World Applied Sciences Journal 4 (1): 09-17, 2008
ISSN 1818-4952
© IDOSI Publications, 2008

Spatial Distribution of Groundwater Quality with Geostatistics (Case Study: Yazd-Ardakan Plain)

[1]R. Taghizadeh Mehrjardi [2]M. Zareian Jahromi, [3]Sh. Mahmodi and [4]A. Heidari

[1]MSc Student of Soil Science, Tehran University, Iran
[2]MSc Student of Dedesertification, Tehran University, Iran
[3]Professor of Soil Science, Tehran University, Iran
[4]Assistant Professor of Soil Science, Tehran University, Iran

Abstract: Groundwater is one of the major sources of exploitation in arid and semi-arid regions. Thus for protecting Groundwater quality, data on spatial and temporal distribution are important. Geostatistics methods are one of the most advanced techniques for interpolation of Groundwater quality. In this research, IDW, kriging and cokriging methods were used for predicting spatial distribution of some Groundwater characteristics such as: TDS, TH, EC, SAR, Cl^- and SO_4^{2-}. Data were related to 73 wells in Ardakan-Yazd plain. After normalization of data, variograme was drawn, for selecting suitable model for fitness on experimental variograme, less RSS value was used. Then using cross-validation and RMSE, the best method for interpolation was selected. Results showed that for interpolation of Groundwater quality, kriging and cokriging methods are superior to IDW method. In cokriging method, one paremeter was selected as auxiliary variable which had the highest correlation with targeted variable. Finally, using cokriging method and GIS, map of Groundwater were prepared.

Key words: Interpolation . saptial distribution . geostatistics . groundwater quality . cross-validation

INTRODUCTION

Water is essential for sustenance of life. The knowledge of the occurrence, replenishment and recovery of potable groundwater assumes special significance in quality-deteriorated regions, because of scarce presence of surface water. In addition to this, unfavorable climatic condition i.e. low rainfall with frequent occurrence of dry spells, high evaporation and etc. on one hand and an unsuitable geological set up on the other, a definite limit on the effectiveness of surface and subsurface reservoirs [1].

During recent years, increasing pollution and lossing of water sources have changed exploitation policy of water and soil sources. As nearly 50 years ago, dominant water of agricultural fields in Yazd-Ardakan plain was supplied by 150 Ghanat. While in recent decades, exploitation of water and soil sources has been changed generally by excavation of more than 800 wells, deep and mid-deep. Also annual falling of 80cm in aquifer of Yazd-Ardakan plain is considered the major challenge of the area, either in view of natural sources, desertification or in view of human sources including unemployment and increasing immigration. Therefore, sustainable management of water and soil sources requires being informed from changes of Groundwater quality. Thus this research has been carried out with the aim of testing the performance of spatial interpolation techniques for mapping Groundwater quality [2].

The accuracy of interpolation methods for spatially predicting soil and water properties has been analyzed in several studies [3]. Safari [4] used kriging method to estimate spatial prediction of Groundwater in Chamchamal plain in west of Iran. Results showed that suitable method of geostatistics to estimate one variable depends on variables type and regional factors which influence this and any selected method for given region can not be generalized to others. Nazari *et al.* [5], used geostatistics method to study spatial variability of Groundwater quality in Balarood plain. Their results showed spherical model is the best model for fitting on experimental variograme of EC, Cl and SO_4 variables. Istock and Cooper [6] used kriging method to estimate heavy metals. They found that the mentioned method is the best estimator for spatial prediction of lead. Dagostino *et al.* [7] studied spatial and temporal variability of nitrate, using kriging and cokriging methods in Groundwater. Their results showed that cokriging method has resulted in increasing accuracy to estimate nitrate concentration. Rizzo and Mouser [8] used geostatistics for analyzing Groundwater quality.

Corresponding Author: M. Zareian Jahromi, MSc Student of Dedesertification, Tehran University, Iran

They used microbial data as auxiliary variable in cokriging method. These researchers' results showed that cokriging method has suitable accuracy to estimate Groundwater quality. Ahmad [9] used kriging method to estimate TDS in Groundwater and demonstrated accuracy of this method to prediction of TDS. Gaus [10] studied pollution of Bangladesh Groundwater in view of heavy metal. They used disjunctive kriging method to estimate arsenic concentration and to prepare risk map. Their results showed that 35milion people are exposed in high concentration of Arsenic (50ppm) and 50 million people are exposed in 10ppm. Finke *et al.* [11] used simple kriging to estimate water surface changes in Netherlands and introduced it as a suitable method for mapping of water surface. Barca and Passarella [12] used Disjunctive kriging and simulation methods to make nitrate risk map in 10, 50(mgr/lit) thresholds, in Modena plain of Italy. Their results showed that Disjunctive kriging method is the suitable method to study deterioration level of Groundwater.

