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Original Research

Predicting Environmental Covariates of Soil Organic Matter at Sub-Regional Scale for Sustainable Agricultural Development in Southeast Nigeria

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Abstract

Soil organic matter is an important indicator of soil health. It is a constituent of the ecological system that is vital to agricultural development and understanding of the global carbon cycle. The study used random forest regression, a machine learning algorithm, to identify relevant predictors of soil organic matter through the integration of field and Sentinel-2 derived vegetation indices and a selected reanalysis of climate data with topography. Three landcover types were purposefully delineated, and 72 soil samples were collected at a soil depth of 20 cm across the entire Cross River State, Nigeria. The samples were labeled and taken to the laboratory, where standard procedures were used in extracting the SOM. 80% of the point data sets were used in model calibration, while 20% were used to validate the model. Model analysis revealed that environmental covariates of SOM (topography, rainfall, maximum air temperature, OSAVI, EVI, and NDVI) produced high prediction accuracy with lower uncertainty. The maximum plot SOM was estimated to be 7.20% with overall mean values of 2.61. The test data sets yielded a model accuracy of 0.85, an RMSE of 36.7, a relRMSE of 34.3%, and a bias of 3.7 t/ha. Based on this, the paper argues that the identified environmental covariates can be optimized for the effective management of SOM for sustained agricultural development. This is pertinent in areas with highly weathered soils characterized by low nutrients and poor crop yields. The SOM map of this study can be used as a baseline for subsequent monitoring and management of SOM in the study area.

Keywords: agricultural development, environmental covariates, Cross River State, SOM, random forest

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Introduction

Soil organic matter is an important indicator of soil health. Although it constitutes only a small portion of the soil body, its relevance in the soil ecosystem and global carbon cycle cannot be ignored [1]. SOM is made up of plant and animal residues at different stages of decomposition [2]. Humus, a properly decomposed, dark-colored organic material in soils, is the most vital component of the soil complex. In addition to being an indicator of soil fertility, it plays a significant role in the physical, chemical, and biological state of the soil complex. Physically, SOM enhances water infiltration capacity, thereby promoting percolation and retention. In its chemical role, SOM boosts the cation exchange capacity of soils (i.e., the ability to attract and retain soil nutrients) and provides nutrients to the soil complex, while its biological role includes the stimulation of microbial activities in soils as well as improving soil organism diversity [3]. However, SOM content, variability, and rate of decomposition in any location and time are mediated by several factors across regions.

In the tropics, where soils are highly weathered and characterized by kaolinitic content and low cation exchange capacity, the content and spatial distribution of SOM are controlled by soil type, topography, land use, and the prevailing climate, among others [2]. It is imperative to note that SOM in the tropics decays faster compared to other regions of the world [4]. Tropical SOM degradation is attributable to increased soil erosion, loss of litter influx after vegetal canopy destruction, and enhanced decomposition and nutrient mineralization rates after deforestation [1]. The destruction of SOM has significant environmental consequences, hence the need to maintain a steady state, i.e., the rate of its destruction should be equal to the rate of its addition to the soil complex, which in turn will boost agricultural production [2].

Significantly, to achieve agricultural development and meet the global goal of keeping the air temperature below 2ºC, the retention and sequestration of SOM are very pertinent. More so, soil structure stability, agricultural productivity, and carbon sequestration depend on the status of the SOM of the region [5]. As a storehouse of soil nutrients, its role as a 'revolving nutrient fund' must be sustained through litter inputs. This is pertinent to agricultural development in tropical regions where the livelihoods of the majority of the population are nature-dependent [6]. In Africa, it is estimated that more than 50 percent of the population's income comes from agriculture [7]. And recent statistics for the region in this sector are anything but gloomy. Estimates indicate that about 60% of the population of Africa experiences food insecurity [ibid], which is exacerbated by extreme weather events [8]. It is in respect of this that soil organic matter information becomes pertinent, especially for precision agricultural development.

Because of this, the goal of this study is to determine the spatial distribution of soil organic matter over the Cross River State (CRS) region as a prelude to precision agricultural development. Specifically, the study aimed to achieve the following: 1). To ascertain the environmental covariates constraining the spatial distribution of soil organic matter in the Cross River State region and 2) to determine the role of soil organic mapping in precision agricultural development in the study area.

