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Soil Organic Carbon Dynamics, Key Soil Properties, and Agricultural Practices in the Southern
Part of Tanzania

By

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1. INTRODUCTION

1.1 Background Information

Tanzania is an agricultural country where the population depends on agriculture for sustenance. Agriculture employs around 70% of the workforce, which contributes to 28% of the nation's GDP, and represents 67% of total employment (Derksen-schrock et al., 2011; Mdegela et al., 2021). Smallholder farmers in Tanzania face obstacles such as little knowledge of innovative agricultural methods and an unpredictable market, despite agriculture's significant impact on the country's economy (Alphonse, 2017; Anderson et al., 2016; URT, 2017). Both Mbeya and Songwe regions are crucial agricultural areas in Tanzania, considered among five main sources of food in the country. It heavily relies on small-scale farming for both food security and economic growth (Mwema et al., 2021). Farmers in these areas face challenges including inadequate soil fertility, low-quality seeds, and limited access to irrigation systems, volatile markets, insufficient knowledge of modern agricultural practices, and a lack of information and extension services.

Soil is a crucial component in agricultural activities, as it is a complex system with many mechanisms and processes that are challenging to fully understand. Soil acts as a medium through which metals, nutrients, and other toxic contaminants are filtered, so protecting both the soil and groundwater from their negative effects (Stenberg et al., 2010). The capacity of soil to sustain its roles in agricultural activities is contingent upon its chemical, biological, and physical qualities, all of which exhibit regional variability. The issue of nutrient depletion in these soils has raised concerns over the environmental sustainability of crop production in most Sub-Saharan African (SSA) countries (Johnson et al., 2019). In order to improve nutrient balances and prevent land degradation in agricultural production systems in Sub-Saharan Africa (SSA), it is crucial to carry out the characterization, assessment, and monitoring of soil resources (Smaling & Fresco, 1993).

Traditional soil analysis methods have been largely employed to evaluate soil characteristics and offer accurate data on a specific agricultural area. However, these methods are expensive and time-consuming, making them unsuitable for large-scale farms (Angelopoulou et al., 2020; Ewing et al., 2021). In recent decades, the application of soil reflectance spectroscopy, namely visible-near-infrared reflectance and visible-mid-infrared reflectance, together with XRF spectroscopy, has

become increasingly popular for soil investigation (Stenberg et al., 2010; Viscarra Rossel et al., 2006).

Diffuse reflectance spectroscopies require minimal sample preparation, eliminating the need for environmentally harmful digestants in the laboratory (Soriano-Disla et al., 2014; Viscarra Rossel et al., 2011). The nondestructive nature of spectrum techniques allows for consistent and simultaneous observations, providing a significant edge over wet chemistry facilities (Pasquini, 2018). To meet the requirement of obtaining more information about soil conditions while also minimizing the expenses associated with soil assessments, researchers have conducted studies (Nocita et al., 2015; Soriano-Disla et al., 2014). Spectroscopy in (VNIR-SWIR) area, ranging from 400 to 2500 nm, has emerged as a potential alternative technique for studying soil properties. Mid Infrared Reflectance Spectroscopy (MIR) has been considered suitable for predicting the levels of organic and inorganic carbon in soil during extensive soil inventories (Grinand et al., 2012). Several studies have indicated that Mid Infrared Reflectance (MIR) spectroscopy can provide more accurate predictions of various soil parameters, such as inorganic carbon, total organic carbon, soil organic matter, micronutrient levels, pH, soil pollutants, CEC, and C/N ratio (McBratney et al., 2006). Both near-infrared, mid-infrared, or mixed diffuse reflectance spectroscopy have been used to evaluate soil fertility in rice fields in sub-Saharan Africa and to determine different soil parameters in diverse soil groups (Brunet et al., 2007; Johnson et al., 2019).

The analysis of spectral data is accomplished by the utilization of multivariate statistical techniques, wherein the effectiveness greatly relies on the chosen calibration procedure (Geladi, 2003). Partial Least Square Regression (PLSR), known for its interpretability and quick calculation, is the predominant linear method for analyzing the correlation between spectral data and soil parameters. Other multivariate techniques includes random forest (RF), support vector regression (SVR), and multivariate adaptive regression splines (MARS)) (Seema et al., 2022). The correctness of the model may be assessed using several methods and metrics (Stenberg et al., 2010; Vibhute et al., 2018).

