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Digital mapping of soil phosphorus using multivariate geostatistics and topographic information

Fereydoon Sarmadian[1*], Ali Keshavarzi[1], Azin Rooien[2], Munawar Iqbal[3], Ghavamuddin Zahedi[4] and Hossein Javadikia[5]

[1]Laboratory of Remote Sensing and GIS, Department of Soil Science Engineering, University of Tehran, P.O.Box: 4111, Karaj 31587-77871, Iran
[2]Department of Soil Science, Faculty of Agriculture, Shahid Chamran University, Ahvaz, Iran
[3]National Center of Excellence in Physical Chemistry, University of Peshawar, Peshawar 25120, Pakistan
[4]Department of Forestry, Faculty of Natural Resources, University of Tehran, Karaj, Iran
[5]Department of Agricultural Machinery Engineering, Razi University of Kermanshah, Kermanshah, Iran

[*]Corresponding author: fsarmad@ut.ac.ir

Abstract

Digital soil mapping (DSM) has emerged an effective tool for the classification of soil using auxiliary landscape data. Various pedometrical methods have been developed to deduce soil characteristics using geographical information, global positioning system, statistical techniques, geostatistical methods and field data. The use of auxiliary environmental variables is less expensive versus field-intensive methods and it also allows soil properties prediction through inter and intra relationships. In this paper, we report digital mapping of soil phosphorus from Qazvin region, Iran through regression-kriging method. Soil samples were collected from 77 points (1000 ha) through grid method and multivariate geostatistical method was used for mapping of soil phosphorus. The performance of the interpolation technique in term of the accuracy of predicted values were assessed by comparing the deviation of estimates from the measured data by performing a cross-validation technique over the validation data set by using the root mean square error. Based on analysis, the best model was selected for estimation of soil phosphorus. The phosphorus distribution varied significantly in selected area and up to 48.32% was observed which indicates a good efficiency of regression-kriging method for the estimation of soil phosphorus by computing easily measurable variables. The results indicated that the regression-kriging method is efficient method for the measurement of target variables and thus, the soil properties can be predicted with low cost and high accuracy which might be helpful to manage soil farming practices.

Keywords: Digital elevation model; Regression-kriging; Spatial interpolation; Target variable; Terrain attributes; Validation.
Abbreviations: CV_Coefficient of Variation, CEC_Cation Exchange Capacity, CL_Chloride, CV_Cross Validation, DEM_Digital Elevation Model, DSM_Digital Soil Mapping, EC_Electrical Conductivity, GIS_Geographical Information System, GPS_Global Positioning System, MSE_Mean Square Error, OC_Organic Carbon, OK_Ordinary Kriging, P_Phosphorus, R^2_Correlation Coefficient, RK_Regression-Kriging, RMSE_Root Mean Square Error and RSS_Residual Sum of Square.

Introduction

Digital soil mapping (DSM) offers a quantitative approach as an alternative to traditional soil mapping methods and can be defined as the development of a numerical or statistical model of the relationship among environmental variables and soil properties, which is then applied to a geographic data base to create a predictive map (Scull et al., 2003). Model for predicting soil landscape distribution relates soil/soil classes to topographic position in certain landforms, geology, vegetation communities and land use (Cook et al., 1996). Thus, it should be theoretically possible to integrate data types within a small mapped area used as a training or reference dataset to develop predictive rules for mapping in a broad region (Bui et al., 1999; Alijani and Sarmadian, 2013).