Materials and Methods

Study Area

The study was carried out in the CRS of southeastern Nigeria. It has a total land area of 20,156 km^2. And is made of varying terrain characteristics, with mountain ranges peaking at 1800 m (5, 936 ft.) in the extreme north and 103 m above sea level in the southern part of the state [9]. The CRS is located at latitude 4^{0} 34^{I} 59.99^{11} N and longitude 8^{0} 24^{I} 59.99^{11} E. It is bordered by Benue State in the north, Akwa Ibom, Ebonyi, and Abia states to the west, and the Atlantic Ocean to the south. The study area contains various land cover types, including mangroves, swamps,and tropical rainforests, which are common in the southern and central parts of the region, and montane vegetation and savanna woodlands, which are prevalent in the northern portion of the study area [9].

Rainfall in Cross River State has two seasons with varying durations in the three agroecological zones: the northern (NAZ), southern (SAZ), and central agroecological zones (CAZ). In the SAZ, the monsoon tropical climate is common, with a mean rainfall of 3500 mm, which sometimes reaches 4000 mm around the Oban Massif [8]. The climate features of this area match the Tropical Monsoon (Am) classification scheme of Koppen [10]. The average yearly air temperature of the zone is 27ºC with little fluctuations throughout the year, and humidity is between 78% and 91% [11]. The mean annual rainfall in the CAZ varies from 2300 mm to 3000 mm, with the mean annual air temperature ranging from 26.9ºC to 30ºC, and the humidity in most parts of the year is about 68% [8]. In the NAZ, the savanna ecosystem is prevalent, with a mean annual rainfall of 1120 mm and an air temperature range of 15 to 30ºC [12]. Two climate seasons are observed in the NAZ: the rainy season lasts for about eight months and the harmattan lasts for about four months, though these vary yearly. In the montane ecoregion of the Obanliku Mountains within the NAZ, climatic conditions are markedly different from other parts of the region. Air temperature has a mean annual range of 4ºC to 10ºC. The terrain is rugged, with hilly escarpments, steep valleys, and mountains that peaked at about 1800 sq. km. above sea level, with an elongation into the southwest region of Cameroons [13].

Field and Laboratory Procedures

A land cover map (Fig. 1) developed by the Cross River State Forestry Commission [14] was used in establishing the plots for soil sample collection. Based on the CRSFC map, the study area was classified into the categories of Undisturbed Forest (UF), Disturbed Forest (DF), and croplands, following Gautam and Mandal's [15] delineation. Overall, 29, 18, and 25 samples were purposely distributed across the CRS in undisturbed, disturbed, and cropland areas, respectively. The locations of each plot in the field were determined using the Garmin etrex GPS [16]. Access to each of the plots was made possible through park rangers or the local community [17]. Alternative plots were laid when it became impossible to access the predetermined plot, a similar practice by REDD+ [18].

Soil samples were collected within each 20 m plot. A soil screw auger 30 cm long and 3.5 cm in diameter was used to collect composite soil samples along the diagonal of each plot. The spacing of soil samples was 6.7, 6.7, and 6.6 meters along the diagonal of each plot, with a total of 3 soil samples collected within each plot. Each sample was then labeled, parcelled, and transported safely to the laboratory for analysis of organic carbon using the modified Walkley and Black wet oxidation methods [19]. The organic matter in the soil samples was then obtained using the formula % organic matter in soil = % organic carbon x 1.729.

Predicting Environmental Covariates of Soil Organic Carbon

Sentinel 2 (S2) is a wide-swath, high-resolution, multispectral imager made up of Sentinel-2A and Sentinel-2B. Sentinel-2A was launched in June 2015, and Sentinel-2B was launched in 2017. Sentinel-2 is made up of 13 spectral bands located from the visible to the shortwave infrared with spatial resolutions of 10 m (red, green, blue, NIR), 20 m (red edge and shortwave infrared bands), and 60 m (atmospheric bands). Top-of-atmosphere (TOA) reflectance was converted to top-of-canopy (TOC) reflectance [20]. The images were sub-set and mosaicked to produce a single image for the study area [21]. The images used in the study were downloaded in November 2022, where cloud cover did not have a significant influence on the image quality.

A range of environmental covariates were used in the modeling protocol. These included the Optimized Soil Adjusted Vegetation Index (OSAVI) from Baret et al. [22], the Modified Soil Adjusted Vegetation Index (MSAVI) from Qi et al. [23], the Atmospherically Resistance Vegetation Index (ARVI) [24], the Modified Red Edge Normalized Difference Vegetation Index (MRENDVI) based [25], the Red Edge Normalized Difference Vegetation Index (RENDVI) from Giytelson and Merzhynak [26], the modified red edge simple ratio [27], as well as the Normalized Difference Vegetation Index (NDVI) and Enhance Vegetation Index (EVI2).

