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MASTER OF SCIENCE (MSc) DEGREE THESIS

ESTIMATION AND MAPPING OF SOME SOIL CHARACTERISTICS OF THE HIRAN REGION OF NORTHERN IRAQ USING GEOSTATISTICAL AND SPECTRORADIOMETRIC TECHNIQUES

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Yüksek Lisans Tezi

KUZEY IRAK HİRAN BÖLGESİ BAZI TOPRAK ÖZELLİKLERİNİN JEOİSTATİSTİK VE SPEKTRORADYOMETRİK YÖNTEMLERLE TAHMİNİ VE HARİTALANMASI

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Toprağın özellikleri, toprağın sağlığı ve verimliliği için önemli göstergelerdir. Bu çalışmanın amacı, Irak'ın kuzeyindeki Erbil Vilayeti'nin Hiran Bölgesinde toprak özelliklerinin mekansal dağılımını belirlemek, haritalamak ve yansıma spektroskopisi ile karşılıklı ilişkisini belirlemektir. Çalışma alanı 500 m x 500 m kare büyüklüğünde parçalara bölünmüş ve Aralık 2021'de 0 – 30 cm derinlikteki numune alma alanlarından alanlarından 65 toprak numunesi alınmıştır. Numune alınan her bir konumun koordinatları coğrafi konum sistemi (GPS) ile kaydedilmiştir. Toprak örnekleri, toprak organik maddesi (SOM), doku, Toprak reaksiyonu (pH), elektriksel iletkenliği (EC) ve kalsiyum karbonat ($CaCO_3$) gibi çeşitli toprak özelliklerinin değerlendirilmesi için, görünür-yakın kızılötesi yansıma spektroskopisi (VNIR) gibi coğrafi istatistik teknikleri kullanılarak analiz edilmiştir. Zemin özelliklerinin her biri kapsamında mekansal yapıyı belirlemek için coğrafi istatistik yöntemleri kullanılmıştır. Her bir toprak özelliğinin mekansal analizini tahmin etmek için ara değer hesaplama yöntemleri olan sıradan krigleme (OK) ve ters mesafe ağırlıklandırması (IDW) kullanılmıştır. Sonuç olarak, % kum, % kil, % alüvyon ve $CaCO_3$ miktarı toprak yansımasından önemli ölçüde etkilenmiştir. Toprak parametrelerindeki güçlü ve orta derecede mekansal bağımlılık, yarı-variograma en uygun model olarak üstel bir model kullanılarak açıklanabilir. Ara değer hesaplama yöntemleri, OK'nin % SOM, % Kum, % Alüvyon, % Kil, pH ve $CaCO_3$ ara değerinin hesaplanması için IDW'den daha doğru sonuç verdiğini ve EC tahmininde IDW'nin sıradan kriglemeden daha iyi olduğunu ortaya koymuştur. VNIRS ile coğrafi istatistiksel yöntem arasındaki karşılaştırma, VNIRS'nin coğrafi istatistiksel yöntemden daha iyi bir teknik olduğunu ortaya koymuştur**.**

ANAHTAR KELIMELER: Tahmin, toprak özellikleri, coğrafi istatistiksel analiz, spektroradyometre, Hiran bölgesi, Erbil

ABSTRACT

MSc Thesis

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Soil properties are important indicators for soil health and productivity. The aim of this study is to determine and map the spatial distribution of soil properties and make a correlation with reflectance spectroscopy in Hiran region of Erbil governorate in the north of Iraq. The study area was divided into 500 m x 500 m square grids 65 soil samples were collected in the sampling sites at 0 – 30 cm depth in December 2021. The coordinates of each location were recorded by geographic position system (GPS). Soil samples were analyzed for soil organic matter (SOM), Sand %, Silt %, Clay%, Soil reaction (pH), Electric Conductivity (EC) and Calcium Carbonate ($CaCO_3$), Visible-near Infrared Reflectance Spectroscopy (VNIR) and geostatistical techniques were used for assessment of diverse soil properties. Geostatistical methods were used to determine spatial structure for each of soil properties. Interpolation methods ordinary kriging (OK) and inverse distance weighting (IDW) were used to estimate the spatial analyze of each soil properties. As a result the amount of Sand %, Clay %, Silt % and $CaCO_3$ were significantly affected with soil reflectance. Strong and moderate spatial dependence in soil parameters might be explained using an exponential model as a best fit in semivariogram. Interpolation methods indicated that OK is more accurate than the IDW for interpolating of SOM %, Sand %, Silt %, Clay %, pH and $CaCO_3$ and IDW was better than the ordinary kriging in estimating of EC. However, Estimation of soil properties by using VNIR spectroscopy in Hiran region is better technique than geostatistical analysis.

KEY WORDS: Estimation, soil properties, geostatistical analysis, spectroradimeter, Hiran region, Erbil

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All praise and gratitude to Allah for helping me to complete this work, I sincerely thank the rectorate of Harran University, especially the Dean of Agricultural Faculty, and Department of Soil Science and Plant Nutrition for allowing me to use the available facilities.

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LIST OF SYMBOLS and ABBREVIATIONS

GIS	Geographic information system
GS+	Geostatistical analysis
SPSS	Statistical Package for the Social Science
DEM	Digital elevation model
GPS	Global Positional System
NDVI	Normalized vegetation index
VNIR	Visible Near Infrared
PLSR	Partial least square regression
SOM	Soil organic mater
pH	Hydrogen ion concentration
EC	Electric conductivity
$CaCO_3$	Calcium carbonate
OK	Ordinary kriging
IDW	Inverse distance weight
SD	Spatial dependence
CV	Coefficient of variance
RMSE	Root mean square error
ME	Mean error
RSS	Residual Sum of Squares
R^2	Coefficient of determination

1. INTRODUCTION

The process of measuring and evaluating soil properties are typically long and expensive. The absence of sample information is frequently made up for by the outcomes of modeling or forecasts. To estimate the geographical distribution of soil characteristics, a variety of modeling techniques known as predictive soil mapping have been developed. The majority of them use geographic databases to build predictive maps or to calculate the values of soil properties at unsampled site utilizing data gathered in the field. They are based on mathematical or statistical models of correlations between various environmental factors and the characteristics of the soil. (Burrough et al., 1997). Techniques like Geostatistics and visible, near-infrared diffuse reflectance spectroscopy are being used more and more in precision agriculture to explain spatial variance within a field, predict soil characteristics at unexplored locations (Ben-Dor, 1995; Chang et al, 2001). Using a technology called visible-near-infrared reflectance spectroscopy; it is possible to quickly evaluation a variety of soil parameters. It has been applied to assess soil quality, pollution, and degradation as well as and measure its spatial fluctuation. (Wu et al., 2005; Chang et al., 2001). This method's utility may depend on how widely it is used (Shepherd et al., 2002). utilized utilizing samples for VNIR spectroscopy taken from a variety of soil types across a wide geographic area. This kind of sampling typically offers a broad variety of soil parameter values, which encourages favorable regressive outcomes. However, a large variety a sample set contains of soils,it is a challenge to the methodology because it necessitates statistical prediction relationships with a higher degree of universality, particularly when taking into account various constituent materials (Reeves, 1999; Shepherd, 2002). Although the ranges of soil parameters are typically narrow, the forecasting formula might simply required to be applicable nearby. With VNIR, a monochromator is used to evaluate the properties of soil reflectance above the full spectrum of the near infrared (700-2500 nm) and visible (350-700 nm) wavelengths. When reviewed alone or in combination with one another, basic information, first and second derivatives all offer useful data that may be examined. Due to implications associated with widening and bending vibrations in chemical bonds such C-C, C-H, N-H, and O-H, soil constituents exhibit distinctive absorption characteristics in these wavelength areas (Dalal and Henry, 1986). The intercorrelation between soil attributes and among soil components and spectra, the procedures of chemical investigation employed for training data sets, and the existence of outliers are all aspects that have an impact on VNIRRS's reliability and accurac predictions. Generally speaking, better outcomes were gotten while calibrations were created for samples related parent materials (Shepherdn et al., 2002). However, their value at intermediate and lower scales is less evident. Geostatistical methods for quantitative soil surveys have shown to be useful at large scales (Webster et al., 1997). Geostatistics offers the tools for describing and quantifying spatial variability, the data used for logical interruption, and calculating the alteration of the values that were interpolated. Adjustment assessment offers useful details proceeding the setup and sampling density required to predicte a property to a given precision. A technique known as geostatistics is used to estimate the soil property values in places that haven't been studied or have had few samples taken. (Yao LX et al., 2004) Deterministic and geostatistical interpolation were separated into two primary categories. Examples of deterministic methods include spline, radial basis function, global polynomial interpolation, local polynomial interpolation, and inverse distance weighting (IDW). On the other hand, the category of geostatistical techniques includes kriging and his variations, such as ordinary, simple, empirical, universal, etc. However, in recent years, Several techniques, including Regression Kriging (RK) and Geographically Weighted Regression (GWR), which include a non-linear interpolation model with a linear model (Shi and Tian, 2006; Zhang and Zhang, 2019). It is clear that there haven't been many studies done on the spatial interpolation of soil qualities at regional levels. This demonstrates the requirement for accurate soil mapping methods.

1.2. Objective of This Study

Both of chemical and spectroradiometer analysis were used to estimate of soil properties in Hiran region in Erbil governorate of Iraq.the aim of this study inclode the following

1- Determination of soil properties by laboratory analysis and estimation of each parameters via spectroradiometer
2- Using both of ordinary kirging and inverse distance wight (IDW) for measuring unsamped location.
3- Assuming the goodness of both calibration and valedation in PLSR model to make a correlation between soil parameters and spectral reflectance
4- Assuming the accuracy of interpolation methods by calculating mean error (ME), root means square error (RMSE), and coefficient of determination.

2. LITRETURE REVIEW

2.1. Soil Properties

Soil properties are important indicators improving soil health and productivity that soil productivity was related to soil parameters unique to each landscape site (Jones, 1989).

The response of a crop to changes in soil variables may also be utilized to help with soil mapping. The crop response is integrated across the root zone, which is a benefit of this strategy over those outlined in the preceding section. Salinity soil nutrient deficits (McMurtrey et al., 1993)), and soil moisture availability have all been inferred from crop response (Colaizzi et al., 2003). Brief examples of crop response to soil parameters are provided in the following paragraphs. Pinter et al. (2003) present a more extensive examination of crop nutrient and water status examples.

2.1.1. Soil texture

Particle size of soil classes were assessed as the measures in land appropriateness classification with different degrees of success, In order to create prediction equations for the percentage of sand, silt, and/or clay at the soil surface, reflectance measurements over tilled areas were employed. (Suliman et al., 1988) (Coleman et al., 1991). Only photography recorded across fields that have consistent tillage conditions allows for reliable connections, and typically the reaction only sufficiently powerful to define textural class at the surface (Barnes et al., 2000).

(GUNAL et al., 2011) 29 soil samples were collected to determine soil texture, as impacted by pretreatments, solid fractal dimension. They found that the contents of clay, organic matter, and calcium carbonate varied from 5.57 to 60.09%, 12.5 to 66.5%, and 0.05 to 4.25%, respectively. After calcium carbonate was removed, the mean fractal values that are the lowest (DSC=2.8343 and Dsoc=2.8336) were found. The study's findings showed that pretreatments had an impact on how quickly particle size distributions change. However, the changes in three parameters of soil texture Concentrations achieved when processed simultaneously with H_2O_2 and NaOAc were not statistically diverse.

2.1.2. Soil organic matter

One of the most vital elements of agricultural soils is unquestionably the amount of soil organic matter (SOM), which serves as a crucial barometer for evaluating the health and quality of the soil in general. Crop productivity is significantly increased by SOM (Stevenson et al., 1999). Organic Substances Several studies have linked SOM to wavelenth measurements obtained over agricultural areas (Coleman et al, 1991; Henderson et al., 1992; Chen et al., 2000) Considering soils that share a parent material.

Henderson et al. (1992) discovered visual wavelengths from 0.425 to 0.695 mm, exhibited a substantial association with SOM; however, For soils derived from various parent materials, the relationship was susceptible to Fe and Mn-oxides. When the soils were from altered parent materials, the practice of middle ultraviolet bands enhanced forecasts of OC concentration. Using real color imaging of a 115-ha field and locally built regression equations, Chen et al. (2000) were capable to reliably forecast SOC.

The concentrations SOM in0-10 cm depth ranged from 0.26 to 2.27 percent, with a mean of 1.24 percent. Within the subsurface soil layer 10 – 50 cm, organic matter values varied from 0.06 to 2.19 percent, with a mean of 1.36 percent. The results showed that the organic matter content from 0–10 cm is often greater than that of the 10–50 cm layer. The findings of this study highlighted the low organic matter content of soils in the Youssef El-Sedik District and the need for adequate yearly applications of organic fertilizers and biofertilizers to improve soil physical, chemical, and fertility status, which will ultimately increase crop production. (El-Gawad et al., 2019). The environmental simulations, modeling, mapping, and agriculture prediction require higher-quality, more cost-effective data. As a result, economical and time-efficient methods and technologies for soil analysis are necessary in order to determine appropriate management approaches and optimal land use.