The present study was therefore, carried out with objectives to evaluate accuracy of different interpolation methods, kriging, cokriging and IDW, for prediction of some Groundwater quality parameters in Yazd-Ardakan Plain.

MATERIAL AND METHODS

Case study: Yazd-Ardakan plain has area about 1595000 ha which is located in Northern part of Yazd Province and included 12.3% of 13 million ha area of the province. This area has been extended between the longitudes of 52^o 57' to 54^o 59' and latitudes 31^o 13' to 32^o 48' of Iran central plateau (Fig. 1). This area is surrounded by mountains and the general slope is from North-West to East-South to Siyah koh plateau. The region climate is dry and cold, in way of modified Domartan method. Precipitation average is 62.1 mm and ETP is 3483mm.

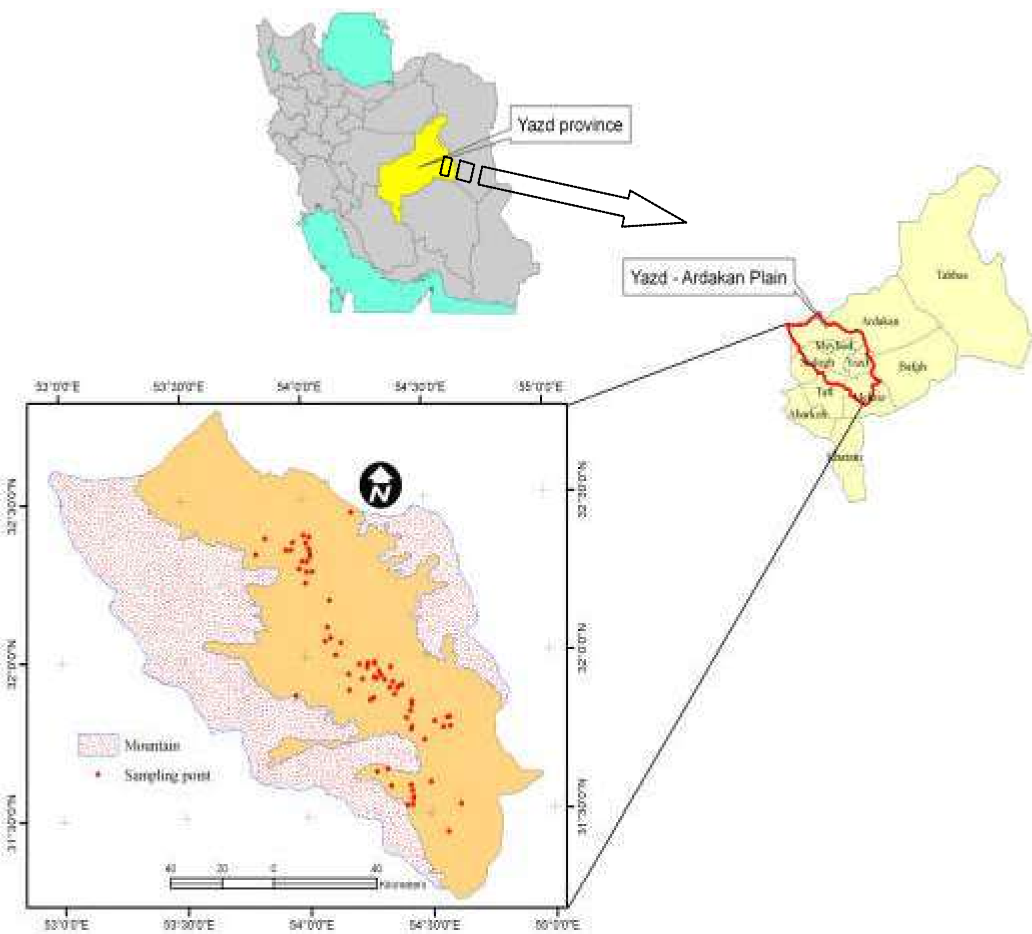

Fig. 1: Situation of studied region and sampling wells distribution

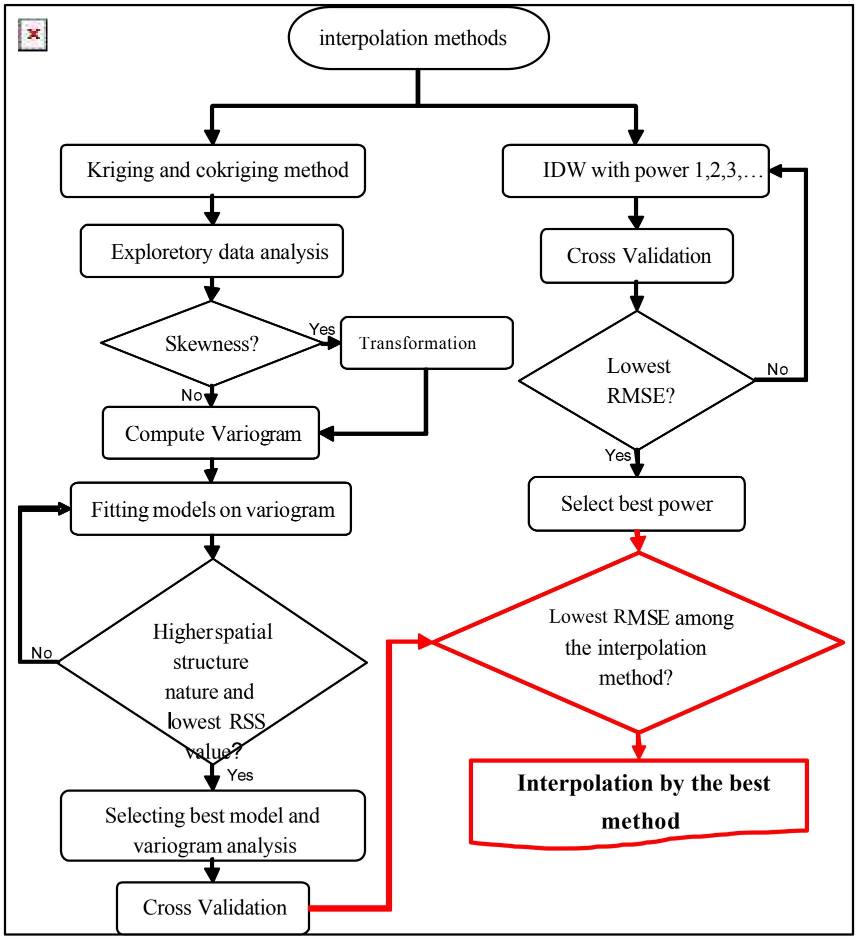

Fig. 2: Flowchart of Geostatistic study and selection of the best model for estimation of variable

Reaserch method: In this study for spatial prediction of Groundwater quality of Yazd-Ardakan plain, 73 data from Yazd organization regional water were used. After normalization of data, for interpolation of groundwater quality, kriging, cokrigong and IDW methods were used. Finally, with the use of cross-validation, the best method of interpolation was selected. We proceeded to prepare the map of groundwater quality based on this interpolation and the help of Geographical Information System (GIS). Figure 2 shows the flowchart of this study.

Spatial prediction methods

Kriging: The presence of a spatial structure where observations close to each other are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics [3, 13]. The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value [14] and thus can depict autocorrelation at various distances. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at z (xi) and the value at z(xi+h) [3, 15]:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} \left[Z(xi) - Z(xi+h) \right]^2 \qquad (1)$$

Where N (h) is the number of data pairs within a given class of distance and direction. If the values at z (xi) and z (xi + h) are auto correlated the result of Eq. (1) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model (e.g. spherical, exponential) is then fitted, usually by weighted least squares and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure.