Phosphorus (P) is the second most important nutrient in plant growth and act as limiting factor in agriculture production. Different soil components that are involved in the absorption of P are iron and aluminum oxides, organic materials, calcium carbonate and silicates (Olsen and Khasawneh, 1980). Furthermore, soil P dynamic is influenced by soil physicochemical properties and farming practices. A better understanding of the factors controlling its distribution is required to manage P for cropping system (Roger et al., 2014). Generally, soil properties are changed seasonally with respect to forming practices (Quine and Zhang, 2002; Godwin and Miller, 2003; Sarmadian et al., 2010). On the other hand, the evaluation of these changes precisely in agricultural soil is difficult. Thus, to improve the profitability and achieving a sustainable productivity, it is necessary to be aware of changes in soil characteristics with the passage of time. In order to provide soil mapping and monitoring the changes in soil properties, common statistical techniques have been used, assuming that the variation in soil properties within soil map units is random. In this way, the natural variables which may affect soil properties were ignored (Hosseini et al., 1994). Although, the soil variability in time and spatial dimensions has created problems regarding the sampling process, the data quality and ultimately the optimal management practices, the key is to understand the formation, classification and mapping of soil (Mohammadi, 2000). Therefore, the main objective of soil sampling is the prediction of soil properties distribution that would affect in response of application and management. DSM integrates many statistical and geoinformation tools and concepts, including supervised and unsupervised classifications (Lagacherie, 2005; Balkovič et al., 2013), geostatistics (Webster and Oliver, 2007) and environmental correlation based models (McKenzie and Ryan 1999; McBratney et al., 2003). In this regard, a review of DSM methods and their applications in soil science was published by McBratney et al. (2003). Increased availability of remote sensing and GIS data has promoted the regression-kriging method (Odeh et al., 1994) as a generic interpolation tool for the mapping purposes (Hengl et al., 2004; Balkovič et al., 2013). Regression-kriging method is based on the existence of a regressive relationship between two variables. In other words, the relationship between two variables can be expressed in a regression form. Next, the initial variable values can be estimated by the model where the second variable is measured. Finally, the variogram model can be obtained from the resulting data and thus, the interpolation function is performed using kriging techniques (Odeh et al., 1995; Lark and Beckett, 1998). In this regard, Amini (1999) studied the saline soil from Rodasht, Isfahan and presented better estimation using co-kriging estimator versus other methods and correlated it with CL and EC. Similarly, Hengl et al. (2004) performed a spatial prediction using regression-kriging and compared it with simple regression. Lopez-Granados et al. (2005) also compared different methods for the estimation of soil properties (texture, organic matter, P and potassium) using secondary spatial data. Statistical prediction methods (simple kriging, ordinary kriging, and regression-kriging) were employed and performance was assessed on the basis of mean square error (MSE). The intensive soil sample collection to study soil properties is expensive and time consuming and in this regard, many interpolation techniques have been developed for predicting soil properties (McBratney et al., 2000). Ordinary Kriging (OK) has been widely used in studies related to natural resources since 1970s. However, with the emergence of desktop Geographic Information Systems (GIS) and the increased availability of remote sensing data in the 1990s, the use of secondary/auxiliary environmental variables in mapping and predicting soil properties has increased (Hengl et al., 2004; McBratney et al., 2000). The use of auxiliary environmental variables is less expensive as compared to field-intensive methods and secondly, it allows prediction of soil properties from remote areas based on the relationships between soil properties and environmental variables (Hengl et al., 2004; McBratney et al., 2000). One of the most accepted and widely used methods implementing this approach is Regression-Kriging (RK) (Moore et al., 1993; Gessler et al., 1995; McBratney et al., 2000; Hengl et al., 2004). Present study was conducted to appraise the soil phosphorus in semi-arid ecosystem from Kouhin area in the Northwestern of Qazvin province, Iran. A regression-kriging model was developed for digital mapping of soil phosphorus. The topographic indicators (terrain attributes) extracted from digital elevation model (DEM) was used to predict soil phosphorus content and established a baseline data on soil phosphorus stocks for future studies related to soil fertility and productivity.

