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Is it necessarily a normally distributed data for kriging? A case study: soil salinity map of Ghahab area, central Iran

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Abstract

After collecting data, in researches, the type of data distribution must be determined; since any analysis requires the distribution of its own data. Soil properties, such as salinity, are also the same case. Due to its direct and indirect effects on plant growth, soil salinity is an important feature that has always been investigated in agriculture and natural resources, leading to a lot of researches. These researches have often focused on the mapping of salinity using different interpolation methods and their accuracy. But the effect of the data distribution on the analysis process has been less considered. Accordingly, the purpose of this study is to investigate the effect of the distribution of soil salinity data on soil salinity mapping using Kriging method. For this purpose, 610 soil samples were taken from 0-50 cm soil depth based on a grid method and their salinity (Electrical Conductivity, EC) was determined in saturated paste extracts. Variography operations for data were performed based on both, the original distribution of the data and the usual data distribution employed for Kriging i.e. normal distribution. Salinity maps were obtained for both data distributions. Estimations were made using cross-validation approach. According to the findings, only the fitness criterion (R^2) is not enough to select the optimal variogram model, while other criteria such as the proportion of the spatial structure, residual sum of square (RSS) and the nugget effect should be analyzed as well. The results showed: 1- the accuracy of the estimation based on the original distribution of the data, (i.e. non-normal distribution) which was greater than the accuracy of the estimated data using normal distribution; 2- the predictions and errors from the both, normally and non-normally distributed data did not have the normal distribution and 3 - data transformation had no effect on the normalization of the distribution of the predictions and the errors. Therefore, it is suggested that in the Kriging, in addition to the conventional method, i.e., performing Kriging using normal distribution data, the original data with non-normal distribution should also be analyzed. Finally, the type of data distribution and the optimal variogram model could be selected by comparing the obtained results.

Keywords: Data distribution; Data transformation; Geostatistics; Error distribution

1. Introduction

Researches need data. Since each statistical test or model requires the distribution of its own specific data, when the data is collected, the distribution of data should be determined for analysis purposes. Using a model or performing a statistical test, regardless of its assumptions or the distribution of data, makes the results vague or even invalid. The distribution of soil data should also be determined before analysis.

Soil salinity is one of the most important soil properties that can directly or indirectly affect plant growth as a limiting factor. Thus, it has always been considered in agriculture and natural resources, causing a lot of studies in this regard (Bagheri Bodaghabadi *et al*., 2006). Among these studies, the mapping of soil salinity, and the methods used to analyze them have a high proportion of researches. There are a lot of investigations in which various methods of mapping and/or interpolating have been compared. The geostatistical approach is one of the methods and models which many researches have adopted. In Iran, geostatistical methods were first investigated by Hajrasuliha *et al*. (1980), which was carried out to study the spatial variations of soil salinity. These methods

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have then continued in various fields such as soil salinity (for example: Javari, 2017; Farajnia and Yarahmadi, 2017; Shahabi *et al*., 2016; Emadi and Baghernejad, 2014; Hosseini *et al*., 2013). According to the researches, to prepare soil salinity map, a comparison between different methods is done and the accuracy of each method has been carried out and a method or model which has minimum evaluation criteria (such as root mean squared error (RMSE), absolute square error (ASE) and Etc.) has been selected as the optimal method and/or model. Usually, in all studies, normalizing data has traditionally been used to run kriging operations in dealing with non-normal distribution data (for example, Al-Kuisi *et al*., 2009; Khaksaran *et al*., 2013; Bazrafshan *et al*., 2017). A primary question, therefore, arises concerning how data distribution can affect the results of kriging when the data collection has a non-normal distribution and whether the normality of the data is a prerequisite for kriging. It is mentioned that "Kriging, has the best result when the data has a normal distribution" (Gorai and Kumar, 2013; Wu *et al*., 2006; Glacken and Snowden, 2001; Isaaks and Srivastava, 1989; Armstrong and Boufassa, 1988; Goovaerts, 1997). In other words, a normal distribution of data is useful only for the best results of kriging. On the other hand, the normal distribution of data is not required for kriging estimations (Negreiros *et al*., 2010), so in kriging, the normal distribution of data is not a basic condition, but an essential condition in the Kriging process "stationary assumption"(Webster and Oliver, 2001). The normal distribution of data, however, improves the stationary assumption of the data (Wu *et al*., 2006). But this does not mean that the non-normal distribution of the data violates their stationary condition. Therefore, it can be expected that kriging will predict the accurate results when the data is not normal. Thus, the aim of the present study is to investigate the effect of data distribution of soil salinity on the estimation of salinity using the ordinary kriging method and to compare the results of Kriging predictions in both, normal and non-normal distributions of salinity.

