Original Research

Comparison of Different Geostatistical Methods for Soil Mapping Using Remote Sensing and Environmental Variables in Poshtkouh Rangelands, Iran

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Abstract

The aims of this study were: 1) to map the different soil parameters using three geostatistical approaches, including; ordinary kriging (OK), cokriging (CK), and regression kriging (RK), 2) to compare the accuracy of maps created by the mentioned methods, and 3) to evaluate the efficiency of using ancillary data such as satellite images, elevation, precipitation, and slope to improve the accuracy of estimations. In the rangelands of the Poushtkouh area of central Iran, 112 soil samples were collected. The maps of different soil parameters were created using the mentioned methods. To assess the accuracy of these maps, cross-validation analyses were conducted. The cross-validation results were assessed by the root mean square error (RMSE) and normal QQ-plot together with sum and average error to suggest the best estimation approach for mapping each soil parameter. The results have shown that, in most cases, taking the ancillary data into account in estimations has increased the accuracy of the created maps. Except for clay, the OK method was suggested as the best estimation method, and the RK and CK were the best recommended estimation methods for the rest of the parameters. The results suggest the application of the framework of this study for similar areas.

Keywords: ordinary kriging, cokriging, regression kriging, soil parameters, ancillary data

Introduction

The quality, quantity and type of vegetation in arid rangelands are usually affected by soil properties. Since soil mapping is a critical step in landscape ecology and rangelands rehabilitation, there is an increasing need to measure and map soil properties in natural ecosystems [1-5].

Geostatistics and remote sensing are among the tools that have been successfully used for soil mapping on a large scale [6-8]. Geostatistical approaches in which environmental variables and remote sensing data correlations are taken into account have become increasingly popular. This is because of employing secondary information that is often available at finer spatial resolution than that of the sampled target variable. Such techniques generally generate more accurate results than those of the univariate methods (for example

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ordinary kriging) when the correlation between primary and secondary variables is significant [9-12]. The application of hybrid methods for soil mapping has represented considerable success in several documented studies [13-16].

Several ancillary data can be used for digital soil mapping. Digital elevation model (DEM), slope, precipitation, remotely sensed images, and measured soil properties are potential ancillary data for such applications [8, 15, 17, 18]. It should be evaluated which ancillary data increase the estimation accuracy of a primary variable at unsampled locations in each study area [15].

Examples of geostatistical hybrid methods that account for environmental correlation are cokriging and regression kriging [9, 11, 19]. The difference among these methods is in the assumptions of the way that the primary and ancillary data are related and how the estimation of primary data is inferred from the secondary data [8, 9]. Various studies have proven the existence of spatial correlation in different soil parameters [1, 7, 11, 20, 21].

The main purposes of this research were:

1) Mapping different soil parameters using three geostatistical approaches (OK, CK, and RK).
2) Evaluating the benefits of using ancillary data such as satellite images, elevation, precipitation, and slope in improving the accuracy of estimation maps.
3) Comparing the accuracy of the maps created by the mentioned approaches.

Materials and Methods

Study Area

This research was conducted in the Poshtkouh rangelands on the southern slopes of the Shirkouh mountains of Yazd province in central Iran (31º33′ 1″ N, 53º40′06″ E - 31º04′27″ N, 54º15′19″ E). Fig. 1 displays the general location of the study area, which is characterized by very diverse terrain conditions. The maximum elevation of the region is 3,990 m and the minimum elevation is 1,400 m. Thus, average annual precipitation is about 300 mm in Shirkouh Mountain in the northern part of the study region, whereas in the margin of Kavir-e-Abarkouh (in the southern part of the region) it decreases to 45 mm. Similarly, average annual temperature shows large differences in the study region ranging from 17.1 in the southern part to 10.8ºC in the northern part, with absolute minimum and maximum temperatures of 0.2 and 29.4ºC.

Soil and Landscape

Soil Classification and Landscape

This area has five dominant physiographic units: mountain, alluvial fans, plateaux, piedmont plain, and low land. The geology of the mountain is granite, reddish limestone, conglomerate, and marl. Alluvial fans, plateaux, and piedmont plain are developed on alluvial deposits of quaternary. Low land has a salty clay flat foundation.

As mentioned before (study area) the environmental variables such as elevation, precipitation, and temperature have a high variability in the study area, causing a high spatial variability of soil classes and properties in the region. According to the soil taxonomy [22], the soil moisture regimes of the area are aridic and aquic, and temperature regime of the area is thermic. The taxonomic classification [22] of the major soils found in the study area respectively identified Entisols and Aridisols as the smallest and largest in relative abundance. Entisols are located in the mountain physiographic unit of the study area. Typic Torriorthents are the dominant soil in this unit. Aridisols contain several soils, which are Typic Calcigypsids, Typic Haplocalcids and Typic Aquisalids. Typic Calcigypsids and Typic Haplocalcids are the dominant soils that have developed in plateaux and piedmont plain units, whereas Typic Aquisalids are located in the lower part of the region, called low land or playa. Alluvial fans have a complex soil that include Typic Torriorthents and Typic Calcigypsids. As expected, the soils that have formed in the upper part of the region have a high content of gravel and sand, whereas the soils in the lower part of the study area have high clay and salt content.

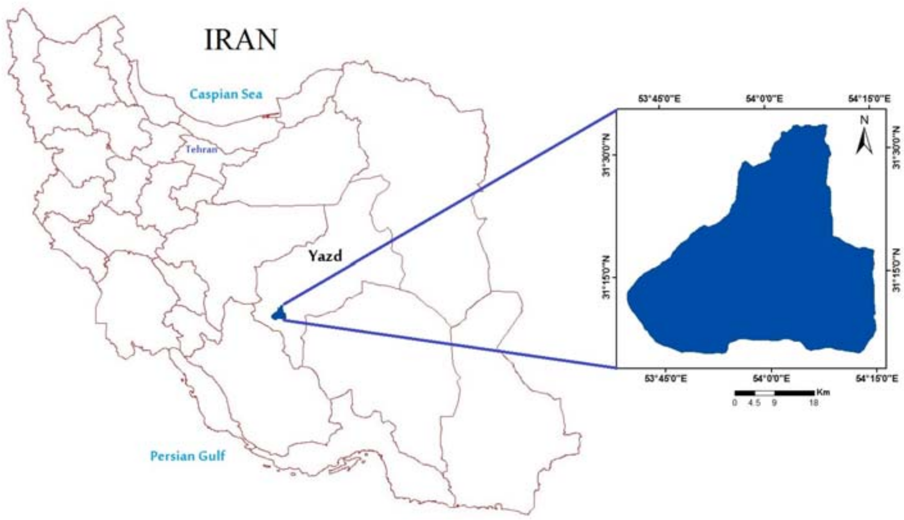


Fig. 1. General location of the study area.

Table 1. Descriptive statistics of soil parameters.

