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Spatial prediction of soil phosphorous using soil electrical conductivity as secondary information

Nikou Hamzehpour* Sara Mola Ali Abasiyan

Department of Soil Science, Maragheh University, Iran

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Key words: Soil phosphorus, Soil electrical conductivity, Spatial prediction, Kriging, Co-kriging.

Abstract

Soil phosphorus (P) plays an important role in soil fertility and availability of micronutrients in soil, especially in arid and semiarid regions. Therefore, monitoring soil P condition is of great importance. The aim of the present study was to investigate the spatial variation of soil phosphorus by taking into account top soil EC data as secondary information. The research was performed on a grid of 0.75-1 km in an area of 367 km^2. Soil phosphorus (P), Potassium (K), Zinc (Zn), Iron (Fe), Copper (Cu), Manganese (Mn), Organic Matter (O.M) and electrical conductivity (EC) were measured. Then variogram was built for P dataset and spatial prediction was done on a grid of 500 m using kriging estimator with taking into account the mean variation. Afterwards soil EC was used as covariate to develop cross-semivarograms in prediction of soil P using co-kriging method. Cross-validating the results from P predictions using only kriging estimator to that of co-kriging with EC data revealed that co-kriging offered better estimations with ME and MSE of 0.11 and 0.149, respectively. Kriging estimator had more smoother and diffused boundaries than that of co-kriging and resulted in more bias estimations (ME and MSE of -0.18 and -0.326, respectively). According to the results, co-kriging method and soil EC could be used successfully in improving spatial prediction of soil phosphor.

***Corresponding Author:** Nikou Hamzehpour ✉ nhamzehpour@maragheh.ac.ir

Introduction

Soil phosphorous (P) is one of the essential elements for plant growth. Farmers especially in developing countries, add thousands of tons of phosphorous fertilizers to soil every year (Shi *et al.*, 2015) resulting in increased amounts of soil P through time (Chen *Et al.*, 2012). In calcareous soils with high pH, due to the formation of the low soluble components of P such as Calcium Phosphate, P is not easily available for plant roots. Therefore, using P-fertilizers not only don't solve the problem, but also lead to the bigger problem which is microelements deficiency in soil, as they can also make insoluble phosphate compounds. Thus it is very important to have information about soil phosphor condition and its spatial variation. Having a general knowledge about soil elements, will reduce unnecessary use of fertilizers followed by decreased risk of environmental and ground waters pollutions (Goetz and Keusch, 2005).

During past decades, spatial prediction methods such as kriging methods have played significant role in both reducing the number of samples necessary to monitor a large area and also data gathering expenses. Recent improvements in the field of geostatistics and advances in calculating complex problems have made the analysis of variables with spatial correlation possible. Kriging methods have widespread use in geostatistical methods and in soil salinity prediction models which have been discussed in detail in several papers (Li and Heap, 2008). There have been numerous attempts in mapping spatial variability of soil electrical conductivity (EC) using kriging methods (Peck and Hatton, 2003; Triantafilis *et al.*, 2004; Malins and Metternicht, 2006; de Clercq *Et al.*, 2009; Giordano *et al.*, 2010; Acosta *et al.*, 2011; Li *et al.*, 2011). In case of soil P, Hendricks *et al.*, 2014 used three multivariate models for predicting groundwater P concentrations for a wide range of water and P inputs. These models used readily available hydrologic, management and soil data monitored by growers. however, there haven't been many works in spatial prediction of soil phosphor as it does not easily show spatial dependency due to different management practices applied by farmers. Among limited works, O'Halloran *et al.*, 1985; Page *et al.*, 2005; Roger *et al.*, 2014; Piotrowaska-Dlugosz *et al.*, (2016) could be mentioned. Therefore, using soil EC as an axillary data in soil phosphorus prediction, where spatial dependency of the soil phosphor is not clear will be a great step in gaining valuable information about soil Phosphorous condition..

There have been attempts to use co-kriging method in spatial prediction of soil variables. Stein and Corsten (1991) discussed the relationship between universal kriging and cokriging with regression kriging. Mondal *et al.*, (2001) used linear and non-linear methods to predict top soil salinity in Bangladesh. De Clercq *et al.* (2009) utilized a first order polynomial equation for mapping spatial and temporal variation of soil salinity. Juan *et al* (2011) took advantage of a spatial Gaussian linear mixed model to calculate soil salinity using soil electrical conductivity and Na content.

