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Continuous mapping of topsoil calcium carbonate using geostatistical techniques in a semi-arid region

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Abstract

Prediction and mapping of soil calcium carbonate are necessary for sustainable management of soil fertility. So, this research was done with the aims of (1) evaluation and analyzing spatial variability of topsoil calcium carbonate as an aspect of soil fertility and plant nutrition, (2) comparing geostatistical methods such as kriging and co-kriging and (3) continuous mapping of topsoil calcium carbonate. Sampling was done with stratified random method and 23 soil samples from 0 to 15 cm depth were collected. In co-kriging method, salinity data was also used as auxiliary variable. For comparing and evaluation of geostatistical methods, cross validation and statistical parameters such as correlation coefficient and RMSE were considered. The results showed that co-kriging method has the higher correlation coefficient (0.76) and less RMSE (4.1) which means its higher accuracy than kriging method to predict calcium carbonate content.

Keywords: Co-kriging, Cross validation, Kriging, Salinity, Spatial distribution
Abbreviations: Bd_Bulk density, $CaCO_3$_Calcium carbonate, CEC_Cation Exchange Capacity, DEM_Digital Elevation Model, EC_ Electrical Conductivity, GIS_Geographical Information System, IDW_Inverse Distance Weighting, OC_Organic Carbon, RMSE_Root Mean Square Error, RSS_Residual Sum of Square, SP_Saturation Percentage

Introduction

Variability is one of the intrinsic characteristics of the soil properties. Within an ecosystem, soil properties have vast spatial variations which mainly arise from factors and processes of pedogenesis and land use (Ersahin, 2003). Soil properties and their spatial distribution on different scales are requirement for different purposes (Shukla et al., 2007). Geostatistics is a useful tool for analyzing the structure of spatial variability, interpolating between point observations and creating the map of interpolated values with an associated error map. Most soils of agricultural areas are calcareous and have an alkaline reaction. pH of calcareous soils is mainly controlled by the amount of calcium carbonate in the soil profile and often is fluctuating between 7.5 to 8.5. Existence or absence of calcium carbonate is an important effect on soil pH and therefore, controlling many chemical reactions in relation to nutrient availability for plants and mobility of these elements in soil. Nutrient variability in two dimensions may be vertical and horizontal and this variability will be caused different levels of fertility. Different levels of fertility are responsible for the preservation and diversity of various plant and animal species. Thus, information on spatial variability of soil fertility status is important for sustainable management of soil fertility. Nowadays, different geostatistical techniques being widely used for prediction of spatial variations of soil properties. Mohammadi (2000) estimated soil salinity, saturation moisture content, sodium adsorption ratio and the percentage of $CaCO_3$ in Ramhormoz area using geostatistical method and the imagery of TM sensor as a secondary variable. He showed the relative advantage of geostatistical methods for estimation of soil spatial data. McBratney et al. (2003) provided the comprehensive maps for physical, chemical and biological soil properties by means of geostatistics, GIS and remote sensing techniques for a large area in Australia. Meul and Van Meirvenne (2003) used ordinary kriging, comprehensive kriging, simple kriging and co-kriging methods for estimation of silt content in Belgium. They also considered digital elevation model (DEM) as a secondary variable and the results showed that the comprehensive kriging method had the lowest estimating error. Ersahin (2003) used kriging and co-kriging methods and soil bulk density as an auxiliary variable for investigation of the spatial variations of infiltration rate in north west of Turkey. The findings revealed that the co-kriging method is a suitable technique for estimation of infiltration rate. Sokoti et al. (2006) used different geostatistical methods in order to predict the soil salinity distribution in Urmia plain, Iran. They found that kriging method with the Gaussian model has higher accuracy for estimating of salinity levels in areas without any information. Robinson and Metternicht (2006) used three different techniques

Table 1. Results of statistical analysis on studied parameters

Soil Parameter	Min	Max	Mean	Std	Kurtosis	Skewness	CV*(%)
$CaCO_3$ (%)	10.92	32.69	21.32	4.99	0.28	0.41	23.4
EC (dSm^{-1})	0.44	3.06	1.41	0.67	0.26	0.63	47.5

*CV = Coefficient of Variation

including co-kriging, IDW and spline for prediction of the levels of the soil salinity, acidity and organic matter. They recognized the spline and co-kriging methods are the best approach for estimation of the soil salinity values and organic matter content. Hence, the present study was carried out for continuous mapping to evaluate the accuracy of different techniques including kriging and co-kriging methods for prediction of spatial distribution of topsoil calcium carbonate in Zanjan province, central Iran.