Descriptive statistics \ Soil parameter	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Min	0.20	6.2	0.1	0	0	26.40	0.42
Max	15.12	30.5	136.32	28.65	4.19	88.80	46.35
Mean	3.38	13.57	11.64	11.67	.570	71.67	14.36
Std. Deviation	2.84	6.02	26.87	5.9	1.16	14.34	10.72
Variance	8.07	36.27	722.28	34.88	1.35	205.91	115.06

Soil Data Collection and Examination

In order to take samples from homogeneous units, hypsometric, aspect, slope, and geologic maps were overlaid. Then 3-5 parallel transects of 300-500 m length were located in each unit. A total of 112 soil samples were collected at 0-30 cm depth (Fig. 2). In the next step, all of the required soil parameters such as available moisture (AM), clay, electrical conductivity (EC), gravel, gypsum (Gyps), sand, and lime were measured in soil laboratory.

Ancillary Data

In this study, satellite images (Landsat ETM+) and some environmental variables (e.g. elevation, slope, and precipitation together with soil parameters) were used as ancillary data. ETM+ images contained three visible bands (blue, green, and red), one near the infrared band, two shortwave infrared bands (MIR-1 and MIR-2), a thermal infrared band, and a panchromatic band. Using digital topographic maps, the images were geo-referenced. Then, digital number (DN) values converted to reflectance. In the next step, the normalized difference vegetation index (NDVI) was calculated based on red and near infrared bands. The NDVI was added as an additional band to the bands set. All of the remote sensing analyses were done in ENVI 4.8. The digital elevation model (DEM) and slope map of the study area were created by the means of digital topographic maps with scale of 1:10,000 in Arc GIS 10. Based on climatic data of the study area, a precipitation map was created using the cokriging method in combination with the DEM as the secondary variable.

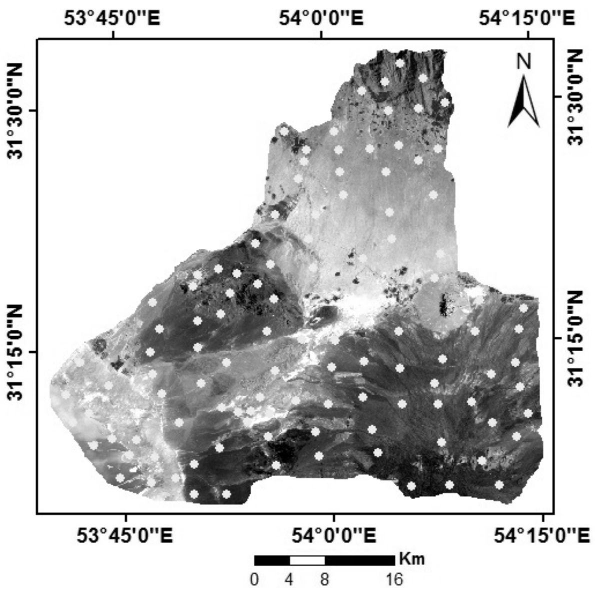


Fig. 2. Location of sample points in the study area.

Descriptive Statistics

The descriptive statistical evaluation is an important step prior to any geostatistical analysis. One of the essential univariate statistics is variance, which is usually applied in estimating the semivariogram sills. It is especially important in recognizing the existence of any considerable trend in each variable when the semivariogram is consistently exceeding the predicted sill.

Bivariate statistical analysis, as the next step, is usual to distinguish the integration capability of secondary data in estimation problems. Among bivariate analyses, regression and correlation analyses have become popular to quantify the relationship between soil parameters and other environmental variables. Regression technique is a useful means to select the variables correlated with soil parameters. The SPSS statistical software can be used for this purpose. In the stepwise regression the best combination of ancillary variables which give the highest R^2 and acceptable significance level would be selected.

In order to use ancillary variables for soil parameters mapping, the following process was done:

- Using the geographic information system, data set of each soil parameter was combined with the ancillary variables of the field samples. Then, the pixel values of the related points were extracted.
- To prepare data for statistical analysis, a matrix was constructed. In this matrix, the X- and Y-coordinates were recorded in the first two columns. The measured soil parameter values were placed in the next columns, and the different ancillary data of pixel values were put in the remaining columns. The rows of the matrix represent the number of sample points. This is in accordance with the method used by Eldeiry and Garcia [7].
- Pearson correlation coefficient was used to identify the correlation coefficient between the measured soil parameters and ancillary data (Table 1), which should be used in cokriging.

Table 2. Parameters of semivariogram analysis for soil parameters.

Soil parameter	Semivariogram model	Nugget effect (C_0)	Sill (C_0+C)	Structured part-to-sill ratio (C/[C_0+C])	Effective Range
AM	Spherical	0.01	7.22	0.99	19770
Clay	Spherical	0.1	35.1	0.99	21420
EC	Exponential	1	587.50	0.99	20400
Gravel	Spherical	0.01	31.26	1	18090
Gyps	Spherical	0.001	1.18	0.99	25950
Sand	Spherical	105	620	0.83	94600
Lime	Spherical	21.30	243.50	0.91	97920

C_0 – Nugget effect, C – Structured part of the semivariogram (=sill-C_0)

- To select suitable parameters and model for predicting and mapping the soil parameters, the simple and the stepwise regression were applied. Finally, regression models that had the highest correlation with the measured soil parameters data were selected to be used in the regression kriging.

SPSS and Excel software were used for the mentioned statistical analysis.

Geostatistical Analyses

Geostatistical analyses have been conducted in three stages of variography, model evaluation, and estimations. A more comprehensive explanation about each step comes below.

Variography

Semivariogram is one of the most essential tools in geostatistical analyses to quantify and model the spatial variability degree of data. These models can later be used to make estimations using kriging, cokriging, etc.

The experimental semivariogram ($\gamma^*(h)$) for a regionalized variable of Z can be defined as follows:

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} \left[Z(x_\alpha) - Z(x_\alpha + h)\right]^2 \quad (1)$$

...where $N(h)$ is the number pairs of data locations separated by the vector h [23].

To deduce the semivariogram values in all points and all directions and to smooth out the effects of fluctuations and ensure the positive definiteness property of semivariograms, analytical models should be fitted to the experimental (or sample) semivariograms.

This analysis of semivariogram behavior and fitting analytical model is termed variography [9, 23].

Stationarity is one of the most essential presumptions in geostatistical analyses. It implies that the statistics (such as mean, variance, and so on) are independent of the location of its calculation. Accordingly, the first- and second-order-moment rules should remain invariant.

In the cease of non-stationarity, in which the relevant statistical moments show a dependence on the location, a characteristic so-called trend exists in data-set.

One of the most practical tools to indicate the existence of a trend in a data-set is its semivariogram. The sample semivariogram and its theoretical sill should be plotted and the general behavior of the semivariogram plot relative to the theoretical sill should be evaluated. If the sample variogram increasingly exceeds the expected sill (σ^2), the existence of a trend can be inferred.

