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Investigation of Spatial Structure of Groundwater Quality Using Geostatistical Approach in Mehran Plain, Iran

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ABSTRACT: Groundwater is a major source of water for domestic, industrial, and agricultural sectors in many countries. The main objective of this research was to provide an overview of present groundwater quality using parameters such as calcium, magnesium, sodium, chloride, sulfate, pH, and electrical conductivity (EC) in the Mehran plain, Ilam province using GIS and geostatistical techniques. A total of 23 deep and semi-profound wells were selected based on the classified randomized sampling method. The sampling locations were obtained by GPS. Plastic containers were used for the collection of water samples. These samples were transferred to the laboratory for analyzing water quality parameters. Statistical characteristics, qualitative data interpolation, and zoning were investigated using SPSS 20 ‹GS$^+$5.3 and ArcGIS10.1. Kolmogorov–Smirnov test were used to test data normality. In order to normalize parameters, logarithm, and 1/*x* were used for sulfate, EC, cation, and anion. Then the variogram analysis was performed to select the appropriate model. Results showed that co-kriging is the best method for cation and anion, whereas local polynomial interpolation is suitable for sulfate. The results of the interpolation of groundwater quality factors showed that there is approximately good adaption among groundwater factors and geomorphology and topology of the region. Because of inappropriate irrigation system, the highest concentration is in the northwest and western parts of the region, where there is the minimum height and maximum agricultural land. Growth of arable land and agricultural activities has caused increasing concentrations of studied elements, especially EC.

Keywords: geostatistical, groundwater, Mehran plain, spatial variations modeling

INTRODUCTION

Groundwater is a major source of water for domestic, industrial, and agricultural sectors in many countries. It is estimated that approximately one third of the world's population (about 2 billion people) use groundwater for drinking (UNDP, UNEP, World Bank, 2000). In arid and semi-arid regions, due to a lack of surface water, groundwater has played a major role in meeting irrigation demands. In several areas of Iran, excessive pumping of groundwater has created cracks with a depression of 0.5–1 km in length. Moreover, excessive use of groundwater has resulted in a sharp decline in both level and quality of groundwater due to the concentration of dissolved solids.

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Moreover, groundwater salinity in most areas has increased to several thousand milligrams per liter. As a consequence of old agricultural systems, pesticides, overuse of groundwater especially in arid and semi-arid regions along with the irrigation of water with physical setting that includes coarse soils and shallow groundwater, there is a significant level of pollution in the groundwater (Stites and Kraft, 2001; Jalali, 2007).

Overall, residential, municipal, commercial, industrial, and agricultural activities can all affect groundwater quality (Nas and Berktay, 2010). The assessment of groundwater quality can be considered as an important index for socio-economic growth and development (Ishaku, 2011). Monitoring the groundwater quality involves collecting samples and carrying out analysis in the lab, which makes it expensive. There are two main approaches for the optimization of monitoring groundwater quality: the statistical approach and the hydrogeological approach. The widely used statistical method is based on kriging (Nunes *et al.*, 2007; Feng-guang, 2008) using the model variogram. For unsampled locations, kriging is a technique to make an impartial and optimal estimation of regionalized variables (David, 1977). The selected model variogram is the one which better represents the experimental data with less root mean square error (RMSE). This approach uses the kriging standard deviation to identify points of high variance as the potential points for monitoring (Baalousha, 2010). Geostatistics can characterize and quantify spatial variability, perform rational interpolation, and estimate the variance of the interpolated values (Pin Lin *et al.*, 2001).

The main objective of this research was to provide an overview of present groundwater quality for parameters such as calcium, magnesium, sodium, chloride, sulfate (SO_4), pH and electrical conductivity (EC) in the Mehran plain using GIS and geostatistical techniques.

MATERIALS AND METHODS

The study area

Mehran plain has a surface area of 911 km^2. It is located in near Iran's western border with Iraq between 33°03′ to 33°13′ north latitude and 46°05′ to 46°15′ east longitude. The average annual precipitation and temperature are 247 mm and 23.5°C, respectively. Two major rivers, Gavi and Kanjanchem, are the major source of surface water in Mehran plain; they join together in the west of the Mehran city (Karimi *et al*., 2011). For this study, groundwater quality data from 23 deep and semi-profound wells were used within the Mehran plain produced by the Regional Water Authority in Ilam province. Figure 1 shows the location of Mehran plain in Iran and wells selected for sampling.

