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Improving spatial prediction of soil organic matter using soil auxiliary data as secondary information

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Abstract

Soil organic matter (SOM) is one of the important soil parameters which directly and indirectly affects several soil physicochemical properties and environmental factors. The aim of this research was to predict soil organic matter (SOM) using kriging and cokriging methods using soil auxiliary data. Soil samples were gathered from an area of 63 km^2 in Bonab Plain, northwest Iran. An overall 78 samples were collected from depth 0-20 cm. SOM and ten other soil physicochemical properties such as electrical conductivity (EC), soil texture, calcium and carbonate equivalent (CCE) were measured. Later, correlation between SOM and soil properties was determined and those properties with high correlation in 1% probability level with SOM were used to develop cross-semivariograms. Then, SOM prediction was conducted on a grid of 100 m with kriging and cokriging methods using BMElib package developed for MATLAB software. Results showed that among the studied soil properties, CCE, silt, sand and wet aggregate stability (WAS) had the highest correlations with SOM and therefore they were chosen as auxiliary data in cokriging of SOM. Spatial prediction of SOM with kriging method resulted in MSE and RMSE of 0.055 % and 0.234% respectively. However, SOM prediction with developed cross-semivarigrams using auxiliary data revealed that CCE and silt could improve SOM prediction with MSE and RMSE of 0.047%, 0.032% and 0.216%, 0.178 % respectively. The better performance of CCE and silt covariates in SOM prediction could be explained by their higher correlation with SOM and decreased nugget effect in developed cross-semivariograms (increased spatial dependency). As a conclusion, due to the nature of SOM which is controlled by some of the soil properties; especially soil texture, CCE, aeration condition in soils, ets., selecting appropriate soil parameters with high correlation with SOM and high spatial dependency can improve spatial prediction of SOM. This facilitates taking a step forward in sustainable management of SOM as a key soil quality index, especially in areas with salinization and desertification danger.

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Introduction

Soil organic matter (SOM) is one of the main components of the soil quality and productivity (Herrick and Wander, 1997). SOM in the soil increases soil aggregation that improves water holding capacity and infiltration. It also improves maintenance of nutrients and soil resilience to environmental degradation (Sullivan et al., 2005; Parras-Alcantara et al., 2016). On the other hand, in arid and semi-arid regions where lack of water is a crucial problem, soil particles can easily be moved by wind due to the absence of SOM (Bruun et al., 2015; Saia et al., 2014). Dust phenomenon has become a serious problem in most parts of the world as a consequence of climate change, resulting in increased soil salinity and decreased soil productivity and quality. It is also hazardous to human health both in the areas of origin and also other areas due to the long-range transport of the soil particles (Middleton, 2017). SOM also plays an important role in global carbon cycle and controlling the emission of greenhouse gasses (Lal, 2004; Heimann and Reichstein, 2008; Marchant et al., 2015; Bradford et al., 2016; Filippi et al., 2016).

Bonab Plain, located at the southeastern part of Urmia Lake in the northwest Iran, is one of the important agricultural plains in the region. During the past decades, this region has experienced several environmental degradations, such as secondary salinization of lands as a consequence of drying of saline Urmia Lake. The conventional agricultural practices along with cultivation of onion and potato as the prevailing cropping products, affected SOM in soils through exposing it to severe decomposition. Low SOM content of soils in the region not only has increased the need for chemical fertilizers but also heightened the risk of environmental pollution. Therefore, due to the limited area of suitable lands for food production in Iran, understanding of SOM content and its spatial mapping is important from agricultural and environmental perspectives (van Wesemael et al., 2011; Dono et al., 2016; Novara et al., 2017).

Statistical approaches such as interpolation methods are one of the common ways in spatial estimation of SOM. Kriging as the best unbiased predictor has been used in SOM prediction worldwide (Chabala et al., 2017; Ye et al., 2017; Elbasiouny et al., 2014). Such methods have shown their best performance where dense SOC measurements are taken (Hoffmann et al., 2014; Piccini et al., 2014).

However, SOM field sampling and laboratory measurements are expensive and time consuming (Miklos et al., 2010; Mulder et al., 2011). On the other hand, SOM shows high degrees of variability due to its inherent changes with regard to the other soil forming factors and processes and disregard of their effects on soil SOM will reduce the accuracy of the SOM predictions. In other words, more than any other soil characteristic, SOM is influenced by environmental factors such as soil physicochemical properties. The rate and effect of these properties on the SOM is different, hence the importance of each one should be examined separately (Allen et al., 2010; Jandl et al., 2013; Viaud et al., 2010). Therefore, conventional kriging methods has been upgraded to be more efficient by taking into account several covariates (Wang et al., 2017; Zaouche and Vaudour, 2017; Mirzaee et al., 2016; Zeng et al., 2016; Qi-yong et al., 2014; Dai et al., 2014; Zhang et al., 2012; Kumar et al., 2012). Cokriging which is a multivariate variant of ordinary kriging have been proven to be superior over other geostatistical methods in spatial prediction of soil properties e.g. CEC (Liao et al., 2011); soil copper (Su et al., 2009); and soil total nitrogen (Wang et al., 2013). It has also been successfully used in spatial prediction of SOM (Singh et al., 2016; Wu et al., 2009). The aim of present research was to investigate the spatial variation of SOM in southeast Urmia Lake in Bonab Plain with soil auxiliary data as covariates.

Material and Methods

Study area

The study area includes 63 km^2 of lands in Bonab Plain, southeast Urmia Lake, northwest Iran (Figure 1). It is located between 45° 58' 41'' to 46° 02' 35'' Eastern longitudes and 37° 20' 21'' to 37° 16' 18'' Northern latitudes with average annual precipitation and temperature of 264.73 mm and 13.4°c respectively. Potential evaporation in the area is between 900-1170 mm.

