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Characterization of Some Properties of Soils Formed on Basalt Parent Material Using Spectroradiometric and Geostatistical Techniques

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Abstract

High soil variability necessitates a large number of samples, which poses disadvantages in terms of labor, time, and economic and environmental impacts. Utilizing spectroradiometers and geostatistical methods can lead to significant savings in chemical inputs and time. In this study, sixty surface soil samples from basaltic parent material areas were analyzed in the laboratory for their physical (clay, silt, sand), chemical (pH, EC, exchangeable cations: Ca, Mg, Na, K, CEC, percent CaCO3) and biological (soil organic matter; OM100mμ, OM2mm) properties. Spectral and geostatistical methods were employed to estimate and map these properties. Spectral reflectance were obtained within the 350 to 2500 nm wavelength range. Modeling the relationships between laboratory measurements and spectral readings were performed using Partial Least Squares Regression (PLSR). Additionally, geostatistical techniques such as Inverse Distance Weighting (IDW), Ordinary Kriging (OK), and Cokriging (COK) were utilized to generate maps illustrating the spatial distribution of soil parameters. The accuracy of the predictions were evaluated using RMSE (Root Mean Square of Estimation) parameter. The predictive success of prediction techniques varied depending on the specific soil property under investigation. The VNIRS-PLSR method achieved the highest accuracy and the lowest RMSE values for parameters such as organic matter, sand, clay contents, cation exchange capacity (CEC), and electrical conductivity (EC). Conversely, geostatistical methods yielded the lowest RMSE results for parameters such as lime (CaCO3), pH, silt, exchangeable Ca, exchangeable K, exchangeable Na, and exchangeable Mg. The application of the COK technique using a secondary variable resulted in a 1 % to 19 % increase in prediction success compared to OK and IDW techniques. Overall, each estimation technique has its own advantages and disadvantages, which should be taken into consideration in the selection of the technique for prediction of soil variables.

Research Article

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PLSR

1. Introduction

Precision agriculture methods should be utilized to boost productivity per unit of land area (Türker and Güçdemir, 2004). The precision farming ensures optimal efficiency by customizing inputs accordingly (Kaplan, 2020). Kaplan (2020), highlighted the significance of identifying regional differences in land through mapping, enabling agricultural practices to align with the specific needs of soil and plants. Furthermore, Qi et al. (2009), recommended precision agriculture practices not only for efficiency but also for environmental protection, aiming to prevent the pollution of nature and ecosystems from unnecessary chemical applications.

Excessive use of inputs leads to infertility and the formation of barren land. Since soil nutrients may vary within the same field, it is crucial to map the variability in the land and apply fertilizers based on these specific needs (Birol and Günal, 2022). For agricultural areas, it is recommended to perform soil content analyses and create maps based on these results to apply practices according to spatial variability. Furthermore, these maps, obtained through geostatistical methods, can be integrated into precision agriculture tools, enabling region-specific applications. (Kaplan and Rufaioğlu, 2023; Kaplan and Öztürk, 2023; Kaplan and Rufaioğlu, 2024; Kaplan et al., 2024). The site-specific management of inputs reduces soil pollution, input costs, and enhances productivity, ultimately ensures the sustainability of agricultural production (McGrath et al., 2004; Trangmar et al., 1985).

The ability of a soil sample to accurately represent an entire land area depends on the soil variation within that land (Trangmar et al., 1985). Variability in soil properties in the field significantly impacts the evaluation and interpretation of these properties. The number of samples taken and the distance between sampling points are crucial for achieving accurate results in studies. Neglecting the distance factor for closely located variables leads to insufficient information for variable identification (Hamlett et al., 1986). Therefore, soil sampling should consider the distance between coordinate points, as closer proximity to real data enhances the likelihood of obtaining more precise results.

Determining soil properties play a crucial role in achieving optimal yield in agriculture. Various methods exist to determine soil properties, geostatistical and spectral techniques have emerged as priorities to estimate soil properties. A map depicting the variation within a field is generated using geostatistical methods. Geostatistical techniques have been applied to create maps showing the spatial distribution of diverse soil properties (İmamoğlu and Sertel, 2016). local variations in precipitation (Çetin and Tülcü, 1998). and to estimate available phosphorus levels in soils (Akbaş, 2012). The geostatistics rely on determining experimental variogram structures from observed values and constructing a theoretical model based on this structure (Çetin and Tülcü, 1998; Baskan, 2004). Estimates of variables in areas without measurements are derived using Kriging analysis results based on semivariogram parameters (Turgut and Öztaş, 2012). COK is a method utilizing information from the cross-correlation of a second variable to minimize the variance of the estimation error (Journel and Huijbregts, 1978). The COK method is useful in the characterization of soil properties because it takes into account the variability of primary and secondary variables, thus improving predictions using measurements of the secondary variable in cases where measurements of the primary variable are inadequate. The creation of geostatistical maps also offers advantages for investment planning in the area and facilitates the establishment of databases (McGrath et al., 2004; Aksakal and Öztaş, 2010; Turgut and Öztaş, 2012).

The Visible and Near-Infrared Spectroradiometer (VNIRS) method has recently gained widespread use in predicting soil and plant properties. This can be attributed to its positive aspects, such as not requiring chemicals used in laboratory chemical analyses for the determined parameters and saving labor within a short period (Dunn, 2002). The VNIRS method has been utilized in various areas, including soil salinity classification (Bilgili et al., 2014), forensic science related to soils (İnci et al., 2021) and creating soil maps (Milos and Bensa, 2018), as well as in precision agriculture (Keskin and Görücü Keskin, 2012).

Between 0.1 % and 1 % of the world's soils consist of basaltic soils, which are typically formed as a result of volcanic activity. These soils are known for their mineral richness and are commonly found in volcanic regions (Soil Servey Mnual, 2017). Soils derived from basaltic parent material typically exhibit a neutral to slightly alkaline pH, and their mineral composition enhances the retention of plant nutrients. These soils are generally regarded as fertile agricultural lands with good drainage systems that promote root development. Characterizing basaltic soils is crucial for evaluating their agricultural suitability. Understanding soil properties helps determine key factors such as plant nutrition, water retention capacity, drainage capabilities, and soil structure. This information is essential for developing appropriate fertilization, irrigation, and soil amendment practices for optimal plant cultivation (Valenzuela-Estrada et al., 2015).

This study aims to characterize, estimate, and map the properties of soils formed from basalt parent material using geostatistical and spectroradiometric methods. Additionally, it seeks to compare the success of both techniques in achieving these objectives.

2. Materials and Methods

2.1. Study area

The study was conducted in soils formed on basaltic rocks in the Siverek district of Şanlıurfa province. The study area, spanning 39 km^2, is situated between latitudes 37°43'16.00 "N - 37°45'20.66 "N and longitudes 39°04'23.82 "E - 39°16'49.82 "E.

The average annual temperature is 26.4 °C and the difference between the driest and wettest month is 90 mm. The annual rainfall is 478.4 mm, 30 % of which falls in spring, 1.4 % in summer, 13.8 % in autumn and 54.7 % in winter (Karakeçili, 2004).

Şanlıurfa is located in the southern foothills of the Southeastern Taurus Mountains and the northern parts of the Arabian plateau. Siverek, Hilvan, Viranşehir and Karacadağ are composed of basalts, while the other part of the province consists of limestone (Erdinç et al., 2011). In Şanlıurfa province, under semi-arid climate conditions, there are red-brown, brown, brown forest, non-calcareous brown, basaltic, colluvial, and alluvial soils (İnci et al., 2023). Karacadağ is an extinct volcano that sprayed lava around itself and formed black stones. The land descends from Viranşehir towards the Harran Plain (Karakeçili, 2004). Most of Şanlıurfa is covered with calcareous soil and has Karst topography. The lavas of Karacadağ are spread over a wide area and consist of basalt. There are many caves, cisterns, dolines and poljes in the region. Soils generally have high clay content and are low in organic matter and phosphorus. The elevation of the study area varies between 549 and 758 meters above sea level.

2.2. Soil sampling

A total of 60 samples were collected from the study area at around 500-meter intervals using GPS, from a depth of 0-30 cm based on a random sampling approach. The distribution of sampling points across the study area is depicted in Figure 1.

