Journal of Hydrosciences and Environment
Available online at http://jhe.usb.ac.ir/

ISSN: 2345-5608

Evaluation of Interpolation Techniques for the Salinity of Groundwater in Wet and Dry Seasons (Case Study: Minab Plain, South Coast of Iran)

O. Bazrafshan[1*], M. Moradi[2], B. Farokhzadeh[3]

1. Assistant Professor, Department of Range and Watershed Management, Faculty of Agriculture and Natural Resources, University of Hormozgan, Bandar Abbas, Iran
2. MSc Student, Department of Range and Watershed Management, Faculty of Agriculture and Natural Resources, University of Hormozgan, Bandar Abbas, Iran
3. Assistant Professor, Department of Range and Watershed Management, Faculty of Natural Resources and Environmental Sciences, Malayer University - Malayer, Iran

ARTICLE INFO

Article history:

Received: *3 April 2017*
Accepted: *24 July 2017*

Keywords:
Groundwater quality,
Geostatistical methods,
Minab plain,
Electrical conductivity.

ABSTRACT

The goal of this study is evaluating the accuracy of geostatistical techniques in map zoning of the salinity of groundwater resources using 40 piezometric wells of Minab plain in the south coasts of Iran. The geostatistical techniques were evaluated using cross-validation with the statistical indices of MAE and MBE. Results show that the GPI technique with Gaussian model had the least error and relative deviation as revealed by its higher MAE and lower MBE. It had an MAE of 11 and 10.7 and and an MBE of 0.05 and 0.04 in wet and dry seasons, respectively. There was a good spatial correlation between the measured data at different points so that effective radius and CO/Sill of an isotropic semi-variogram model for wet and dry seasons were 0.14, 0.025, 9.8 and 8.4, respectively. Finally, GPI technique was used as the most appropriate interpolation method to prepare the spatial salinity map.

1. Introduction

Groundwater resources are one of the most important resources in arid and semi- arid regions of Iran. It plays a key role in agriculture production (Delbari et al., 2013). Sufficient knowledge about quality and quantity of aquifers should be gathered for optimum management of groundwater resources. Nowadays, one of the basic subjects is the shortage of high-quality water resources in the agricultural sector, especially in arid and semi-arid regions (Kim et al., 2004; Beltrán, 1999). Qualitative factors of irrigation water have an important impact on most soil features (Masoud Alaa, 2014). Hence, knowing the spatial variability of qualitative parameters of water is an important tool for better understanding and management of water resources and lands.

Geostatistical methods use classic and spatial statistics in earth sciences. Nowadays, geostatistics is used in many types of research to investigate the different issues of water and soil sciences (Fernández and Bravo, 2007; Costa et al., 2008). Studies have shown that the use of interpolation methods of hydro-chemical characteristics and water quality are so helpful. Extensive studies have focused on the spatial changes of physicochemical characteristics of water (e.g. Hosseini et al.,1994; Moustafa and Yomota, 1998; Fetouani et al., 2008; Mehrjardi et al., 2008; El-Yaouti et al., 2009; Arslan, 2012; Monjerezi et al., 2011; Masoud Alaa, 2014; Narany et al., 2015).

Hosseini et al. (1994) used Ordinary Kriging, TPSS, Nearest Adjacency, Moving Average, and Inverse Distance Weighted to estimate the soil salinity in Khuzestan province. Deviation from the methods was high due to the high magnitude of the ratio of nugget effect to the sill and finally, TPSS with a power value of 2. Ordinary Kriging was identified as the best method. Moustafa and Yomota (1998) used geostatistical methods for assessing soil salinity and hydraulic conductivity. By comparison of the estimated amounts of these parameters with Kriging method and the preparation of iso-value maps of the mentioned parameters, they concluded that Kriging method prepared more logical maps to study the drainage projects. Fetouani et al. (2008) used Ordinary Kriging to prepare the qualitative map of groundwater to study the groundwater quality of agricultural plains of Trifa in the northeast of Morocco in terms of the rate of ammonium nitrate and bacteriological contamination. Mehrjardi et al. (2008) did the spatial analysis of some of the qualitative characteristics of groundwater resources in Yazd plain using Inverse Distance Weighted (IDW), Kriging, and Co-kriging methods. Their results showed that Kriging method was better than two other methods and it was selected as the final and appropriate method to prepare the map of qualitative characteristics of groundwater in that region. Arslan (2012) explored the amount of salinity in an aquifer using the data of 97 wells in seven years of the statistical period (2004-2010) in Bafra plain in Turkey. The variograms fitted to the