2. Materials and Methods

2.1. Study Area

The study area is located in the center of Iran, the east of Isfahan city, Isfahan province, between 32° 30' to 32° 45' N and 51° 40' to 51° 59' E, with an area of about 238000 hectares (Fig. 1). The climate is arid and the soil moisture and temperature regimes are Aridic and Thermic, respectively. The soils of the region originate mainly from the sediments of the Zayandehrood River and are deposited on different terraces. According to USDA Soil Taxonomy (2014), soils in the study area can be classified as Fluventic Haplocambids, Fluventic Aquicambids, Typic Calcigypsids, Typic Haplocalcids, and Typic Torriorthenrs subgroups. 610 soil samples were collected at the distance of 450 to 1000 m and taken at depths of 0 to 50 cm based on a grid method (Fig. 1). The air drying samples were passed from the 2 mm sieve and then salinity or electrical conductivity (EC) was determined in the saturated paste extract.

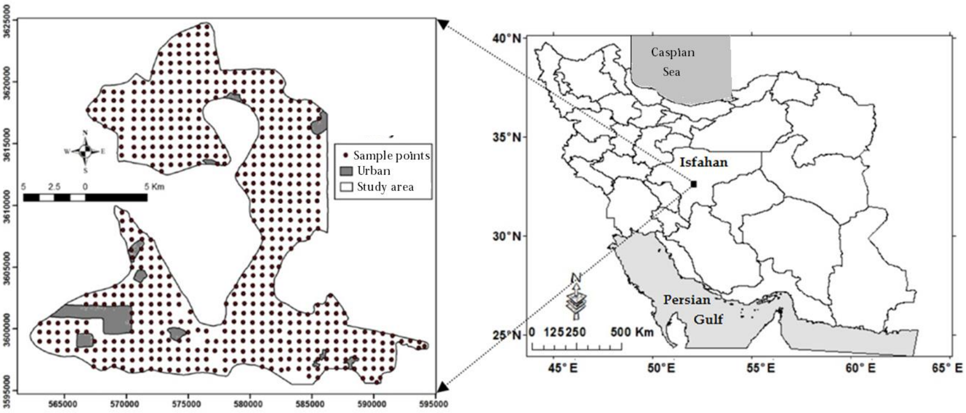

Fig. 1. Study area and locations of sampling points

2.2. Kriging and Variography

The Kriging technique is a basic geostatistical approach that provides the best linear unbiased estimation (BLUE) for spatially dependent variables. The Kriging technique weights the surrounding measured values to derive a prediction for an unmeasured location.

The general formula for this interpolators is formed as a weighted sum of the data (Oliver, 2010)

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \quad (1)$$

where:
Z(si) = the measured value at the ith location;
λi = a weight obtained from the ordinary kriging system; On the other hand λi is a weight for the measured value at the ith location;
S0 = the prediction location; and
N = the number of measured values.

λi is calculated using spatial variability models (variograms). Spatial variability is often modeled as a function of distance between sample locations called semi-variogram (γ) which was originally defined by Matheron (1969). Locations that are closer to each other are often more similar than locations that are farther apart, and are thus more highly correlated. Semi-variogram (γ) is defined as:

$$\gamma(h) = \frac{1}{2|N(h)|} \sum_{N(h)} (z_i - z_j)^2 \quad (2)$$

where:
γ(h) is semi-variogram;
N(h) is the number of pairs separated by a lag (h) between i and j;
|N(h)| is the number of distinct pairs in N(h), and zi and zj are data values at locations i and j, respectively.

Semi-variograms or variograms are defined through three particularly important parameters (Fig. 2):

1- The nugget: It represents micro-scale variation or local variance component and is the estimate of the variance at distance (h) equal to 0.
2- The sill (threshold): It shows the variance of the random field or total variance; and
3- The range (length): It is the distance at which data is no longer auto-correlated