2.1.3. Calcium carbonate ($CaCO_3$)

Calcium carbonate precipitation is prevalent in soils and regoliths, especially in dry regions. From solitary crystals and discrete elementary features to calcic/petrocalcic horizons and diversified calcrete profiles, it generates a wide range of shapes.the amount of Calcium carbonate in the depth 0–10 cm varied from 3.24 to 81.38 percent with an average of 15.04 percent, and in the subsoil layer 10–50 cm, they ranged from 3.57 to 51.04 percent with an average of 14.02 percent. In the first depth 0-10 cm and the second depth10 – 50 cm soil layers, respectively, more than 91 percent and roughly 87.75 percent of soils in the study region possessed more than 10% $CaCO_3$ The calcic character of the parent material from which the soils of study region evolved might explain the high soil calcicity.

(Elfaki et al., 2016) Calculations of several calcium carbonate determination techniques (Calcimetric and Titrimetric) using 26 georeferenced soil profiles in Sudan. The results showed that, with the exception of samples from the Gedaref area, there are no appreciable discrepancies between the calcimeter and titration techniques for calcium carbonate quantification in any of the samples under study. We came to the conclusion that when the Calcimeter technique was used for $CaCO_3$ measurement, individual variances in recognizing the titration end point would be avoided, and quick and accurate results would be produced compared to titration method. Less chemicals would be utilized, and time would also be savedIn light of the findings of this research, we strongly advise adopting the calcimeter method to estimate $CaCO_3$ in Sudanese soils.

2.1.4. Soil pH

Soil hidrogen reaction (pH) in natural areas is changed by industrial actions, not merely indirectly, not just by human-caused climate change, but also by other anthropogenic activities including land usage, manuring, nitrogen deposition, and more lately, pollution ((Roem ve Berendse, 2000).

(Darija et al., 2009) Measurements of the samples in three media: water, KCl, and calcium chloride—were used to determine the pH of the soil in the Republic of Croatia's dominant soil types. The researchers claimed that the correlation coefficients ranged between the groups of strong, very strong, and absolute. All samples' correlation coefficients that were evaluated were r=0.96 for pH KCl/H2O, r=0.97 for pH KCl/CaCl2, and r=0.99 for pH $H_2O/CaCl_2$ (absolute correlation).

(Guo, 2022) 134 samples of soil from Fuzhou, China were Using the help of the SVM-RFE Feature Selection Algorithm, predict and map the pH of the soil. The authors reported that the outcome highlighted the 5 most important ecological factors for value of soil pH, including mean annual temperature (MAT), slope, Topographic Wetness Index (TWI), modified soil-adjusted vegetation index (MSAVI), and Band5. Additionally, the SVM-RFE article choice approach might successfully increase the goodness of the model, and the best prediction outcomes were achieved by the extreme gradient boosting (XGBoost) model following SVM-RFE feature selection (coeficint of determination = 0.68, mean absolute error = 0.16, root mean square error = 0.26).

2.1.5. Electric conductivity

EC was traditionally used in soil science to messure soil salinity (Rhoades et al., 1990; Corwin and Lesch, 2005), to define soil components, clay texture, or hardpan coating (Samoue¨lian et al., 2005; Weller et al., 2007) and, further recently, to recognize structure of soil (Besson et al., 2004; Samoue¨lian, 2005), Surprisingly, little or no research has been committed to estimating soil unsaturated hydraulic In soil, conductivity is used to measure electrical resistance (Mualem, 1991)**.**

2.2.Digital Elevation Model (DEM)

A digital elevation model (DEM) is a numerical depiction of the land surface that offers basic figures regarding topography relief (Guth et al., 2006) digital elevation model in addition its related features (slope, aspect, drainage area and network, , and so on) are critical factors aimed at getting data otherwise assessing some manner that uses topography analysis. (Wolock et al., 1994). Many academics have utilized digital terrain data to forecast soil features. (Moore and colleaguse, 1993; Bell et al., 1994; Gessler et al., 1995). Biggs and Slater (1998) conducted a medium-scale soil study using a soil landscape and DEM. They employed a 15-m digital elevation model and its products, including slope, curvature, topographic wetness index TWI, relative elevation, and slope position. The fast soil feature map, with a measure of about 1:100,000, improved field substantiation and mapping assurance. Till recently, there had been no use of low spatial resolution DEM data for limited soil drawing. (Weismiller et al., 1977) created a soil inventory in Missouri using Landsat and topography data. The researchers did not, however, challenge to link land cover to soil type. (Franklin 1987) stated a fourty six percent to seventy five percent increase in classification accuracy after utilized Landsat MSS data with DEM-derived landscape descriptor layers for landscape class categorization.

2.3. Spatial Distribution of Soil Properties

(Bilgili et al., 2010) In the Harran Plain, Shanliurfal, a geostatistical technique predicted the soil salinity. 151 soil tasters were collected from the research between 0 and 15 and 15 and 30 cm depth. The authors claimed that the Results confirmed that the truthfulness of forecasts and mapping of soil properties exhausting multivariate geostatistical approaches that syndicate primary and secondary parameters is largely based upon the power of the relationship between soil salinity parameters and environmental variables used as covariables. The overall findings suggested that, depending on the strength of the interaction between the covariable environmental factors and the soil salinity parameters, estimate and mapping accuracy may be increased utilizing multivariate geostatistical approaches.

(González et al., 2022) An vital assignment for accurate soil mapping is determining which interpolation technique is best for each case study. This stays especially true in place of studies carried out at the regional scale from more than 400 sampling sites at three different depths (0-5, 5-10, and >10 cm) in the Separate Area of Extremadura, in the southwest of Spain. According to the authors, the best approach depended on the property and scope of the research. (EBK) existed the best truthful method for predicting soil qualities such as clay R^2 = 0.767 and RMSE = 3.318 for first depth. However, the IDW (Inverse Distance Weighted) approach was used at depths of 5 to 10 cm, with R^2 is equal 0.689 and RMSE =5.131.

(Shit et al., 2016) employed geostatistical technique to examine the geographical distribution of soil characteristics from 32 soil samples in India. The authors said that structural elements including climate, parent material, environment, soil features, and additional natural factors require an influence on the geographical distribution of Electric conductivety , hidrogen reaction , and organic carbon in soil.

(Omran, 2012) 146 soil samples from the Egyptian region of Ismailia were used to predict the precision of soil mapping using geostatistical techniques. The authors discovered that the maps produced using the three interpolation techniques—Ordinary Kriging, Inverse Distance Weighting, and splines—clearly demonstrate that the map produced using Universal Kriging (UK) is superior than those produced using the other two techniques. In light of this, UK can be regarded as an accurate approach for extrapolating the soil's (EC, pH, CaCO3) characteristics.

(Reza et al., 2015) using data from 85 soil samples, it assessed the geographical distribution of physical characteristics in northeastern Bihar. The author’s revealed that Based on least RMSE, semi-variogram parameters (C_0, C_0 + C, and range) for each soil indicators through the greatest fit model were found. Although the field capacity, PWP, and available water content. semi variograms were explained by spherical model, Analysis of the isotropic variogram revealed that the exponential model adequately characterized the semi variograms for soil particle size distribution, with the distances of spatial dependence being 1989, 1787, and 1654 m, respectively.

(Almasi et al., 2014) used a few interpolation methods to map the geographical dispersal soil surface and organic mater in Iran. Fifteen thousent hectares of South West Shahrekord soils were examined, 92 soil profile resulted. The authors demonstrated that, compared to other approaches, ordinary kirging (with an exponential model) might predict the variation in depth of A layer more accurately than IDW. Due to impacts of heterogeneity in soil developing variables in the progression of soils formed in various landforms of the research region, that might negate stationary assumptions, kriging's forecast of spatial stability of A horizon is poor.

(Zhang, 2020) derived predictions of the spatial variability of SOC stocks in China using 732 sample sites at six distinct soil depths (0–10, 10–20, 20–40, 40–60, 60–80, and 80–100 cm). The authors stated that the In the current reading, Mean error provided 0.01 to 0.1for soil organic carbon, indicating that the prediction of the soil organic carbon contents using inverse distance weight and ordinary kriging were generally neutral, and The IDW approach was preferable than the OK method for the spatial interpolation of SOC, as evidenced by the R^2 values of the IDW method being marginally higher than those of the OK method.

(Gawad et al., 2019) Projected the geographical distribution of soil parameters ($CaCO_3$, salinity, pH, partial size, and SOM) for 69 soil samples at surface (0- 10 cm) and subsurface in the Youssef El-Sedik District region, Fayoum Governorate, Egypt (10 – 50 cm). The researchers discovered that the EC ranged from 0.68 to 132 dSm^{-1} at 0-10 cm and 0.92 to 82 dSm^{-1} at 10-50 cm soil depth, respectively. The findings revealed that, in the upper 10 cm and the (10 - 50 cm) layers, respectively, 91.23% and 78.97% of the studied region have ECe > 4 dSm-1. Salt-affected soils may be found across the research region, with approximately 47.62 and 30.39% of the district soils having ECe values > 10 dSm-1 in the top and subsurface layers, respectively. Approximately 92.53% of the soils in the study region were calcareous (> 10% $CaCO_3$ equivalent), which is attributable to the origin of the parent material. About 46.69% of soils had a pH higher than 7.5, and less than 1% of soils had a pH higher than 8.0, with an average pH value of 8.2. In Youssef El-Sedik soils, the organic matter values seldom went beyond 2%. Several diverse soil texture classes were identified, however in the 0–10 cm and 10–50 cm depth, respectively, 46.38% and 42.65% of the soils had a clay texture.

2.4. Spectroradiometer

Radiation from models of 7 Indiana soil sequences was measured using a field spectroradiometer in the spectral region of 430 to 730 nm. This variety encompasses the majority of the perceptible section of the band. The ratio of the radiation from the target soil divided by the incident radiation was used to calculate the percentage reflectance of the soils. Reflectance curves were produced for soils in wet and dry situations with the crust shattered, as well as for certain soils in a thirsty incrusted state. Initial results acquired through the device's examination suggested that it was capable of evaluating the radiance qualities of diverse soil series. (Cipra, 1971).

(Bilgili et al., 2011) By combining the expenditure of hyperspectral VNIR reflectance spectroscopy and kriging, 512 site samples in the north of Turkey's soil were used to predict the spatial analysis of soil variability. The researcher found that the VNIRRS-PLSR technique produced better prediction consequences for SOM, clay, and sand than conventional kriging, with R^2 values of 0.56-0.73, 0.79-0.85, and 0.65-0.79, respectively, and lesser RMSE of prediction (values of 2.7-4.1, 37.4-43, and 46.9-61 respectively) (values of 2.7–4.1, 37.4–43, 46.9–61, respectively). Both techniques provided poor predictions for the Electric conductivity, pH, sodium, potasium, and silt content.

(Bilgili et al., 2010) employed VNIR reflectance spectroscopy to evaluate the characteristics of soil in 512 soil samples collected from a depth of 0 to 30 cm in a semi-arid region in Turkey. According to the scientists, the exchangeable Ca and Mg, CEC, OM, clay, sand, and calcium carbonate concentrations all showed the highest connections.

(Mohameda et al, 2016) assessed the soil contamination in Egypt, by 25 soil samples and near-infrared spectroscopy methods. (R^2 = 0.82, 0.75, and 0.65 for Cr, Mn, and Cu, respectively.) The authors demonstrated that the derived regression models were of high quality. As a result, Visible and Near-Infrared (Vis-NIR) reflection spectroscopy may be utilized as an affordable and quick process to replace the conventional methods of determining the presence of heavy metals in soil.

(Lihua et al., 2005) Used spectrophotometer and a spectroradiometer to assess the soil fertility spectroradiometer, which uses 150 georeferenced data from China, it has a measurable range of 4000 – 12000 cm-1, while the spectroradiometer has a range of 325–1075 nm with a resolution of 1 nm. The authors indicated that the majority of soil properties may be assessed using NIR spectral reflectance data acquired from both spectrophotometers and spectroradiometers, according to the results.

2.5. Normalized Vegetation Index (NDVI)

(Lihua et al., 2005) used a spectrophotometer and a spectroradiometer to assess the soil fertility the spectrophotometer, which uses 150 georeferenced data from China, has a measurable range of 4000 – 12000 cm-1, while the spectroradiometer has a range of 325–1075 nm with a resolution of 1 nm. The authors indicated that the majority of soil properties may be assessed using NIR spectral reflectance data acquired from both spectrophotometers and spectroradiometers, according to the results.

