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Spatial variation analysis of soil properties using spatial statistics: a case study in the region of Sabalan mountain, Iran

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Abstract

Detailed soil information and soil maps are essential for the monitoring, management, conservation and restoration of natural ecosystems, rangelands and protected areas. Semi-automated mapping methods have advantages over conventional ones, and the selection of the best interpolation method and accurately predicted soil property maps are important for effective management and conservation strategies. Spatial soil information is important also for managing natural resources, predicting soil properties, improving sampling designs in future agro-ecological studies, and for assessing protected areas. We investigated the suitability of different interpolation methods for spatial variability predictions and for studying various soil properties within a rangeland ecosystem and the Sabalan National Natural Monument protected area, in northwestern Iran. Soil samples were collected randomly from a depth of 0–30 cm, and various properties were measured in the laboratory. Normality of data was examined and spatial statistics was applied to determine spatial variation of the properties. Interpolation methods of inverse distance weighting, Kriging and Cokriging were applied and compared for suitability. Results were evaluated using cross-validation. The results of applying spatial statistics demonstrated that soil properties had spatial dependence; Cokriging emerged as the most accurate technique overall.

Profile

Protected area

Sabalan National Natural Monument

Mountain range

Alborz mountain range

Country

Iran

Introduction

Soil spatial variability evaluation can be made on scales ranging from the micro-level (millimetres) to the plot level (metres), up to landscape (kilometres) scale (Garten et al. 2007). Soil information and knowledge of spatial soil variation are important, having useful applications such as enhancing natural resources management (Wang et al. 2009), management of protected areas (Zinck 1995; Varallyay et al. 1998; Eagles & McCool 2002; Majaliwa et al. 2010), predicting soil properties at unsampled locations (Wei et al. 2008; Liu et al. 2009), improving sampling designs for future agro-ecological studies (Yan et al. 2007), and evaluating protected areas (Majaliwa et al. 2010).

Spatial statistics is a powerful tool for spatial variability evaluations (Sauer et al. 2006); several studies have used spatial statistics to determine spatial variability of soil properties (Wei et al. 2008; Glendell et al. 2014; Longa et al. 2014; Li et al. 2015).

The most commonly used spatial statistical methods are inverse distance weighting (IDW), and Kriging and Cokriging interpolations (ESRI 2012; Gong et al. 2014). Kriging is a widely used stochastic method and is generally considered the best linear unbiased estimator, as it minimizes variance of the estimation error (Webster & Oliver 2001; Dai et al. 2014). The method has shown considerable advantages in making predictions of soil properties when compared with deterministic interpolation methods (Liu et al. 2008, 2009; Worsham et al. 2010). Many studies have compared the accuracy of IDW and Kriging and have variously reported which is the more successful method. For example, Yasrebi et al. (2009) evaluated and compared Ordinary Kriging and IDW for the prediction of spatial variability of various chemical properties of soil, and concluded that the Kriging method performed better than IDW for all the properties examined. However, Robinson and Metternicht (2006) examined the performance of spatial interpolation techniques (IDW and Kriging) for mapping soil properties and concluded that Kriging performed better as an interpolated method for pH in the top soil, and lognormal Ordinary Kriging also performed better in measuring EC in the top soil. Sajid et al. (2013) evaluated and compared Kriging and IDW for the spatial analysis of soil bulk density. Their results indicated that neither method reflected the true variation of bulk density.

The Cokriging method is appealing because estimations consider other potentially important variables such as covariates (ESRI 2013). There are several other advantages of using Cokriging (Pardo-Iguzquiza et al. 2015): (i) problems of classical Indicator Cokriging, such as estimates outside the interval (0, 1) and order relations, are avoided; (ii) secondary variables (e.g. topographic parameters) can be contained in the estimation of probability maps; (iii) uncertainty maps (versus probability maps) can be obtained; (iv) there are modelling advantages, because variograms and cross-variograms of real variables do not have the restrictions of indicator variograms and indicator cross-variograms (Pardo-Iguzquiza et al. 2015). It appears