In this study, using semivariogram analyses, spatial variability structure of each attribute was determined and proper semivariogram models (e.g., spherical, Gaussian, exponential) were fitted (Table 2).

The mentioned analyses were conducted using ArcGIS 10, and GS+ 5.1.1 software.

Model Evaluation or Accuracy Assessment:

To ensure that the variogram models being applied in the estimation stages are reliable and appropriate, the variogram models have to be validated first. The validation of the variogram models was done using the cross-validation technique.

Cross-validation is a “leave-one-out” technique in which each sample (with the known variable) is omitted once and its value is estimated using the rest of the samples with different semivariogram models and parameters [14].

In order to evaluate the cross validation results, in the first step, scatter plots of measured vs. estimated were evaluated. Then, root mean square error (RMSE), sum errors, average errors, and QQ-plots of cross-validations were simultaneously applied to decide about the best estimation method.

Each of the above-mentioned criteria reflects a side of estimation accuracy. For example, RMSE can describe the distance between measured and estimated values. Furthermore, sum errors, average errors, and QQ-plots represent the normality of estimation errors distribution.

Estimation Methods

The kriging method is applied to estimate the values at unsampled locations by a weighted linear combination of

Table 3. Best regression equations between soil parameters and ancillary data.

Regression equation	R^2
AM = -7.58 × Band7 – 0.12 × Band62 + 0.22 × Clay + 1.14 × Gyps + 8.32	0.86
Clay = 15.8 × Band5 – 0.43 × Gravel + 1.17 × AW + 9.91	0.67
EC = 229.73 × Band4 – 283.82 × Band7 – 0.015 × Elevation + 3.26 × AW + 37.35	0.83
Gravel = -0.79 × Clay+22.46	0.78
Gyps = -6.98 × Band1 – 0.23 × Band61 – 0.002 × Elevation + 0.27 × AW + 12.77	0.84
Sand = -0.006 × Elevation – 0.23 × EC – 1.49 × Clay + 106.74	0.81
Lime = -0.22 × EC1 – 0.02 × Elevation + 64.88	0.59

nearby samples. The kriging equations guarantee the two main characteristics of unbiasedness and minimum errors in estimations. To achieve the mentioned weights for this estimation, semivariogram models are required [24]. Based on the variation of mean value, the kriging methods can be classified into several techniques such as ordinary kriging, simple kriging, and universal kriging.

Cokriging is an extension of kriging method in which the correlation between primary and secondary data is taken into account. The application of this method can enhance the quality of estimations.

In this study, three estimation approaches, including OK, CK, and RK, were applied.

Ordinary Kriging (OK)

In OK the mean value of regionalized variable is considered constant and unknown throughout the study area. The application of OK is proper when the stationarity condition is nearly fulfilled.

Cokriging (CK)

CK makes the estimations based on probable correlation between the variable of interest and other measured variables such as remote sensing and elevation data [13]. CK is among the useful techniques that can be used in estimation when both primary and secondary variables exist, and it has been used widely in soil science [25-27].

In the present research, the variables that represented the highest significant correlation coefficient with the variable of interest which generated the most accurate CK maps were selected as ancillary variables for the application in CK method. The RMSE was employed as the criteria to evaluate which CK map was the most accurate.

Regression Kriging

Regression kriging (RK) is an estimation method that makes use of the combination of a regression predictor (of a primary variable, using ancillary variables) with kriging of the regression residuals. The advantage of the RK method is using ancillary variables such as elevation and remote sensing data to improve the accuracy of estimation for primary variables. This method is equivalent to universal kriging and kriging with external drift, where ancillary predictors are used to estimate the means of the primary variable in kriging equations [15, 28]. It uses the ancillary data to characterize the spatial trend of the primary variable in a regression step before carrying out the simple kriging on the residuals and adding back the trend value to the estimation of residuals [9].

In this research, in order to perform RK, the regression analysis was performed to estimate the trend of primary variables and residuals. Then, simple kriging on the residuals was carried out. The final estimate of every soil variable was achieved by adding the approximated trend to the estimate of the residuals calculated by simple kriging [9, 29].

The estimation parameters such as cell size and number of neighboring data were the same for all of the methods (OK, CK, and RK) applied in this study.

Soil Texture Map

In rangeland management and landscape ecology, in addition to the aforementioned soil maps, soil texture map is also beneficial for different applications such as to investigate the relation between soil and vegetation as well as rehabilitation of the area. In this step, the created maps of clay and sand were integrated into the GIS environment to create the soil texture map. To do so, a script in ILWIS software was created and employed. The resulting map represents homogeneous soil texture units.

Results and Discussion

Prior to any geostatistical analysis, it is of vital importance to evaluate some general statistical characteristics of data, such as data distribution and variance. In addition, some characteristics of important measures such as semivariogram sills can be approximated by the variance of related data (σ^2). Table 3 represents some descriptive statistics of soil parameters. Based on the table, EC and Gyps demonstrate the highest and lowest variances, respectively. It is expected that across the study area these parameters would also represent the highest and lowest variations, respectively.

According to the discussion in the material and methods, the stationarity condition of data has been evaluated by examining the general behavior of the semivariograms relative to their theoretical sills. This evaluation does not reflect the existence of any considerable trend in the soil parameters (Fig. 3).

The spatial dependence of each soil attribute was modeled using analysis of semivariance. Parameters of semivariogram analysis for various soil attributes have been represented in Table 2.

In this stage, the quality of each semivariogram model was assessed and the model semivariogram parameters improved by cross-validation method and RMSE criterion for different estimation methods (OK, CK, and RK). The semivariogram interpretations have also been considered during this variography stage. Table 4 and Fig. 5 illustrate the cross-validation results.

Fig. 3 shows experimental semivariograms of each soil parameter and their corresponding models. Each variogram shows and evaluates the spatial structure of data.