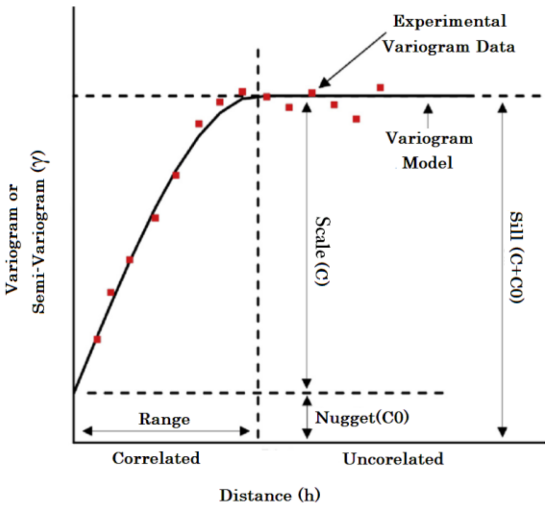

Fig. 1. Parameters of a variogram and/or a semi-variogram

2.3. Statistical calculations

Descriptive statistics including minimum and maximum, mean, skewness, kurtosis and standard deviation of salinity variable or EC were calculated using SPSS software version 22. The spatial structure of EC was analyzed using the variogram function in GS+ 9 software. The ordinary kriging operation was performed in ArcGIS version 10.4.1. All calculations and operations were performed for two data distribution modes, namely, the main distribution of data (abnormal distribution) and normal distribution. The goodness of fit for the variogram models was evaluated by the spatial structure contribution criteria, the residual sum of square (RSS) coefficient of determination (R^2). The cross valid method was employed for analysis of estimations using mean error (ME), square The Root Mean Square Error (RMSE), the Root Mean Square Standardized (RMSS) and the Absolut Square Error (ASE) (Ding Yu, 2014, Li *et al*. 2015). The stronger the spatial structure, the smaller RSS, and the larger R^2 represent better variogram model (Robinson and Metternicht, 2006). To evaluate the estimates, the smaller the criteria is, the better and the more accurate the estimates.

3. Results and Discussion

Table 1 shows the descriptive statistics of salinity data for the two non-normal and normal distributions of salinity data. As it can be seen, the range of salinity changes in the soils of the study area is very high and is about 87.23 dS/m. Therefore, the limitation of the salinity in the area changes from no limitation to very severe limitation. Figure 3 shows the cumulative graph of salinity values. According to the results, 25, 50 and 75 percent of the data have salinity less than 1.50, 2.74 and 5.76 dS/m, respectively. It is worth noting that although about 64% of the data has a salinity of less than 4 dS/m (see Fig. 3), classified to class S0 or without salinity limitation (EC<4.00 dS/m), but due to the high amounts of salinity for some of the samples, the average salinity of the soils is about 4.93 dS/m classified in the class S1 or low salinity limitation class (8> EC> 4 dS m^{-1}). The standard deviation of 7.7 and the variance of about 59.1 also indicate a strong variability of salinity values. High values of skewness (5.85) and kurtosis (44.71) demonstrate non-normal distribution of salinity data, as well.

Table 1. The descriptive statistics of salinity data for Non-normal distribution and normal distribution

Kurtosis		Skewness		Variance	Std. Dev.*	Mean		Max.	Min.	Range	Data
Std.Er.	Stat.	Std.Er.	Stat.	Stat.	Stat.	Std.Er.*	Stat.	Stat.	Stat.	Stat.*	Distribution
0.198	44.704	0.099	5.850	59.132	7.690	0.311	4.932	87.40	0.17	87.23	Non-Normal
0.198	0.400	0.099	0.202	0.180	0.424	0.017	0.466	1.942	-0.773	2.715	Normal

