



Research article

Use of infrared spectroscopy and geospatial techniques for measurement and spatial prediction of soil properties

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ABSTRACT

The main aim of this research was to assess the use of mid-infrared (MIR) spectroscopy and geostatistical model for the evaluation and mapping of the spatial variability of some selected soil properties across a field. It is with the view of aiding site-specific soil management decisions. The performance of the model for the prediction of the components (soil parameters) was reported using the coefficient of determination (R^2) and root mean square error (RMSE) values of the validation data set. Results revealed that least square regression model performed better in predicting cation exchange capacity-CEC ($R^2 = 0.88$ and RMSE = 8.98), soil organic carbon-OC ($R^2 = 0.88$, RMSE = 0.55), and total nitrogen-TN ($R^2 = 0.91$ and RMSE = 0.04). The first five principal components (PC) accounted for 78.17% of the total variance (PC1 = 25.75%, PC2 = 18.06%, PC3 = 13.85%, PC4 = 11.12%, and PC5 = 9.39%) and represented most of the variation within the data set. The coefficient of variation ranged from 6.73% for soil pH to 57.02% for available phosphorus (av. P). The soil pH values ranged from 4.21 to 6.57. The mean soil OC density was 2.14 kg m⁻² within 50 cm soil depth. Nearly 96–97% of the soils contained av. P and sulfur (SO₄²⁻-S) below the critical levels. The overall results revealed that soil properties varied spatially. Hence, we suggest that mapping the spatial variability of soils across a field is a cost-effective solution for soil management.

1. Introduction

One of the major driving factors to the application of the general precision farming concept is soil heterogeneity. Soils vary spatially because of soil-forming factors (Silva and Alexandre, 2005; Jankowski et al., 2011) and management practices (Ozpinar and Cay, 2006; Galka et al., 2016). Testing and understanding the spatial variability of the physical and chemical properties of soils are required for precise determination of the best soil management practices and amendments to improve crop quantity and quality while being environmentally sustainable (Awe et al., 2015; Aranyos et al., 2016). Applying agricultural inputs based on site-specific requirements of soils and crops entails the quantification of the spatial variability of soil properties across the field (Fraisie et al., 1999; Hatfield, 2000; Wang et al., 2009).

Analysis of soil physical and chemical properties for many samples to derive soil fertility or acidity index is time-consuming, which in practice makes it impossible to map the soil properties of a field with the required spatial resolution (Idowu et al., 2008). The need for fast and cheap

technological methods that would enable the analysis of a large number of samples have been stressed in numerous studies (Janik et al., 1998; Shepherd and Walsh, 2007; Canasveras et al., 2012), and infrared spectroscopy has long been recognized as one of the most promising techniques (McCarty and Reeves, 2006). Although near-infrared spectroscopy can be very useful for some soil analyses, several comparative studies have shown the superiority of the mid-infrared techniques in most cases (Canasveras et al., 2010; Soriano-Disla et al., 2014; Sebold et al., 2019). Meanwhile, according to African Soil Information Service (AfSIS) approach, 20% of the total samples collected for MIR spectroscopy analysis need to be tested using wet-chemistry method to calibrate and predict spectral values (Vagen et al., 2010).

Multivariate data analysis (partial least squares regression-PLSR and principal component analysis-PCA) is used to process large amounts of data for exploring and understanding the relationship between soil parameters (Goovaerts, 1997; Sena et al., 2002). Once the spectral values of MIR spectroscopy are measured and calibrated using the wet chemistry test, the quality of prediction can be

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determined using the PLSR model (Naes et al., 2002). The performance of the prediction by the PLSR model can be evaluated through the coefficient of determination (R^2) and the root mean square error (RMSE) (Hair and Anderson, 1995; Barker and Rayens, 2003). Besides, the PCA shows the correlation between independent variables and detects data outliers (Miller and Miller, 2005).

Geostatistical techniques aid the spatial prediction of soils. Geospatial prediction is the analysis of spatial distribution and variability of soil properties based on the spatial scale of the study area, the distance between sampling points, and their patterns (Shit et al., 2016). It helps to evaluate the spatial correlation in soils and to analyze the continuous variability of soil properties in space (Liu et al., 2014; Bhunia et al., 2018). Studies showed that MIR spectroscopy can be directly linked to geostatistics for a broad and quick evaluation of the spatial variability of soils across a field (McBratney et al., 2006; Cobo et al., 2010). Therefore, integrating MIR spectroscopy with geostatistical analysis is a cost-effective and powerful approach for soil assessment, mapping, and monitoring at a landscape level.

In East African countries like Ethiopia, where the availability of soil information is highly limited, spatial prediction and mapping of soil properties at reasonable resolution are predominantly vital for soil management. The main aim of this study was to measure some soil properties (soil pH, OC, N, P, S, CEC, K, Mg, Ca, Na) using MIR spectroscopy and predict as well as map their spatial distribution by geospatial techniques. The study would be used to build soil data to strengthen the Ethiopian Soil Information System (EthioSIS) as it is increasingly required by government and development partners to undertake soil improvement measures to boost crop production. Specifically, the results could aid soil management decisions such as lime and fertilizer applications.

2. Materials and methods

2.1. Study site

The study was conducted in the agricultural lands of Sibule district in western Oromia National Regional State, Ethiopia. Geographically, it is located between $36^{\circ}35'42.37''$ and $36^{\circ}44'28.29''$ E longitude and $8^{\circ}57'16.26''$ and $9^{\circ}22'42.59''$ N latitude. The elevation of the study area ranged from 1,240 to 3,140 m above sea level. The study area receives precipitation ranging from 1171 to 1719 mm with an annual average of 1348.6 mm. Besides, the mean annual minimum and maximum temperatures are 14.2 and 28.4 °C, respectively. The parent materials of the study area are dominated by granite with some evidence of basaltic rocks. According to the FAO (2006), the predominant soil types in the study area are Dystric Nitisol and Orthic Acrisol. The dominant agriculture in the district is a mixed farming system. The major crops grown in the area are maize (*Zea mays L.*), sorghum (*Sorghum bicolor*), teff (*Eragrostis tef*), and oil crops such as Noug (*Guizotia abyssinica*) and groundnut (*Arachis hypogaea*). The study covered 76844 ha of agricultural land.

2.2. Research methods and procedures

The study was carried out following three consecutive stages: the pre-fieldwork, fieldwork, and post fieldwork.

2.2.1. Pre-fieldwork

The pre-fieldwork stage was an office work mainly emphasized on preparing base maps and planning of soil survey activities. The base maps of the study site were produced using ARC GIS 10.3 software by overlaying a 30 m resolution LANDSAT ETM+ and Google earth imagery. The slope of the study site was classified from 30 m resolution digital elevation model (DEM) using Global Mapper 30.2 software. The base maps produced for agricultural land use and landform were used to delineate the study boundary and execute soil survey. The probable number of soil sampling points was estimated using 1.5 km × 1.5 km grid

surveys (Figure 1). Then, the locations of the sampling points were distributed on the base map with a resolution of 1:50,000. The points identified as pre-defined sample locations on the base map were navigated and the exact sampling points were determined by the geographic positioning system (GPS).

2.2.2. Fieldwork

The second step was fieldwork. The actual survey activities including site description, soil characterization in the field, and soil sampling were performed at this stage. Surface soil samples were collected from agricultural lands using the 1.5 km × 1.5 km grids. The sampling points were laid on the grid intersection points. Nine sub-samples were collected around each grid intersection point using an Edelman auger at a depth of 20 cm for annual crops and 50 cm for perennial crops. The sub-samples were mixed to make a composite sample for each grid intersection point separately for annual and perennial crops. Thus, nearly 149 composite samples were collected from the study site using predetermined GPS coordinates on the base map.

2.2.3. Post fieldwork

The post-fieldwork stage was focused on activities such as soil sample preparation and analysis (wet chemistry test and MIR spectroscopy test), multivariate data analysis, model validation and calibration tests, geospatial analysis, and nutrient and lime recommendations.