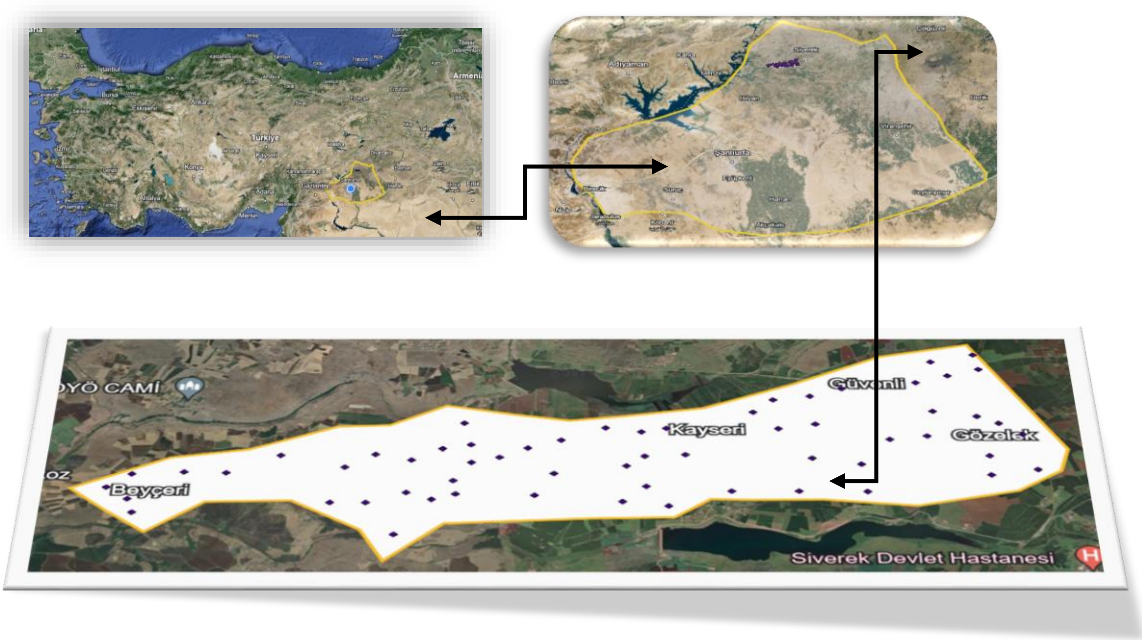


Figure 1. Study area and sampling points

2.3. Topographical analyses

The contour lines from the topographic maps of the study area were digitized to create a digital elevation map (DEM) in the ArcMap environment. Subsequently, a slope map of the study area was generated from the obtained DEM (Figure 2). The soil sampling coordinates were then matched with elevation data and slope values corresponding to the sampling points.

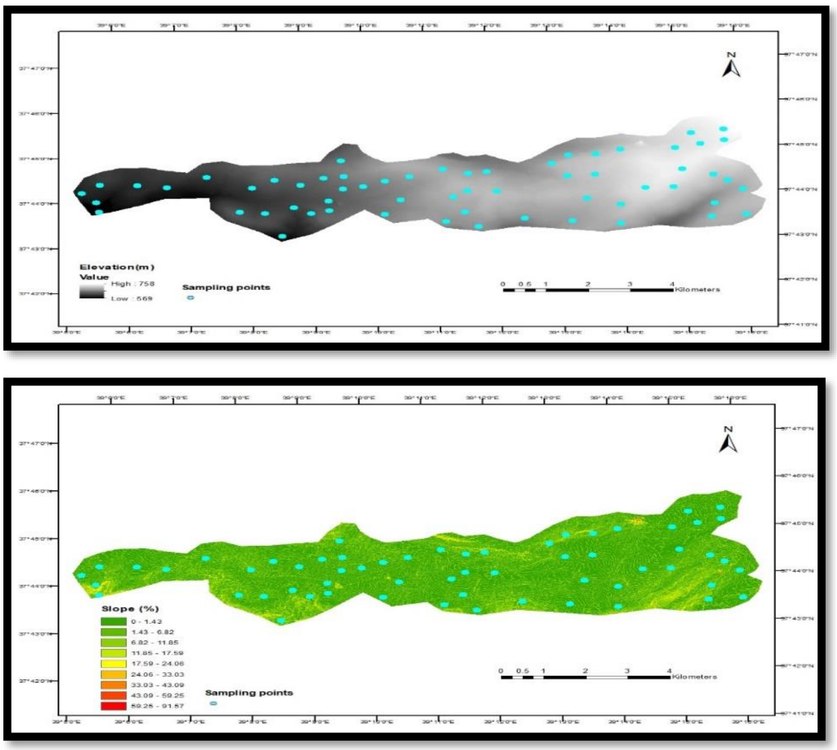


Figure 2. Slope and elevation maps of the study area

2.4. Soil analyses

To prepare the soil samples for analysis, air-dried disturbed soil samples were passed through 2 mm. A 100 micron sieve was additionally used for soil organic matter analyzes. Texture analysis in soil samples was performed with the Bouyoucos method (Bouyoucos, 1951). Exchangeable cations (Ca, Mg, K, and Na) were determined using the 1 N ammonium acetate method (Thomas, 1983). Cation exchange capacity (CEC) was determined using the 1 N ammonium acetate (pH = 7.0) method (Jackson, 1958). Lime ($CaCO_3$) content was measured using the Scheibler calcimeter (Gedikoğlu, 1990). Soil reaction (pH) was determined using a pH meter with the extract obtained from saturation paste (Soil Survey Laboratory, 2004). Electrical conductivity (EC) was measured using an EC meter with the filtrate obtained from the saturation paste (Soil Survey Laboratory, 2004). The organic matter contents of soils both sieved through 2 mm (OM2mm) and 100 micron sieve (OM100mμ) were determined using a modified version of the Walkley-Black method (Jackson, 1958).

2.5. Spectroradiometric analyses

To obtain the spectral reflections of air-dried soil samples sieved through a 2 mm sieve in the visible and near-infrared range, soil samples were placed in glass petri dishes at approximately 20-25 grams. Spectral reflections with a 1 nm resolution in the 350-2500 nm wavelength range were obtained using a Spectroradiometer (ASD FieldSpec 3) at Harran University (Figure 3). The Spectroradiometer was calibrated using white spectralon when needed, and the final reflectances of soil samples were obtained by ratioing the soil spectra to the white spectralon spectra (Equation 1) The Partial Least Squares Regression (PLSR) method was employed to model the relationships between reflectance measurements taken from the soil and the soil properties.

Figure 3. Taking reflections of soil samples with the Field Spec III Spectroradiometer instrument

$$R = \left(\frac{\text{Soil Reflection}}{\text{White Spectralon Reflection}}\right) \qquad \text{Equation 1}$$

2.6. Partial least square regression (PLSR)

PLSR is particularly useful for interpreting and evaluating a large number of X variables that have significant correlations between them, such as spectral data (Esbensen and Geladi, 2010). In this method, spectral reflections form the X matrix, while the soil parameters to be estimated (laboratory analysis values) form the Y matrix. The validation of PLSR calibration models was conducted using a leave-one-out cross-validation approach. In this technique, each sample is removed from the dataset, and a model is created with the remaining samples. This process is repeated for all samples, ensuring that each sample goes through the same procedures, and results are obtained for the entire dataset (İnci et al., 2021). The cross-validation method is also utilized in the PLSR technique for calibration and validation to determine the optimal number of variables (Milos and Bensa, 2018). PLSR models were developed using The Unscrambler program.

Basic descriptive statistics (Minimum, Maximum, Average, Standard Deviation, Range, Coefficient of Variation) of the soil parameters investigated in the study and correlations among soil parameters were obtained using the JMP program.

2.7. Geostatistical analyses

The steps followed when using geostatistics are: the first, data is collected and exploratory data analysis is performed. Before proceeding to kriging analysis, parameters that did not exhibit a normal distribution were normalized. Parameters with skewness values exceeding 1 were normalized through logarithmic transformation before being subjected to kriging analysis. Then, the spatial correlation between data points is analyzed by creating a semi-variogram. Based on the semi-variogram, the most appropriate mathematical model is selected. Using this model, values at unknown points are estimated and mapped using the kriging method. Finally, the accuracy and precision of the predictions are evaluated by cross-validation (Isaaks and Srivastava, 1989). In the study, soil properties were estimated and mapped using the IDW, kriging and COK techniques. IDW predominantly conducts predictions based on distance, whereas kriging incorporates both distance and spatial dependency among samples. Conversely, COK, unlike IDW and kriging, anticipates the utilization of an alternate variable correlated with the primary variable rather than a singular variable. Consequently, these three techniques, each with distinct structures, were subjected to testing. The operational principles of these three methods diverge from one another.

2.8. Inverse distance weighting (IDW)

The Inverse Distance Weighting method creates estimates by using a linear combination of the values at the sampled points and the values at the non-sampled points, with the inverse distance functions of the distances (Burrough and McDonnell, 1998). Where the point r is the exponent that determines the assigned range of each of the observations, and d is the distance between the observation point Xi and the prediction point X0 (Equation 2).

$$Z(X_0) = \frac{\sum_{i=1}^{n} Z(Xi).\, d_{i0}^{-r}}{\sum_{i=1}^{n} d_{i0}^{-r}} \qquad \text{Equation 2}$$

2.9. Ordinary kriging

The Kriging technique is widely employed in the field of geostatistics (Caruso and Quarta, 1998). Ordinary Kriging is a spatial interpolation method widely used for estimating characteristics in areas where no sampling has been conducted. In this method, neighboring samples are utilized to make predictions. The value of the point to be predicted is determined by calculating the average weight based on the distances to neighboring points (Equation 3) (Isaaks and Srivastava, 1989).

$$Z(Xo) = \sum_{i=1}^{N} Wi\, Z(Xi) \qquad \text{Equation 3}$$

where Z(Xo) is the kriging estimate for point Xo, n is the number of samples in a search neighborhood, and Wi is the weights assigned to the i'th observation Z(Xi). Weights are determined for each variable using a variogram, which measures the spatial correlation and covariance structure between data points (Journel and Huijbregts, 1981) (Equation 4);

$$r(h) = \frac{1}{2} N(h) \sum_{i=1}^{N} [Z(Xi) - Z(Xi + h)]^{2} \qquad \text{Equation 4}$$

2.10. Co-kriging

In the Co-Kriging method, the auxiliary variable is estimated as a co-variable of the primary parameter. The weights ⋋i and ⋋j refer to the Z and Y variables, respectively, and m and n represent the number of data used in the estimation of Z and Y variables, respectively (Equation 5). COK leverages the covariance between primary and secondary variables in estimations. When the primary variable is not sufficiently sampled but the secondary variable is better sampled, and the covariance between the primary and secondary variables can be well modeled, the Co-Kriging method is utilized to enhance the estimation quality (Chang, 2002). Geostatistical analysis was conducted using ArcMap program version 10.5.

$$Z^{*} = \sum_{i=1}^{n} ⋋_{\mathrm{i}}\ Z_{\mathrm{i}} + \sum_{j=1}^{m} ⋋_{j}\, y_{i} \qquad \text{Equation 5}$$

2.11. Accuracy evaluations

The accuracy of predictions made by both geostatistical and VNIRS methods was evaluated, and comparisons between the methods were made using the RMSE (Root Mean Square Error) parameter. RMSE is calculated as the square root of the mean of the squared differences between the actual measurement values and the predicted values (Equation 6).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Xi - Yi)^{2}}{n}} \qquad \text{Equation 6}$$

Xi: X1, X2,….Xn (estimated values). Yi: Y1, Y2,….Yn (observed values). n: number of observations (Equation 6).