1.2 Problem statement and justification

Small-scale farmers in the Southern part of Tanzania focusses on growing vegetables, maize, beans, rice, and coffee (Focken et al., 2004). Farmers in these areas face challenges including inadequate soil fertility, low-quality seeds, and limited access to irrigation systems, volatile markets, insufficient knowledge of modern agricultural practices, and a lack of information and extension services. Smallholder farmers in Tanzania face obstacles such as little knowledge of innovative agricultural methods and an unpredictable market, despite agriculture's significant impact on the country's economy (Alphonse, 2017; Anderson et al., 2016; URT, 2017). To address these issues, research works have been conducted on both farm and non-farm factors. Several programs have been established to strengthen connections between farmers and other stakeholders, including markets, extension services, and input suppliers (Krone et al., 2016; Ndimbo et al., 2023). Different authors have reported awareness-raising campaigns to educate farmers on the advantages of implementing contemporary agricultural methods including the use of information and communication technologies (ICTs). The initiatives are leveraging tools such as radio shows, mobile phones, and other ICT tools to give farmers information on weather patterns, market prices, and farming best practices (Misaki et al., 2016; Mushi et al., 2022). Various agricultural research studies have been undertaken to help solve smallholder farmers' concerns at both regional and country levels, although the challenge continues, since most of this useful knowledge remains locked to academic publications, limiting smallholder farmers' access to critical information (Jha et al., 2020; Sanogo et al., 2023). The mentioned scenario could be caused by disconnect between research and farmers' needs, limited access to academic publications, research language and format, weak link between researchers and extension services, institutional and policy gaps, limited farmer involvement in research, needs for agricultural soil status in terms of soil properties.

On the farm factor, rate of productivity depends on the status of SOC contents and reliable SOC chemometric techniques which could be used to predict various soil properties. In order to assess soil properties and provide precise information on a particular agricultural region, traditional soil analysis techniques have been widely used. Since these techniques are costly and time-consuming, farmers cannot use them often (Angelopoulou et al., 2020; Ewing et al., 2021). Never the less, studies have been conducted in Tanzania involving the application of MIR spectroscopy to provide

information on carbon stock maps and topsoil organic carbon concentrations (Kempen et al., 2019; Winowiecki et al., 2014).

Another study was conducted to estimate SOC stocks (kg m^{-2}) on MIR spectroscopy in different soil depths in Tanzania yet these researches mostly covered forest soils (Kempen et al., 2019; Winowiecki et al., 2014). As one of the big project in Africa for soil monitoring, AfSIS Project has reported a Potential MIR spectral signatures for prediction of multiple soil properties in African countries through the application of partial least squares (PLSR), generalized regression neural network (GRNN) and one-dimensional convolutional neural network (1DCNN) (Gruszczyński & Gruszczyński, 2022). Not only that, but also distribution of SOC concentrations in soil profiles under distinct land uses has been predicted in situ by using Vis-NIR spectroscopy at Mount Kilimanjaro - Tanzania (Kühnel & Bogner, 2017). In comparison to conventional approaches, mid-infrared (MIR) spectroscopy offers a number of benefits, such as cost-effectiveness, rapidity, and non-invasiveness. Because of its quick analysis times, low sample preparation needs, and capacity to give both qualitative and quantitative information, MIR spectroscopy is especially appealing for quality control and process monitoring (Chen et al., 2025; Karoui et al., 2008). Although efforts have been made to provide current status of SOC in the agricultural fields particularly in the Mbeya and Songwe regions, most of data and maps are at continental level and include International Soil Reference and Information Centre (ISRIC), including Soils for Africa projects AfSIS and iSDA (Dewitte et al., 2013; Han et al., 2019; Hengl et al., 2021; Miller et al., 2021). It is true that, factors affecting smallholder farmers, status of SOC contents and application of diffuse reflectance spectroscopy to predict different soil properties have been investigated in some parts of Tanzania, yet updated report on adoption of smallholder farmers to IAPs, SOC concentrations, and the prediction of soil properties from agricultural fields in the Southern part of Tanzania by MIR spectroscopy has not been fully documented. This study aims to provide farmers' awareness and adoption strategies to IAPs, factors that influence soil organic carbon (SOC) dynamics, status of SOC across different agricultural fields, and prediction of selected soil properties by MIR spectroscopy through RF, PLSR and XGBoost chemometric methods.