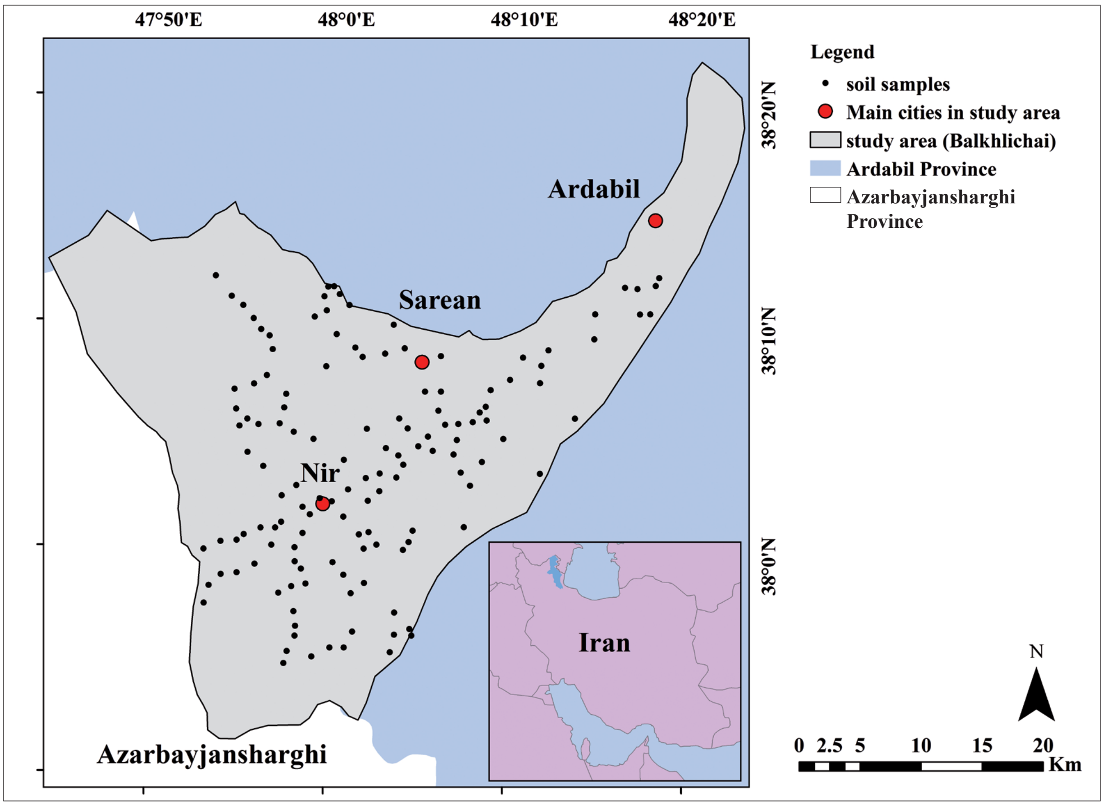


Figure 1 – Location of the study area (Balkhlichai watershed), main cities in the study area, and sampling points in Ardabil province, Iran.

that the optimal method depends on circumferences, and parameters such as the nature of the targets to be estimated (e.g. ground arsenic concentration and rainfall) (Wu et al. 2006). Because of the benefits of data transformation and Cokriging in making predictions, Zn was assessed using a georeferenced set of data from northern North Dakota. Cokriging on Zn, using OC or pH as auxiliary variables, was consistently more effective than Kriging on Zn alone. Considering the importance of mapping soil properties, the objectives of this study were to: (i) compare the accuracy of the interpolation techniques IDW, Kriging and Cokriging, and select the most suitable technique(s) for future studies in soil mapping; (ii) investigate changes in various soil properties on the southeastern slopes of Sabalan mountain. The aim was to create a framework that was appropriate for a particular soil, in order to preserve, restore and reform rangelands and protected areas. Maps produced in this study can be used in future studies to determine the relationship between these elements and parent material, as well as in analysing land use in other areas. They can also be used in future studies of these particular rangelands and of this protected area in order to enhance natural resource management, and to predict soil properties at unsampled locations. In addition, the maps can be of use in improving sampling designs, providing a baseline for future studies.

Methods

Area under study

The area under study is located at 1 150 to 4 811 m a.s.l., at 47° 45' E to 48° 23' N (at the Balkhlichai watershed, southeast of Sabalan mountain, Ardebil province, Iran; see Figure 1). It falls partly within the Sabalan National Natural Monument protected area. In terms of its ecological abiotic and biotic factors, the area can be divided into four main utilization and vegetative units: (i) plains with gentle slope (less than 12 %) and an elevation of 1 150 to 1 500 m (mainly agricultural, residential and industrial areas, and sparsely used rangeland in areas with limited slope; the rangeland is grazed mainly by rural livestock); (ii) hilly areas, intermediate between the plains and Sabalan mountain, at an altitude of 1 500 to 2 500 m, with slope variation and relatively deep soil (the lower slopes are cultivated as dry farming; the rest of the area is rangeland). Rural livestock and the livestock of the Shahsevan nomads graze rangelands in these areas, which are extremely degraded; (iii) low mountainous areas of Sabalan mountain, at 2 500 to 3 600 m, with limited rangeland use; mainly grazed by the Shahsevan nomads' livestock; these areas are also extremely overgrazed; (iv) elevated mountainous areas, over 3 600 m, also grazed by the Shahsevan nomads' livestock; area designated as the Sabalan National Natural Monument (6 643 ha) by the Department of the Environment of Iran (Ghorbani et al. 2013, 2014, 2015). The area under study has temperate summers and cold winters; for three to four months of the year, it is covered with snow and ice; mid-June to mid-October is the dry season. At lower altitudes, the climate is semi-arid; high altitudes are cold and semi-arid (Ghorbani et al. 2013). Despite considerable anthropogenic effects, plant species diversity is high; some plants, such as *Artemisia melanolepis* Boiss, and *Nepeta menthoides* Boiss and Buhse, are endemic to Iran; *Nepeta menthoides* Boiss and Buhse has been reported only in Iran's Sabalan mountain. Due to the high anthropogenic effects on the habitat of Sabalan more broadly, wildlife variation is low, particularly in unprotected areas. On the other hand, in the protected area (the Sabalan National Natural Monument), there is still a considerable variety of flora (more than 600 species) and fauna (more than 40 species). The wildlife includes birds such as *Tetraogallus caspiuscaspius*, and mammals such as *Ovis orientalis gmelini* and *Capra aegagrusaegagrus*; *Tetraogallus caspiuscaspius* and *Ovis orientalis gmelini* are of particular importance because they are found only on Sabalan mountain (Sheikh & Sheikh 2006).