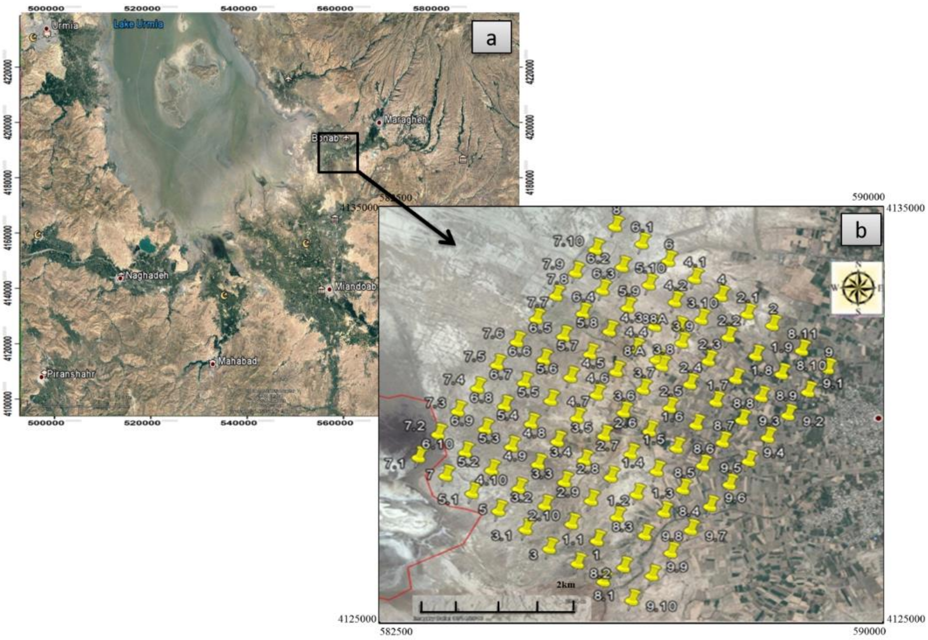

Figure 1. The study area in the southestern part of Uromieh Lake in Bonab Plain.

Data description

A number of 78 soil samples were gathered on a 500-meter grid from 0-20 cm depth during autumn 2018. At each sampling point, 10 separate soil samples within 1 m radius were taken and mixed to obtain a homogeneous soil sample. As soil organic matter (SOM) shows significant correlations with other soil properties such as soil texture (Jegajeevagan et al., 2013; Forth, 1991; Zaouche et al., 2017) these auxiliary data can be used as covariates in SOM prediction. Therefore, after passing soil samples through 2 mm sieve, soil electrical conductivity (EC), pH, Na^+ and Ca^{2+}+Mg^{2+} were determined in saturated paste extracts of soil samples (Rhoades, 1982). Calcium carbonate equivalent (CCE) was measured using back titration of the remaining HCl (Page et al., 1992). Soil texture was measured using a hydrometer method (Bouyoucos, 1962). Soil organic matter (OM) was measured with acid digestion (Page et al., 1982). Wet aggregate stability (WAS) was determined using wet sieving (John and Kim, 2002). Sodium adsorption ratio (SAR) was determined using Equation 1 (Taxonomy, 2014).

$$SAR = \frac{soulable\ Na\ (mmol(+).l^{-})}{\sqrt{\frac{(soulable\ (Ca+Mg)(mmol(+).l^{-}))}{2}}} \quad (1)$$

Then spatial dependency of the soil SOM were checked and based on developed variogram with SOM data, spatial prediction of SOM were implemented on a grid of 500 m using ordinary kriging. Then to see if other measured soil properties as covariates, could improve the SOM prediction; measured soil properties were used to improve the variogram of SOM. Afterwards, once more spatial prediction of soil SOM was conducted using cokriging method and finally the performance of the different methods was compared.

Cross-semivariance functions

In order to have better idea about how auxiliary data can improve predictions quality, first one needs to know how kriging and cokriging methods work. Kriging estimators' basic equation is defined as follows (Li and Heap, 2008):

$$Z(x_0) - \mu = \sum_{i=1}^{n} \lambda_i [Z(x_i) - \mu(x_0)] \quad (2)$$

Equation 2 can be extended to incorporate the additional information as follows:

$$\hat{Z}_1(x_0) - \mu_1 = \sum_{i_1=1}^{n_1} \lambda_i \left[Z_1(x_{i_1}) - \mu_1(x_{i_1})\right] + \sum_{j=2}^{n_v} \sum_{i_j=1}^{n_j} \lambda_{i_j} \left[Z_j\left(x_{i_j}\right) - \mu_j\left(x_{i_j}\right)\right] \quad (3)$$

Where μ_1 is stationary mean of the initial variable, $Z_1(x_{i_1})$ is the data at point i_1,

$\mu_1(x_{i_1})$ is the average 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 reduce estimation variance of the initial 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 $\mu_j(x_{i_j})$ is the mean of samples of j^{th} secondary variable within the search window.

The estimation of cross-semivariance can be done using the following equation:

$$\hat{\gamma}_{12}(h) = \frac{1}{2n}\sum_{i=1}^{n}[z_1(x_i) - z_1(x_i) - z_1(x_i + h)][z_2(x_i) - z_2(x_i + h)] \tag{4}$$

In the present research, Z_1 refers to the SOM and Z_2 refers to the soil covariates.

Validation and comparison criteria

The following global performance criteria were computed to compare the kriging and cokriging methods: mean error (ME), mean squared error (MSE), and root mean square error (RMSE). Superior predictions exhibit a ME value close to zero, as well as small MSE and RMSE values. The BMElib toolbox (Christakos, 2002), implemented in Matlab (MathWorks, 1999), was employed for all analyses.

Results and Discussion

Soil Chemical Properties

A summary of the statistical analysis for the measured soil properties in the collected soil samples is presented in Table 1. In Figure 2, color plots of the soil chemical properties and their corresponding coordinates are depicted. Based on these results, the mean soil electrical conductivity (EC) was 10.94 dS.m^-1, with a minimum value of 0.33 dS.m^-1 and a maximum of 107.5 dS.m^-1. The lowest EC values were observed in the agricultural lands, while the highest values were found in the Urmia Lake playa sediments. Due to the diverse nature of the study area, consisting of two distinct landforms (alluvial plain and playa), sharp variations in some other soil properties such as sodium (Na), calcium plus magnesium (Ca+Mg), and sodium adsorption ratio (SAR) were also observed (Table 1 and Figure 2). Previous studies have highlighted the presence of a distinct boundary between saline and non-saline lands in the study area (Hamzehpour and Rahmati, 2016). However, soil organic matter (OM) did not exhibit significant variations throughout the study area, even though the areas located on the alluvial plain (Bonab Plain) were under intensive cultivation, while lands on Urmia Lake playa sediments were either covered with native vegetation or were barren due to high soil salinity (Table 1 and Figure 2e). The relatively low levels of SOM in the study area (mean SOM was 0.6%) can be attributed to the saline nature of Urmia Lake playa sediments and unsustainable land management practices, leading to the accelerated decomposition of SOM.

According to Table 1, the mean calcium carbonate equivalent (CCE) in the studied soil samples was 18.57%, indicating that the soils in the study area were predominantly calcareous, with neutral to alkaline pH values (Table 1 and Figure 2g).