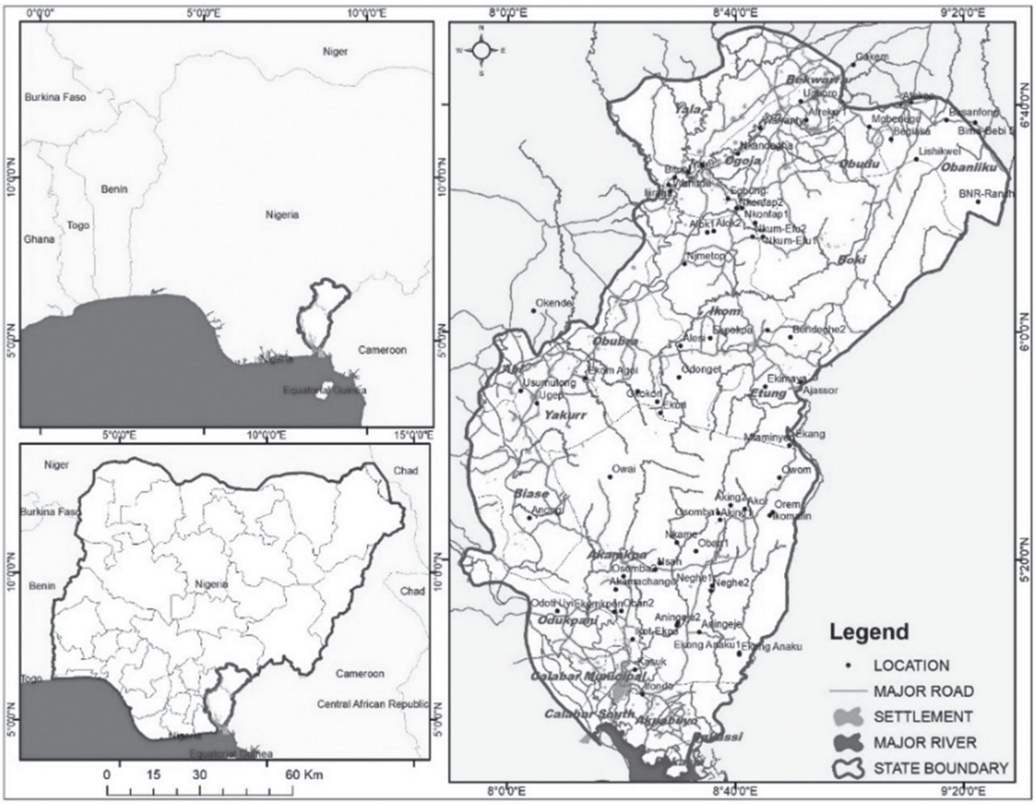

Fig. 1. Map of Cross River State with an insert location in West Africa and Nigeria with sample plots overlaid (black dots). Source: Culled from the Cross River State Forestry Commission (2019) [14].

In addition, topography also has an important influence on soil organic carbon [28], hence the 30 m Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) was used in the study [21].

In addition, the ERA5 and CHIRPS gridded rainfall and air temperature time-series data for the last 35 years per pixel were used to assess climate variability over the study area. All images used in this study were resampled to 20 m resolution using the nearest neighborhood method. This resampling method was used because it is known to be computationally efficient and often maintains the image pixel values [29]. The resampling was required to ensure the plot size matched with the pixel size at the point of SOM extraction.

Random Forest (RF) a Machine-Learning Algorithm

RF is used in this study to spatially extrapolate the plot-level estimates of SOM to the whole of the CRS. It is a nonparametric multivariate algorithm developed as an extension of the decision trees to improve prediction accuracy and reduce overfitting [30]. As a supervised machine learning algorithm, it uses several decision trees on subsets of predictor datasets [31]. It is characterized by a tree-like sequence of decision nodes that splits into different branches continuously until it reaches the tree leaf. At this point, the algorithm has reached the prediction of a decision [30]. Some of the advantages of RF over traditional statistical models include its ability to handle many explanatory variables at a time, it can manipulate very complex interwoven sets of variables, it is not affected by highly covariate variables; hence it does not require data transformation, and most importantly, it reduces overfitting with the right number of subsets of data [32].

The optimal features for a robust model can be reached through the process of feature selection. Random Forest has an in-built mechanism that checks for important variables in the model [33]. Feature selection provides an opportunity for the less relevant features to be removed, thereby enhancing the model performance and generalizing the result [34]. In this study, the recursive feature selection method was used [35] in selecting the relevant environmental variables for SOM prediction.