3. Results and Discussion

3.1. Soil properties

The average values of the soil variables investigated are presented in Table 1. These soils exhibit a low $CaCO_3$ content, ranging from 0.23 % to 3.74 % (with an average of 1.38 %), which is characteristic of soils formed on basalt rocks with minimal $CaCO_3$ content (Brady and Weil, 2008). The soils had a neutral pH averaging 7.2, ranging from 6.5 to 7.7, and relatively low to moderate organic matter content, averaging 1.38 % and varying from 0.23 % to 3.74 %. These soils are predominantly clayey in texture and exhibit high levels of exchangeable cations such as Ca, Mg, Na, and K (averaging 7971 ppm, 477 ppm, 1028 ppm, and 106 ppm, respectively), along with a CEC ranging from 10.06 to 97.79 me/100g. Silicates resulting from the decomposition of basalt promote the formation of clay minerals in the soil. These minerals increase the clay content of the soil (Brady and Weil, 2008). The average organic matter content (2.42 %), $CaCO_3$ content (6.12 %), clay content (52.64 %), silt content (21.33 %), sand content (26.02 %), pH (7.57), and EC (0.66 dS m^{-1}) at the surface depth of three different soil profiles developed on basalt parent material in the region reported by İnci (2020) were consistent with the values in this study. Additionally, the exchangeable Ca, Mg, Na, K values (51.66, 13.16, 0.49, 1.40, respectively) and CEC values (14.25 me/100 g) were found to overlap with the findings of this study. In another study conducted by Ekberli and Dengiz (2017), the surface soil of the profile formed on the basalt parent material exhibited varying values for clay (32.1-56.2 %), organic matter (1.65-2.35 %), pH (7.03-7.87), and lime ($CaCO_3$) content (0.20-0.79 %). Additionally, the exchangeable Na, K, and Ca+Mg (cmol kg^{-1}) values ranged between 0.22-0.41, 0.24-1.67, and 33.16-42.24, respectively, aligning with the results of our study as well. The Coefficient of Variation (CV) provides valuable insights into the distribution (variability) of soil parameters. CV values less than 15 % indicate low variability, values between 16-35 % indicate moderate variability, and values greater than 36 % indicate high variability (Cambardella et al., 1994). Based on this classification, some parameters in the study area exhibited significant variability. Among these parameters, OM100mμ had the highest coefficient of variation (71.8 %), indicating the greatest variability in the study area. Factors such as vegetation diversity, biological activity, land slope and drainage may lead to differences in organic matter accumulation and transport, causing more organic matter to accumulate in flat areas and less organic matter to accumulate in sloping areas due to erosion (Brady and Weil, 2008). In this study, a negative correlation was found between organic matter values determined from soils of different sizes and topographic parameters (elevation and slope) (Table 2). Conversely, pH had the lowest coefficient of variation (3.19 %), indicating the least variability in the study area. Clay, silt, and sand showed low variability, while exchangeable Ca, exchangeable Mg, exchangeable K, OM2mm, lime ($CaCO_3$), CEC, exchangeable Na, and EC exhibited moderate variability (Table 1). The general chemical properties of soils associated with basaltic parent materials show significant differences that are dependent on mineralogy, particularly clay mineralogy. For example, the pH of soils derived from basaltic materials typically ranges from 5.0 to 7.5 (Singer, 1987), and these high pH values can be maintained even in tropical regions unless subjected to intensive weathering (Isbell et al., 1976, 1977; Gillman and Sumpter, 1986). The base saturation percentage of these soils is generally over 60 %, and their cation exchange capacity (CEC) is high (Mitchell and Jarvis, 1956), even in silt fractions (Wilson and Logan, 1976). In this research, the variability in the CEC parameter determined in soils on the same parent material can also be explained by the topography of the study area. As a matter of fact, a statistically significant positive correlation (r: 0.34^*, $p<0.05$) was obtained between CEC and slope (Table 2). Soil parameters with high variability based on coefficients of variation are expected to have low spatial dependency rates, whereas parameters with less variability tend to have higher spatial dependency (Tekin et al., 2011; Akbaş, 2012). In a different study similar to this one, the pH parameter also had the lowest coefficient of variation. However, unlike our study, the $CaCO_3$ parameter exhibited the highest coefficient of variation (Başbozkurt et al., 2013).

Table 1. Introductory statistics of soil parameters

Soil variables	**Unit**	**Min.**	**Max.**	**Average**	**Std.Sd**	**Skewness**	**Range**	**CV**[†]
$CaCO_3$	%	0.23	3.74	1.88	1.12	1.89	3.5	59.57
OM2mm	%	0.23	3.74	1.38	0.58	1.65	3.5	42.02
pH		6.5	7.7	7.2	0.23	-0.33	1.2	3.19
EC	µS/cm	268	2460	586	401.5	2.88	2192	68.46
Sand	%	17.12	37.12	26.12	5.01	0.45	20	19.18
Clay	%	46.88	66.88	57.57	5.36	-0.31	20	9.31
Silt	%	12	22	16.3	2.51	0.60	10	15.39
OM100mµ	%	0.65	7.99	2.38	1.71	1.95	7.34	71.84
CEC	me/100g	10.06	97.79	26.28	15.78	3.19	87.73	60
E. Ca	ppm	0	14020	7971	2541	0.13	14024	31.87
E. K	ppm	0	1132	477.6	188	1.33	1136	39.36
E. Mg	ppm	0	1714	1028	339.9	-0.08	1724	33.06
E. Na	ppm	0	426,8	106	70.16	2.47	428.2	66.18

[†]: Coefficient of Variation ((Standard deviation/mean) *100), E. Ca: Exchangeable Ca, E. K: Exchangeable K, E. Mg: Exchangeable Mg, E. Na: Exchangeable Na,

Several statistically significant ($p<0.05$) positive and negative relationships were recorded among soil variables (Table 2). These include a significant negative correlation between pH and EC ($p<0.05$), a significant positive correlation between pH and exchangeable Ca ($p<0.05$), a significant negative correlation between $CaCO_3$ and Mg ($p<0.05$), and a significant negative correlation between OM2mm and EC, K ($p<0.05$). Additionally, significant positive correlations were found between clay and Mg ($p<0.05$), and between Ca and K, Mg, and Na ($p<0.05$). Furthermore, a significant positive correlation was observed between K and Mg ($p< 0.05$), as well as between Mg and Na ($p<0.05$) (Table 2). These correlations highlight the interrelationships among various soil parameters in the study area.

Table 2. Correlation between soil parameters

	$CaCO_3$	OM_{2mm}	pH	EC	Sand	Clay	Silt	$OM_{100m\mu}$	CEC	Ca	K	Mg	Na	S[ǂ]	E[ɨ]
$CaCO_3$(%)	1														
OM_{2mm}(%)	-0.17	1													
pH	-0.04	-0.12	1												
EC (µS/cm)	-0.14	0.31*	-0.39*	1											
Sand (%)	0.18	-0.24	-0.16	0.07	1										
Clay (%)	-0.11	0.2	0.2	-0.09	-0.8*	1									
Silt (%)	-0.1	0.05	-0.12	0.06	-0.1	-0.36*	1								
$OM_{100m\mu}$ (%)	-0.09	0.28*	-0.28	0.07	0.03	-0.14	0.23	1							
CEC (me/100g)	-0.11	0.17	0.08	-0.06	-0.19	0.2	-0.04	0.13	1						
Ca(ppm)	-0.03	-0.11	0.26*	-0.08	0	0.21	-0.45*	-0.28	0.01	1					
K(ppm)	-0.18	0.35*	-0.12	0.22	-0.19	0.22	-0.08	0.17	0.19	0.55*	1				
Mg(ppm)	-0.36*	0.11	0.23	-0.07	-0.15	0.36*	-0.46*	-0.07	0.22	0.60*	0.40*	1			
Na(ppm)	-0.13	-0.02	0.09	0.01	0.2	-0.06	-0.26*	0.03	0.03	0.33*	0.15	0.30*	1		
S (%)	-0.19	-0.10	-0.08	0.03	0.07	-0.09	0.06	-0.03	0.34*	-0.21	-0.12	-0.09	-0.10	1	
E (m)	-0.22	0.09	0.39**	0.11	-0.28*	0.28*	-0.04	-0.23	0.21	0.25*	0.17	0.15	0.03	-0.21	1