Soil physical properties

Summary statistics for some of the soil physical properties are presented in Table 1 and Figure 3. According to Table 1, there were significant variations in soil texture fractions among the soil samples. The sand content of the studied soil samples ranged from 14% to 90%, with a mean value of 61.54%. In Figure 3a, the color plot displays the sand content of the soil samples along with their respective coordinates. Interestingly, the highest sand content was observed in the Bonab Plain, where it was expected to have finer textured sediments based on geomorphological considerations. The high sand content in this area can be attributed to the common cultivation of crops such as onions and potatoes, which are predominant agricultural productions in the region. Sand is often added to these soils to improve soil texture, enhance soil aeration, and facilitate water movement. This practice is also responsible for the very low levels of soil organic matter (SOM) observed in soil samples from agricultural lands. In coarse-textured soils, SOM is less protected by mineral particles due to their larger size and lower specific surface area (Kennedy et al., 1992). Consequently, coarse-textured soils tend to lose a significant amount of SOM through microbial respiration, resulting in a negative correlation between soil sand fraction and soil organic carbon (SOC) content, making it challenging to improve SOC levels in sandy soils (Magdoff and Weil, 2004; Adhikari and Hartemink, 2017).

Table 1. Summary of statistical analysis of measured soil properties used as auxiliary data in soil organic matter spatial prediction.

Soil property	Unit	Mean	SD	Max	Min	Skewness	Kurtosis
EC	$(dS.m^{-1})$	10.95	20.48	107.5	0.33	2.94	9.01
pH	-	8.16	0.44	8.97	7.10	-0.5	-0.24
Na	$(meq.l^{-1})$	29.58	67.60	436.92	0.92	4.04	18.32
(Ca+Mg)	$(meq.l^{-1})$	24.58	16.19	108.00	4.00	11.28	2.88
SAR	-	4.92	8.82	48.25	0.23	16.02	3.67
OM	(٪)	0.6	0.32	1.92	0	1.09	2.56
CCE	(٪)	18.57	3.91	30.58	12.64	0.72	0.95
Sand	(٪)	61.55	18.19	90.00	14.00	2.41	1.39
Silt	(٪)	26.70	13.03	56.00	6.00	-0.65	0.39
Clay	(٪)	11.75	7.12	36.00	2.00	-0.34	-0.66
WAS	(٪)	16.41	20.26	87.11	0.00	3.24	1.83

OM: organic matter; EC: electrical conductivity; SAR: sodium adsorption ratio; CCE: calcium carbonate equivalent; WAS: wet aggregate stability

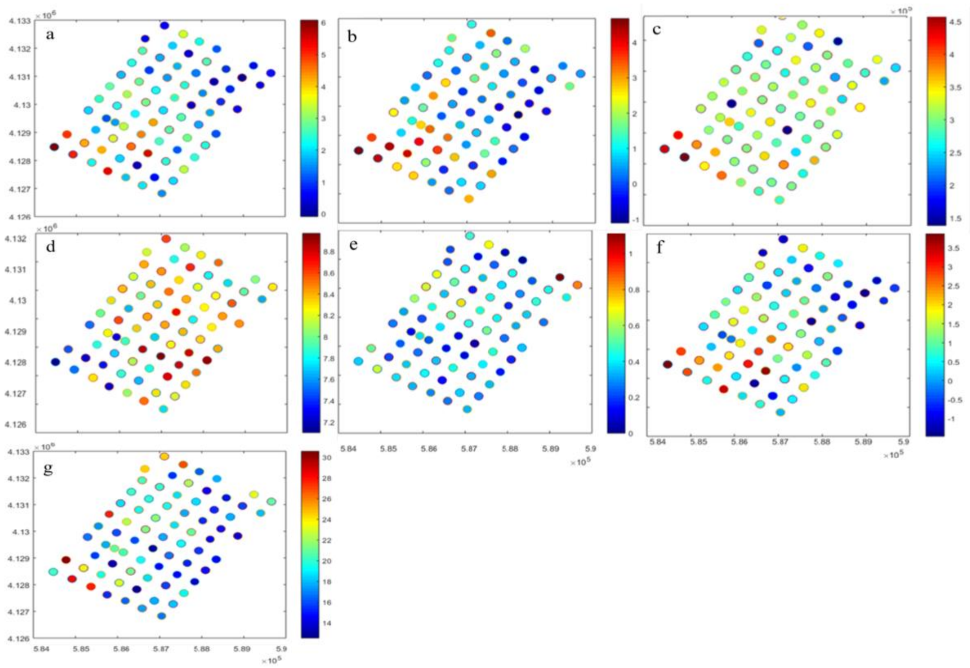

Figure 2. Plots for the sampling campaign. The level of color reflects values of measured soil property. a: electrical conductivity (EC) (dS.m-); b: log of Na (meq.l-); c: log of (Ca+Mg) (meq.l-); d: pH; e: soil organic carbon (%); f: log of SAR; g: calcium carbonate equivalent (CCE) (%).

In comparison to the sand and silt contents of the studied soil samples, the clay content was generally low, except for a few locations situated on the Urmia Lake playa sediments (Figure 3c). Studies have shown a positive correlation between SOM content and soil clay content (Forth, 1991). One of the primary reasons is the high water-holding capacity and cation exchange capacity (CEC) of clay particles, which promote improved vegetation cover. Conversely, in soils with high clay content, the intensity of soil organic matter decomposition decreases due to limited aeration (Minasny et al., 2013). In fine-textured soils, SOM is effectively shielded by mineral particles, protecting it from microbial degradation.

As SOM plays a crucial role in increasing the size and stability of soil aggregates, it was expected that the wet aggregate stability (WAS) values would be low. In Figure 3d, the color plot illustrates the distribution of WAS in the study area. Overall, except for a few locations, WAS values in the study area were low, with a mean value of 16.41%. Since WAS is a key factor in soil resistance to water erosion (Cañasveras et al., 2010), these low values could increase the risk of flooding and water erosion in the study area. Several studies have emphasized the role of SOM and clay content in enhancing WAS in soils (e.g., Cañasveras et al., 2010; Cantón et al., 2009; Amezketa, 1999). Therefore, the observed low WAS values can be explained by the low levels of both SOM and clay in the study area.