(Poblete et al., 2009) Utilizing a portable spectroradiometer, researchers in Talca Valley, Maule Region, Chile studied the geographic variability of the NDVI across a Merlot grape plot. The study discovered that the average NDVI values for vines (0.73) were 69% higher than NDVI for soil (0.23) and that vine spatial variability was twice as great as soil variability. In the experimental field, three homogenous zones were identified where high and low NDVI values were comparatively time stable.

3. MATERIALS and METHODS

3.1. Study Area

The study was carried out in the northern Iraq province of Erbil, in the Hiran area. Figure 3.1. depicts the broad geographic region, which ranges from 4927500 to 4935000 latidude N and 437600 to 438400 longtude E.

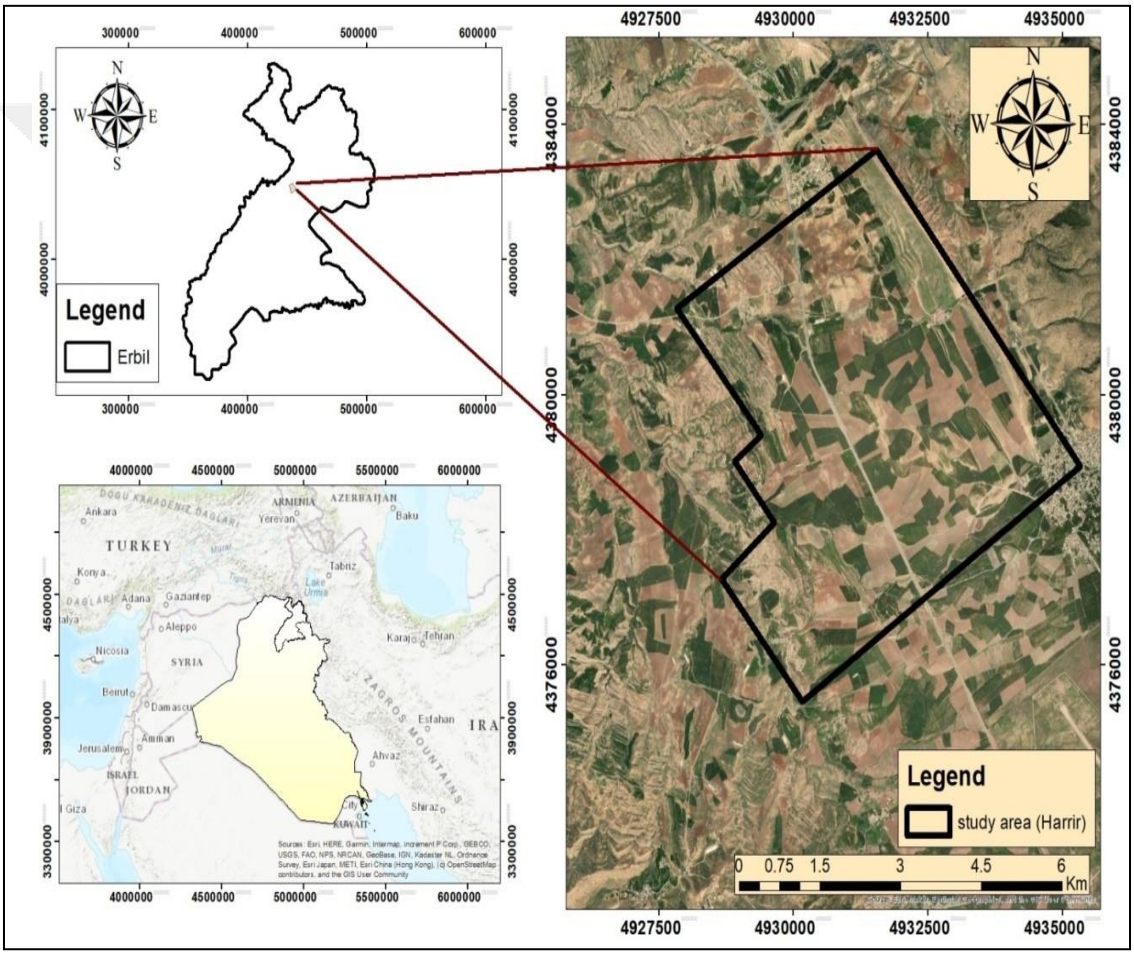


Figure 3.1. Location of study area

3.2. Climate Data

The whether data was taken from shaqlawa station, is the nearst station from study area Temperatures change greatly during the day and night, as well as during the winter and summer seasons. As a result, the research area's climate has been described as hot and dry in the summer and cold and rainy in the winter. Spring and fall are shorter than summer and winter. The annual average rainfall ranges was 448.7 mm from 2020 to 2021 and 489.8 mm from 2021 to 2022 in the study area table 1 and 2 shown the climatological data. The rainfall in the study area begins from October and continues until May. Therefore, rainfall of these months was averaged as recommended by the Ministry of Agriculture/General Directorate of Agriculture-Erbil.

Table 3.1. Climate data of study area

Soil 10MAX	Soil 10MIN	Soil 20AVG C	Soil 20MAX	Soil 20MIN	SM vg %	MMAX%	MMIN %	BPAVG (mB)
7.6	5.7	8.6	10.1	7.5	42.2	46.2	38.4	908.3
9.6	7.3	10.0	11.4	8.8	44.4	48.4	42.0	907.3
12.4	10.2	12.4	13.6	11.2	40.2	42.1	38.2	903.9
21.4	17.4	19.9	21.1	18.3	29.2	29.6	28.8	905.0
28.9	24.5	27.0	28.2	25.5	18.6	18.9	18.4	900.8
33.6	28.5	30.5	31.7	29.2	12.3	12.4	12.1	900.0
36.4	31.6	33.3	34.4	32.2	9.8	9.9	9.6	896.2
35.7	31.1	32.9	34.1	31.8	9.0	9.2	8.9	898.9
33.5	29.0	30.8	31.8	29.7	8.5	8.7	8.4	901.0
26.4	23.0	24.9	25.8	24.0	9.2	9.5	8.9	906.4
16.5	13.4	15.7	16.7	14.6	18.4	18.9	18.0	907.8
10.1	7.8	10.5	11.6	9.4	35.9	39.7	33.3	907.7

Table 3.2. Annual precipitation of Shaqlawa from 2020 to 2022

Year	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	April.	May.	Jun.	Average
2020 - 2021	1	110.5	53.5	145.2	71.4	57.3	4.8	5	_	448.7
2021 - 2022	40.8	6.5	135	165	68	74.5	_	_	_	489.8

3.3. Soil Sampling

The study was done in December 2021. Soil samples were collected in Hiran region of Erbil governorate. Grids of 500 × 500 m squares were used to divide the research area and 65 soil samples were taken around from the center of each grid point illustrated in Figure 3.2. In the item of soil being faraway at the center of the cell due to urban area, road, river, etc., an alternate location was selected as close as possible. the samples were taken from 0-30 cm depth.

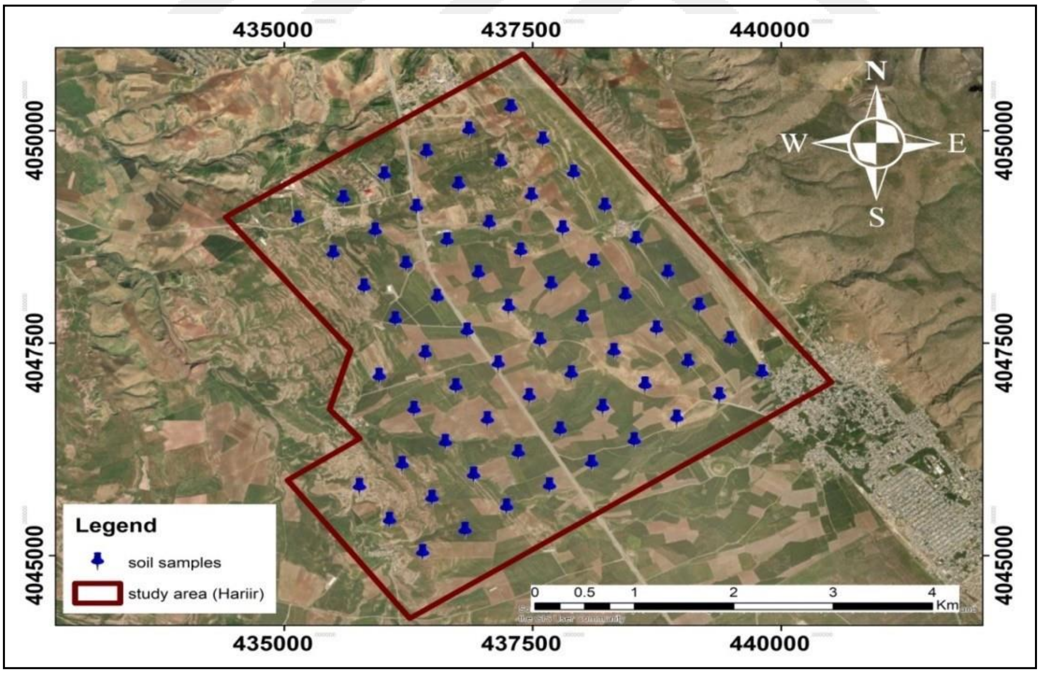


Figure 3.2. Points of soil sampling

3.4. Field survaice and preparing for the laboratory

After exposing the profile, the face of each samples were gently cleaned, 30cm depth of all samples were noted (number of the sample, coordination (x, y) and reading the place of the sample) with the succession the samples to a polythene bag and label it were transferred. The sample gathered from the field in the shade by spreading it on a clean sheet was dried, the soil through a 2 mm sieved. The samples were prepared for analyzing of soil properties (texture, organic matter, pH, EC, $CaCO_3$) shown in Figure 3.3. and with spectroradiometer were analyzed.

Figure 3.3. Taking soil samples in the field

3.5. Laboratory Analysis

The soil samples were air dried, avoided with roots and residue and grinded to pass 2 mm sieve then prepared for investigation of soil properties ofsoil texture Additionally, in a settling cylinder with sodium hexametaphosphate, the hydrometer technique was used to determine the particle size distribution (Gee and Bauder, 1986)., SOM Walkey-Black method (Nelson and Sommers, 1996)., electric conductivity, calcium carbonate ($CaCO_3$) contents were determined by the Scheibler calcimeter method (Allison and Moodie, 1965) and soil pH by pH meter).

Figure 3.4. Laboratory analysis of soil texture

3.4. Reflective Hyperspectral Spectrum

Utilizing the Field Spec Pro hyperspectral sensor from Analytical Spectral Devices, Inc. (Colorado, 1997). To provide a total of 2150 data points per spectrum, soil samples were scanned. Absolute Reflectance (decimal percent) of the samples was collected for 350-2500 nm at 1 nm spectral resolution. Then Air-dried and put into four cm span, and a Tungsten Quartz halogen spotlight light source contained intimate a Muglight sensor accessory was used to illuminate the samples. On a distance of four cm from the device, reflection was measured concluded the glass bottom of each dish at a fixed angle (55 degrees from horizontal). To prevent any spectral changes resulting from variances in particle size within soil samples, the sample was rotated 90 degrees and five further readings were taken after five consecutive readings, each average of ten sequential reflectance spectra. A Spectralon standard was used to calibrate the accuracy and detector responses and optimize the signal. The instrument was reset if the white (Spectralon) measurement was unstable.

Figure 3.5. Laboratory analysis of sectroradiometer

3.5. Processing Data

Reflectance data were exported in batches using ViewspecPro (Analytical Spectral Devices, Inc., Boulder, CO, 80301), which converts binary data to ASCII. A master data file with one representative reflectance spectrum for each soil sample was created by using Splus to average the ten subsequent reflectance readings from each sample (a total of 100 scans). Spectral data were processed using UnscramblerV.8.05 (CAMO, 2003), first by formulaic processing utilizing the Savitsky-Golay is observed (Savitzky and Golay, 1994). These phrases stand for the derivative order, first smoothing, second smoothing, and polynomial order, respectively. The first generation spectra often accentuate the absorption features indicative of the contents of the soil elements and also minimize variability across samples, according to (Martens and Naes, 1989). First derivative and raw spectra were both used to try to predict soil characteristics.

3.6. Statistical Analysis

The prediction method involved applying cross-validation with all of the calibration sample subsets first, and then testing the precision of the forecast using different validation sample sets. Due to calibration, the datasets were (n = 65). Once for calibration and once for validation, each subset was used. Partial least square (PLSR) regression was used to calibrate the relationship between soil reflectance and soil characteristics.