Material and methods

Site description

The study area is located in Zanjan province in centeral Iran, which has the area about 420 hectares, between latitudes of 36° 40´ and 36° 41´ N and longitudes of 48° 23´ and 48° 24´ E (Figure 1). The average, minimum and maximum elevation points of Zanjan region are 1589, 1566 and 1612 meters above sea level, respectively. The soil moisture and temperature regimes of the region by means of Newhall software are Xeric and Mesic, respectively. Based on soil taxonomy (USDA, 2010), this region has Entisols and Inceptisols orders.

Data collection and soil sample analysis

After preliminary studies of topographic maps (1:25000), using GPS, study location was appointed. For geostatistical analyzing, sampling was done with stratified random method and soil samples from 0 to 15 cm depth were collected from 23 soil profiles located in Zanjan province. Measured soil parameters included texture (determined using Bouyoucos hydrometer method), Organic Carbon (OC) was determined using Walkley-Black method (Nelson and Sommers, 1982). The clod method (Blake and Hartge, 1986) was used to determine Bulk density (Bd). The moisture contents at field capacity and wilting point were determined with a pressure plate apparatus (Cassel and Nielsen, 1986) at -33 and -1500 kPa, respectively. Water saturation percentage (SP) was determined using gravimetric method, $CaCO_3$ and gypsum contents were determined using calcimetry and acetone methods, respectively. Meanwhile, CEC (Cation Exchange Capacity in Cmolc kg^{-1} soil) was determined by the method of Bower (Sparks et al., 1996). pH, Electrical Conductivity (EC), dissolved Ca^{2+} , Mg^{2+}, Na^+ and K^+ were also measured using standard methods (USDA, 1998). For evaluation and estimation of spatial variation of topsoil calcium carbonate, GS^+ 5.1 software was used.

Spatial prediction method

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 (Goovaerts, 1999; Robinson and Metternicht, 2006). The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value (Deutsch and Journel, 1998) 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 $z(x_i)$ and the value at $z(x_i+h)$ (Lark, 2000; Robinson and Metternicht, 2006):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i + h) - z(x_i)]^2 \qquad (1)$$

Where: N(h) is the number of data pairs within a given class of distance and direction. If the values at $z(x_i)$ and $z(x_i+h)$ 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 is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure.

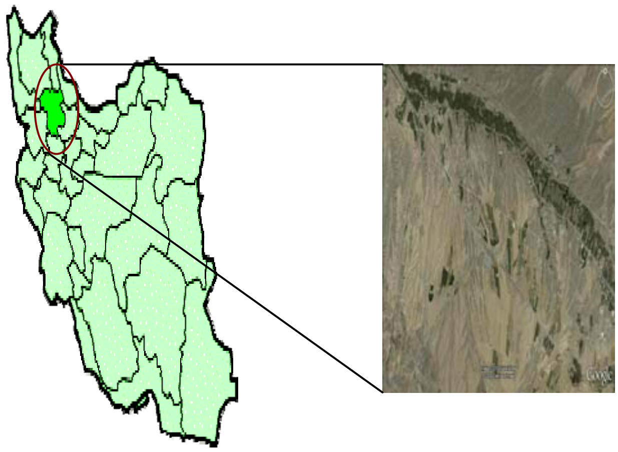

Fig 1. Location of the study area

Table 2. Selection of the most suitable model for evaluation of experimental variogram according to RSS value

Soil Parameter	Model		
	Spherical	Exponential	Gaussian
$CaCO_3$ (%)	0.08	0.12	0.18
EC (dSm^{-1})	0.15	0.10	0.13

Co-kriging

The “co-regionalization” (expressed as correlation) between two variables can be exploited to advantage for estimation purposes by the co-kriging technique. In this sense, the advantages of co-kriging are realized through reduction in costs or sampling effort. The cross semi-variogram is used to quantify cross spatial auto-covariance between the original variable and the covariate