Accuracy Assessment

Three indices coefficient of determination (R^2), root mean square error (RMSE), and relative mean square error (relrmse) were used to measure the accuracy of the predicted SOM content map [24]. All the indices mentioned are computed based on the differences between the predicted and observed SOM content values at the validation soil sample locations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{1}$$

$$relRMSE\% = 100 \,.\left(\frac{RMSE}{\hat{Y}}\right) \tag{2}$$

Where y_i is the predicted value series, $\hat{y}_i$ is the observed value series, n is the sample size, and $\bar{Y}$ is the average value of the observed series.

Results

Descriptive Analysis of Plot-Derived Soil Organic Matter in the Cross River Region

Table 1 is the summary analysis of the soil organic matter data obtained in the field across three land cover types: undisturbed, disturbed, and crop fields in the CRS ecological region. From the table, the minimum and maximum values of SOM in undisturbed landcover are 1.80 and 7.20, respectively, while in disturbed and cropland land cover, the maximum and minimum values are 2.10 and 5, and 1.20 and 3.80, respectively. More so, the mean values of SOM in the three land cover types are 3.49, 3.16, and 2.11, respectively with standard deviations of 1.43, 0.82, and 0.60 for undisturbed, disturbed, and crop land cover, respectively. The table also indicates that the coefficient of variation for the three land cover types is 40.97%, 25.94%, and 28.43% for undisturbed, disturbed, and cropland land cover types, respectively.

Table 1. Descriptive statistics of plot soil organic matter collected across the delineated land cover types in Cross River State, Nigeria.

Land cover types	N0.	Minimum	Maximum	Mean	Std. deviation	Variance	CV (%)
Undisturbed LCT	29	1.80	7.20	3.49	1.43	2.06	40.97
Disturbed LCT	18	2.10	5.00	3.16	0.82	0.67	25.94
Cropland LCT	25	1.20	3.80	2.11	0.60	0.36	28.43

Environmental Covariates Constrain the Spatial Distribution of Soil Organic Matter in the Study Area

The spatial distribution of soil organic matter and any other geographic phenomena in space and time is fundamental to environmental studies. When we know where, how, and why, we can effectively provide the required policies for its utilization and/or management. Given this, Fig. 2 shows the ranking of important features in the prediction of soil organic matter in the CRS of Nigeria, considering topography, climate, and vegetation indices. Using the mean increasing node purity, the figure indicates that OSAVI was the most important variable in predicting SOM with the highest node purity. The other five variables used in predicting SOM are taken to be the Otimizsed Soil Vegetation Index (OSAVI), mean annual maximum air temperature, Enhanced Vegetation Index (EVI), rainfall, topography, and the Normalized Difference Vegetation Index (NDVI).

More so, Fig. 3 is the scatterplot derived from important features from the test model. From the figure, we can observe that the model accuracy is 85%

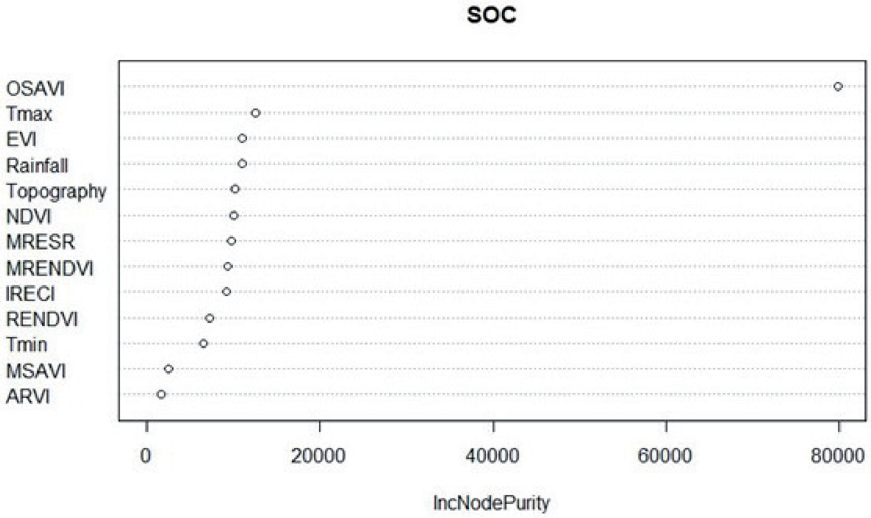

Fig. 2. All environmental covariates (topography, climate, and vegetation index variables) used to predict SOM using Random Forest, ranked from highest to lowest node purity. The model configuration uses all these 13 covariates to predict SOM.

