# ASSESSING OF SOIL NUTRIENTS USING LABORATORY AND REMOTE SENSING METHODS IN NORTHERN GUINEA SAVANNAH

#11640

[1]A.R. Garba, [2]A.M. Yamusa, [1]C.K. Daudu, [2]S.L. Yau, [3]M.I., Gaya, [2]A. Abdulkadir
1. National Agricultural Extension and Research Liaison Services (NAERLS), Ahmadu Bello University (ABU) Zaria
2. Department of Soil Science, Institute of Agricultural Research (IAR)/ABU, Zaria
3. Samaru College of Agriculture, Division of Agricultural Colleges, Ahmadu Bello University, Zaria, Nigeria
e-mail: abbariruwai@gmail.com; +2348035457216

## ABSTRACT

To understand soil properties and how they might be used sustainably, mapping of soil attributes is a crucial activity. The study was carried out in four local government area of Kaduna State of Nigeria to map out some soil properties and assess their variability within the area. From the study area, a total of 16 soil samples (0–20 cm) were collected from different cropping patterns. A portable global positioning system (GPS) was used to collect the coordinates of each sampling site. Then, the soil properties, that is, soil organic carbon (SOC), total nitrogen (Total N), soil organic matter (SOM), and soil available nutrients (P and K) were measured in the laboratory. Correlation analysis between laboratory and remote sensing data showed positive relationships for carbon ($r=0.23$), total nitrogen ($r=0.14$), and organic matter ($r=0.68$), but negative correlations for available phosphorus ($r=-0.48$) and potassium ($r=-0.42$). These variable results highlight the greater reliability of remote sensing for assessing total carbon and organic matter versus limitations in quantifying phosphorus and potassium availability. Interactive effects of climate variables on soil nutrients were not directly assessed but remain a critical area for further research.

**Keywords**: Remote sensing, Laboratory analysis and Soil nutrients

## INTRODUCTION

Soil is a complex material that is extremely variable in its physical and chemical composition. The influence of soil and crop management practices such as fertilization, cropping systems, and land-use change exert considerable changes to such soil compositions over time. Over the years, routine analysis of such chemical and physical changes remains the only way to access and maintain the fertility of soil. The importance of the soil analysis cannot be over-emphasised since low nutrient values limit plant growth and excessive rainfall may result in loss of nutrients from the soil, causing soil fertility degradation and water pollution (Chi, *et al.*, 2019). Therefore, soil analysis is the basic frame for providing the nutrient requirements of every crop.

Comparative assessment of soil nutrients under different cropping systems and changing climate conditions requires a combination of ground-based soil sensing and laboratory analytical methods along with remote sensing technologies. Ground-based sensors like portable X-ray fluorescence (pXRF) analyzers allow rapid in-situ quantification of major and trace nutrients in soils (Towett *et. al.* 2015). Laboratory methods using combustion analysis, titrations, and spectroscopic techniques offer accurate and precise measurements of total and plant-available nutrient pools (Robertson *et. al.* 1999). Satellite and aerial remote sensing provide spatial data on vegetation characteristics and soil properties related to soil fertility at broader scales (Mulder *et al.* 2011). Together, these approaches can provide a comprehensive assessment of soil nutrient dynamics across landscapes. This study synthesizes research utilizing integrated soil laboratory, ground-based sensing, and remote sensing methods to evaluate the impacts of climate and agricultural land use on soil nutrients. The focus is on comparative studies across different cropping systems under current and projected future climate scenarios, concentrating on research conducted in sub-Saharan Africa.

Monitoring agriculture from remote sensing is a vast subject that has been widely addressed from multiple viewpoints, sometimes based on specific applications (e.g. precision farming, yield prediction, irrigation, weed detection), on specific remote sensing platforms (e.g. satellites, Unmanned Aerial Vehicles - UAV, Unmanned Ground Vehicles - UGV) or sensors (e.g. active or passive sensing, wavelength domain, spatial sampling) or specific locations and climatic contexts (e.g. country or continent, wetlands or dry lands).