2.3. Soil analysis

2.3.1. Wet chemistry analysis

For wet chemistry tests, soil samples brought to the laboratory were air-dried and crushed to pass through 2 mm sieve size. Soil particle size distribution was determined by the Bouyoucos hydrometer method (Bouyoucos, 1962). Soil pH was determined in H₂O using 1:2 soil to water ratio using an ELMETRON pH-meter (Black, 1965). Exchangeable acidity (EA) was determined by leaching the sample with KCl and titrating with NaOH (Hesse, 1971). Soil organic carbon (OC) was determined by Walkley-Black oxidation method (Walkley and Black, 1934). Total nitrogen (TN) was determined using Kjeldahl method (Bremner and Mulvane, 1982). Available phosphorus (av. P), sulfate-sulfur (SO₄²⁻-S), cation exchange capacity (CEC), and exchangeable bases (K, Na, Ca, and Mg) were determined using Mehlich-III soil test procedure at Yara analytical service, UK, England (Mehlich, 1984). Inductively coupled plasma (ICP) spectrometer was used to determine the concentrations of exchangeable bases (K, Na, Ca, and Mg), SO₄²⁻-S, and av. P in the Mehlich-III extract.

2.3.2. Mid-infrared (MIR) diffused reflectance analysis

For MIR diffuse reflectance analysis, the soils including reference samples were sub-sampled and ground using Retsch mortar grinder RM 200 to powder with size fraction smaller than 0.5 mm. A powdered sample weighing 0.035 g was loaded in four consecutive wells of an aluminum micro-plate. This was done for all soil samples. The absorbance of diffuse reflectance spectra was obtained by scanning using the HTS-XT accessory of a Bruker-TENSOR 27 spectrometer. The background was scanned using the roughened surface well of the aluminum micro-plate. The MIR region spectra, in the wave number range of 4000–600 cm⁻¹ (2500–16667 nm) were used for the analyses to predict soil properties (Viscarra Rossel et al., 2006; Soriano-Disla et al., 2014). Absorbance spectra of the entire soil samples were measured using OPUS version 7.0 software with 32 scans and a spectral range of 7400–600 cm⁻¹ (wave numbers) including part of the NIR region.

2.4. The PCA and PLS regression analysis

Multivariate analysis including principal component analysis (PCA) and correlations was carried out using XLSTAT Version 2017 software.

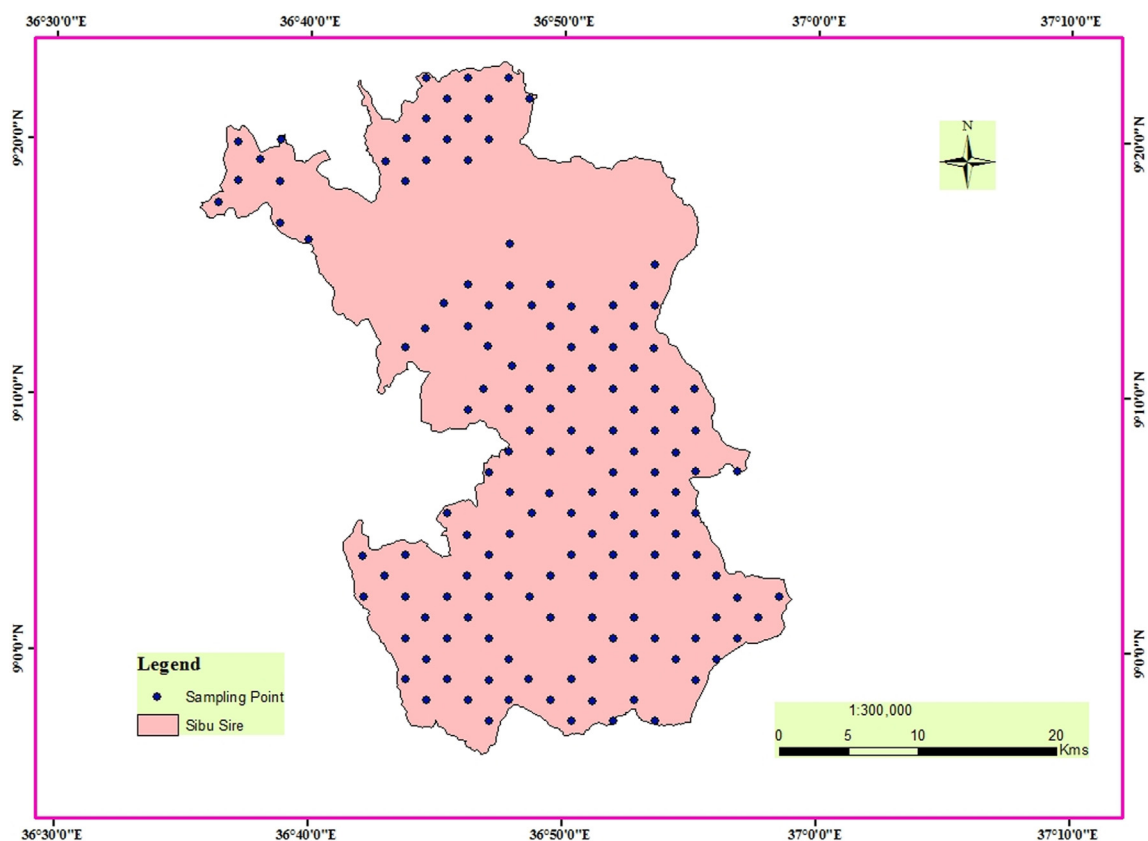


Figure 1. Grid sampling distribution and sample locations.

The partial least square regression (PLSR) modeling tool in the Unscrambler X10.3 was used to determine the best correlation between the chemical test reference data and spectral data. The MIR spectra for Mehlich-III extracted soil parameters were calibrated and validated using 776 and 5992 reference samples, respectively. The reference samples were obtained from the EthioSIS database. The optimum number of factors in the PLSR model was determined using cross-validation. The prediction performance of the PLSR model was evaluated on predicted and measured values of soil attributes using a coefficient of determination (R^2) and root mean square error (RMSE) (Naes et al., 2002). The R^2 measures the proportion of total variation accounted for by the model, while the remaining variation is attributed to random error. A good model would have high values of R^2 . The R^2 values were rated as very good (>0.81), good (0.61–0.8), fair (0.41–0.6), and poor (<0.4) according to Rossel and McBratney (2008). The value of R^2 was assessed as follows:

$$R^2 = \left(1 - \frac{SSE}{\sum (x_i - y_m)^2} \right) \quad \text{eq (1)}$$

where SSE is the sum of squared error, x_i is the true value, and y_m is the mean component value.

The RMSE is a statistical parameter that is more dependable than any other parameters as it shows deviation from the real measurements. Its value depends on the type of soil attributes. The validation and accuracy of PLSR model was assessed using RMSE:

$$RMSE = \sqrt{\frac{1}{N} \sum (x_i - y_i)^2} \quad \text{eq (2)}$$

where x_i is the predicted value, y_i is the measured (reference) value, and N is the number of soil samples.

2.5. Nutrients and lime recommendation techniques

Critical values of soil parameters were used to judge the fertility status of the soils. We used the critical values adopted by Bruce and Rayment (1982) for soil pH, Landon (2014) for OC and CEC, Havlin et al. (2013) for TN, Karlton et al. (2013) for av. P, SO_4^{2-} -S, and K, and Hazelton and Murphy (2007) for Ca and Mg. The critical values of soil nutrients were used for nutrient management decisions. The logic of acid saturation method recommended by Farina and Chanon (1991) was used to estimate the lime requirement of the soils. It was determined based on acid tolerance or permissible acid saturation (PAS) of major crops grown in Ethiopia. A PAS of 10% adopted for Ethiopian soils and a modified lime requirement factor of 1160 kg lime ha^{-1} $cmol_c^{-1}$ was used to estimating the lime rate (Taye, 2008):

$$LR = 1160(EA - (ECEC * PAS)) \quad \text{eq (3)}$$

where LR is the recommended lime rate ($kg\ ha^{-1}$), EA is exchangeable acidity ($cmol_c\ kg^{-1}$), ECEC is effective cation exchange capacity ($cmol_c\ kg^{-1}$), and PAS is permissible acid saturation of a crop in percent (%).