[*]Corresponding author's email: *O.bazrafshan@hormozgan.ac.ir*

data included exponential and spherical models in ordinary Kriging and Kriging. The salinity of 31% of the plain was from 5 to 9 ds/cm in 2004 to 2010. Zhou et al (2012) did the spatial analysis of groundwater level and some of the chemical parameters related to 130 wells in Behi plain in the north of China. They reported that the best models fitted to the logarithmic data of groundwater level and TDS, TH, and EC were spherical, exponential, and Gaussian models, respectively. The preparation of zoning map showed that the trend of groundwater level was from the west to east, TDS and EC had an increasing trend, and the highest amount was located in the middle parts and shoreline of the plain. Masoud Alaa (2014) showed that more attention should be paid to the temporal monitoring of an area and local scale for better control of both the mixture of seawater and other salinization or contamination resources. Narany et al. (2015) argued that the concentration of magnesium and residual sodium carbonate could be influenced by the amount of precipitation and evaporation during both seasons in the plain. Hence, lithology, seawater intrusion, and land use patterns mostly control the concentration of groundwater quality parameters, and seasonal variation has a less significant role in groundwater quality in the Amol-Babol Plain.

Minab plain is located in southern coasts of Iran. It is one of the fertile plains in southern Iran and supplies drinking water besides its important role in providing the tropical agriculture products such as vegetables and horticulture products in southern Iran. Studies have shown over 7 meters subsidence of groundwater level and salinization of this plain in the last two decades (Madani, 2014). Many studies have been done in Minab plain but none has been focused on its salinity.

This overall goal was attempted by the following specific aims of the analysis:

(a) Analysis of the performance of different interpolation techniques including Kriging, Cokriging, GPI and IDW for specific ground water quality

b) Spatial mapping of salinity in Minab plain in the southern coast of Iran.

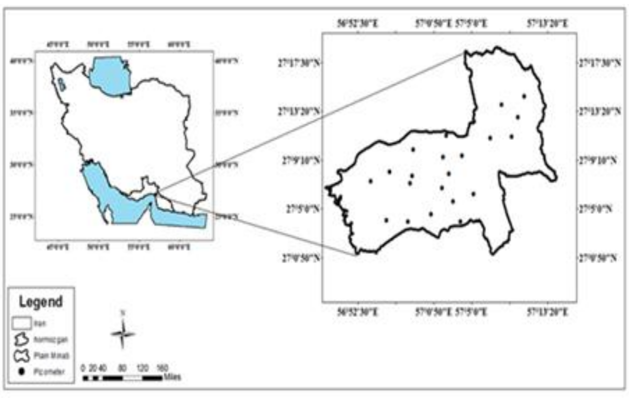


Figure 1. Map of Iran and Minab plian

2. Material and Methods

2.1. Study Area

Minab Plain is located in the eastern region of Hormozgan Province in the south coasts of Iran. The region lies between the latitudes of 26°52´ and 27°18' N. and the longitudes of 55°41' and 57°05' E. covering an area of approximately 5392.91 km^2 (Figure 1).

Mean altitude of Minab plian is 16 meters from the sea level, and Minab fresh water river flows in this plain. Based on the climatic categorization of Domarten, this region has an arid climate and its mean annual rainfall is 192 mm yr^{-1}, which mainly occurs in winter. Nine months of the year from April to December is considered as arid season and from January to March is considered as the wet season. The mean temperature is 35°C and 18°C in summer and winter, respectively. The rainfall regime is mostly originated from wet Mediterranean and Sudan fronts that enter into the country from the west and southwest, and affect whole south and southwest, including the "Esteghlal dam of Minab" catchment (Farajzadeh et al., 2015). Cultivation of vegetables and citrus fruit covers 60% and 20% of the agricultural lands, respectively, and it provides about 100% of drinking water of the commercial and economic city of Bandarabbas in Persian Gulf coasts (Mousazadeh, 2013). Minimum depth of alluvial deposits is 10 meter in the margin of eastern highlands and the maximum depth of these deposits with an amount of 200 meters is located in the western regions and the mean depth of the deposits is equal to 102.5 meters. This region is in the faulted Zagros which was created in the last period of Alpine orogeny in Polio-Pleistocene (Nohegar and Hosinzade, 2003). Minab plain consists of fine-grained particles and alluvial sediments of sedimentation in the Quaternary period that is affected by the hydrodynamic features of Minab plain (Figure 2). Main river basin has been created by joining two Roudan and Jaghin rivers in the upstream. The plain has been constructed on the river above Esteghlal dam in 30 km of the Persian Gulf coast (Farajzadeh et al., 2015).