Results and discussion

Data summary statistics

Statistical description of soil and terrain properties is summarized in Table 1. A relatively wide range of variations were observed in soil and terrain variables. Roger et al. (2014) stated that soil from the same category often shared similar properties. However, variation of 25 to 59% was recorded in clay particles, whereas OC content showed variation of 0.13 to 1.33% with an average value of 0.68. The coefficient of variation (C.V) of soil OC was recorded to be enough high which might be due the application of fertilizers and soil cropping system. Fard and Harchagani (2009) also reported a high coefficient variation of soil OC and correlated it with fertilizer application. The observed difference in soil properties could influence the phosphorus content because sorption and desorption may influence under these conditions. The clay content, Fe and Al oxides enhance P sorption (Freese et al., 1992; Frossard et al., 1995; Singh and Gilkes, 1991), whereas soil OC has reverse effect (Dubus and Becquer, 2001). Simard et al. (1994) and Demaria et al. (2013) revealed that soil pH and metal ions have also a significant effect soil P contents and the variation in phosphorus contents might be due the variation in soil properties since soil OC and clay particles distribution were also found to be considerably different in studied area. According to Kolmogorov-Smirnov normality test, the P value did not follow normal distribution and logarithmic transformation was employed and results are depicted in Table 1. The correlation between variables was established by applying Pearson correlation coefficient and included in regression equation according to their weights. As can be seen from Eq. 3, P logarithm showed a good correlation with elevation, band 3 and plan curvature. The R^2 value was 0.64 with -2.687 constant values. These three parameters showed positive correlation with P, however, plan curvature effect was most significant. Similar to present investigation, Roger et al. (2014) also investigated the spatial autocorrelation between environmental variables for the estimation of P distribution through regression modeling and found that some of the environmental predictors correlated positively with P value e.g. the correlation coefficient (r) between slope and altitude was 0.64. The profile and planform curvatures were also found to be highly correlated with curvature (r =0.84 and 0.90, respectively). Furthermore, the step-wise multiple regression analysis for P value prediction reduced the number of environmental predictor. The adjusted R^2 indicated that terrain attributes were the major contributor for explaining the spatial variability of P value.

$$\mathrm{Log\,P} = -2.786 + 0.002 Elevation + 0.004 Band3 + 0.208 Plan\_curvature \quad R^2 = 0.64$$
(Eq. 3)

The model fitness and variography

For the evaluation of model fitness, variography was performed using GS^+ 5.1 software and P residuals were plotted. The appropriate model was fitted to variogram based on the lower residual sum of squares (RSS) and higher R^2 and thus, variogram obtained, can be seen in Fig. 3. The nugget effect, sill and range effect were considered to construct variogram. In fact, nugget effect indicates the unstructured (random) variance and the sill effect is the approximation of the total variance. The range effect value represents the distance above which the samples can be considered independent. The strength and degree of spatial dependence

Table 1. Data summary statistics of soil and terrain parameters.

Variable	Unit	Min	Max	Mean	Skewness	Kurtosis	C.V (%)
Available P *	mg/kg	0.65	1.38	1.01	0.30	-1.38	48.32
Clay		25.00	59.00	40.70	-0.186	-0.821	22.59
Silt		16.00	44.00	26.30	0.60	0.66	21.70
Sand	%	10.00	57.00	32.00	0.43	0.33	34.95
OC		0.13	1.33	0.68	0.39	-0.69	42.64
Slope **		0.91	5.80	3.07	0.45	1.05	52.93
CEC	$Cmol^{+}kg^{-1}$	17.03	29.43	23.08	0.13	-0.38	12.35
Elevation	Meter	1311.40	1543.33	1404.50	0.69	0.32	3.80
Plan Curvature	Deg/m	-0.21	0.26	-0.01	0.59	2.36	63.16
Band 1	-	77.00	151.00	122.77	-0.44	-0.68	16.23
Band 2	-	54.00	142.00	99.02	-0.58	-0.66	22.71
Band 3	-	65.00	144.00	109.34	0.59	-0.87	20.96
NDVI	-	-1.00	-0.46	-0.69	-0.41	-0.56	22.62