Table 3. Best-fitted variogram models of soil properties and their parameters

Soil property	Model	Nugget (C_0)	Sill ($C+ C_0$)	Range effect (km)	$C_0/C+C_0$ (%)	RSS
$CaCO_3$ (%)	Spherical	0.01	25.98	0.98	0.04	0.08
EC (dSm^{-1})	Exponential	0.43	0.87	15.10	49.40	0.10

(Webster and Oliver, 2001). The cross semi-variance is computed through the Eq. (2):

$$\gamma_{uv} h = ½\ N(h) \sum \ [Z_u\ (x) - Z_u\ (x+h)][\ Z_v(x) - Z_v\ (x+h)] \quad (2)$$

Where: $\gamma_{uv} h$ is cross semi-variance between u and v variables, $Z_u\ (x)$ is primary variable and $Z_v(x)$ is secondary variable. In co-kriging method, salinity data was used as auxiliary variable because salinity (EC) had more correlation coefficient than other soil parameters. For comparing and evaluation of geostatistical methods, cross validation was used by statistical parameter of RMSE.

Comparison of different methods

Finally, we used the RMSE to evaluate model performance in cross-validation mode. The lowest RMSE indicate the most accurate predictions. The RMSE was derived according to Eq. (3) (Wösten et al., 1999):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (z(x_i) - (z^*(x_i))^2} \quad (3)$$

Where: $z(x_i)$ is observed value at point x_i, $z^*(x_i)$ is predicted value at point x_i, n is number of samples.

Results and discussion

A summary of statistical data related to two soil parameters ($CaCO_3$ and EC) is presented in Table 1. The normality of data was tested by Kolmogorov-Smirnov method (P-value > 0.05). With due attention to the levels of skewness for calcium carbonate ($CaCO_3$) and soil salinity (EC), these parameters were normal. The first step in using of kriging and co-kriging methods is to check the presence of spatial structure among data by variogram analysis. Geostatistical methods were developing to create mathematical models of spatial correlation structures with a variogram as the quantitative measure of spatial correlation. The variogram commonly used in geostatistics and the interpolation techniques, known as kriging, provides the "best", unbiased, linear estimate of a regionalized variable in an unsampled locations, where "best" is defined in a least-squares sense. The kriging estimation variances are independent of the value being estimated and are related only to the spatial arrangement of the sample data and to the model variogram (Webster and Oliver, 2001). Semi-variograms related to kriging method are presented in Figures 2 and 3. The best model for fitting on experimental variogram was selected based on less RSS value (Table 2). Therefore, we recognized the spherical model to be suitable for estimation of topsoil $CaCO_3$. Also exponential model was the best for evaluation of the topsoil EC. The variograms of studied soil parameters are shown in Table 3. The ratio of nugget variance to sill expressed in percentages ($C_0/C+C_0$) can be regarded as a criterion for classifying the

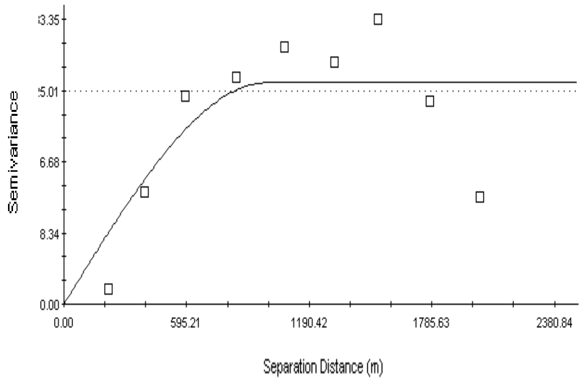

Fig 2. Omni-directional semi-variogram related to topsoil $CaCO_3$ using kriging method

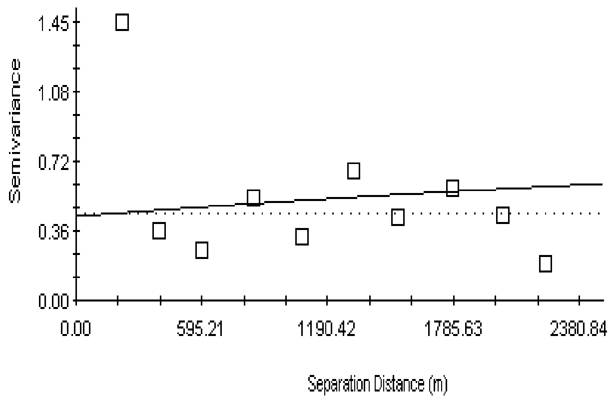

Fig 3. Omni-directional semi-variogram related to topsoil EC using kriging method