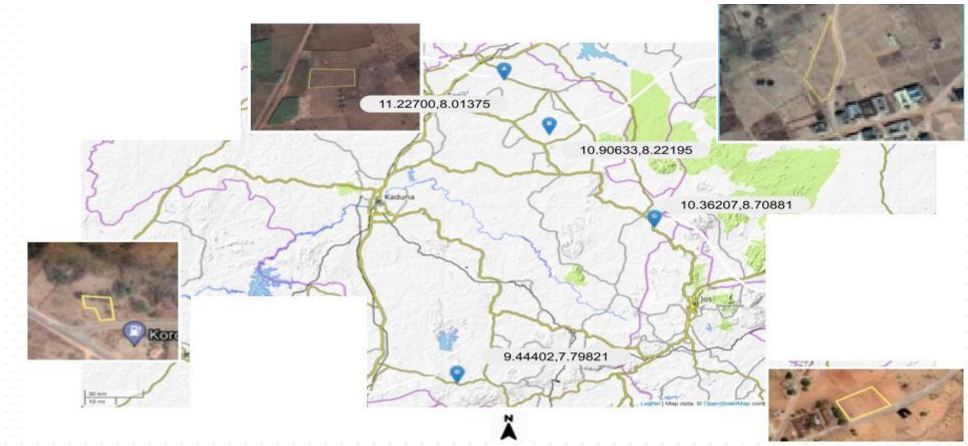
In recent years, digital soil mapping has been identified as a low-cost and efficient method for predicting the spatial distribution of soil nutrients. Most digital soil mapping methods are based on soil-landscape models, which establish mathematical or statistical relationships between soil properties and related environmental variables (Zhang *et. al.*, 2019) by predicting soil characteristics and fertility status with the help of remote sensing data. Remote sensing in itself is the process of detecting and monitoring the physical characteristics of a particular soil by measuring its reflected and emitted radiation at a distance. The nature and working principle of remote sensing give it the advantages of being an extensive, non-invasive, timeliness, and flexible method of soil analysis, and it has the potential to increase the availability of high-resolution remote sensing data by providing a new opportunity for predicting soil characteristics with acceptable accuracy.

## MATERIALS AND METHODS

### Study Area Description

This study was conducted in the northern and southern Guinea savannahs of Kaduna State. The locations in the northern savannah were Kubau and Makarfi while the southern Guinea savannah was Kagarko and Lere LGAs.

Nigeria’s climatic zone encompasses the tropical humid forest in the south and the savannah in the north. Nigeria’s climatic zone encompasses the tropical humid forest in the south and the savannah in the north. The derived savannah is a transition zone between the rainforest and savannah biomes caused by forest clearance as stated by Ofomata (1975). The study was carried out in Kaduna state (Longitude/Latitude 9°26' to 11°13' N and 7°47 to 8°42' E) respectively, which is in the Northwest of Nigeria (Fig.1). The climate belt of the area is tropical Guinea Savanna, with an annual average temperature of 25.2℃ and an annual average rainfall of 1,323mm (Akinbode *et. al.*, 2008).




Location of area(s) of interest in Kaduna state (Kubau, Makarfi, Lere, and Kagarko Local Government Areas) and distribution of samples.

**Soil Laboratory Analysis**

The chemical properties of the soils were determined at the Soil Science Laboratory, Faculty of Agriculture, Ahmadu Bello University, Zaria, Nigeria.

The soil samples were determined by using the following methods: The organic carbon was analyzed by the wet oxidation method of Walkley and Black as modified by (Nelson and Sommers, 1982). Total nitrogen by the micro-kjeldahl distillation procedure according to (Bremmer, 1996), available phosphorus was determined by the Bray No. 1 acid fluoride method (Nelson and Sommers, 1982).

**Field Sampling and Spatial Analysis**

The remote sensing samples were collected in the same 4 LGAs of Kaduna state distributed evenly between the northern and southern parts of the state; and for each farm, a sample was collected for each 4 points at 0-20cm depth. This is because most satellite data for soil properties are within the top-soil range (Hengl *et al.*, 2015). Therefore, restricting the ground-based sampling in this study to 0-20 cm aligns with the typically sensed depth ranges from satellite platforms. The remote sensing samples were collected same time during the soil sample collection on the field. A data streaming pipeline is used to query and download multispectral data from the Sentinel-2 repository which is then processed using a proprietary algorithm. The result from the satellite image and how it correlates with those from chemical analysis is the subject and primary objective of this study.