Methodology

A total of 23 deep and semi-profound wells were selected to the classified randomized sampling method. The sampling locations were obtained with the help of Global Positioning System (GPS). Figure 1 shows the study area and location of the selected wells. For the collection of water samples, plastic containers were used; these samples were carried to the laboratory for analyzing the parameters of water quality such as calcium, magnesium, sodium chloride, SO_4, pH and electrical conductivity (EC). The specific methods of estimation of these parameters are given in Table 1. The value of these parameters is shown in Table 2. Statistical characteristics, qualitative data interpolation, and zoning were investigated in SPSS 20 ،GS^+ 5.3 و ArcGIS 10.1.

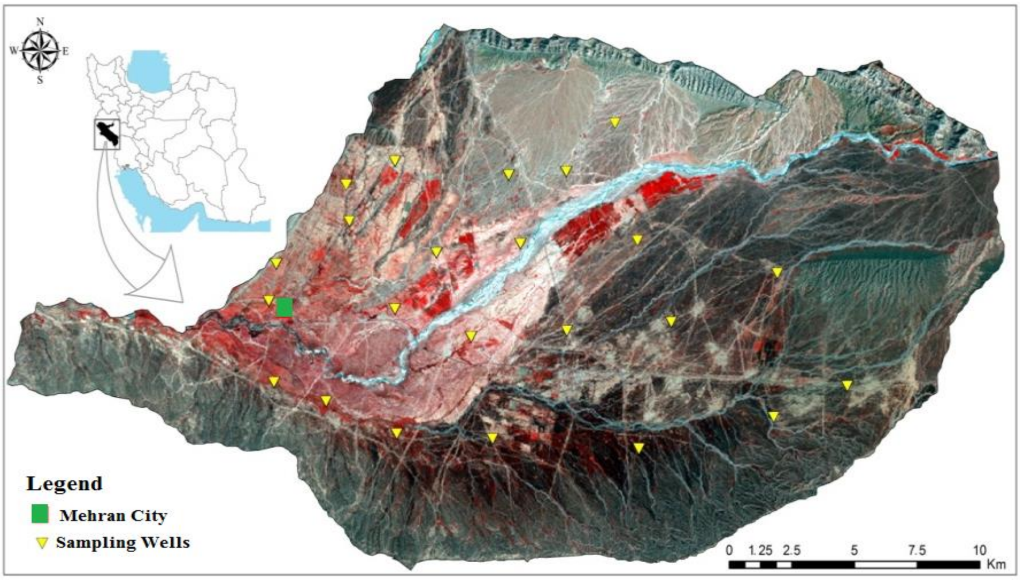

Fig 1. LANDSAT Satellite image (TM) of the study area and the location of studied well

Table 1. Specific methods of estimation of parameters

No.	Parameters		Methods
1	Anion	Calcium	ICP Mass Spectrometry
2		Magnesium	ICP Mass Spectrometry
3		Sodium	Flame Photometric method
4	Cation	Chloride	Titrating with standard $AgNo_3$.
5		Sulfate	Turbidity Method
6		pH	Digital pH meter

