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Impacts of Soil Environmental Factors on Variability of Soil Organic Carbon and Particle Size Fractions in Obudu Cattle Ranch, Nigeria

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Abstract: The knowledge of the influence of environmental factors on soil properties and spatial distribution of soil organic carbon (SOC) and soil particle size fractions is crucial to soil management and sustainable productivity. SOC provides an insight about soil capacity to perform ecosystem services while soil particle size fractions influence several key soil characteristics. This study assessed the impacts of environmental elements on spatial changes in SOC and sand, silt and clay using random forest (RF), regression kriging (RK), cubist regression (CR), multiple linear regression (MLR) and ordinary kriging (OK) models. Sixty (60) composite soil samples were obtained at 0-30 cm depth and distance of 200-500 m apart, and analyzed for physicochemical properties. The digital elevation model (DEM) of the area was acquired at the spatial resolution of 30 m from USGS and processed. The models were evaluated using bias, coefficient of determination (R2), correlation concordance coefficient (CCC), mean square error (MSE) and root mean square error (RMSE). The soil had sandy clay loam, sandy loam and loam texture with strongly acidic pH (pH <5.5) and high OC (2%). Available P and exchangeable cations were all low while cation exchange capacity and base saturation were high. Soil pH> SAVI (soil adjusted vegetation index)> NDVI (normalized difference vegetative index) > rainfall were found to be the top four environmental variables influencing OC prediction while temperature and slope had the least effect. Again, MLR model better predicted OC (R2 of 0.324, CCC of 0.537, MSE of 0.585, RMSE of 0.764), OK better predicted clay (MSE=2.680, RMSE=3.490), CK in sand (MSE = 7.434, RMSE =5.568). Also, MLR, CK and OK proved to have the best capacity in prediction SOC and sand, silt and clay in mountainous soils. The findings could therefore be used by policy makers and planners as tools for decision making on sustainable soil and environmental management and precision agriculture.

Keywords: *SOC, environmental elements, models, soils.*

1. Introduction

Soil organic carbon (SOC) is the equilibrium of plant supply and biologically mediated losses (Arthur *et al.*, 2022). Soils are the highest carbon warehouse of the earth carbon cycle and almost thrice the amount of carbon is preserved in soils than in plants and soils contain twice the quantity of carbon that the atmosphere holds (Shiekh *et al.*, 2009). Organic carbon content of first 100 cm of soil is estimably 1500 Pg meaning more C than the quantity contained in both atmosphere and vegetation (Lehmann & Kleber, 2015). SOC improves soil nutrient cycling, plant growth and maintenance of soil structure (Wang *et al.*, 2016). It is the measure of soil capacity to perform ecosystem services including nutrient supply to crops because SOC performs several roles including soil pH moderation, nutrients supply, soil structure and hydraulic conductivity improvement, and control of microbial activity (Nisha *et al.*, 2007; Hussain *et al.*, 2019). Critical evaluation of the effects of elements of environment on SOC is necessary in order to identify areas with varying soil characteristics and to assess their performance under a given land management practice and potential ease of degradation specifically for sustainable crop cultivation and environmental management. This is because SOC performs additional ecosystem services such weather moderation, provision of raw materials and food to man, nutrient release, runoff and erosion mitigation (Veronesi & Schillaci, 2019; Mayer *et al.*, 2019). Concise and correct mapping of C storage in mountainous soils provides information about the relationship between biogeochemistry cycle and global climatic condition (Bangroo *et al.*, 2017) and since SOC play crucial roles soil functioning (Lal *et al.*, 2018)

The area of the study, Obudu Cattle ranch, located in hills of Obanliku in Cross River, is well known because of its peculiar land form which is characterized by high mountains, abyss, canyons and cold weather condition. The Obudu Cattle ranch has an elevation of over 1650 m above sea level (asl) and, in Nigeria it is next to Chappal Waddi mountain of Taraba State in height with an elevation of about 2400 m asl. The Cattle ranch has characteristically different climatic conditions; cloudy weather, steady snow fall, low temperature and steady rainfall from other parts of Obanliku and the State. This is because mountains soils regulate climatic variables at local level (via evapotranspiration which reduces the amount of heat in the air and is mostly important in urban areas) and on universal scale via the storing of SOC that forestall its release into the outer space as greenhouse

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gas (Stanchi *et al*., 2021). It is discovered that SOC stock in mountainous soils is often affected by several factors among which are: vegetation diversity, topographic attributes and impacts of climate (Bangroo *et al*., 2017) which in turn influence the soil physicochemical and biological characteristics essentially in the first soil horizon (Fu *et al.,* 2020; Zhang *et al.*, 2021). Therefore, having a fair knowledge on the effect of environmental variables on how SOC changes with distance in mountainous soil is crucial in decision making for effective land management option particularly for mountainous soils. Accurate mapping of SOC in mountainous soils is therefore crucial in solving local environmental problems, aptly planning best land management alternatives and advocating/enhancing land use practices without damaging effects (Tang *et al*., 2015). It is suggested that among the best processes to efficiently manage agricultural operations and to plan for life long growth is acquisition of accurate understanding on spatial heterogeneity of soil physicochemical characteristics (AbdelRahman *et al.,* 2018) and this can only be perfectly achieved using geospatial technologies or spatial interpolation. Spatial interpolation has been described as a way of estimating the exact values of variable or quantification of substance in an area not sampled (Kalivas *et al.*, 2002), that basically provides valuable information for precision agriculture, planning of soil fertility management and environmental studies (De Menezes *et al*., 2016; Brevik *et al.*, 2015). The emphasis here is on precision agriculture, therefore, understanding space heterogeneity and dynamism of soil characteristics and SOC and particle fractions in particular as this could necessary to provide information for government policy formulation to guide farmers on proper and sustainable utilization and management of soils with minimal inputs.