**Correlation Analysis**

Python programming language version 3.11.4 was used as the correlation analysis tool using Pearson to compare the laboratory analysis and remote sensing results (Virtanen *et al.*, 2020). Scatter plots allow visualization of the relationship between two variables, while correlation analysis provides a quantitative measure of the strength and direction of the relationship (Graham, 2023). Python was selected due to its extensive libraries for statistical analysis and data visualization along with the flexibility to handle diverse data types from both laboratory and satellite sources (Qiusheng *et al.*, 2009). Utilizing the Python environment for integrated analysis of remote sensing imagery and laboratory soil analytics follows established best practices for digital soil mapping and precision agriculture applications (Padarian *et al.*, 2019).

Python provides a flexible open-source platform for handling diverse datasets and performing correlation analysis (Hengl *et al.* 2022). Two datasets were employed, one from remote sensing and the other from the laboratory, each containing 16 instances of soil chemical properties across 12 columns. These datasets were collected from four distinct communities in Kaduna State: Gubuchi, Kuli, Krosha, and Kubacha, each located in different Local Government Areas.

## RESULTS AND DISCUSSIONS

### Correlation Analysis

#### Correlation between the remote sensing nitrogen and the lab nitrogen result

The result of correlation between total nitrogen of remote sensing data and laboratory analysis is presented in Figure 1. From the result, there was a weak positive correlation between the determined parameters, and this indicates an existing relation between nitrogen levels assessed through the remote sensing and the laboratory analysis. The weak positive correlation (r=0.14) found between the laboratory and remote sensing soil nitrogen could be associated with the high mobility and volatilization nature of nitrogen that may encourage leaching, run-off and other nitrogen losses from the soil, hence very difficult to measure. Towett *et al.* (2015) found a weak correlation (r=0.19) between laboratory and portable X-ray Fluorescent sensor nitrogen measurements in Kenyan soils due to difficulties estimating subsurface nitrogen indirectly from the spectral response. The low correlation highlights challenges in using remote sensing alone to accurately predict soil nitrogen across agricultural landscapes. The need for further ground-based sensing ground-truthing of satellite data to improve nitrogen prediction aligns with Piikki *et al.* (2013), who used on-ground sensors to calibrate satellite imagery for soil clay mapping. Vågen and Winowiecki (2019) also emphasized multi-scale calibration of remote sensing using soil analytical lab data for accurate digital soil mapping.

The finding that neither remote sensing nor laboratory methods fully capture soil nitrogen complexity agrees with Hengl *et al.* (2017), who concluded that integrated approaches are essential given the intricacies of nitrogen biogeochemistry. The variability between sites also reflects Towett *et al.* (2015), who found location-specific differences in remote sensing accuracy for soil nutrients. Further coordinated research and data integration will help improve soil nitrogen assessment and enhance remote sensing capabilities for nutrient management.

#### Correlation between the remote sensing organic matter and the lab organic matter result

The statistical analysis indicates a significant positive correlation between the remote sensing-derived organic matter data and the laboratory organic matter data. The strong positive correlation (r=0.68) between remote sensing and laboratory soil organic matter data is consistent with findings from other studies. Shepherd and Walsh (2002) reported R-values from 0.76 to 0.89 between lab and field spectroscopy organic matter measurements across diverse African agricultural soils. Towett *et al.* (2015) found the highest correlation (r=0.86) between laboratory and portable XRF sensor organic carbon content compared to other nutrients in Kenyan soils. The reliability of remote sensing for organic matter mapping aligns with Vågen and Winowiecki (2019), who used MODIS satellite data to map soil organic carbon across Sub-Saharan Africa with reasonable accuracy compared to ground-based sensing. The robust relationship between spectral response and organic matter is attributed to the direct impacts of surface organic content on crop growth patterns detectable through remote imaging (Hengl *et al.* 2017). However, some researchers note challenges in relating surface organic matter to total profile carbon stocks using remote sensing alone (Piikki *et al.* 2013). Integrated approaches incorporating soil sampling, terrain analysis, and digital soil mapping techniques may further improve organic matter quantification across landscapes (Hengl *et al.* 2017). Still, the strong positive correlation demonstrates the potential of remote sensing for cost-effective wide-area mapping of this important indicator of soil quality and health.