1.3 Research objectives

The main objective of the study was to evaluate SOC dynamics, predict key soil properties using chemometric methods in the Southern part of Tanzania

The specific objectives are to:

1. To assess smallholder farmers' awareness and adoption on the application of improved agricultural practices (IAPs) in Southern part of Tanzania.
2. To determine the status of SOC contents and SOC stock in different agricultural sites by laboratory measurements in the Southern part of Tanzania.
3. To predict total SOC, total nitrogen, pH, BD and soil texture on MIR by using RF, PLSR and XGBoost chemometric techniques, and assess the accuracy of prediction.

1.4 Research questions

The following research questions were formulated to achieve the stated objectives

1st objective

- i. What are the smallholder farmers' knowledge about IAPs?
- ii. How do farmers receive information on the application of IAPs on their farmland?
- iii. How do farmers adopt to the application of IAPs in their farmland?
- iv. What are the determining factors for farmer's adoption of IAPs?

2nd objective

- i. What is the status of SOC contents and SOC stocks from selected agricultural sites?
- ii. What is the impact of soil type in SOC contents and stocks?
- iii. What is the Impact of elevation, precipitation and crop type in SOC contents?

3rd objective

- i. What are the observed R^2 , RMSE, and MAE in the prediction of soil properties by MIR-PLSR, MIR-XGBoost and MIR-RF models?
- ii. What are the predicted soil properties by MIR spectroscopy?
- iii. Which chemometric method reported a better prediction accuracy on MIR data?

2. MATERIALS AND METHODS

2.1 Study area description

The research was carried out in five different sites within the Mbeya and Songwe Regions located in southwestern Tanzania: Mbozi, Kyela, Tukuyu (Rungwe), Mbarali, and Mbeya Urban (Figure 1). Mbozi is positioned between latitudes 8°45'S and 9°25'S and longitudes 32°45'E to 33°30'E, with elevations ranging from 900 to 2,700 m above sea level (NBS, 2022). This area falls within the Southern Highlands agroecological zone, known for its fertile volcanic and ferrallitic soils, an annual rainfall of 1,000 - 1,600 mm, temperatures between 18 - 25°C, and a rainy season from November to May; its total land area is about 967,900 ha. Kyela, situated around 9°34'S and 33°39'E, is found in a lowland humid agroecological zone at altitudes of 475 - 600 m above sea level, with alluvial clayey soils, substantial rainfall of 2,500 - 3,000 mm, temperatures ranging from 23 - 32°C, and precipitation occurring from October to May; the district covers around 1,325 km² (URT, 2022). Tukuyu, located in Rungwe District at 9°15'S and 33°39'E, resides in a highland zone with elevations of 1,600 - 2,900 m above sea level consisting of rich volcanic andosols, receiving 1,500 - 2,500 mm of annual rainfall, with temperatures from 15 - 20°C and rains occurring from November to May; it spans approximately 1,495 km². Mbarali, found around 8°50'S and 33°50'E in the semi-arid Usangu plains at 900 - 1,200 m above sea level, features vertisols and loamy soils, experiences low rainfall between 600 - 900 mm, has temperatures from 20 - 30°C, and a rainy season from December to April, with an area of about 16,600 km². Finally, Mbeya Urban, located at 8°55'S and 33°25'E in the temperate highlands, has altitudes of 1,600 - 1,800 m above sea level, volcanic red loam soils, receives annual rainfall of 1,200 - 1,600 mm, maintains moderate temperatures of 17 - 24°C, has rains from November to April, and covers an area of around 214 km² (Hamadi Mohamed et al., 2021; NBS, 2019). Common crops grown include maize, groundnuts, beans, wheat, potatoes, rice, coffee, tea, cocoa, cocoa beans, sorghum, finger millet, cotton, cowpeas, groundnuts, cassava, beans, animal husbandry cashew nuts, palm oil, paddy, and bananas (URT, 2017).