Variation in environment, soil type, vegetative cover and land use are major causes of spatial variations of SOC in mountainous environment (Hoffmann *et al*., 2014). The space changes in TOC are determined by topographic features and soil texture at the plot scale, especially where it is affected by texture of the soil at the landscape level (Zhu *et al*., 2020). Also, Feng *et al*. (2021) opined that elevated temperature and wrong agricultural operation reduced SOC buildup. Therefore, apart from human influences through land preparation for crop production, SOC is controlled by myriads of environmental variables including lay of the land, altitude, climate and soil characteristics such as soil reaction and arrangement of soil separates. SOC levels appeared to be influenced by weather indices according to a study by Zhang *et al*. (2022). It is also affected by altitude and vegetation (Massaccesi *et al*., 2020; Xu *et al*., 2014) that control nutrient cycling and release (Zhang *et al*., 2014) and elevation has been reported as an alternative for change in temperature used to evaluate the impacts of temperature on SOC level and dynamics (Massacesi *et al*., 2020). Nature of land surface, climate and other environmental elements have been confirmed as factors affecting soil characteristics (Bamutaze *et al*., 2021). Again, Bangroo *et al*. (2017) in their study discovered that SOC stock was decreasing with increasing elevation and concluded that it has an unfavorable influence on SOC stability. The authors suggested that altitude effect should be included in SOC stock assessment equations. Although studies have been conducted on the impacts of environmental factors on SOC stock, little has been done on both SOC and particle size in mountainous soils especially in Nigeria. Most studies in Nigeria on mountainous soils are merely on soil physicochemical properties (Akpanidiok *et al*., 2014; Essoka *et al*., 2010); they have been no detailed studies on spatial distribution or mapping of SOC and soil particle size fractions on mountainous soils.

Considering the importance of SOC and soil separates in management of soil fertility and the need to overcome the challenge of meeting up with the increasing world food demand resulting from rapidly growing population, it is imperative to double effort in evolving strategies that engender sustainable crop production. One of such strategies is the acquisition of proper knowledge of the effect of soil environmental indices on distribution of soil SOC and particle size fractions spatially as yardstick for proper land use and management. These challenges have led to mounting of pressure on mountainous soils which were initially underused or used for forest reserve, watershed and wildlife conservation as a result of stress involved in climbing high mountains for the purpose of crop cultivation. According to FAO (2019), as of the year 2017, only fifteen percent of global population were living and cultivating crops on and around mountains. Consequently, intensive studies on mountainous soils are therefore needed. This study is therefore anchored on the evaluation of the impacts of environmental elements on SOC and particles size fractions and to predict and assess spatial heterogeneity of SOC and particle size fractions of mountainous soils using geostatistics. However, at the global level some studies have been done that focused on land use effect on organic carbon storage (Li *et al*., 2019; Hussain *et al*.,2019; Bamutaze *et al*., 2021; Ota *et al*., 2024) and a few on the influence of environmental factors on soil organic carbon levels (Feng *et al*., 2021) in mountainous soils (Bangroo *et al*., 2017). Mousavi *et al*. (2022), De Menezes *et al*. (2016) and Kalivas *et al*. (2002) have shown that geostatistics can be used to map soil properties, but only Isong *et al*. (2022), Komolafe *et al*. (2021) and Peter-Jerome *et al*. (2022) worked on such concept at the national level in Nigeria. Nevertheless, these studies were not on understudied mountainous soils and also did not consider the effect of environmental factors such as rainfall, temperature, slope, pH, elevation etc on spatial distribution of SOC and particle size. Accurate evaluation of the impact of environmental factors on prediction of SOC and particle size in mountainous soils is therefore needed to guide on soil use and management since SOC and particle are key determinants soil fertility and productivity.

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2. Materials and Methods

The Study Area, Soil Sample Collection and Laboratory Analysis

This study was done in Obudu Cattle Ranch, Obanliku, Cross River State, located at latitudes 6° 21′ N – 6° 24′ N and longitudes 9° 22′ E – 9° 25′ E (Fig. 1) in the tropical rain forest belt of Nigeria with moist tropical humid climate, diverse land use cover types and has an altitude varying from 689 m to 1654 m above sea level, rainfall range of above 2000 mm/annum and temperature of 15 to 31.80 ^{0}C. Geologically, the area is underlain by basement complex rocks. Major crops cultivated in the area include cassava, cocoa, maize, yam, okra, groundnut and cocoyam. Sixty georeferenced composite soil samples were obtained randomly at 0-30 cm depth from the study area at the distance of 200 m - 500 m apart using soil auger and transported to the laboratory, processed using standard procedures and analyzed for physicochemical properties. Particle size analysis was done using Bouyocous hydrometer method (Gee and Or 2002).

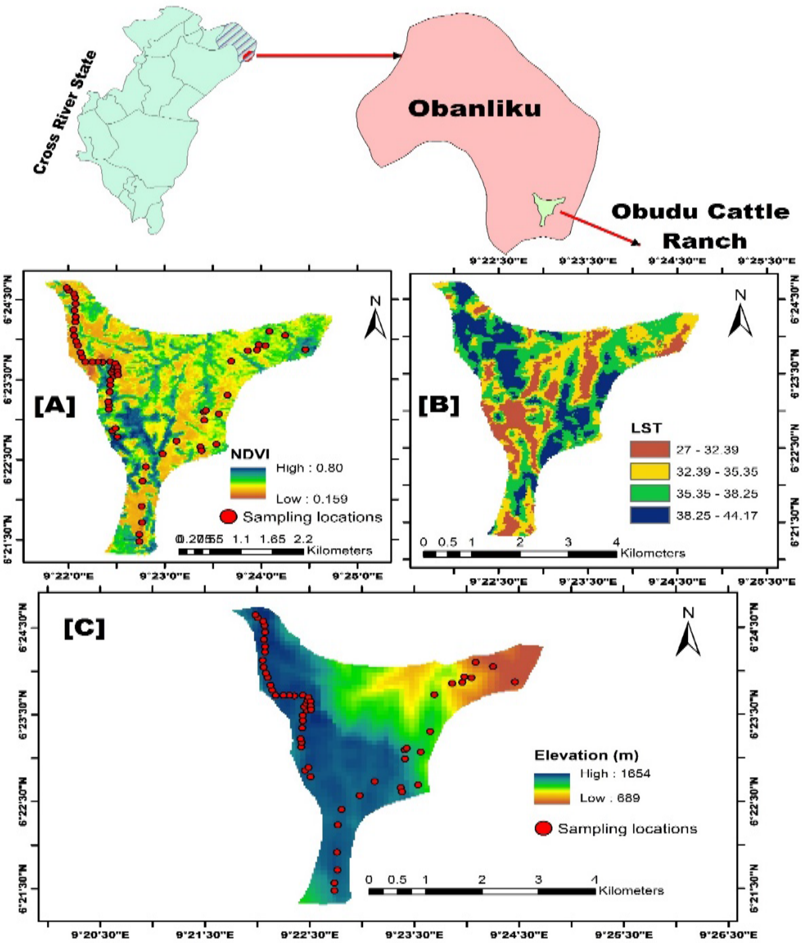

Figure 1. Map of Cross River State showing location of the study area [A] Normalized difference vegetation index (NDVI), [B] Land surface temperature (LST) and [C] Elevation