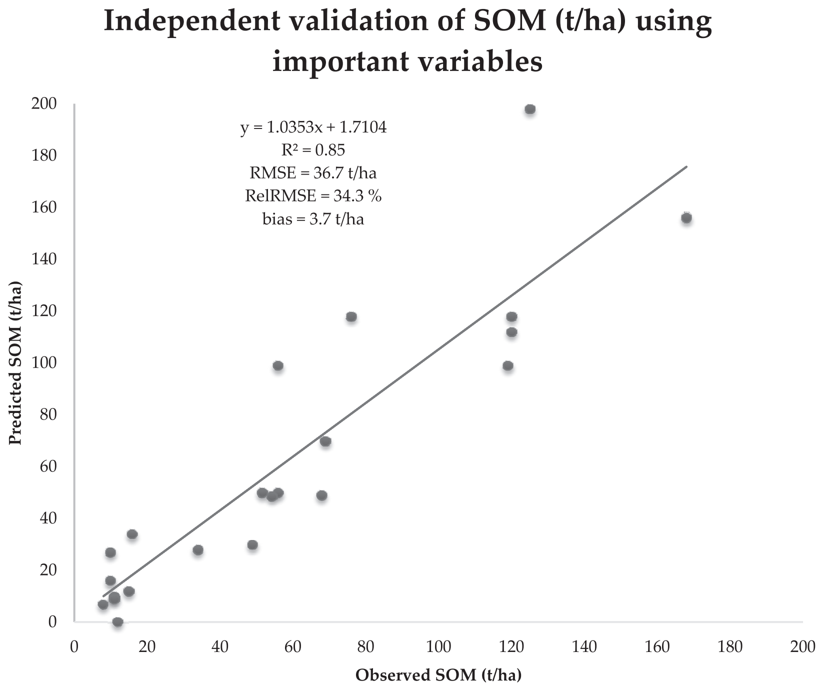

Fig. 3. Evaluation of the Random Forest predicted SOM over the 22 testing forest inventory plots using important variables.