IDW: In interpolation with IDW method, a weight is attributed to the point to be measured. The amount of this weight is depended to the distance of the point to another unknown point. These weights are controlled on the bases of power of ten. With increase of power of ten, the effect of the points that are farther diminishes. Lesser power distributes the weights more uniformly between neighboring points. We should keep in mind that in this method the distance between the points count, so the points of equal distance have equal weights [16]. In this method the weight factor is calculated with the use of the following formula:

$$\lambda_i = \frac{D_i^{-\alpha}}{\sum_{i=1}^{n} D_i^{-\alpha}} \qquad (2)$$

λ_i = the weight of point, D_i = The distance between point i and the unknown point, α = The power ten of weight

Cokriging: The "co-regionalization" (expressed as correlation) between two variables, i.e. the variable of interest, groundwater quality in this case and another easily obtained and inexpensive variable, can be exploited to advantage for estimation purposes by the co-kriging technique. In this sense, the advantages of co-kriging are realized through reductions in costs or sampling effort. The crosssemivariogram is used to quantify cross-spatial auto-covariance between the original variable and the covariate [17]. The cross-semivariance is computed through the equation:

$$\lambda_{uv} h = \frac{1}{2} E\left[\left\{z_u(x) - z_u(x+h)\right\}\left\{z_v(x) - z_v(x+h)\right\}\right] \qquad (3)$$

Where: γ_{uv} (h) is cross-semivariance between u,v variable, Z_u (x) is primary variable and Z_v (x) is secondary variable.

Comparison between the different methods: Finally, we use the RMSE to evaluate model performances in cross-validation mode. The smallest RMSE indicate the most accurate predictions. The RMSE was derived according to Eqs. (4)

$$R.M.S.E = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z(xi) - Z^{*}(xi))^2} \qquad (4)$$

Z (xi) is observed value at point xi, Z^*(xi) is predicted value at point xi , N is number of samples.

RESULTS

A statistical summary of the groundwater qulity properties is presented in Table 1. Data which had high skewness were normalized using logarithmic method.

After data normalizing, experimental variogram was computed. The best model for fitting on experimental variogram was selected based on less RSS value (Table 2). These variograms were shown in Fig. 3.

Also, Table 3 illustrates parameters of Groundwater quality variograms. The ratio of nugget variance to sill expressed in percentages can be regarded as a criterion for classifying the spatial dependence of ground water quality parameters. If this ratio is less than 25%, then the variable has strong spatial dependence; if the ratio is between 25 and 75%, the variable has moderate spatial dependence and

Table 1: Results of statistical analysis on groundwater quality

Groundwater quality	Min	Max	Mean	Std	Kurtosis	Skewness
TH (mg/L)	139.00	2427.70	736.19	584.90	0.89	1.35
TH (mg/L)**	4.93	7.79	6.32	0.75	-0.81	0.20
SAR	0.37	36.97	9.67	8.48	1.25	1.29
SAR**	-0.99	3.61	1.84	1.00	-0.22	-0.45
EC (ds/m)	0.30	18.83	4.31	4.24	2.37	1.64
EC (ds/m)**	-1.20	2.94	1.00	1.00	-0.58	-0.12
SO_4^{2-}(meq/L)	0.42	45.80	11.72	10.53	1.80	1.48
SO_4^{2-}(meq/L)**	-0.87	3.82	2.03	1.03	0.53	-0.68
Cl^-(meq/L)	0.45	170.60	29.48	36.43	4.41	2.04
Cl^-(meq/L)**	0.80	5.14	2.59	1.43	-0.30	-0.47
TDS (mg/L)	190.00	12600.00	2765.60	2778.00	2.79	1.72
TDS (mg/L)**	5.25	9.44	7.45	1.01	-0.60	-0.09