pH was obtained potentiometrically in soil and water suspension (1:2.5) as reported by Udo *et al*. (2009) while organic carbon was determined by Walkley-Black wet oxidation method using acid dichromate($K_2Cr_2O_7$) method (Nelson and Sommers 1996). Total nitrogen was analyzed with modified micro-kjeldhal method (Udo *et al*., 2009) while available phosphorus was obtained using Bray P-1 method outlined by Kuo (1996). Exchangeable cations were also determined using the extract obtained after leaching samples with one normal neutral ammonium acetate (1 *N*, NH_4OAC, pH 7.0) solution. Again, calcium and magnesium were analyzed using the EDTA titration method while potassium and sodium were estimated by Flame photometer. Furthermore, aluminum and hydrogen were determined by titration using 0.1*N* Na0H solution presented by Udo *et al.* (2009). CEC was gotten using the method proposed by Udo *et al*. (2009). And finally, ECEC and base saturation were obtained by computation method.

Environmental Covariates

Environmental covariates used to derive environmental data were digital elevation model (DEM) and Sentinel-2. Elevation, slope and aspect were gotten from DEM obtained at the space resolution of 30 m from ASTER data (https://earthexplorer.usgs.gov) and were processed with the aid

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of SAGA-GIS software terrain analysis toolbox. The European Space Agency's Copernicus Open Access was used to acquire Cloud-free Sentinel-2 imageries, processed using Google Earth Engine (GEE) to estimate land surface temperature (LST), normalized difference moisture index (NDMI), normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI) and cannel network base level. Soil pH and clay were obtained through interpolation techniques using the interpolated soil database at a resolution of 30 m. Climatic parameters including mean rainfall, minimum temperature, maximum temperature and mean temperature covering the study area were gotten from WorldClim database version 2 (Fick *et al.,* 2017) and processed using ArcGIS software. All the maps used in this study were geo-referenced to the Universal Transverse Mercator (UTM) Zone 32 N coordinate system. The area of interest (AOI) for the soil and environmental data were demarcated using polygon feature of the study areas with aid of ArcGIS 10.8 software (ESRI, Redlands, USA) environment.

The covariates used in this study were selected using recursive feature elimination (RFE) and variance inflation factor (VIF). RFE was employed for feature selection to identify the optimal subset of variables that contribute significantly to OC prediction. The RFE algorithm was then executed to determine the most influential variables according to the root mean square error (RMSE). The resulting subsets were visualized using plots, thus allowing the researchers to assess the performance of different subset sizes. The covariates were further screened via variance inflation factor (VIF) which was implemented through multiple linear regression.

Statistical Analysis

Data distributions done using classical statistics are minimum, maximum, mean, standard deviation, coefficient of variability, skewness and kurtosis. The statistical analyses for preprocessing environmental variables were done using SAGA-GIS software terrain analysis toolbox. Again, geostatistics and machine learning modeling and prediction were carried out using R and Rstudio software. ArcGIS 10.8 was used for preparing maps. The descriptive statistical analysis was computed in SPSS v25. The flowchart of the steps followed in prediction of soil properties (OC, sand, silt and clay) is presented in Figure 2.

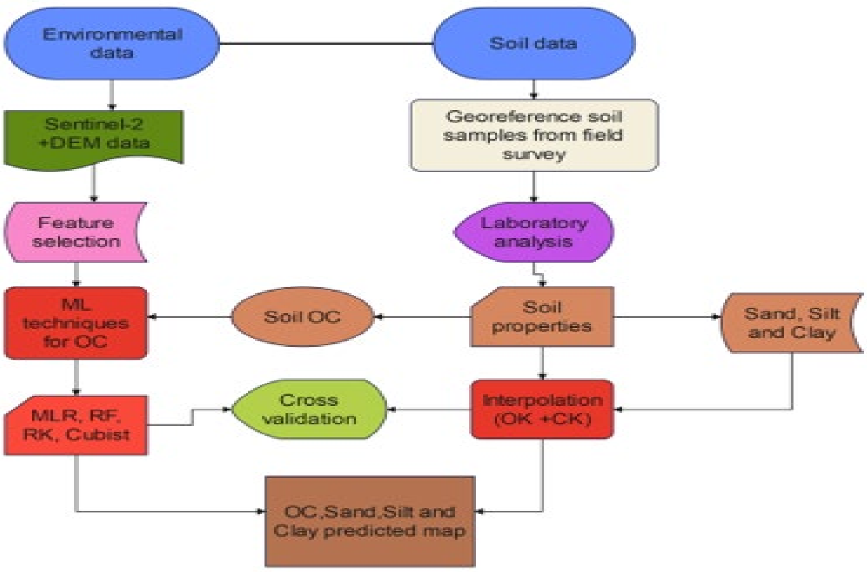

Figure 2. Flowchart illustrating the steps for soil organic carbon and particle size fractions prediction

Geostatistical Interpolation Methods

The geostatistical techniques used in this study were ordinary kriging (OK) and cokriging (CK). OK is broadly used geostatistical method that creates an optimal estimated surface using semi variogram based on regionalized variables. According to Grunwald *et al*. (2008), the OK makes use of an assessed average of a given soil characteristics in a location known to forecast the value of location not sampled (see Eqn. 1). CK is an aspect or continuation of the kriging procedure which combines the information determined by a secondary index in relation to the primary quantity that is being forecasted.

$$Z'(x_0) = \sum_{i=1}^{n} \lambda_i . Z(x_i) \quad (1)$$

where: $Z'(x_0)$ is the estimated/forecasted value for point x_0, $Z(xi)$ is the value known, and λi stands for kriging weight for the $Z(xi)$ values. It obtained using a semi-variance function of the variables with criterion that the predicted value is not biased and optimal (Eqn. 2).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} [Z(X_i) - Z(X_i + h)]^2 \quad (2)$$

where γ(h) is the semivariance, h the lag distance, Z stands for soil property, N(h) the number of pairs of areas disconnected by a lag distance h, Z(xi), and $Z(X_i+h)$ are values of Z at positions xi and xi + h according to Wang *et al.* (2013).Exponential, linear,

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spherical and Gaussian semi variograms models were employed to describe the semi variograms or cross-semi variograms and the most suitable models chosen with the lowest RMSE, MSE and ME between estimated variances and the determined values of soil characteristic. The nugget/sill ratio were employed as a condition to classify how soil characteristics depend of spatial features. Ratio < 25% depicts that property has high dependence on spatial features; varying from 25 to 75% connotes that property has high dependence on spatial features while > 75% depicts the property spatial dependence is feeble (Cambardella *et al.,* 1994).