2.6. Geospatial prediction

Geospatial prediction of soil properties and lime rates were performed by kriging interpolation technique using ArcGIS 10.3 software. The basic equation for interpolation by kriging at an un-sampled location S_0 was given by:

$$\hat{Z}(S_0) = \sum_{i=1}^n \lambda_i Z(S_i) \quad \text{eq (4)}$$

where $Z(S_i)$ is the measured value at the i^{th} location, λ_i is an unknown weight for the measured value at the i^{th} location, S_0 is the prediction

location and n is the number of measured values. The final maps of soil properties and variable lime rates were produced at 1:10000 finer resolutions.

2.7. Statistical analysis

Conventional statistics (minimum, maximum, median, mean, standard deviation, coefficient of variation, and skewness) and principal component analysis were carried out using XLSTAT software version 2017. Pearson correlation coefficient was used to evaluate the relationship between soil properties at a significance level of 0.05.

3. Results

3.1. Model calibration and validation

The calibration and validation statistics for measured soil properties were presented in Table 1. We observed high R^2 and low RMSE values for the measured CEC, OC, and TN (Table 1). Conversely, we got low R^2 and high RMSE values for exchangeable K, Ca, and Mg. The observed correlation for the soil quality markers varied widely in the evaluation using MIR spectroscopy.

Table 1. Model calibration and validation for soil properties.

Soil property	Calibration		Validation
	R^2	RMSE	R^2
pH (H ₂ O)	0.52	0.73	0.52
CEC (cmol _c kg ⁻¹)	0.88	8.98	0.90
Av. P (mg kg ⁻¹)	0.60	43.58	0.50
Ex. K (cmol _c kg ⁻¹)	0.29	234.36	0.21
Ex. Ca (cmol _c kg ⁻¹)	0.52	3514.65	0.49
Ex. Mg (cmol _c kg ⁻¹)	0.29	523.88	0.39
Ex. Na (cmol _c kg ⁻¹)	0.14	64.41	0.13
Av. S (m kg ⁻¹)	0.50	159.46	0.00
OC (%)	0.87	0.55	0.89
TN (%)	0.91	0.04	0.88

R^2 : coefficient of determination; RMSE: root mean square error; CEC: cation exchange capacity; Ex. K: exchangeable potassium; Ex. Ca: exchangeable calcium; Ex. Mg: exchangeable magnesium; Ex. Na: exchangeable sodium; Av P: available phosphorus; Av S: available sulfur; OC: organic carbon; TN: total nitrogen.

Table 2. Descriptive statistics for soil properties (n = 149 samples).

Soil attribute	Min.	Max.	Median	Mean	SD (\pm)	CV (%)	Skewness
Clay (%)	20.00	79.19	49.54	49.50	12.23	24.71	0.01
Silt (%)	2.69	50.14	22.50	22.44	7.29	32.48	0.34
Sand (%)	2.81	66.25	27.50	28.08	12.24	43.60	0.58
pH	4.21	6.57	5.65	5.65	0.38	6.73	-0.40
OC (%)	0.04	6.64	3.14	3.06	0.74	24.22	-0.04
TN (%)	0.08	0.70	0.30	0.29	0.08	27.56	0.39
Av. P (%)	1.00	49.00	3	4.13	2.35	57.02	1.21
Av. S (mg kg ⁻¹)	6.00	35.00	12	13.30	5.58	42.01	1.08
EA (cmol _c kg ⁻¹)	0.00	6.18	0.21	0.82	0.43	51.88	0.93
Ex. K (cmol _c kg ⁻¹)	0.14	3.26	0.79	0.96	0.44	46.30	1.02
Ex. Ca (cmol _c kg ⁻¹)	0.66	23.17	4.17	5.22	2.57	49.16	0.97
Ex. Mg (cmol _c kg ⁻¹)	0.31	7.19	1.31	1.69	0.52	30.34	0.87
Ex. Na (cmol _c kg ⁻¹)	0.05	0.35	0.08	0.11	0.02	19.73	1.14
CEC (cmol _c kg ⁻¹)	7.16	66.00	28	29.15	11.42	39.18	0.89

EA: exchangeable acidity; Min: minimum; Max: maximum; SD: standard deviation; CV: coefficient of variation.

3.2. Spatial variability of soil properties

Data presented in Table 2 was computed from two datasets. The values of soil OC, TN, and CEC were derived from prediction using MIR spectroscopy. The values of the remaining soil properties (texture, pH, Av. P, Av. S, exchangeable acidity and exchangeable bases) were obtained from wet chemistry analysis or reference data, because PLSR-MIR model showed poor prediction performance for these properties.

Data presented in Table 2 gives descriptive statistics of soil properties while the spatial maps (e.g. Figure 2, Figure 3, etc) depict the variability of soil properties across the landscape. Clay content varied from 20 to 79.20% (Table 2). The pH of surface soils ranged from 4.21 to 6.57 (Table 2). The soil pH map of the study area showed that major portions of the soils had pH values between 5.5 and 6.5 (Figure 2). The mean exchangeable acidity of the soils was 0.82 cmol_c kg⁻¹ (Table 2). We found a soil pH value as low as 4.56 at places where the exchangeable acidity was as high as 6.18 cmol_c kg⁻¹; and it was zero at locations where the pH value was 5.52 and above. The soil OC varied between 0.04 and 6.64% with a mean value of 3.06% (Table 2). About 98.5% of the study site showed soil OC content of 2–4% (Figure 3a). The total N content of surface soils ranged from 0.08 to 0.70% (Table 2). The average total N in the soils was 0.29%. Nearly 94% of the area comprised greater than or