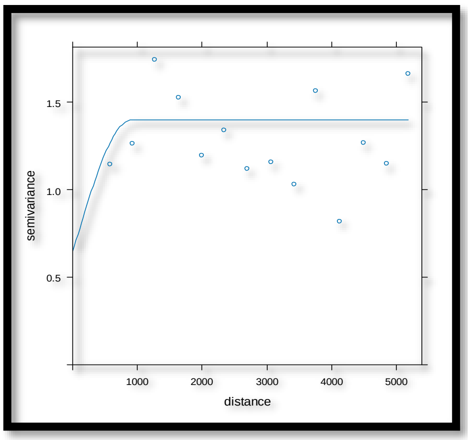
*$p<0.05$: significant at level, **$p<0.01$: significant at level, ǂ : Slope, ɨ : Elevation

3.2. Estimation and mapping of soil parameters with geostatistical methods

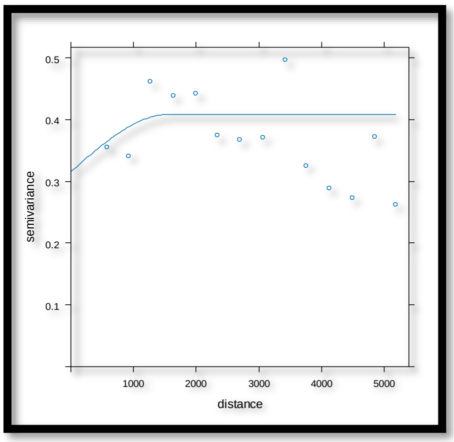
The soil parameters investigated were estimated using geostatistical methods such as Ordinary Kriging, IDW, and Co-Kriging, and maps depicting the estimated distribution of these soil parameters were generated.

The variogram graphs illustrating the spatial distribution of soil parameters, along with the variogram parameters (range, nugget, sill), are provided in Figure 4 and Table 3, respectively. The spatial patterns of soil parameters are predominantly characterized by Spherical variogram models, as shown in Table 3 and Figure 4. The Nugget/Sill ratio offers insights into the spatial dependencies of the examined parameters within the study area. A Nugget/Sill ratio below 25 % indicates a strong spatial distribution, between 25-75 % suggests a moderate spatial distribution, and above 75 % indicates a weak spatial distribution (Cambrella et al., 1994). Based on these criteria, parameters such as K, OM2mm, Clay, Silt, Sand, and CEC exhibited a Nugget/Sill ratio of 75 % and above, while pH displayed a Nugget/Sill ratio below 25 %. Other parameters ($CaCO_3$, silt, EC, Ca, Mg, Na) fell within the range of 25-75 % for the Nugget/Sill ratio, indicating a moderate spatial dependence (Table 3). It is noted that the Nugget/Sill ratio parameters can influence the success of predictions (Kravchenko, 2003).

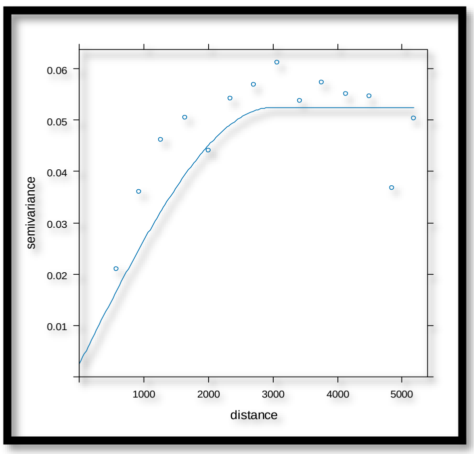
Lime ($CaCO_3$)