**Using logarithm to normalize data

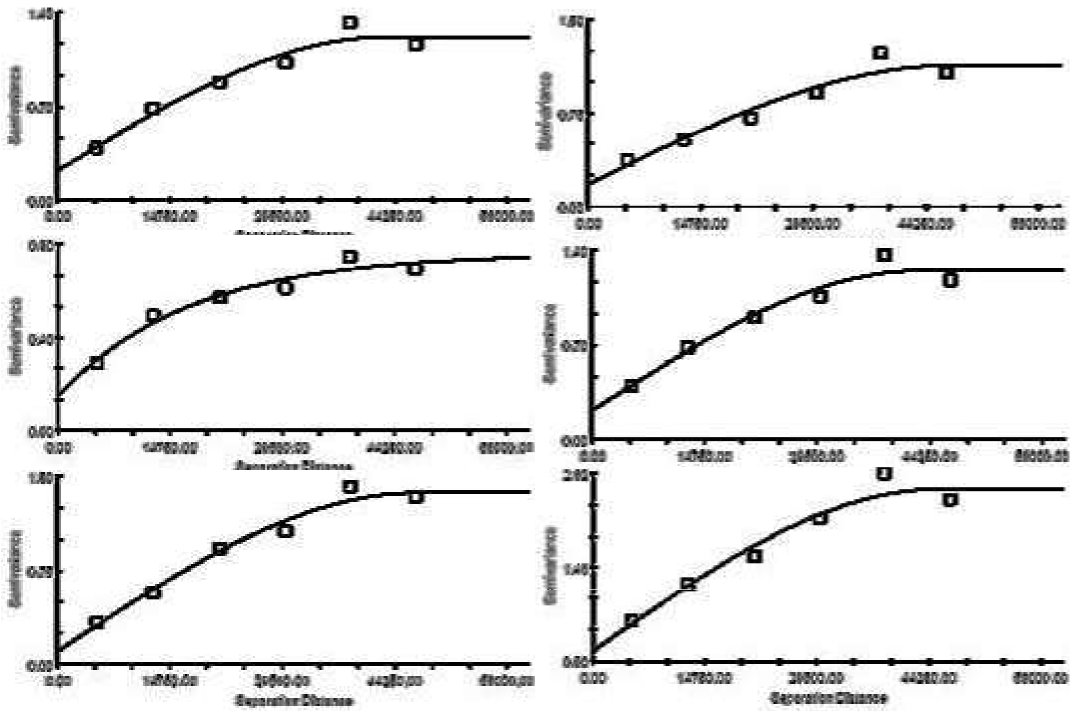

Fig. 3: Variograms related to Groundwater quality

Table 2: Selection of the most suitable model for evaluation on experimental variogram according to RSS

Groundwater quality	Models		
	Spherical	Exponential	Guassian
EC	**0.0255**	0.034	0.033
TDS	**0.028**	0.038	0.035
Cl	**0.171**	0.267	0.181
SO_4	**0.022**	0.031	0.024
TH	0.007	**0.005**	0.009
SAR	**0.034**	0.043	0.036

greater than 75%, the variables shows only weak spatial dependence [18, 19]. All parameters of ground water quality have strong spatial structure except Cl-. Also effective range of most parameters is close together and with the range of 43 to 51 Km.

In cokriging method, after conducting of correlation matrix, a parameter which has the highest correlation coefficient with primary variable was selected as an auxiliary variable (Table 4). Consequently, Ca^{2+}, Na^{+}, EC, TDS, EC and TDS variables were selected as auxiliary variables for estimation of TH, SAR, SO_4^{2-}, EC, TDS and Cl^{-}, respectively. Cross variograms are presented in Fig. 4.

RMSE, for determination of the most suitable method, among Kriging, cokriging and IDW, was used. Results showed that geostatistic methods had more considerable accuracy than IDW method. Furthermore, cokriging method increased prediction accuracy and had less RMSE for all studied parameters (Table 5). Finally, maps of groundwater quality were prepared using GIS and cokriging which was the bast method for interpolation.

DISCUSSION AND CONCLUSION

Results showed that the majority of studied parameters had high skewness, due to insufficient number of samples and unsuitable distribution. However, data were normalized using logarithmic method. Also results showed that effective range of most qualitative parameters of groundwater are closed to each another indicating their high correlation. Spatial structure model was very strong in all the studied water parameters which indicate high accuracy in interpolation.

Geostatistics is superior to IDW which is similar to the results of Safari [4], Nazarizade *et al.* [5], Ahmad [9], Barca and Passarella [12]. In the present research, results from evaluation of different methods showed that cokriging method has higher accuracy than others

Table 3: Best-fitted variogram models of ground water quality and their parameters

Groundwater quality	Model	Nugget (C_o)	Sill (C_O+C)	Range effect (Km)	(C_O/C_O+C)	r^2
EC	Spherical	0.22	1.21	42.9	0.18	0.955
TDS	Spherical	0.22	1.25	42.9	0.17	0.954
Cl^-	Spherical	0.16	0.268	45.4	0.59	0.954
SO_4^{2-}	Spherical	0.10	1.37	47.0	0.07	0.975
TH	Exponential	0.15	0.76	51.9	0.19	0.955
SAR	Spherical	0.18	1.13	47.4	0.13	0.935