Table 2. Average value of parameters

Well Number	EC (µmho/cm)	pH	SO4 $_{(meq/l)}$	Cl $_{(meq/l)}$	Ca $_{(meq/l)}$	Mg $_{(meq/l)}$	Na $_{(meq/l)}$
1	648.42	7.67	2.58	1.17	3.67	0.74	1.94
2	668.28	7.61	2.37	1.32	3.75	1	2.01
3	643.57	7.56	3.16	0.77	4.17	0.98	1.58
4	1234	7.42	9.37	1.014	9.37	2.31	1.77
5	1629.57	7.44	11.84	2.1	12.8	2.2	2.84
6	2552.85	7.5	18.58	6.07	21.06	5.5	5.77
7	3487.66	7.31	22.61	12.65	19.76	5.81	12.51
8	495.57	7.55	2.2	0.471	3.32	1	0.68
9	978.8	7.29	7.216	0.86	7.6	1.84	1.16
10	1681	7.49	14.68	1.03	14.11	2.65	1.92
11	688.39	7.72	3.42	1.34	3.23	1.4	2.83
12	662.03	7.27	3.9	0.88	4.2	1.1	2.39
13	563	7.46	2.6	0.90	3.3	0.8	1.73
14	670.48	7.43	0.3	0.03	3.7	0.8	2.37
15	647.67	7.50	3.5	0.74	0.2	0.9	1.45
16	1266	7.23	11.5	0.90	10.6	0.0	1.85
17	1661.69	7.20	17.0	1.00	16.4	0.1	1.85
18	981.12	7.15	7.45	0.80	7.4	1.9	1.52
19	610.12	7.40	3.10	0.77	4.1	0.7	1.52
20	1170.23	7.98	8.02	1.00	9.1	1.4	1.78
21	963.58	7.44	7.11	0.96	7.3	1.48	1.93
22	475.45	7.8	2.25	0.44	3.09	1.2	0.56
23	940.32	7.31	6.24	0.94	8.11	1.62	0.52

For the analysis of groundwater characteristics, spatial variations geostatistical approach was used (Reed *et al*., 2010; Cameron and Hunter, 2002; Lee *et al*., 2007). Geostatistical prediction has two stages: (a) identification and modeling of spatial structure, in which the homogeneity and spatial structure of a given variable is studied using a variogram; (b) geostatistical estimation using kriging technique that depends on the properties of the fitted variogram, which affects all the stages of the process. In this study, different types of semi-variogram models including ordinary kriging, simple kriging, universal kriging, and disjunctive kriging were tested for each parameters of water quality that are summarized below. For the selection of best model, cross validation tests including the values of mean error (ME) and mean square error (MSE) were done. If the predictions were unbiased, the ME should be near to zero. Due to some important drawbacks, ME depends on the scale of the data, and it is insensitive to inaccuracy in the variogram. Therefore, usually MSE is used on behalf of ME. Being ideally zero, that is, an accurate model would have a MSE value close to zero. The smallest RMSE value indicates the most accurate predictions. RMSE is derived according to Equation (1).

$$RMSE = \sqrt{\left[\sum_{k=0}^{n}\left(Z\,(xi\,) - z\,(xi\,)^2\right)\right] / n} \qquad (1)$$

where $Z(xi)$ is observed value at point xi $z(xi)$ is predicted value at point xi, and N is number of samples.

RESULTS AND DISCUSSION

Kriging methods work best if the data are approximately normally distributed. Kolmogorov–Smirnov test in SPSS was used to test the normality of the data. To normalize the parameters, logarithm and $1/x$ were used respectively for SO_4, EC and cation, anion. The first step for geostatistical application for a set of data is variogram analysis. The results of variogram analysis in the study area are presented in Table 3.

Table 3. The results of variogram analysis.

Variable	RSS	R^2	C0 /(C0+C)	R_0 (Effective Range)	Sill	Nugget effect	model	kurtosis	skewness	Standard deviation	average
Cation	7.262	0.61	0.092	13896.22	0.005	0.0004	linear	-1.19	0.36	0.0583	0.0984
Anion	7.653	0.69	0.930	46678.77	0.023	0.0016	exponential	-1.27	0.32	0.0632	0.1052
SO4	6.207	0.82	0.956	55529.55	1.238	0.054	exponential	-1.54	-0.09	0.3819	0.8268
EC	5.597	0.96	0.976	54576.92	0.878	0.0012	exponential	-1.02	0.37	0.279	3.062

As it can be inferred from Table 1, exponential semi-variogram and linear semi-variogram model are used for our study parameters. The strongest spatial structure can be observed in EC and SO_4 that is calculated as 0.959 and 0.819, respectively. However, cation is the lowest in this calculation. In order to find the best spatial correlation with the intended variable, cross-variogram was calculated in GIS +. The results of the cross-variogram data are shown in Table 4 and Figures 2–5.