Machine Learning Algorithms

Four most effective machine learning algorithms for handling small datasets were used in this study to map organic carbon and soil particle size fractions, namely multiple linear regression (MLR), random forest (RF) model, cubist regression (CR) and regression kriging (RK). In MLR, SOC was forecasted as straight line combination of soil-environmental factors. Therefore, the soil characteristic of interest is estimated using;

$$\hat{y}_{(i)} = \hat{\beta}_0 + \sum_{k=1}^{k} \hat{\beta}_k X_{k(i)} \quad (3)$$

Where, ŷ(i) is the estimated soil characteristic at point i, $\hat{\beta}_0$ the predicted intercept, $\hat{\beta}_k$ the predicted regression coefficient for predictor k and $X_k(i)$ the value for the k^{th} predictor at a given point i.

According to Freeman *et al.* (2015) and Fox *et al.* (2019), RF modeling is a commonly used method for regression and grouping with intricate or difficult data sets. Contrary to MLR, RF is an algorithm method that does no *a priori* suppositions concerning the interaction among the predictor quantities and the response. RF has a capacity for better prediction achievement when the data have much number of predictor quantities and there seem to be difficult non-linear and interactive impacts in the association between the predictor quantities and response property (Biau, 2012; John *et al.,* 2020). Nevertheless, RF is not sensitive to the option of tuning parameters and the defaults provided by the RF program perform efficiently for almost all data sets (Freeman *et al.,* 2015). Quinlan (1992) developed cubist regression (CR) model as an extension of the M5 tree model which has same approach as RF. The model design according to Kuhn (2013) is made of parts or piecewise function which acts like choice making tree, join together with MLR models. These trees are diminished or lowered to a set of guidelines that are removed via trimming or joined for ease of usage. This model was put in practice using R with tuning of two hyper-variables which are likely variables having the highest influence on the overall action or achievement of CR model. Also, RK is an extension of MLR. It is a spatial soil mapping method that adds a regression of dependent variables on predictor quantities with kriging of the prediction residuals. RK prediction of $Y(\boldsymbol{s}_0)$, at site not visited $\boldsymbol{s}_0$, is presented thus:

$$Z^*(x_0) = \hat{m}(x_0) + \hat{e}(x_0) = \sum_{k=0}^{P} \hat{\beta}_k * q_k(x_0) + \sum_{i=1}^{n} \lambda_i * e(x_i) \quad (4)$$

where $\hat{m}(x_0)$ is the fitted deterministic part, $\hat{e}(x_0)$ is the interpolated residual, $\hat{\beta}_k$ are the estimated deterministic model coefficients, λ_i are the kriging weights determined by the spatial dependence structure of the residual and e(xi) is the residual at position xi.

Evaluation of Model Performance

Evaluation of the performance or achievement of any model gives valuable ideas into the prediction capacities of various machine learning models for soil characteristics (Barrena-Gonzalez *et al*., 2023). Each model was t improved with 70 % of the dataset which makes up 42 sampling spots) and the authentication or confirmation set which was evaluated using the remaining 30% of the dataset (18 sampling spots). In order to evaluate capabilities of models in mapping organic carbon, the cross-authentication or validation was run on different models. RF, Cubist, MLR, OK and CK were assessed with the aid of bias, coefficient of determination (R^2) and root mean square error (RMSE), mean square error (MSE) and Lin's concordance correlation coefficient (CCC) (see Eqns. 5,6,7,8 & 9)

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}(Z_{oi} - Z_{pi}) \quad (5)$$

$$R^2 = 1 - \frac{\sum_i^n (Z_{oi} - Z_{pi})^2}{\sum_i^n (Z_{oi} - \bar{Z}_{pi})^2} \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_{pi} - Z_{oi})^2} \quad (7)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Z_{pi} - Z_{oi})^2 \quad (8)$$

$$CCC = \frac{2r\sigma_o\sigma_p}{\sigma_o^2 + \sigma_p^2 + (\bar{Z}_p \_ \bar{Z}_o)} \quad (9)$$

where, Zpi= predicted values, Zoi= observed values, n =observations size for the i-th term observation, $\bar{Z}_i$ = average of the measured variable, σ_o^2 and σ_p^2 are the variances of the estimated and measured values; and r is the coefficient of correlation between the estimated and measured values. Nevertheless, best model estimation is meant to have low bias, MSE, RMSE, CCC and R^2 value close to 1.

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3. Results and discussion

Properties of The Studied Soil

The results of soil samples used for prediction are given in Table 1. The textural classes of the soil were sandy loam, loam and sandy clay loam indicating higher content of clay. Sand, silt and clay had means of 58.9 %, 26.6 % and 25.9 % respectively. Higher clay values have been reported to improve water and nutrient retention capacity of soils according to Barrena-Gonzalez et al. (2023). The particle size fractions of soil play vital function in determining the structure and infiltration rate of soil. The values of soil reaction(pH) in the area ranged from 5-6.6 with a mean value of 5.4 implying strongly acidic condition. This strong acidity may be responsible for higher content organic carbon in the soil since acidic condition enhances organic matter accumulation in soil. Organic carbon varied from 0.26 % to 4.47 % with a mean of 2.53 % in the soil. These values are very high following the critical limit of Landon (2014). Further result as presented in Table 1 show that TN varied from 0.01 % to 0.38 % with an average value of 0.27 % while available P varied from 2.0 mg/kg to 27 mg/kg averaging 4.3 mg/kg and was rated low following the rating of Landon (2014). The low total nitrogen and available phosphorous in the soil may be due to loss of these nutrients through surface runoff which is common in the area as a result of steep slope which is typical characteristic of mountainous terrain. The mean exchangeable cations; Ca (1.98 cmol/kg), Mg (0.78 cmol/kg), K (0.094 cmol/kg), Na (0.074 cmol/kg) and exchangeable acidity, H^{+} (0.58 cmol/kg) and Al^{3+} (0.39 cmol/kg) obtained in the mountainous soil were found to be all low.