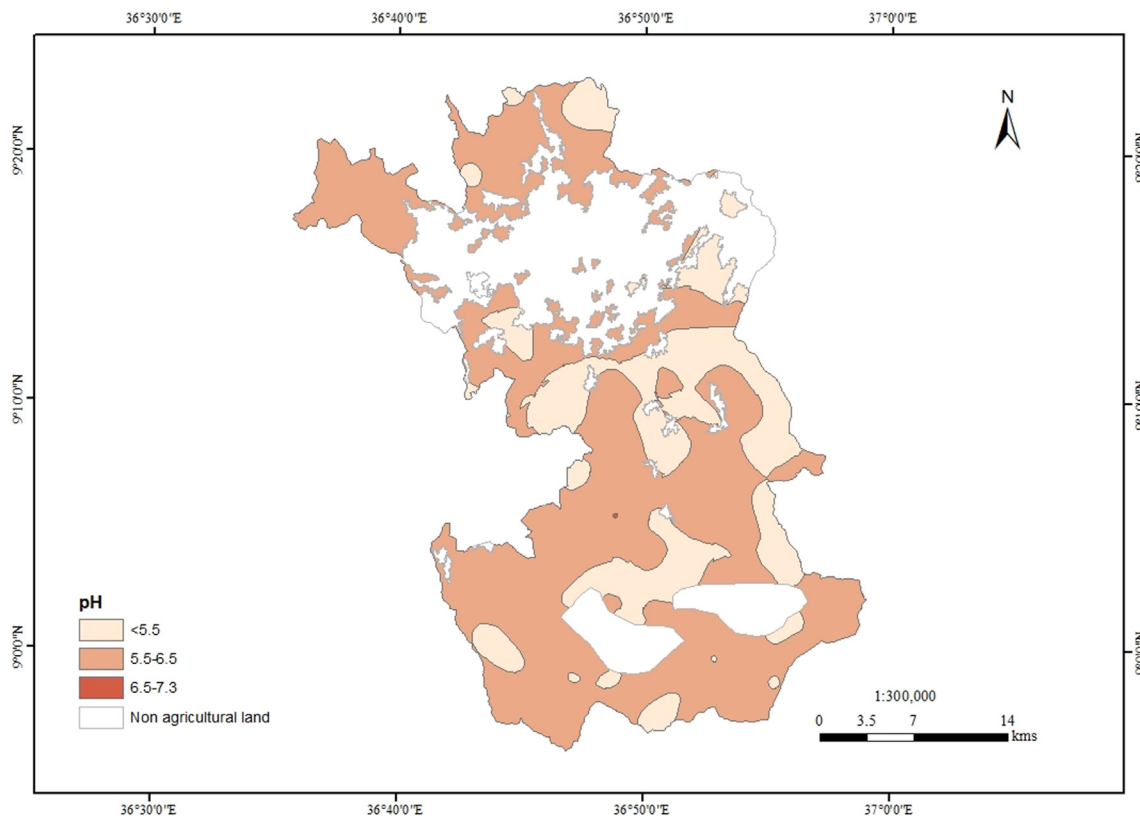


Figure 2. Spatial variability map of soil pH (the data were reference values).

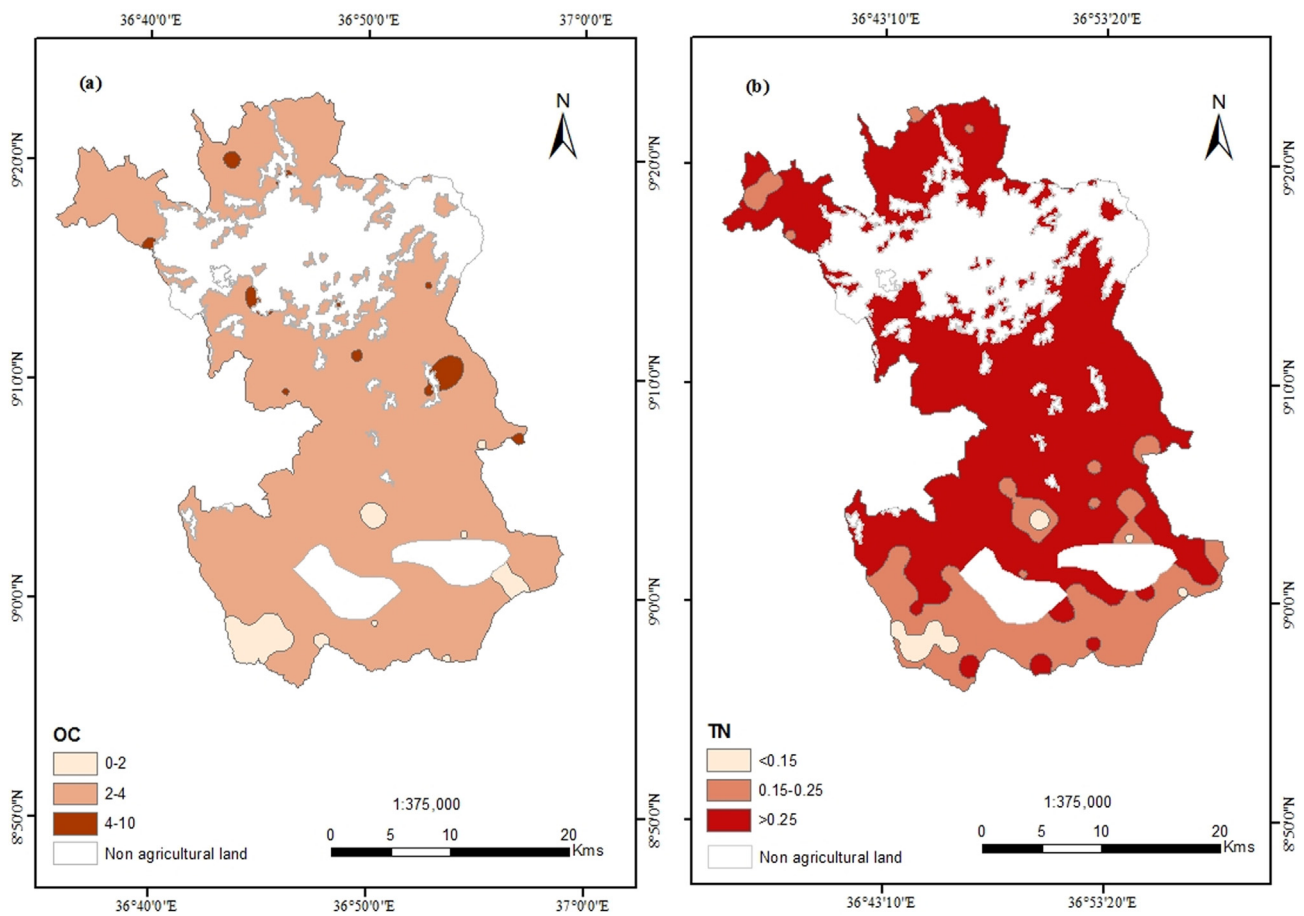


Figure 3. Spatial variability map of (a) soil organic carbon (OC) and (b) total nitrogen (TN) (the data were values predicted by MIR spectroscopy).

Table 3. Pearson correlation among soil properties.

Variables	pH	EA	Av. P	Av. S	Ex. K	Ex. Ca	Ex. Mg	Ex. Na	OC	TN	CEC	Clay	Silt	Sand
pH														
EA	-0.65													
Av. P	0.16	-0.54												
Av. S	-0.14	0.05	-0.17											
Ex. K	0.10	-0.10	0.24	-0.12										
Ex. Ca	0.15	-0.14	0.26	-0.50	0.30									
Ex. Mg	0.12	-0.11	0.15	-0.49	0.28	0.96								
Ex. Na	0.10	-0.13	0.08	-0.31	0.10	0.86	0.84							
OC	-0.30	0.09	-0.03	0.15	-0.08	-0.11	-0.11	-0.06						
TN	-0.36	0.17	-0.06	0.17	-0.11	-0.15	-0.14	-0.10	0.94					
CEC	-0.05	0.02	-0.16	0.14	-0.07	0.14	0.11	0.05	0.55	0.50				
Clay	0.06	-0.08	-0.34	0.06	-0.11	0.29	0.35	0.33	0.01	0.01	0.37			
Silt	-0.13	0.07	0.02	0.17	0.31	-0.12	-0.12	-0.14	-0.06	-0.11	-0.17	-0.30		
Sand	0.02	0.04	0.33	-0.16	-0.08	-0.22	-0.27	-0.24	0.02	0.06	-0.27	-0.82	-0.30	

Values in bold are significantly correlated at alpha = 0.05.

equal to 0.15% total N (Figure 3b). As presented in Table 3, a positive and significant correlation ($r = 0.94^{**}$, $p < 0.01$) was observed between OC and total N.

The av. P content of the soils varied spatially (Figure 4a). The mean value of av. P in the soils was 4.13%. Available P was negatively but significantly correlated with exchangeable acidity ($r = -0.54^*$, $p < 0.05$) and clay content ($r = -0.34^*$, $p < 0.05$) (Table 3). The mean value of available $\text{SO}_4^{2-}\text{-S}$ was 13.30 mg kg^{-1} . Available $\text{SO}_4^{2-}\text{-S}$ content of nearly 97% of the soils were below 20 mg kg^{-1} (Figure 4b).