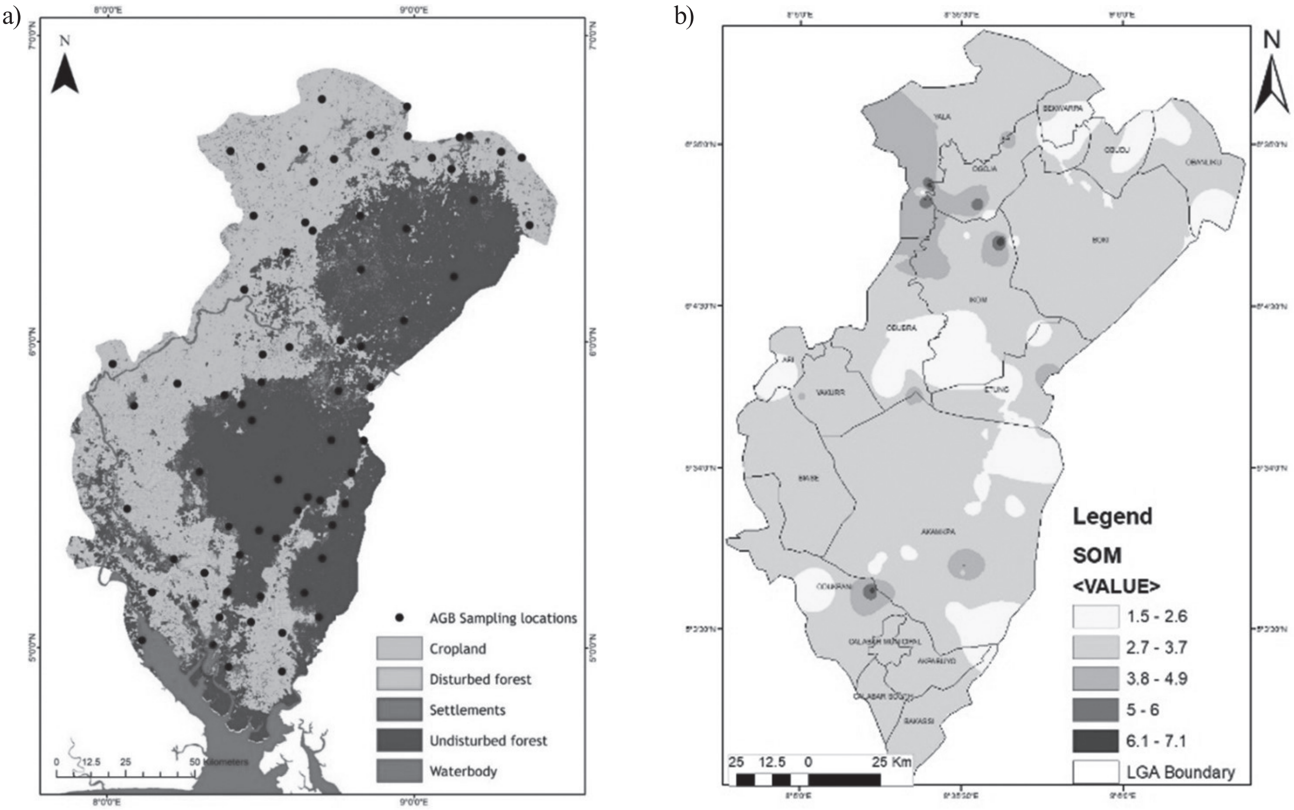

Fig. 4. a,b) Sample points (black dots) across land cover types and the spatial distribution of SOM as derived from the top five important variables (Fig. 2) in Cross River State, Nigeria, at 20 m spatial resolution.

with an RMSE of 36.7 t/ha and an uncertainty of 34%. This implies that 85% of the predicted soil organic matter did not occur by chance. The spatial distribution of the predicted SOM over the CRS is presented in Fig. 4. From the figure, higher values of SOM are recorded in the extreme Northwest ecological zone, while other parts of the study area have high values sparingly dotted across the landscape. Lower values of SOM occur more in the central agroecological zone and the far north and northeast enclaves. The areas with seemingly high SOM distribution coincide with areas of dense forest cover.

Discussion

Nigeria, like any other tropical country, is beseeched by a plethora of socio-environmental challenges, including an increasing population without the attendant capacity to meet the food demand, high incidences of climate change-linked problems like recurrent floods, land scarification, farmer/Fulani conflicts, and low crop yields, among others. Mapping the distribution of soil organic matter provides a potential opportunity to efficiently use the soil for agricultural development as well as other soil-derived ecosystem services [36, 37]. With regards to land use change, Global Forest Watch [38] statistics indicate that in the last 20 years, Cross River State lost 30% of its humid tropical forest, which is equivalent to 67.4 metric tons of CO^{2}e emisions. The huge disappearance of tree cover in the area is driven by agricultural expansion and illegal logging activities [39], and these invariably translate to soil organic matter lost; hence, the geospatial assessment of SOM contents and distribution becomes a viable option for land cover restoration.

In addition, the assessment of soil organic matter content will help boost agricultural production in the region and subsequently aid in gathering the required data geared towards meeting the monitoring, reporting, and verification goals of the UNREDD project. This is particularly pertinent given that topsoil has the largest carbon sequestration potential in the tropics [40]. Because of this, it is appropriate that we understand factors that are relevant in predicting the spatial distribution of SOM as a prelude to agricultural development and mitigating the effects of increased warming in Nigeria, especially in Cross River State.

Factors of soil formation such as climate, time, parent materials, organisms, and terrain are not static but can be fairly uniform over space; however, variability in soil characteristics is mediated by the inherent forming factors [41, 42]. The conditions of these intrinsic and extrinsic factors are key to SOM stability. In the tropics, where soils are inherently poor in nutrients, highly weathered, and vulnerable to climate change, understanding the distribution patterns of these factors is pertinent to the effective management of SOM [43]. The need to generate this soil information is further heightened with the aim of meeting the Paris Agreement goal of keeping air temperatures below pre-industrial levels [44]. The cost of field data collection on a large scale and subsequent laboratory analysis of soil physiochemical parameters is prohibitive, especially for African researchers who remain underfunded. Therefore, reliance on digital mapping through the integration of factors of soil formation with multispectral derived indices in predicting soil nutrients with sophisticated nonlinear statistical tools (like a random forest machine learning algorithm) can boost model accuracy [45, 46]. However, when the model performance is low, Lieb et al. [47] attribute it to one or more of the following reasons: (a). poor relation to the environmental predictor variables, (b). extreme local variation due to unknown or random effects, (c). the collection of data spans a very small interval in the total range of the response variable. In general, model accuracy can be improved by removing redundant variables. The removal of less important variables from the model helps with computational efficiency, improves model accuracy with the right combination of variables, makes overfitting minimal, and makes data interpretation less tasking [33, 48].