Soil sampling

The study area is mountainous and has limited access only, by nomadic roads. Thus, it was impossible to collect samples in a systematic grid format and some parts remained unsampled. Soil samples were therefore collected randomly, according to accessibility by road, from 151 sites (Figure 1). The criteria used in selecting sites for soil sample collection were that the sites had to be: (i) at least 1 000 m away from each other; (ii) in the natural rangelands; (iii) some distance from villages, cultivated land and recreational areas to avoid edge effects; (iv) representative of all landforms and soil types of the area in terms of elevation, slope and aspect. As the region is mountainous, samples were taken from a depth of 0 to 30 cm (the effective depth of plant roots; Ghorbani et al. 2013, 2015). In each site, a 100 m transect was established perpendicular to the main slope (for vegetation sampling for another study). Soil samples were collected from the start, middle and end of each transect and mixed together as one sample for each site. The position of each soil sample was recorded using GPS. Soil samples were transferred to the laboratory of the University of Mohaghegh Ardabili and prepared for analysis.

Measuring soil properties

Prior to analysis, all soil samples were air dried and hand-sieved through a 2 mm mesh to remove roots and other debris. pH, EC, OC, $CaCO_3$, absorbable K and P, and percentages of sand, silt and clay were measured according to standard procedures. pH and EC were measured using a pH meter and WTW (Bauer & Knorr 2004) respectively. OC was measured using the Blac-Valkly (Sato et al. 2014) method; $CaCO_3$ was measured by neutralization with acid and titration (Bitter et al. 2010); K and P were measured by ammonium acetate (Patel et al. 2014) and Olsen methods (Betencourt et al. 2012) respectively. The Baykas hydrometer (Kettler et al. 2001) method was used to determine soil texture in terms of sand, silt and clay, which were measured without separation.

Conventional statistical analyses

Descriptive statistics, including the mean, standard deviation, coefficient of variation, maximum, minimum, Kurtosis, Skewness and Kolmogov-Smirnov (K-S) tests, were performed for each of the soil variables measured. Descriptive statistical analyses were performed using the SPSS16.0 software package (SPSS Inc., USA).

Spatial statistics of estimated soil properties

Spatial statistical methods were used to study spatial variability of soil properties. The semivariograms were calculated from the data, and fitted models were derived for the properties of each soil sample. In the second stage, predictions were made for the unsampled locations. The semivariogram of each soil property was constructed using equation (model) 1:

$$\gamma(h) = 1/2N(h)\sum_i \sum_{i+h}[z(i) - z(i+h]^2 \tag{1}$$

where γ is the semi-variance for N data pairs separated by a distance lag h, and z is the variable under consideration at positions *i* and *i+h*. As semivariogram construction assumes a Gaussian distribution (Reimann & Filzmoser 2000; Olea 2006; Wang et al. 2015), variables were transformed if necessary to approximate normality and stabilize variance (Goovaerts 1999; Wang et al. 2015). Data was detrended by fitting low-order polynomials according to the exhibited trend (if existent) to account for any systematic variation (i. e. global trend) and hence satisfy the assumption of stationarity (Bekele & Hudnall 2006; Sauer et al. 2006; Wang et al. 2015). Thus, after detrending, particular residuals were used to determine standardized isotropic semivariograms in the soil sample from each location. Therefore, according to the distribution of the collected samples, anisotropy (the effect of direction on the intensity of spatial dependence) was not considered in the interpretation, as such an analysis would have required a higher number of samples in each direction in order to build a stable semivariogram. Isotropic characterization of spatial dependence is reportedly more suitable when there are only a small number of samples (Davidson & Csillag 2003). After the semivariograms had been constructed, theoretical semivariogram models were fitted to the data, by selecting the model with the lowest residual sum of squares and highest R^2 (e. g. Wei et al. 2008; Liu et al. 2009; Wang et al. 2009). In these models, C_o is the nugget, C_o+C is the sill, and *a* is the range. These parameters were used to describe and compare the spatial structure of soil properties. Soil variables were then interpolated using IDW, Kriging and Cokriging methods.

