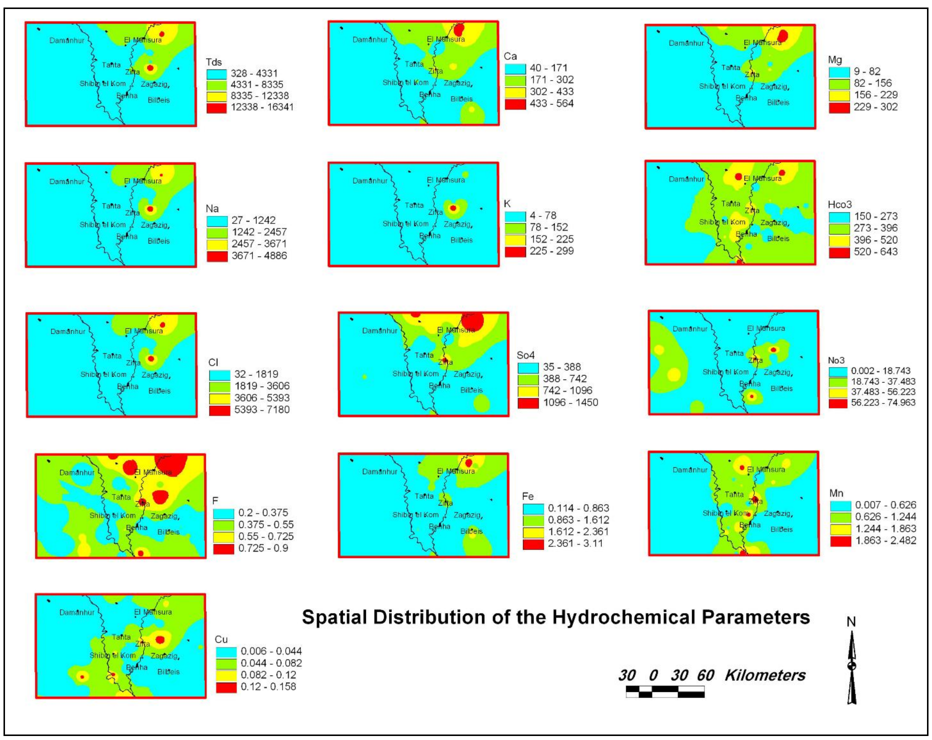

Figure 2. Spatial Distribution of the Hydrochemical Parameters

4.3 Applying the Classification Procedure

The procedure followed to implement the pixel-based classification of the input grids of the interested area was realized in the following steps as follows:

- Carrying out unsupervised classification.
- Evaluating the signature created by the unsupervised classification.
- Doing the supervised classification.

5. Implementation of the Spatial Classification Technique

To implement the pixel-based classification of the input grids belong to the study area, the elements of the multivariate tool available in the Spatial Analyst tools located in the Toolbox of the ARCGIS 9.3 (ArcInfo) were utilized. The author went through the above mentioned steps of the classification procedure as explained below:

5.1 Unsupervised Classification

On the basis of cluster analysis, unsupervised classification algorithms are optimal in cases where detailed knowledge such as ground truth data is not readily available for a study region. Unsupervised classification was carried out using the Iso Cluster tool. The Iso prefix of the ISODATA clustering algorithm is an abbreviation for the Iterative Self Organizing Data clustering technique. It is an iterative optimization clustering procedure, also known as the migrating means technique. This algorithm is an iterative process for computing the minimum Euclidean distance when assigning each candidate cell to a cluster. The process starts with arbitrary means being assigned by the software, one for each cluster as predefined at the beginning. Every cell is assigned to the closest of these means (all in the multidimensional attribute space). New means are recalculated for each cluster based on the attribute distances of the cells that belong to the cluster after the first iteration. Based on user-defined parameters, the process is repeated and the unknown grid pixel data is iteratively grouped together in clusters until either some proportion of pixels' class values remains unchanged or a maximum number of iterations have been reached (Lillesand and Kiefer, 1994; Russ,1995).

Iso Cluster was applied using the 13 input grids with 16 clusters, 100 maximum number of iteration and 20 cells as a minimum number in a valid class to have pre-knowledge about the site. This algorithm determines the characteristics of the natural groupings of cells in multidimensional attribute space and store the result in an output ASCII signature file.

5.2 Evaluating the Signature of the Unsupervised Classification

To produce a more accurate classification, the signature file created by unsupervised classification should be examined by Dendrogram which uses a hierarchical clustering algorithm. A dendrogram is a diagram that shows the attribute distances between each pair of sequentially merged classes. To avoid crossing lines, the diagram is graphically arranged so that members of each pair of classes to be merged are neighbors in the diagram. Then modifying and updating the existing signature file by reducing the number of classes.