The aims of this research were to study 1. Spatial variation of soil phosphorous using ordinary kriging estimator and 2. To use top soil electrical conductivity (EC) data as covariate to predict soil phosphor using co-kriging method.

Material and methods

Study area

Study area includes 367 km^2 of lands in the western part of Urmia Lake, north-west of Iran (figure 1). It is located between 45° 5" to 45° 15" E and 37° 23" to 37° 36" N. The mean annual precipitation is 367 mm. The mean annual temperature for the coldest month is -5.2°c and for the warmest one is 32°c. Potential evaporation in the area is between 900-1170 mm. In terms of geology, the study area is composed of two different deposits: saline playa deposits and young alluvial terraces and alluvial fans with very low salinity.

Data description

Soil samples were taken from agricultural lands on a grid of 0.7-1 km. 186 samples was gathered from depth 0-30 cm (Figure 2). In each sampling point, in order to get a homogeneous soil sample, 10 separate soil samples were taken within 1m radius and then samples were mixed. In each mixed sample, Phosphorous (P), Potassium (K), Iron (Fe), Manganese (Mn), Copper (Cu), soil texture, organic matter (OM) and soil electrical conductivity (EC) were analyzed.

Fig. 1. Study area in the Northwest Iran, west of Urmia Lake.

Then spatial dependency of the soil P were checked and based on developed variogram with soil P data, spatial prediction of soil phosphorus were done on a grid of 500 m using ordinary kriging. Later, in order to see if other measured soil properties as covariate, could improve the P prediction; soil EC were used to improve the variogram of soil P. Then once more spatial prediction of soil P was done using co-kriging method and results were compared.

Cross-semivariance functions

In order to have better idea about how axillary data can improve predictions quality, first one needs to know how kriging and co-kriging methods work.

Kriging estimators' basic equation is defined as follows (Li and Heap, 2008):

$$Z(x_0) - \mu = \sum_{i=1}^{n} \lambda_i [Z(x_i \tag{1}$$

quation 1 can be extended to incorporate the additional information as follows:

$$\hat{Z}_1(x_0) - \mu_1 = \sum_{i_1=1}^{n_1} \lambda_{i_1} [Z_1(x_{i_1}) - \mu_1(x_{i_1})] + \sum_{j=2}^{n_v} \sum_{i_j=1}^{n_j} \lambda_{i_j} [Z_j(x_{i_j}) - \mu_j(x_{i_j})]$$

(2)

Where μ_1 is an acknowledged stationary mean of the primary variable, $Z_1(x_{i_1})$ is the data at point i_1, $\mu_1(x_{i_1})$ is the mean of samples within the search window, n_1 is the number of sample points within the search window for point x_0 used to make the esmination, (λ_{i_1}) is the weight selected to minimize the estimation variance of the primary variable, n_v is the number of secondary variables, n_j is the number of j^{th} secondary variable within the search window, λ_{i_j} is the weight assigned to i_j^{th} point of j^{th} secondary variable, $Z_j(x_{i_j})$ is the data at i_j^{th} point of j^{th}

secondary variable, and μ_j (x_(i_j)) is the mean of samples of j^th secondary variable within the search window.

The cross-semivariance can be estimated from data using the following equation:

$$\hat{\gamma}_{12}(h) = \frac{1}{2n}\sum_{i=1}^{n}|z_1(x_i) - z_1(x_i) - z_1(x_i+h)||z_2(x_i) - z_2(x_i+h)| \quad (3)$$

In the case of this research, Z_1 refers to the soil phosphorus and Z_2 refers to the soil salinity, which can be possibly used as an indicator of soil salinity.

Validation and comparison criteria

In order to compare kriging with cokring method (soil EC as covariate), two thirds of available data were used for modeling and the rest for comparing the two different models. Hence three global performance criteria were computed: *r*, which is the Pearson correlation coefficient, the mean error (ME), and the mean squared error (MSE). Accurate predictions are thus characterized by a ME value that should be close to zero and a MSE that should be as small as possible. All the analyses were done using the BMElib toolbox (Christakos *Et al.*, 2002) written using Matlab (MathWorks, 1999).