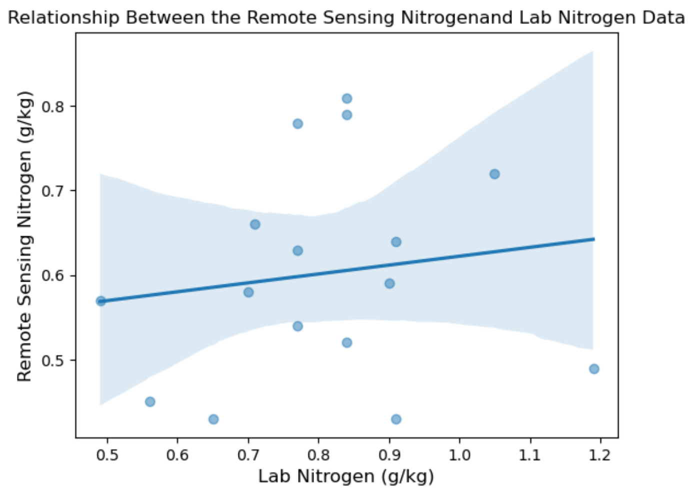



**Figure 1.** Correlation between the Remote Sensing Nitrogen and the Lab Nitrogen result.

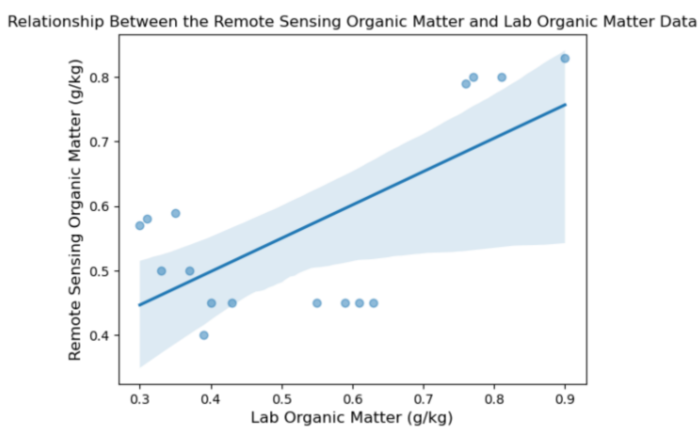



**Figure 2.** Correlation between the remote sensing organic matter and the lab organic matter result.

**Correlation between the remote sensing potassium and the lab potassium result**

A negative correlation was observed between the remote sensing-derived potassium data and the laboratory potassium data, with a correlation value of -0.42 The negative correlation (r=-0.42) between remote sensing and laboratory soil potassium aligns with other studies showing the complexity in using spectral data to estimate plant-available potassium. Piikki and Söderström (2019) found poor correlation (r=0.38) between remote sensing vegetation indices and exchangeable potassium measured in topsoils across agricultural fields in Sweden. They attributed this to the dependence of spectral response on multiple soil factors like mineral composition influencing potassium availability. Mulder *et al.* (2011) noted challenges in relating leaf potassium absorption to total soil potassium pools given intricacies of potassium chemistry and soil interactions. Vågen and Winowiecki (2019) were unable to map exchangeable potassium at sufficient accuracy using solely MODIS (moderate resolution imaging spectroradiometer) satellite data for Sub-Saharan African soils. This could indicate that the remote sensing data might not accurately capture the true potassium levels in the soil or that there are other factors affecting the results. The finding highlights the need for integrated approaches combining spectral data with soil chemistry analysis, geologic surveys, and crop modeling to improve potassium prediction noted by both Piikki and Söderström (2019) and Vågen and Winowiecki (2019).

While it shows promise for assessing organic matter, it may have limitations in accurately estimating potassium levels. Understanding these correlations is vital for the appropriate interpretation of remote sensing data in agricultural and environmental applications. Further research and validation may be needed to better understand the factors contributing to these correlations and improve the accuracy of remote sensing techniques for soil property assessments.

