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Using OK and IDW Methods for Prediction the Spatial Variability of A Horizon Depth and OM in Soils of Shahrekord, Iran

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Abstract
This study attempts to evaluate some interpolation techniques for mapping spatial distribution of A horizon depth and OM in Shahrekord, Iran. 15000 hectares of South West Shahrekord soils were studied in which totally 92 soil profiles were excavated and classified according to USDA. The performance of methods was evaluated by RMSE, ME and R^2. Calculated RMSE for depth of A horizon were 0.01074, 0.19670 and 0.19858, respectively by IDW and OK (with Spherical and Exponential models). The RMSE for surface horizon OM were obtained 0.05593, 0.12121 and 0.05078, respectively by IDW and OK (with Spherical and Exponential models). The results showed that IDW could estimate the variability of A horizon depth and Ok (with Exponential semivariogram) could estimate the variability of depth of A horizon more better than other methods. The weakness of kriging in prediction of spatial continuity of depth of A horizon is due to effects of variability of soil forming factors in evolution of soils evolved in different landforms of study area which could take out the stationary assumptions.
Keywords: Ordinary Kriging, Inverse Distance Weighting, Evaluation of models

Introduction

Hilinski (2001);Soil organic matter (SOM) is the fraction of the soil that consists of plant or animal tissue in various stages of decomposition. Most of the productive agricultural soils have organic matter between 3 and 6%percentages. SOM exerts numerous positive effects on soil physical and chemical properties, as well as the soil's capacity to provide regulatory ecosystem services. The vertical distribution of SOM in mineral soils is a general decrease of OM content with depth. The vertical decreasing of OM is non-linear and frequently modeled by an exponential function. Based on published results there appear to be distinct differences between the distribution of SOC in topsoil and the subsoil section depending on land use. Jobbagy and Jackson (2000); At a global scale not only the amount of OC but also the specific characteristics of the exponential relationship of OC with depth in the profile were found to vary strongly with vegetation type. Post et al (1982); Climatic conditions seem to be the dominant factor determining SOC for the upper soil layer while for deeper soils clay content becomes increasingly influential. In reality SOC increases with increasing precipitation and decreases with increasing temperature. The major conditions influencing SOC independently of climatic conditions are; Land use / cover, SOC content, Soil depth and Clay content of soils. Shrub lands and arable lands have the lowest rate of decrease of SOC with depth. Soils with high SOC show less of a decrease in OC with depth than soils low in OC. In shallow soils SOC decreases more rapidly with depth than in deeper soils. For deep soils clay content is more closely related to SOC than for shallow soils.

Goovaerts (1998); Soils are characterized by high degree of spatial variability due to the combined effect of physical, chemical and biological processes that operate with different intensities and at different scales. Knowledge on spatial variation of soil properties is important in several disciplines, including agricultural field trial research and precision farming. Goovaerts (1998); Corwin (2003); Godwin and Miller (2003); Vrindts et al (2005); Reports have shown that there is large variability in soil, crop, disease, weed and yield not only in large-sized fields, Mouazen et al (2003); but also in small-sized fields. In recent years, geostatistics such as Webster (1994); Zhang et al (1998); Zhang et al (2000); Webster and Oliver (2001); Corwin et al (2003); Mueller et al (2003); Sun et al (2009);has been proven to effectively assess the variability of soil properties. Geostatistics provides a set of statistical tools for analyzing spatial variability and spatial interpolation. These techniques produce not only prediction surfaces but also error or uncertainty surfaces. Cressie (1993); Spatial prediction techniques, also known as spatial interpolation techniques, differ from classical modeling approaches by the way they incorporate information on the geographic position of the sample data points. The most common interpolation techniques calculate the estimate for a property at any given location by a weighted average of nearby data. Salder et al (1998); A number of factors affect map quality including the nature of the soil variability, intensity of sampling and methods of interpolation. Availability of a variety of interpolation methods has posed questions to the users as to which is the most appropriate method in different contexts and has stimulated several comparative studies of relative accuracy. Deutsch (2002); Nalder and Wein (1998); Among statistical methods, geostatistical kriging-based techniques are widely applied and among deterministic interpolation methods, inverse distance weighting (IDW) method is most often applied. Both models estimate values at un-sampled locations based on the measurement at surrounding locations with certain assigned weights for each measurement. A stochastic (also called geostatistical) interpolator incorporates the concept of randomness and yields both an estimated value (the deterministic part) and an associated error (the stochastic part, e.g. an estimated variance). On the other hand, a deterministic method does not provide any assessment of the error made on the interpolated value.

Olea (1991); Kriging is a collection of linear regression techniques that takes into account the stochastic dependence among data. Miller et al (2007); Ordinary Kriging (OK) is one of the most basic kriging methods. It provides an estimate at an unobserved location of variable z, based on the weighted average of adjacent observed sites within a given area. The correlations among neighboring values are modeled as a function of the geographic distance between the points across the study area, defined by a variogram.