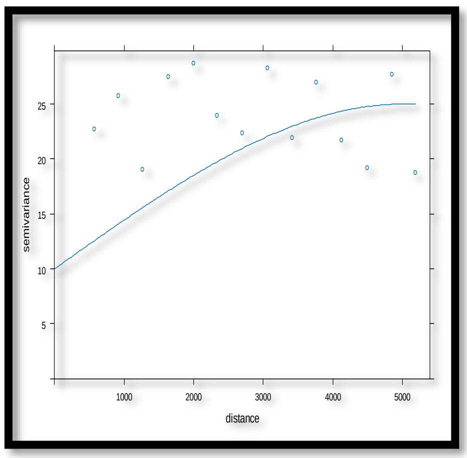
OM_{2mm}



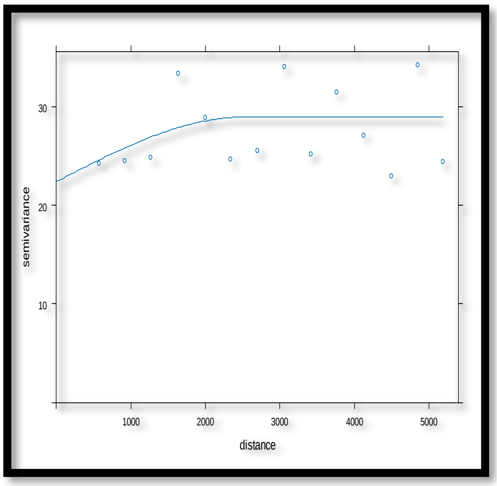
pH



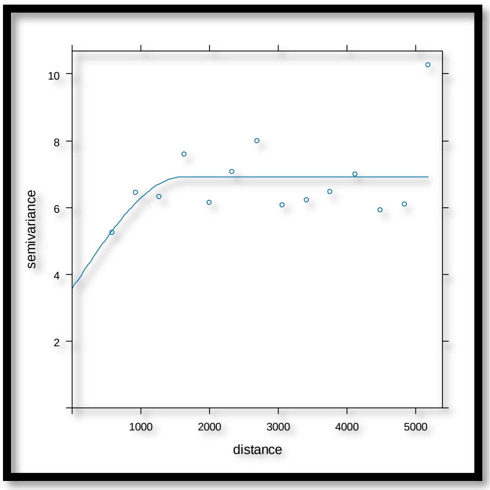
Sand



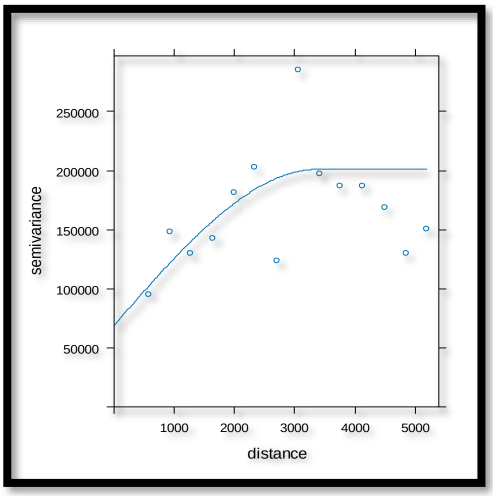
Clay



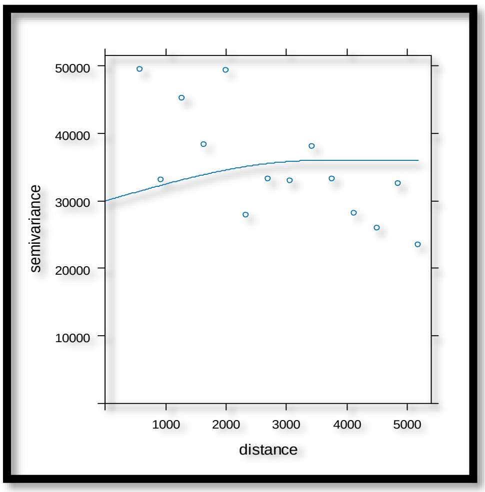
Silt



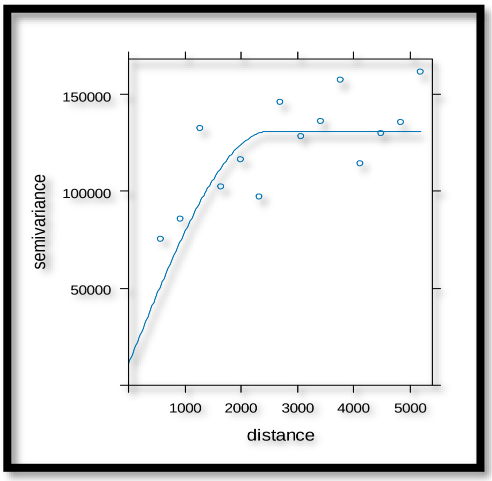
EC



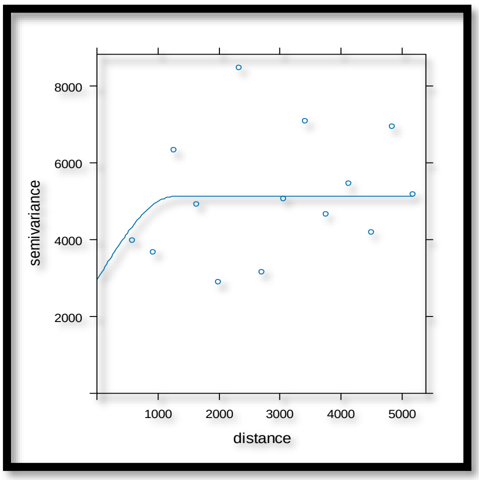
K



Mg



Na



Ca

CEC

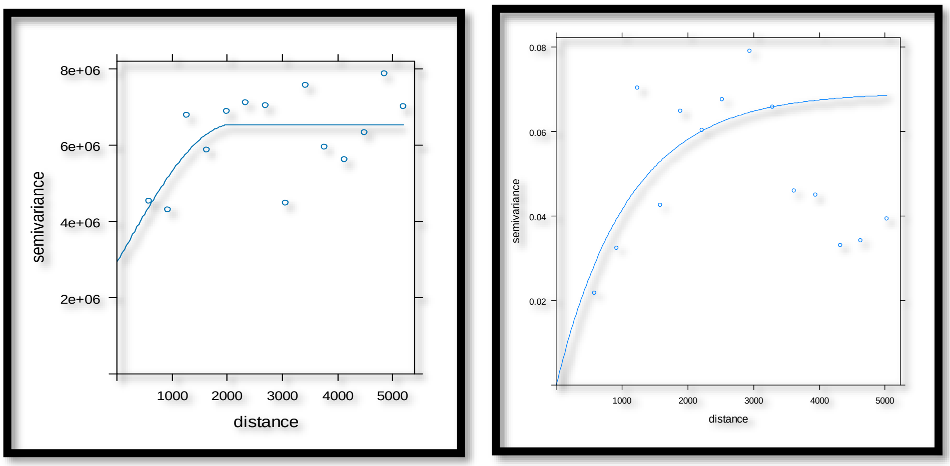


Figure 4. Variograms of soil parameters

Table 3. Parameters of variograms of soil parameters

Soil parameters	Model	Range	Co	C	Co + C	Co/CoC *100	Model Quality
Lime (%)	Spherical	899	0.64	0.75	1.39	46	Moderate
OM_{2mm}(%)	Spherical	1566	0.315	0.092	0.407	77	Poor
pH	Spherical	1955	0.013	0.052	0.065	20	Powerful
Sand(%)	Spherical	2847	22.12	2.987	25.10	88	Poor
Clay(%)	Spherical	2519	22.38	6.55	28.93	77	Poor
Silt(%)	Spherical	1613	3.57	3.34	6.91	51	Moderate
EC(µS/cm)	Spherical	3389	69051	132047	201099	34	Moderate
E. Ca(ppm)	Spherical	2091	2922072	3619622	6541694	44	Moderate
E. K(ppm)	Spherical	3500	50158	0	50158	100	Poor
E. Mg(ppm)	Spherical	4999	0.0250	0.0100	0.035	71	Moderate
E. Na(ppm)	Spherical	1257	2952	2160	5112	57	Moderate
CEC(me/100g)	Spherical	16180	227.6	72.03	299.63	75	Poor

Nugget to Sill: Co/Co+C*100 ratio, Sill: Co + C, Partial Sill: C, Nugget: Co, E. Ca: Exchangeable Ca, E. K: Exchangeable K, E. Mg: Exchangeable Mg, E. Na: Exchangeable Na,

Following the derivation of variograms and cross-variograms, soil parameter estimates were generated at unsampled points using the Ordinary Kriging (OK) and Co-Kriging (COK) methods. The accuracy of these predictions was assessed through a cross-validation approach. Cross-validation is a method used to measure how well a model works. In this method, the data set is divided into several parts. The model is trained with one part, and tested with the other part. If the model performs well in training and also performs well in testing, reliability is high. However, if it performs well in training but poorly in testing, the model has low reliability. This method provides important information about the generalization ability of the model. Graphs depicting the relationship between the predictions from cross-validation and the actual laboratory measurements using the Ordinary Kriging, Inverse Distance Weighting (IDW), and Co-Kriging methods for soil parameters were constructed. The Root Mean Square Error (RMSE) values obtained from the cross-validation of each estimated parameter are presented in Table 4. Ordinary Kriging, IDW, and Co-Kriging, and maps depicting the estimated distribution of these soil parameters were generated (Figure 5).

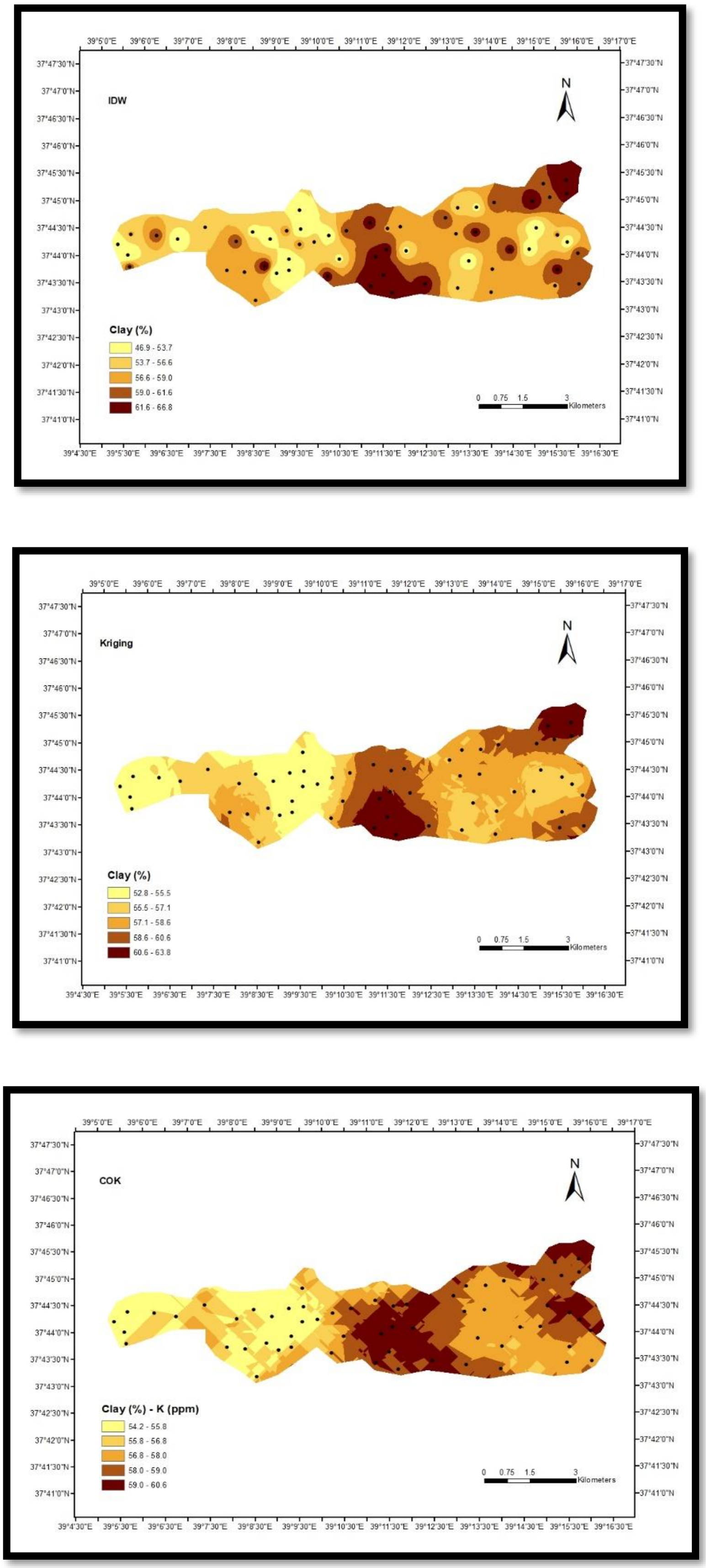


Figure 5. Mapping clay content in the research area with IDW, Kriging and COK methods

3.3. Spectroradiometric analyzes

The spectral reflectance data of soils derived from basaltic parent material are illustrated in Figure 6, covering the range of 350-2500 nm. Upon examining the soil reflections, distinct absorption peaks were observed at wavelengths of 1400, 1900, and 2200 nm, which are associated with soil moisture held at various pressures (Bilgili et al., 2010). It is well-documented that soil moisture significantly influences both the reflection and absorption properties of soil (Lobell and Asner, 2002).