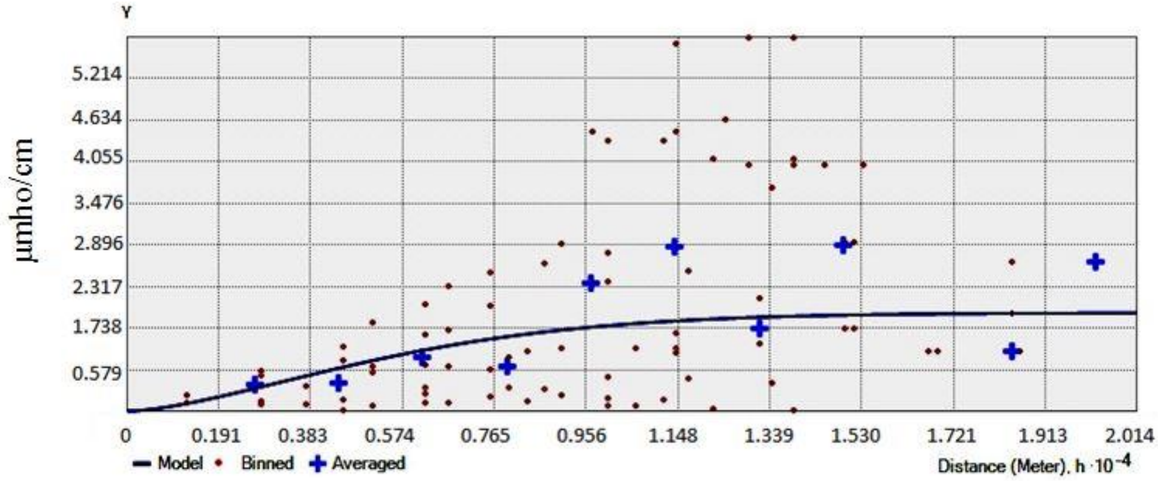

Fig 2. Cross variogram of SO_4 and EC

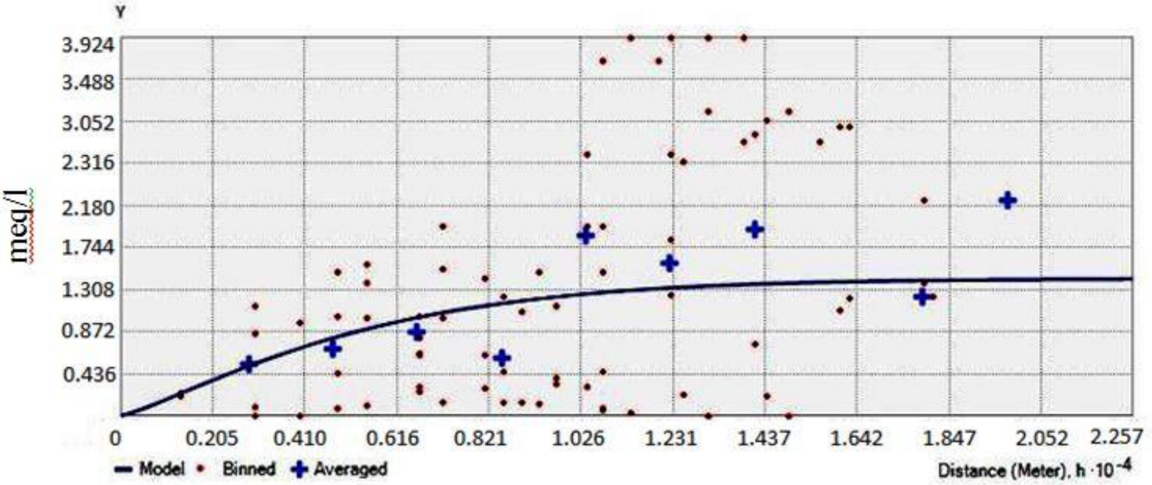

Fig 3. Cross variogram of SO_4 and anion

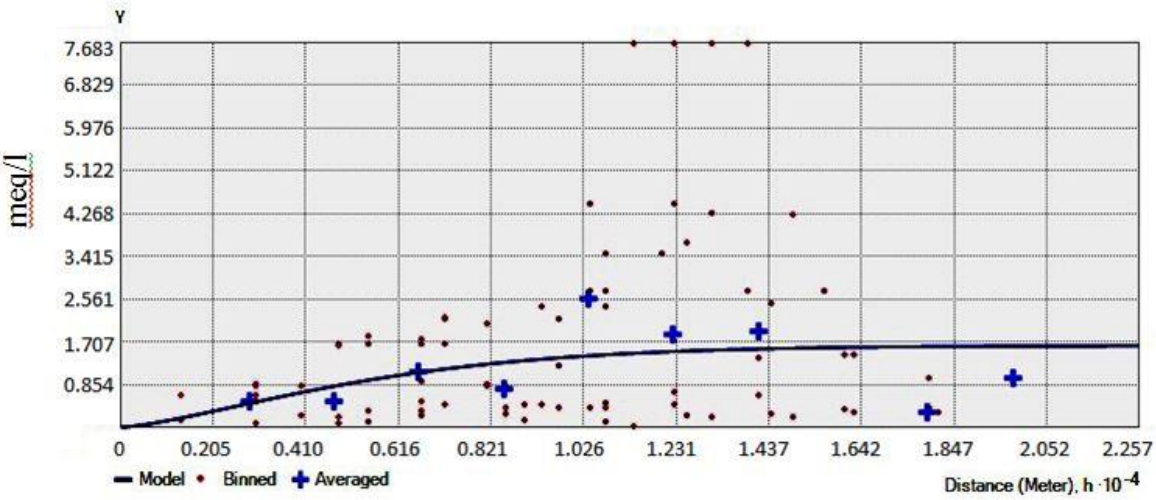

Fig 4. Cross variogram of anion and

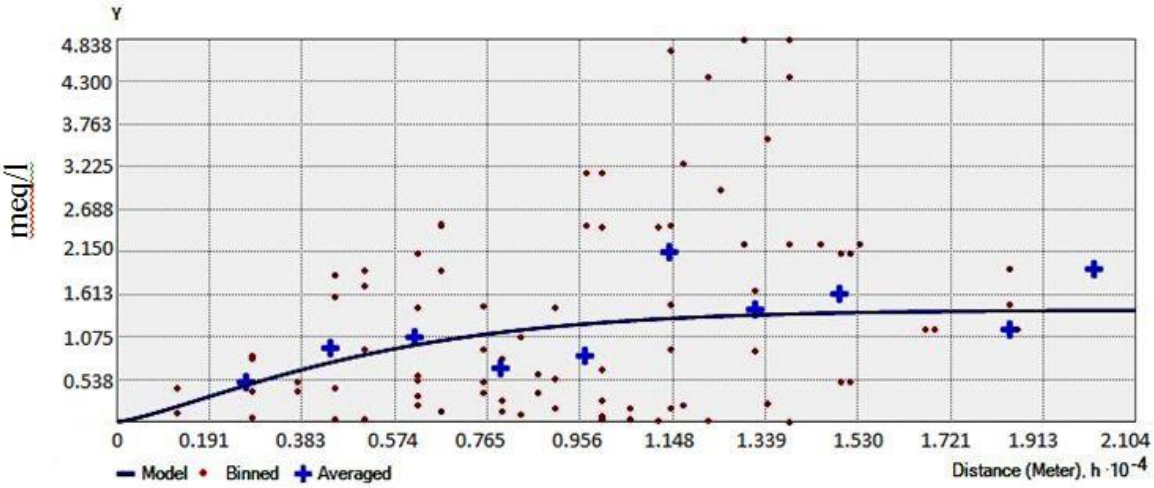

Fig 5. Cross variogram of cation and anion

Table 4. The results of cross-variogram analysis.

Variable	Auxiliary Variable	correlation coefficient	Spatial correlation coefficient	Model	R_0(Effective Range	Sill	Nugget effect
Cation	Anion	0.989	0.656	Exponential	50956.9348	0.02410	0.00185
Anion	Cation	0.989	0.729	Linear	31100.00	0.00599	0.00065
SO_4	Anion	0.958	0.711	Exponential	55373.6643	-0.192	-0.0106
EC	SO4	0.925	0.528	Exponential	54854.0491	1.195	0.1

Correlation matrix must be formed to predict the water quality in co-kriging. After that, one factor is used in this method that is known as the auxiliary variable. This is the highest correlation with the intended variable. Therefore, to estimate cation, anion, SO_4, and EC, the auxiliary variables were used. RMSE was used to determine the best method of interpolation. Accordingly, the best method has the lowest RMSE. Table 5 shows the various amounts of RMSE in methods of interpolations.