Table 4: Correlation matrix of groundwater quality parameters

	TH	SAR	Na^+	Mg^{2+}	Ca^{2+}	SO_4^{2-}	Cl^-	HCO_3^-	TDS	EC
TH	1									
SAR	0.684**	1								
Na^+	0.822**	0.949**	1							
Mg^{2+}	0.947**	0.688**	0.794**	1						
Ca^{2+}	0.949**	0.609**	0.764**	0.797**	1					
SO_4^{2-}	0.856**	0.876**	0.921**	0.803**	0.82**	1				
Cl^-	0.886**	0.899**	0.177	0.851**	0.829**	0.888**	1			
HCO_3^-	0.147	0.227	0.986**	0.259	0.024	0.294	0.091	1		
TDS	0.900**	0.917**	0.917**	0.865**	0.842**	0.946**	0.986**	0.193	1	
EC	0.904**	0.913**	0.983**	0.869**	0.846**	0.949**	0.985**	0.196	0.999**	1

*p<0/05, **p<0/01

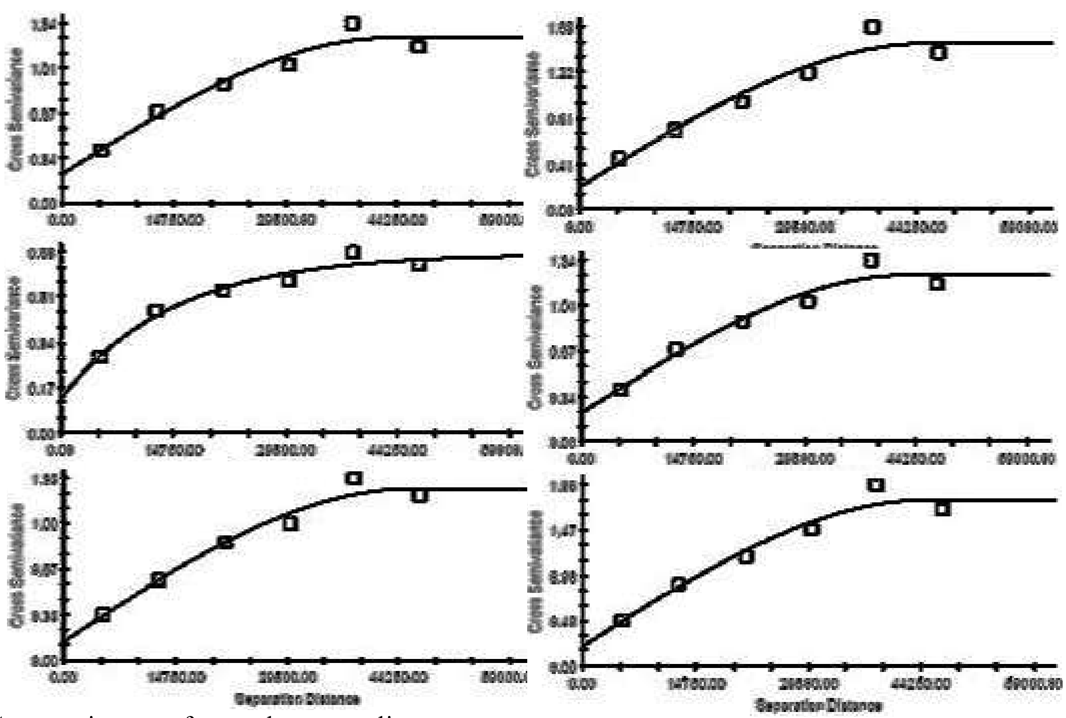

Fig. 4: Cross variogram of groundwater quality

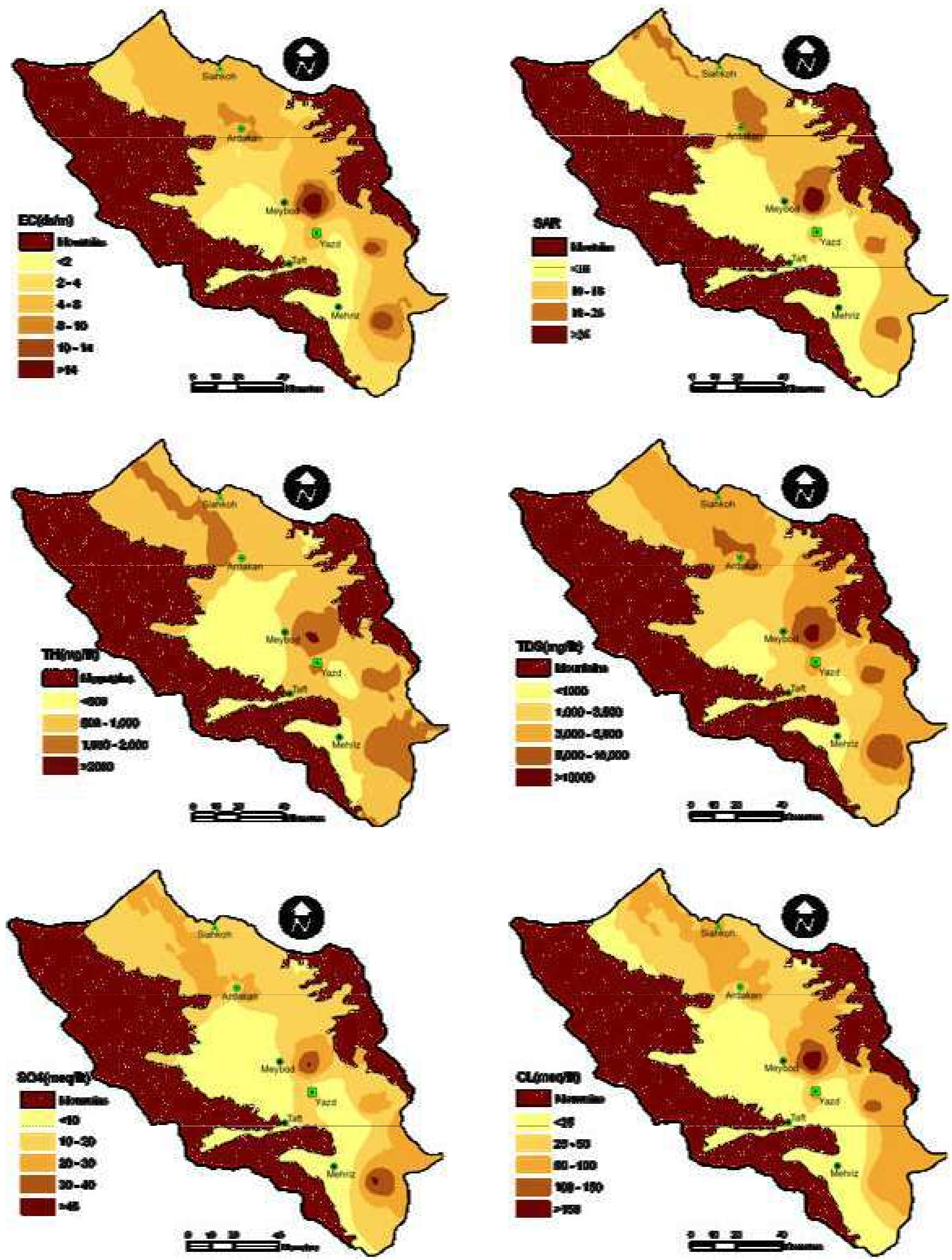

Fig. 5: Interpolation groundwater quality map (a,b,c,d,e,f) are respectively the parameters of EC, SAR, TH, TDS, $SO4^{2-}$ and Cl^{-} based on cokriging method

Table 5: Selecting the best interpolation method according to RMSE

			IDW			
Groundwater quqlity	Cokriging	Kriging	Exp 1	Exp 2	Exp 3	Exp 4
EC	**2.01**	3.40	3.66	3.65	3.72	3.81
TDS	**1412.00**	2256.00	2420.00	2428.00	2477.00	2483.00
Cl^-	**20.51**	28.01	31.62	31.58	32.25	32.44
SO_4^{2-}	**7.74**	8.98	9.52	9.78	9.99	10.05
TH	**185.30**	415.70	476.70	448.70	451.60	456.36
SAR	**5.32**	6.80	7.19	7.34	7.45	7.63

for estimating spatial distribution of groundwater quality which is in line with the work done by Rizzo and Mouser [8], who had considered cokriging as a suitable method for mapping of quality indicators such as: Na^+, Cl^-, SO_4^{2-}, Ca^{2+} and EC.