* :Stat. = Statistic ؛Std.Er. = Standard Error Std. Dev.= Standard Deviation

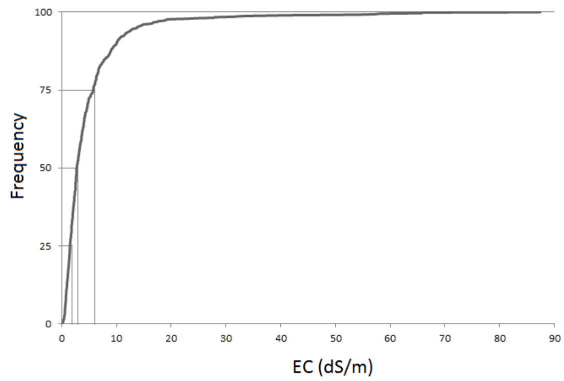

Fig. 3. Cumulative distribution of salinity values

In order to better understand the distribution of the data, histogram charts and Q-Q (quantile-quantile) plots were plotted. A Q–Q plot is a probability plot, which is a graphical method for comparing two probability distributions by plotting their quantiles against each other. So, it's worth noting that normal Q-Q plots can be used to check whether data is normal or not. A normal Q–Q plot compares randomly generated, independent standard normal data on the vertical axis to a standard normal population on the horizontal axis. The linearity of the points suggests that the data is normally distributed. However, the closer the data is to this line, it indicates that the distribution of the data is close to the normal distribution. Figure 4a shows the frequency of the data. Regarding this figure, it can be seen that the distribution of the data is highly skewed to the right (positive skew). As shown in the Q-Q diagram (Fig. 5a), the data points are very contradictory to the normal standard line.In other words, such data cannot have normal distribution. This data distribution that has a strong skewness to the right (positive skew) typically represents a logarithmic distribution. The data that has a logarithmic distribution, a logarithm transformation usually transforms them to a normal distribution.

The descriptive statistics of log-transformed data of EC are presented in Table 1. As it can be seen, the values of skewness and kurtosis have changed from 5.85 to 4.70 for the raw (non-normal) data to 0.202 and 0.400, respectively. Therefore, it is probable a normally distributed data of log-transformed data. This is also obvious with the data histogram in Fig. 4b. As the histogram shows, using a logarithmic transformation of salinity data, the data is closely related to a normal distribution. The Q-Q plot (Fig. 5B) also shows the normality of the transformed data, since the data is placed on the normal reference line as well.

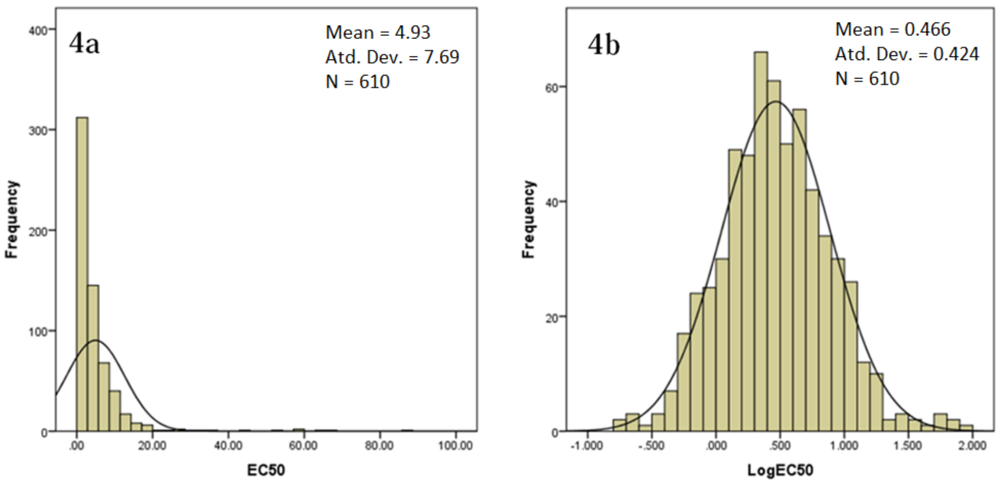

Fig. 4. Histograms of data in Non-normal (left) and normal (right) distributions with normal curve

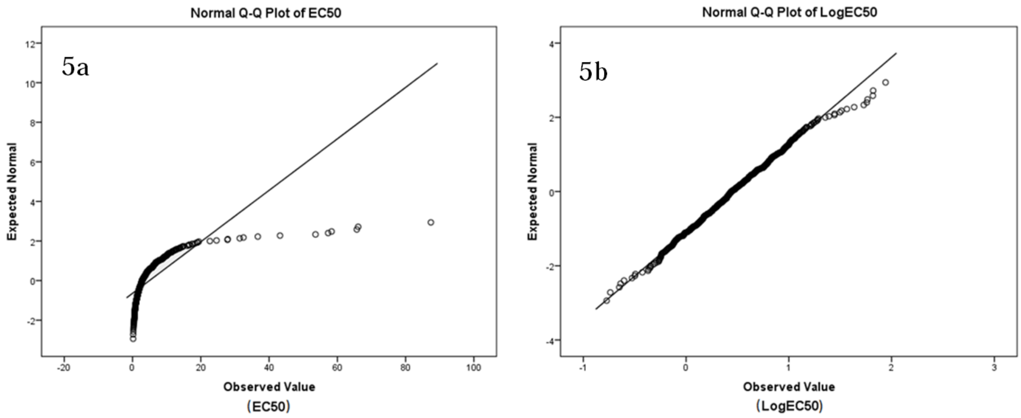

Fig. 5. Q-Q Plot of the data in non-normal distribution (left) and normal distribution (right)

In addition to the abovementioned, in which non-normal distribution of the original data and normal distribution of the log-transformed one were shown, the normality test was done using Kolmogorov-Smirnov test. In the normality test, the null hypothesis assumes the data distribution is normal. Therefore, if the significance level (p-value) of the statistic is greater than 0.05, then the null hypothesis cannot be rejected, indicating the data distribution is normal. The results of the normality test are presented in Table 2. As it can be seen, the p-value of the test for the original and transformed data is 0.000 and 0. 200 respectively, indicating the original data is not normally distributed, but the log-transformed data has a normal distribution. Since, this data is normally distributed using a logarithmic transformation, the distribution of the raw or original data is a logarithmic distribution.