The results of the unsupervised cluster analysis are shown in Figure 3 by a dendrogram, which lists all of the clusters and indicates at what level of similarity any two clusters were joined. The x-axis is some measure of the similarity or distance at which clusters join.

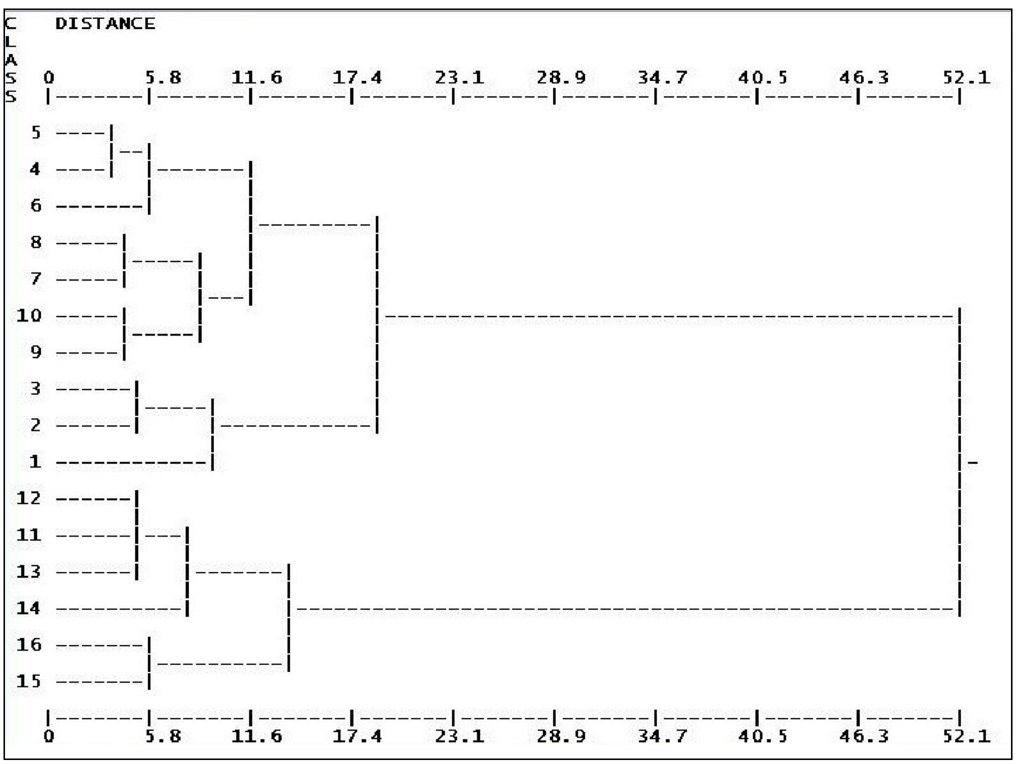

Figure 3. The Dendrogram of the Unsupervised Classification

The dendrogram clearly states that there are seven classes. The first class is represented by cluster 1. Class two results from merging clusters 2 and 3. The third class includes clusters 4, 5 and 6. The fourth class consists of clusters 7 and 8. The fifth class comprises clusters 9 and 10. The sixth class results from merging clusters 11, 12, 13 and 14. The last class comprises clusters 15 and 16. A new signature file was created for the new seven classes which would be used as training areas for the supervised classification procedure.

5.3 Supervised Classification

Supervised classification relies on the modified signature file, in which study area training sets are selected so as to be reasonably representative of only one class. The Maximum Likelihood is one of known several significant methods of supervised classification. The algorithm is based on two principles the cells in each class sample in the multidimensional space are normally distributed and Bayes' theorem of decision making. This approach assumes that statistics for each class in each input grid are normally distributed. Probabilities that a given pixel belongs to an arbitrary class (Gaussian value distribution) are computed, and the pixel is assigned to the most likely of these within a probability threshold, if specified (Schowengerdt, 2007).

Supervised classification algorithm (Maximum Likelihood) has been applied to the input grids based on using knowledge gained from the unsupervised classification, and the new signature sets that were generated for the desired classes. In this supervised classification, all classes were used by default. The spatial distributions of the final classes are illustrated by means of map as shown in Figure 4.