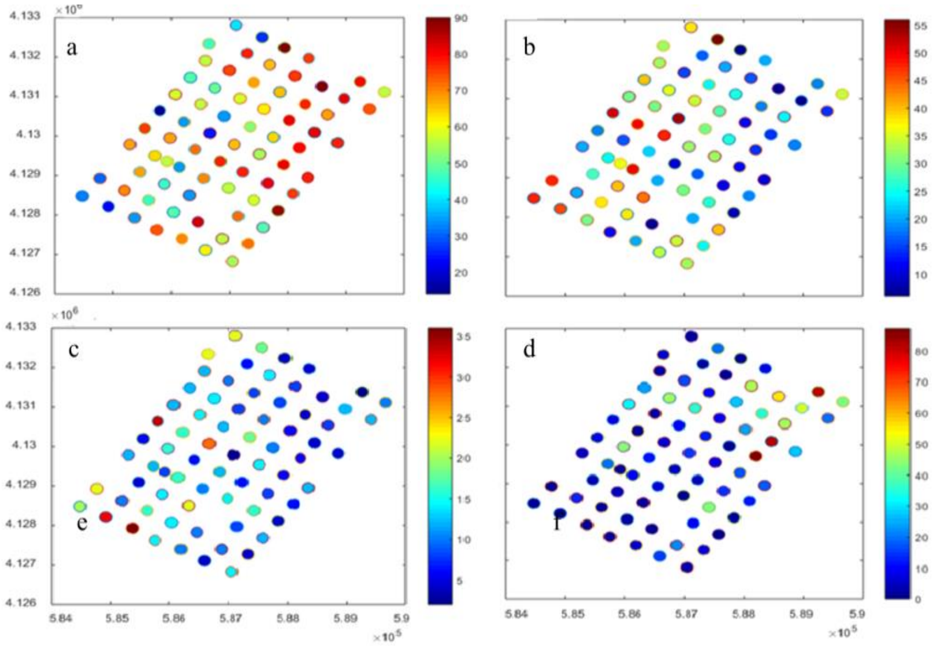

Figure 3. Plots for the sampling campaign. The level of color reflects values of measured soil property. a: sand (%) (dS.m-); b: silt (%); c: clay (%); d: wet aggregate stability (%).

SOM prediction with ordinary kriging

The results for the fitted semi-variogram on the SOM (Soil Organic Matter) dataset and its corresponding parameters are presented in Figure 4a and Table 2. The semi-variogram model with the smallest sum of squared residuals was selected as the best fitting model (Table 2). A SOM prediction map, generated using the ordinary kriging method along with cross-validation points, is also displayed in Figure 4b. The obtained variogram model exhibited a nugget effect of 0.049, a spherical component with a sill of 0.107, and a range of 2.4 km. The nugget-to-sill ratio (NE) was employed to describe the level of spatial dependence and random variation in SOM content. An NE value less than 25% indicates strong spatial dependence, while NE values between 25% and 75% signify moderate spatial dependence, and NE values exceeding 75% indicate weak spatial dependence.

Validation results demonstrated that the spatial prediction of SOM using the kriging method yielded acceptable performance, with a mean squared error (MSE) of 0.055% and a root mean square error (RMSE) of 0.234% (Table 5). Comparable studies by Song et al. (2017) and Zhang et al. (2012) reported RMSE values of 2.071 g.kg-1 (0.207%) and 1.87 g.kg-1 (0.187%) for the spatial prediction of SOM using the ordinary kriging method in China. However, the nugget-to-sill ratio of 0.45 (indicating moderate spatial dependency) suggests that, despite the expectation of fitted semi-variogram values at each sampling point to be zero or close to zero, there were unaccounted sources of error in the semi-variogram modeling process. This reduced the validity of the fitted semi-variogram for understanding spatial variations and predictions of SOM.

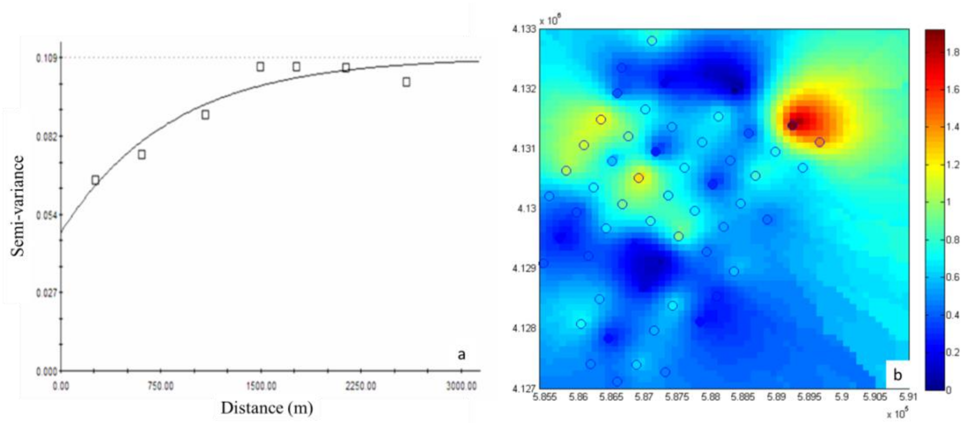

Figure 4: a) Spatial semi-variogram function for soil organic matter during autumn 2018. Dots correspond to the calculated values; solid line is the corresponding fitted model. b) Spatial prediction of soil organic matter with validation points in Bonab Plain using fitted semi-variogram function.

Table 2. Fitted semi-variogram parameters on SOM dataset.

Model	Nugget effect	sill	Nugget/sill	Effective range	R
exponential	0.049	0.107	0.457	2460	0.914

Covariance and Cross-semivariance functions

Selecting appropriate auxiliary variables is crucial in obtaining better understanding of SOM variations. In order to use a soil property as covariate in spatial prediction of SOM, first, covariate should have significant correlation with SOM. To investigate the role of the studied soil properties in improving spatial prediction of SOM, Pearson correlation coefficient was determined between SOM and soil properties and results are presented in Table 3. As shown in Table 3, SOM had significant correlation with soil CCE, WAS, silt and sand in 1% probability level. Among these, the highest p-value was seen for CCE and the lowest was observed for WAS. Therefore, these four soil parameters were selected as covariates in spatial prediction of SOM. In Figure 5 plots of the correlation between selected covariates and SOM and fitted linear models are also presented.

Table 3. The correlation between soil organic matter and some of the studied soil properties.