Table 2. Normality test of salinity data for non-normal distribution and normal distribution

	Kolmogorov-Smirnov		
Data	Statistic	No.	Sig.
EC50	0.268	610	0.000
LogEC50	0.031	610	0.200*

*: This is a lower bound of the true significance.

In this study, three models used in most researches namely spherical, exponential and Gaussian models were employed in kriging operations and their results were compared for non-normal distribution and normal distribution of data. Parameter values for variograms and the employed models are presented in Table 3. In optimal mode and theoretically, the nugget effect (C0) should be zero, but in reality it is less because of some errors in measurements and stochastic process. So, the more C0 is for a smaller model, the better it is. Because considering C0 alone can be misleading, typically the proportions of spatial structure of the data, i.e. the ratio of the scale (C) to the sill (C + C0), is used. The closer it is to one, the stronger is the spatial structure of the data in that model. The values, greater than 0.75, 0.25 to 0.75 and less than 0.25, respectively, indicate a strong, moderate, and weak spatial structure (Cambardella *et al*., 1994; Wang *et al*., 2009, Hu *et al*. ., 2014). Based on the findings, the exponential model in both data distributions has a strong spatial structure, although in non-normal distribution, the spatial structure contribution is equal to 0.998 and in the normal distribution it is equal to 0.778, which represents a stronger spatial structure in non-normal conditions. Spherical and Gaussian models in both data distributions have an average spatial structure, although it is stronger for the spherical model than Gaussian. Also, the RSS and R2 values for the exponential model in both non-normal distribution and normal distribution are greater than these values for the other two models (Table 3). These values also indicate that the exponential model is more appropriate than the other two models. Figure 6 shows the semi-variograms of the exponential model for non-Normal distribution (6a) and normal distribution (6b). Moreover, kriging operations were used for the both, normal distribution and non-normal distribution, in all three spherical, exponential and gaussian models, and the criteria for evaluating the estimates or the estimation error values were obtained (Table 3).

Table 3. Parameters related to variograms of models and evaluation criteria for estimates

Prediction Errors				Model Parameters								
ASE	RMSS	RMSE	ME	R^2	RSS	Effective Range (m)	Range (m)	C/C+C0	C+C0	C0	Data Distribution	Model
5.44	1.15	6.28	-0.07	0.804	261	4770	4770	0.653	52.81	18.3	Non-Normal	Sperical
6.63	1.14	6.54	-0.34	0.916	0.002	6660	6660	0.646	0.17	0.062	Normal	
5.34	1.16	6.27	-0.03	0.859	268	3990	1330	0.989	53.06	0.6	Non-Normal	Exponential
5.65	1.17	6.28	-0.23	0.943	0.001	7740	2580	0.778	0.18	0.04	Normal	
6.56	0.96	6.32	-0.1	0.478	902	14601	8430	0.500	71.41	35.7	Non-Normal	Gaussian
7.21	1.21	6.78	0.56	0.896	0.002	5438	3140	0.529	0.17	0.08	Normal	

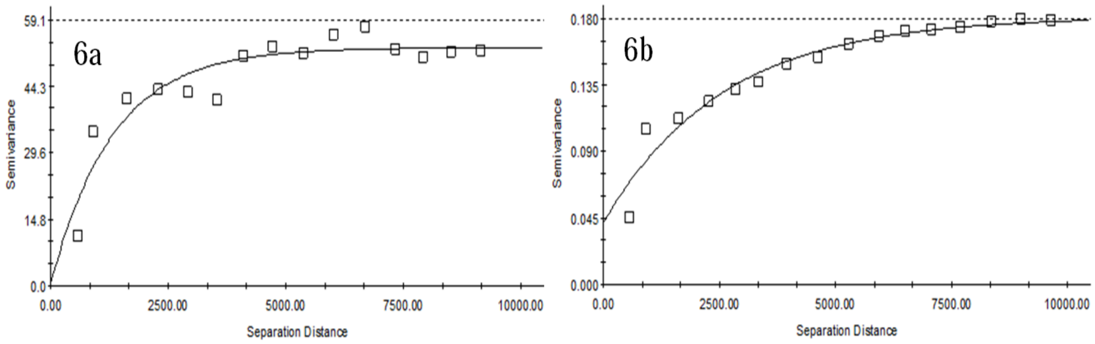

Fig. 6. The semi-variogram of data in non-normal distribution (left) and normal distribution (right) for exponential model