Table 1. Summary Statistics for Spatial Soil Properties

	PH	OC	TN	Av.P	Ca	Mg	K	Na	Al	H	ECEC	BS	CEC	CLAY	SILT	SAND
		%	%	mg/kg				cmol/kg				%	cmol/kg	%	%	%
Minimum	5	0.26	0.01	2	0.8	0.2	0.07	0.05	0	0.08	2.3	68	15	6.8	16	49.2
Maximum	6.6	4.47	0.38	27	7.6	2.8	0.13	0.11	1.12	1.16	10.68	96	44	26.8	37	73.2
Arithmetic Mean	5.443	2.526	0.217	4.3	1.989	0.777	0.094	0.074	0.397	0.584	3.926	70.713	25.9	14.5	26.6	58.9
SD	0.438	0.96	0.083	3.309	1.302	0.593	0.011	0.012	0.313	0.165	1.635	14.374	6.701	3.567	5.353	6.471
CV (%)	8	38	38.1	77	65.5	76.3	11.8	16.1	78.9	28.3	41.6	20.3	25.9	24.6	20.1	11
Skewness	1.329	-0.155	-0.252	5.725	2.812	1.88	0.765	0.621	0.12	0.586	2.476	-1.196	0.66	0.623	0.101	0.492
Kurtosis	0.399	-0.441	-0.261	38.586	8.157	3.217	1.329	0.341	-1.004	2.429	6.638	5.328	-0.026	1.532	-0.703	-0.512

CV = Coefficient of Variation, SD = Standard Deviation, OC=organic carbon, TN= total nitrogen, Av.P=available P, BS=base saturation.

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The effective cation exchange capacity (ECEC) ranged from 2.3 cmol/kg to 10.68 cmol/kg with an average of 3.93 cmol/kg. ECEC of soil of the site was low following the rating of Landon (2014), while base saturation was high (> 68 %). The CEC obtained from the laboratory results ranged from 15 cmol/kg – 44 cmol/kg averaging 25.9 cmol/kg and was high following critical limit of Landon (2014). The results of physicochemical properties in this study are contrary to observation reported in a similar parent material by Afu *et al*. (2022)

Selected Covariate for Modelling

The results of RFE and Optimal number, VIF and relative importance of covariates are shown in Figure 3. In building of machine learning model, it is highly recommended to employ a feature selection process that aims to minimize the number of predictors and select the most relevant ones. As shown in Figure 3, the optimal number of covariates obtained via RFE was 8, reflecting the variables associated with the lowest RMSE. When the soil properties used for RFE analysis were further subjected to regression analysis, the result obtained showed the respective values of covariates with VIF < 10 (Table 2) to include clay (1.4), minimum temperature (6.19), pH (1.6), slope (1.43), aspect (1.44), NDVI (8.67), mean rainfall (6.76) and SAVI (7.04). RF, cubist and MLR were used to quantify the effect of predictors on the SOC (see Figures 4 to 6). Soil pH was ranked first, with a relative importance of about 100 % in all models used except MLR as variable for predicting soil organic carbon. The result showed that pH, SAVI, NDVI and rainfall were among the top 4 variables influencing SOC prediction in the mountainous areas. NDVI was also found to be the most essential factor that influenced variation of SOC in a study carried out by Falahatkar *et al.* (2016). In a related study Zhang *et al*. (2019) reported that time series properties of NDVI were conducive for predicting soil organic carbon.

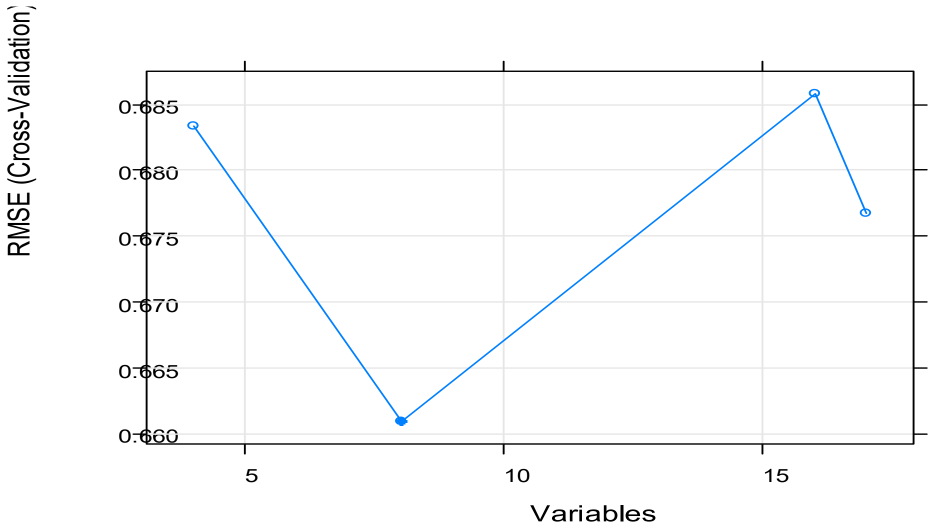

Figure 3. The RMSE values for different numbers of variables as determined by recursive feature elimination (RFE)

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Table 2. Result of Multiple Regression

Variables	Coefficients	Std. Error	t value	Pr(>|t|)	VIF
Constant	-80.26	49.58	-1.62	0.12	
Clay	-0.04	0.04	-0.98	0.33	1.41
Min temp	0.80	0.61	1.31	0.20	6.19
CNBL	0.03	0.04	0.71	0.48	41.67
pH	-1.08	0.41	-2.62	0.01	1.60
Slope	-0.01	0.01	-0.89	0.38	1.43
Elevation	0.0001	0.00	-0.58	0.56	43.24
Aspect	0.0001	0.00	0.11	0.91	1.44
NDVI	7.99	3.44	2.32	0.03	8.67
SAVI	-9.15	7.49	-1.22	0.23	7.04
NDMI	-5.95	5.64	-1.06	0.30	12.78
Mean rainfall	0.03	0.03	0.83	0.42	6.76
R^2	0.48				
Adjusted R^2	0.29				
F(11,30)	2.15, p = 0.02				