Isaake and Srivastava (1989); From a theoretical stand point, kriging is the optimal interpolation method; however, its correct application requires an accurate determination of the spatial structure via semivariogram construction and model-fitting. Phillips (1986); Robertson (1987); Semivariogram, has been widely used to analyze spatial structures in ecology. Gundogdu and Guney (2007); Uyan and Cay (2010);A semivariogram is used to describe the structure of spatial variability. The semivariogram plays a central role in the analysis of geostatistical data using the kriging method. It takes into account the spatial autocorrelation in data to create mathematical models of spatial correlation structures commonly expressed by variograms.

Hosseini et at (1994); Dalthorp et al (1999); Kravchenko and Bullock (1999); Kravchenko (2003); Reinstorf et at (2005); The IDW procedure has been used primarily because it is simple and quick while kriging has been used because it provides best linear unbiased estimates. Many researchers have compared IDW and kriging. In some cases, the performance of kriging was generally better than IDW. Istock and Cooper (1998); used kriging method to estimate heavy metals and found that the used method is the best estimator for spatial prediction of metals. Mueller et al (2001); One study found that by better resolving the spatial structure with additional closely spaced samples, ordinary kriging generally outperformed IDW. Kravchenko (2003); In a simulation study, IDW was compared with kriging with known (i.e., semivariogram models were determined from an exhaustive dataset) and unknown (i.e., semivariogram models were determined from the sample dataset) spatial structure. As might be expected, the performance of kriging improved relative to IDW when the spatial structure was known. Given the importance of the spatial structure, it may be possible to use geostatistical indices to predict the relative performance of ordinary kriging and IDW. Taghizadeh Mehrjardi et al (2008); in Ardakan-Yazd plain of Iran applied the Inverse Distance Weighted (IDW), kriging and cokriging methods for predicting spatial distribution of some groundwater characteristics such as: EC, SAR, Cl^- and $SO4^{2-}$. Results showed that kriging and cokriging methods are superior to IDW. The cokriging has higher accuracy than other methods for estimating spatial distribution of groundwater quality. Gotway et al (1996); have studied the relationships between OK and IDW for mapping soil nitrate (NO^{-3}) and organic matter content for variable-rate fertilizer applications in corn production on Midwest soils. They found that OK provided reasonably accurate results in all cases. They also found that model accuracy was dependent upon the soil parameter being mapped. Isaaks and Srivastava (1989); compared OK, IDW, and triangulation on several clustered data sets and found that OK produced the lowest prediction error in their applications. Kravchenko and Bullock (1999); conducted a comparative study of various interpolation methods for mapping soil test P and K data. They found OK with the optimal number of neighboring points and an appropriate variogram performed better than IDW. In other studies, Nalder and Wein (1998); IDW generally out-performed kriging. Warrick (1998); reported kriging to be better than IDW for mapping potato yield and soil properties. Maroofi et al (2009); indicated that Inverse Distance was the best method to estimate EC and pH, respectively, in stream drained water in Hamedan-Bahar plain, west of Iran. The results, however, have often been mixed, Schloeder et al (2001); Mueller et al (2001); Lapen and Hayhoe (2003). The results of prediction are mostly dependent of the site specific conditions in which the methods and models are used. The description of the environmental condition and the studied area ecological set may define the priority of methods being used. The aim of this study is

1. Provide the continuous maps of depth of A horizon and OM amount by OK and IDW methods by 30*30 meter grids.
2. Determine the error and access to accuracy maps by OK and IDW methods.

Method and material

Study Area

The study area is located in Chaharmahal e Bakhtiari province , in the Southwestern of Shahrekord city between 32° 07′ and 32° 20′ north latitude and 50° 42′ and 50° 52′ east longitude containing 15000 hectares of area (Fig 1). Soil moisture temperature regimes of study area are Xeric and Mesic, respectively. The slope of the area decreases moving from west to east in this area. The altitude varies between 2000 to 3500 meter. According to

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De-Martine advanced climatic classification system, this area has Mediterranean climatic class.