3.7. Partial Least Square Regression

It is common practice to employ PLSR regression, a technique for connecting 2 data matrices (X and Y) using a linear multivariate model. The latent variables discovered by PLSR are orthogonal and biased linear combinations of X variables. They are created by decomposing both the X and Y variables. Then, with X being soil reflectance and Y being a measured soil characteristic, these new X variables are utilized to predict Y variables. In contrast to multiple linear regression, it is capable of handling data with significant co-linearity in independent (X) variables, which may also have a larger number of observations. The column averages are subtracted from each reflection in the column preceding to the analysis to center variables X and Y. To avoid overfitting or underfitting the data in PLSR, which would result in models with low predictive power, the number of latent variables must be carefully chosen. The models were built repeatedly using cross-validation, separation some samples from the calibration data set to be used in the validation process until all samples or groups were evaluated. UnscrumblerV.8.0.5 software was used to conduct PLSR.

3.8. Prediction Accuracy

The root mean square error of prediction (RMSEP) and coefficient of determination (R^2) of measured and forecasted values of samples were used to assess each VNIR technique's capacity to predict a soil attribute (Equation 3.1).

$$\text{RMSEP} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{\text{pred.}} - Y_{\text{meas.}}\right)^2}{n-1}} \tag{3.1}$$

3.9. Statistical Analysis

min, max, mean, standard deviation (SD) and coefficient of variation (CV), values of soil properties were determined at 0-30cm depth by used SPSS ver. 20.0 (IBM Corp., Armonk, NY, USA). To examine the correlations between soil qualities and sample geographic information, Pearson's correlation analysis was used. A semi-variogram was created in this research to describe the variability of the soil properties . The model with the lowest residual sum of squares (RSS) and the highest coefficient of determination (R2) performed greatest To establish the spatial structure of the soil properties at a particular scale, the semi-variogram model parameters (nugget variance (C0), structural variance (C), sill variance (C0 + C), and the spatial autocorrelation range) were utilized. To assess the degree of geographical dependence, the nugget to sill variance ratio (C0/(C0 + C)) was computed; a ratio of 0.25 reflects a significant degree of spatial autocorrelation; 0.25–0.75, medium autocorrelation; and >0.75, moderate autocorrelation. (Equation (3)) was used to calculate the semi-variogram model (Equation 3.2).

$$\gamma(h) = \frac{1}{2N(h)}\sum_{1}^{N(h)}\left[z(xi) - z(xi+h)\right]^2, \tag{3.2}$$

h is the lag distance, N(h) is the number of sample point pairs separated by h, and z (xi) and z (xi + h) are the paired data values separated by h. (h) is the experimental semi-variogram. The geographic distribution of soil attributes was shown using the interpolation techniques of ordinary kriging (OK) and inverse distance weighting (IDW). A leave-one-out cross-validation method was used to evaluate the interpolation performance. The following are the metrics that were used to assess the spatial interpolation's prediction accuracy: root mean square error (RMSE), mean error (ME), and coefficient of determination (R^2) (Equation 3.3, 3.4, 3.5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum{}_{i=1}^{n}(Pi - Mi)^2}, \tag{3.3}$$

$$\mathrm{ME} = \frac{1}{n}\sum{}_{i=1}^{n}(Pi - Mi), \tag{3.4}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(Pi - \overline{M}\right)^2}{\sum_{i=1}^{n}\left(Mi - \overline{M}\right)^2}, \tag{3.5}$$

Where Pi and Mi. stand for the predicted measured values, respectively; M and P stand for the average of the measured and anticipated values; and n stands for the number of samples.

3.10. Terrain Variable

DEM was used to create maps for surface elevation, aspect and slope for topographical describing the study area. Landsat 8 was utilized to make the map normalized deference vegetation index NDVI, the ecological indicator NDVI was calculated depended on This equation represents the spectral reflectance measurements obtained in the red (visible) and near-infrared areas as red and NIR, respectively (Equation 3.6).

$$\mathrm{NDVI = NIR - Red / NIR + Red} \quad , \quad \mathrm{NDVI = band\ 5 - band\ 4 / band\ 5 + band\ 4} \tag{3.6}$$

The value is deferent between -1 to +1 from non-vegetation cover to dense vegetation.

4. RESULTS and DISCUSSION

4.1. Soil Variable

The variation in elevation values within a region is known as topographic heterogeneity. Specific indices describing the rate of elevational change in response to changes in can be quantified. Topographical variables of aspect, slope, and elevation and ecological NDVI parameter are shown in Figure 4.1. The directions of study area were expressed in aspect map, is started from the flat area -1 to the north 337 degree. The topographical of entire study area with elevation ranging from low (483– 713 m) The grade of slope was started starting 0 to 66.89, slope value was classified of different variety of the most of zone has a flat and moderate elevation with a verity from 0 – 8 is flat to 8 -15 slopping, 15 – 25 rather steep, 25 – 40 steep and >40 is very steep slope, the value ecological parameter NDVI from 0.0072 to 0.38 this value indicate that there wasn't any water sheet in the study area, While the whole area was used for agriculture practices. The study area was mostly planted with wheat, and sections of it are still planted with wheat and rice.

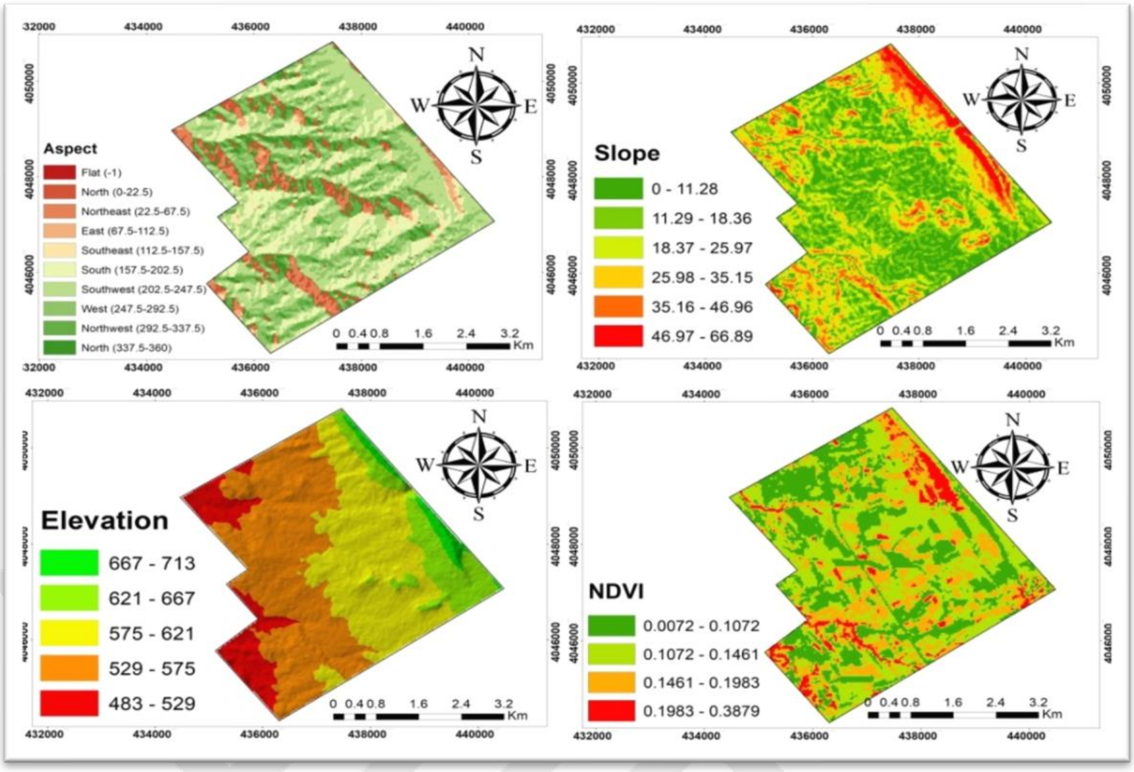


Figure 4 1.Topographical variable of aspect, slope, elevation and NDVI

Were certain in table 4.1., the amount of sand %, silt % and clay % content ranged from 13.44 to 75.44 %, 9.28 to 43.28 % and 13.28 to 61.28 % respectively, with the mean value 26.94 %, 27.64 % and 45.40 % respectively. SOM %, pH, EC and CaCO3 were from 0.049 to 5.197 %, 6.91 to 7.61, and 170.8 to 804 and 15.2 to 34.96 respectively, with the mean value 1.74, 7.30, 341.95 and 24.44. The coefficient of variance (CV) % was calculated to know the variability of each soil properties. CV ≤15% is low, 16-30% is medium; and ≥30% is high variability (Wilding and Dress, 1983). CV indicate low variation of soil pH (1.84 %), therefore the medium variation of soil clay %, silt % and $CaCO_3$ (26.01 %, 25.28 % and 20.30) respectively, compared to the high variation of SOM, sand % and EC (68.84%, 50.21 % and 37.90 %) respectively.

Table 4.1. Descriptive statistic of laboratory analysis of soil properties

	OM %	Sand %	Clay %	Silt %	PH	EC	CaCO3%
Minimum	0.049	13.44	13.28	9.28	6.91	170.8	15.2
Maximum	5.197	75.44	61.28	43.28	7.61	804	34.96
Mean	1.74	26.94	45.40	27.64	7.30	341.95	24.44
Standard Deviation	1.201	13.53	11.81	6.99	0.13	129.60	4.96
CV %	68.84	50.21	26.01	25.28	1.84	37.90	20.30
Skewness	0.90	2.13	-1.03	-0.13	-0.11	1.62	0.020
Kurtosis	0.36	4.48	0.30	0.64	0.66	3.32	-0.58

CV = coefficient of variation, OM = Organic matter, EC = Electric conductivity

To comprehend how soil nutrients are related, a correlation matrix was created (Table 4.1.). The correlation between training variable and soil properties there isn't any related between soil properties and topographical variable because the entire area is used for agriculture practices, NDVI have weak positive correlation with slope (r = 263), SOM concentration and EC showed a substantial and positive correlation. Consequently, there was a negative connection between SOM and pH EC value and concentration had a substantial link (r = 0.502, p 0.05), although EC value and sand, silt, and clay had weak and negative correlations. $CaCO_3$ and SOM had minor correlations as well. Additionally, sand and clay, silt, and $CaCO_3$ exhibited substantial negative correlations with one another, while clay and silt and $CaCO_3$ have positive correlations with one another (r=0.207, r=0.351, respectively). Then, EC and pH show a substantial negative connection (r=0.64). The both of statistic parameter (kurtosis and skewness) are used to assess the normal distribution of symmetry. A negative kurtosis of $CaCO_3$ indicated that the distribution has lighter tails than the normal distribution and sand have positive kurtosis. Higher kurtosis value of Sand % indicates that the distribution has more outliers falling relatively far from the mean. OM%, Sand%, EC, and $CaCO_3$ all had positive skewness values, but Clay%, Silt%, and pH had negative values, indicating that a distribution's tail is on the right side of the distribution. A soil data's skewness value can be taken into account while determining the distribution tendency. If the data's Skewness value is less than 0.5, no transformation is needed; if it is between 0.5 and 1.0, a square root transformation is performed; and if it is greater than 1.0, a log transformation is used to restore the information's distribution to the typical distribution (Webster et al., 2001). Skewness sand value (2.13) revealed that the records did not follow a standard distribution. Before conducting the statistical and geostatistical studies, the PAP data underwent log transformation

Table 4.2. Correlation coefficients between soil properties

	Aspect	**Elevation**	**Slope**	*NDVI*	*OM (%)*	*Sand (%)*	*Clay (%)*	*Silt (%)*	*pH*	*EC(μs/cm)*	*CaCO3*
aspect	1										
elevation	-0.099	1									
slope	-0.198	0.139	1								
NDVI	-0.113	-0.051	0.263	1							
OM (%)	0.017	0.032	0.075	0.131	1						
Sand (%)	0.082	-0.212	-0.012	-0.184	0.061	1					
Clay (%)	0.008	0.139	0.026	0.156	-0.052	-0.85**	1				
Silt (%)	-0.173	0.175	-0.019	0.091	-0.029	-0.488*	-0.031	1			
pH	-0.100	-0.252	0.008	-0.071	-0.377	0.017	-0.080	0.103	1		
EC(μs/cm)	0.042	0.235	0.009	0.157	0.502**	-0.070	0.114	-0.057	-0.64**	1	
CaCO3	0.054	0.394	0.086	-0.193	-0.159	-0.363	0.207	0.351	0.0132	-0.155	1

* = p < 0.005, ** p < 0.001

4.3. Soil Reflectance

For each soil sample, the first derivatives of the raw reflectance spectra are shown in Figure 4.2. According to Islam (2003), soil reflectance was often lower in the visible range and greater in the near-infraredinfrared, with particular absorption bands occurring around 1400, 2200, and 2400 nm. These have a good correlation with the OH characteristics of free water at 1400 and 1900 nm and the OH features of clay lattice at 1400 and 2200 nm (Hunt, 1980). Basic soil constituents with soil water, clay type and content, OM, and Fe-Al all have an influence on how the soil reflects light. Oxides (Bowers et al., 1965). The correlation between soil properties and reflectance spectroradiometer was calculated. Table 4.3. showed that both positive and negative correlations at several wavelengths through the spectrum. The positive correlation was found between reflectance and soil properties of sand, silt and $CaCO_3$ while negative correlation with clay. However, there weren't any association between soil reflectance and soil variables of SOM, pH, and EC according our study.