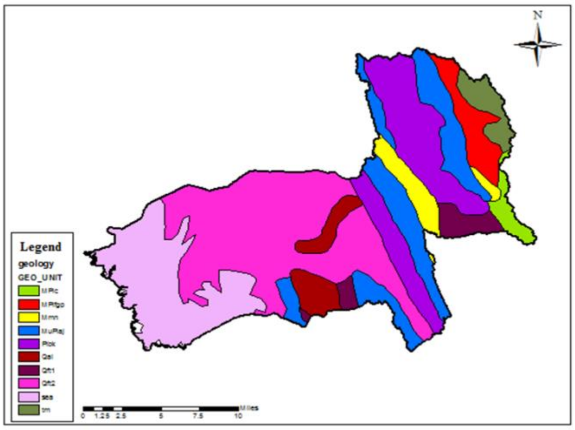


Figure 2. Geology map of Minab Plain

2.2. Sampling

Over the eight-year study period (2008-2015), electrical conductivity was collected for 45 piezometric wells of Minab plain (*Fig. 1*), amounting to 2296 samples for dry and wet season. After the preparation of base maps, different methods of interpolation were used to explore the spatial changes of the salinity of groundwater resources using electrical conductivity data of the wells in the region in dry and wet seasons.

2.3. Geostatistical Analysis

Inverse Distance Weighted (IDW), Kriging, CoKrigin and ordinal kriging and semi-variogram modeling were applied to estimate the spatial mapping of the major salinity variable related to groundwater quality. These techniques generally applied in hydro-geomorphological studies are appraised for building the feature data levels as it effectively models the reduced sampling density within an efficient way weighed against the easier methods as well as it offers a probabilistic estimation of the interpolation quality itself (Bohling, 2005).

2.4. Ordinary Kriging (OK)

Ordinary Kriging is the most widely used geostatistical methods. This method is based on the logic of weighted moving average and the best linear unbiased estimator that determines the amount of estimation at any point (Goovaerts, 1997; Kumar et al., 2011). This property can help delineate the sampling network and determine the additional points to decrease the estimation error (Mehrjardi et al., 2010). The following formula is used to estimate in Ordinary Kriging method:

$$Z^*(X_o)=\sum_{i=1}^{n} \lambda i Z(X_i) \quad (1)$$

where $z(x_0)$ is the estimated z variable in a point with X_0 coordination, $Z(X_i)$ is the observed value of z variable in a point with Xi coordination, $\lambda i$is the assigned weight to z variable in point of X_i, and n is the number of observations (Masoud Alaa, 2014).

2.5. Invert Distance Weighted (IDW)

The IDW function should be utilized when the group of points is thick enough to fully capture the amount of local surface variance needed for examination. IDW determines cell principles by using a linear-weighted mixture group of sample factors. The allocated weight is a function of the length of a suggestions point from the productivity cell location. The higher the length of the cell, the lower the effect it would impose and the lower the weight it would have in results (Lu and Wong, 2008). The statistical expression of this weighting procedure is as follows:

$$Z_o=\frac{\sum_{i=1}^{N} z_i d_i^{-n}}{\sum_{i=1}^{N} d_i^{n}} \quad (2)$$

In which,

d_i: the distance between estimation point and each adjacent sample point

Z_o: the value estimated of the variable z in point i

Z_i: the value of sample in point i

d_i: the distance of the sample to the estimation point

n: a coefficient that determines the weight based on the distance

2.6. Global Polynomial Interpolation (GPI)

Global Polynomial Interpolation fits a smooth surface to the point data. It is impossible to search and estimate the unknown points by the use of points in their adjacency. The changes of the surface in Global Polynomial are gradual and the effects of sudden changes are low. In this method, only a polynomial is fitted to all data (Johnston et al., 2001).