* Logarithm transformation, ** Square root transformation

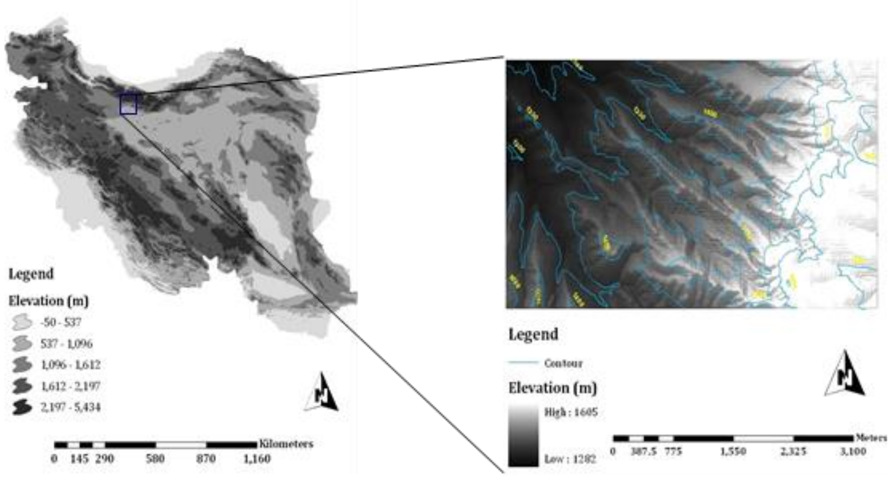

Fig 1. Location of study area in Qazvin province, Iran (The blue lines show the contour lines).

of a regional variable was achieved by dividing the nugget effect to the total variance (sill) which was expressed as percentage and if the observed ratio is less than 25% then the variable has strong spatial dependence class. In case, the ratio is between 25 to 75%, the spatial dependence class of the variable is medium and above than, the spatial dependence class of the variable is considered weak (Cambardella et al., 1994; Shi et al., 2005). Table 2 depicts the variogram of P residual, indicated a good spatial structure. Spherical model was considered most appropriate for P value that fitted well to the data in view of RSS and R^2 values. Variance ratio displays the spatial structure in the data and it was found that the spatial variation in P value was not random, but a spatial continuity was observed. The range effect revealed a range within which the variation structure of the variables can be recognized which in turn depends on the spatial variation pattern of soil properties. As it is clear from variogram that P variation is spatially dependant up to 1500 meter and considered to be independent beyond this distance. Roger et al. (2014) also obtained the nugget/sill ratio from different P forms from 1% to 41%. After conducting variography, the desired properties were interpolated using ordinary kriging and the interpolated maps of predicted values were combined with the interpolated map of regression residuals to obtain final map.

Digital mapping of soil phosphorus and uncertainty map

The final digital map of P developed using regression-kriging can be seen in Figs. 4 (A) & (B). By comparing the images, uncertainty in data was observed where slope steepness and the elevation were high (Figs. 1, 4 (A) & (B)). The P value decreased from the eastern to western part in the study area. The elevation and slope gradient increased in this direction also. Visual inspection of uncertainty of RK model and RMSE estimates revealed positive correlation with P values and uncertainty level (Fig. 5). Overall, it was observed that higher the soil P, higher the uncertainty was in the data (Fig. 4B). The uncertainty in P value was also observed in the western part of the study area which might be due to lack of observations from this area. Roger et al. (2014) also observed an increasing uncertainty due to canton boundaries and lack of observations outside the study area as well. As noted previously, the moderate relationships between soil P and environmental predictors and inadequate number observations, contributed to the moderately accurate prediction. Some previous studies have shown that RK was not suitable where all the auxiliary variables could not be exhaustively sampled (Wu et al., 2010; Roger et al., 2014) and generally ordinary kriging (OK) performed better (Zhu and Lin, 2010) or where the study area displayed a high heterogeneity in soil properties (Umali et al., 2012). Zhu and Lin (2010) also concluded that the result of accuracy estimation between ordinary kriging and regression-kriging approaches on maps were different and sample size, spatial structure and auxiliary variables (terrain indices) controlled the results. In the agricultural land, ordinary kriging was generally more accurate. When spatial structure could not be

Table 2. Best fitted model of residuals of P with variogram parameters.

Variable	Model	Nugget (C_0)	Sill ($C+C_0$)	Range effect (m)	[C_0/ $C+C_0$] (%)	R^2	RSS
Available P	Spherical	0.0019	0.0221	1471	8.597	0.908	2.79×10^{-4}