One of the most essential considerations in semivariogram modeling is bearing in mind the semivariogram interpretation and the expert's knowledge and experience about the study area. Usually, there could be a big uncertainty in semivariogram modeling since the data from soil samples can rarely reflect the existing soil condition sufficiently. Hence, the linkage between the soil characteristics and the semivariogram behavior should be understood very

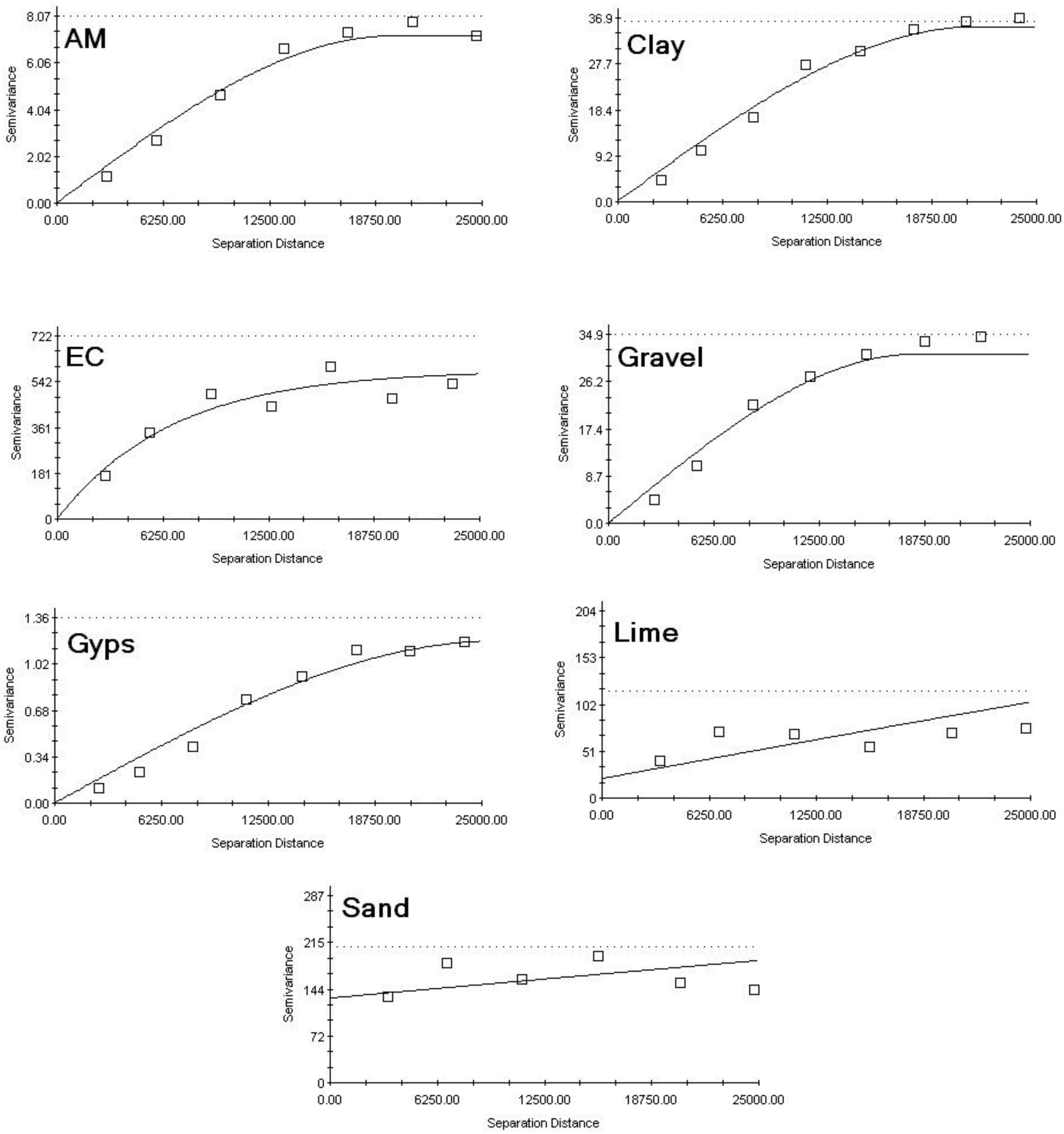


Fig. 3. Semivariogram of different soil parameters.

Table 4. Pearson correlations between target and secondary variables used in CK.

Target variable	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Secondary variable	Band1	AM	AM	Band2	Band1	Clay	Precipitation
Correlation coefficient	0.55*	0.82**	0.69**	0.62*	0.47**	0.87**	0.69**

*Statistically significant at $p > 0.05$, **Statistically significant at $p > 0.01$.

well before and during the semivariogram modeling by considering the parameters such as nugget effect, range, and anisotropy. Conversely, the semivariograms and their models can be employed to understand the behavior of the data structure.

It is clear in the semivariograms (Fig. 3) that all of the parameters have a spherical model except EC, which has an exponential model. The exponential model usually represents the quick variation in data. The field observations in this study and previous reports [30] from this area confirm this variability behavior of the EC.

The ratio of the structured part of the semivariogram to sill ($C/[C_0+C]$) was considered as a criterion to evaluate the strength of the spatial variability structure of each semivari-