2.7. Semivariogram fitting

Variogram is used to determine the amount of spatial correlation of a variable in sampled distances and to extract the required parameters in interpolation stages. Variogram is the first step in modeling the spatial structure in order to use in Kriging method. It is computed by the following equation (Webster and Oliver, 2007).

$$\gamma(h)=\frac{1}{2n(h)}\sum_{i=1}^{n(h)}[z(x_i)-z(x_{i+h})]^2 \quad (3)$$

In which;

$\gamma(h)$: The value of semivariogram for the pair points with a distance of h

n: the number of pair points with a distance of h

$z(x_i)$: The observed value of the variable a point x

$z(x_{i+h})$: The observed value of a variable with a distance of h from x

Before using the semivariogram, it is necessary to fit the most appropriate theory on it. The process of fitting an appropriate theory on an experimental semivariogram is very important. Generally, the theoretical models that can be fitted on semivariogram are divided into two categories: the group without sill including Parabolic, Dewijsian and linear models, and the group with sill including Spherical, Exponential, Gaussian and Nested models (Hernandez-Stefanoni and Ponce-Hernandez, 2006)

In order to ensure the predictability of the theoretical model, prediction performances were validated for all models. Cross-validation helps to find which model provides the best prediction. We used mean from absolute error (MAE) (Eq.4) and mean brightness error (MBE) (Eq.5) for validation model (Chica- Olmo et al., 2014).

$$MBE=\frac{\sum_{i=1}^{n}\left|(Z^*(X_i)-Z(X_i))\right|}{n} \quad (4)$$

$$MBE=\frac{\sum_{i=1}^{n}(Z^*(X_i)-Z(X_i))}{n} \quad (5)$$

In which;

$Z^*(X_i)$: the estimated value in each point X_i

$Z(X_i)$: the observed value in point X_i

n: the number of observations

The ratio of nugget to sill applies the classification of groundwater quality parameters (Uyan and Cay, 2010). The variance of nugget shows that the stochastic changes data level (Mehrjardi et al., 2010). Sill shows that the distance of asymptotic from the curve in which structural variance reaches its peak remains constant (Delgado et al., 2010). The lag time shows the value of sill in semivariogram.

2.8. Statistical Analysis

One-sample Kolmogorov–Smirnov (K-S) test was used to analyze the normality of groundwater salinity data (Yu et al., 1993). The Kolmogorov–Smirnov statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples. In this test, P-value> α (α=0.05) shows the normality of data at the 95% level and otherwise, data are not normally distributed (Nas and Berktay, 2006).

3. Results and Discussion

3.1. Statistical summary

Table 1 shows the statistical characteristics of groundwater salinity in dry and wet seasons. Results revealed that the mean and standard deviation of EC is high in dry season, whilst EC in dry and wet seasons do not have a normal distribution and there is a need to normalize the data.

Therefore, data were normalized for wet and dry seasons by log-normal transform and sine transform, respectively. Data histogram (*Figure 3)* shows the results. Based on the data histogram, mean and median of data are very close (mean=7.6 and median=7.72) and hence the data normality was established using geostatistical technique. In order to explore the presence or absence of spatial correlation in electrical conductivity of groundwater, it is necessary to select one of the circular, spherical, exponential, Gaussian or similar models after fitting them to electrical conductivity. Hence, different models were tested on data using ArcGIS 10.3 software and the Gaussian model was selected among them as the most appropriate model because of having less error (ESRI, 2003). This model is started from the origin of coordinates and has a linear behavior near the origin. Then, the slope decreased gradually and in a certain distance – that is called effect range - reaches its threshold and remains in the same value (Uyan and Cay, 2010).

Characteristics of the fitted model on the amount of electrical conductivity semivariogram are shown in Table 2.