Table 4.3. Correlation between soil variable and reflectance

Column1	OM (%)	Sand (%)	Clay (%)	Silt (%)	pH	EC(μs/cm)	CaCO3
350-450	0.157	.357**	-.450-**	0.068	-0.080	0.101	0.077
451-550	0.082	.379**	-.540-**	0.178	-0.014	-0.006	0.107
551-650	-0.046	.305*	-.521-**	.290*	0.090	-0.167	0.211
651-750	-0.033	.277*	-.505-**	.317**	0.089	-0.173	.250*
751-850	0.005	.278*	-.517-**	.335**	0.070	-0.144	.255*
851-950	0.052	.274*	-.520-**	.349**	0.041	-0.099	.263*
951-1050	0.078	.258*	-.522-**	.382**	0.028	-0.076	.290*
1051-1150	0.090	.250*	-.528-**	.408**	0.027	-0.070	.306*
1151-1250	0.089	.266*	-.548-**	.412**	0.032	-0.075	.295*
1251-1350	0.089	.290*	-.574-**	.409**	0.032	-0.075	.275*
1351-1450	0.098	.332**	-.621-**	.406**	0.015	-0.061	.245*
1451-1550	0.093	.352**	-.638-**	.396**	0.020	-0.068	0.235
1551-1650	0.092	.355**	-.639-**	.392**	0.028	-0.071	0.235
1651-1750	0.093	.366**	-.649-**	.389**	0.029	-0.069	0.228
1751-1850	0.098	.378**	-.663-**	.389**	0.022	-0.062	0.220
1851-1950	0.107	.415**	-.711-**	.397**	-0.014	-0.042	0.182
1951-2050	0.105	.426**	-.716-**	.384**	-0.011	-0.048	0.177
2051-2150	0.096	.411**	-.697-**	.382**	0.018	-0.067	0.199
2151-2250	0.110	.412**	-.699-**	.383**	0.009	-0.051	0.198
2251-2350	0.104	.412**	-.704-**	.392**	0.009	-0.061	0.184
2351-2450	0.116	.431**	-.725-**	.391**	-0.010	-0.043	0.176
2451-2500	0.112	.446**	-.742-**	.390**	-0.018	-0.043	0.154

*p < 0.005, ** p < 0.001

The highest positive correlation was found at 2400, 1200 and 1100nm for sand, silt and $CaCO_3$ respectively. Therefore, the highest negative value was revealed at 2400nm for clay.

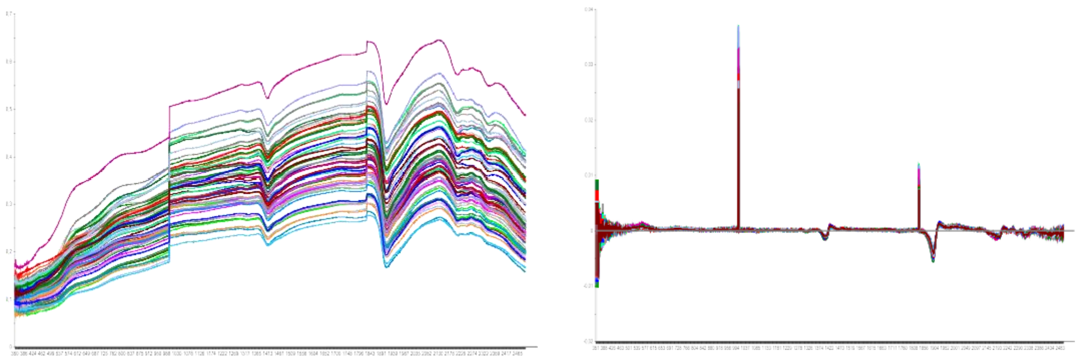


Figure 4 2. Raw spectra and first derivative equivalents for all soils of the study area

4.4. Prediction of Soil Properties

To assess the soil variable prediction accuracy depended on the whole data set (n = 65), the ten-out cross-validation strategy was performed with PLSR. For a variety of soil parameters, approaches were contrasted using cross-validation R^2 and RMSEP. Table 6 Use raw and first derivative spectra independently (2150 data points), to calculate PLSR cross-validation and calibration statistics for physiochemical indicators. Good correlations among soil spectra and other soil parameters were provided by PLSR. By merging first derivatives and raw spectra with a bigger data collection, no notable improvement was made. According to Reeves et al. (2002), the estimate outcomes could vary depending on various calculated processing techniques and derivatives of spectra, Scanned by rotating the sample 90 degrees when ten interpretations with an illuminating source that was essentially constant. The most accurate models were found for Clay (R^2 = 0.0.79), sand (R^2 = 0.65), $CaCO_3$ (R^2 = 0.46), and Silt (R^2 = 0.32)

Table 4.4. Calibration and validation between reflectance and soil variable

	Calibration		Validation	
Soil variable	RMSEP	R^2	RMSEP	R^2
Sand	7.85	0.65	9.42	0.51
Silt	5.69	0.32	6.12	0.24
Clay	5.32	0.79	6.24	0.73
$CaCO_3$	3.61	0.46	4.35	0.24

Then-out calibration method may produce too optimistic forecasts for brand-new untested samples. Are observed, it is best to calibrate them using alternative sample sets that are unrelated to the validation data set. Figure 4.3. and Table 4.4. display indicator parameters for the VNIR spectroscopy prediction performance using PLSR. Although the RMSEP values were lower and the R^2 values were higher in the calibration set compared to the validation set, statistical.

Performance was not significantly different. Though the data sets came from the same spatial domain, it is difficult to find comparable prediction values if validation is carried with using separate samples (Dardanne et al., 2000).

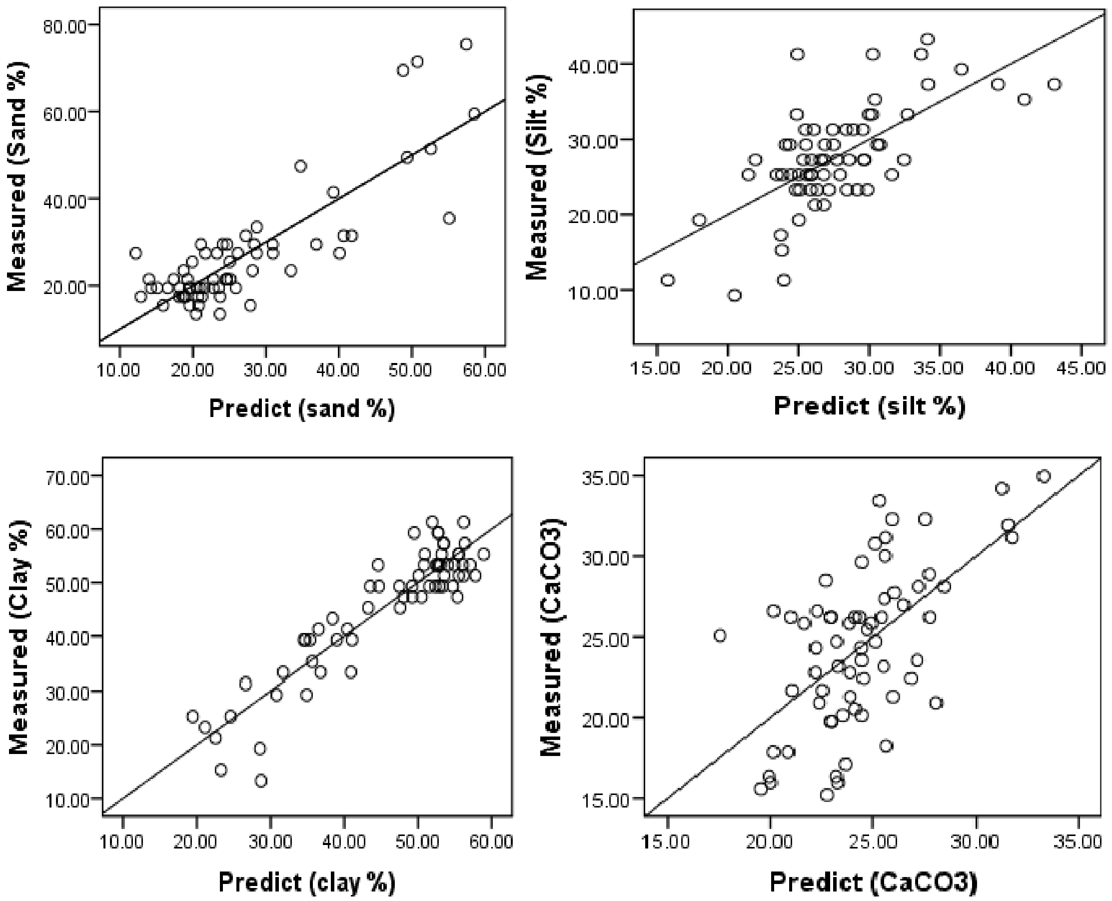


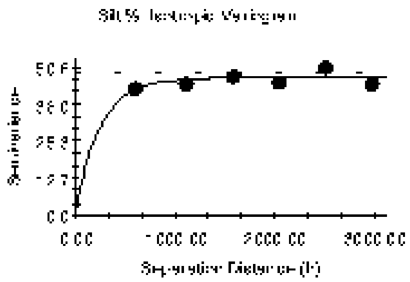
Figure 4.3. Regression between measured values and VNIR predictions for all soil variables

4.5. Spatial Analysis of Soil Properties

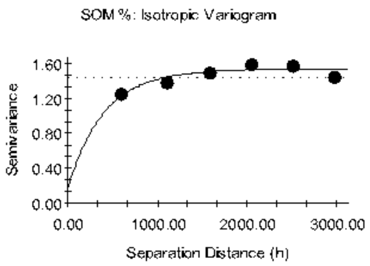
Although the fundamental properties of the change in soil variability content are well shown by the standard statistical techniques, so, using GS+ software, we conducted experimental semi-variogram evaluations of the soil parameters shown in figure 9. The findings demonstrated that an exponential model had the lowest RMSE and highest R^2, and that it was this model that best fit the semi-variograms. Table 4.5. Indicating a moderate degree of spatial dependence between the $CaCO_3$, Sand%, and Clay%, the ratios of the spatial dependence were 36.49%, 28.82%, and 34.12%, respectively. While OM%, PH, EC, and Silt% had high auto correlation and were, respectively, 10.7%, 18.26%, 9.40%, and 1.27%, these values suggest less than 25% in the other soil variable (Cambardella, et al., 1994) Previous research demonstrated that intrinsic influences, such as landscape, soil texture, and parent material, controlled the strong spatial dependence of the soil variables (C0/(C0 + C) 25%), while extrinsic factors, such as land use management, fertilization, and cultivation practices, simultaneously affected the moderate spatial dependence (25% C0/(C0 + C) 75%). (Wendroth et al., 1999; Cambardella et al., 1994; Liu and Wang, 2013).

Table 4.5. Geostatistical parameters of soil properties

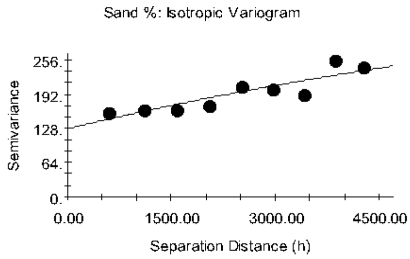
Soil variable	Model	Nugget(C0)	Sill (C0 + C)	Range(m)	RSS	SD % C0/C0 + C
OM	Exponential	0.165	1.541	400	0.0171	10.70
$CaCO_3$	Exponential	17.03	46.67	6328.55	5.48	36.49
PH	Exponential	0.00339	0.01856	426.05	1.440E-05	18.26
EC	Exponential	1720	18280	543	6366125	9.40
Sand%	Exponential	127.7	443	10110	2226	28.82
Silt %	Exponential	0.60	46.97	246	22.1	1.27
Clay %	Exponential	104.3	305.6	10112	850	34.12



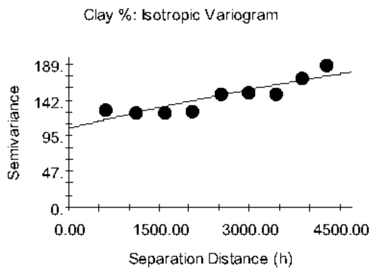
Exponential model (Co = [illegible]; Co + C = [illegible]; Ao = [illegible]; r2 = [illegible]; RSS = [illegible])



Exponential model (Co = 0.16500; Co + C = 1.54100; Ao = 400.00; r2 = 0.797; RSS = 0.0171)



Exponential model (Co = 127.70000; Co + C = 443.00000; Ao = 10110.00; r2 = 0.780; RSS = 2226.)