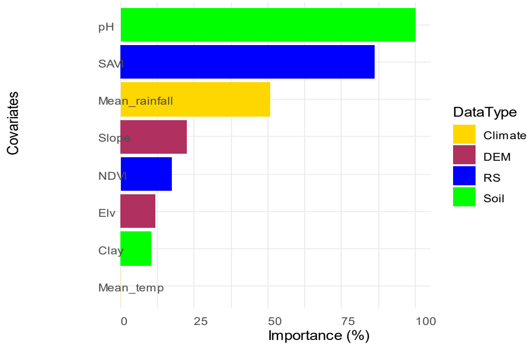

Figure 4. Effect of variables in predicting OC via RF

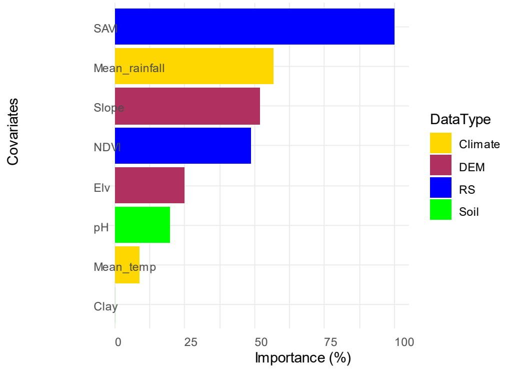

Figure 5. Effect of variables in predicting OC via cubist regression

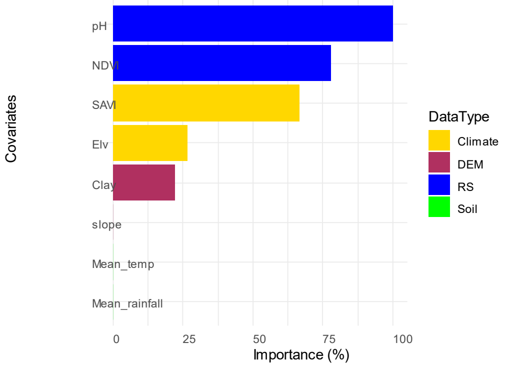

Figure 6. Effect of variables in predicting OC via MLR

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Spatial Dependency of Measured Soil Organic Carbon and Particle Size

The results presented in Table 3 show the parameters of measured OC model through semi variogram (Figure 7). Soil OC was best modelled by spherical model. In a similar study, John *et al.* (2019) concluded that pH and SOC are perfectly modelled with spherical models. The SOC had a Nugget/Sill ratio of 18.92. The SOC model estimated through OK had strong degree of spatial dependence (Nugget/Sill ratio < 25 %) as shown in Table 3. A lower Nugget/Sill ratio for SOC suggests that parameters such as elements of weather, parent material of soil, terrain, soil characteristics and other natural influences are the determinants of spatial variation of SOC in the study site. As presented in Table 3, the range value of 1669.74 m was obtained for SOC. Therefore, in distance wider than this obtained range of values in present research spatial reliance is found to be nonexistent for SOC.

The geostatistical analysis results (Table 4) for OK and CK show that semivariograms of sand and clay were fitted well by Gaussian model while that of silt was fitted by spherical model. The cross-semivariogram of particle fraction or soil separates were seen to be all suited well by a Gaussian model. The nugget/sill ratios of OK semi variogram of sand, silt and clay were 0.098 %, 0.17 % and 1.92 % while the nugget/sill ratios of the CK cross-semi variogram of sand, silt and clay were 56.25 %, 54.23 % and 55.24 % correspondingly. The range of values of the semivariogram of OK were 65, 100 and 80 m for sand, silt and clay accordingly while that of CK were all 65m for the three soil fractions. The described properties are well shown or observed using the semivariogram plots of the soil particle size fraction as presented in Figure 8 below.

Table 3. Semi Variogram Parameters of Measure SOC

Variable	Model	Nugget (C_0)	Partial Sill(C_1)	Sill (C_0+C_1)	Range (m)	Nugget/Sill	Spatial class
OC (%)	Spherical	0.211	0.904	1.115	1669.74	18.92	Strong

Table 4. Semivariogram Parameters of Particle Size Fractions

	Model	Nugget (C_0)	Partial Sill (C_1)	Sill (C_0+C_1)	Range (m)	Nugget /Sill (%)	Spatial Class
Semivariograms							
Sand	Gaussian	0.056	56.49	57.05	65	0.098	Strong
Silt	Spherical	0.050	28.43	28.48	100	0.17	Strong
Clay	Gaussian	0.25	12.77	13.02	80.97	1.92	Strong
Cross-semivariograms							
Sand	Gaussian	235.70	183.29	418.99	65	56.25	Moderate
Silt	Gaussian	217.23	183.29	400.52	65	54.23	Moderate
Clay	Gaussian	-224.04	181.47	-405.51	65	55.24	Moderate