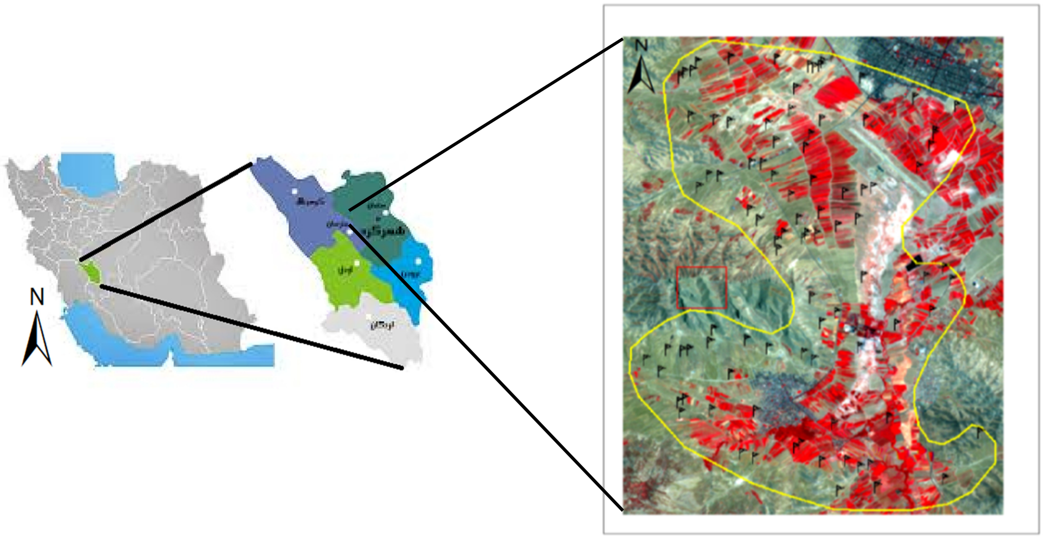

Figure 1.Location of the study area and sampling points in study area

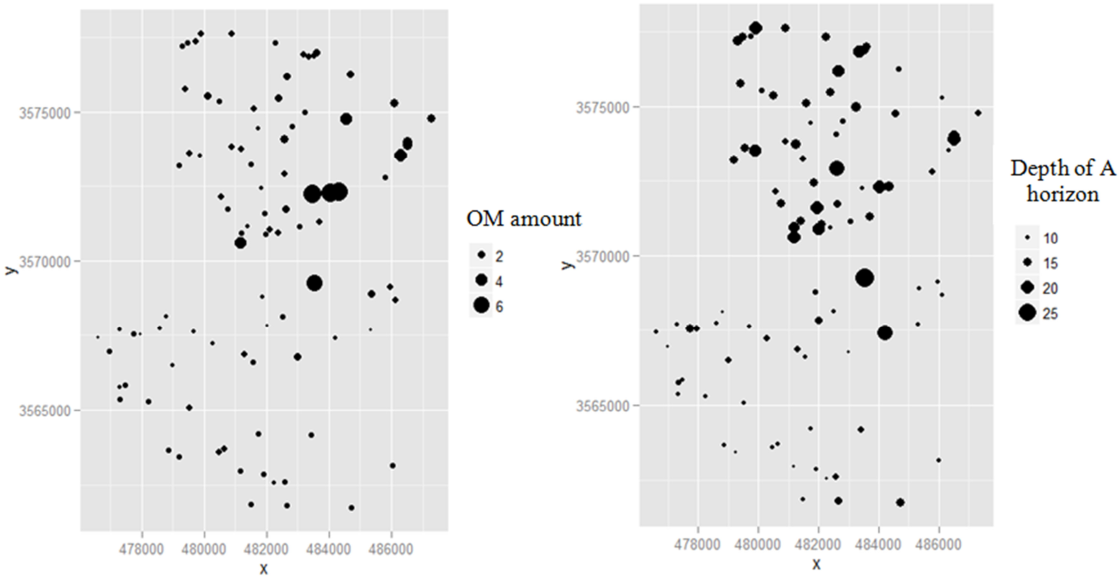

Figure 2. The amount of two variables distributed in study area

Data Sampling and Analysis

Geomorphic units of the study area were extracted by interpretation of 1:55000 aerial photos. Soil profiles (92 points) were randomly located in different geomorphic units in 2013. The soils of study area, are classified as Inceptisols and Alfisols according to USDA. These soils were positioned on the Hill, Piedmont, Alluvial Plain and Alluvial fan geomorphic units. The distribution of sampled points is shown in Fig two. Size of circles in sampling points indicates the depth of A horizon and OM amount of surface horizon in mentioned figure. The bigger the circles the ticker the A horizon and higher the OM amounts. Fig 3 show the three dimensional scatterplot of the amount of two variables measured in sampled points. The first and second dimensions were showed latitude and longitude and third dimension shows the depth of A horizon and/or OM amount of surface horizon. After morphological study, samples were taken from identified horizons and air-dried to remove stones and coarse crop residues. Soil texture, amount of organic carbon, $CaCO_3$, pH, EC and CEC were analytically measured in sampled soils.

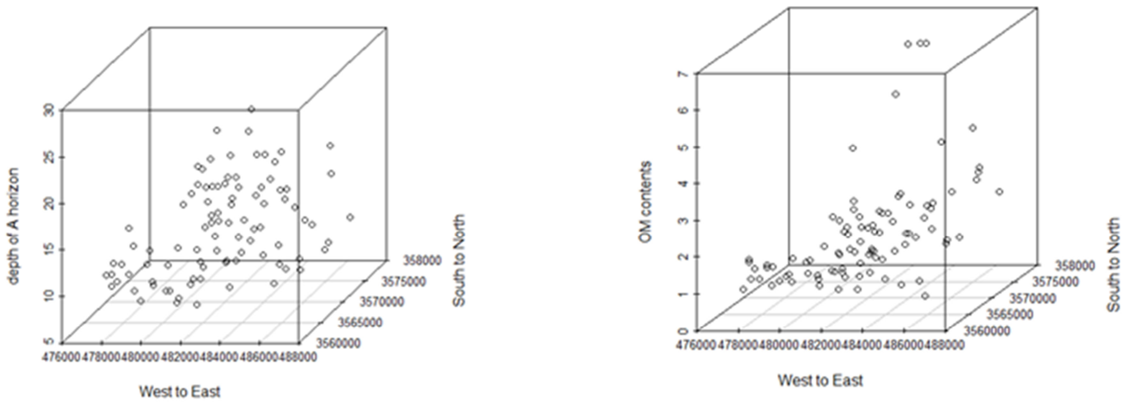

Figure 3. three dimensional scatterplot of depth of A horizon and OM amount in the study area