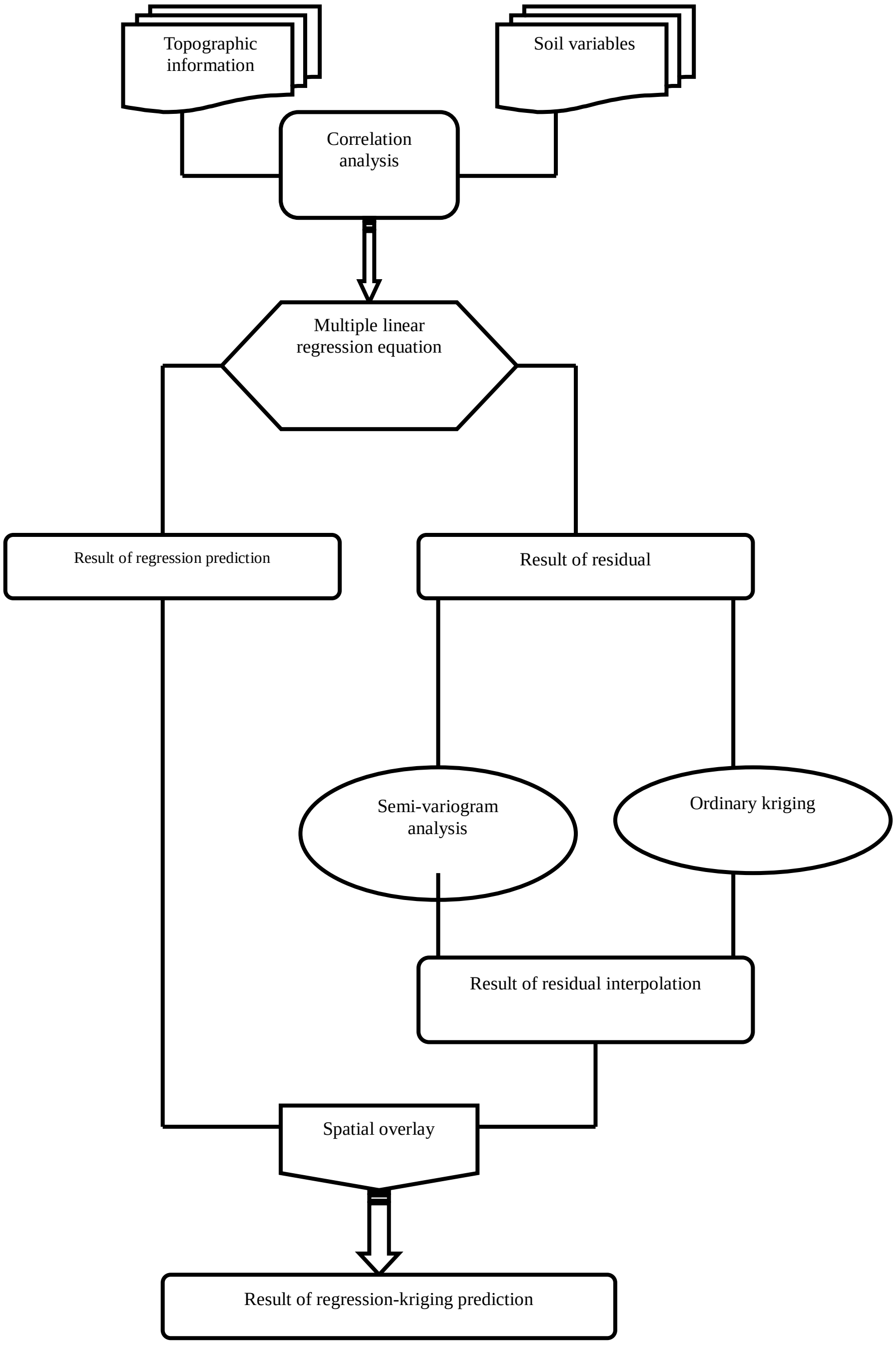

Fig 2. A generic framework for spatial prediction of soil variables based on regression- kriging (Hengl et al., 2004).

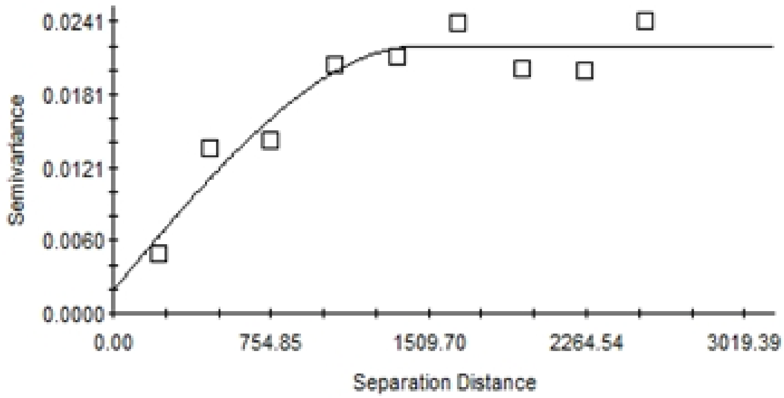

Fig 3. Omni-directional variogram related to residuals of P with spherical model.