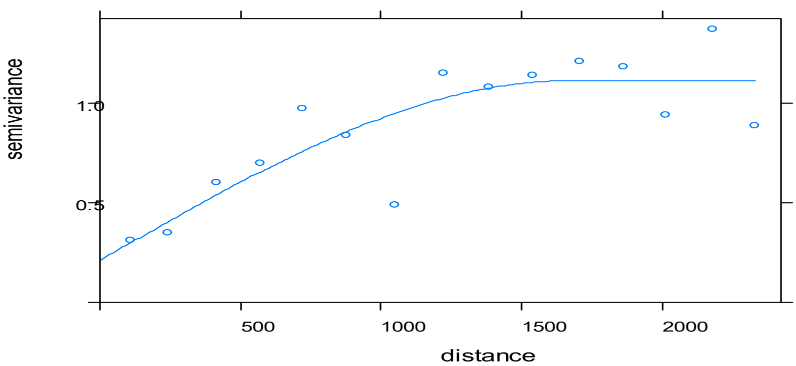

Figure 7. Semi variogram model for measured soil OC

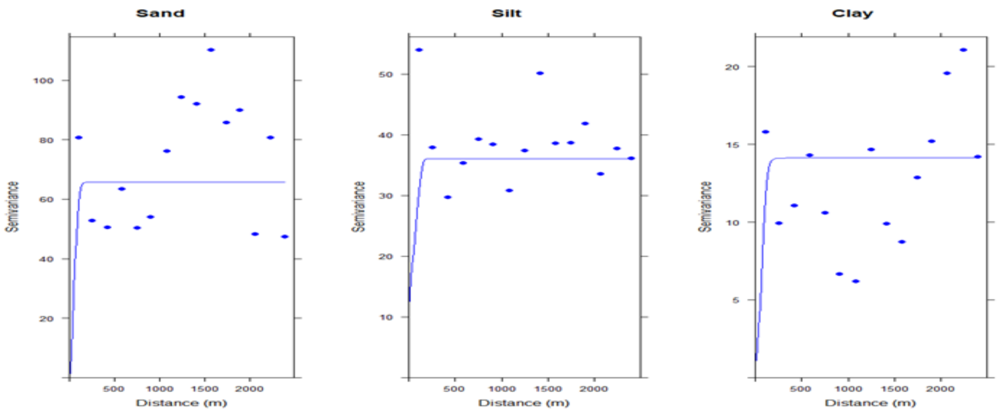

Figure 8. Semivariograms of soil sand, silt and clay content

Mapping of SOC and Particle Size Fractions

The spatial maps of soil OC estimated by RF, cubist, RK, OK and MLR are in Figure 9 and their statistics are shown in Table 5. The mean prediction of OC for the entire study area were 2.25% (Cubist), 2.32% (RF), 2.24%(RK), 2.52% (OK) and 2.40% (MLR). The predictions from all models reported in this study were contained within the observed or laboratory determined OC range, except that obtained from MLR model. This discovery corroborates the finding of Silva *et al*., (2017) who obtained better modelling and validation results for soil properties with RF than MLR. The highest determined OC in the study area was 4.47 and the maximum estimated using RF, OK, RK, Cubist and MLR were 3.78 %, 2.92%, 4.93%, 4.89%, and 6.37%, respectively (see Table 5) which were dominant in the Southwestern side of the research location in all the models investigated. The least laboratory determined OC was 0.26 and the least estimated OC by RF, OK, RK, Cubist and MLR were 1.41%, 1.13%, 0.67%, 0.70% and 0.27 respectively (see Table 5) which were dominant in the Northeastern side of the research location across all the models investigated. These results corroborate the results of research carried out by John *et al.* (2020) and Falahatkar *et al.* (2016), and are further confirmed by report of Mosleh *et al.* (2016) who had carried out related research in Iran. Also, Solly *et al.* (2020) reported results in Switzerland on how SOC can be built up using CEC including other factors in line which is line with this current study.

The spatial variability of soil separates or particle size fraction predicted by OK and CK are illustrated in Figure 10 and Table 6. The mean predicted sand content for both OK and CK were nearly the same and only slightly lower (about 0.49 %) than the laboratory determined sand content. Similarly, the mean predicted silt content for both OK and CK were 26.65 % and 26.64 % respectively which were nearly the same, and only slightly higher (about 0.04 %) than the laboratory determined silt content. Further result showed that the mean predicted clay content for both OK and CK were 14.42 % and 14.96 % respectively which were nearly the same with the clay content (14.5 %) obtained from the laboratory. However, from the results it was also observed that OK model under estimated low sand contents and over-estimated low values of silt and clay whereas, CK model under-estimated low clay values and over-estimated low sand and silt contents. For higher particle size fractions in the study area, CK model under-estimated sand and silt contents and overestimated clay. In both OK and CK predicted map (Fig. 10), sand contents greater than 55 % were found to be dominant in the studied soil. However, for silt predicted maps, it was observed that silt contents greater than 25 % predominated the study area with CK modelled silt map while with OK modelled map, silt content between 22-27% dominated the study area. Meanwhile in clay predicted map, both OK and CK modelled maps, clay contents that were between 14 -20 % were prevalent in the study area. Similar observation was made by John *et al.* (2020) in their study in southern part of Nigeria where they observed that high predicted SOC values occurred in centre, northeastern, easter and northwestern parts of the study.

Table 5. Descriptive Statistics of Predicted Soil OC in this Study

	Min (%)	Max (%)	Mean (%)
Laboratory determined OC	**0.26**	**4.47**	**2.53**
RF predicted OC	1.41	3.78	2.32
OK predicted OC	1.13	2.92	2.52
RK predicted OC	0.67	4.93	2.24
Cubist predicted OC	0.70	4.89	2.25
MLR predicted OC	0.27	6.37	2.40

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Table 6: Descriptive Statistics of Predicted Soil Particle Fractions in this Study

	Min (%)	Max (%)	Mean (%)
Laboratory determined sand	**49.2**	**73.2**	**58.90**
OK	32.34	72.80	58.41
CK	48.23	63.01	58.40
Laboratory determined silt	**16.0**	**37.0**	**26.60**
OK	17.01	35.77	26.65
CK	18.47	30.35	26.64
Laboratory determined clay	**6.8**	**26.8**	**14.50**
OK	8.22	23.34	14.42
CK	6.64	33.30	14.96

OK = ordinary kriging predicted, CK = Cokriging predicted

Evaluation of The Competence Of Machine Learning Algorithms in Mapping SOC

The average values MSE, RMSE, R^2 and CCC for SOC estimation depict that the models had variations in their capabilities to map or predict SOC at sites not sampled in the research site (Table 7). This is assumed to be as a result of variations in the mathematical program of each machine model and the differences in covariates that were used in fitting. Values of SOC estimated using RF, OK, RK, cubist and MLR were also subjected to comparison and disparities discovered among the models. It was discovered that MLR had the highest R^2 (0.324) indicating very high precision while regression kriging (RK) had the least R^2 of 0.059 and CCC of 0.202. The results further showed that MLR had the largest CCC (0.537) signifying good concordance with the 45^o line, as well as the lowest root mean square error (RMSE = 0.764) and mean square error (MSE = 0.585) signifying high accuracy, compared to other models which indicated extreme cases of over- or underestimation (see Figures 11 to 15). In a related study Farooq *et al*. (2022) found that SOC was best estimated by RF (RMSE 8.21 and R^2 0.9) than OK (RMSE 15.60 and R^2 0.53) and RK (RMSE 17.73 and R^2 0.29)

The MLR model predicted OC was better than other models as seen in the regression lines of observed verses forecasted which are nearer to the 1:1 line compared with what is obtainable by other models under consideration.

Table 7. Performance of Machine Learning Algorithms in Estimating SOC

	R^2	CCC	MSE	RMSE	Bias
RF	0.167	0.319	0.596	0.771	**-0.082**
MLR	**0.324**	**0.537**	**0.585**	**0.764**	-0.031
Cubist	0.085	0.233	0.783	0.885	-0.266
RK	0.059	0.202	0.855	0.925	-0.261
OK	0.202	0.401	0.610	0.781	-0.068