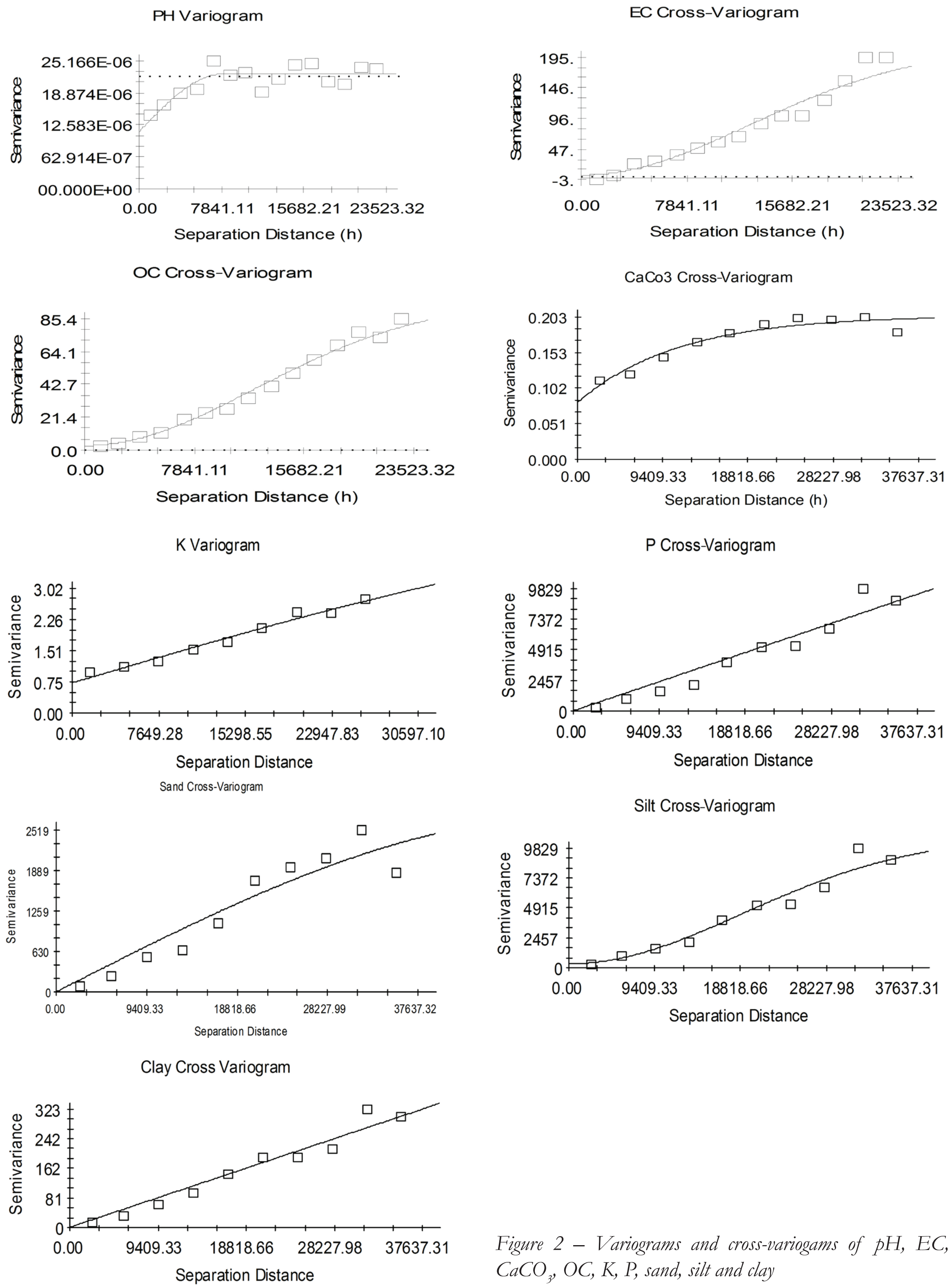


Figure 2 – Variograms and cross-variogams of pH, EC, $CaCO_3$, OC, K, P, sand, silt and clay

Based on minimization of the sum of the squared deviations between experimental and theoretical semi-variograms, a spherical model (equation 2), an exponential model (equation 3), and a Gaussian model (equation 4) were selected for the further investigation of spatial structure:

$$\gamma(h) = C_0 + C_1 \left(\frac{3h}{2a} - \frac{h^3}{2a^3}\right) for h \leq a = C_o + C_1 for h \geq a \quad (2)$$

$$\gamma(h) = 0 \, for h = 0 = C_0 + C_1 \left(1 - e^{\frac{-h^2}{a^2}}\right) for h > a \quad (3)$$

$$\gamma(h) = 0 \, for h = 0 = C_0 + C_1 \left(1 - e^{\frac{-h^2}{a^2}}\right) for h > 0 \quad (4)$$

Table 1 – Descriptive statistics for soil properties.

Soil properties	Mean	Median	SD	Variance	Skewness	Kurtosis	CV
pH	7.76	7.75	0.27	0.07	1.04	7.97	0.27
EC (ds/m)	0.25	0.20	0.26	0.06	5.46	34.70	0.29
OC (%)	1.32	1.15	0.80	0.64	0.94	3.43	0.60
$CaCO_3$ (%)	9.68	8.20	7.99	63.84	1.30	4.67	0.82
K (mg/kg)	351.40	274.68	254.00	63862.00	2.60	13.11	0.71
P (mg/kg)	0.31	2.37	833.00	53.14	50.00	28.85	0.54
Sand (%)	0.20	2.60	160.00	44.17	42.65	12.63	0.28
Silt (%)	45.32	45.32	14.94	223.20	0.17	1.94	0.32
Clay (%)	10.33	6.01	8.74	76.38	2.78	13.00	0.84

Table 2 – The parameters of the semivariogram models.