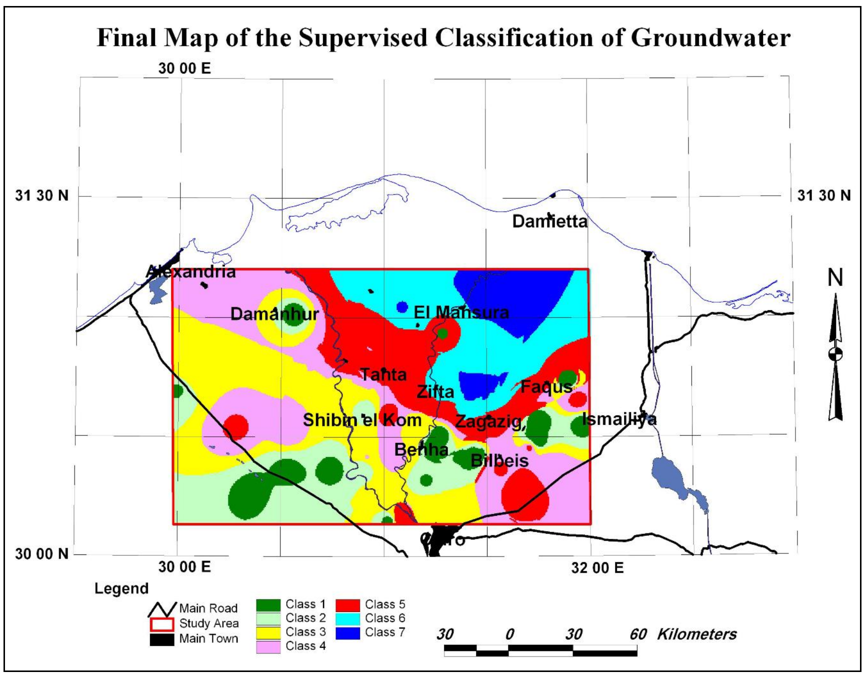

Figure 4. Final Map of the Supervised Classification of Groundwater.

6. Results and Discussion

To evaluate the groundwater classes, the descriptive statistics such as average value of the concentration level, minimum value, maximum value, range and standard deviation of the groundwater parameters of each class can be extracted from the input grids with the help of the ARCGIS capabilities. The average value of the concentration level for each hydrochemical parameters in each class was considered as a comparative value. The mean values in ppm of the different chemical prosperities of each class compared to WHO (1993) standards are listed in Table 1. The highest average value recorded for each parameter was marked in bold face.

Groundwater Quality

The concentration and composition of dissolved constituents in the groundwater determine its quality for different purposes. Based on the results the study area showed that concentration levels of all constituents are in increasing order from class one to class seven, which means that seven degrees of groundwater quality can be achieved. It can be noticed that the average concentration level of K, HCO3, NO3, F and Cu are within the permissible level in all classes. The first five classes had average values of Ca and SO_4 within the permitted limit while the last two exceeded the limit. Class seven has Mg higher the tolerable limit while all the others were below the limit. Classes one and two were only within the permissible limit of Ca. All classes except the first one had higher Cl as well as Fe concentration level than the WHO limit. On the other hand the mean values of Mn were higher than the permitted limit in all classes; it may be due to leachate from waste discharge in the study area. Higher concentration of Ca, Fe and SO_4 these could be conceived to mainly originate from the ionic dissolution in the course of groundwater migration as recorded by classes 6 and 7. High chloride concentration in groundwater of classes 4 and 5 may indicate pollutions by sewage, industrial waste or saline water intrusion. On other hand the high concentration level of both chloride and total dissolved solid is an indication that groundwater in contact with water of marine origin and that there is a possibility of salt water intrusion in classes 6 and 7.

Table 1. The Mean Values of the Chemical Parameters of Groundwater Classes

Parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	WHO
TDS	741.68	1035.45	1361.12	1686.79	2372.97	5221.15	**9177.04**	1000
Ca	66.52	85.84	108.89	130.08	161.86	241.12	**348.55**	200
Mg	28.72	36.95	41.72	47.81	64.97	118.33	**179.61**	150
Na	129.13	191.34	271.12	343.19	522.65	1329.79	**2473.79**	200
K	8.36	9.54	10.87	11.53	19.31	45.92	**74.42**	200
HCO_3	235.59	260.83	284.50	293.94	343.39	363.26	**391.02**	600
Cl	181.28	272.69	390.85	506.18	772.62	2011.16	**3873.79**	250
SO_4	110.44	168.74	229.04	285.33	378.21	688.37	**959.26**	400
NO_3	6.23	12.86	**15.29**	13.52	10.60	15.09	9.14	45
F	0.3456	0.3956	0.3923	0.3887	0.4446	0.6445	**0.7424**	1.50
Fe	0.2995	0.3815	0.4538	0.5684	0.7082	0.9129	**1.4728**	0.30
Mn	0.1759	0.3395	0.4567	0.3262	0.6325	0.8505	**0.9131**	0.10
Cu	0.0385	0.0459	0.0410	0.0307	0.0384	0.0564	**0.0722**	1.00