Table 5 shows that co-kriging is the best method for cation and anion, whereas local polynomial interpolation is suitable for SO_4. Finally, the maps were interpolated in Arc map (Figs. 6–9).

Table 5. Comparison of the RMSE values of geostatistical techniques

Techniques	RMSE			
	EC	SO4	Anion	Cation
Co-Kriging	0.09933	0.2081	0.0231	0.0217
Disjunctive Kriging	0.1131	0.213	0.0519	0.0481
Universal Kriging	0.1121	0.1931	0.0366	0.0336
Simple Kriging	0.1190	0.2081	0.0289	0.0479
Ordinary Kriging	0.111	0.193	0.0366	0.0336
IDW	0.234	0.3176	0.0253	0.0482
Radial Basis function	0.153	0.026	0.0361	0.0320
Global Polynomial Interpolation	0.0913	0.0209	0.0429	0.0398
Local Polynomial Interpolation	0.0854	0.1970	0.0306	0.0278

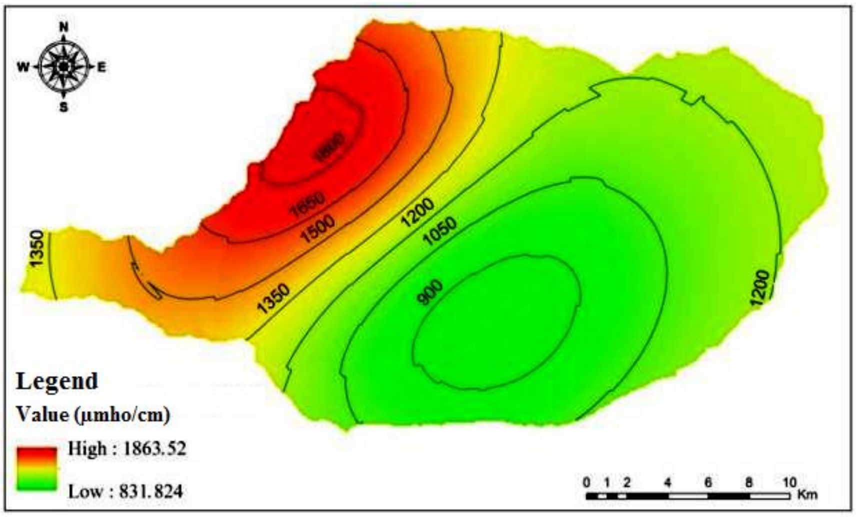

Fig 6. Variation amplitude of EC value

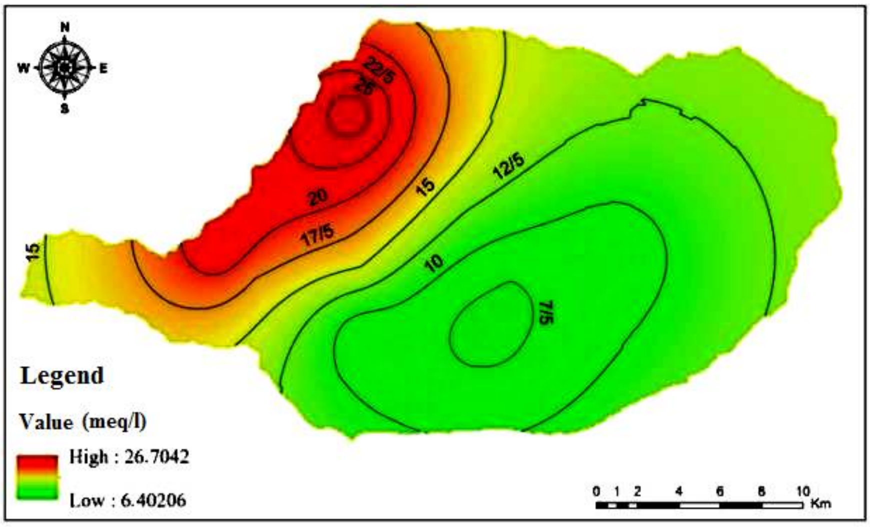

Fig 7. Variation amplitude of anion value

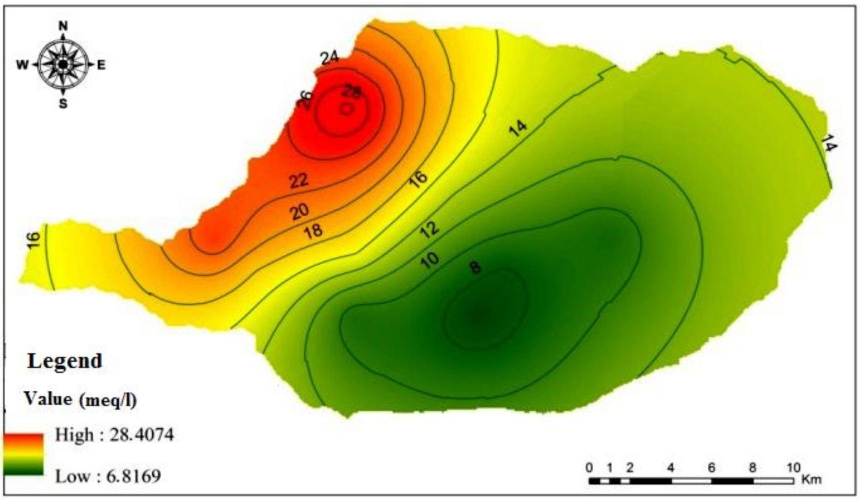

Fig 8. Variation amplitude of cation value

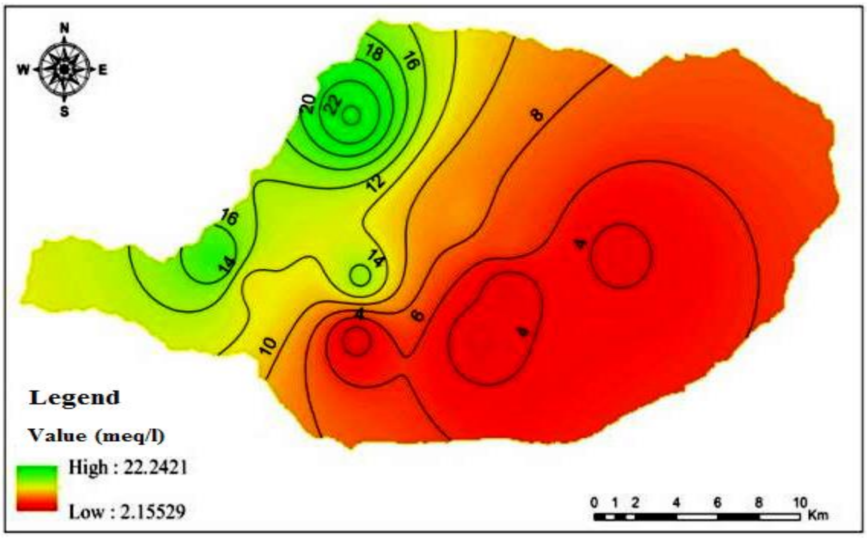

Fig 9. Variation amplitude of SO_4 value

CONCLUSION

The primary objective of this study was to map and evaluate spatial variations modeling of groundwater in Mehran plain. The results of the interpolation of groundwater quality factors (Figs 7–9) showed that there is approximately a good adaption between selected parameters and geomorphology and topology of the region. The highest concentration is in the northwest and western parts of the region, where it has the minimum height and agricultural land. Inappropriate irrigation system causes the west of the Mehran plain to have high concentrations of elements (Karimi *et al*., 2011). However, growth of arable land and agricultural activities has caused increasing concentration of studied elements, especially EC, in this region. Groundwater quality gives a clear picture about the usability of water for different purposes; therefore, choosing the best evaluation method is significant. The studied variables are spatial and temporal parameters that are measured with great difficulty because of the large surface area of land and also impossible in some areas, especially when there is a shortage of time and high cost. Therefore, the use of a suitable tool to monitor groundwater quality parameters using limited sampling points is essential. The results indicate that geostatistical methods, especially co-kriging and kriging are appropriate to assess the groundwater quality. Our results concur with that of studies by Hudak and Sanmanee (2003) in Texas, Zehtabian *et al*. (2010) in Garmsar of Iran, Maghami *et al*. (2011) in Abadeh-Iran and Yan *et al*. (2013) in China.

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