Exponential model (Co = 104.30000; Co + C = 305.60000; Ao = 10110.00; r2 = 0.788; RSS = 850.)

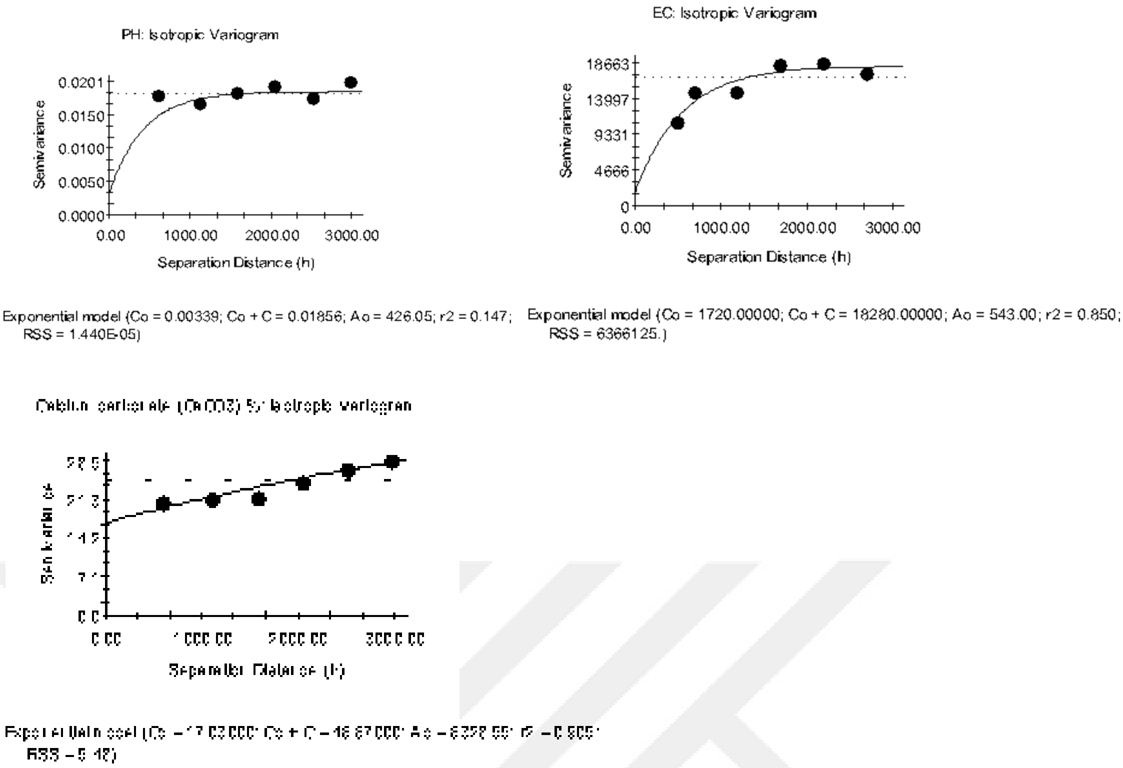


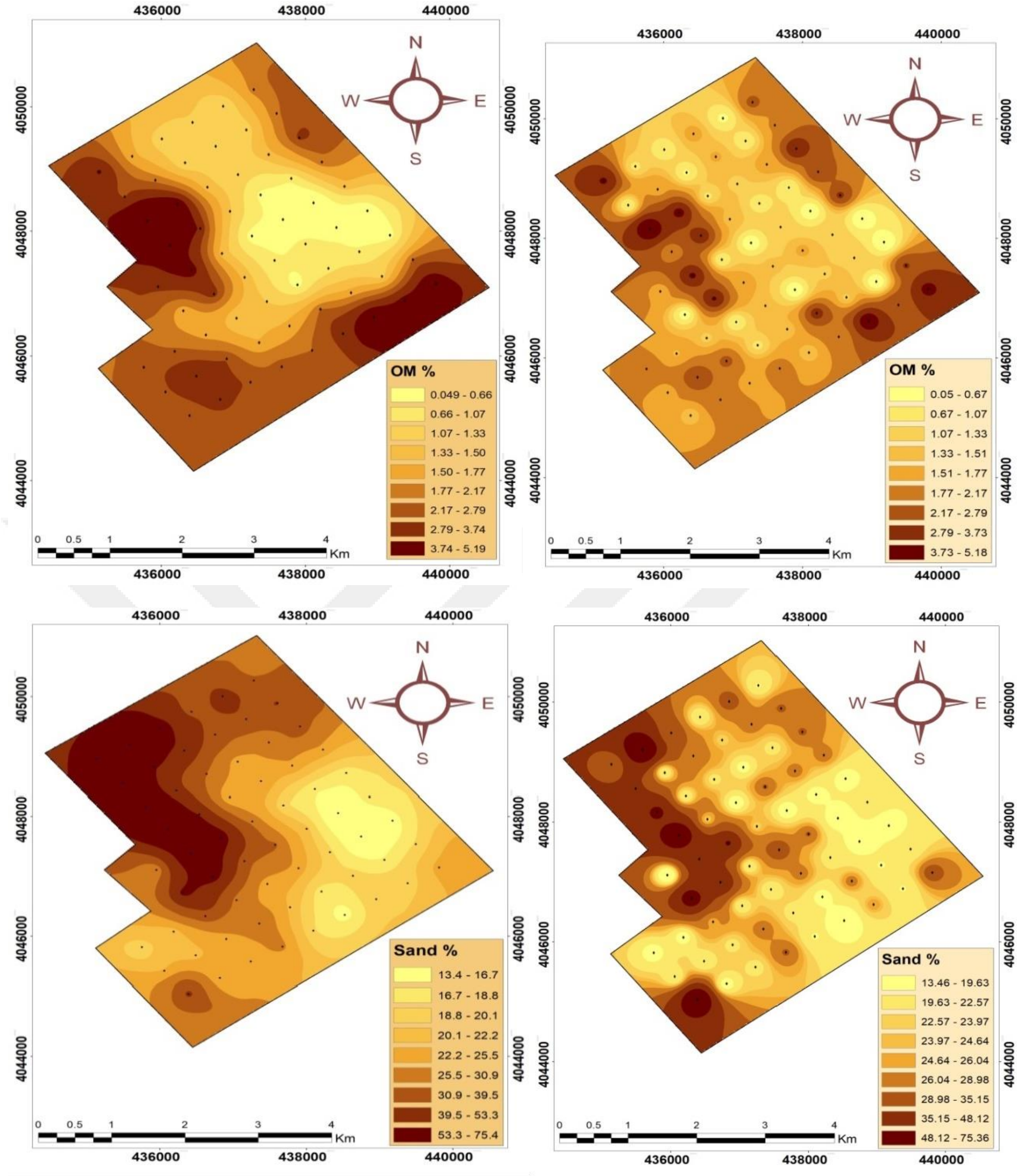
Figure 4.4. Experimental semivariograms of soil properties (0 - 30 cm)

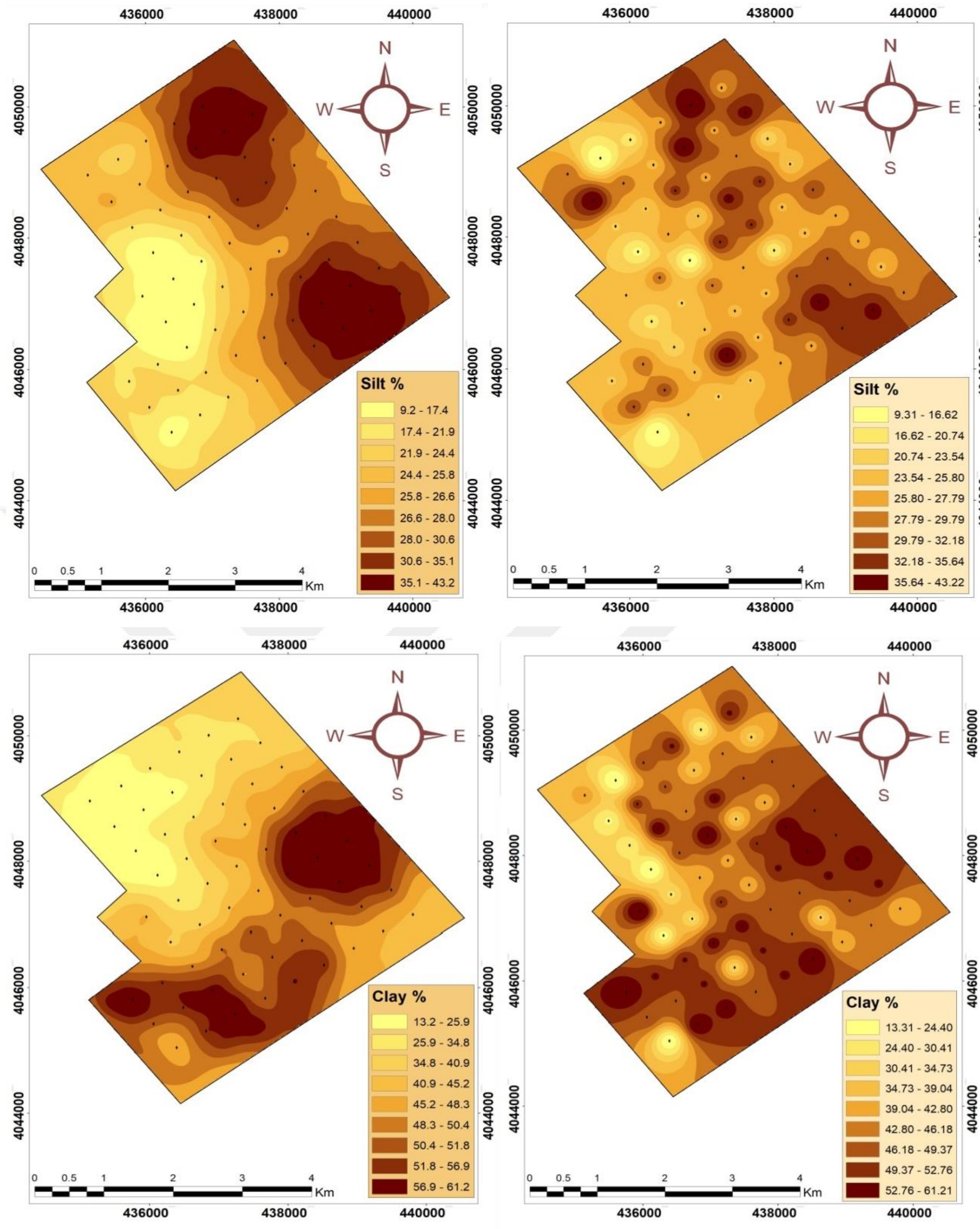
4.6. Estimation of Soil Properties

IDW and OK interpolation techniques were used to create maps of the soil properties were shown in figure 4.5. in order to further highlight the geographic diversity of each soil variable. SOM content generally rose with decreasing latitude and increasing of vegetation cover across the whole study region. This increase was progressive from the south east and North West decertified district area with hills and gullies. Generally speaking, terrain, height, climatic conditions, and soil texture all have an impact on SOM (Baldock et al., 2017). The amount of sand was decreased from the North West to south east, while silt was high in north east and south east, in addition that the amount of clay content was increased from the north to the south, parent material an elevation was controlling the formation of texture. The spatial map of soil pH indicated the pH value was high in the north and west south portion and low in the southwest, however although

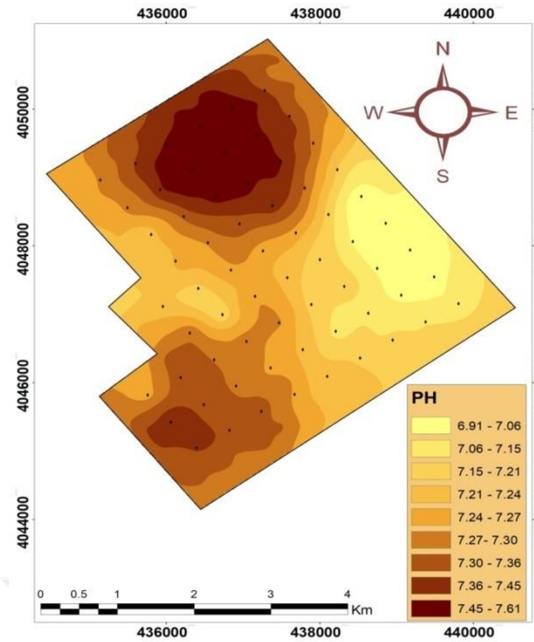
EC is high in the east, Since pH and EC are inversely correlated, areas with high pH also tend to have low EC. As a result, low soil pH values, which are present in all stations, should have large levels of soluble salts and, consequently, high levels of electrical conductivity. Lower pH values for the soil, according to (Brudner, 2012), imply that there are more hydrogen ions present. The level of electrical conductivity can be impacted by the presence of hydrogen ions, which might be present in variable amounts in the soil environment. Electrical conductivity will increase if there are more hydrogen ions present in the soil. Soil electrical conductivity may be facilitated by low pH caused by a high concentration of H^+ in the soil.