The goodness of fitting a mathematical or theoretical model with the experimental model (points) is indicated by the coefficient of determination of R2. As R2s in Table 3 show, for the normally distributed data, the value of R2 is greater than the non-normally distributed data. This indicates that the experimental distribution for the normally distributed data is more consistent with theoretical or mathematical models (spherical, exponential, and Gaussian). For example, as shown in Fig. 6, the exponential model for normally distributed data has a better fit than the non-normally distributed one (original data). The value of R2 for normal and non-normal distribution for the exponential model is 0.943 and 0.859 respectively (Table 3). However, although the normally distributed data has a greater R2 than non-normally distributed data, the estimates from the exponential model for normally distributed data are not only less accurate, but also more error-prone. For example, non-normally distributed data has an ME = -0.03, but it has been increased to -0.23 (absolute value) in normally distributed data, indicating more error in estimations. This result is also supported by other criteria, RMSS, RMSE and ASE. Therefore, it is not possible to ensure that estimates are better using R2 alone, since this coefficient is the only criterion for optimizing the fitting of the model to empirical data and not a criterion for better estimates. Given that the estimates of spherical and gaussian models have more errors in the normal distribution than in the non-normal one, it can be concluded that for salinity variables in the study area, the raw or original data although not normally distributed, presents better estimates rather than the normally distributed data. Therefore, the choice of whether to use the original data with any distribution in a research, or to transform it into a specific distribution such as normal distribution, can also depend on the research purpose. For example, in the current research, the accuracy of estimates has been considered only, and in all models the non-normal distribution data has better results. However, if the purpose of the study is to obtain an error map or the confidence interval of each estimate, the data that is normally distributed may be used, although its estimates are less accurate. In the present study, given that there is an incremental error in all estimation criteria, it can be said that the estimation of the data obtained from the normal distribution data has less accuracy than the original data which has a non-normal distribution.

To determine the effect of data transformation on the predictions, errors and their distributions, the histogram and Q-Q plot were drawn, as shown in Figures 7 and 8, respectively. As it can be seen, both, predictions and errors from the both sets of data (i.e., normally and non-normally distributed data) do not have normal distribution. In other words, data transformation has no effect on the normalization of the distribution of the predictions and the errors. On the other hand, the mean of estimates in the original and the transformed data are 4.92 and 3.64 respectively and, as mentioned before, the mean of salinity in the region is 4.93 (Table 1). It is worth noting that any type of data transformation and back-transformation usually causes errors, especially when nonlinear transformations such as logarithmic transformations occur. For example, the mean of the values of 10, 100 and 1000 is 370. But the mean of the logarithm of these values is 2, and if it is back-transformed, the mean will be equal to 100. Therefore, the mean of data has been changed 270 units only by a transformations and a back-transformation.