Table .1. Normality test using K-S test

	Mean	ST dev	Min	Max	P-value	Data distribution
Wet	1733.163	1061.891	1010	6354	0.00	Non-normal
Dry	2037.708	1228.703	1015	8415	0.00	Non-normal

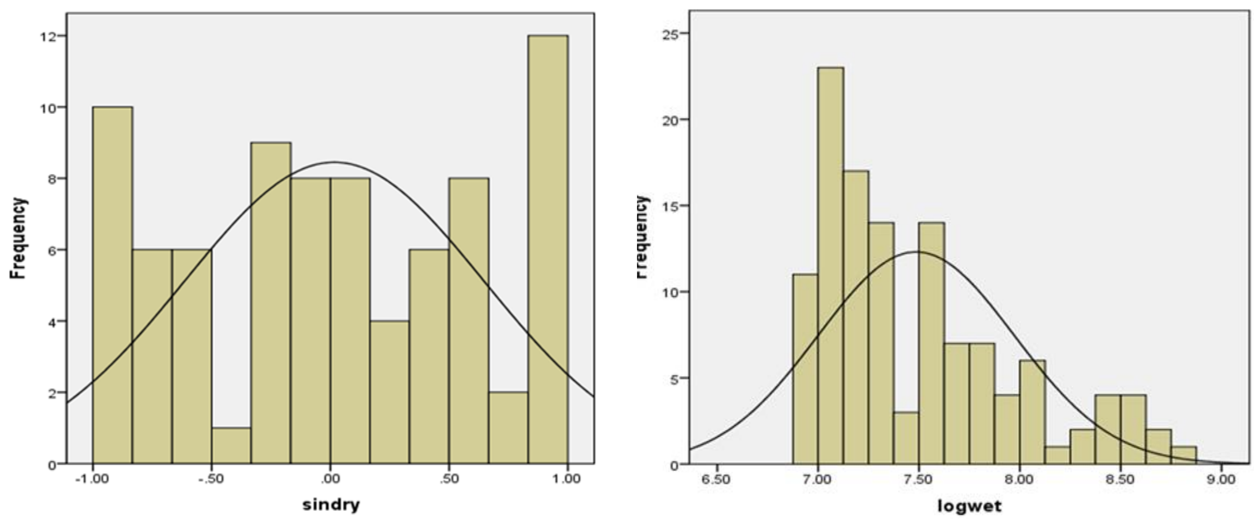


Figure 3. Histogram of logarithmic and sine conversion of dry (right) and wet (left) seasons data to normal distribution

Table 2. Adjusted variogram models for EC Parameter

Season	Type	Nugget (C0)	Sill (C)	Range (m)	C0/C0+C
	Nested Structure	0.033	1.407	0.756	2.2
Wet	Gaussian	0.138	1.266	67.5	9.8
	Exponential	0.014	1.424	117.3	0.97
	Spherical	0.032	1.398	85.6	2.2
	Nested Structure	0.007	0.314	8.063	2.1
Dry	Gaussian	0.025	0.272	8.063	8.4
	Exponential	0	0.293	8.063	0
	Spherical	0.007	0.321	8.06	2.1

Results of the evaluation of different interpolation methods are presented in Tables 3 and 4. Considering that in IDW method, the distance between known and unknown points is the initial weighting to known points, the magnitude of the distance has an impact on the accuracy of the estimation. Comparison of different methods of interpolation reveals that GPI has the highest accuracy of MAE=10.7 and the lowest error of MBE=-0.036 in the wet season and the highest accuracy of MAE= 11 and the lowest error of MBE=0.047 in the dry season. Figure 4 shows the semivariogram of electrical conductivity in wet and dry seasons. Based on the semivariogram, it can be understood that with a nugget of 0.14 and 0.25 in wet and dry seasons, respectively and with sill of 1.3 and 0.3, semivariogram error, C0/C0+C, would be 9.8% and 8.4%. Figure 5 depicts results of the best interpolation method in wet and dry seasons.

The average EC of groundwater is higher in northern parts of plain. These results were reported by Nohegar and Hoseinzade (2003) in the Minab plain.