IDW

All interpolation methods have been developed based on the theory that closer points have higher correlation and similarities than those farther away. In the IDW method, it is assumed that the rate of correlations and similarities between neighbors is proportional to the distance between them. It is assumed that this correlation can be defined as a reverse distance function of every point from neighboring points. The definition of the neighboring radius and the related power to the reverse distance function are considered as important factors. The main factor affecting the accuracy of the IDW interpolator is the value of the power parameter p (Isaak and Srivastava, 1989). Few researchers have attempted to explain the underlying factors that impact the relative performance of IDW. Mueller et al (2004) have investigated the impact of scale of sampling on the relative performance of ordinary kriging and IDW. The performance of kriging improved relative to IDW interpolation as sampling intensity increased. The impact of scale is important because sampling intensities may vary widely. The degree to which spatial structure is known impacts the relative performance of IDW and kriging. Nearly all methods of spatial interpolation share the following general spatial prediction formula:

$$\hat{z}(x_0) = \sum_{i=1}^{N} \lambda_i z(x_i) \qquad (1)$$

where x_0 is a target point where the value should be estimated, the $z(x_i)$ are the locations where an observation is available and the λi are the weights assigned to individual observations. N represents the number of points involved in the estimation.

Inverse distance weighting (Shepard 1968) is one of the oldest spatial interpolation method but also one of the most commonly used. The estimated value $z(x_0)$ at a target point x is given by Eq. (1) where the weights λi are of the form:

$$\lambda_i = \frac{1}{d^p(x_0, x_i)} \Big/ \sum_{i=1}^{N} \frac{1}{d^p(x_0, x_i)} \, p \geq 0 \sum_{i=1}^{N} \lambda_i = 1 \qquad (2)$$

In the above expression, $d(x_0; x_i)$ is the distance between points x_0 and x_i, p is a power parameter and N is the number of points found in some neighborhood around the target point x_0. Scaling the weights λi so that they sum to unity ensures the estimation is unbiased. The rationale behind this formula is that data points near the target points carry a larger weight than those further away. The weighting power p determines how fast the weights tend to zero as the distance $d(x_0; x_i)$ increases. That is, as p is increased, the predictions become more similar to the closest observations and peaks in the interpolation surface become sharper. In this sense, the p parameter controls the degree of smoothing desired in the interpolation.

Power parameters between 1 and 4 are typically chosen and the most popular choice is p = 2, which gives the inverse distance-squared interpolator. IDW is referred to as ”moving average” when p = 0 and ”linear interpolation” when p = 1.

For a more detailed discussion on the effect of the power parameter p, see e.g. Collins &Bolstad (1996); Burrough (1988). Another way to control the smoothness of the interpolation is to vary the size of the neighborhood: increasing N yields greater smoothing. IDW is a local interpolation technique because the estimation at x_0 is based solely on observations points located in the neighboring region around x_0 and because the influence of points further away decreases rapidly for p > 0. It is also forced to be exact by design since the expression for λi in Eq. (2) reaches the indeterminate form ∞=∞ when the estimation takes place at the point x_0 itself. IDW is further labeled as deterministic because the estimation algorithm relies purely on geometry (distances) and does not provide any estimate on the error made.

Kriging

Kriging is a spatial prediction technique initially created in the early 1950's by mining engineer Daniel G. Krige (Krige 1951) with the intent of improving ore reserve estimation in South Africa. But it was essentially the mathematician and geologist Georges Matheron who put Krige's work a firm theoretical basis and developed most of the modern Kriging formalism (Matheron 1962, 1963). Following Matheron's work, the method has spread from mining to disciplines such as hydrology, meteorology or medicine, which triggered the creation of several Kriging variants. It is thus more accurate to refer to Kriging as a family of spatial prediction techniques instead of a single method. It is also essential to understand that Kriging constitutes a general method of interpolation that is in principle applicable to any discipline, such as astronomy. Kriging takes into account the spatial correlation existing in the data. In fact, Kriging method is built on the underlying process of second-order stationarity called intrinsic stationarity. Second-order stationarity is traditionally defined as follows:

1. The mathematical expectation E(Z(x)) exists and does not depend on x

$$E[Z(x)] = m, \quad \forall x \qquad (3)$$

2. For each pair of random variable Z(x); Z(x + h), the covariance exists and only depends on the separation vector h = xj _ xi,

$$C(h) = E\{[Z(x+h) - m][Z(x) - m]\}, \quad \forall x \qquad (4)$$

Kriging's intrinsic stationarity (Matheron 1963, 1965) is a slightly weaker form of second-order stationarity where the difference Z(x + h) _ Z(x) is treated as the stationary variable instead of Z(x):

$$E[Z(x+h) - Z(x)] = 0, \qquad \forall x \qquad (5)$$

$$Var[Z(x+h) - Z(x)] = E\{[Z(x+h) - Z(x)]2\} = 2\gamma(h) \qquad (6)$$

The function γ(h) is called semivariance and its graph semivariogram or simply variogram. One reason for preferring intrinsic stationarity over secondary stationarity is that semivariance remains valid under a wider range of circumstances. When covariance exists, both stationarities are related through:

$$\gamma(h) = C(0) - C(h), \qquad C(0) = Var[Z(x)] \qquad (7)$$

Over the years about a dozen Kriging variants have been developed. We will concentrate here on ordinary Kriging (OK), which is, by far, the most widely used. Ordinary Kriging is a local, exact and stochastic method. The set of Z(x) is assumed to be an intrinsically stationary random process of the form

$$Z(x) = m + \varepsilon(x) \qquad (8)$$

The quantity ε(x) is a random component drawn from a probability distribution with mean zero and variogram γ(h) given by (6). The ordinary Kriging predictor is given by the weighted sum

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \qquad (9)$$

where the weights λ_i are obtained by minimizing the so-called Kriging variance

$$\delta^2(x_0) = Var\big[\hat{Z}(x_0) - Z(x_0)\big] = E\{\big[\hat{Z}(x_0) - Z(x_0)\big]^2\} \qquad (10)$$

subject to the un-bias-ness condition

$$E\big[\hat{Z}(x_0) - Z(x_0)\big] = 0 = \textstyle\sum_{i=1}^{N} \lambda_i E[Z(x_0)]\text{-m} \qquad (11)$$

The resulting system of "N + 1" equations in N + 1 unknowns λi is known as the ordinary Kriging equations. It is often expressed in matrix form as Aλ = b with

$$A = \begin{bmatrix} \gamma(x_1,x_1) & \gamma(x_1,x_2) & \cdots & \gamma(x_1,x_N) & 1 \\ \gamma(x_2,x_1) & \gamma(x_2,x_2) & \cdots & \gamma(x_2,x_N) & 1 \\ \vdots & \vdots & & \vdots & \\ \gamma(x_N,x_1) & \gamma(x_N,x_2) & \cdots & \gamma(x_N,x_N) & 1 \\ 1 & 1 & & 1 & 0 \end{bmatrix} \tag{12}$$

$$\lambda^T = [\lambda_1 \lambda_2 \ldots \lambda_N \mu] \sum_{i=1}^{N} \lambda_i = 1 \tag{13}$$

$$b^T = \left[\gamma_{(x1,x0)} \gamma_{(x2,x0)} \cdots \gamma_{(xN,x0)} \quad 1\right]$$

The weights λi, along with the Lagrange multiplier μ, are obtained by inversing the A matrix

$$\lambda = A^{-1}b \tag{14}$$

Most of the strengths of Kriging interpolation stem from the use of semivariance instead of pure geometrical distances. This feature allows Kriging to remain efficient in condition of sparse data and to be less affected by clustering and screening effects than other methods. In addition, as a true stochastic method, Kriging interpolation provides a way of directly quantifying the uncertainty in its predictions in the form of the Kriging variance specified in Eq. (10).

In this research, we used OK and IDW methods for production of continuous maps of depth of A horizon and OM amount. For kriging method selected two semivariograms models that were Exponential and Spherical models.

Model Validation

Essentially, whenever we fit a model, we generate some predictions. The question one needs to ask is how good are those predictions? Generally, we confront this question by comparing observed values with their corresponding predictions. Some of the more common "quality" measures are the root mean square error (RMSE), bias, coefficient of determination or commonly the R^2. The RMSE is defined as:

$$RMSE = \sqrt[2]{\left(\frac{\sum_{i=1}^{N} obs_i - pred_i}{N}\right)^2} \tag{15}$$

Where obs is the observed soil property, pred is the predicted soil property from a given model, and n is the number of observations i. Bias, also called the mean error of prediction is defined as:

$$ME\ or\ Bias = \frac{\sum_{i=1}^{N} obs_i - pred_i}{N} \tag{16}$$

The R^2 is evaluated as the square of the sample correlation coefficient (Pearson's) between the observations and their corresponding predictions. Pearson's correlation coefficient (r) when applied to observed and predicted values is defined as:

$$r = \frac{\sum_{i=1}^{N}\left(obs_i - \overline{obs}\right)(pred_i - \overline{pred})}{\sqrt[2]{\sum_{i=1}^{N}(obs_i - \overline{obs})^2}\ \sqrt[2]{\sum_{i=1}^{N}(pred_i - \overline{pred})^2}} \tag{17}$$

The R^2 measures the precision of the relationship (between observed and predicted).