Soil properties	Model	C_0	$C+C_0$	Range [m]	$C/(C+C_0)$	R^2	RSS
pH	Exponential	0.06	0.11	33980	0.50	0.76	0.04
EC (ds/m)	Gaussian	4.70	210.00	30570	0.97	0.95	0.00
OC (%)	Gaussian	2.90	96.80	29860	0.97	0.98	0.33
$CaCO_3$ (%)	Exponential	0.08	0.20	11190	0.60	0.92	0.00
K (mg/kg)	Spherical	0.73	4.27	66150	0.82	0.97	0.06
P (mg/kg)	linear	10.00	10130.00	40740	0.99	0.95	0.00
Sand (%)	Spherical	1.00	2721.00	53470	1.00	0.91	0.80
Silt (%)	Gaussian	320.00	10750.00	26860	0.97	0.95	0.00
Clay (%)	linear	1.00	399.00	46520	0.99	0.96	0.00

where h is lag distance, C_0 the nugget effect (the local variation occurring at scales finer than the sampling interval, or fine-scale variability, measurement or sampling error), $C_0 + C_1$ is the total variance, and a is the range of spatial dependence.

Continuous maps of individual attributes were generated by point Kriging without drift, which estimates values of points at the grid nodes (Candela et al. 1988). Construction of semivariograms and model fitting were performed in GS$^+$ version 5 (Gamma Design Software, USA); ArcGIS10.2 (ESRI, ArcGIS Desktop, USA) geostatistical analyst tool was used for interpolation and mapping.

Assessment of the accuracy of predictions

Cross-validation was used to test the accuracy of the maps produced, and MAE (equation 5), MBE (equation 6) and RMSE (equation 7) were used to measure the accuracy (Wang et al. 2015). The mean absolute error (MAE) is a useful measure widely used in model evaluations (Elshorbagy et al. 2010). Elshorbagy et al. reported that the root mean square error (RMSE) is used as a standard statistical metric to measure model performance in meteorology, air quality, climatic and soil studies. Furthermore, they reported that while MAE gives the same weight to all errors, RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. In addition, MBE is a measure of overall bias error or systematic error and is usually written as a percentage error.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|O_i - P_i\right| \quad (5)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(O_i - P_i\right) \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(O_i - P_i\right)^2}{N}} \quad (7)$$

where N represents the number of instances presented to the model; Oi and Pi represent observed and predicted equals; and O and P represent the means of the corresponding variables.

Results and discussion

Analysis of descriptive statistics

Descriptive statistics, including mean, median, standard deviation (SD), variance, skewness, kurtosis and coefficient of variation (CV) for soil properties, are presented in Table 1. Most of the soil properties did not have a normal distribution; exceptions were P and percentage of sand. Since the deviation from the normal distribution may have an undesirable effect on statistical analysis, especially in semivariogram computation, this study applied several normalization functions, and the inverse method was then used for normalization of silt, $CaCO_3$ and K using a logarithmic converter, amount of soil OC using square root, clay content, EC and pH.

Results of spatial statistical analysis

The results of semivariogram analysis for soil parameters showed that with normal distribution of samples, error rate reduced and solidarity and precision increased. As presented in Table 2 and Figure 2, a semivariogram of all parameters was derived as isotropic or independent of direction. Different soil variables followed different variogam models. For example, $CaCO_3$ and pH conformed to an exponential model, while EC, OC and silt conformed to a Gaussian model. The same results are reported in Cobo et al. (2010), in which soil properties clay, silt, sand and pH were very well represented by spherical modelling, with variable parameters depending on the property and the area under evaluation. Moreover, Bitencourt et al. (2016) reported that physical properties of soil, including sand, clay and silt, followed the Gaussian model. Results of the spatial properties examined in this case also imply that most soil variables have strong spatial correlation, with the exception of pH and $CaCO_3$, which have moderate spatial structure. Based on the results of semivariogram elements, it was observed that K, with 66150 m, had the maximum impact domain, and $CaCO_3$, with 11190 m, had the smallest impact domain among the elements studied (Table 2). The corresponding results in Cobo et al. (2010), for the smallest and largest impact ranges, were for sand (506 m) and clay (695 m) respectively, which were very low in comparison to our results. If we look at the range of K (66150 m), it can be concluded that the spatial structure of this parameter, in comparison with that of other elements (e.g. lag distance), was much larger. This makes it possible to select greater values for the various elements, reducing the number of actual samples required, to estimate unsampled locations. Moreover, in the design of the sampling network for this parameter, it was possible to increase the sampling intervals.

Selection of the best model

After processing the appropriate model and extracting semivariograms from the data, the best interpolation method based on RMSE was selected. For pH and EC, a Simple Kriging interpolation method was selected; for OC, Disjunctive Cokriging; for $CaCO_3$, K, silt and clay, Ordinary Cokriging; and for P and sand Indicator, Cokriging (see Tables 3 and 4). According to metrics such as MAE and RMSE, the Cokriging method had a lower error rate than Kriging. This could reflect the fact that the spatial distribution of soil properties was highly correlated with elevation, which tends to reduce variance estimation. Yanl et al. (2007) compared the Cokriging and Kriging methods for improved prediction and reduction of sampling density for soil salinity. They reported that, in all cases, the RMSE of the Cokriging estimation was significantly lower than for the Kriging estimation. Bameri et al. (2015) also report lower RMSE for Ordinary Cokriging in estimating OC using clay content as the covariant. This gave better results over the whole slope in comparison with the Kriging and IDW methods. In our study, using covariates such as elevation, which was highly correlated with the main variable (Ghorbani et al. 2015), resulted in an increase in accuracy in interpolation. Thus, for the prediction of soil properties (except pH), in order to convert the point data to an area, we recommend the use of auxiliary variables that are highly correlated with the main variables, such as elevation.