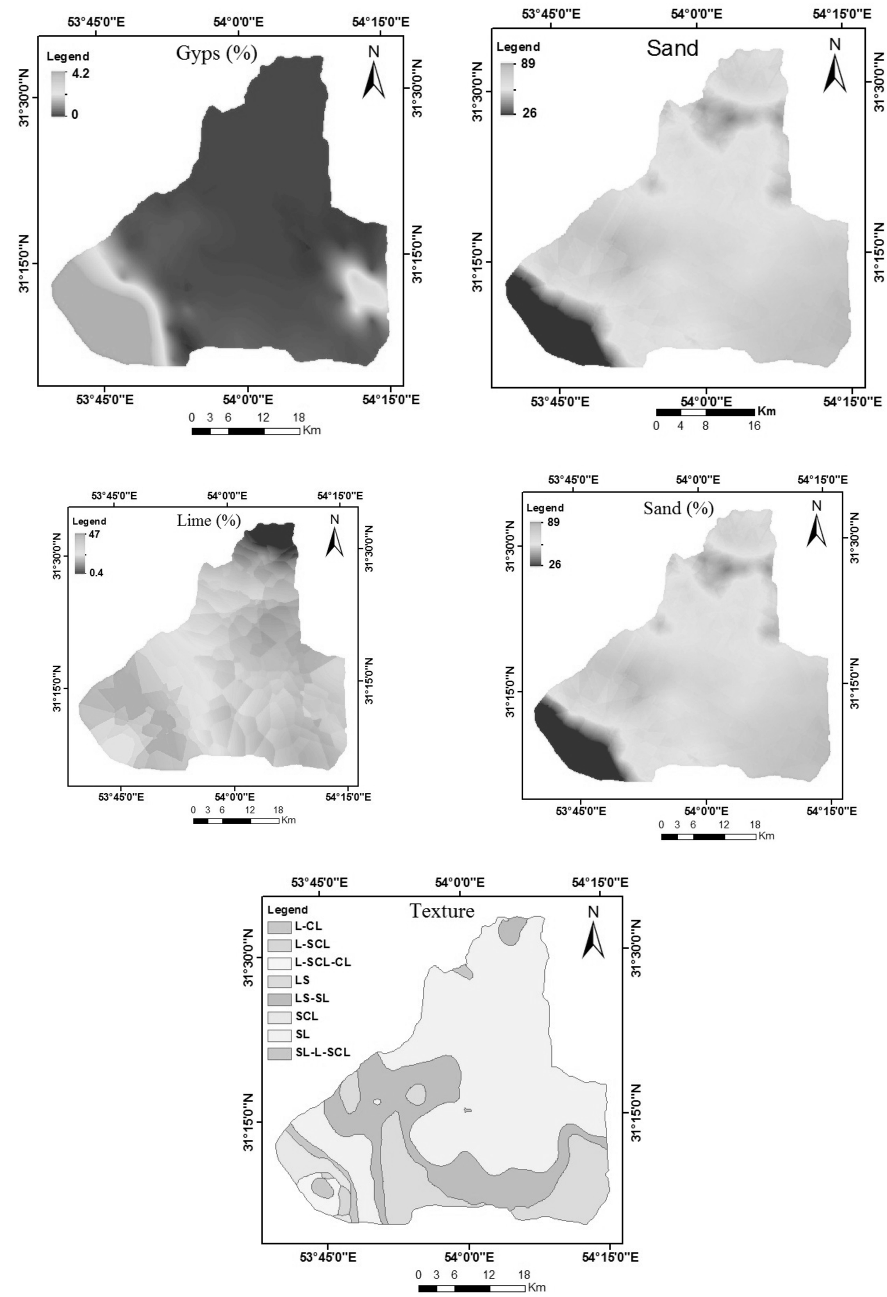


Fig. 4. Created maps of different soil parameters with highest accuracy.

Table 5. Error measure for the compared prediction methods.

Error measure	Soil parameter / Estimation method	AM	Clay	EC	Gravel	Gyps	Sand	Lime
RMSE	OK	0.89	2.38	11.40	1.96	0.34	12.73	7.59
	CK	0.74	1.85	11.47	1.8	0.33	9.32	7.22
	RK	0.92	1.72	14.29	1.12	0.38	5.90	6.32
Sum error	OK	1.20	3.18	20.59	-4.22	0.11	-10.66	1.15
	CK	0.70	4.55	21.92	-2.74	0.25	6.53	-2.47
	RK	-1.25	-6.54	5.33	3.20	1.77	-4.64	1.17
Average error	OK	0.01	0.02	0.18	-0.03	0.009	0.16	0.01
	CK	0.006	0.04	0.19	-0.02	0.002	0.10	-0.03
	RK	-0.01	-0.05	0.04	0.02	0.01	-0.007	0.01
	RK	6.32	5.90	0.38	1.12	14.29	1.72	0.92

Table 6. The suggested method for mapping each soil parameter based on different criteria.

Soil parameter / Suggested method based on	AM	Clay	EC	Gravel	Gyps	Sand	Lime
Only sum/average error	CK	OK	RK	CK	OK	RK	RK
Only RMSE	CK	RK	OK	RK	CK	RK	RK
Sum/average error, RMSE, and QQ-plot	CK	OK	RK	RK	CK	RK	RK

ogram. Hence, the bigger this ratio, the stronger the spatial autocorrelation of the variable. According to Table 2, most of the parameters have a similar structure-to-sill ratio. Based on this ratio, gravel has represented slightly a stronger spatial variability structure compared to the others.

Semivariograms of sand and lime have demonstrated the highest effective range among all soil parameters, showing the higher degree of continuity for these variables. Gravel semivariogram has the shortest effective range representing that the change of this parameter in very short-distance is higher than the others.

Among the investigated variables, the semivariogram models of sand and lime have represented the highest nugget effect. This might be interpreted as the existence of rather high spatial variations of Sand and Lime in very short distances (lower-than-average sample spacing) compared to those of the others.

Table 3 summarizes the best regression equations between soil target parameters and ancillary data. As can be seen from this table, most of the models have high R^2 values, demonstrating good prediction power of the regression model for related soil properties.

Referring to the table, EC, Gyps, and Lime have a negative relationship with elevation. This could be due to the fact that leaching causes the salts to move from highlands and mountainous areas to the lowlands. Consequently, the lower the elevation, the higher the concentration of salts. This feature also has been reflected in the corresponding estimation maps (Fig. 4).

The results of Pearson correlation coefficient were used to select proper secondary variables in CK analysis so that the selected variables (as secondary) had the highest significant correlation coefficient with the target variable. Among the mentioned secondary variables, the ones that produced the CK maps with the lowest RMSE were suggested to be used in estimation of the target variables using CK. Table 1 summarizes the selected variables for CK based on the mentioned method and the corresponding correlation coefficient with each target variable.

As the table shows, ancillary data are significantly correlated to the target variables. These significant correlations can suggest the ancillary data that could be cooperated in CK estimation to improve prediction accuracy.

Table 4 demonstrates the root mean square error (RMSE), along with the sum and average error for the compared prediction methods when estimating the soil parameters. As the table shows, the mentioned criteria for different soil parameters are different in different prediction approaches.

As mentioned in the material and methods, RMSE and QQ-plots (Fig. 6), together with the sum and average errors, were considered to suggest the best estimation methods (Tables 4 and 6). About AM, sand, and lime, all the aforementioned criteria suggest the same method as the best esti-