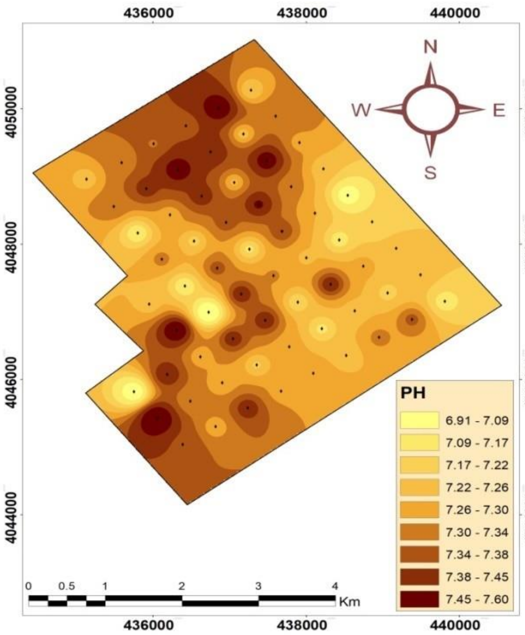
Elevation was controlling the formation of texture. The spatial map of soil pH indicated the pH value was high in the north and west south portion and low in the southwest, however although EC is high in the east, Since pH and EC are inversely correlated, areas with high pH also tend to have low EC. As a result, low soil pH values, which are present in all stations, should have large levels of soluble salts and, consequently, high levels of electrical conductivity. Lower pH values for the soil, according to (Brudner, 2012), imply that there are more hydrogen ions present. The level of electrical conductivity can be impacted by the presence of hydrogen ions, which might be present in variable amounts in the soil environment. Electrical conductivity will increase if there are more hydrogen ions present in the soil. Soil electrical conductivity may be facilitated by low pH caused by a high concentration of H^+ in the soil. Then, $CaCO_3$ was high in the east and low in the west area.

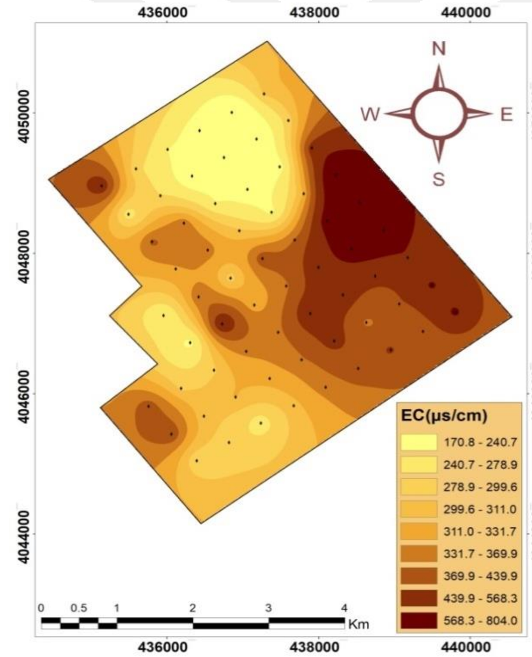

OM %
0.049 - 0.66
0.66 - 1.07
1.07 - 1.33
1.33 - 1.50
1.50 - 1.77
1.77 - 2.17
2.17 - 2.79
2.79 - 3.74
3.74 - 5.19
OM %
0.05 - 0.67
0.67 - 1.07
1.07 - 1.33
1.33 - 1.51
1.51 - 1.77
1.77 - 2.17
2.17 - 2.79
2.79 - 3.73
3.73 - 5.18
Sand %
13.4 - 16.7
16.7 - 18.8
18.8 - 20.1
20.1 - 22.2
22.2 - 25.5
25.5 - 30.9
30.9 - 39.5
39.5 - 53.3
53.3 - 75.4
Sand %
13.46 - 19.63
19.63 - 22.57
22.57 - 23.97
23.97 - 24.64
24.64 - 26.04
26.04 - 28.98
28.98 - 35.15
35.15 - 48.12
48.12 - 75.36
N
S
W
E
436000
438000
440000
4044000
4046000
4048000
4050000
0 0.5 1 2 3 4
Km

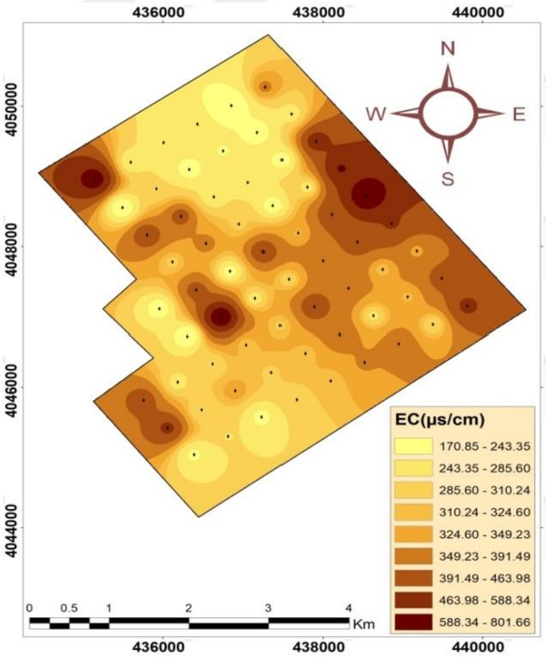


436000
438000
440000
4050000
4048000
4046000
4044000
N
W
E
S
Silt %
9.2 - 17.4
17.4 - 21.9
21.9 - 24.4
24.4 - 25.8
25.8 - 26.6
26.6 - 28.0
28.0 - 30.6
30.6 - 35.1
35.1 - 43.2
0 0.5 1 2 3 4 Km
Silt %
9.31 - 16.62
16.62 - 20.74
20.74 - 23.54
23.54 - 25.80
25.80 - 27.79
27.79 - 29.79
29.79 - 32.18
32.18 - 35.64
35.64 - 43.22
Clay %
13.2 - 25.9
25.9 - 34.8
34.8 - 40.9
40.9 - 45.2
45.2 - 48.3
48.3 - 50.4
50.4 - 51.8
51.8 - 56.9
56.9 - 61.2
Clay %
13.31 - 24.40
24.40 - 30.41
30.41 - 34.73
34.73 - 39.04
39.04 - 42.80
42.80 - 46.18
46.18 - 49.37
49.37 - 52.76
52.76 - 61.21


PH
6.91 - 7.06
7.06 - 7.15
7.15 - 7.21
7.21 - 7.24
7.24 - 7.27
7.27- 7.30
7.30 - 7.36
7.36 - 7.45
7.45 - 7.61
Km


PH
6.91 - 7.09
7.09 - 7.17
7.17 - 7.22
7.22 - 7.26
7.26 - 7.30
7.30 - 7.34
7.34 - 7.38
7.38 - 7.45
7.45 - 7.60
Km


EC(µs/cm)
170.8 - 240.7
240.7 - 278.9
278.9 - 299.6
299.6 - 311.0
311.0 - 331.7
331.7 - 369.9
369.9 - 439.9
439.9 - 568.3
568.3 - 804.0
Km


EC(µs/cm)
170.85 - 243.35
243.35 - 285.60
285.60 - 310.24
310.24 - 324.60
324.60 - 349.23
349.23 - 391.49
391.49 - 463.98
463.98 - 588.34
588.34 - 801.66
Km

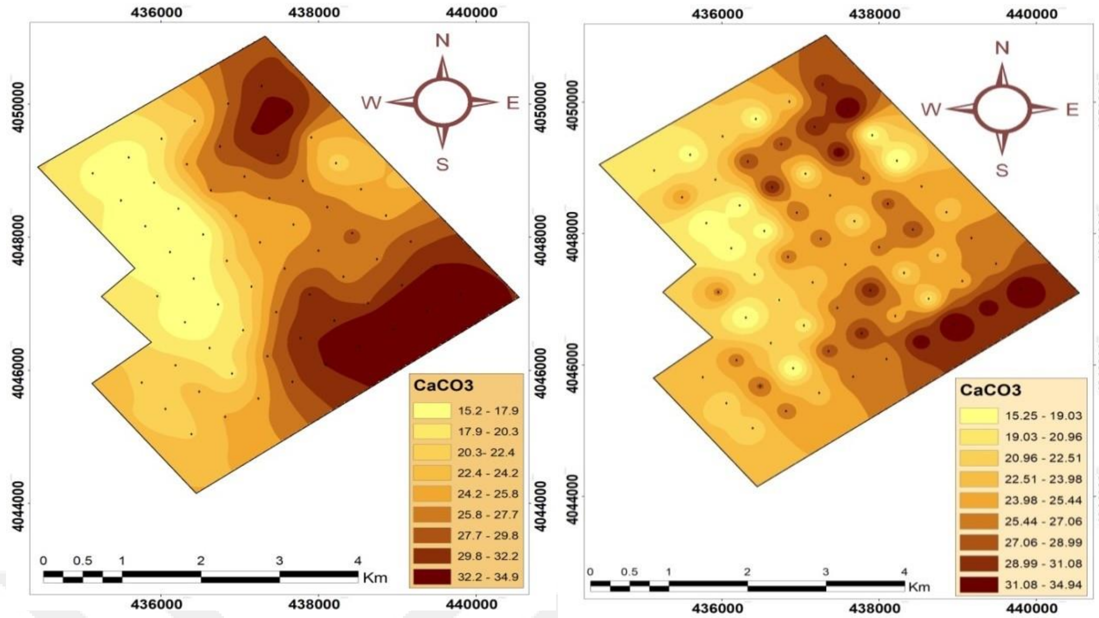


Figure 4.5.Spatial distribution maps of soil properties

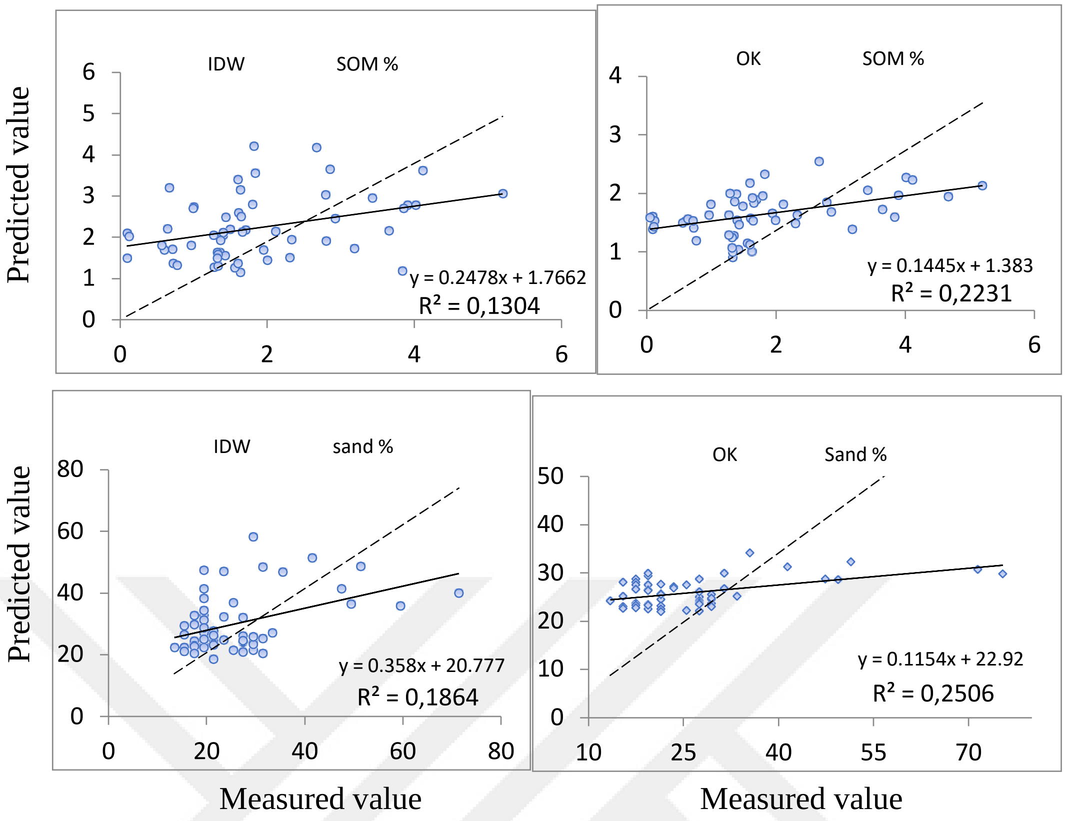
4.7. Assessing the Accurate of Interpolation Methods