Exchangeable K varied spatially (Figure 5) with a mean value of $0.96 \text{ cmol}_c \text{ kg}^{-1}$ (Table 2). Exchangeable Ca and Mg were accounting for over 89% of exchangeable bases. The mean values of exchangeable Ca and Mg were 5.22 and $1.69 \text{ cmol}_c \text{ kg}^{-1}$, respectively. The exchangeable Ca and Mg showed significant spatial variation (Figure 6a and 6b) with coefficients of variation (CV) of 49.16 and 30.34%, respectively. The level of exchangeable Na was low. The CEC of the soils ranged from 10.81 to $46 \text{ cmol}_c \text{ kg}^{-1}$ (Table 2), and major portions of the soils (70%) exhibited CEC between 15-25 $\text{cmol}_c \text{ kg}^{-1}$ (Figure 7). They were higher in the highland areas than the lowlands. The CEC of the soils were not

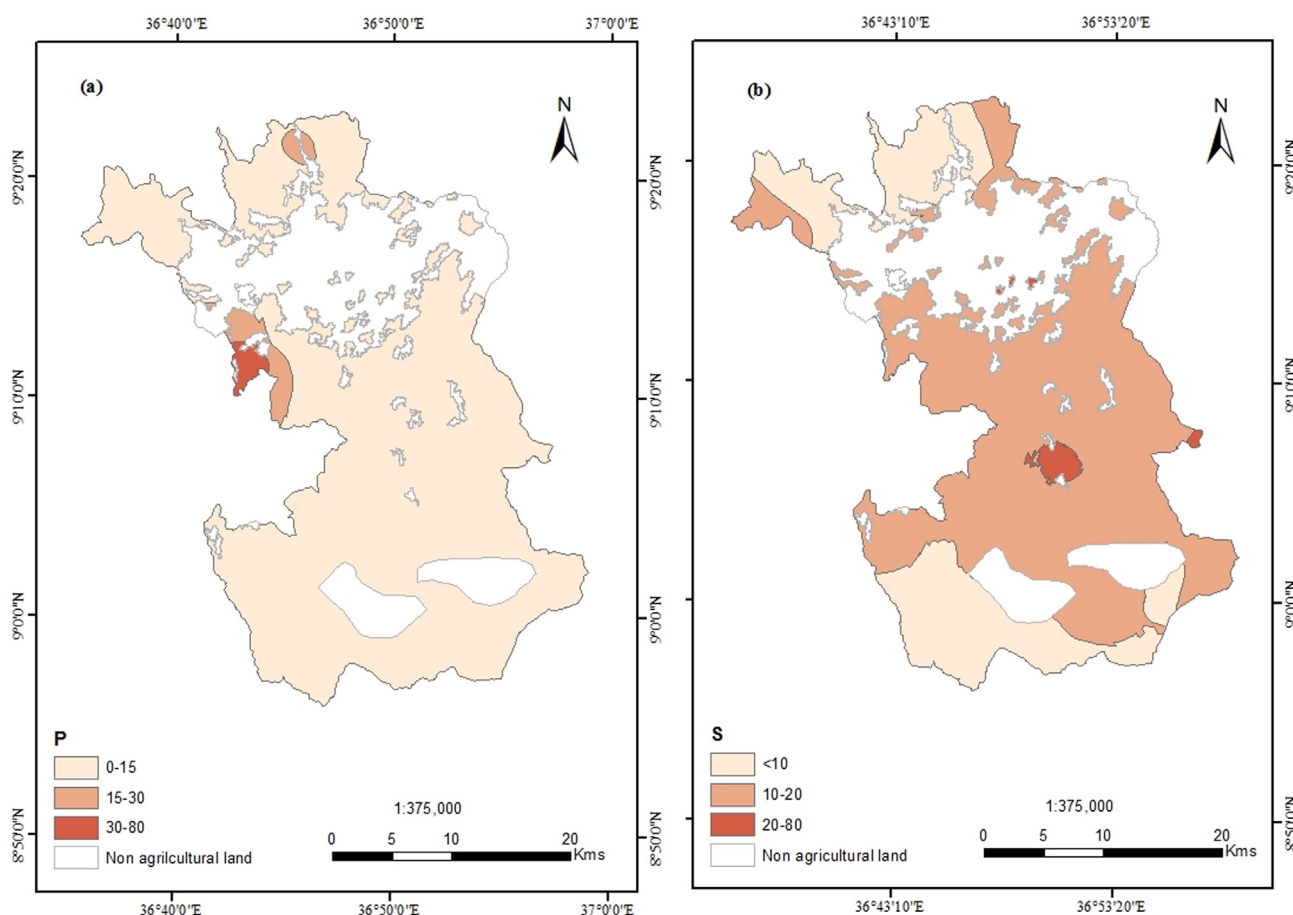


Figure 4. Spatial variability map of (a) available phosphorus (P) and (b) available sulfate-sulfur (S) (the data were reference values).

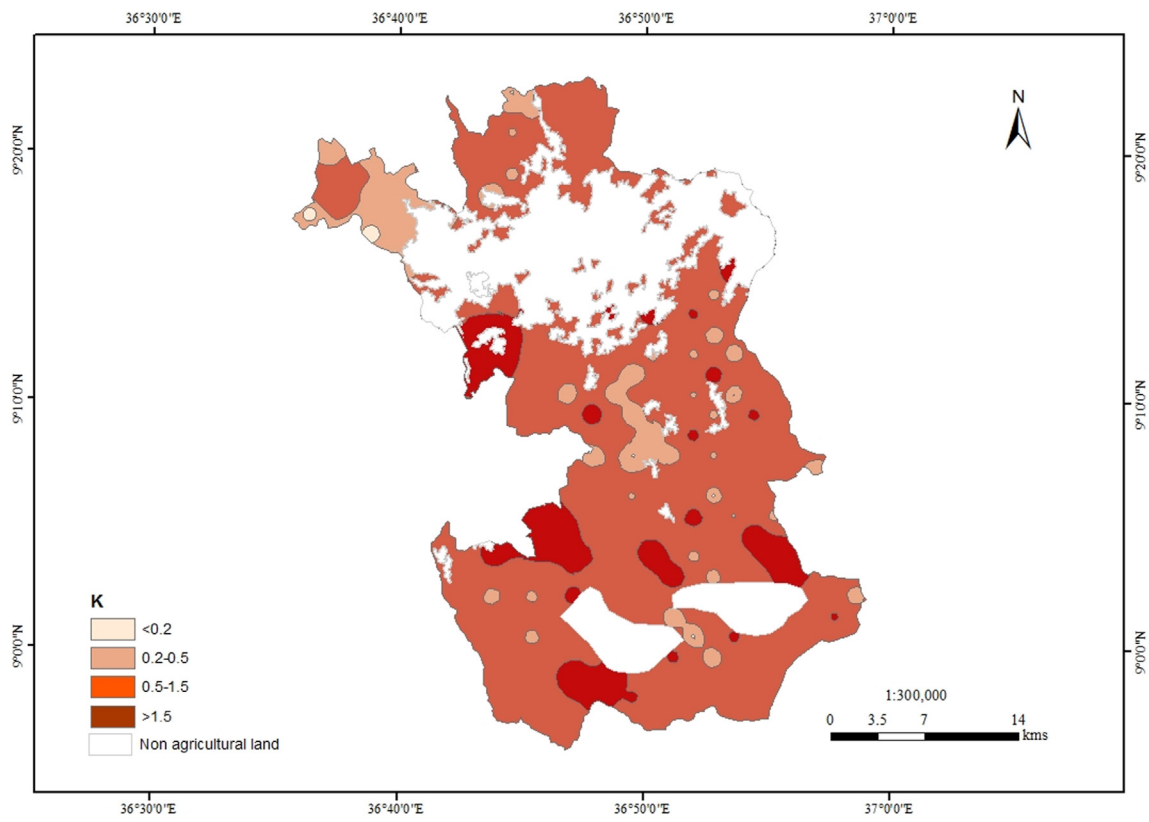


Figure 5. Spatial variability map of exchangeable potassium (K) (the data were reference values).