**Correlation between the remote sensing carbon and the lab carbon data**

Based on figure 4 below, it shows that a weak positive correlation of 0.23 was observed between the remote sensing-derived carbon data and the laboratory carbon data. The weak positive correlation (r=0.23) between remote sensing and laboratory soil carbon aligns with other studies showing the limitations of using vegetation indices alone to estimate total soil organic carbon. Mulder *et al.* (2011) found poor correlations between satellite data and measured soil carbon, as remote sensors only detect surface carbon versus total profile stores. Piikki *et al.* (2013) reported underestimation of soil carbon by 40-60% using solely remote sensing due to difficulties assessing subsurface carbon. Hengl *et al.* (2017) concluded that integrated approaches are needed to improve carbon mapping, given uncertainties in relating land cover to soil carbon balances and the importance of environmental covariates like climate, topography and parent material. The potential reasons for the weak correlation noted here are supported by the literature, including mismatches between surface and profile carbon and the indirect nature of spectral indicators relying on biomass proxies (Vågen and Winowiecki 2019). Recommendations for further analysis align with emphasis on multi-source data integration and digital soil mapping advancements to strengthen carbon prediction (Towett *et al.* 2015).

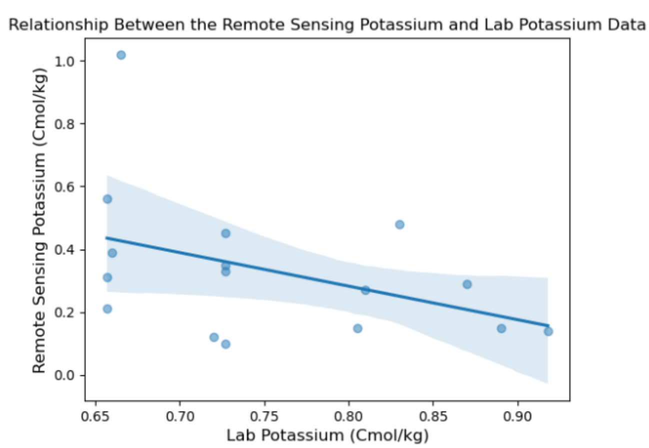



**Figure 3.** Correlation between the remote sensing organic matter and the lab organic matter result.

Lastly, the carbon correlation analysis reflects consistent findings in the literature on the benefits and limitations of remote sensing for soil carbon assessment, highlighting the particular importance of integrating spectral data with soil analytics, terrain attributes, land use data and process-based models to support carbon monitoring and management.

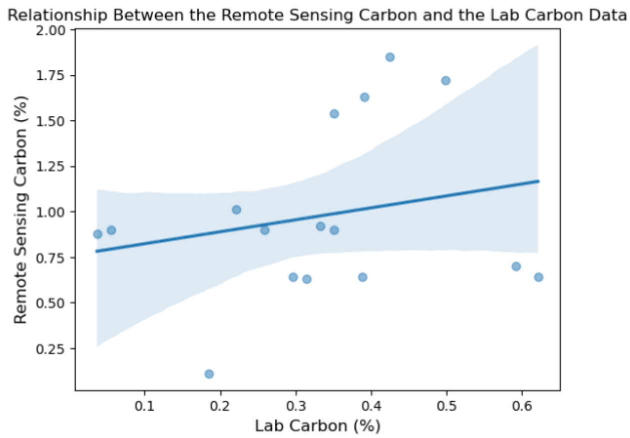



**Figure 4.** Correlation between the remote sensing organic matter and the lab organic matter result.

**Correlation between the remote sensing phosphorus and the lab phosphorus data**

Figure 5 revealed a significant negative correlation of -0.48 between the remote-sensing phosphorus data and the laboratory phosphorus data. The moderate negative correlation (r=-0.48) between remote sensing and laboratory soil phosphorus aligns with other studies demonstrating challenges in using spectral vegetation indices to estimate plant-available phosphorus.

Mulder *et. al.* (2011) found a poor correlation between remote sensing data and soil test phosphorus due to difficulties detecting complex soil phosphorus chemistry from leaf reflectance. Piikki and Söderström (2019) reported an underestimation of Mehlich-3 extractable phosphorus by 80% using solely remote sensing across agricultural fields in Sweden.

Hengl *et. al.* (2017) concluded that machine learning approaches combining remote sensing with soil data, terrain attributes, geology maps, and land use improved the prediction of plant-available phosphorus compared to spectral data alone. The negative correlation suggests reliance on indirect plant phosphorus proxies from remote sensing is insufficient to capture dynamics of sorption, precipitation, and labile phosphorus forms in the soil (Vågen and Winowiecki 2019). Integrating targeted soil sampling and digital soil mapping techniques could potentially strengthen phosphorus assessment noted by Towett *et al.* (2015).