R overview and history

R is a software system for computations and graphics. R was originally developed in 1992 by Ross Ihaka and Robert Gentleman at the University of Auckland (New Zealand). The R language is a dialect of the S language which was developed by John Chambers at Bell Laboratories. This software is currently maintained by the R

Development Core Team, which consists of more than a dozen people, and includes Ihaka, Gentleman, and Chambers. Additionally, many other people have contributed code to R since it was first released. The source code for R is available under the GNU General Public Licence, meaning that users can modify, copy, and redistribute the software or derivatives, as long as the modified source code is made available. R is regularly updated; however, changes are usually not major. We have used R program to execute the needed analysis of this study. To do so the sp, raster, rgdal, ggplot2, gstat and MASS packages were used.

Results

Table 2 lists the summary statistics of the raw data of depth of A horizon and OM in surface soil horizon, including mean, maximum, minimum, standard deviation, skewness, and kurtosis. To evaluate the normality of data a formal Anderson-Darling statistic test was executed. For this data to be normally distributed the p value should be less than 0.05, but p-value for raw depth of A horizon and OM amount of surface horizon data were 1.671e-05 and 2.2e-16, respectively. This is confirmed when we looked at the histogram and qq-plot of this data (fig 4).

Table 2.The statistical values of soil properties

Soil properties	mean	Min	Max	Median	SD	Skewness	Kurtosis
A horizon	12.75	8	26	12	0.281	0.21	1.15
OM amount	1.705	0.265	6.723	1.388	0.281	0.16	1.45

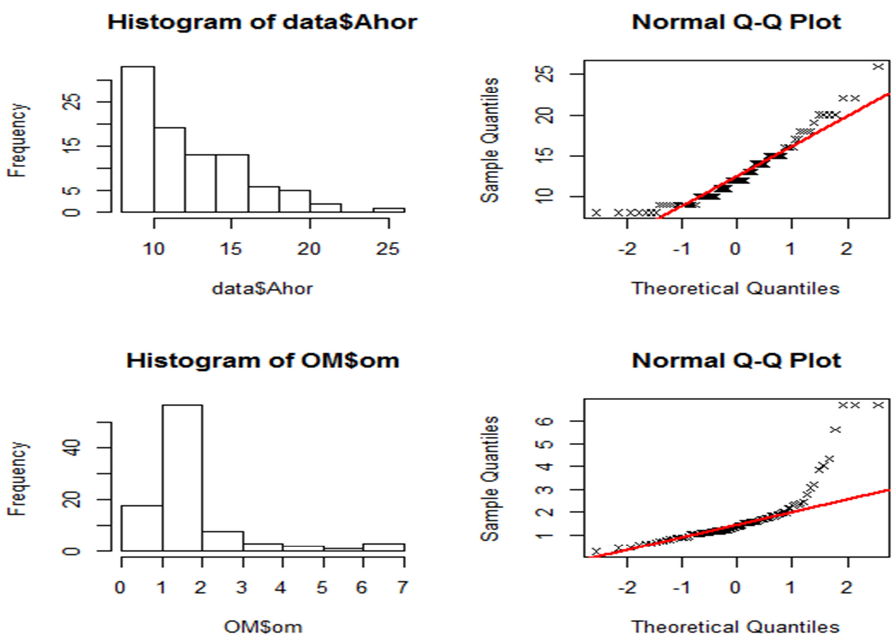

Figure 4.Histogram and qq-plot of raw depth of A horizon and OM amount of surface horizon

Generally for fitting statistical models, we need to assume our data is normally distributed. Currently it is not, so we have to transform the a log-transformation is popular to convert the abnormal data to normal ones. The Log-Transformation resulted in reduced skewness and kurtosis values to 0.1, 1.084 for depth of A horizon and 0.027, 1.33 for OM surface horizon, respectively. Anderson-Darling Test statistic for transformed data had p-value less than 0.05. While not perfect, this is an improvement. This was also apparent when weided the histograms and qq-plots (fig 5).

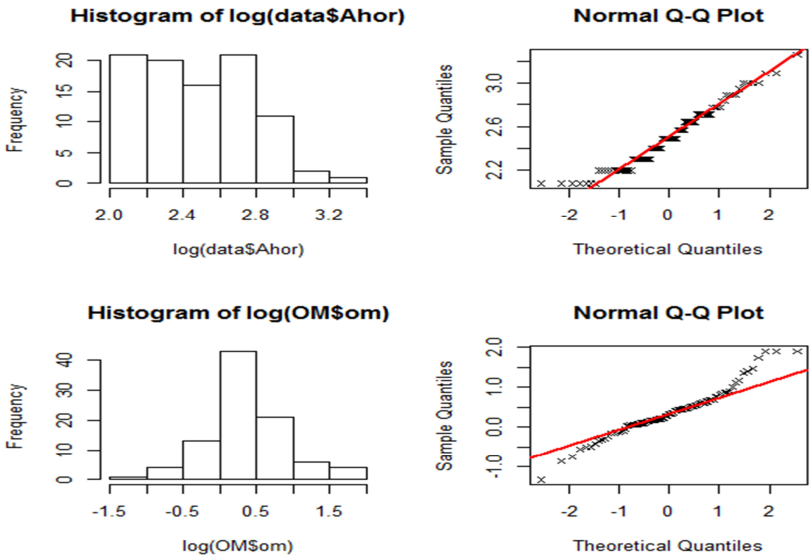

Figure 5. Histogram and qq-plot of transformed depth of A horizon and OM surface horizon data