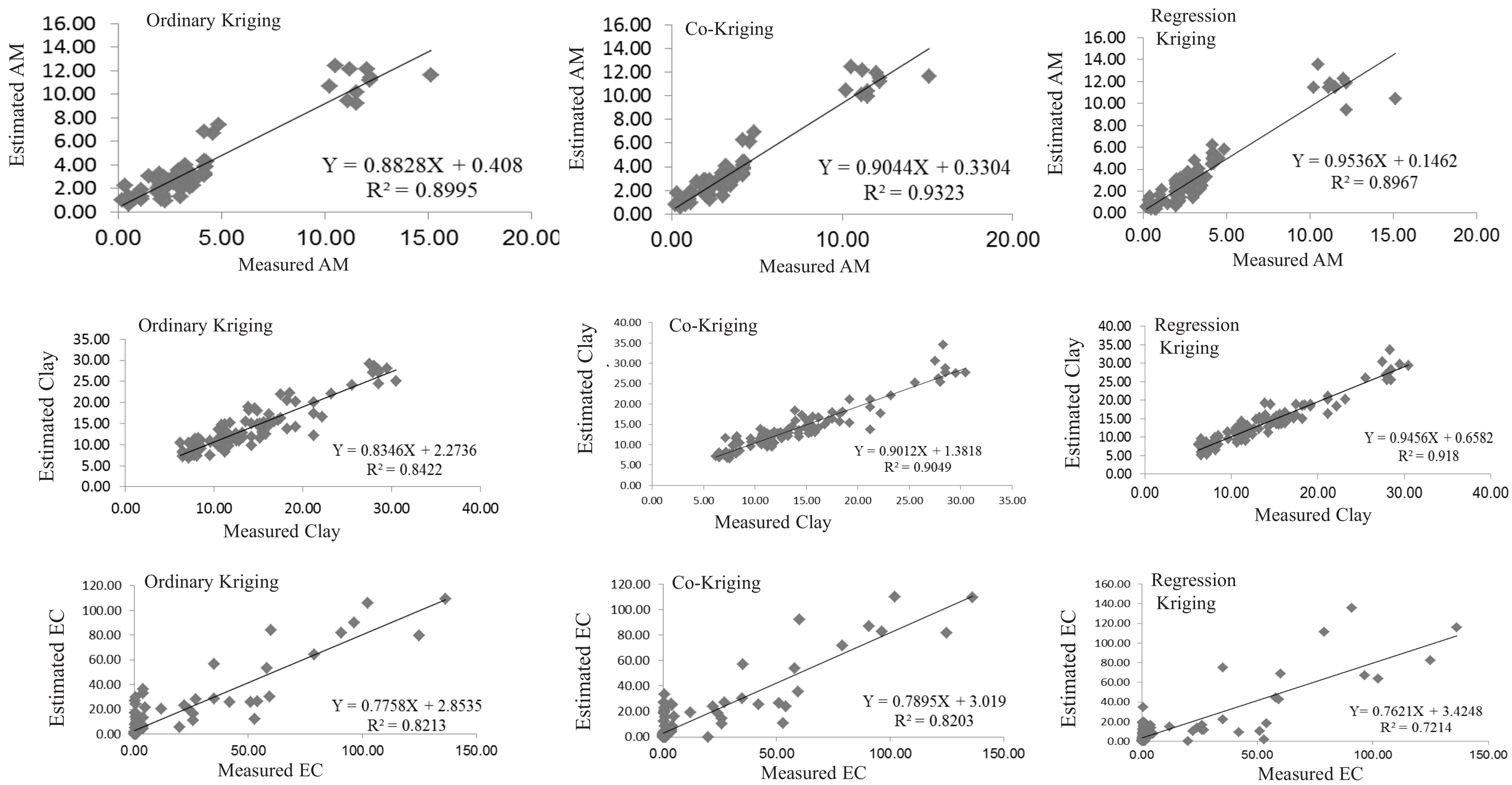
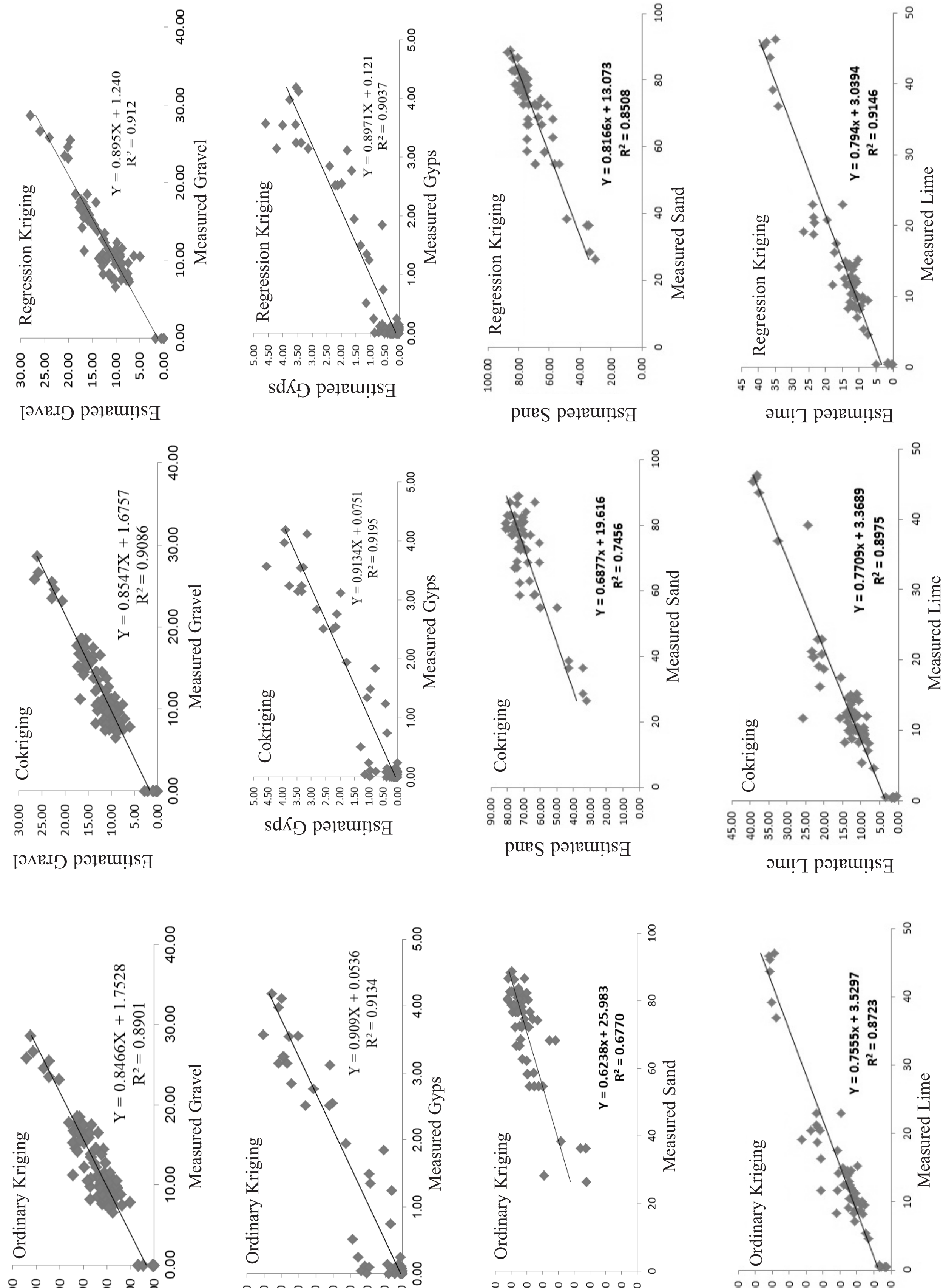


Fig. 5. Scatter plot of estimated versus measured different soil parameters in different estimation methods. Points (diamond symbols) represent the observed values and the solid line shows the fitted least-square regression line.