Spatial distribution of soil properties

Figure 3 shows interpolated maps for soil variables based on the best derived models and methods. According to map 3a, which was produced using Simple Kriging, the average pH in the study area was 7.76 (Table 1). North and south of the area had higher estimates for pH (7.97–8.80). EC, in the entire area of study, was less than 0.61 ds / m (Figure 3b). Based on these results, there was a relationship between soil OC and elevation.

Figure 3c shows the map produced using discrete Cokriging for OC. The north and northwestern areas showed unexpectedly high OC content because in other areas rangeland vegetation cover in comparison was high (Ghorbani et al. 2013, 2014, 2015). In contrast, the samples taken at lower altitudes and in areas degraded by grazing showed lower soil OC. It seems that at higher elevations, reduced temperature and increased humidity led to a reduction in the decomposition of litter, causing an accumulation of OC (Franzluebbers 2002).

Table 3 – Results of interpolation methods for soil properties, showing the best model for each parameter.

Soil properties	Method type	Lag size	Model type	RMSE
pH	Simple Kriging	2 000	Exponential	0.00
EC (ds / m)	Simple Cokriging	1 500	Gaussian	1.36
OC (%)	Disjunctive Cokriging	1 000	Gaussian	0.27
$CaCO_3$ (%)	Ordinary Cokriging	1 500	Gaussian	0.36
K (mg / kg)	Ordinary Kriging	1 500	Gaussian	0.23
P (mg / kg)	Indicator Cokriging	1 000	Exponential	0.49
Sand (%)	Indicator Cokriging	1 800	Exponential	0.45
Silt (%)	Ordinary Cokriging	2 000	Gaussian	0.13
Clay (%)	Ordinary Cokriging	1 500	Gaussian	0.06

Table 4 – Results of accuracy assessment of the various interpolation methods.

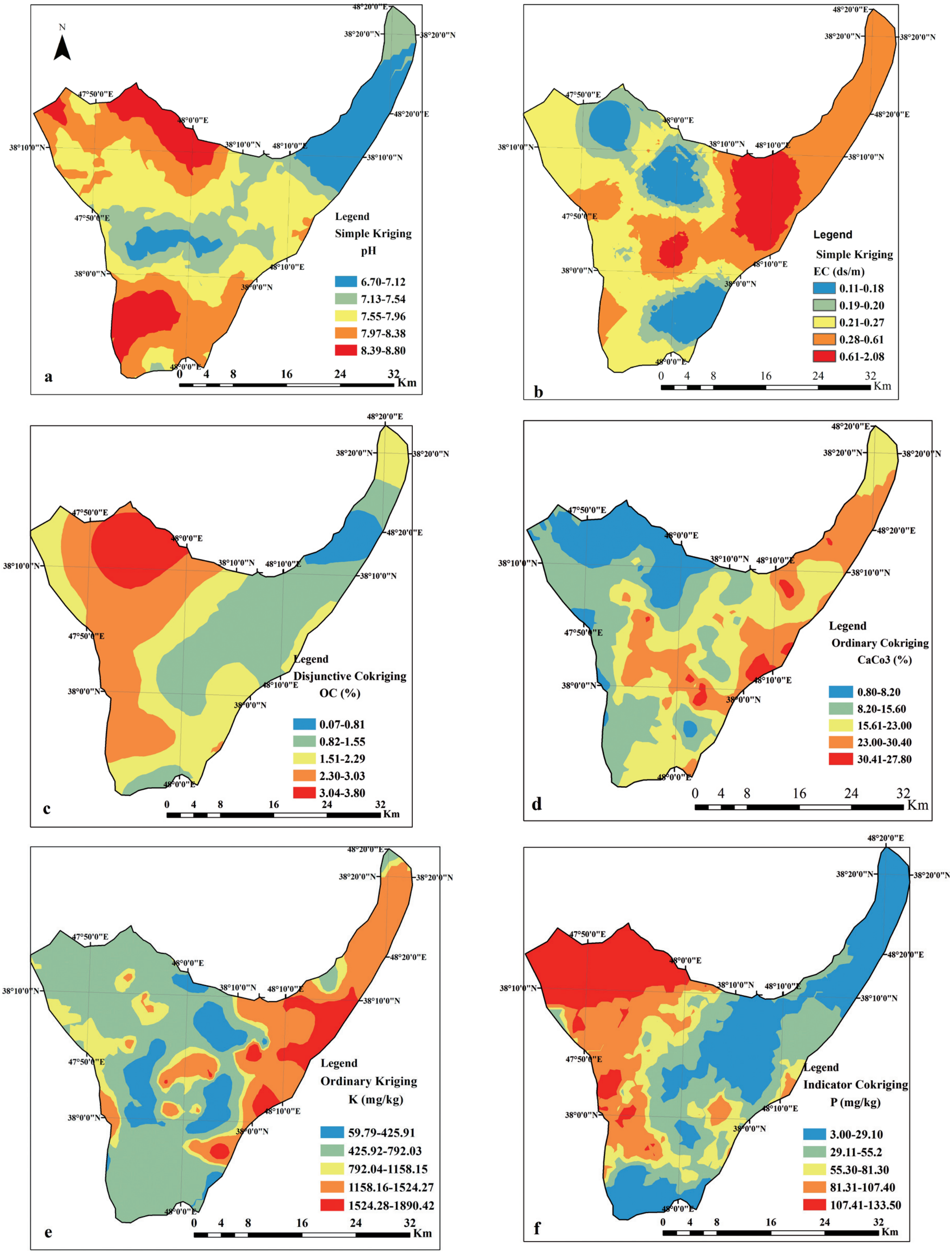
Soil properties	Method type	MBE	MAE	RMSE
pH	Simple Kriging	0.00	0.00	0.00
EC (ds/m)	Simple Cokriging	0.06	0.07	0.25
OC (%)	Disjunctive Cokriging	−0.04	0.22	0.27
$CaCO_3$ (%)	Ordinary Cokriging	0.18	0.27	0.36
K (mg / kg)	Ordinary Kriging	−0.03	0.11	0.23
P (mg / kg)	Indicator Cokriging	5.90	21.74	0.49
Sand (%)	Indicator Cokriging	6.12	10.75	11.34
Silt (%)	Ordinary Cokriging	0.04	0.11	0.13
Clay (%)	Ordinary Cokriging	0.00	0.04	0.06