Table 2. Ionic Variation in the Groundwater of the Study Area

Class	Unit	K^+	Na^+	Mg^{2+}	Ca^{2+}	Cl^-	SO_4^{2-}	HCO_3^-	Water Type
1	ppm	8.36	129.13	28.72	66.52	181.28	103.24	235.59	Na-Ca-Mg-Cl-HCO_3
	epm	0.21	5.61	2.36	3.33	5.11	2.15	3.86	
	%	1.86	**48.75**	**20.51**	**28.88**	**45.92**	19.34	**34.73**	
2	ppm	9.54	191.34	36.95	85.84	272.69	168.74	260.83	Na-Ca-Cl-HCO_3-SO_4
	epm	0.24	8.32	3.04	4.29	7.68	3.52	4.28	
	%	1.54	**52.34**	19.12	**27.00**	**49.64**	**22.72**	**27.64**	
3	ppm	10.87	271.12	41.72	108.89	390.85	229.04	284.50	Na-Ca-Cl-SO_4-HCO_3
	epm	0.28	11.79	3.43	5.44	11.01	4.77	4.66	
	%	1.33	**56.29**	16.38	**26.00**	**53.85**	**23.34**	**22.81**	
4	ppm	11.53	343.19	47.81	130.08	506.18	285.33	330.00	Na-Ca-Cl-SO_4-HCO_3
	epm	0.30	14.92	3.93	6.50	14.26	5.94	5.41	
	%	1.15	**58.17**	15.33	**25.35**	**55.67**	**23.21**	**21.12**	
5	ppm	19.31	522.65	64.97	161.86	772.62	378.21	343.39	Na-Ca-Cl-SO_4
	epm	0.50	22.72	5.34	8.09	21.76	7.88	5.63	
	%	1.35	**61.99**	14.58	**22.08**	**59.38**	**21.50**	15.36	
6	ppm	45.92	1329.79	118.33	241.12	2011.16	688.37	363.26	Na-Cl
	epm	1.18	57.82	9.73	12.06	56.65	14.34	5.96	
	%	1.46	**71.57**	12.05	14.92	**73.62**	18.64	7.74	
7	Ppm	74.42	2473.79	179.61	348.55	3873.79	959.26	391.02	Na-Cl
	Epm	1.91	107.56	14.77	17.43	109.12	19.98	6.41	
	%	1.35	**75.92**	10.43	12.30	**80.52**	14.75	4.73	

Finally, the groundwater quality of these classes can be ranked in descending order from class one to class seven. The first class has the highest quality because all its constituents below the maximum allowable limits while class seven showed the worst degree of quality due to the highest values of concentration levels compared to WHO limits. Class two can be considered as a good quality although the slight increase of TDS, Fe and Mn. The quality of classes three and four can be accepted in spite of the higher concentration of Cl, Fe and Mn. The quality degree of class five could be fair relative to class six.

Groundwater Type

Classification of groundwater types in the study area can also be estimated for each class from the concentration of cations and anions that were incorporated in Table 1. The total equivalents of cations and anions as 100% and ions, as more than 20% (meq/L), were evaluated in the classification (Tatawat and Singhchandel, 2008) and marked in bold as presented in Table 2.

The results revealed that the study area had five groundwater types named as Na-Ca-Mg-Cl-HCO_3 found in class 1, Na-Ca-Cl-HCO_3-SO_4 which characterizes class 2, Na-Ca-Cl-SO_4-HCO_3 covers both of classes 3 and class 4, Na-Ca-Cl-SO_4 coats class 5 and finally Na-Cl is the water type of both classes 6 and 7. Also, a groundwater type map for the study area can be extracted as shown in Figure 5. The obtained groundwater types could be considered as an indication of the underlying hydrogeochemical processes happened in the study area. They could be refreshing due to recharge with fresh water of irrigation water, or mineralization of the geological components of soils, or cation-exchange processes at soil water interface or may indicate pollutions by sewage, industrial waste or that groundwater in contact with water of marine origin which make possibility of salt water intrusion. Finally, resultant classes of groundwater revealed reliable agreement between the groundwater quality and type in the same class.