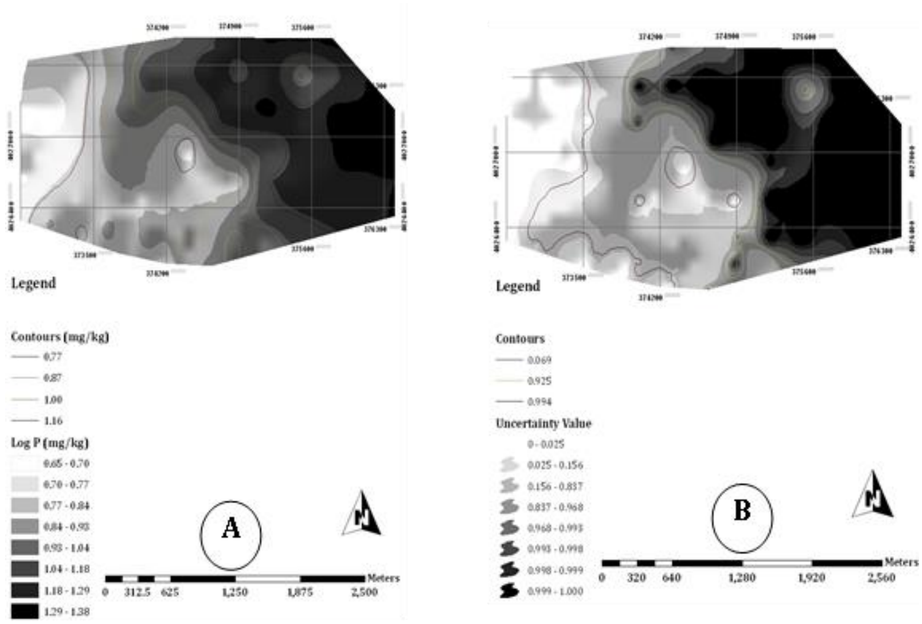

Fig 4. Digital mapping of soil phosphorus based on regression-kriging approach (A) and uncertainty map at the 95% confidence interval (B).

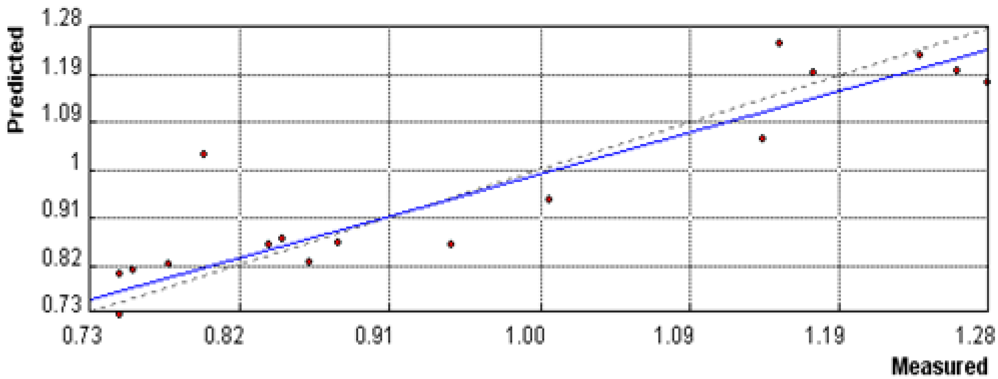

Fig 5. The scatter plot of the observed versus predicted values for soil P estimation.