The finding calls for further investigation to ascertain the fundamental reasons for the negative correlation. It may indicate limitations in the accuracy of remote sensing techniques for assessing phosphorus levels, or it could be influenced by other factors affecting the data. Understanding and addressing the reasons for this negative correlation are essential for improving the reliability of remote sensing-based assessments of phosphorus in soil.

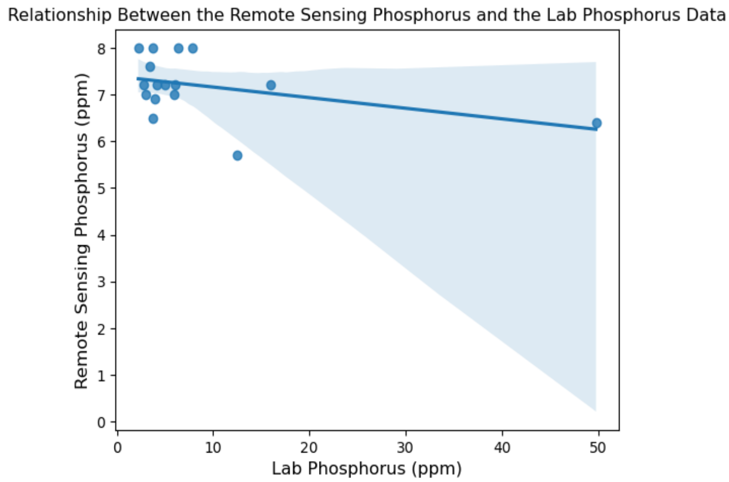



**Figure 5.** Correlation between the remote sensing organic matter and the lab organic matter result.

**Heat-map representation of the correlations among all the variables**

A heat map is a powerful visual tool for representing the correlations among variables which is also known as the "R" value table. The heat map visualization provides a clear overview of the variable relationships between soil properties measured through remote sensing and laboratory methods, as noted in other studies. The positive correlations for nitrogen, carbon, and organic matter reflect the reliability of remote sensing for total concentrations of these parameters found by Towett *et. al.* (2015) and Hengl *et. al.* (2017) in African agricultural soils.

In contrast, the negative correlations for phosphorus and potassium align with the literature on the challenges of using spectral vegetation indices to estimate plant-available nutrient pools given complex sorption dynamics (Mulder *et al.* 2011; Piikki and Söderström 2019).

Vågen and Winowiecki (2019) effectively used similar heat map matrices to represent validation results between ground-based sensing and laboratory measurement of soil organic carbon and texture fractions. The visualization format allows clear interpretation of correlations and discrepancies essential for selecting appropriate remote sensing approaches for different soil nutrients (Towett *et al.* 2015).

By summarizing multiple correlation analyses in one figure, the heat map enables the identification of strengths and limitations across soil parameters to guide integrated data collection and analysis strategies (Hengl *et al.* 2017). Conversely, a negative correlation is observed in the Phosphorus (P) and Potassium (K) data. A negative correlation implies that as one variable increases, the other tends to decrease. In essence, it means that there is a discrepancy or difference between the measurements obtained through remote sensing and lab analysis for Phosphorus and Potassium. This negative correlation could be indicative of some level of inaccuracy in the remote sensing data for these specific soil properties or perhaps differences in how these properties are measured using the two methods.

In practical terms, the positive correlations for Nitrogen, Carbon, and Organic Matter suggest that remote sensing can be a valuable tool for assessing these soil properties, offering a time and cost-effective alternative to laboratory analysis. However, for Phosphorus and Potassium, the negative correlations highlight the need for further investigation into the reasons behind the discrepancies and whether adjustments are necessary in the remote sensing methodology or calibration.