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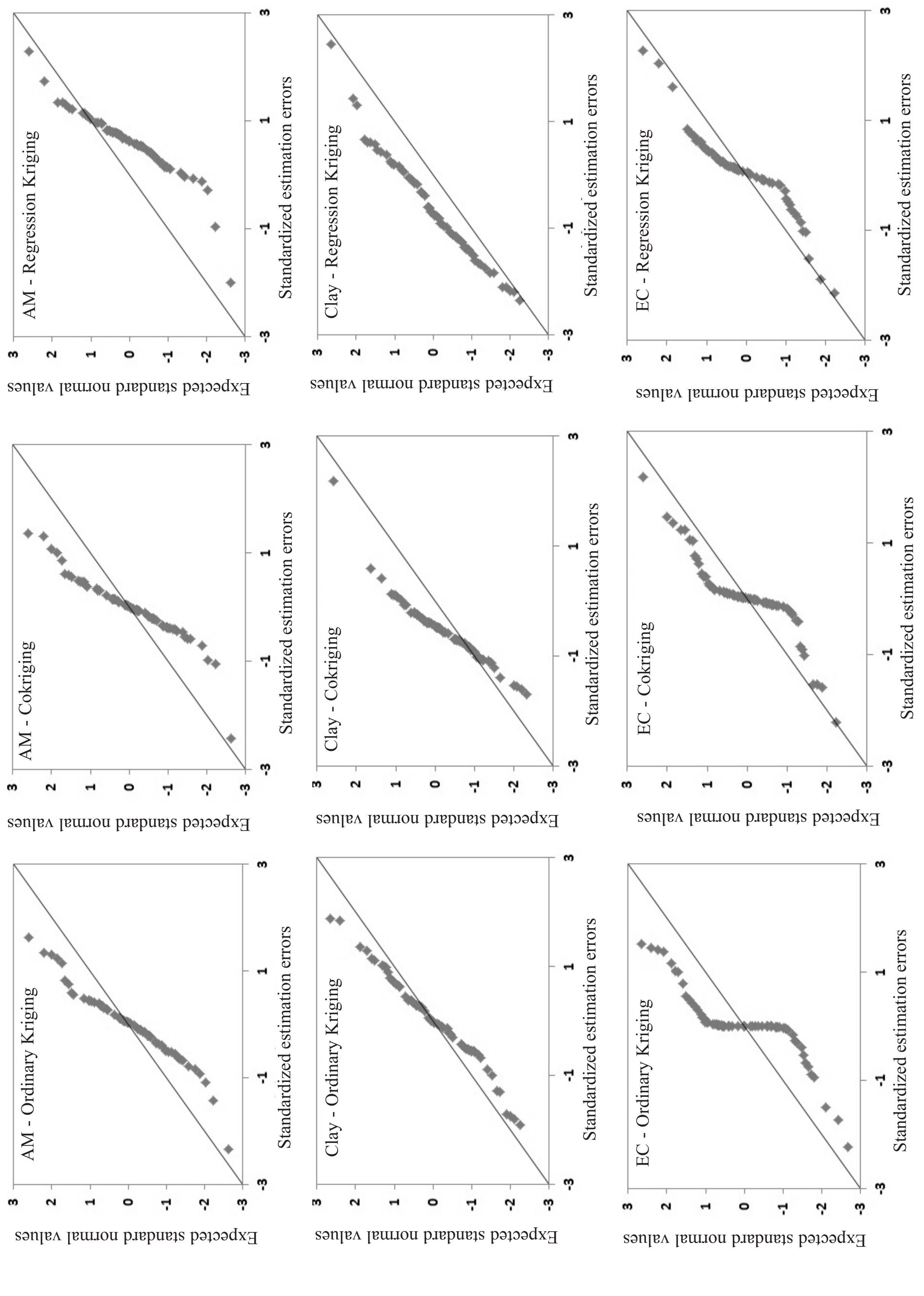
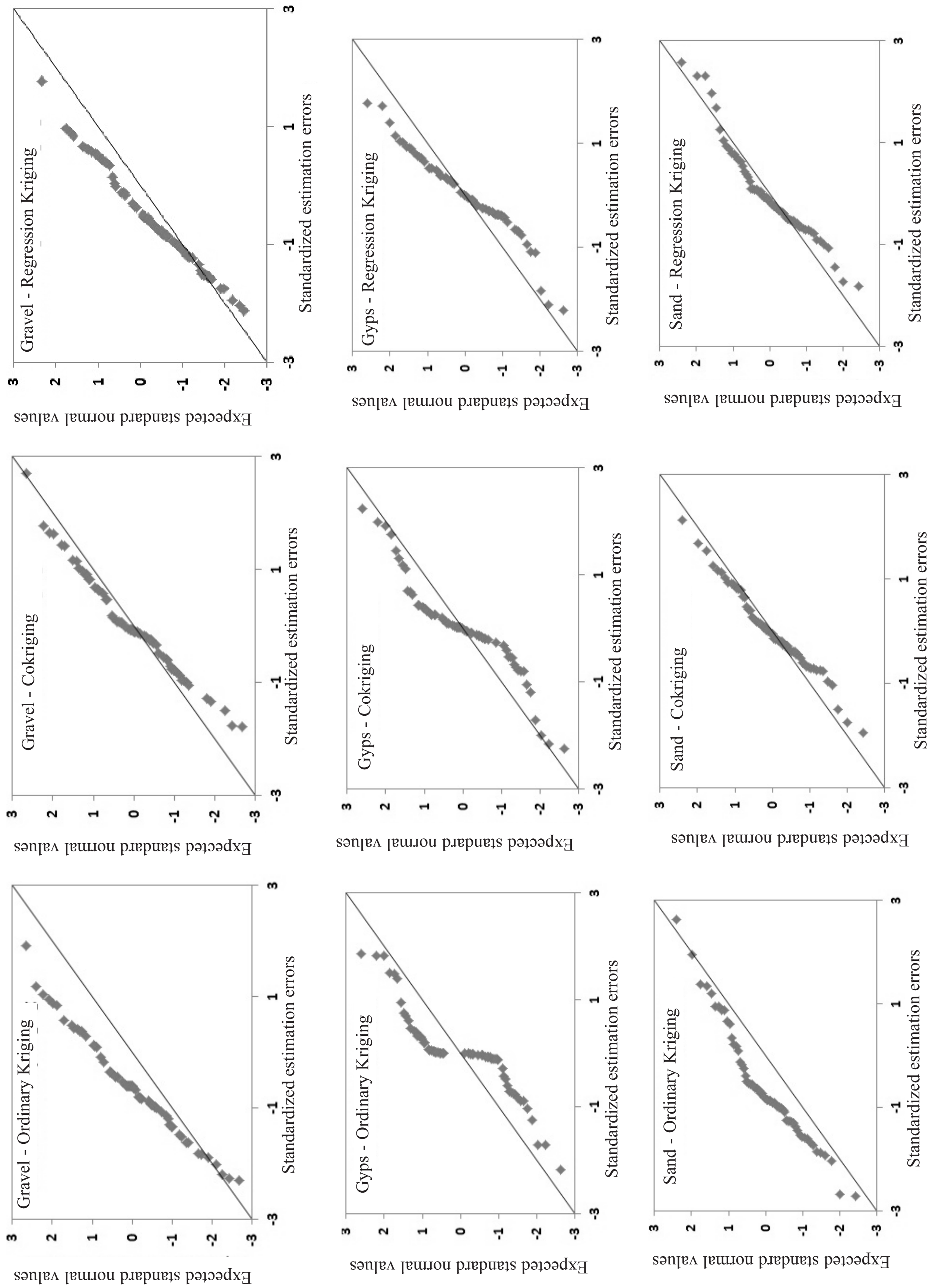


Fig. 6. Normal QQ-plot of standardized estimation errors of different soil parameters in different estimation methods. Points (diamond symbols) represent the observed standardized error values and the solid line shows the ideal standard normal distribution line.