well captured by point-based observations (e.g., when the ratio of sample spacing over correlation range was > 0.5), or when a strong relationship existed between target soil properties and auxiliary variables (e.g. their R^2 was > 0.6), regression-kriging (RK) was more accurate for interpolating soil properties; otherwise, ordinary kriging (OK) was better. It is also reported that if the distribution in soil P is affected by translocation which is a function of slope gradient then co-regionalized models such as co-kriging and regression-kriging along with a more easily obtainable DEM might potentially improved the prediction efficiency (Kozar et al., 2002). It is noted that the sampling scheme may also affect the prediction of desired parameter. The moderate relationship between P and selected predictor in our study (R^2 = 0.64) pointed out that land use may affect the relationship among variables and previous studies also demonstrated similar results (Lemercier et al., 2008; Jia et al., 2011; Reijneveld et al., 2010). The spatial distribution of P could be related to geology, especially parent material of the study area (Wang et al., 2009). The use of auxiliary data such as geology and land use or soil type as well as sub-division of study area may improve the prediction by reducing the overall variability and better to highlight the P relationship with environmental predictors. A major limitation of grid sampling is that more samples are required to resolve the spatial variability in soil nutrient levels, which could be highly complex within the field (Kozar et al., 2002). In addition, the quality of DEM is important and a valuable and inexpensive source of secondary information in the DEM provides explanatory variables for predicting model of soil properties (Gessler et al., 2000). The rationale for this approach is that topography influences soil properties due to local re-distribution of water, solar radiation and soil material (Gessler et al., 2000; Kozar et al., 2002). Similar to our study, Triantafilis et al. (2001) also developed maps using regression-kriging and revealed a good efficiency of this method for the estimation of target parameter as compared to interpolation values. Author's compared five geostatistical methods for salinity measurement and found that the regression-kriging method offered better estimation versus ordinary kriging, three dimensional kriging and co-kriging. Wong et al. (2012) developed a digital technique for soil available P mapping at field scale (80-ha cropping field, Corrigin, Western Australia) by performing multivariate analysis of soil chemical properties. Seven variables were estimated from soil samples containing measured soil location and properties by migrating the geostatistical estimate to the nearest soil sample. Hong et al. (2010) assessed the efficacy of spatial resolution of remote sensing images to predict soil phosphorus. A stratified random sampling design based on land use and soil order was used to collect soil samples from four layers and compared ordinary kriging, regression-kriging and co-kriging to predict and map geospatial distributions of soil P for each layer using remote sensing images and ancillary spatial environmental datasets. Results showed that multivariate method with finer resolution of remote sensing furnished better performance for the prediction of soil P versus others.

The validation of the method

For the validation of model, samples were divided into training point (60 samples) and validation point (17 samples) with 4 to 1 ratio. The validation set was employed to measure the error (Fig. 5). The RMSE was used to demonstrate the accuracy of the method. The RMSE value of 17 samples of validation set was 1.25 mg/kg and this value is comparable with Yasrebi et al. (2009). Author declared this value for OC as 1.5% and 1.8 mg/kg for P using kriging method. Kazemi et al. (2012) reported RMSE = 11.1 mg/kg for available P using kriging method. This study confirmed the priority of regression-kriging over others and RMSE compared to other survey results which confirmed the validity of the selected model (Odeh et al., 1995; McBratney et al., 2000; Hengl et al., 2004; Yasrebi et al., 2009). Knotters et al. (1995) also reached to similar conclusion in comparison to different interpolation methods for predicting soil horizon thickness using an auxiliary variable. Author's concluded that the regression-kriging method demonstrated the best performance for the estimation of target parameter.

Materials and Methods

Study area and sampling

Hilly area in the northwestern province of Qazvin (Kouhin region), Iran was selected to study variation in phosphorous content distribution (Fig. 1). Height amplitude varies from 1300 m to 1600 m above sea level. This belt covers about 1000 hectares, situated between latitude of 36° 20' to 36° 23' north and longitude of 49° 34' to 49° 38' east. The selected area climate is semi-arid in nature. The soil temperature and moisture regime are mesic and xeric, respectively (Newhall and Berdanier, 1996). Soil of the region is developed on the surface of alluvial deposits of marl and brown to grey limestone parental materials and is covered by plateau from east to west direction. The soils have been classified as Entisols and Inceptisols according to US soil taxonomy system (USDA, 2006) and has rainfed farming system. During 1993-2006, the average annual rainfall and average annual temperature were recorded to be 327 mm and 11.2 ^{0}C, respectively (Iran Meteorological Organization) (http://www.weather.ir).