Results and discussion

Soil phosphorous data analyses

Statistical analysis of the soil samples from the study area are presended in Table 1. According to Table 1, soil P had large variations from 1.9 to 346 ppm in the area. Therefore, the logaritmic transferred form of P dataset were used to normalize the data. Color plot for soil P is also presented in Fig. 2. According to Fig. 2, exept for a small area in the northern part of the study area where high values of the soil P could be observed, in other parts, variations of soil P is monotone. In several reseraches P contamination in soils are also reported (e.g. Leopold *Et al.*, 2006; Pease *Et al.*, 2010; Chen *Et al.*, 2012;) which could be due to local overuse of chemical P-fertilizers (Marquez-Molina *Et al.*, 2014). In the study area of the present research, application of organic fertilizers like sewage slug could result in local increase of soil P up to 100 or more mg/kg, while in other parts of the area soil P normally varies from 10 to 50 mg/kg.

Table 1. Summary statistics of top soil salinity (dS/m) in 1:2.5 soil to water ratio in seven time instants.

	N	Mean	S.D	Min	Max	Skewness
P (ppm)	186	20.16	28.98	1.9	346	6.07
K (ppm)	186	438.88	195.58	38.8	1200	0.54
Fe (ppm)	186	4.32	5.31	0.14	50.94	4.97
Zn (ppm)	186	0.78	0.70	0.04	5.32	2.87
Mn (ppm)	186	5.18	3.97	0.3	21.88	1.11
Cu (ppm)	186	1.67	0.96	0.2	5.92	0.91
O.M (%)	186	0.79	0.62	0	3.9	1.36
TNV (%)	186	12.88	7	0.25	33	0.33
Clay (%)	123	33.95	12.76	4	66	0.11
EC (dS/m)	236	4.73	59.68	0.14	45	0.16

Covariance and Cross-semivariance functions

As it was mentioned in previous sections, soil P had a variable mean throughout the study area. Therefore in order to consider the mean variation among dataset, the spatial component of the mean trend were computed and subtracted from measured P values, which resulted in residuals. Then P varigram was calculated and modeled based on the residuals (Fig. 3a). The fitted variogram model had a nugget effect equal to 0.4; spherical part with sill of 0.95 and range of 4.5 km. In order to use soil EC in prediction of soil P, the covariance function of available EC data (Table 1) was calculated. Then cross-variogram was calculated using EC as covariate (Fig. 3b). According to Fig. 3b, the calculated cross-semivariogram has significantly improved the P prediction by reducing the nugget effect; although the range has also reduced resulting in shorter distance applicability of the developed cross-semiviriogram. Although calculation of the cross-semivariance reduced the range of the prediction, still the prediction range is convincing in comparison to other attempts of soil P prediction by other researcher, who were only successful in field scale spatial prediction of soil P. for instance Mouazen and Kuang (2016) used on-line visible and near infrared (vis-NIR) spectroscopy to predict soil P condition.

Table 2. Cross-validation criteria to compare two methods of soil phosphorus prediction.

Criterion	Ordinary kriging	Co-kriging
r	0.85	0.97
ME (dS m^{-1})	-0.18	-0.11
MSE (dS $m^{-1})^2$	0.33	0.15

r: correlation coefficient; ME: mean error; MSE :mean square error;

Their results showed the on-line vis–NIR soil sensor is an effective tool to manage and minimize only within field variation of soil P in arable crops. In other study by Pease *Et al.*, 2010 . A poor correlation was observed when comparing the model's predicted nitrogen, phosphorus, and sediment with the observed counterparts. They assumed that the model's poor performance was most likely a result of the large size of the study area and the high variability in land use and management practices.

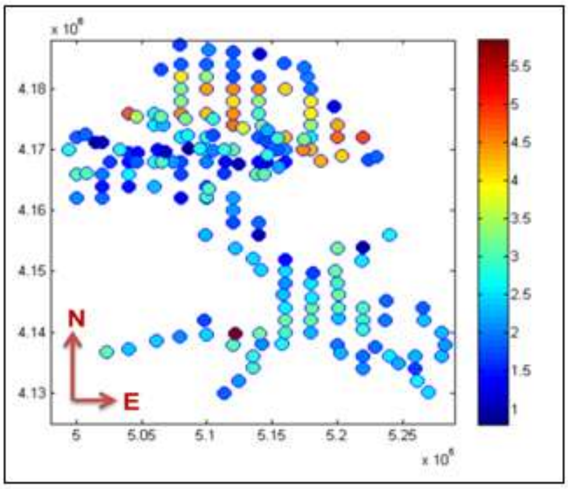

Fig. 2. Soil sampling locations and phosphorous values in Urmia Plain, Northwest Iran.