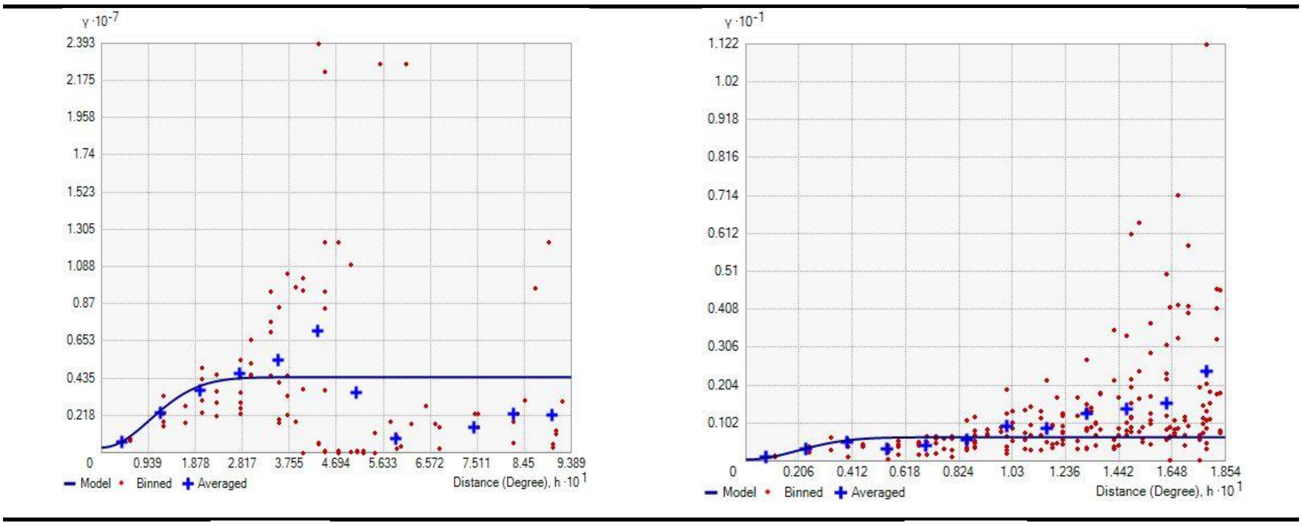
The GPI method showed the lowest error among all techniques. This is in agreement with Narany et al. (2015) in Amol-Babol plain and Mehrjardi et al. (2008) in Yazd plain.

Table 3. Results of interpolation of different methods in wet season

Method	MAE	MBE
Invert Distance Weighted with power value of 1	8.126	0.41
Invert Distance Weighted with power value of 2	8.324	-0.012
Invert Distance Weighted with power value of 3	8.98	0.365
Invert Distance Weighted with power value of 4	8.613	-0.023
Invert Distance Weighted with power value of 5	9.329	0.394
Local Polynomial Interpolation	9.678	0.326
Global Polynomial Interpolation	10.69	-0.036
Simple Kriging	9.128	0.213
Ordinary Kriging	9.326	0.529

Table 4. Results of interpolation of different methods in dry season

Method	MAE	MBE
Invert Distance Weighted with power value of 1	8.397	0.632
Invert Distance Weighted with power value of 2	8.659	0.781
Invert Distance Weighted with power value of 3	8.981	0.265
Invert Distance Weighted with power value of 4	9.32	0.165
Invert Distance Weighted with power value of 5	9.327	0.095
Local Polynomial Interpolation	9.782	0.321
Global Polynomial Interpolation	10.987	0.047
Simple Kriging	9.631	0.236
Ordinary Kriging	9.361	0.236