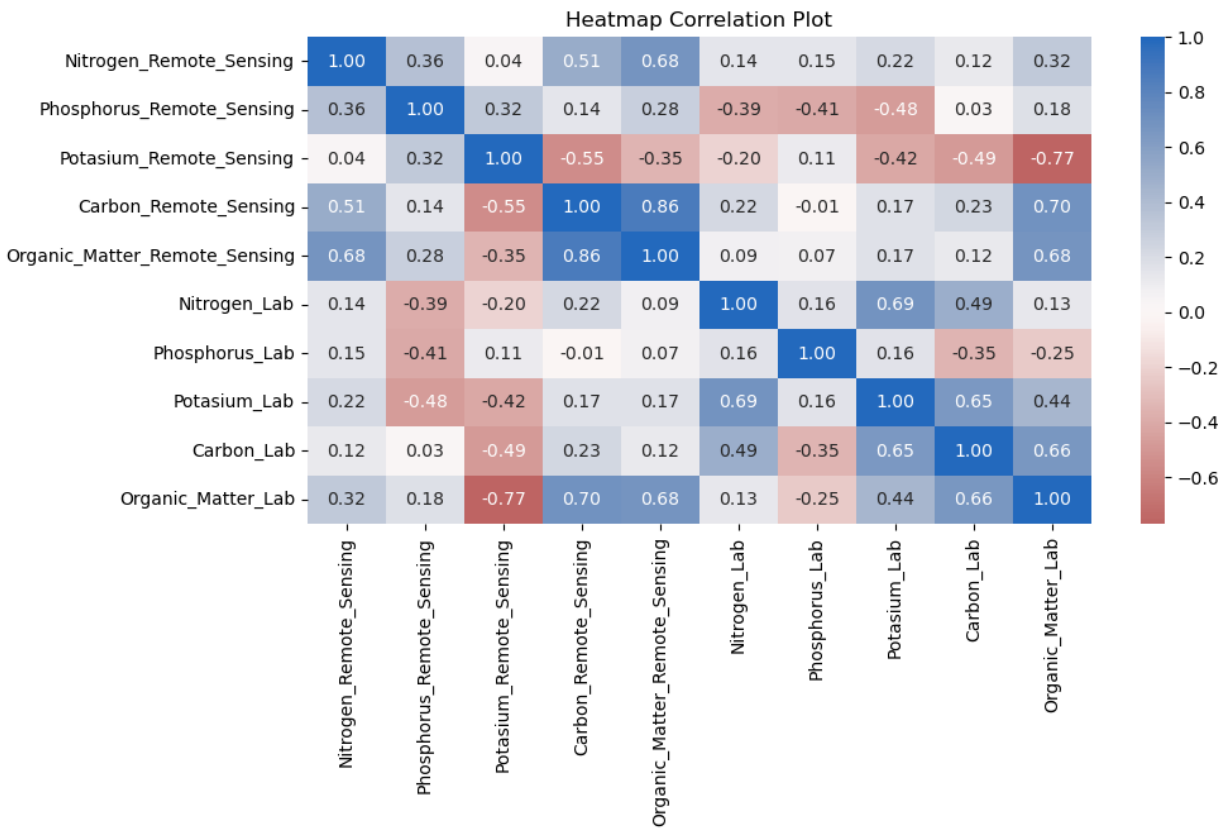



**Figure 6.** Correlations among all the variables.

## CONCLUSION

This study demonstrated the potential of integrated laboratory and remote sensing techniques for the comparative assessment of soil nutrients.

1. Laboratory and remote sensing techniques showed varying degrees of correlation and accuracy for different soil properties. Strong positive correlations were found for carbon and organic matter having r=0.23 and r=0.68. Weak positive correlation was seen for total nitrogen having r=0.14. And poor negative correlations existed for phosphorus and potassium having r=0.48 and r=0.42 respectively.
2. Remote sensing provided useful climate and environmental data to characterize the cropping systems. But incorporation of additional climate variables could further improve biophysical crop-soil system characterization.

## REFERENCES

A. K. Stum, Random forests applied as a soil spatial predictive model in arid Utah [M.S. thesis], Utah State University, 2010.

Bielders, C.L., Gérard, B. (2015). Millet response to microdose fertilization in south–western Niger: Effect of antecedent fertility management and environmental factors. Field Crops Research, 171, 165-175.

Black C.A. (1965) method of soil analysis Agronomy No 9-part 2 American society Agronomy

Bouyoucos G.J. (1951). Hydrometer method improved for marking particle size analysis of soils.