Kriging method executed with Spherical and Exponential semivariograms and IDW model were performed on data and compared the two OK models with each other and IDW . The attributes of the semivariograms for the data are summarized in Table 3. Preliminary calculations of variograms in different directions showed that all semivariogram were isotropic. Semivariogram analysis indicated that depth of A horizon was best fitted to Spherical model with nugget, sill, and nugget/sill equal to 0.0404, 0.199 and 0.2025, respectively. For the amount of OM in surface horizon Exponential model was fitted the best with nugget, sill, and nugget/sill equal to 0.0073, 0.3391 and 0.021, respectively. In this research, nugget/sill ratio 20% and 2% for depth of A horizon (Spherical model) and OM surface horizon (Exponential model), respectively indicated well spatial dependence for the data in study area (table 3).The nugget/sill ratio of depth of A horizon (Exponential model) and OM surface horizon was 0.339 and 0.128, respectively. Commonly, weak spatial dependency can be recognized because of extrinsic factors such as industrial production, fertilization and other soil management practices. The anthropogenic factors may change the spatial correlation of the variables after a long process of utilization (Cambardella et al., 1994; Shi et al., 2007). In this research, Exponential model could estimate the distribution of A horizon depth and Spherical model estimated amount of OM more better.

Table 3. The fitted semivariogram models and their parameters for study data

Soil properties	Model	Nugget	Sill	Nugget/Sill	Range
Depth of A horizon	Exponential	0.03660527	0.10779205	0.339	21600
	Spherical	0.04044522	0.19931629	0.2025	25798
Content of OM	Exponential	0.007327816	0.339185062	0.021	1250.531
	Spherical	0.03672733	0.28606525	0.128	2749.347

The results of geostatistical analyses of depth of A horizon and OM of surface horizon have been presented in Tables 4 and 5. The results showed that IDW and kriging (Exponential model) were the best methods to estimate depth of A horizon and OM of surface horizon, respectively, because they had the highest precision and lowest error for estimation of these elements (tables 4 & 5). The performance of kriging (Spherical and Exponential) and IDW methods have been compared by cross-validation. According to the resulted cross-validation parameters, generally two models performed fairly well but IDW was the best model to estimate the depth of soil A horizons and Kriging with exponential variogram was the best model to estimate the amount of OM in soil surface horizons (tables 4 &5).

Table 4. Results of validation analyses of depth of A horizon

Method	Model	RMSE	R^2	Bias
	Exponential	0.1985871	0.5202948	0.0003598261
Kriging	Spherical	0.1967001	0.529896	0.0003599674
IDW	Power 2	0.01074181	0.9987832	0.0007679674

Table 5. Results of validation analyses of OM surface horizon

Method	Model	RMSE	R^2	Bias
	Exponential	0.05078149	0.9933969	-1.0945e-05
Kriging	Spherical	0.1212131	0.9696227	-0.0016408
IDW	Power 2	0.05593931	0.9814762	-0.0013790

In order to visually understand the difference of spatial variation resulted by the best models for the depth of A horizons and OM of surface horizons, maps provided by kriging (Exponential models) and IDW methods for study area are shown in figure 6.The results showed the high dependence of these parameters on slope. These parameters is higher in the northern, less slope, than in the south and west.

Webster and Englung (1992) findings are in agreement with our results in which these researchers reported that IDW was the best method for estimated soil properties. Spatial interpolation techniques such as kriging utilize the co-regionalization structure of soil properties and so provide unbiased estimates and minimum variance (Ali and Malik, 2011). Generally, geostatistics is superior to IDW which is similar to the results of Ahmad (2002), Barca and Passarella (2007), Mashayekhi et al., (2007); Liu et al., (2004) and Ali and Malik (2011) but our study resulted that it would not be a global rule and the estimation may be affected by the environmental condition of local area.