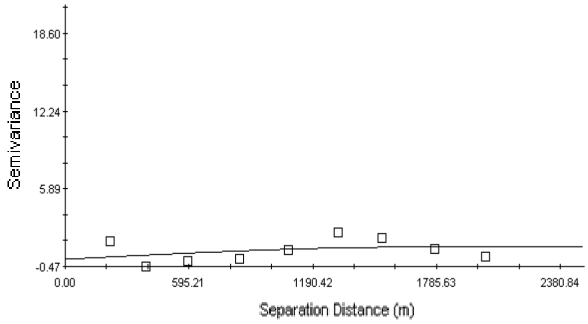

Fig 4. Cross-variogram of soil properties using co-kriging method

Table 4. Results of the interpolation error for estimation of soil $CaCO_3$

Geostatistical method	RMSE (%)	Correlation coefficient between observed and predicted value (r)
Kriging	4.54	0.7*
Co-kriging	4.10	0.76*

*Correlation is significant at the 0.05 level

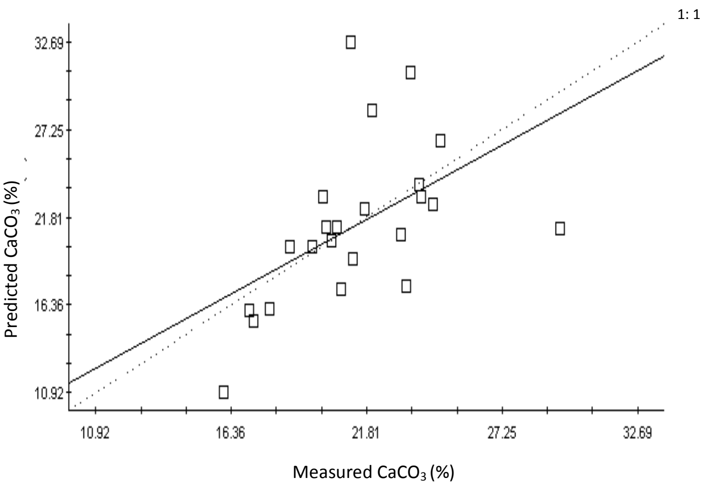

Fig 5. The scatter plot of the measured versus predicted topsoil $CaCO_3$ in kriging method

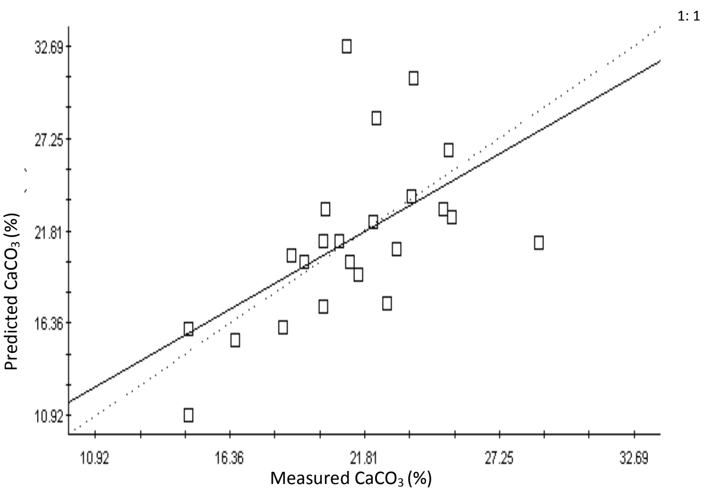

Fig 6. The scatter plot of the measured versus predicted topsoil $CaCO_3$ in co-kriging method