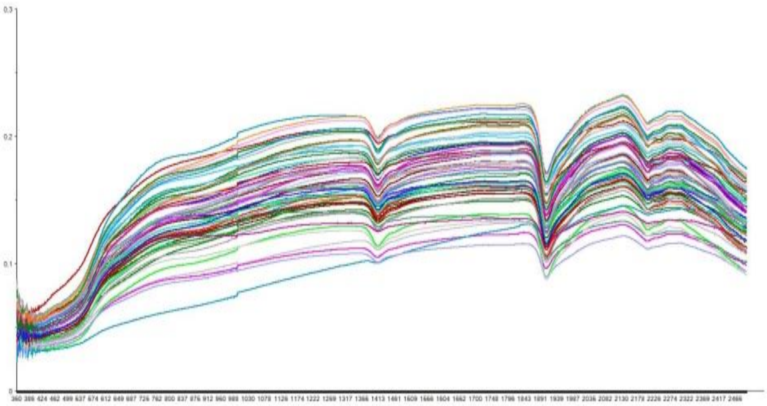
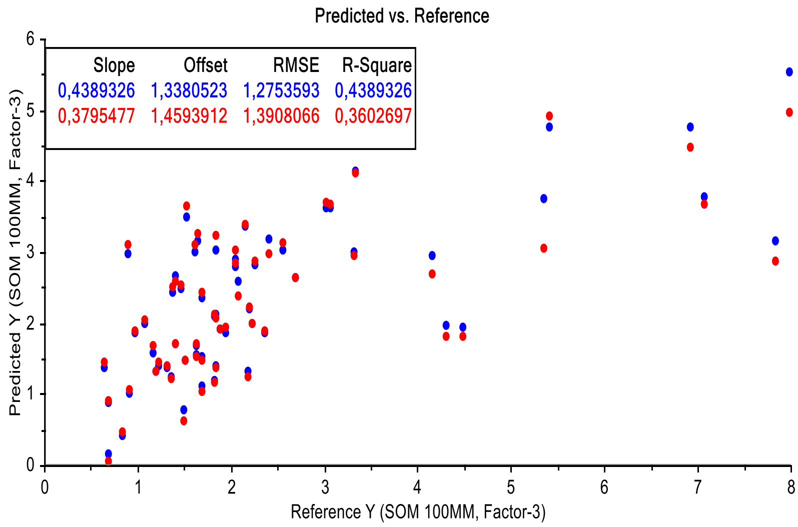


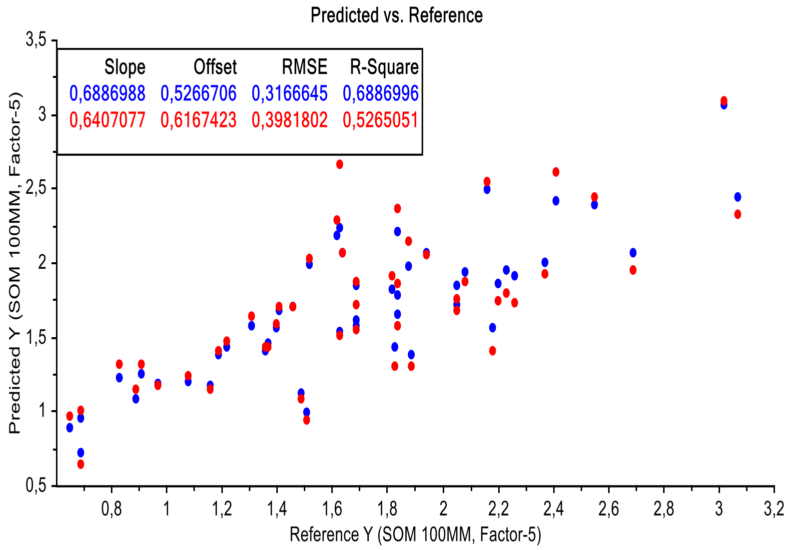
Figure 6. Raw reflections of soil parameters in the range of 350-2500 nm

The obtained spectral data was used for modeling and predicting soil parameters. The models and predictions between laboratory measurements and spectral data were performed using Partial Least Square Regression (PLSR) analysis, and the accuracy of the models was tested using cross-validation method.

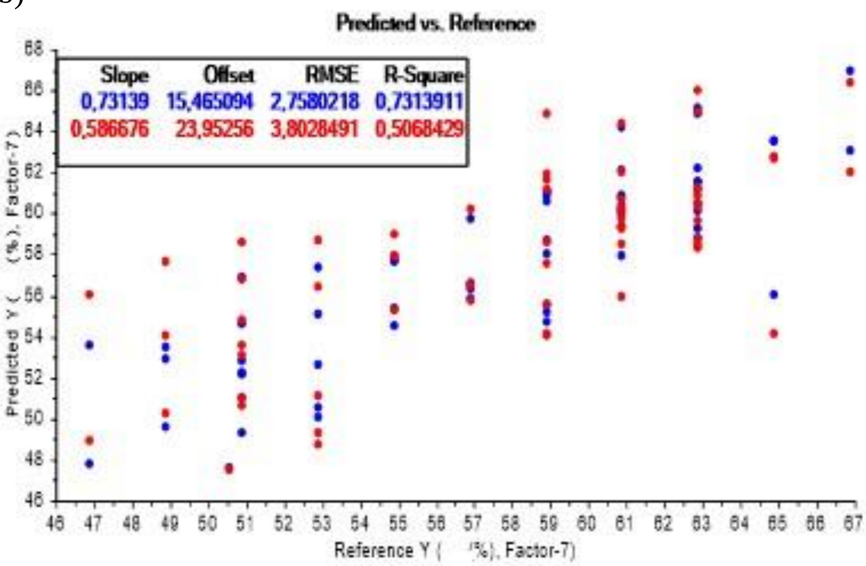
The graphs illustrating the relationship between laboratory measurement results of soil parameters and PLSR estimates, created using the reflections obtained from the spectroradiometer, are shown in Figure 7. The cross-validation prediction success results of the models are provided in the Table 4.



a)



b)



c)

Figure 7. Relations between predictions with VNIRS-PLSR and actual values of soil variables according to cross validation approach; a) OM100 mμ (*), b) OM100 mμ (**), c) clay (%). $OM100_{m\mu}$ (*): Prediction chart obtained without subtracting values with organic matter content above 3% from the data (R^2:0.36). $OM100_{m\mu}$ (**): Prediction chart obtained when values with organic matter content above 3% are removed from the data (R^2:0.52).

The accuracy of prediction measurements can be assessed using R^2 values. According to the classification by Saeys et al. (2005), R^2 values between 0.50-0.66 indicate the model's ability to differentiate between increasing and decreasing trends, values between 0.66-0.80 suggest close numerical predictions, values between 0.81-0.90 are considered good predictions, and values above 0.90 indicate very good predictions. In this study, the R^2 value for the OM100mμ parameter was determined as 0.52, and for the clay parameter, it was measured as 0.50, indicating the model's capability to recognize trends with reasonable accuracy. Among the parameters evaluated, variables such as Mg, Ca, K, Na, CEC, sand, silt, pH, $CaCO_3$, OM2mm, OM100mμ, and EC demonstrated R^2 values suggesting a low level of accuracy, while OM100mμ and clay parameters showed a moderate level of accuracy. In a previous study by Şenol and Akgül (2013), the clay parameter was reported with an R^2 value of 0.59 using visible-near-infrared reflection spectroscopy. Organic matter content is a significant soil parameter that accounts for variations in soil quality, influencing various soil physical, chemical, and biological properties. (Kara et al., 2022; Aydemir and Kara, 2023; Kara and Yakupoğlu, 2023; Kara et al., 2024). In spectral readings for organic matter detection, factors such as soil texture, moisture content and surface conditions affect organic matter signals. High moisture content can obscure organic matter signals, while sandy soils and different surface conditions make organic matter detection difficult. There exists a close relationship between soil organic matter content and soil color, where soils with high organic matter content tend to have darker colors. This relationship also extends to light reflections in the visible region (Ting et al., 2009). Studies have shown that the Visible and Near-Infrared Spectroscopy (VNIRS) method has been effective in estimating soil organic matter content (Wetterlind et al., 2013; Bilgili et al., 2010; Ting et al., 2009). However, the success rate of the VNIRS - Partial Least Squares Regression (PLSR) model established for soil organic matter was found to be relatively low, possibly due to the suppressive effects of other soil properties on reflections (İnci et al., 2021). Wetterlind et al. (2013), discussed that light distribution in soils rich in sand can hinder organic matter adsorption, suggesting that sandy soils in the dataset should be excluded to achieve accurate estimates for soil organic matter. Additionally, the high lime content in soils can also impede the adsorption effect of organic matter, leading to weaker models between organic matter and soil reflections (İnci et al., 2021). Previous studies on organic matter estimation using the spectroradiometer method and PLSR method have reported R^2 values ranging from 0.80 to 0.93 (Lazar et al., 2020).

3.4. Comparison of Geostatistical and VNIRS Methods for the estimation of Soil Parameters

Soil parameters were estimated using four different techniques (OK, IDW, COK, and VNIRS), and the accuracy of the predictions was assessed through cross-validation. The cross-validation RMSE values and percentage improvement rates obtained with the Co-Kriging technique are detailed in Table 4.

Table 4. RMSE values of geostatistical and VNIRS methods in estimating soil parameters

Soil parameters	**IDW**	**OK**	**COK**	**Variables used in COK**	**PI (%)**	**VNIRS-PLSR**
$CaCO_3$ (%)	1.19	1.23	**1.03**	**$CaCO_3$ᵻ -Mg‡**	**1.34**	1.13
OM_{2mm} (%)	0.62	0.63	0.62	OM_{2mm}ᵻ-Clay‡	1.58	**0.54**
pH	**0.18**	**0.18**	0.19	pHᵻ-Clay‡		0.21
Sand (%)	4.95	4.90	4.67	Sandᵻ-OM_{2mm}‡	5.65	**4.04**
Clay (%)	5.25	5.25	4.94	**Clayᵻ-K‡**	**5.90**	**3.8**
Silt (%)	2.60	2.58	**2.20**	**Siltᵻ-Mg‡**	**15.38**	2.49
$OM_{100m\mu}$ (%)	1.75	1.68	1.64	$OM_{100m\mu}$ᵻ-Clay‡	6.28	**1.39**
EC (µS/cm)	417	402	388	ECᵻ-OM_{2mm}‡	6.95	**328**
E.Ca (ppm)	2299	2306	**1855**	**Caᵻ-Mg‡**	**19.31**	2471
E.K (ppm)	203	**182**	187	Kᵻ-OM_{2mm}‡	**7.88**	192
E.Mg (ppm)	311	312	**291**	**Mgᵻ-Clay‡**	**6.73**	304
E.Na (ppm)	74.1	73.4	**70.9**	**Naᵻ-K‡**	**4.31**	72.1
CEC (me/100g)	18.7	16.8	17	CECᵻ-Clay‡	9.09	**16.5**

IDW: Inverse Distance Weighting, OK: Ordinary Kriging, COK: Co-Kriging, VNIRS PLSR: Mean Least Squares Regression, ᵻ: primary variable (PV), ‡: secondary variable (SV), E. Ca: Exchangeable Ca, E. K: Exchangeable K, E. Mg: Exchangeable Mg, E. Na: Exchangeable Na, % PI (Percentage Improvement): A*C/B (A: 100, B: IDW or OK RMSE values, C: B - COK RMSE values).