EC	pH	$Na_{(eq)}$	$Ca+Mg_{(eq)}$	SAR	CCE	WAS	Clay	Silt	Sand
0.027	-0.058	0.04	0.18	-0.03	0.55^{**}	0.33^{**}	0.27^{*}	0.44^{**}	-042^{**}

SOM: soil organic matter; CC: Correlation coefficient

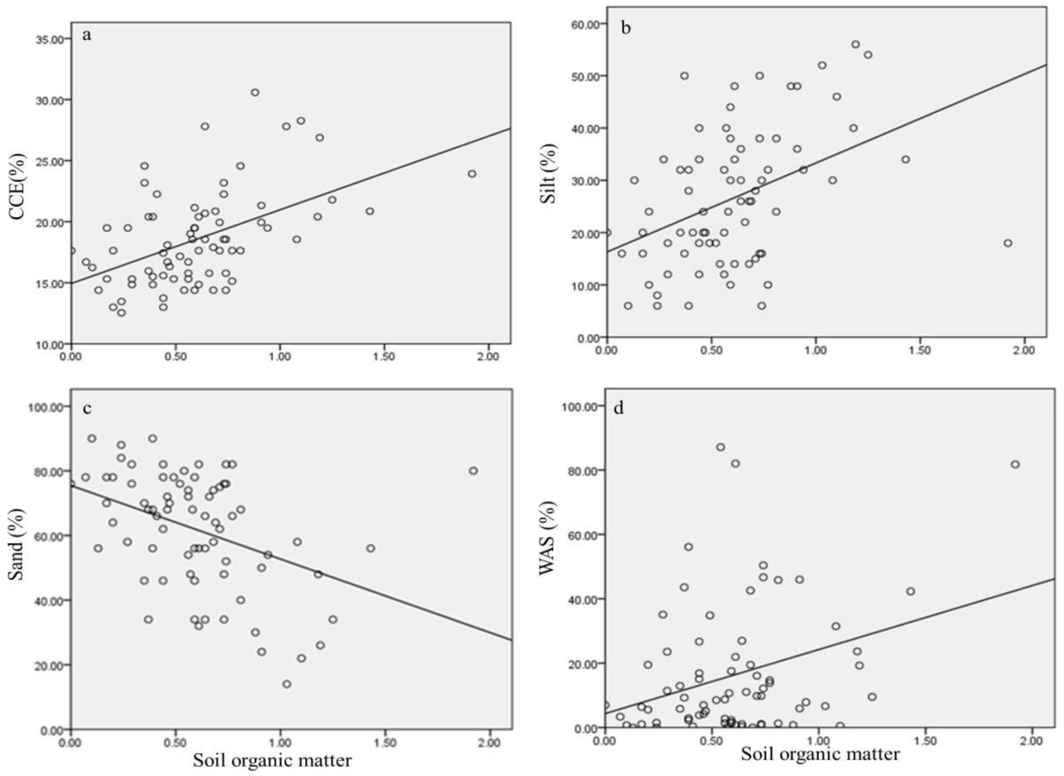

Figure 5. Plots of the correlations between SOM and selected soil properties as covariates. a: calcium carbonate equivalent (CCE); b: silt; c: sand; d: wet aggregate stability (WAS).

Subsequently, cross – semi - variance functions were computed between SOM (Soil Organic Matter) and the four chosen covariates, as illustrated in Figure 6. The best-fitting model and its corresponding parameters were extracted and are presented in Table 4. The results indicated that the calculated cross-semi-variance functions significantly improved the nugget-to-sill ratio for all selected covariates. However, it's worth noting that the range reduced, leading to a shorter applicable distance for the developed cross-semi-variograms (with the exception of WAS, which followed the nature of the fitted linear model). Among these results, the cross-semi-variograms for silt and sand exhibited the lowest nugget-to-sill values, while the highest R values were associated with silt and CCE, with values of 0.89 and 0.86, respectively.

Figure 7 displays spatial prediction maps of SOM (Soil Organic Matter) with various covariates. Overlaid onto these predicted maps are cross-validation points, and the similarity in color between the points and the background maps reflects the accuracy of the predictions. As depicted in the figure, predictions of SOM with CCE and silt as covariates yielded superior results compared to the use of sand and WAS as covariates.

Table 4. Fitted best cross-semivariograms and model parameters for SOM prediction using soil covariates.

	Model	Nugget effect	sill	Nugget/sill	Effective range	R
CCE	spherical	0.27	0.612	0.44	1811	0.864
Silt	spherical	0.001	2.140	0.00	975	0.896
sand	spherical	-0.001	-2.811	0.00	1507	0.822
WAS	linear	0.754	3.127	0.24	7000	0.736

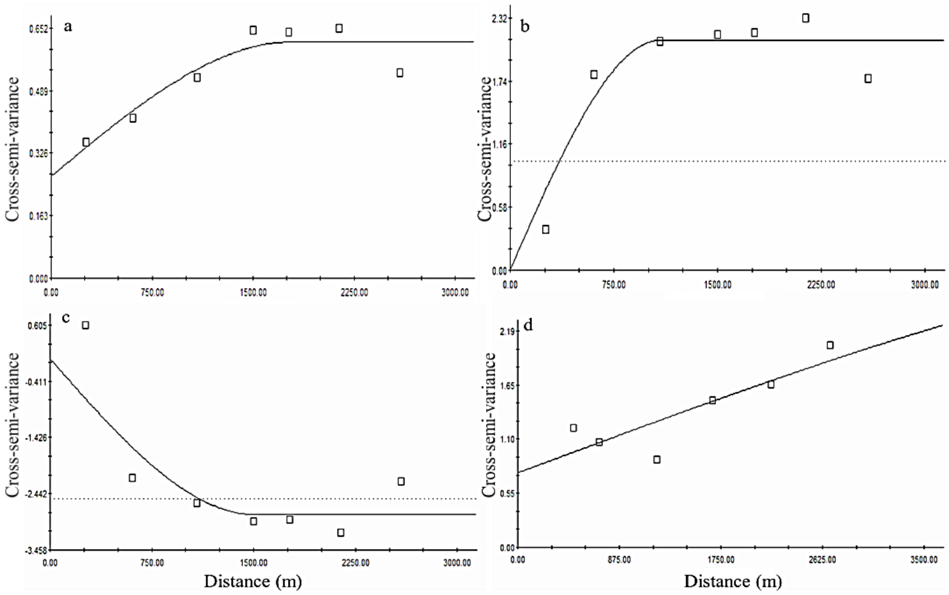

Figure 6. Cross-semivariance functions for SOM spatial prediction with different covariates. a: CCE; b: silt; c: sand; d: WAS.