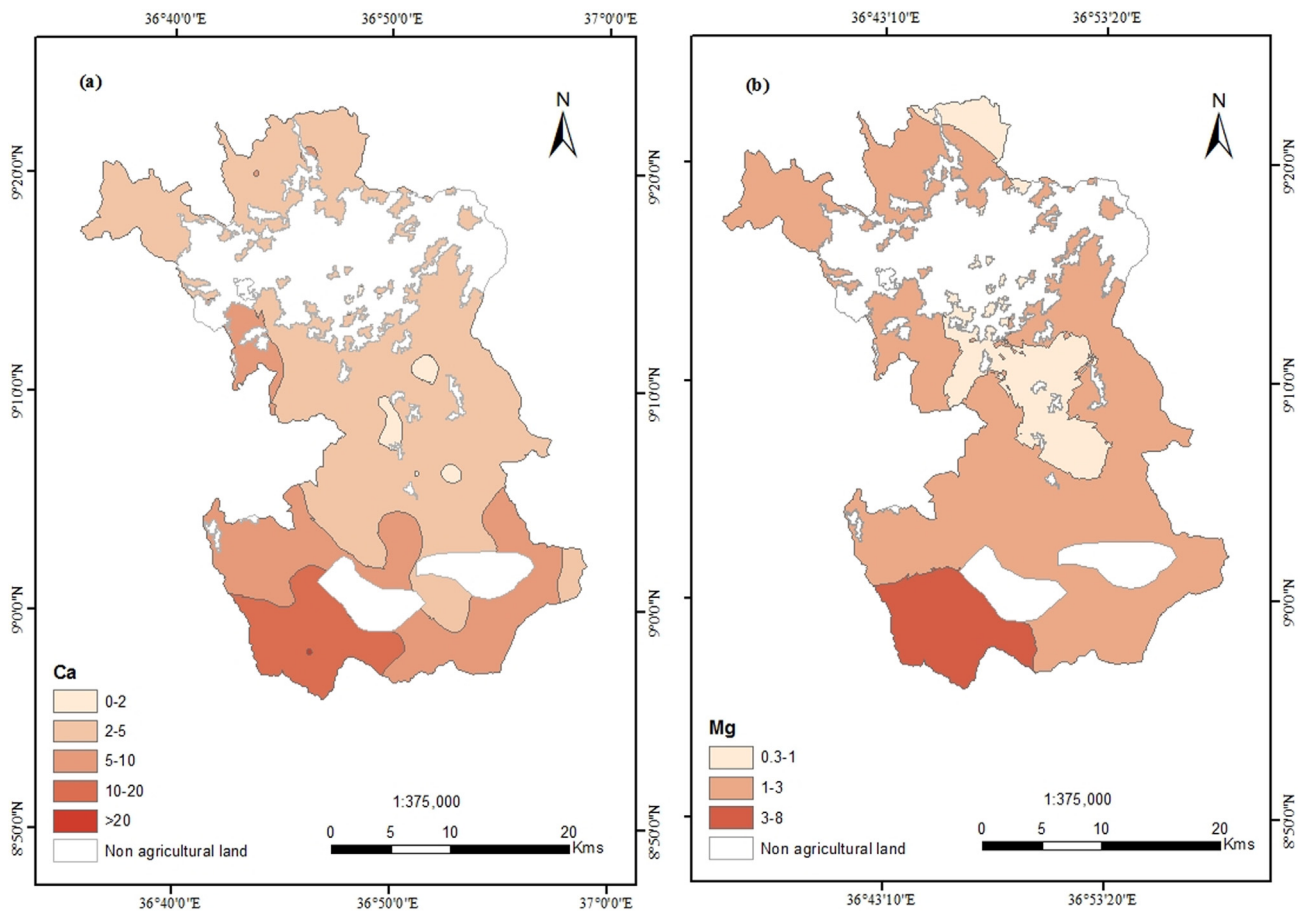


Figure 6. Spatial variability map of (a) exchangeable calcium (Ca) and (b) exchangeable magnesium (Mg) (the data were reference values).

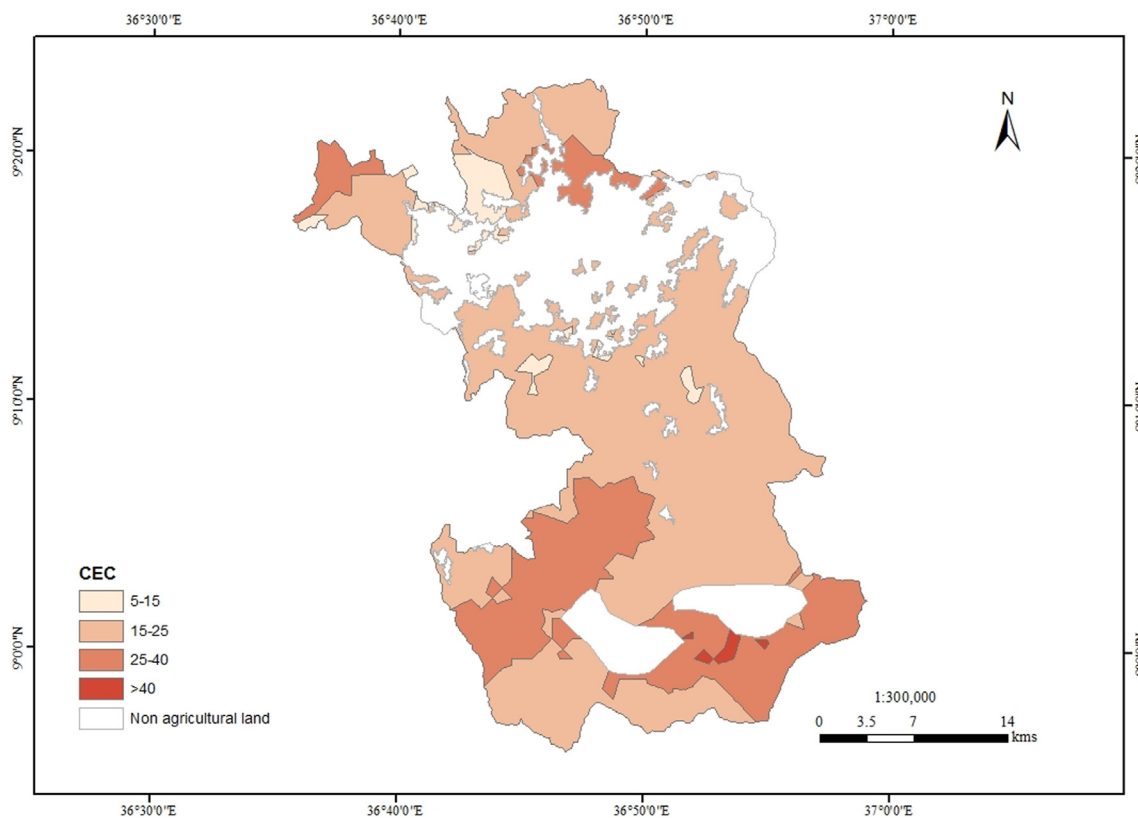


Figure 7. Spatial variability map of cation exchange capacity (CEC) (the data were values predicted by MIR spectroscopy).

significantly correlated with exchangeable Ca ($r = 0.14$) and Mg ($r = 0.11$) at $p < 0.05$ (Table 3).

Our results revealed that spatial variation was relatively highest for av. P (CV = 57.0%) and lowest for soil pH (CV = 6.73%) (Table 2). The skewness coefficient ranged from (-) 0.40 for the soil pH to (+) 1.21 for the av. P.

3.3. Variance and relationship between soil properties

In the present study, the first five principal components (PC) accounted for 78.17% variance in the data (PC1 = 25.75%, PC2 = 18.06%, PC3 = 13.85%, PC4 = 11.12%, and PC5 = 9.39%) (Table 4). The first five components showed eigenvalues greater than 1 (Table 4). We used the total variance of the principal components that showed eigenvalues greater than 1.