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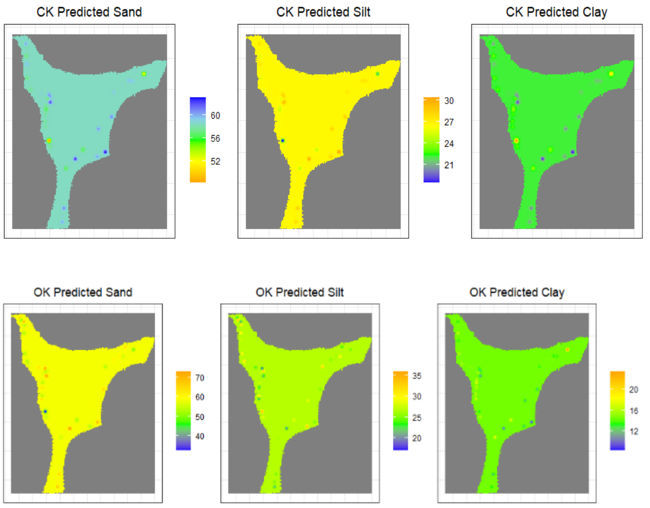

Figure 10. Spatial distribution of particle size fraction using OK & CK

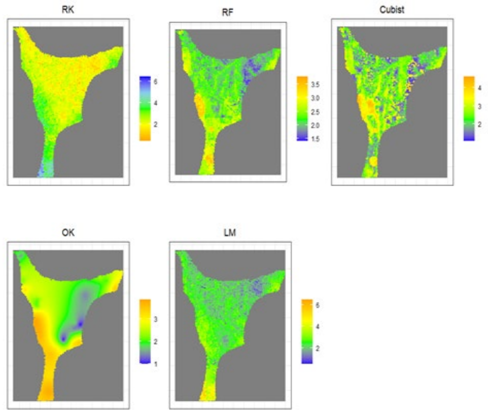

Figure 9. Spatial distribution of SOC using RF, Cubist, MLR, RK & OK

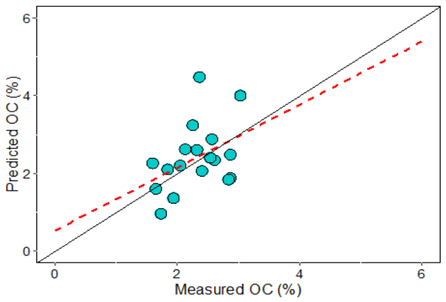

Figure 11. Measured and estimated values of SOC using RF

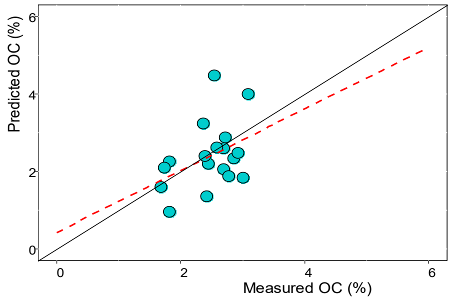

Figure 12. Measured and estimated values of SOC using MLR

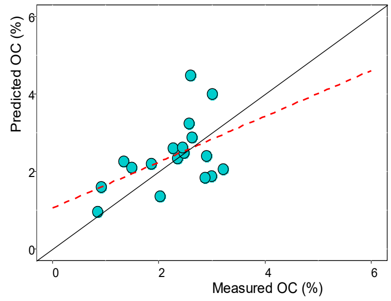

Figure 13. Measured and estimated values of SOC using cubist regression model

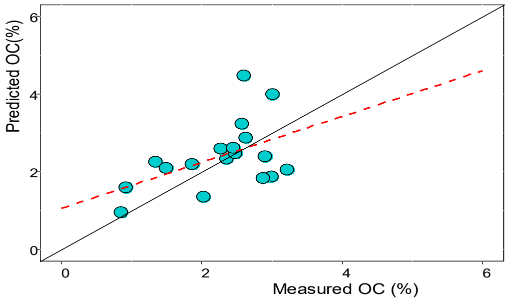

Figure 14. Measured and estimated values of SOC using RK

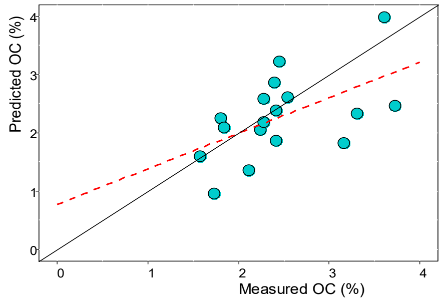

Figure 15. Measured and estimated values of SOC using OK

Evaluation of the Competence of OK And CK Models in Mapping Particle Size Fractions

The cross-validation results of OK and CK are in Table 8. Prediction values of particle size fractions using OK and CK were compared and it was realized that the models have different competence or performing characteristics. Particularly for sand prediction, CK model performed better than OK as shown by lower RMSE (7.434) and MSE (5.568), while for silt and clay contents, OK model performed better than CK model with lower MSE and bias values. Contrary to this study, Barrena-Gonzalez *et al*. (2023) stated that sand content presented more difficulty for prediction in all models- cubist and random forest and stated that the challenges of predicting sand may be determined by rather difficult pattern more than spatial patterns.

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Table 8. Performance of OK and CK in Estimating Soil Particle Size Fractions

PSF	Model	MSE	RMSE	Bias
Sand	OK	5.702	7.609	**0.071**
	CK	**5.568**	**7.434**	0.082
Silt	OK	**4.229**	5.297	**0.064**
	CK	4.262	**5.278**	0.083
Clay	OK	**2.680**	**3.490**	0.015
	CK	2.967	3.726	**-0.880**

OK = ordinary kriging predicted, CK = Cokriging predicted; PSF= particle size fraction

Summary and Recommendation

This research was conducted to assess the effects soil of environmental elements on spatial distribution of SOC and soil particle size fractions in mountainous area of Obudu cattle ranch using machine learning models. The soil had sandy loam, loam and sandy clay loam texture with acidic pH. Available P, exchangeable cations and exchangeable acidity as and ECEC were high while CEC and base saturation were high. The SOC estimated through OK had strong degree of spatial dependence. The maximum predicted SOC was dominant in the southwestern side of the research site in all the models investigated while minimum predicted SOC was within the northeastern side of the research site in all the models investigated. The MLR model better predicted SOC than other models since it had the highest R^2 (0.324) and CCC (0.537) as well as the lowest RMSE (0.764) and MSE (0.585) signifying high accuracy compared to other models. The mean predicted sand content for both OK and CK were nearly the same, silt was slightly lower than the laboratory determined values while predicted clay were nearly the same with the laboratory determined clay content. In sand prediction, CK model performed better than OK while for silt and clay contents, OK model performed better than CK model. Therefore, the study validates that MLR, CK and OK can be used for assessment of spatial change in SOC and soil particle size fractions in mountainous areas and could also be employed by policy makers and planners as decision support tools for sustainable soil and environmental management and precision agriculture.

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