Table 5 provides cross-validation results for SOM prediction using the kriging method, cokriging with different covariates, and relevant comparison criteria. According to the table, among the four soil properties under study, the prediction of SOM with silt as a covariate demonstrated better performance, with a Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) of 0.032% and 0.178%, respectively. This approach also outperformed ordinary kriging. Additionally, cokriging SOM with CCE as a covariate yielded more accurate predictions than ordinary kriging (Table 5).

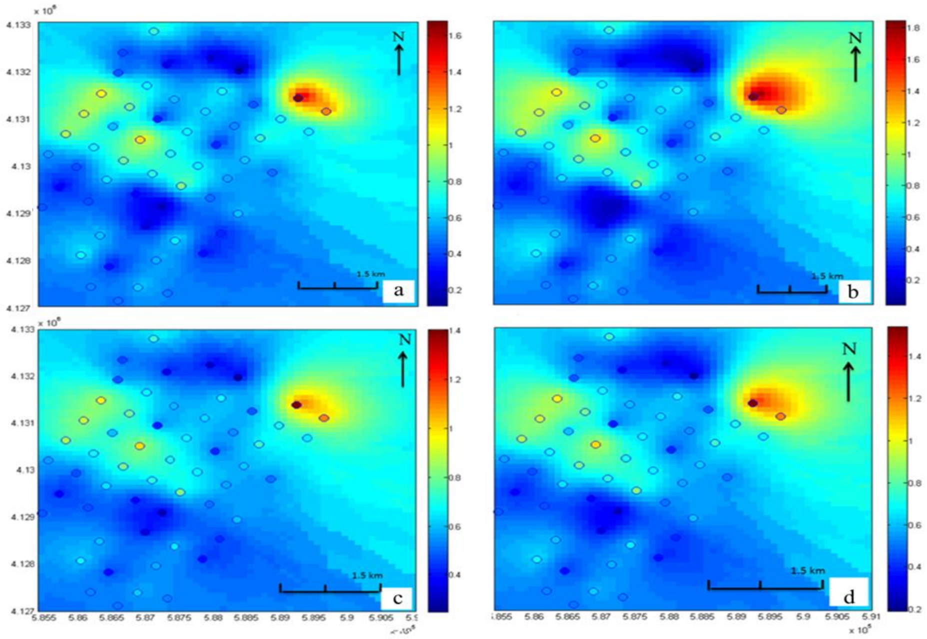

Figure 7. Spatial prediction of SOM with covariates. Dots show the cross-validation points. The level of color reflects the SOM %. a: CCE; b: silt; c: sand; d: WAS.

Table 5. Cross-validation criteria to compare SOM prediction with ordinary kriging and co-kriging methods with different covariates.

	OM	CCE	Silt	Sand	WAS
	kriging	Co-kriging			
ME (%)	0.015	0.012	0.002	0.023	0.017
MSE (%)	0.055	0.047	0.032	0.11	0.138
RMSE (%)	0.234	0.216	0.178	0.331	0.371

Several studies have explored the effectiveness of co-kriging compared to ordinary kriging (Stein and Coresten, 1991; Zhang et al., 1997; Wu et al., 2003). Co-kriging offers an advantage by allowing the incorporation of additional covariates in soil variable predictions. However, it's important to note that co-kriging may not necessarily outperform kriging when auxiliary data are poorly correlated with the target variable (Martínez, 1996; Triantafilis et al., 2001). This underscores the significance of selecting appropriate auxiliary variables. For instance, Yates and Warrick (1987) found that co-kriging tends to perform better than kriging when the correlation between auxiliary data and the target variable exceeds 0.5.

Therefore, the relatively lower performance in predicting sand and WAS content can be attributed to their weak correlations with SOM (0.33 and -0.42, respectively). In contrast, even though silt exhibited a lower correlation with SOM compared to CCE, its stronger spatial dependence outweighed the lower correlation coefficient, resulting in more accurate SOM predictions. Overall, research has consistently highlighted the importance of soil texture as a covariate in the spatial prediction of SOM.

Stevens et al. (2015) demonstrated that soil texture plays a primary role in controlling SOM at the regional scale, accounting for 65.7% of the total SOM variance in their study. Additionally, Zhang et al. (2012) suggested that the spatial distribution of SOM is predominantly influenced by terrain indices, soil texture, and soil genetic types.

Conclusion

Spatial estimation of the soil organic matter (SOM) is required to map and monitor soil quality in order to better manage soils especially in areas where soil SOM stocks are limited due to lack or low quality of irrigation water and miss management of agricultural lands. In the present research, SOM was studied in one of the major agricultural production plains in the northeast of Iran. This region is primarily and secondarily affected by consequences of hyper-saline Lake Urmia dry up. SOM content of the investigated soil samples was low with a mean value of 0.6 %. High decomposition of SOM in the soils as a result of the yearly addition of huge amounts of sand to the top soil in the region was one of the major reasons for observing low SOM content in this area. As a step forward in sustainable management of SOM in the region, the knowledge about spatial distribution of SOM and major soil properties affecting its content, are highly critical. Therefore 78 soil samples were gathered and along with SOM, ten other soil properties were measured. SOM showed high correlations with soil silt, sand, calcium carbonate equivalent (CCE) and wet aggregate stability (WAS). Among these, soil sand content showed negative correlation with SOM emphasizing on the destructive effects of increase in soil sand on accelerated decomposition of SOM. Cokriging of SOM with selected soil properties as auxiliary data and comparison of the results with those of ordinary kriging revealed that cokriging with soil silt and CCE content led to a lower MSE and RMSE values and therefore more precise maps of SOM, through improving SOM spatial dependency and reducing nugget effect. Understanding of the major factors affecting SOM as one of the most important soil quality parameters in this region and production of continuous maps of SOM with high accuracy would help in better management of agricultural lands, sustainability of agricultural productions and conserving lands from more degradation in the future of the area.

References

Adhikari, K., and Hartemink, A.E. 2017. Soil organic carbon increases under intensive agriculture in the Central Sands, Wisconsin, USA. Geoderma Regional. 10, 115-125.

Allen, D.E. Pringle, M.J., Page, K.L., and Dalal, R.C. 2010. A review of sampling designs for the measurement of soil organic carbon in Australian grazing lands. The Rangeland Journal. 32(2), 227-246.

Amezketa, E. 1999. Soil aggregate stability: A Review. Journal of sustainable agriculture. 14(2-3), 83-151.