The RMSE (Root Mean Square Error) values from cross-validation serve as indicators of prediction accuracy, with lower RMSE values indicating higher accuracy.

RMSE is a metric that measures how close the predicted values are to the actual values. A lower RMSE value indicates that the model's predictions are closer to the real values, signifying higher accuracy. Upon examination of the RMSE values from the study, the OK method yielded the lowest RMSE value for the exchangeable K parameter (178); the IDW and OK methods had the lowest RMSE values for the pH parameter (0.18); the COK method resulted in the lowest RMSE values for lime ($CaCO_3$) (1.03), silt (2.20), exchangeable Ca (1855), Mg (291), and Na (70.95) parameters. For the parameters OM2mm (0.54), clay (3.8), OM100mµ (1.39), EC (328), sand (4.04), and CEC (16.5), the PLSR method exhibited the lowest RMSE values, indicating the best prediction results (Table 4). The Co-Kriging method was applied to assess prediction accuracy for parameters showing statistically significant correlations ($CaCO_3$-Mg, Sand-OM2mm, Clay-K, OM2mm-Clay, CEC-Clay, Mg-Clay, Silt-Mg, Ca-Mg, OM100mµ-Clay, Na-K, EC-OM2mm, K-OM2mm). COK demonstrated improved prediction success for several examined parameters. For instance, utilizing the COK method with exchangeable Magnesium as a secondary variable resulted in a lower RMSE value for $CaCO_3$ content compared to the OK and IDW methods. The RMSE values for exchangeable Magnesium were 311 and 312 with the OK and IDW methods, respectively. When estimated using clay as the secondary variable with COK, the RMSE value decreased to 291, indicating a 6.73% improvement in prediction accuracy. In another study, kriging and IDW methods were employed to estimate the properties of 53 surface soils formed on basalt parent material. Upon examination of the RMSE values, the kriging method yielded the lowest values for EC, pH, organic matter, silt, and sand parameters, while the IDW method yielded the lowest value for the clay parameter. These results align with the findings of the current study (Aygür, 2020).

4. Conclusion

Methods such as geostatistics and spectroradiometry serve as efficient alternatives to traditional laboratory analyses, offering savings in both chemicals and time when determining soil properties. In this study, spectral and geostatistical approaches were employed to estimate characteristics of the soil samples collected in areas with basaltic parent material. These methods were compared in terms of their prediction accuracy. The VNIRS-PLSR method demonstrated the highest success and lowest RMSE values for parameters such as OM2mm, OM100mµ, sand, clay, EC, and CEC. Conversely, the geostatistical method yielded the highest RMSE values for lime ($CaCO_3$), silt, pH, exchangeable Ca, exchangeable K, exchangeable Mg, and exchangeable Na. With the implementation of the COK technique, which utilizes a secondary variable, there was an enhancement in prediction success ranging from 1.34 % to 19.31 % compared to OK and IDW techniques. The aim of employing these methodologies is to optimize the process of determining soil properties, accurately apply necessary agricultural inputs, and promote sustainable agricultural practices. Therefore, there is a growing need for more studies utilizing these methods to further advance agricultural practices.

Declaration of Author Contributions

The authors declare that they have contributed equally to the article. All authors declare that they have seen/read and approved the final version of the article ready for publication.

Declaration of Conflicts of Interest

All authors declare that there is no conflict of interest related to this article.

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References

Akbaş, F., 2012. Modeling and mapping of the available phosphorus level of Kazova soils with geostatistical estimation and simulation methods Konya soil water and desertification combat research station directorate. *Journal of Agricultural Science*, 18: 63-76.

Aksakal, E.L., Öztaş, T., 2010. Effects of polyvinylalcohol, humic acid and polyacrylamide applications on structural stability and soil losses. *III. National Black Sea Forestry Congress*, Volume: III, 20-22 May, pp. 953-962.

Aydemir, M., Kara, Z., 2023. The Effect of Soft Core Fruit Tree Leaves on Some Soil Properties. *ISPEC Journal of Agricultural Sciences*, 7(1): 45–52.

Aygür, O., 2020. Estimation and mapping of the properties of soils formed on basaltic parent material with different geostatistical methods. Msaster's Thesis, The Graduate School of Natural and Applied Science of Harran Uuniversity Institute of Sciences, Şanlıurfa.

Başkan, O., 2004. Geostatistical application in engineering and physical property relationships of gölbaşı region soils. Ph. D Doctoral Thesis, The Graduate School of Natural and Applied Science of Ankara University Institute of Science and Technology, Ankara.

Başbozkurt, H., Öztaş, T., Karaibrahimoğlu, A., Gündoğan, A., Genç, A., 2013. Determination of spatial change patterns of soil properties using geostatistical methods. *Atatürk University Journal of Agricultural Faculty*, 44(2): 169-181.

Bilgili, A.V., Esb Van, H.M., Akbaş, F., Durak, A., Hivel, W.D., 2010. Visible-Near infrared reflectance spectroscopy for assessment of soil properties in a semi-arid area of Turkey. *Journal of Arid Environments*, 74: 229–238.

Bilgili, A.V., Çullu, M., Aydemir, S., 2014. Investigation of the potential for characterizing salt-affected soils with the help of near infrared reflection spectroradiometer and electromagnetic induction technique. *Harran Journal of Agricultural and Food Sciences*, 18(1): 33-46.

Birol, M., Günal, H., 2022. Field scale variability in soil properties and silage corn yield. *Soil Studies*, 11(1): 27-34.

Brady, N.C., Weil, R.R., 2008. The nature and pproperties of soils (The Nature and Properties of Soils, vol, ed. 14 edn.). Prentice-Hall Inc., Upper Saddle River, New Jersey.

Bouyoucous, G.J., 1951. A recalibration of hydrometer for making mechanical analysis of soils. *Agronomy Journal*, 43(9): 434-443.

Budak, M., Günal, H., 2016. Visible and near infrared spectroscopy techniques for determination of some physical and chemical properties in Kazova watershed. *Advances in Environmental Biology*, 10(5): 61-73.

Burrough, P.A., McDonnell, R.A., 1998. Principles of Geographical Information Systems. Oxford University Press. New York.

Caruso, C., Quarta, F., 1998. Interpolation methods comparison. *Computers and Mathematik with Application*, 35(12): 109-126.

Cambardella, C.A., Moorman, T.B., Novak, J.M., Parkin, T.B., Karlen, D.L., Turco, R.F., Konopka, A.E., 1994. Field scale variability soil properties in central iowa soils. *Soil Science Society America Journal*, 58: 1501-1511.

Chang, K.L., 2002. Optimal estimation of the granulometric composition of soils. *Soil Science*, 167: 135-146.

Çetin, M., Tülcü, K., 1998. Examination of local variations in monthly precipitation in the eastern mediterranean region by geostatistical method. *Journal of Engineering and Environmental Science*, 22(4): 279-288.

Dunn, A.J., 2002. Survey of Legislation, Agricultural Law. University of Arkansas at Little Rock. LawReview.

Erdinç, A., Öndegiden, E., Kendirci, A., Sezer, T., Işık, P., Bahrioğlu, O., 2011. Şanlıurfa Provincial Environmental Paper. Şanlıurfa, 206p.

Esbensen, K.H., Geladi, P., 2010. Principles of Proper Validation: Use and Abuse of Re-Sampling for Validation. *Journal of Chemometrics Call for Papers Special Issue for*, 24: 168–187.

Ekberli, İ., Dengiz, O., 2017. Determination of linear regression models between basalt parent material and some topographic and physicochemical properties of soils formed on different topographic positions. *Soil Water Journal*, 6 (1): 15-27.

Hamlett, J.M., Horton, R., Cressie, N.A.C., 1986. Resistant and Explatory Techniques for Use in Semivariogram Analysis. *Soil Science Society of American Journal*, 50: 868-875.

Isaaks, E.H., Srivastava, R.M., 1989. An Introduction to Applied Geostatistics. Oxford University Press. New York.

Gedikoğlu, İ., 1990. Soil Laboratory Analysis Methods Used in Determining Soil Productivity. KHGM, Şanlıurfa Research Institute Directorate Publication. General Publication No: 55, Technical Publication No: 11, 75 pp. Şanlıurfa.