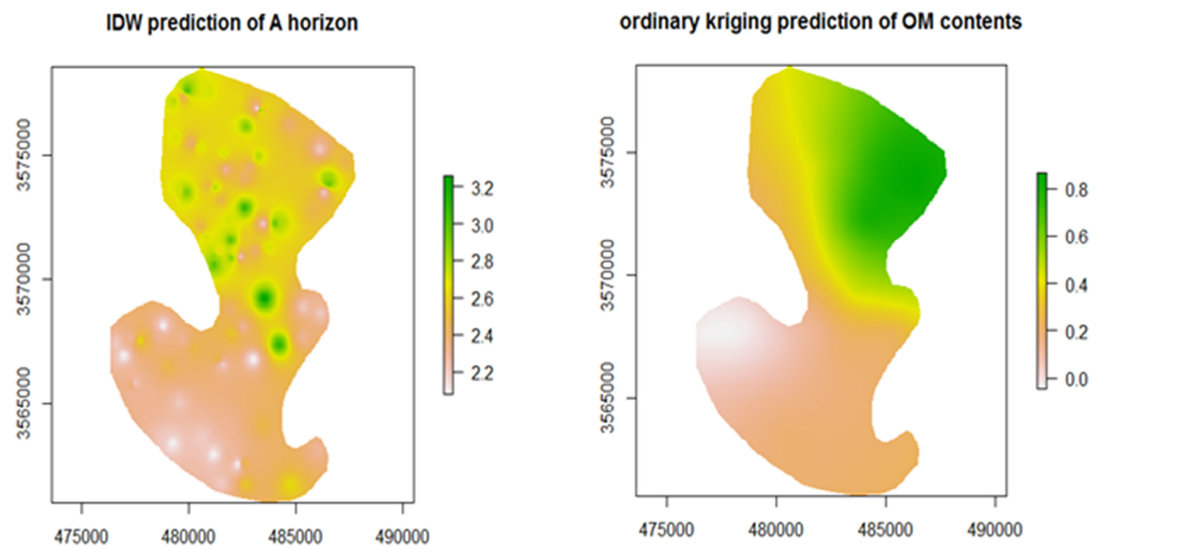

Figure 6. Interpolation maps of OM producted by kriging (Exponential model) and A horizon by IDW methods

Spatial patterns of data estimated by kriging show the high dependence of parameters on slope and geomorphic units. Slope is associated with these results, because, there is a inverse slope gradient toward the north of study area, therefore the value of target variables are high. This is because the geomorphic units such as Alluvial plains are in the north but, high slope geomorphic units such as Pediment and Aluvial fan are positioned in the south of studied area. Not only Correlations between depth of A horizon and OM surface horizon with slope and geomorphic units are high, but also correlation between OM surface horizon and clay content is also high (fig 7). Due to the geologic and geomorphic set of study area, the realizations of the spatial variability of the target variables are more site dependent in this area. The amount of the OM surface horizon is completely dependent of land use map units. The main superiority of kriging to the other methods such as IDW is the ability of kriging to present the estimation error map of each study. Another advantage of the kriging compared to other interpolation methods like IDW is that produced maps of kriging shows gradual variation of the nature, while IDW method estimations are more point specific localities.

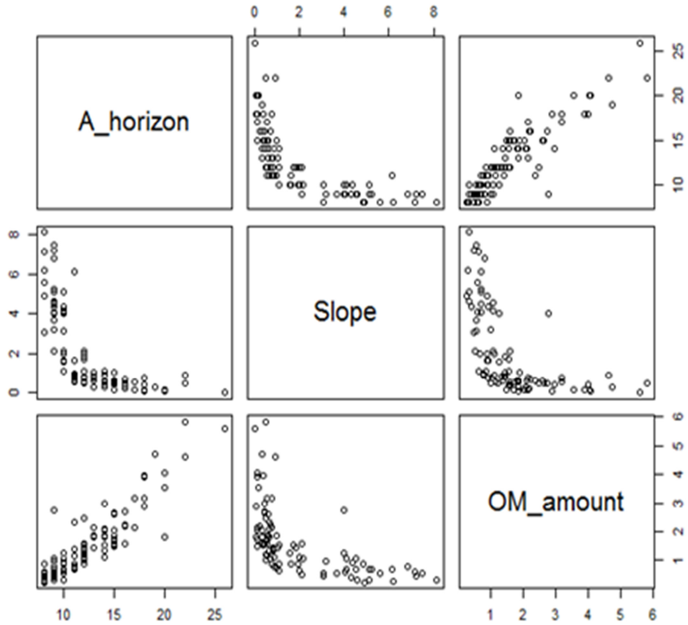

Figure 7. A pairs plot of A horizon, slope and OM amount from the study area

Conclusions

This study has shown that, out of the two spatial prediction methods, there is not a single interpolator enable to generate the best results for every attempt to map the soil properties. Therefore expecting the kriging to be always the better interpolator may be not a true assumption. In all implementations of IDW the power of two was the best choice (over powers of one, three and four), which is possibly due to the relatively low skewness inherent in all soil properties modelled (as also found by Kravchenko and Bullock, 1999). When the noise is low and spatial correlation is high it may generally be expected that kriging performs better than IDW but not in all other cases. However, as our results indicates, the expectation of kriging to perform better in case of amount of OM was true but for the depth of A horizon was false. Although our results are somewhat different from the results of Weber and Englund (1992), who found, to their surprise, that the accuracy of OK was not significantly affected by noise level. Possible explanations for this discrepancy is:

the amounts of noise, as measured by the ratios of error variance to total variance, in our experimentis considerably more disparate (roughly 20% and 27%) vs. 0% and 10% in the study of Weber and Englund).

Based on this research, geomorphological units and slope had a high correlation by depth of A horizon and OM amount. Hence, besides using interpolation methods, the data derived from DEM and satellite information can be used for other interpolation methods such as Cokriging and MLR as auxiliary variables in next studies.

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