Grid (300 m x 300 m) method was used for sampling and few samples were also collected from off-grid to present different physiographic positions and total 77 samples (0 to 20 cm depth) were taken. Geographical location of sampling points was recorded by Global Positioning System (GPS). The collected soil samples were air dried, crushed and sieved using 2 mm sieve size. Soil properties such as particle size distribution (Gee and Bauder, 1986), organic carbon (OC) content (Black, 1982), CEC (Bower et al., 1952) and available P (Olsen and Khasawneh, 1954) were measured. For image processing, Landsat 8 satellite images from 2013 were used. Geometric corrections of images were performed using digital elevation model (DEM) and orthoimages procedure. DEM was extracted from a paper-based topographic map using GIS platform with scale of 1:25000 and contour lines interval of 10 meter (National Cartographic Center, 2010). The satellite images were processed by spectral ratio, principal component analysis and Tasseled Cap transformation. Classifications of images (digital - visual) were conducted integratedly and the band values of 1, 2 and 3 at each sampling point were extracted through PCI Geomatica software. The terrain attributes such as slope value, elevation, plan & profile curvature, flow direction and flow accumulation were extracted from a digital elevation model (grid size of 10×10m; National Cartographic Center, 2010) with a resolution of 10 meter (Wilson and Gallant, 2000).

Statistical analysis

In order to investigate distribution and summary of statistical data, SPSS software (version 20.0) was used. Kolmogorov-Smirnov normality test was applied to examine the normal distribution of variables. Transformation operations (logarithm, square root) were performed for the normalization of the data. Using Pearson correlation coefficient, the relationship between target (P) and secondary variables were determined and parameters of high correlation were computed for constructing the regression equation.

Geostatistical analysis

The regression relation was established between target (P) and other variables using SPSS 20.0 software and the model showing highest correlation coefficient with lower RMSE value was selected. Regression equation was used to determine purposed variable. The residual was estimated from observed and predicted values and plotted using GS^+ 5.1 software. Variogram was used to determine the structural properties of the regional variables and variation in the data. Based on correlation coefficient value (R^2) and residual sum of squares (RSS), the most appropriate model was selected and anisotropy in the study area was investigated. After calculating the appropriate model variogram and fitness, the variogram parameters such as nugget effect, sill value and range effect for each parameter was measured. The interpolation was run after residual variogram step by step and included in the regression equation.

Geostatistical method performance evaluation

Regression-kriging is a hybrid interpolation technique that is a combination of a regression model with a simple or ordinary kriging models. Figure 2 shows a generic framework for spatial prediction of soil variables based on regression-kriging (Hengl et al., 2004). The data points were divided into two set for the evaluation of the performance of selected model and 60 samples (80%) were randomly selected as the training set and 17 (20%) samples were chosen as the validation set by cross validation (CV) method. The estimates were determined by interpolation method and compared to the observed value. The root mean square error (RMSE) and R^2 were calculated using Eqs. (1) and (2) (Wosten et al., 2001).

$$RMSE = \sqrt{\sum_{i=1}^{N} (y_o - y_p)^2 / N} \qquad \text{(Eq. 1)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_o - y_p)^2}{\sum_{i=1}^{N} (y_o - \bar{y}_i)^2} \qquad \text{(Eq. 2)}$$

Where y_o, y_p, $\bar{y}_i$ and N are representing the measured, predicted, mean value and total number of data points, respectively. The RMSE was used to measure accuracy and validity of the training and validation data sets. Finally, the spatial distribution map of available phosphorus was plotted using ArcGIS (10.1) software.

Conclusion

The regression-kriging method was successfully used for digital mapping of soil phosphorus from Kouhin region, Qazvin province, Iran. Overall, high variations in soil and terrain attributes were observed in the study area. The moderate relationship of phosphorus with predictors indicates the overwhelming influence of land use practices. The findings of the current study suggest that soil P variation is spatially dependent up to 1500 meters. Form results it is concluded that digital soil mapping can be used for the estimation of soil properties and regression-kriging method is recommended for analysis due to its simplicity and better performance.

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