Soil phosphorus prediction

Soil P prediction map with only top soil P data and also EC data as covariate are shown in Figure 4. In figure 5, validation points (not used in modeling and prediction processes) are overlaid the predicted maps to validate the results. Comparing parts a and b form Figure 5, it is clear that using soil EC as covariate, has improved the prediction of soil P in the study area as in part b, tones of colors form predicted map are much closer to the points rather than part a. in other words, spatial prediction of soil P with only ordinary kriging (OK) method has resulted in smoother maps which results in meaningful differences locally between map predictions and validation data. Leopold *Et al.*, 2006 found similar results in a study aimed to model mineral Phosporous concentration in Netherlands. They believed that differences between field measurements of P and predicted values by OK method is partly attributed to the smoothing of the krigigng interpolator.

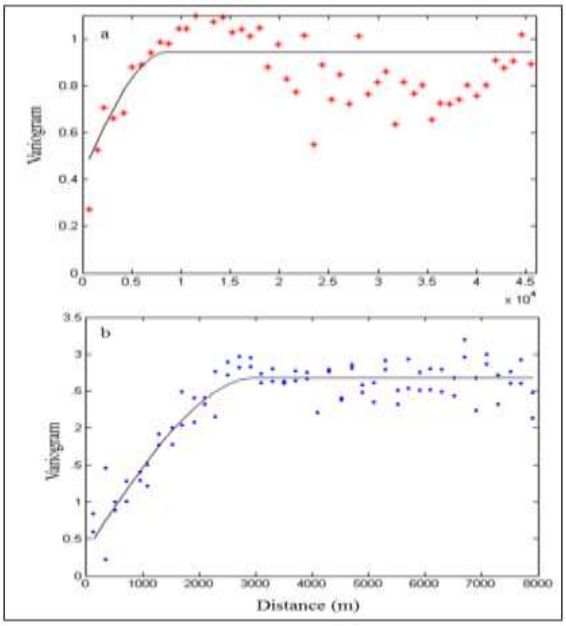

Fig. 3. Spatial variogram and cross-semivariance function for top soil P prediction. a: variogram for soil

P, b: cross- semivariance function for top soil P using soil EC as covariate.

As mentioned previously, usin top soil EC values and related cross-semivariance model resulted in better predictions. Comparing the cross-validation results from soil P predictions using only top soil phosphor data with those of soil EC as covariate indicated that the use of soil EC data as secondary information in top soil P prediction resulted in higher r (0.97 versus 0.85) and lower ME (-0.18 versus -0.11) and MSE (0.33 versus 0.15) (Table 2).

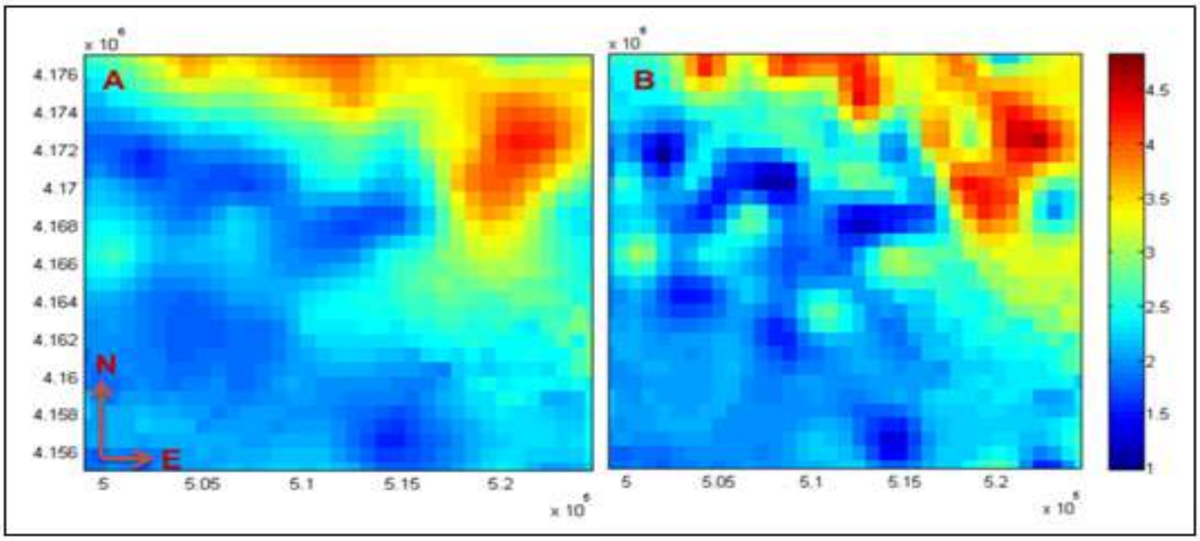

Fig. 4. Soil P prediction maps. a: soil P with only top soil phosphor values; b: soil P prediction with soil EC values as covariate.