Dry season Wet season

Figure 4. Semivariogram of electrical conductivity in wet and dry seasons

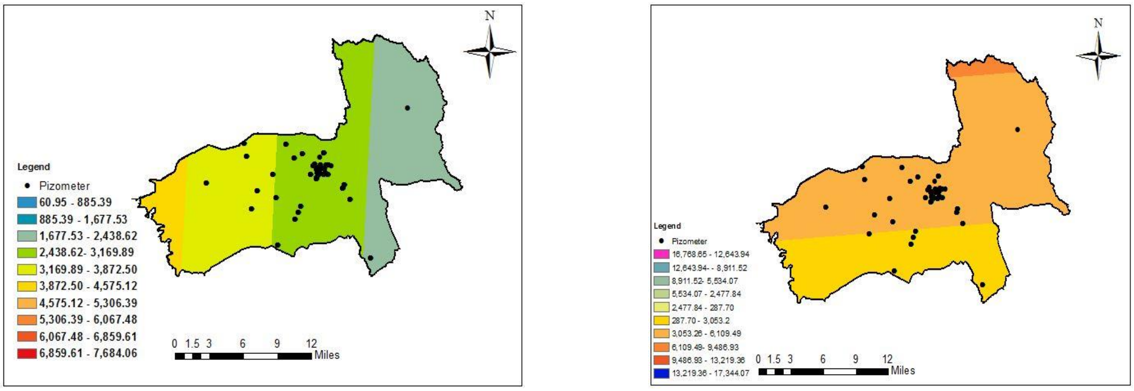


Figure 5. Zoning of groundwater salinity of wet and dry seasons in Minab plain

4. Conclusion

It was hypothesized that geostatistical methods can be used to estimate the salinity throughout the plain and a method can be suggested as the best one regarding the conditions of the region. Based on the results and the spatial autocorrelation of data, different geostatistical methods can be integrated with Geographic Information System. The variograms used in this paper showed that delineation is capable of modeling the spatial correlation changes in different aspects besides proving the spatial correlation among rainfall erosivity data. Also, according to the results, Global Polynomial Interpolation method was found to have the lowest error and was introduced as the best method for zoning water salinity factor in Minab plain while Kriging was introduced as appropriate method of interpolation. Analysis of semivariogram and evaluation of different interpolation methods showed that semivariogram of groundwater electrical conductivity in Minab plain follows the Gaussian model. Generally, results of semivariogram analysis showed a good spatial correlation for electrical conductivity in the studied plain.

Furthermore, results shown in Table 3 revealed that GPI had the lowest error among all interpolation methods.

The aquifer system of Minab plain that is the main water resource for municipal, agricultural and industrial uses is under high pressure in the Hormozgan province. It is of crucial importance to reduce water use. Developing artificial recharge projects in the area can be helpful.

5. References

1. Arslan, H. 2012. Spatial and temporal mapping of groundwater salinity using ordinary kriging and indicator kriging: the case of Bafra Plain, Turkey. Agricultural Water Management, 113, 57-63.
2. Beltrán, J.M. 1999. Irrigation with saline water: benefits and environmental impact. Agricultural water management, 40(2), 183-194.
3. Bohling, G. 2005. Introduction to geostatistics and variogram analysis. Kansas Geological Survey, 1-20.