The interpolated map (Figure 3d) of Ordinary Cokriging showed that the $CaCO_3$ in the area did not have a random pattern, and was affected by elevation. Thus, the lowest amount of $CaCO_3$ (0.8–15.6%) was mapped in the south and southeast at lower elevations. It seems that destructive activities such as overgrazing carried out in steep mountainous areas caused increased erosion and leaching into the soil, increased dissolution of limestone, and ultimately increased $CaCO_3$ percentage in soil at lower altitudes.

Figure 3e shows the map for K content produced using the Ordinary Kriging method. The central and northeastern areas had higher amounts of K. Evaluation in the rangeland areas located below 2 500 m a.s.l. may have been affected by changes such as dry farming, planting of high-yield varieties, and use of groundwater rather than surface water; these considerations may need further investigation. There was a radical change in P availability in the area.

As seen in Figure 3f, the northern part of the area had higher levels of P. Since rangeland vegetation in the mid-highland areas had dense cover, and absorbed P from different layers of the soil, phosphorus accumulated at the soil surface after the destruction of the soil layers. Moreover, there were increasing amounts of P in the northeastern part of the study area.

Figure 3g shows a map of sand evaluations and their variation. In the northern parts of the study area, as expected, high altitude rangeland had low soil depth, high slope and rocky outcrops in comparison with the lowland areas, which had deeper soil, and


a
Legend
Simple Kriging
pH
6.70-7.12
7.13-7.54
7.55-7.96
7.97-8.38
8.39-8.80
b
Legend
Simple Kriging
EC (ds/m)
0.11-0.18
0.19-0.20
0.21-0.27
0.28-0.61
0.61-2.08
c
Legend
Disjunctive Cokriging
OC (%)
0.07-0.81
0.82-1.55
1.51-2.29
2.30-3.03
3.04-3.80
d
Legend
Ordinary Cokriging
CaCo3 (%)
0.80-8.20
8.20-15.60
15.61-23.00
23.00-30.40
30.41-27.80
e
Legend
Ordinary Kriging
K (mg/kg)
59.79-425.91
425.92-792.03
792.04-1158.15
1158.16-1524.27
1524.28-1890.42
f
Legend
Indicator Cokriging
P (mg/kg)
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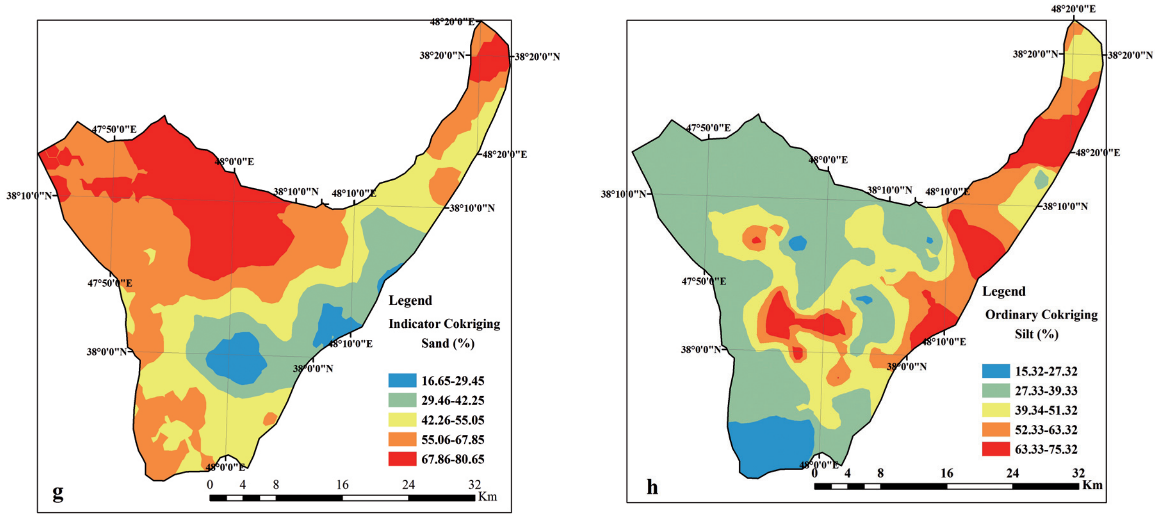
29.11-55.2
55.30-81.30
81.31-107.40
107.41-133.50
0 4 8 16 24 32 Km