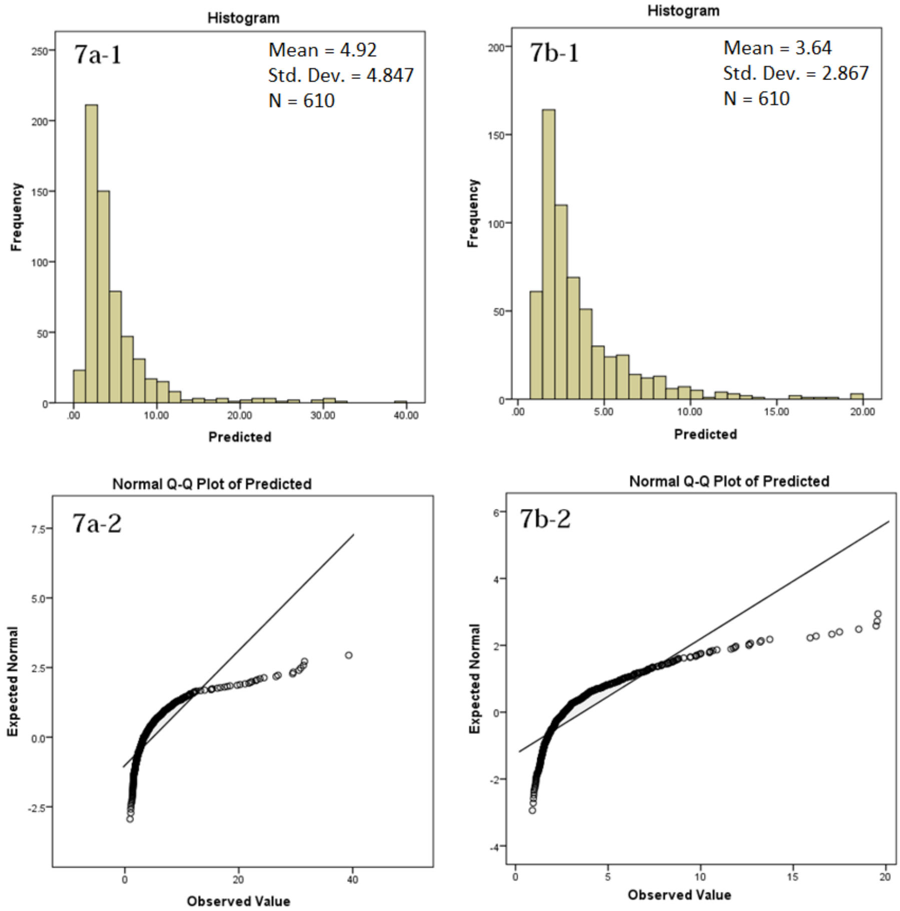

Fig. 7. Histograms (top) and Q-Q plots (down) of predictions of Kriging in non-normal distribution (7a-1 and 7a-2) and normal distribution (7b-1 and 7b-2) for exponential model

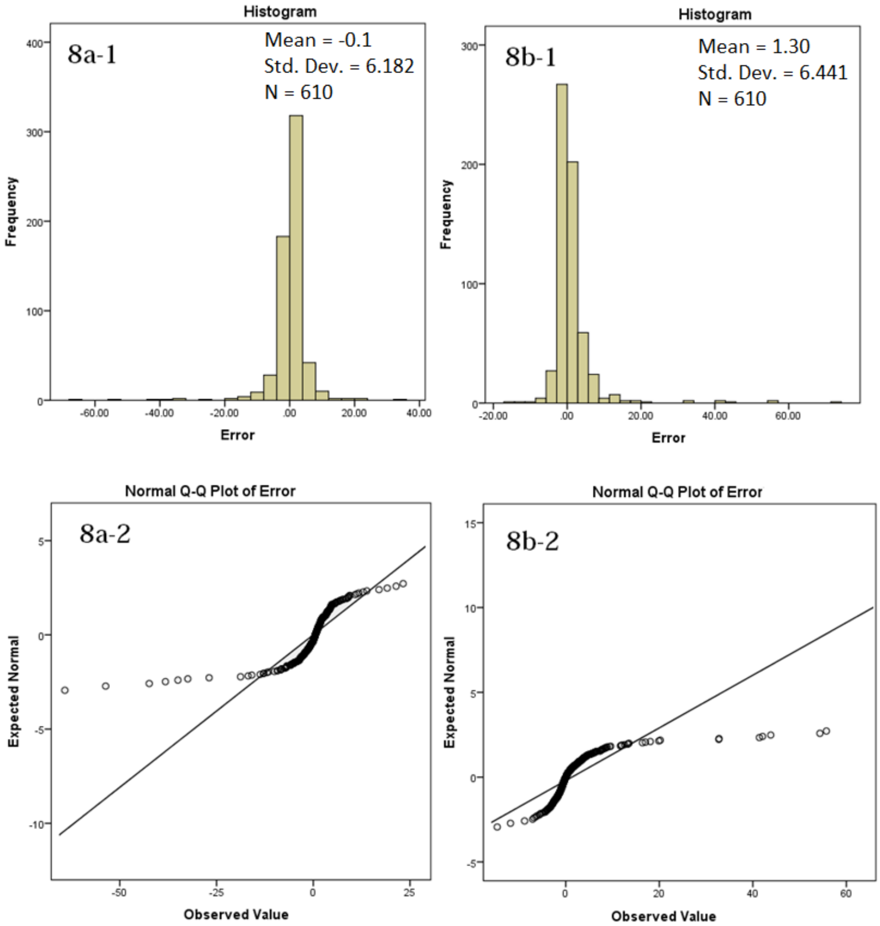

Fig. 8. Histograms (top) and Q-Q plots (down) of errors of Kriging in non-normal distribution (8a-1 and 8a-2) and normal distribution (8b-1 and 8b-2) for exponential model