As all parameters show, demolition of groundwater is concentrated on east and Norh-West of the region (Fig. 5). For example, EC is very high in Eastern region because it is near to residential and agricultural area. As 91% of total depletion from aquifers (618m^3) is related to agricultural, these activities without considering the potential of the region along with excessive use of groundwater by other human activities intensify this process. Besides, high concentration of EC in the N-E of the area is related to Siyahkoh Kavir and geological factors.

Generally, results of this research showed that geostatics are suitable methods for estimation of water quality. It is suggested that in the future studies, other methods especially indicator and disjunctive kriging is used in order to prepare risk maps.

REFERENCES

1. Todd, D.K., 1980. Groundwater hydrology. John Wiley and Sons, New York.
2. Ekhtesasi, M.R, 2004. Morphometric and morphodynamic study of wind erosion facies of Yazd-Ardakan plain and determination of indicator of this process for function in desertification evalution models, Ph.D Thesis, Faculity of Natural Resources, Tehran University.
3. Robinson, T.P. and G. Metternicht, 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. Computer and Electeronics in Agriculture, 50: 97-108.
4. Safari, M., 2002. Determination filtration network of Groundwater using geostatistic method. M.Sc Thesis. Tarbiyat Modares University Agricultural Faculty, Persian Version.
5. Nazari Zade, F. and F. Arshadiyan Behnaz and Zand Vakily Kamran, 2006. Study of spatial variability of Groundwater quality of Balarood Plain in Khuzestan province. The first congress of optimized exploitation from water source of Karoon and Zayanderood Plain.Shahre kord University, Persian Version, pp: 1236-1240.
6. Istok, J.D. and R.M. Cooper, 1998. Geostatistics Applied to Groundwater Pollution. III: Global Estimates. Journal of Environmental Engineering, 114 (4): 915-928.
7. Dagostino, V., E.A. Greene, G. Passarella and M. Vurro, 1998. Spatial and temporal study of nitrate concentration in groundwater by means of coregionalization. Environmental Geology, 36: 285-295.
8. Rizzo, D.M. and J.M. Mouser, 2000. Evaluation of Geostatistics for Combined Hydrochemistry and Microbial Community Fingerprinting at a Waste Disposal Site, pp: 1-11.
9. Ahmed, S., 2002. Groundwater monitoring network design: Application of Geostatistics with a few Case studies from a granitic aquifer in a semi-arid region. In: Groundwater Hydrology. Sherif, M.M., V.P. Singh and M. Al-Rashed (Eds.). Balkema, Tokyo, Japan, 2: 37-57.
10. Gaus, I., D.G. Kinniburgh, J.C. Talbot and R. Webster, 2003. Geostatistical analysis of arsenic concentration in groundwater in Bangladesh using disjunctive kriging. Environmental Geology, 44: 939-948.
11. Finke, P.A., D.J. Brus, M.F.P. Bierkens, T. Hoogland, M. Knotters and Vries. F. de, 2004. Mapping groundwater dynamics using multiple sources of exhaustive high resolution data, Geoderma, 123: 23-39.
12. Barca, E. and G. Passarella, 2007. Spatial evaluation of the risk of groundwater quality degradation. A comparison between disjunctive kriging and geostatistical simulation, Environ Monit Assess, (In Press).

13. Goovaerts, P., 1999. Geostatistics in soil science: State-of-the-art and perspectives. Geoderma, 89: 1-45.
14. Deutsch, C.V. and A.G. Journel, 1998. GSLIB: Geostatistical Software Library and User's Guide. Oxford University Press, Oxford, UK.
15. Lark, R.M., 2000. Estimating variograms of soil properties by the method-of-moments and maximum likelihood. Eur. J. Soil Sci., 51: 717-728.
16. Burrough, P.A. and R.A. McDonnell, 1998. Creating continuous surfaces from point data. In: Burrough, P.A., M.F. Goodchild, R.A. McDonnell, P. Switzer and M. Worboys, (Eds.). Principles of Geographic Information Systems. Oxford University Press, Oxford, UK.
17. Stefanoni, L.H. and R.P. Hernandez, 2006. Mapping the spatial variability of plant diversity in a tropical forest: Comparison of spatial interpolation methods. Environmental Monitoring and Assessment, 117: 307-334.