Predicting Environmental Covariates of SOM in Tropical Cross River State

Digital mapping of spatial soil attributes can now be carried out effectively with the availability of environmental covariates at the fine spatial resolution, given that direct measurements are limited in scope, labor-intensive, and expensive to execute [49, 50]. This technique involves the prediction of soil quality as a function of a suite of environmental covariates, which include soil properties, topographic features, land use types, and proxies of vegetation covariates [51]. In fact, image-based soil mapping has shown strong potential unlike its traditional counterpart [52]. On the strength of this, estimating the spatial distribution and soil fertility status of soils using satellite derived vegetation indices as proxies of soil condition, especially in the tropics, where soils are known to be highly weathered, is pertinent to agronomic and environmental management [52]. Leveraging these technologies and tools, we ordered the essential variables based on their relevance in predicting SOM in the region using Random Forest, a machine-learning algorithm (Fig. 2). Guided by the fact that predictor-response relationships are significantly mediated by landscape and coverage [43], 72 point data were collected, and 80 percent of this data was used for model calibration while the remaining 20% was used in model testing.

Model analysis revealed that OSAVI, mean annual air temperature, rainfall, topography, and NDVI were the topmost important environmental covariates in predicting SOM in the study area, with a model accuracy of 85%, an RMSE of 36.7 t/ha, a relRMSE of 34.3%, and a bias of 3.7 t/ha. This analysis is in consonance with a recent study by Chala and Ray [53], where all four tested machine learning algorithms consistently produced high model accuracy. Similarly, extant studies [43, 48] also confirmed that these variables (temperature, rainfall, topography, and NDVI) are relevant in predicting soil properties such as SOM. However, the estimation of soil properties based on spectral signatures is not without some challenges. Hengl et al. [43] advised that because of the potential intrusion of photosynthetic and non-photosynthetic vegetation cover and the difference in soil moisture or surface roughness in signal quality when estimating soil properties, there is a need to integrate spectral-based signatures with the soil forming factors in model training. On account of this, Hengl et al. [43] used Sentinel-2 sensor-derived vegetation indices combined with parent materials, landform parameters, and climatic variables to predict selected soil properties with SOM prediction, resulting in the goodness of fit of the model. More so, Hu et al. [54], using spectral-derived vegetation indices (VIs) and soil forming factors, identified topographic elements such as elevation, aspects, slope, and plane curvature, and cross-sectional curvature and topographic health index as predictors of SOM in a subtropical region.

In modeling predictors of soil organic carbon, Sreenivas et al. [55] identified NDVI and land cover types as the leading predictors of soil organic carbon. In another study, Ramiferiarivo et al. [56] identified elevation, precipitation, temperature, and vegetation as leading predictors of soil organic matter in Madagascar, while Were et al. [57] found that elevation, along with other data such as silt content and satellite band data, were the main predictors of soil organic matter in tropical regions. Similarly, Wang et al. [45] reported that organic matter in the tropics increases with precipitation, elevation, and lower temperatures. Wang's findings are in line with the result of this study, as climate variables, elevation, and vegetation data were identified as having significant control over the spatial distribution of soil organic matter in Cross River State, Nigeria. Taminru et al. [58] recently compared the capacity of random forest and ordinary kriging in predicting soil properties in the tropical forests of Ethiopia. The result revealed that random forest recorded higher prediction accuracy and a lower error margin, with the digital elevation model and NDVI being the most important variables in the prediction and understanding of the spatial distribution of soil organic matter in the study area.

Though regional, spatially referenced soil properties maps exist across the region [43, 50, 59], these studies either relied largely on legacy data, used inadequate point data, established a bias field sample locations, relied only on conventional survey methods, presented fragmented soil information, and used coarse spatial resolution imageries, and is not detailed enough to reveal the variability of soil properties at farm level. The calibration of models with legacy soil data may reduce model accuracy and may not reflect the landscape conditions as they exist in space and time [60], reducing the reliability of such soil information. But in this current study, we relied on field data collected across the study region for model calibration, and the resulting SOM map is an outcome of a robust model with a fine spatial resolution (Fig. 4b), with detailed variability at the farm level.

In terms of the spatial distribution of soil organic matter based on the land cover types, the study indicates that forest land cover contains more organic matter compared to disturbed and cultivated fields (Table 1). More so, qualitative analysis of the spatial distribution of SOM (Fig. 2) indicates that the distribution of SOM seems to follow the forest cover pattern with few exceptions. For instance, Fig. 2 revealed that more SOM is recorded in the extreme northeast and southeast parts of the study area, except for the same range of SOM found in the northwestern part of the study area. Though the northwestern part of the study area is predominantly made up of cultivated lands and settlements, the pockets of high SOM in these areas may have a history of anthropogenic accumulation of farm residues, decayed wood, or buried biomass. A similar observation was made by Venter et al. [35] in South Africa. It is imperative to note that vegetation is a strong determinant of the amount and vertical distribution of organic matter in soils [61].