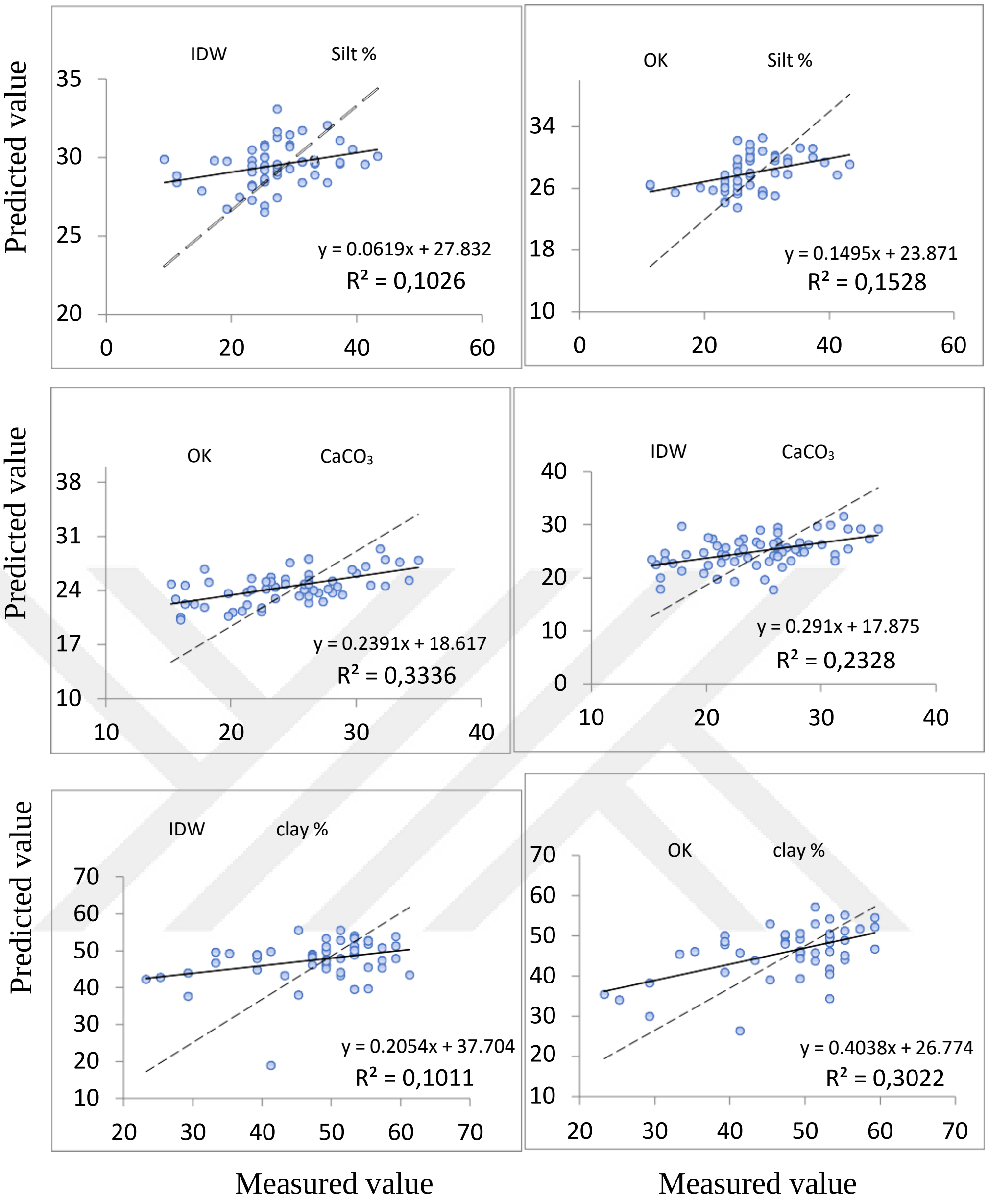
Cross-validation indices for ME and RMSE were produced to estimate the effectiveness of the interpolation methods were shown in Table 4.6. The IDW and OK values for SOM, sand, silt clay, pH, EC and $CaCO_3$ content's ME values in the current study varied from -0.05, -0.38, 0.18, 0.19, 0.004, -5.6 and -0.01 to -0.02, -0.18, 0.11, 0.25, 0.0009, -1.9 and 0.05 respectively, which showed that the IDW and OK interpolations of soil properties contents were largely objective.

Table 4.6. Cross validation data of inverse distance weighting (IDW) and ordinary kriging (OK)

	IDW			Ordinary kirging		
soil variables	RMSE	ME	R2	RMSE	ME	R2
SOM	1.196	-0.059	0.13	1.186	-0.029	0.22
Sand	13.404	-0.381	0.18	13.941	-0.189	0.25
Silt	7.137	0.185	0.10	7.198	0.116	0.15
Clay	12.020	0.195	0.10	11.955	0.252	0.30
pH	0.142	0.004	0.10	0.134	0.0009	0.20
EC	126.32	-5.683	0.30	126.28	-1.966	0.15
$CaCO_3$	4.516	-0.017	0.23	4.360	-0.055	0.33

Although there were no appreciable differences in the RMSE values between the IDW and OK for each soil attribute, the R^2 values of the OK method were marginally higher than those of the IDW method, indicating that the OK method was superior to the IDW method for the spatial interpolation of all soil properties except EC. The OK technique was better to the IDW method for the spatial interpolation of each soil property except EC illustrated in Figure 4.6. as evidenced by the R^2 values of the OK method being marginally higher than those of the IDW method. The accurate for predicting of SOM, sand, silt, clay, pH and $CaCO_3$ were OK, showing R^2value were (0.22, 0.25, 0.15, 0.30, 0.20 and 0.33) respectively, and RMSE value were (1.18, 13.94, 7.19, 11.95, 0.13 and 4.36), however the IDW is the more accurate for EC (R^2 = 0.30 and RMSE = 126.32). The sampling allocations and the soil attributes' autocorrelation may be to blame for these conflicting results. It has been found that sample density, distribution, and applicability, therefore the validation procedure, had an impact on the R^2 ratio of the forecast and observed values (Yao et al., 2019; Ye et al., 2017). To the design of the leave-one-out cross-validation approach, Furthermore, we found that low measured values were exaggerated by both interpolation algorithms whereas high measured values were underestimated. We developed a regression curve with a range of 0–30 cm between the measured values and the projected values from IDW and OK interpolation.


IDW
SOM %
y = 0.2478x + 1.7662
R² = 0,1304
OK
SOM %
y = 0.1445x + 1.383
R² = 0,2231
IDW
sand %
y = 0.358x + 20.777
R² = 0,1864
OK
Sand %
y = 0.1154x + 22.92
R² = 0,2506
Predicted value
Predicted value
Measured value
Measured value


Predicted value
IDW
Silt %
y = 0.0619x + 27.832
R² = 0,1026
OK
Silt %
y = 0.1495x + 23.871
R² = 0,1528
Predicted value
OK
CaCO₃
y = 0.2391x + 18.617
R² = 0,3336
IDW
CaCO₃
y = 0.291x + 17.875
R² = 0,2328
Predicted value
IDW
clay %
y = 0.2054x + 37.704
R² = 0,1011
OK
clay %
y = 0.4038x + 26.774
R² = 0,3022
Measured value
Measured value

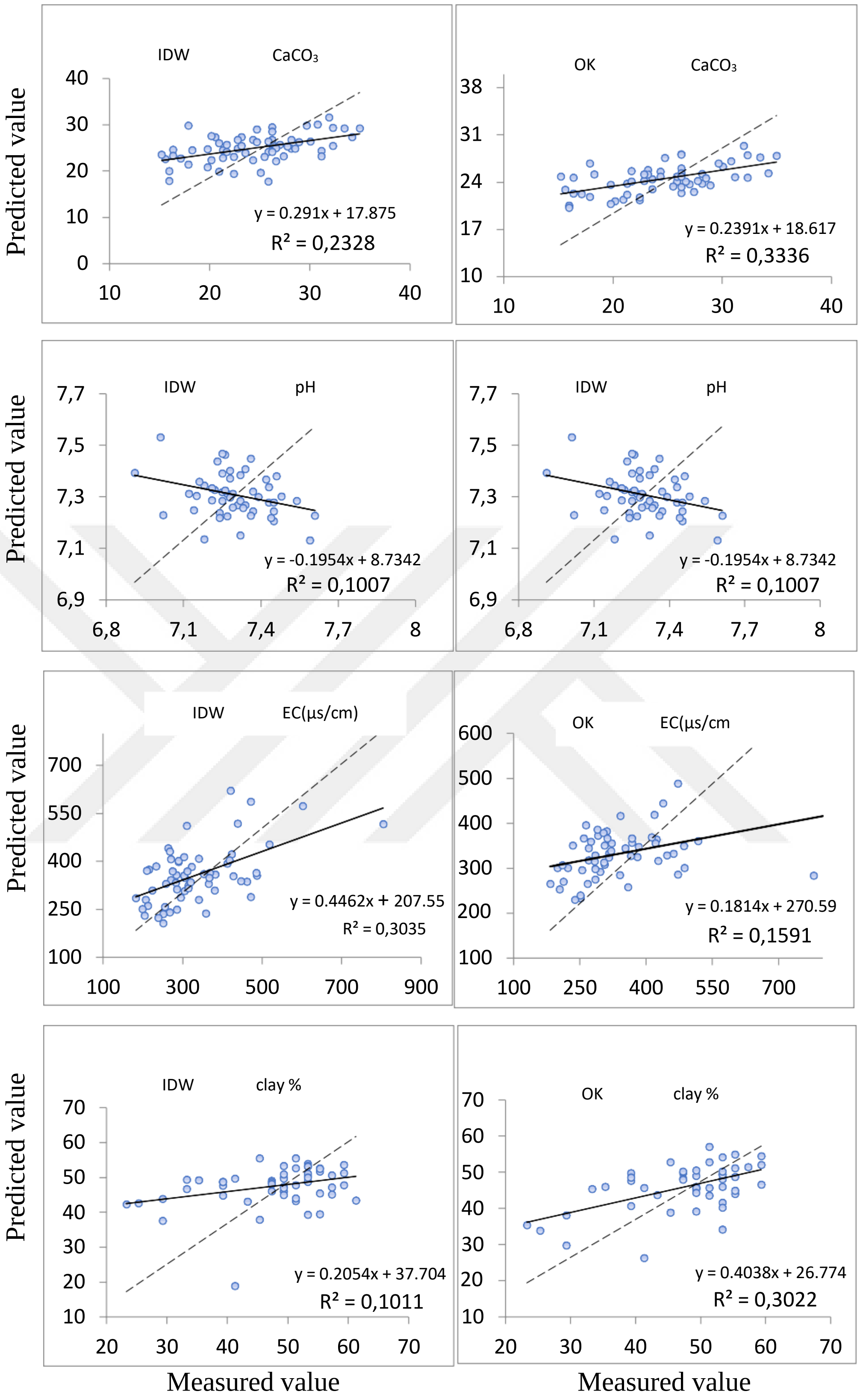


Figure 4.6. Scatterplots of the measured and predicted soil variables from validation sites using ordinary kriging (OK) and inverse distance weighting (IDW).

5. CONCLUSIONS and RECOMMENDATIONS

5.1. Conclusions

This study showed the various approaches such as spectral processing and data analysis with an emphasis on the application of VNIR and geostatistical analysis for forecasting soil properties. Using hyperspectral VNIR spectroscopy, significant environmental soil factors as clay and sand concentration could be accurately predicted. Even though they were carried out at different scales and in different geographical areas, the results were generally consistent with those of the other investigations. In the case of calibration, PLSR was better for estimated outcomes for almost all variables. However, when employing data sets for calibration and validation, the outcomes of calibration were significantly different from validation. The range of data values and the degree of autocorrelation appear to have a greater impact on the validation models' accuracy than model choice or spectral preprocessing of the reflectance data. Strong and moderate spatial dependence in soil parameters might be explained using an exponential model as a best fit in semivariogram. However, the interpolation maps obtained from IDW were considered by small patches, whereas those from OK were smoother. The spatial distributions of SOC derived from IDW and OK exhibited like tends, with a diminishing tendency from the southwest to the northeast. The derivation predicted by OK is more accurate than the IDW in all soil parameter except EC.

5.2. Recommendations

Over the past several decades, VNIR has made significant advancements in the field of soil sciences. However, no conclusive findings on theoretical calculations have yet been discovered because the majority of soil investigations take place on a regional basis, therefore their findings are only regionally representative. In spite of the challenges brought on by the significant soil variability around the world, it is crucial to continue developing theoretical calibrations of VNIR that are more appropriate for soil samples globally. The derivatives of field data set and differences in minerals, wetness, organic matter, and their interactions have not been studied in more logical manner. Therefore, these kinds of studies—rather just lab spectra—should be the emphasis of future research.

More soil sampling in a region scale is more accurate and provide a better resolution in the spatial estimation of soil properties Future research is required to define spatial variability on a bigger scale and comprehend the variables influencing spatial variability of soil parameters.

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