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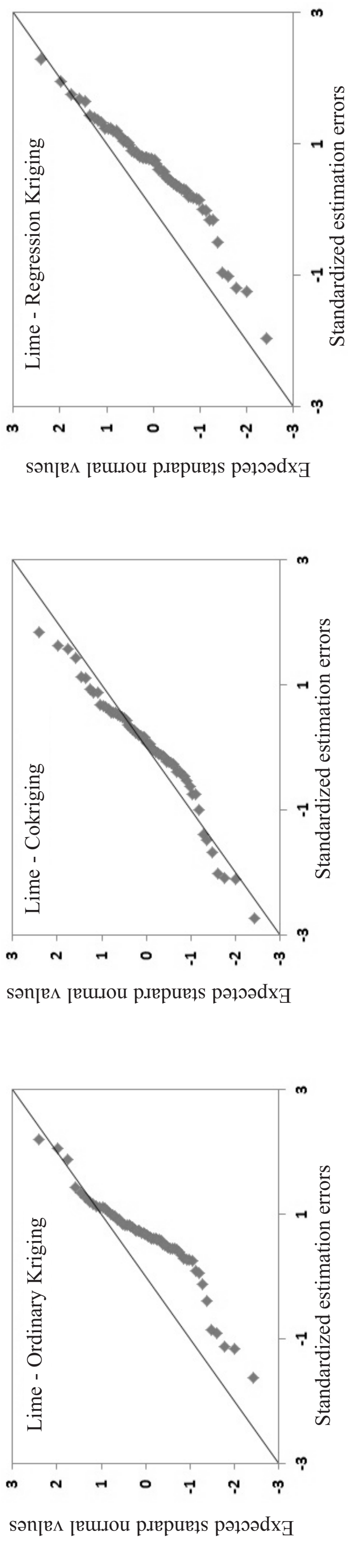

Fig. 6. Continued.

Table 7. Legend of the soil texture map.

Abbreviation	Description
SL	Sandy Loam
SL-L-SCL	Sandy Loam-Loam-Sandy Clay Loam
SCL	Sandy Clay Loam
LS-SL	Loamy sand-Sandy Loam
LS	Loamy Sand
L-SCL-CL	Loam-Sandy Clay Loam-Clay Loam
L-SCL	Loam-Sandy Clay Loam
L	Loam
L-CL	Loam-Clay Loam
SCL-CL	Sandy Clay Loam-Clay Loam
CL	Clay Loam

mation approach. For clay and EC, because the QQ-plots as well as the sum and average errors represented more acceptable values, in spite of their lower RMSE, OK and RK were suggested as the best estimation methods, respectively (even though RMSE values for estimating these two soil parameters were not notably different). For suggesting the best estimation method for Gyps, the QQ-plot was the determining factor (Fig. 6). This is because the sum error for estimating the Gyps by the RK was rather larger than those of the OK and CK methods, while the sum error and RMSE values were not dramatically different. About Gravel, the difference in RMSE for the RK with those of the OK and CK approaches was rather considerable, whereas the QQ-plots (Fig. 6), along with the sum and average errors of them, do not represent remarkable differences.

Fig. 4 illustrates the best estimation soil attribute maps selected from different estimation methods (OK, CK, and RK). This selection was based on the aforementioned criteria (Table 6).

Table 7 summarizes the abbreviations of soil texture map legend. According to the maps, the highest values of AM, Clay, EC, and Gypsum are related to the southwest of the study area. This part of the area is located in lowlands with lowest elevation, highest level of ground water, and high concentration of salts [30]. Other studies also suggested similar results [31, 32]. Hydrologic processes can be suggested as one of the main factors that can affect the soil properties in the study area. These processes can directly influence the weathering, decalcification, and clay illuviation. Consequently, soil properties would represent notable variations from the mountainous areas to the lowlands.

Fig. 5 shows the scatter plot of estimated versus measured soil parameters data using OK, CK, and RK Models. Generally, scatter plot is a tool for quality control and accuracy assessment of predictions. It is also useful when there are large numbers of sample points and can provide information about the strength of a relationship between two variables. Based on Fig. 5, all the scatter plots confirm the results of RMSE (Table 4). The strongest relationships between measured and estimated for AW, Clay, EC, Gravel, Gyps, Sand, and Lime are observed in CK, RK, OK, RK, CK, RK, and RK models, respectively.

Conclusions

Creating accurate soil maps is of vital importance in landscape ecology and rangeland management. In this study, soil data and some ancillary variables, including ETM+ images, elevation, slope, and precipitation of Poshtkouh rangelands were collected. The estimation maps of relevant soil parameters were created and compared to each other using different geostatistical methods as the next step. Based on the cross-validation analyses, the results suggest that the application of the ancillary data (ETM+ images and environmental variables) have increased the estimation accuracy in most cases.

The better efficiency of RK over OK and CK for estimating most of the soil attributes might be due to the better capturing of the variations of the residuals of these parameters in the RK framework.

Although with very low differences for estimating the EC, OK has represented the lowest estimation RMSE compared to those of the CK and RK. However, according to Table 6, considering the QQ-plots along with the sum and average errors besides the RMSE criterion, RK could be suggested as the best estimation approach for EC. This implies the positive role of remote sensing and environmental variables as ancillary variables in improving the estimations.

In the majority of parameters, taking the secondary variables into account has increased the estimation accuracy. Therefore, it is revealed that to improve predictions of soil attributes, it would be very beneficial to use the cheap and easily available ancillary data such as satellite images and elevation data. To achieve the best mapping performance, the secondary variables such as environmental variables and satellite images should be present for the whole study area. Several studies have suggested the use of satellite images and environmental variables in the framework of CK and RK to improve the accuracy of estimations [9, 12, 14, 23, 34]. The success of this idea depends on the strength of relationships between soil and the ancillary data.

Characterization of soil parameters such as texture, available moisture, and salinity, etc., is a vital step in rangeland rehabilitation, management, and ecological modelling, these methods are considerably useful. In the mentioned applications, a detailed map of soil properties can be more efficient than traditional soil maps. These continuous soil maps also will benefit rangeland scientists to describe the distribution of soil patterns. The created soil attribute maps could be used as input for the ecological models such as species distribution models.

Finally, it can be concluded that the geostatistical approaches can successfully model the spatial variability of different soil properties in rangelands. This is specifically because the geostatistical methods not only take the spatial variability of target parameters into account but they also offer estimation reliability measures such as estimation error and cross validation analyses parameters. The applied framework in this study, which is fast and automated in Arc GIS software, can be recommended for similar cases. Using satellite images with higher spatial and spectral resolution as ancillary variable can be suggested to increase the estimation accuracies.

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