Bradford, M.A., Wieder, W.R., Bonan, G.B., Fierer, N., Raymond, P.A., and Crowther, T.W. 2016. Managing uncertainty in soil carbon feedbacks to climate change. Nature Climate Change. 6(8), 751.

Bouyoucos, G.J. 1962. Hydrometer method improved for making particle size analyses of soils 1. Agronomy journal. 54(5), 464-465.

Bruun, T.B., Elberling, B., de Neergaard, A., and Magid, J. 2015. Organic carbon dynamics in different soil types after conversion of forest to agriculture. Land Degradation and Development. 26(3), 272-283.

Cañasveras, J.C., Barrón, V., Del Campillo, M.C., Torrent, J., and Gómez, J.A. 2010. Estimation of aggregate stability indices in Mediterranean soils by diffuse reflectance spectroscopy. Geoderma. 158(1-2), 78-84.

Cantón, Y., Solé-Benet, A., Asensio, C., Chamizo, S., and Puigdefábregas, J. 2009. Aggregate stability in range sandy loam soils relationships with runoff and erosion. Catena. 77(3), 192-199.

Chabala, L.M., Mulolwa, A., and Lungu, O. 2017. Application of ordinary kriging in mapping soil organic carbon in Zambia. Pedosphere. 27(2), 338-343.

Christakos, G. 2002. On the assimilation of uncertain physical knowledge bases: Bayesian and non-Bayesian techniques. Advances in Water Resources. 25(8-12), 1257-1274.

Dai, F., Zhou, Q., Lv, Z., Wang, X., and Liu, G. 2014. Spatial prediction of soil organic matter content integrating artificial neural network and ordinary kriging in Tibetan Plateau. Ecological Indicators. 45, 184-194.

Dono, G., Cortignani R., Dell'Unto, D., Deligios, P., Doro, L., Lacetera, N., and Roggero, P.P. 2016. Winners and losers from climate change in agriculture: Insights from a case study in the Mediterranean basin. Agricultural Systems. 147, 65-75.

Filippi, P., Minasny, B., Cattle., S.R. and Bishop, T.F.A. 2016. Monitoring and Modeling Soil Change: The Influence of Human Activity and Climatic Shifts on Aspects of Soil Spatiotemporally. In Advances in Agronomy.139, 153-214.

Elbasiouny, H., Abowaly, M., Abu_Alkheir, A., and Gad, A. 2014. Spatial variation of soil carbon and nitrogen pools by using ordinary Kriging method in an area of north Nile Delta, Egypt. Catena. 113, 70-78.

Forth, H. 1990. Fundamentals of soil science. 8th Ed. New York: Wiley. ISBN: 0-471-52279-1.

Hamzehpour, N., and Rahmati, M. 2016. Investigation of soil salinity to distinguish boundary line between saline and agricultural lands in Bonab Plain, southeast Urmia Lake, Iran. Journal of Applied Sciences and Environmental Management. 20(4), 1037-1042.

Heimann, M., and Reichstein, M. 2008. Terrestrial ecosystem carbon dynamics and climate feedbacks. Nature. 451, 289.

Herrick, J.E., and Wander, M.M. 1997. Relationships between soil organic carbon and soil quality in cropped and rangeland soils: the importance of distribution, composition, and soil biological activity (pp. 405-425). Boca Raton, CRC Press.

Hoffmann, U., Hoffmann, T., Jurasinski, G., Glatzel, S., and Kuhn, N.J. 2014. Assessing the spatial variability of soil organic carbon stocks in an alpine setting (Grindelwald, Swiss Alps). Geoderma 232: 270-283.

Jandl, R., Rodeghiero, M., Martinez, C., Cotrufo, M.F., Bampa, F., van Wesemael. B., and Lorenz, K. 2014. Current status, uncertainty and future needs in soil organic carbon monitoring. Science of the total environment. 468, 376-383.

Jegajeevagan, K., Sleutel, S., Ameloot, N., Kader, M.A., and Neve, S. De. 2013. Organic matter fractions and N mineralization in vegetable-cropped sandy soils. Soil Use and Management, 29(3), 333-343.

John, R.N. and Kim, S.P. 2002. Aggregate stability and size distribution. (pp. 201-414), In: Jacob, H.D., and Clarke Topp, G (Ed.), Methods of Soil Analysis. Part 4. Physical Methods. Soil Science Socienty of America, Madison, WI., USA.

Kennedy, M.J., Pevear, D.R., and Hill, R.J. 2002. Mineral surface control of organic carbon in black shale. Science 295(5555), 657-660.

Kumar, S., Lal, R., and Liu, D. 2012. A geographically weighted regression kriging approach for mapping soil organic carbon stock. Geoderma. 189,627-634.

Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. Science. 304(5677), 1623-1627.

Li, J., and Heap, A.D. 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: performance and impact factors. Ecological Informatics. 6(3-4), 228-241.

Liao, K.H., Xu, S.H., Wu, J.C., Ji, S.H., and Qing, L.I.N. 2011. Cokriging of soil cation exchange capacity using the first principal component derived from soil physico-chemical properties. Agricultural sciences in China. 10(8), 1246-1253.

Magdoff, F., and Weil, R.R., (Eds.). 2004. Soil organic matter in sustainable agriculture. CRC press.

Marchant, B.P., Villanneau, E.J., Arrouays, D., Saby, N.P.A., and Rawlins, B.G. 2015. Quantifying and mapping topsoil inorganic carbon concentrations and stocks: approaches tested in France. Soil Use and Management. 31(1), 29-38.

Martínez-Cob, A. 1996. Multivariate geostatistical analysis of evapotranspiration and precipitation in mountainous terrain.

Math Works Inc. 1999. MatLab, the language of technical computing, using MATLAB version 5. the Mathwork Inc. http://www.mathworks.com, Natick.

Middleton, N.J. 2017. Desert dust hazards: A global review. Aeolian research. 24, 53-63.

Miklos, M., Short, M.G., McBratney, A.B., and Minasny, B. 2010. Mapping and comparing the distribution of soil carbon under cropping and grazing management practices in Narrabri, north-west New South Wales. Soil Research. 48(3), 248-257.

Mirzaee, S., Ghorbani-Dashtaki, S., Mohammadi, J., Asadi, H. and Asadzadeh, F. 2016. Spatial variability of soil organic matter using remote sensing data. Catena. 145, 118-127.

Mulder, V.L., De Bruin, S., Schaepman, M.E., and T.R. Mayr. 2011. The use of remote sensing in soil and terrain mapping—A review. Geoderma. 162(1-2), 1-19.