The relationship between soil properties was described using factor plot that shows the results of the first two components (Figure 8). Here, the soil properties were displayed on the two-dimensional space by using the first two components. There were strong correlations between TN and OC; OC and CEC; Ex. Ca and Ex. Mg; and av. S and elevation as observed from the magnitude and direction of correlation lines (Figure 8). But Ex. Ca and Ex. Mg; av. P and clay; av. P and OC; K and OC showed diverging relationships.

4. Discussion

4.1. The PLSR and PCA

The PLSR model and PCA were used to measure the predictability and reliability of the methods for predicting soil chemical properties. Good predictions are those having $R^2 = 0.75$, satisfactory predictions for R^2 from 0.65 to 0.75, and predictions below those values are poor (Chang et al., 2001; Shepherd and Walsh, 2002). Considering this information, the MIR spectroscopic based PLSR model best predicted OC, TN, and CEC. These parameters dominated the MIR spectra of the soils, and the correlations were expectedly high enough for accurate estimation of soil contents for those components. Though the RMSE values were high for exchangeable K, Ca, and Mg, the PLSR model cannot predict these ions as the calibration and validation values of R^2 were low. Because these simple ions might form a bond with soil water and absorb spectral radiation. In this way, it would not be expected that MIR would give high-quality information and predict the exchangeable ions. Ben-Dor (2002) reported that the presence of salt ions in soils may result in subtle spectral responses when combined with $-OH$, which is common in soils. Similarly, the spectroscopic technique did not provide a good prediction for the rest of the soil properties. Boruvka et al. (2005) reported that a few components account for about 60–90% of the total variance in an analysis, which is the only component used for data representation. In

Table 4. Eigenvalues.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14
Eigenvalue	3.86	2.71	2.08	1.67	1.41	0.73	0.68	0.60	0.46	0.36	0.25	0.12	0.05	0.03
Variability (%)	25.75	18.06	13.85	11.12	9.39	4.85	4.55	3.98	3.05	2.43	1.68	0.77	0.34	0.18
Cumulative %	25.75	43.82	57.66	68.78	78.17	83.02	87.57	91.55	94.60	97.03	98.71	99.48	99.82	100

PC: principal component.

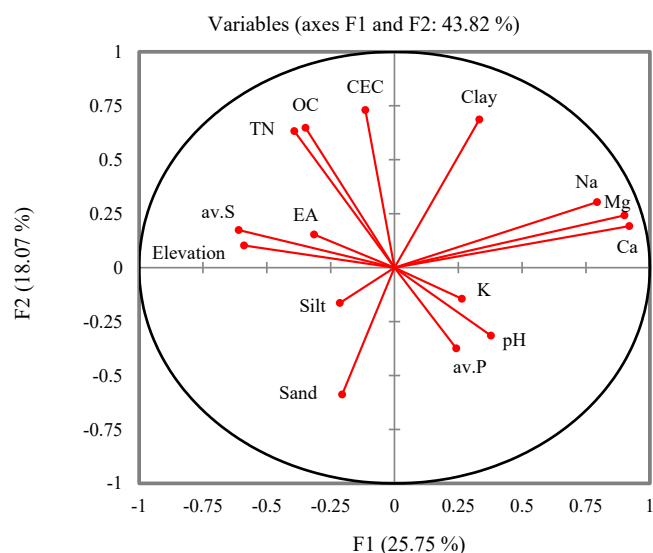


Figure 8. Factor plot of the first two principal components. The factor loading shows the relationship between soil properties.

PCA, the loss of information should be as small as possible, accepting a loss of less than 40% (Johnson and Wichern, 2002). The components that show eigenvalues greater than 1 explain most of the variation within the data set (Gniadzowski, 2017). In this study, we chose the first five principal components that showed eigenvalues greater than 1 as they best explained the variance.

The PCA and Pearson correlation results showed that all exchangeable bases did not significantly correlate with CEC. This implies that the source of CEC might be a high concentration of exchangeable acids (Al and H) but not exchangeable bases. The magnitude and direction of the correlation between av. S and elevation in Figure 8 showed that av. S was higher in soils of elevated lands. In contrast, the findings of Li et al. (2017) showed that av. S changed non-linearly with elevation, which might be due to variation in other factors such as climate and vegetation cover. Exchangeable Ca and Mg showed diverging relations with elevation (Figure 8) indicating Ca and Mg status were higher in the lower altitudes than the highlands. Clay content was negatively correlated with av. P. This might be caused by a high tendency of exchangeable Al to fix av. P in extremely leached clay soils. Similar to the report of Birhanu and Chalsisa (2018), the weak correlation observed between av. P and OC as well as K and OC indicated that the main source of av. P and K might be mineral rocks but not organic matter. The study revealed that sand content was negatively correlated with elevation (Figure 8). This was similar to the findings of Oku et al. (2010) who observed higher mean sand content at the upper slope or crest (583 g kg^{-1}) than at the valley floor (744.70 g kg^{-1}). Similar to the findings of Vasu et al. (2016), there was a strong correlation between TN and OC; CEC and OC; clay and CEC; pH and av. P; and Mg and Ca.

4.2. Critical levels of soil nutrients and their management

Knowing critical levels of soil nutrients would help variable rate fertilizer applications to improve farm productivity. Based on critical values suggested by Havlin et al. (2013), nearly 94% of the soils contain TN above or equal to the optimum range ($\geq 0.15\%$). Similar to the report of Fageria and Baligar (2005), total N was higher at the highlands of the study area compared to the lowlands; because lowlands are warmer, leading to OC decomposition and associated loss of N. When CV of soil nutrients increases, the response of crops to a specific rate of fertilization would become non-uniform (Cao et al., 2012; Ichami et al., 2020). Here, the spatial map of soil nutrients

could aid variable rate fertilization programs according to the site-specific needs of soils and crops.

The critical levels adopted for Ethiopian soils (Karlton et al., 2013) showed that nearly 96% of the soils had very low av. P content (0–15%) and the rest exhibit low to optimum av. P. This showed that av. P was one of the most limiting nutrients in the soils of the study site. The availability of P had decreased, perhaps owing to the problem of fixation. Besides to the fixation by Fe in acid soils, the decline in av. P content of Ethiopian soils might be attributed to low OM content, abundant crop harvest, erosion, and dominance of the HPO_4 anion than $\text{H}_2\text{PO}_4^{2-}$ (Dawit et al., 2002; Achalu, 2014). Based on the critical value of 20 mg kg^{-1} adopted for SO_4^{2-} -S content in the soils (Karlton et al., 2013), nearly 97% of the soils showed below this point. This shows that SO_4^{2-} -S was highly deficient and probably one of the most limiting nutrients in soils of the study site. Jamal et al. (2010) reported that excessive amounts of N on low organic matter soils (low C:N ratio) is the cause for S deficiency due to imbalance between TN and SO_4^{2-} -S. Besides, as SO_4^{2-} form of S is easily leachable (Kovar and Grant, 2011; Gallejones et al., 2012), S nutrient deficiency is the major problem in the highly weathered kaolinitic soils of western Ethiopia. As a result, optimum P and S fertilizers application across the farm helps to improve crop production.

Based on the ratings suggested by Karlton et al. (2013), nearly 2 and 93% of the soils exhibited low and optimum values of exchangeable K, respectively. Only the remaining 5% found to have high exchangeable K. Even though the mean value of exchangeable K was in the optimum range, there could be an increasing loss of K through continuous removal by crops and vertical movement by leaching. Because of limited knowledge on the K dynamics in Ethiopian soils and the absence of a remarkable response to K application, there has been sweeping generalization on K status in Ethiopian soils and as a result, there has not been adequate focus given to potassium in the national fertilizer scheme (Mesfin, 2007). Recently, however, a highly negative K balance and deficiency as well as responses to application of K fertilizer is reported in different parts of Ethiopia, contrary to the general perception that K fertilizer was unnecessary for the soils (EthioSIS, 2016; Mulugeta et al., 2019). So, site-specific applications of K-fertilizers would help to gain more responses from crops. More than 64% of the soils exhibited low exchangeable Ca based on the rating recommended by Hazelton and Murphy (2007). Whereas, 75% of the site comprised moderate Mg, indicating only 15% holds low Mg nutrient. Owing to high leaching in the highland areas, more Ca is required as a production input and the response to Ca application in the form of fertilizer or lime more likely increases productivity.