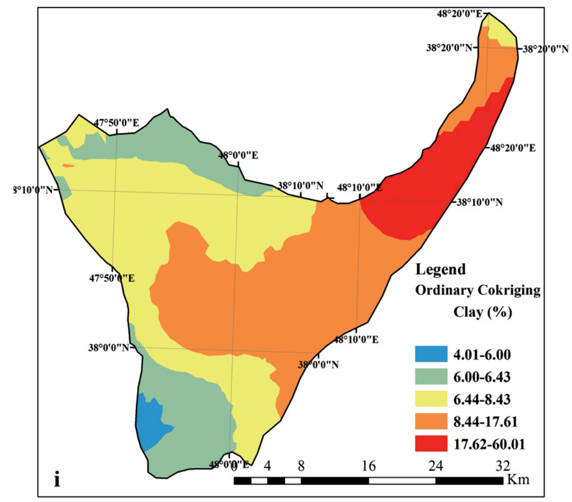


Figure 3 – Spatial distributions of soil properties; a) pH, b) EC, c) OC, d) $CaCO_3$, e) K, f) P, g) sand, h) silt, i) clay.

shallow slope in the south and east, which showed lower amounts of sand in the soil contents.

The spatial distribution of silt was almost the opposite of the OC distribution (Figure 3h). Mapping showed that where silt occurred, it did so in higher concentrations in the southeast, although overall this area had relatively little silt. In contrast, the percentage of silt was higher towards the north and west, in the steeper areas, as was expected because of the shallow soil and the low outcrops.

Figure 3i shows the map for clay content, which was as expected. However, the percentage of clay particles was lower towards the western areas.

Application of results: emphasis on protected area

Ecosystems, including rangelands and protected areas, require constant monitoring (Zinck 1995; Várallyayet et al. 1998; Hockings 2009), and soil maps are one of the basic sources of information in this regard (Webster & Oliver 2000). Monitoring natural ecosystems and protected areas is necessary for the collection of reliable physical data, such as certain soil types and special soil features relating to broad geographical areas (e.g. natural rangelands), or smaller land units (such as protected areas). The availability of such information helps in the conservation, management and monitoring of biological and physical features of regions or land units (Alberta Natural Heritage Information Centre 2002).

Providing reliable physical data can enhance decision-making related to resource- and / or land-use. Data must be collected to help evaluate an area's biodiversity, such as presence, distribution, status and trends of plant species, and which species are at risk and to what extent. The impact of human activities also needs to be determined (Alberta Natural Heritage Information Centre 2002). Producing detailed information such as soil maps based on conventional methods is time-consuming but cost effective, particularly when these maps need to be produced every 5 to 10 years for monitoring purposes. Semi-automated methods are therefore needed to produce detailed soil information maps, including for the whole of Iran, and in particular for natural environments and protected areas such as Sabalan mountain and Sabalan National Natural Monument (Ghorbani et al. 2013, 2014, 2015). The results of this study provide basic information of interest for various fields of study, such as quantitative vegetation studies and ecotourism development planning. Moreover, this study presents a method that can be applied to soil parameter mapping in other rangelands and protected areas.

Conclusion

We conducted this study in order to help overcome the need for relatively low-cost, detailed information. This study compared interpolation methods to determine the spatial distribution of soil properties, including pH, EC, OC, $CaCO_3$, K, P, sand, silt and clay, on the southeastern slope of Sabalan mountain rangelands and at the Sabalan National Natural Landmark. Selection of the best interpolation method and accurately predicting soil property maps can help range management to conserve and restore the rangeland, and can be instrumental in identifying new areas to be protected and monitoring them.

The maps produced can be used to locate the distribution of soil properties and improve sampling design. Based on the results of the interpolation methods for soil variables, the Kriging method was found to be the best predictor for pH and K; the Cokriging method was more suitable for other variables. Comparison among the Cokriging, Kriging and IDW methods showed that Cokriging produced more reliable results. In other words, although the application of the Kriging method in this study presented acceptable predictions, Cokriging increased the accuracy of the maps. This could reflect the fact that the spatial distribution evaluations for individual soil properties were highly correlated with elevation, which tends to reduce the variance of the predictions. Mapping the variables showed that pH, EC and OC was effective in enhancing management efficiency.

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