Novara, A., Gristina, L., Sala, G., Galati, A., Crescimanno, M., Cerdà, A., and Mantia, T. La. 2017. Agricultural land abandonment in Mediterranean environment provides ecosystem services via soil carbon sequestration. Science of the Total Environment. 576, 420-429.

Page, A.L., Miller, R.H. and Kenney, D.R. 1992. Methods of Soil Analysis Part II, Chemical and Mineralogical Properties, 2nd ed. SSSA Pub, Madison (1159 pp).

Page, A.L., Miller R.H., and Keeney, D.R. 1982. Methods of Soil Analy*sis*: Part 2. Chemical and Microbiological Properties, 2nd edition. Agronomy, vol. 9. ASA, SSSA Publishing, Madison, WI, p. 1159.

Parras-Alcántara, L., Lozano-García, B., Keesstra, S., Cerdà, A., and Brevik, E.C. 2016. Long-term effects of soil management on ecosystem services and soil loss estimation in olive grove top soils. Science of the Total Environment. 571, 498-506.

Piccini, C., Marchetti, A., and Francaviglia, R. 2014. Estimation of soil organic matter by geostatistical methods: Use of auxiliary information in agricultural and environmental assessment. Ecological indicators. 36, 301-314.

Qi-yong, Y., Zhong-cheng, J., Wen-jun, L., and Hui, L. 2014. Prediction of soil organic matter in peak-cluster depression region using kriging and terrain indices. Soil and Tillage Research. 144,126-132.

Rhoades, J.D. 1982. Soluble salts. In: A.L. Page (ed.) Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties. Agronomy monograph no. 9. 2nd ed. SSSA and ASA,Madison,WI, 167-179.

Saia, S., Benítez, E., García-Garrido, J.M., Settanni, L., Amato, G., and Giambalvo, D. 2014. The effect of arbuscular mycorrhizal fungi on total plant nitrogen uptake and nitrogen recovery from soil organic material. The Journal of Agricultural Science. 152(3), 370-378.

Singh, A., Santra, P., Kumar, M., Panwar, N., and Meghwal, P.R. 2016. Spatial assessment of soil organic carbon and physicochemical properties in a horticultural orchard at arid zone of India using geostatistical approaches. Environmental Monitoring and Assessment. 188(9), 529.

Song, Y.Q., Yang, L.A., Li, B., Hu, Y., Wang, M., Zhou, A.L. and Liu, Y.L. 2017. Spatial Prediction of Soil Organic Matter Using a Hybrid Geostatistical Model of an Extreme Learning Machine and Ordinary Kriging. Sustainability. 9(5), 754.

Stein, A., and Corsten, L.C.A. 1991. Universal kriging and cokriging as a regression procedure. Biometrics. 575-587.

Stevens, F., Bogaert, P., and Van Wesemael, B. 2015. Detecting and quantifying field-related spatial variation of soil organic carbon using mixed-effect models and airborne imagery. Geoderma. 259, 93-103.

Su, P.A.N.G., Li, T.X., Wang, Y.D., Yu, H.Y., and Xi, L.I. 2009. Spatial interpolation and sample size optimization for soil copper (Cu) investigation in cropland soil at county scale using cokriging. Agricultural Sciences in China. 8(11), 1369-1377.

Sullivan, D.G., Shaw, J.N., and Rickman, D. 2005. IKONOS imagery to estimate surface soil property variability in two Alabama physiographies. Soil Science Society of America Journal. 69(6), 1789-1798.

Taxonomy, S. 2014. Key to soil taxonomy. Soil Survey staff. AID. USDA. SMSS. Technical Monograph, 19.

Triantafilis, J., Odeh, I.O.A. and McBratney, A.B. 2001. Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. Soil Science Society of America Journal. 65(3), 869-878.

Van Wesemael, B., Paustian, K., Andrén, O., Cerri, C.E., Dodd, M., Etchevers, J., and S. Ogle. 2011. How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO 2 fluxes in agricultural soils? Plant and Soil. 338(1-2), 247-259.

Viaud, V., Angers, D.A., and Walter, C. 2010. Toward landscape-scale modeling of soil organic matter dynamics in agroecosystems. Soil Science Society of America Journal. 74(6), 1847-1860.

Wang, T., Kang, F., Cheng, X., Han, H., Bai, Y., and Ma, J. 2017. Spatial variability of organic carbon and total nitrogen in the soils of a subalpine forested catchment at Mt. Taiyue, China. Catena. 155, 41-52.

Wang, K., Zhang, C., and Li, W. 2013. Predictive mapping of soil total nitrogen at a regional scale: A comparison between geographically weighted regression and cokriging. Applied Geography. 42, 73-85.

Wu, C., Wu, J., Luo Y., Zhang, L., and DeGloria, S.D. 2009. Spatial prediction of soil organic matter content using cokriging with remotely sensed data. Soil Science Society of America Journal. 73(4), 1202-1208.

Wu, J., Norvell, W.A., Hopkins, D.G., Smith, D.B., Ulmer, M.G., and Welch, R.M. 2003. Improved prediction and mapping of soil copper by kriging with auxiliary data for cation-exchange capacity. Soil Science Society of America Journal. 67(3), 919-927.

Yates, S.R. and Warrick, A.W. 1987. Estimating Soil Water Content Using Cokriging 1. Soil Science Society of America Journal. 51(1), 23-30.

Ye, H., Huang, W., Huang, S., Huang, Y., Zhang, S., Dong, Y., and Chen, P. 2017. Effects of different sampling densities on geographically weighted regression kriging for predicting soil organic carbon. Spatial statistics. 20, 76-91.

Zaouche, M., Bel, L., and Vaudour, E. 2017. Geostatistical mapping of topsoil organic carbon and uncertainty assessment in Western Paris croplands (France). Geoderma Regional. 10, 126-137.

Zeng, C., Yang, L., Zhu, A.X., Rossiter, D.G., Liu, J., and Wang, D. 2016. Mapping soil organic matter concentration at different scales using a mixed geographically weighted regression method. Geoderma. 281, 69-82.

Zhang, S., Huang, Y., Shen, C., Ye, H., and Du, Y. 2012. Spatial prediction of soil organic matter using terrain indices and categorical variables as auxiliary information. Geoderma. 171, 35-43.

Zhang, R., Shouse, P., and Yates, S. 1997. Use of pseudo-crossvariograms and cokriging to improve estimates of soil solute concentrations. Soil Science Society of America Journal. 61(5), 1342-1347.