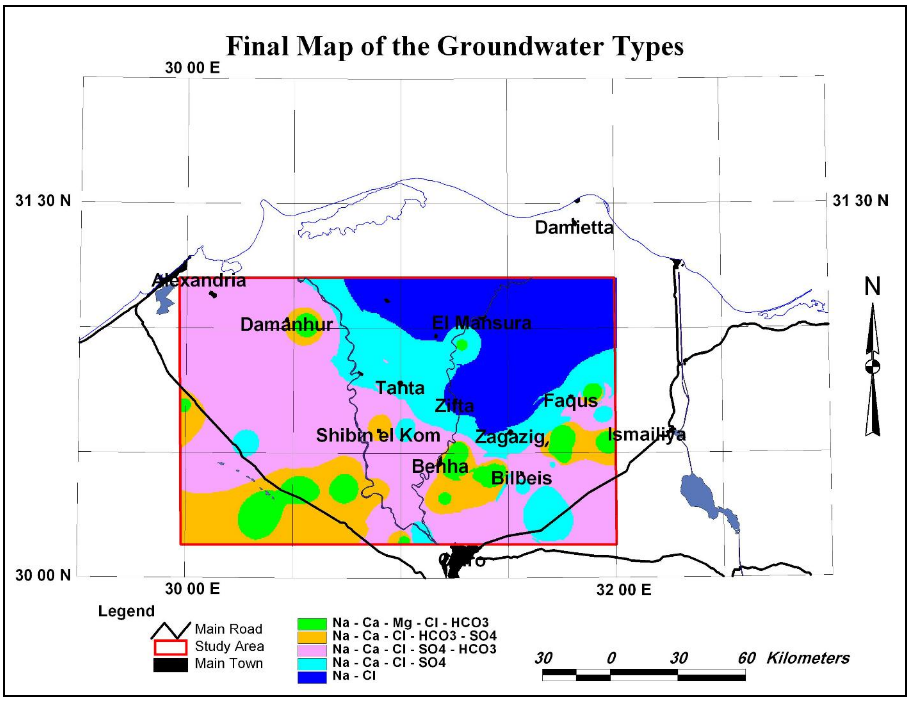

Figure 5. Spatial Distribution of Groundwater Types in the Study Area.

7. Conclusion and Recommendations

- Classification of groundwater can offer great advantages, especially in regional hydrochemical investigation. It provides a quick processing and interpretation of a lot of complete water analysis and a short, concise presentation of the results in graphical form makes understanding of complex groundwater system simpler and quicker.
- Applying spatial based clustering to groundwater data gives direct and sophisticated insight into a large database, on the basis of as many parameters as desired. It also reveals homogenous groundwater classes and geochemically interpretable which form a basis for reliable groundwater quality assessment.
- Spatial based classification of groundwater parameters help understanding the spatial variability of measured parameters in the study

area more easily by providing a visual representation in great details.

- Differentiating water types in aquifers help to identify and quantify water resources as well as to characterize the natural system, understand contaminant migration, and design remediation programs.
- Having clear cluster and a definite water type zones help in the development based on the groundwater and its suitability for different purposes.
- In general, the total number of data points (wells) and their spatial distribution in the study area can greatly influence the interpolation and classification accuracy. As the number of the sample points is high the accuracy would be high. Also, if the sample points have good spatial distribution, i.e. no area with poor data would enhance the interpolation and classification accuracy.
- On the basis of cluster analysis especially with unavailable pre-knowledge of the study area, the unsupervised classification process is usually carried out first. The optimal number of classes to specify is usually unknown. Therefore, it is advised to enter a conservatively high number, analyze the resulting clusters, and rerun the function with a reduced number of classes.
- The number iterations should be large enough to ensure that, after running the specified number of iterations, the migration of cells from one cluster to another is minimal; therefore, all the clusters become stable. Also, when increasing the number of clusters, the number of iterations should also increase.
- Overlying the classified maps with satellite imagery is recommended which can identify the water quality problems and can correlate them with the landuse to interpret the reasons for deterioration of environmental quality.
- This approach can be used for different classification purposes by choosing the most relevant variables defining the targets and selecting the right mix of data sources and has become critical to the generation of high quality classified maps.
- Accuracy assessment of the classification process using different classification algorithms is also recommended.
- Reuse of this classification approach at regular and suitable temporal resolution with different classification algorithms is recommended to investigate the spatial and temporal changes of the groundwater quality and type in same area and other different locations.

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