Figure 9 shows the obtained soil salinity maps for the exponential model for the both, normal distribution and non-normal (logarithmic) distributions. As it can be seen, the overall trend of salinity changes is almost the same in both maps, but in the created map using logarithmic or non-normal distribution data, areas with high salinity (EC> 32 dS m^{-1}) are better mapped in the south of the study area, which is more coherent with the reality of the region. These areas are mapped to the high salinity class (EC of 16 to 32 dS m^{-1}) using the normal distribution data which is not coherent with the reality of the region. These findings are in line with the error estimation criteria (Table 3), indicating better accuracy of estimates for non-normally distributed data. It is worth noting that the soil in this area is classified in the great group of Fluventic Aquicambid, illustrating the high level of groundwater. Since the soil texture of this area is clay (clay content is more than 55%), the capillary action is strong. Thus, the salts from the groundwater are raised by capillarity to the surface of the soil. Dayani *et al*. (2013) have also expressed such a process for salinization of soils in the western regions of the Karun River. At the end, it is necessary to note that, as the effect of the distribution of data on the kriging operation is less considered, in order to generalize these results to other regions or variables, more research is needed.

4. Conclusion

In the Kriging operation, the basic condition for the truth is the stationary assumption. Normalizing the distribution of data can only improve the conditions for the stationary assumption. Therefore, the normal distribution of data is not a necessary condition for the kriging technique. According to the findings of this study, the optimum semi-variogram model for salinity variable was an exponential model with the original non-normally distributed data, although in terms of the goodness of fit, R^2, another exponential model with normally distributed data seemed to be a better model. According to the results obtained from the estimates, it was found that in the study area for the salinity variable, the accuracy of the estimates for the original non-normally distributed data was higher than those with normally distributed data. Therefore, if the purpose of the research is to predict a better estimation with higher accuracy, then the original data, although its distribution is not normal, can be used and it is not necessary to normalize the distribution of data. Also, the predictions and errors from both, normally and non-normally distributed data did not have the normal distribution. Therefore, data transformation had no effect on the normalization of the distribution of the predictions and errors. Of course this issue/finding may not always be true given the place and type of the variable. Therefore, in the kriging technique, in addition to the conventional method, i.e. performing this technique on normally distributed data, it is suggested that the original data (with their distribution not being normalized) be investigated. Finally, the optimal distribution and appropriate model should be selected using a comparison of the obtained results.

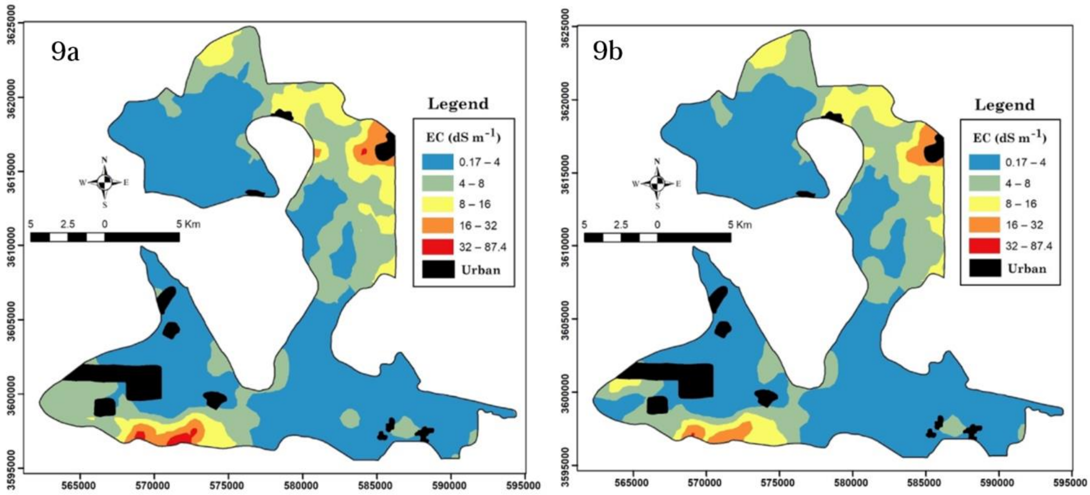

Fig. 9. Soil salinity map with non-normal distribution (left) and normal distribution (right) for exponential model

Appreciation

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