spatial dependence of the soil parameters. If this ratio is less than 25%, then the variable has strong spatial dependence (Shi et al., 2005). As shown in Table 3, $CaCO_3$ has strong spatial structure. Also, the range effect for soil $CaCO_3$ is approximately 0.98 km and this parameter which is mainly related to soil salinity (EC) is about 15 km as well. First step for co-kriging is computing of cross-variogram. The cross-variogram can be modeled in the same way as that of variograms, and the same restricted set of functions is available. Typically the aim is to estimate just one variable, plus those of one or more other variable, which we regard as auxiliary variable. Co-kriging approach reduces the estimations variance which is the advantage of this technique. We used soil salinity (EC) as auxiliary variable to develop the cross-variogram (Figure 4). After variogram modeling, different techniques including kriging and co-kriging methods were used for prediction of spatial distribution of the soil properties and the RMSE was used for comparison of the results. According to Table 4, co-kriging method was expected to be superior to kriging method for estimating of soil $CaCO_3$. These results are similar to the findings of Meul and Van Meirvenne (2003), Shi et al. (2005), Sokoti et al. (2006) and Ayoubi et al. (2007). They recognized that the co-kriging method had the most superiority to other methods to predict soil properties as well. Wei et al. (2006) evaluated the soil organic matter distribution in northeast of China and found that the kriging method could predict organic matter distribution with a higher accuracy. Shao et al. (2006) by using of geostatistics techniques and kriging method determined the spatial distribution of the soil nutrients in Hebei province, China. Shi et al. (2005) provided the salinity distribution maps in a coastal saline area in China using geostatistics methods. They reported that for prediction of SAR and EC, the co-kriging method was the most suitable one. The scatter plot of the measured against predicted soil $CaCO_3$ for kriging and co-kriging methods are given in Figures 5 and 6. Accordingly, the best fitted line has the angle of near to 45° that shows the high accuracy of estimation by the co- kriging method. Finally, the maps of spatial distribution of topsoil $CaCO_3$ were prepared using the geostatistical methods (Figures 7 and 8).

Discussion

Spatial variability in the soil is natural, but understanding these changes, particularly in agricultural lands for planning and management is inevitable. Soil properties change with time and space of the small scales to large scales, which are influenced by intrinsic properties (such as soil parent materials) and non-inherent characteristics (such as management, fertilizer and crop rotation) (Quine & Zhang, 2002; Godwin & Miller, 2003). In this study, spatial variability of topsoil $CaCO_3$ was studied using geostatistical techniques. Spatial variability of many nutrient elements and heavy metals in the soil is a very important issue, so understanding of the changes and spatial distribution of soil $CaCO_3$ seems to be necessary. Most soils of Iran are located in arid and semi-arid regions with high pH value (more than 7) and high amount of calcium carbonate which results in higher calcification rate. Plant growth is usually difficult in calcareous soils. This limitation is mostly related with higher pH values and concentration of calcium ion that cause fixation and unavailability of those elements dependent to pH, especially phosphorous and some micro nutrients such as Fe, Zn, Mn and Cu (Vijayan, 2009). Many variables do not exhibit a normal distribution of measured values and therefore do not initially satisfy the basic assumption of geostatistics of statistical normality. The normality test in this research showed that calcium carbonate ($CaCO_3$) and soil salinity (EC) were normal. After calculating the variogram and fitting the most suitable