The K:Mg ratio of the soils varied from 0.19:1 to 4.32:1. Nearly 36% of soils in the study site exhibited a problem of Mg induced K deficiency according to the guideline of Loide (2004). Potassium fertilizer application to bring the K to Mg ratio closer to 0.7:1 could correct the problem. Similarly, Mg induced K deficiency in soils was observed in the Vertisols of the central highlands of Ethiopia (Hillette et al., 2015). In contrast, very high rates of Mg fertilizers would indeed depress K absorption by plants, but this antagonism was not nearly as strong as the inverse relation of K on Mg (Fageria, 2001). So, a high soil K^+ level or high application rates of this element in soils with low Mg levels could induce Mg^{2+} deficiency; therefore its application should be based on spatial variability of the nutrient across the field.

4.3. Lime recommendation rate

The pH of nearly 27% of the surface soils was strongly acidic ($\text{pH} \leq 5.5$) according to Bruce and Rayment (1982) soil pH classification system. These soils are rarely suitable for crop production unless management measures are executed. Exchangeable acidity was almost absent in soils with pH values < 5.5 . Considering the optimum pH for many plant species to be 5.5 to 6.8 (Amacher et al., 2007) and the absence of free

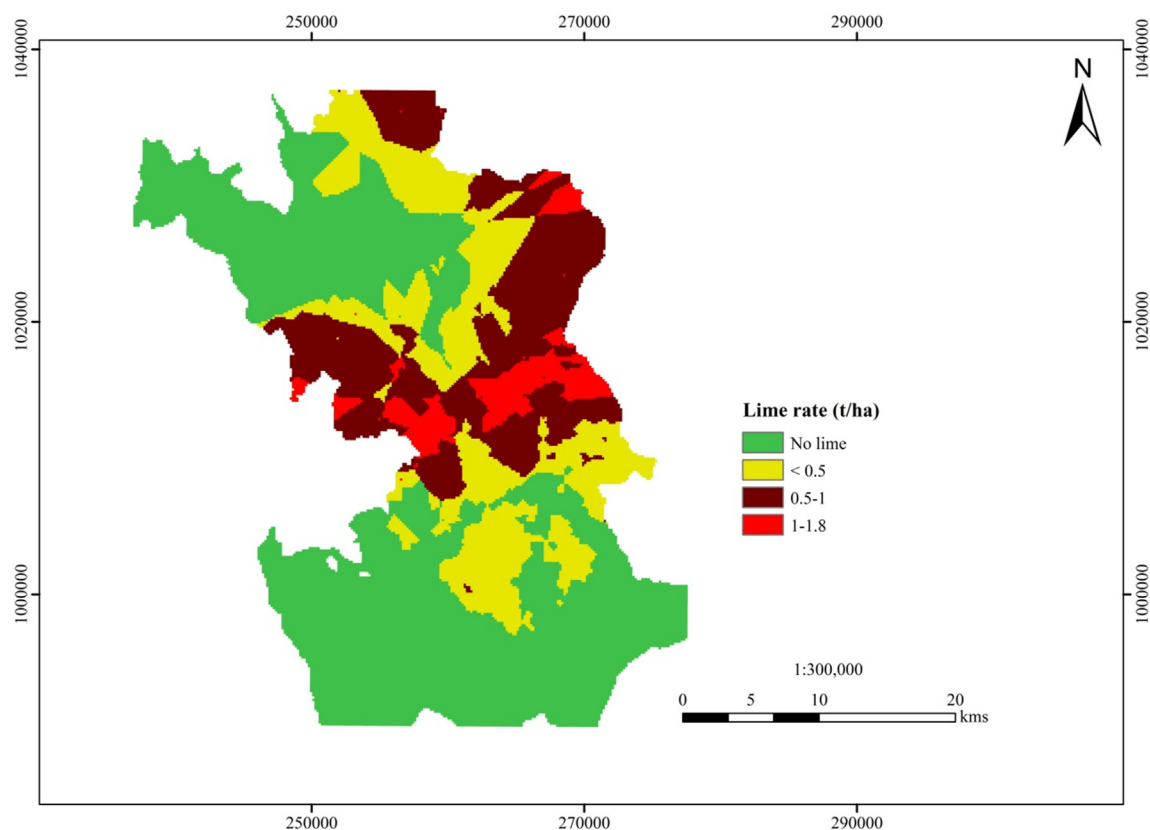


Figure 9. Variable rate lime recommendation map for soils of the study site.

exchangeable Al in this range, nearly 73% of the soils in the study area could be considered as suitable for most crop production.

The overall analysis of lime requirement showed that 22, 21, and 5% of agricultural soils in the district require <0.5 , $0.5-1$, and $1-1.8$ $t\ ha^{-1}$ of lime, respectively (Figure 9). So, different lime rates are typically needed to neutralize acid soils sufficiently for crop production; and lime requirements varied across the farmland depending on the soil types and the level of acidity (Anderson et al., 2013; Birhanu and Chalsissa, 2019). However, the use of organic methods such as charcoal, manure, compost, and selection of acid-tolerant crop varieties could reduce the lime requirement and ensure environmental sustainability.

4.4. Soil carbon density and its management

Most soils in the study site showed low soil OC ($<4\%$) based on Landon (2014) classification. The relatively low soil OC content could be owing to complete removal of the aboveground biomass and extensive nutrient depleting crop rotation practices. The mean OC density of the soils was $2.14\ kg\ m^{-2}$ within 50 cm soil depth. In the highlands of the study site, comparatively, we found a maximum OC density of $4.65\ kg\ m^{-2}$ to a depth of 50 cm. Our results revealed that lowland parts of the study site had lower soil OC content than the highland parts. That means OC content was minimum in locations having lower elevations. Low to medium amount of soil OC in lowlands might be attributed to the warmer climate, which enhances the rapid rate of mineralization.

Soil OC density estimates for arable soils during the present study was smaller than that of Ireland ($17.1\ kg\ m^{-2}$ to a depth of 50 cm) (Xu et al., 2011), and Belgian cropland soils ($7.9\ kg\ m^{-2}$ for the top 30 cm) (Meersmans et al., 2009). This difference might be caused by variation in the soil OC concentration, climate, management practices, and the depth of sampling. Moreover, the use of crop residues for energy, animal feed, construction, and also slash and burn that are the most common practices in Ethiopia have contributed to the depletion of soil OC (Birhanu and

Chalsisa, 2018). The carbon sequestration potential of the soils could be improved by using animal manures, cover crops, green manures, and avoiding slash and burn practices. Controlled grazing and subsequent incorporation of crop residues into the soils would also help to increase the carbon content of the soils. These management practices also have implications on climate change mitigation through the reduction of carbon emissions to the atmosphere.

5. Conclusions

Integrating MIR spectroscopy and geostatistical techniques is useful for broad and quick quantification and prediction of soil properties. The PLSR model proved that the model performed better in predicting CEC, OC, and TN. Except for soil pH, most soil properties showed considerable variation across the farmland. The exhaustive burning of crop residues coupled with intensive and continuous tillage practices had led to depletion of soil OC. The soils showed a broad spectrum of nutrient deficiencies. Soil acidity and associated deficiencies of av. P and SO_4^{2-} -S were among the major limiting factors of crop production in the study area. Linking MIR spectroscopy with geospatial methods increases the efficiency of site-specific applications of soil nutrients. This technique also supports site-specific lime applications. Finally, further research is required to improve the prediction efficiency of infrared spectroscopy and its combination with geospatial tools to aid precision soil management.

Declarations

Author contribution statement

Chalsissa Takele: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Birhanu Iticha: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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