Gillman, G.P., Sumpter, E.A., 1986. Surface Charge Characteristics and Lime Requirements of Soils Derived From Basaltic, Granitic and Metamorphic Rocks in High-Rainfall Tropical Queensland. *Australian Journal of Soil Research*, 24, 173–192.

İmamoğlu, M.Z., Sertel, E., 2016. Analysis of Different Interpolation Methods for Soil Moisture Mapping Using Field Measurements and Remotely Sensed Data. *International Journal of Environment and Geoinformatics*, 3(3): 11-25.

İnci, Y., Gündoğan, R., Bilgili, A., Ramazanoğlu, E., 2023. Morphological, Physical, and Chemical Properties, Classification, and Forensic Applications of Soils Formed on Common Parent Materials in Şanlıurfa. *ISPEC Journal of Agricultural Sciences*, 7(4):891-903.

İnci, Y., Bilgili, A., Gündoğan, R., 2021. Spectral Characterization and Prediction of Properties of Soils Formed on Different Parent Materials Using VNIRS Technique for Forensic Science. *Harran Journal of Agricultural and Food Sciences*, 25(4): 497-513.

İnci, Y., 2020. Determining the spatial variation of soil properties with different methods for forensic uses. Doctoral Thesis Ph.D Thesis, The Graduate School of Natural and Applied Science of Harran University, Institute of Science, Şanlıurfa.

Isbell, R.F., Stephenson, P.J., Murtha, G.G., Gillman, G.P., 1976. Red Basaltic Soils in North Queensland. Commonwealth Scientific and Industrial Research Organization, Melbourne. I. Environment, Morphology, Particle Size Characteristics and Clay Mineralogy. II. Chemistry. Division of Soils Technical Paper. CSIRO. No. 28, 1–42.

Isbell, R.F., Gillman, G.P., Murthe, G.G., Jones, P.N., 1977. Brown basaltic soils in North Queensland. Commonwealth Scientific and Industrial Research Organization, Melbourne. In: Division of Soils Technical Paper. vol. No. 34 CSIRO (25 pp.).

Isaaks, E.H. Srivastava, R.M., 1989. An Introduction to Applied Geostatistics. Oxford University Press, New York. 561 pp.

Jackson, M.L., 1958. Soil Chemical Analysis. Prentice Hall Inc., Englewood Ccliffs, New Jersey: Prentice Hall Inc.

Journel, A.G., Huijbregts, C.H.J., 1978. Mining Geostatistics. Academic Press, New York.

Journel, A.G., Huijbregts, C.H.J., 1981. Mining Geostatistics. Academia Press Inc. (London) Ltd.

Kara, Z., Yürürdurmaz, C., Çokkızgın, A., Keskiner, A. D., 2022. Determination of The Effects of Different Doses of Wheat Straw and Urea Fertilizer on Soil and Wheat Plant (Triticum aestivum L.). *ISPEC Journal of Agricultural Sciences*, 6(3), 610–619.

Kara, Z., Yakupoğlu T., 2023. Time-Dependent Changes in Moisture Content of Some Organic Matter Sources Used as Soil Conditioners. ISPEC *Journal of Agricultural Sciences*, 7(1), 95–104.

Kara, Z., Çokkızgın, A., Yururdurmaz, C., Gırgel, Ü., Yakupoğlu, T., 2024. Changes in Some Soil Compaction Indicators in A Field Treated with Leonardite and Chicken Manure. *ISPEC Journal of Agricultural Sciences*, 8(1), 150–159.

Karakeçili, M.V., 2004. Soils of Siverek District. Ms. Thesis, The Graduate School of Natural and Applied Science of Harran University. Graduation Thes, is, Harran University Institute of Natural Sciences, Şanlıurfa., 25s.

Kaplan, F., 2020. Comparison of Geostatistical and Spectroradiometric Methods in the Estimation of Soil Properties, Master Thesis, Harran University Institute of Science, Şanlıurfa, 1-63.

Kaplan, F., Öztürk, H., 2023. Determination of Soil Properties with Geostatistical Methods. *International Çankaya Scientific Studies Congress*, Conference Proceedings Book, 10-12, April, Ankara, pp. 99-100.

Kaplan, F., Rufaioğlu, S.B., 2023. Estimation and Mapping of Soil Parameters Using Multivariate Geostatistical Method. Isarc *1st International Blacksea Scientific Research and Innovation Congress*, Conferencegress Proceedings Book, 23-24 December 2023, Trabzon, Turkey, pp. 1195-1196

Kaplan, F., Bilgili, A.V., Rufaioğlu, S.B., İnci, Y., 2024. The Importance and Contribution of Precision Agricultural Technologıes in Reducing Greenhouse Gas Emissions, At The 12th Global Conference on Global Warming Held in Sanliurfa, Conference Congress Proceedings Book, Turkey, 16th-19th Of May, Şanlıurfa,p p. 443-446.

Kaplan, F., Rufaioğlu, S.B., 2024. The Use of Geostatiıstiıcs in Soil Science and an Overview of Studies (Ed. G. Bengisu),, A View of Agriculture from an Academic Perspective: Iiksad Ppublishing Hhouse, Ankara.

Keskin, M., Görücü Keskin, S., 2012. Precision Agriculture Technologies. Mustafa Kemal University Publications, Hatay.

Kravchenko, A.N., 2003. Influence of Spatial Structure on Accuracy of Interpolation Methods. *Soil Science Society of America Journal*.

Lazaar, A., Mouazen, A.M., Hammouti, K.E., Fullen, M., Pradhan, B., Memon, M.S., Monir, A., 2020. The Application of Proximal Visible and Near-Infrared Spectroscopy to Estimate Soil Organic Matter on the Triffa Plain of Morocco. *International Soil and Water Conservation Research*, 8(2), 195-204.

Lobell, D.B., Asner, G., 2002. Moisture Effect on Soil Reflectance. *Soil Sci. Soc. Am. J.*, 66, 722-725.

Milos, B., Bensa, A., 2018. Estimation of organic carbon and calcium carbonates in agricultural soils by Vis-NIR Spectroscopy. *Poljoprivreda*, 24 (1): 45-51.

Mitchell, B.D., Jarvis, R.A., 1956. The soils of the country around kilmarnock in: Department of Agriculture for Scotland Memedir of the Soil Survey of Great Britain; Scotland. HMSO, Edinburgh.

McGrath, D., Zhang, C., Carton, O.T., 2004. Geostatistical analyses and hazard assessment on soil lead in silvermines area. *Environmental Pollution*, 127(2): 239-248.

Qi, Y., Jeremy, L., Darilek, B.H., Yongcun, Z., Weixia, S., Zhiquan, G.U., 2009. Evaluating soil quality indices in an agricultural region of Jiangsu province, China. *Geoderma*, 149(3-4): 325- 334.

Saeys, W., Mouazen, A.M., Ramon, H., 2005. Potential for onsite and online analysis of pig manure using visible and near infrared reflectance spectroscopy. *Biosystems Engineering*, 91(4): 393–402.

Singer, A., 1987. Land Evaluation of basaltic terrain under semi-arid mediterranean conditions in the golan heights. *Soil Use Management*, 3, 155–162.

Soil Survey Laboratory, 2004. Soil Survey Laboratory Methods Manual Soil Survey Investigations Report. USDA, No: 42.

Soil Survey Manual, 2017. United States Department of Agriculture (USDA) Agriculture Handbook No. 18. Washington, DC: Government Printing Office.

Şenol, H., Akgül, M., 2013. Determination of some soil properties with near infrared reflection spectroscopy (NIRS). *Journal of Agricultural Sciences Süleyman Demirel University*, 18: 197-213.

Ting, H., Jing, W., Zongjian, L., Ye, C., 2009. Spectral features of soil organic matter. *Geo-spatial Information Science*, 12(1): 33-40.

Tekin, A.B., Günal, H., Sındır, K., Balcı, Y., 2011. Spatial structure of available micronutrient contents and their relationships with other soil charecteristics and corn yield. *Fresenius Environmental Bulletion*, 20: 783-792.

Trangmar, B.B., Yost, R.J., Wehara, G., 1985. Application of Geoistatistical to Spatial Studies of Soil Properties. *Advances in Agronomy*, 38, 65-91.

Thomas, G.W., 1983. Exchangeable cations. In A.L. Page (Ed.). Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties. Wiley, New York, pp.159-165.

Turgut, B., Öztaş, T., 2012. Determination of local changes in some soil properties using geostatistical methods. *Süleyman Demirel University Faculty of Agriculture Journal*, 7(2): 10-22.

Türker, U., Güçdemir, İ., 2004. A Research on determination of small-scale spatial variability in the fallow-cereal system in atatürk forest farm using precision agriculture technologies. *Journal of Agricultural Sciences*, 10(3): 305-312.

Valenzuela-Estrada, A., Undurraga, P., Salazar, O., Pino, I., 2015. Characterization of Basalt-Derived soils for optimizing ırrigation and fertilization management in the semiarid region of chile. *Soil Science Society of America Journal*, 79(2): 316-327.

Wetterlind, J., Stenberg, B., Rossel, R.A.V., 2013. Soil analysis using visible and near infrared spectroscopy. *Methods in Molecular Biology*, 953: 95-107.

Wilson, M.J., Logan, J., 1976. Exchange properties and mineralogy of some soils derived from lavas of lower old red sandstone (Devonian) age. I. exchangeable cations. *Geoderma*, 15: 273–288.

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