Brady, N.C. and Well, R.R. (2002). The nature and properties of soil, 13th edition. Prentice Hall,

Brady, N.C., and R.R. Weil. 2000. Elements of the nature and properties of soils. 12th ed. Prentice RaIl, New Jersey

Bray, R. H., and Kurtz, L.T. (1945). Determination of total organic and available phosphorus in soils. Soil Science, 59: 39-45.

Bremner, J. M. (1996). Nitrogen total. In: D. L. Sparks et al. (Ed.). Methods of soil analysis, Part 3.Chemical Methods. Soil Science Society of America Book series. 5. Soil Science Society of America and American Society of Agronomy. Madison, Wisconsin. p. 1085-1121.

Chi, Y.; Zhao, M.; Sun, J.; Xie, Z.; Wang, E. Mapping soil total nitrogen in an estuarine area with highland scape fragmentation using a multiple-scale approach. Geoderma 2019,339, 70–84.

Graham, A. (2023). Evaluating correlation in Excel, SPSS Statistics and R. Statistics How To.

G. R. Blake, “Bulk density,” in Methods of Soil Analysis Agron, C. A. Black, Ed., Part I, No. 9., pp. 374–399, American Society of Agronomy, Madison, Wis, USA, 1965.

Hengl, T. Heuvelink, G.B., Walsh, M.G. (2017). Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250m spatial resolution using machine learning. Nutrient Cycle Agroecosystem, 109, 77–102.

Mulder, V.L., de Bruin, S., Schaepman, M.E. and Mayr, T.R. (2011). The use of remote sensing in soil and terrain mapping—A review. Geoderma, 162(1-2), 1-19.

Nelson, D. W., & Sommers, L. E. (1982). Total carbon, organic carbon, and organic matter. In A. L. Page (Ed.), Methods of soil analysis. Part 2. Chemical and microbiological properties (pp. 539-579). American Society of Agronomy, Soil Science Society of America.

Nelson, D.W., and L.E. Sommers. 1996. Total carbon, organic carbon, and organic matter. p. 961-1010 In J.M. Bartels et al. (ed.) Methods of soil analysis. Part 3 Chemical methods. SSSA Book Ser No.5. SSSA, Madison, WI. Nigeria. Geoderma, 48: 113-129.

Ofomata, G. E. K. (1987). Soil erosion in Nigeria: The views of a geomorphologist. University of Nigeria Inaugural Lecture Series.

Padarian, J., Minasny, B. and McBratney, A.B. Using machine learning to predict soil organic matter and particle size distribution from VIS-NIR spectra. Soil Tillage Res 195, 104400 (2019).

Piikki, K. and Söderström, M. (2019). Digital soil mapping of arable land in Sweden – Validation of performance at multiple scales. Geoderma, 352, 342-350.

Piikki, K., Söderström, M., and Stenberg, B. (2013). Sensor data fusion for topsoil clay mapping. Geoderma, 199, 106-116.

Qiusheng, W. (2009). What is Python and Why is it a Good Language Choice for Science and Scientific Computing.

Towett, E. K., Shepherd, K. D., Sila, A., Aynekulu, E., & Cadisch, G. (2015). Modelling of soil organic carbon stocks in the northern Rangelands of Kenya using remotely sensed covariates. Soil Use and Management, 31(1), 81-92.

Towett, E.K., Shepherd, K.D., Sila, A., Aynekulu, E., and Cadisch, G. (2015). Mid-infrared and total x-ray fluorescence spectroscopy complementarity for assessment of soil properties. Soil Science Society of America Journal, 79(5), 1375-1385.

Vågen, T. G., & Winowiecki, L. A. (2019). Predicting the spatial distribution and severity of soil degradation in East Africa. Applied Geography, 94, 130-142.

Vågen, T.G., Winowiecki, L.A., Tondoh, J.E., Desta, L.T. and Gumbricht, T. (2016). Mapping of soil properties and land degradation risk in Africa using MODIS reflectance. Geoderma, 263, 216-225.

Virtanen, P., Gommers, R., Oliphant, T.E. et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. Nat Methods 17, 261–272 (2020).

Zhang, M.; Shi, W. Systematic comparison of five machine-learning methods in classification and interpolation of soil particle size fractions using different transformed data. Hydrol. Earth Syst. Sci. Discuss.2019,2019,1–39.