Molina *Et al.*, 2014 also used bulk EC measurments as an indicator of spatial distribution of nitrogen and P in Argentina. In their study, the major contents of nitrogen and bioavailable phosphorous in the soil were associated with high bulk electrical conductivity when water content was above an equivalent depth of water of 100 mm. but they concluded that the soil moisture status should be taken into account before an electromagnetic exploration for detecting soil contamination.

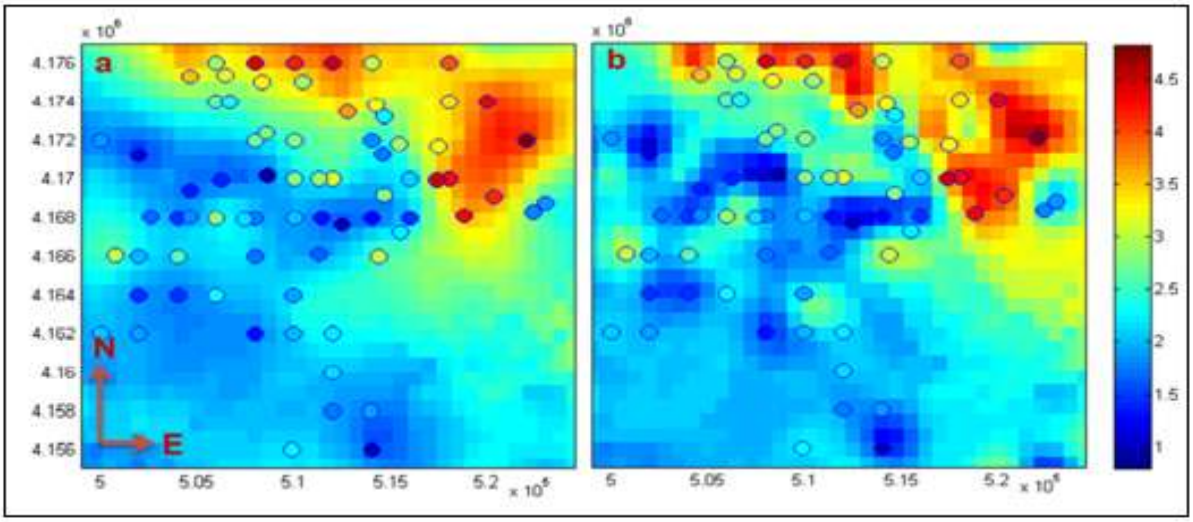

Fig. 5. Soil P prediction maps with validation points. a: soil P with only top soil phosphor values; b: soil P prediction with soil EC values as covariate.

Leopold *Et al.*, 2006 developed a model chain (STONE) to study specificly minral P concentration in the top soil. They used regression kriging to aggregate the point observations to the block support.

Their results showed that there was a good correspondence between the kriging observations and STONE predictions, with no evidence of bias in the model predictions. As the STONE model had three parts namely: 1. the fertiliser distribution model CLEAN; 2. the atmospheric transport and deposition model OPS; and 3. the soil and soil-water quality model ANIMO, It seems that using co-kriging method with only top soil EC as covariate could successfully prevent the need for extra analysis and measurements while leading to logical and convincing results, specially in developing countries with low incomes and budgets for field studies and analysis.

Conclusion

Results revealed that soil P mean wasn't constant all over the study area therefore, to take into account the mean variation in kriging equations, some assumptions were made and soil P was predicted on a 500 m grid. Afterwards soil EC was used to develop the cross-semivariograms. Soil P prediction maps using kriging and cokriging method showed that using soil EC data as covariate had a significant effect on soil P covariance functions and produced more accurate predictions, which resulted in more unbias (low ME) predictions rather than that of kriging. Therefore, it could be concluded that co-kriging method and soil EC could be used successfully in improving spatial prediction of soil phosphor.

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