However, the lower values of organic matter observed in the cultivated fields may be caused by higher oxidation of organic matter and the destruction or removal of crop residues, which aligns with the studies of Nabiollahi et al. [61] and Lal et al. [62]. Continuous cultivation leads to organic matter depletion; hence, the small quantities of SOM in cultivated fields reported in this study are expected. Sandy soils and loamy sandy soils are known to deplete organic matter at rates of 4.7 and 2%, respectively, yearly, in the West African region [63]. This is expected as land cultivation leads to a rapid rate of organic residue decomposition. On a global scale, it is estimated that in the last 12, 000 years, land use change resulting from cropping and grazing caused the loss of 116 petagram of carbon in the top 2 m of the soil of savannas, croplands, and grasslands; hence, the need for wise utilization of land resources, especially in Africa, where hunger remains a rift [7].

Digital Soil Mapping for Precision Agriculture

Understanding the spatial distribution and variability of soil attributes over the field is a prerequisite for environmental management and the effective use of resources [52]. This is pertinent in a climate (such as Africa) where diverse challenges intermingle to clock the wheel of development. Among the panoply of crises confronting Africa, food shortage and environmental crises of climate change origin remain daunting. It has been reported that cereal grain yield in Africa grows at 1% while the population of the region increases at 3%. This is compounded by African arable land being battered at 16% per year [64], hence the widening food gap. Therefore, sustainable farming and effective management of the soil are required to meet the food demand of the teaming population [7], and with digital mapping for precision agricultural development and climate change mitigation and resilience, this plethora of problems can be reduced if not eliminated [43].

Assessment of soil organic matter and, by extension, soil organic carbon, can achieve the twin objectives of climate change mitigation and in reducing food insecurity in sub-Saharan Africa. This is within the clarion call of the International '4 per 1000 Initiative: Soils for Food Security and Climate Change' which places a high premium on agricultural soil assessment at different geospatial levels as a fulcrum of climate change mitigation and improved food security [65]. The initiative is anchored on the understanding that the assessment of soil organic matter will aid natural resource managers in deploying resources to improve areas of SOM depletion while sustainably managing zones of adequate content. This is imperative, as sustaining SOM in the environment in an adequate proportion will buffer the soil against soil erosion, improve soil water content, improve soil fertility status, and improve soil biodiversity [66].

Extant literature [67-69] confirmed that improved yields can be achieved with precision agriculture, but most African farmers do not carry out soil surveys before the cultivation of crops. It is a fact that tropical soils are poor in fertility, and poor management of soils leads to nutrient depletion. Adverse weather and climate events remain major threats to food security in the region [70]. In fact, African nations are not on track to meeting the sustainable development goals by 2030, and with only 7 harvest years left until the dateline for meeting the MGDs [71], the stakes are higher than ever, hence transforming the agricultural sector has become an urgent matter. The transformation can be achieved through digital mapping of SOM as a prelude to sustainable agricultural development to enhance food crop production in the region.

Conclusion

The projected climate scenario indicates that the agricultural sector will be hit, especially in Africa, where the majority of the population depends on rain-fed agriculture. And with the prognosis indicating that the world population will reach 8.7 billion by 2030 and 9.7 billion by 2050, food production will most likely fall short of demand [7]. More so, the growth model projects that Africa's current 1.3 billion people will double to 2.5 billion by 2050 and has the potential to maintain this path [71]. Estimates further revealed that 21% of the continent's population is food insecure [7] and remains highly vulnerable to climate change and the associated socioeconomic malaise [71]. The brunt of these challenges has been coined the 'perfect storm' [ibid]. However, the aftermath of these crises can partly be managed through effective planning [72].

This study recognized that soil organic matter plays a significant role in the natural processes that determine nutrients and water availability for crop production, where the majority of farmers depend on rainfed systems. It must be stated that SOM may not be the limiting factor in crop production as other environmental predictors have modulating roles; hence, farmers must identify these factors before adopting any management strategy.

Increased food production in the Cross River region is an objective that requires a holistic approach, putting in place the best management strategy that ensures the smooth integration of human and natural capital is attained with minimal negative impacts on the environment. We need to stop unsustainable land use practices and the old ways of doing things to adopt new and proven approaches to farming. Stakeholders need to put in place programs that will enlighten indigenous farmers on how best to use the soils and other natural resources within the farm scale to attain sustainable food production.

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Conflict of Interest

The authors declare no conflict of interest.

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