4. Chica-Olmo, M., Luque-Espinar, J. A., Rodriguez-Galiano, V., Pardo-Igúzquiza, E., Chica-Rivas, L. 2014. Categorical Indicator Kriging for assessing the risk of groundwater nitrate pollution: the case of Vega de Granada aquifer (SE Spain). The Science of the Total Environment, 470, 229-239.
5. Costa, A.C., Durao, R., Soares, A., Pereira, M.J. 2008. A geostatistical exploratory analysis of precipitation extremes in southern Portugal. REVSTAT–Statistical Journal, 6(1), 21-32.
6. Delbari, M., Motlagh, M. B., Kiani, M., Amiri, M. 2013. Investigating spatiotemporal variability of groundwater quality parameters using geostatistics and GIS, International Research Journal of Applied and Basic Sciences, 4(10), 3623-3632.
7. Delgado, C., Pacheco, J., Cabrera, A., Batllori, E., Orellana, R., Bautista, F. 2010. The quality of groundwater for irrigation in tropical karst environment: the case of Yucatan, Mexico. Agricultural Water Management, 97(10), 1423-1433.
8. El-Yaouti, F., El-Mandour, A., Khattach, D., Benavente, J., Kaufmann, O. 2009. Salinization processes in the unconfined aquifer of Bou-Areg (NE Morocco): a geostatistical, geochemical, and tomographic study. Applied Geochemistry, 24(1), 16-31.
9. ESRI, ARC GIS. 2003. Environmental Systems Research Institute, Using ArcGIS geostatistical analyst USA.
10. Farajzadeh, M., Kamangar, M., & Bahrami F. 2015. Assessing landscape change of Minab delta morphs before and after dam construction, Natural Environment Change, 1(1): 21-29.
11. Fernández, C. J., Bravo, J. I. 2007. Evaluation of diverse geometric and geostatistical estimation methods applied to annual precipitation in Asturias (NW Spain). Natural Resources Research, 16(3), 209-218.
12. Fetouani, S., Sbaa, M., Vanclooster, M., Bendra, B. 2008. Assessing ground water quality in the irrigated plain of Triffa (north-east Morocco). Agricultural water management, 95(2), 133-142.
13. Goovaerts, P. 1997. Geostatistics for natural resources evaluation. Oxford University Press on Demand.
14. Hernandez-Stefanoni, J.L., Ponce-Hernandez, R. 2006. Mapping the spatial variability of plant diversity in a tropical forest: comparison of spatial interpolation methods. Environmental Monitoring and Assessment, 117(1), 307-334.
15. Hosseini, E., Gallichand, J., Marcotte, D. 1994. Theoretical and experimental performance of spatial Interpolation methods for soil salinity analysis, Transactions of the ASAE, 37(6): 1799-1807.
16. Johnston, K., Ver Hoef, J. M., Krivoruchko, K., Lucas, N. 2001. Using ArcGIS geostatistical analyst (Vol. 380). Redlands: Esri.
17. Kim, D. W., Lee, K. H., Lee, D. 2004. On cluster validity index for estimation of the optimal number of fuzzy clusters. Pattern Recognition, 37(10), 2009-2025.
18. Kumar, P.S., Jegathambal, P., James, E.J. (2011). Multivariate and geostatistical analysis of groundwater quality in Palar river basin. International Journal of Geology, 4.
19. Lu, G.Y., Wong, D.W. 2008. An adaptive inverse-distance weighting spatial interpolation technique. Computers & Geosciences, 34(9), 1044-1055.
20. Madani, K. 2014. Water management in Iran: what is causing the looming crisis?. Journal of environmental studies and sciences, 4(4), 315-328.
21. Masoud Alaa, A. 2014. Groundwater quality assessment of the shallow aquifers west of the Nile Delta (Egypt) using multivariate statistical and geostatistical techniques, Journal of African Earth Sciences, 95, 123-137.
22. Mehrjardi M. Z., Mehrjardi R., Akbarzadeh A. 2010. Evaluation of Geostatistical Techniques for Mapping Spatial Distribution of Soil pH, Salinity and Plant Cover Affected by Environmental Factors in Southern Iran, Notulae, Scientia Biologicae, 92–103.
23. Mehrjardi, R.T., Jahromi, M. Z., Mahmodi, S., Heidari, A. 2008. Spatial distribution of groundwater quality with geostatistics (case study: Yazd-Ardakan plain). World Applied Sciences Journal, 4(1), 9-17.
24. Monjerezi, M., Vogt, R. D., Aagaard, P., Saka, J. D. 2011. Hydro-geochemical processes in an area with saline groundwater in lower Shire River valley, Malawi: an integrated application of hierarchical cluster and principal component analyses. Applied Geochemistry, 26(8), 1399-1413.
25. Mousazadeh, R. 2013. Chemical and microbiological quality of drinking water in Bandar Abbas. European Journal of Experimental Biology, 3(4), 254-256.
26. Moustafa, M. M., Yomota, A. 1998. Spatial modeling of soil properties for subsurface drainage projects. Journal of irrigation and drainage engineering, 124(4), 218-228.
27. Narany, T. S., Ramli, M. F., Aris, A. Z., Sulaiman, W. N. A., Fakharian, K. 2015. Groundwater irrigation quality mapping using geostatistical techniques in Amol–Babol Plain, Iran. Arabian Journal of Geosciences, 8(2), 961-976.
28. Nas, B., Berktay, A. 2006. Groundwater contamination by nitrates in the city of Konya,(Turkey): A GIS perspective. Journal of Environmental Management, 79(1), 30-37.

29. Nohegar, A., Hosinzade, M. 2003. Ocean dynamics and determinants of fluctuations in sea level in the northern deltas change case stydy: Strait of Hormu, Geography and Environmental Planning Journal, 3, 125-142.

30. Uyan, M., Cay, T. 2010. Geostatistical methods for mapping groundwater nitrate concentrations. In 3rd International conference on cartography and GIS.

31. Webster, R., Oliver, M.A. 2007. Geostatistics for environmental scientists. John Wiley & Sons.

32. Yu, Y. S., Zou, S., Whittemore, D. 1993. Non-parametric trend analysis of water quality data of rivers in Kansas. Journal of Hydrology, 150(1), 61-80.

33. Zhou, Z., Zhang, G., Yan, M., Wang, J. 2012. Spatial variability of the shallow groundwater level and its chemistry characteristics in the low plain around the Bohai Sea, North China. Environmental monitoring and assessment, 184(6), 3697-3710.