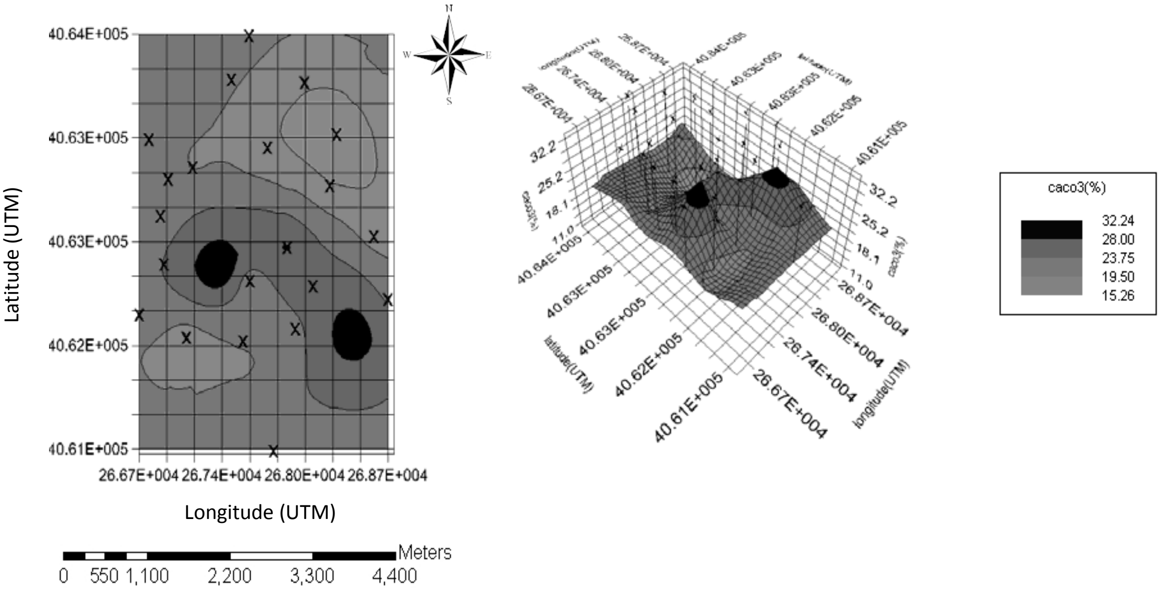

Fig 7. Map of spatial distribution of topsoil $CaCO_3$ using kriging method

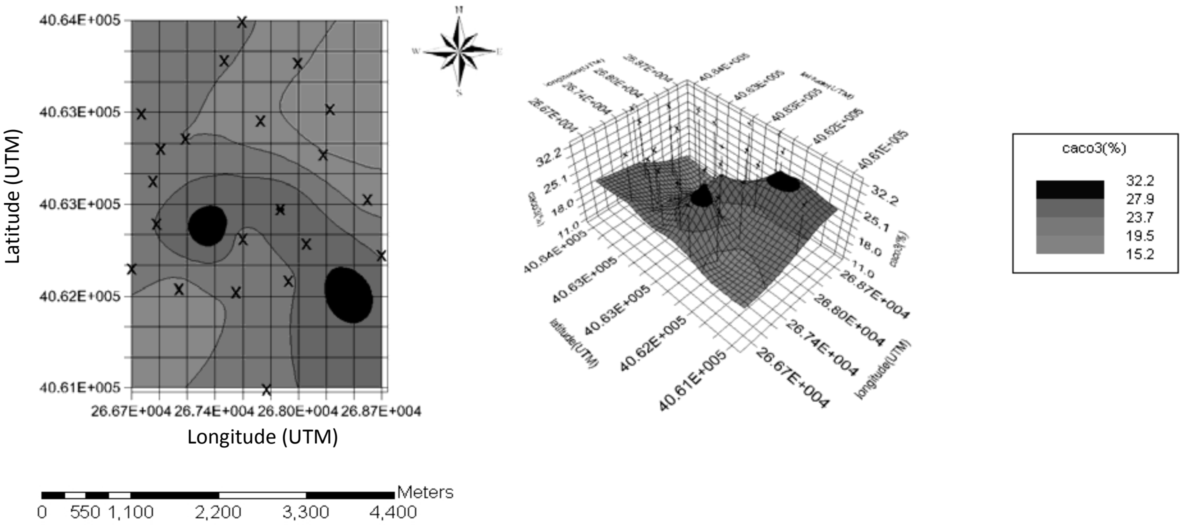

Fig 8. Map of spatial distribution of topsoil $CaCO_3$ using co-kriging method

model, different parameters were extracted. In this study, the kriging and co-kriging methods were used in order to determine the spatial distribution of topsoil $CaCO_3$. The results showed that co-kriging method has the higher correlation coefficient (0.76) and less RMSE (4.1). Then its higher accuracy than kriging method to predict the calcium carbonate content in unsampled areas was proven. Geostatistics does obviously not offer a statistical model which is advantageous in every situation. Careful analysis of the measurement data using common sense can some times result in the same conclusions as those resulting from lengthily and computationally heavy calculations. In general, as spacing between samples is large compared to the dimensions of the investigated field, the potential advantageous of a geostatistical analysis becomes less. For spacing beyond the range of spatial auto-correlation, kriging estimates reduce the same results as for the classical random sampling. The sustainable agriculture will take place just with classification of the lands according to their abilities and proportions for different types of land use. For achievement to this issue, the map of the soil properties is one of the basic resources for giving valuable information about various types of lands. Therefore, by means of the most developed techniques such as geostatistical methods we can provide the maps of soil properties using the lowest number of data. Hence, we recommended that besides using of interpolation methods, the data derived from satellite images can be used for co-kriging method as an auxiliary variable in future studies.

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