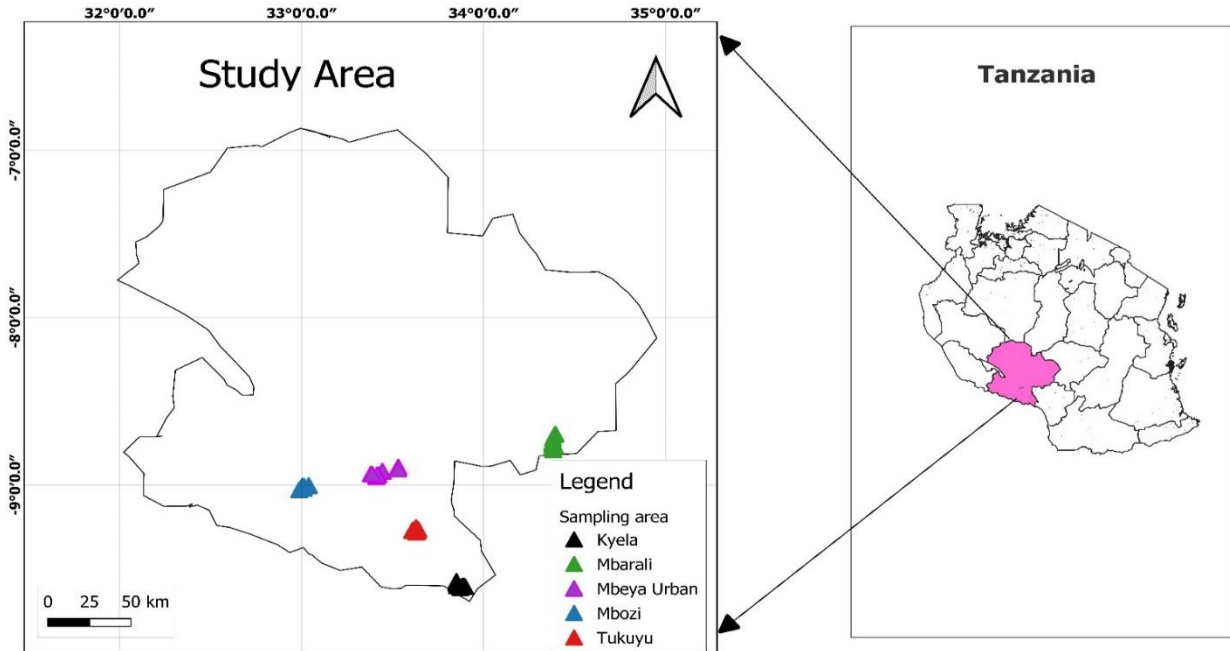


Figure 1: Selected study sites in the southern part of Tanzania

2.2 Farm household questionnaires

2.2.1 Preparation of questionnaires

The survey questionnaires were organized to cover questions on smallholder farmers' demographic characteristics, site characteristics, pest control management, farming practices, weed control, soil conservation practices, farmers' awareness, and the adoption of IAPs. These questionnaires were prepared using the ODK/Ona platform and filled out using ODK Collect for efficiency, minimal staffing requirements, and real-time analysis facilitated by data synchronization.

2.2.2 Ethical consideration

Before the commencement of the present study, we obtained a signed letter of consent from the village chairperson, and the letter was distributed to all trained surveyors. Data was collected from well-prepared digital questionnaires. Furthermore, verbal consent was obtained from household heads prior to starting the surveys. Furthermore, the study adhered to ethical guidelines outlined in the Hungarian Academy of Sciences code on research ethics and the European code of conduct for scientific integrity. All participants provided informed consent prior to questionnaire administration.

2. 2.3 Target population, sample size, and sampling technique

In this study, both purposive and systematic random sample approaches were utilized in a mixed - sampling approach to select sites and choose respondents respectively.

First step involved choosing a representative ward in each district based on literatures and conversations with agricultural extension officers in the target areas. Wards were selected purposively due to their high agricultural activities, topographic variety, and accessibility. Systematic random sampling was employed in the second stage to obtain the target population (smallholder farmers) in order to represent the variations in terrains on the studied wards. The target population consisted of about 425 active and registered smallholder farming households (HHs) according to Tanzania Agricultural Research Institute (TARI) from five different wards (Table 1). Slovin's sampling formula (Ismail et al., 2022), was applied to determine the sample size of participating active smallholder farmers for the questionnaire survey.

$$n = \frac{N}{1+Ne^2} \quad (1)$$

Where:

n = Number of samples, N = Total population and e = Error tolerance level (5%)

$$\text{Therefore, } n = \frac{425}{1+425(0.05)^2}$$

$$n = 206.06 \approx 206$$

Thus the study employed a mixed research approach, by combining qualitative and quantitative research methods. The quantitative research approach was used to collect data on IAPs and factors influencing their awareness and adoption, while the qualitative research design was utilized to collect and analyze qualitative data to supplement and connect the quantitative research method's gap.

To ensure fair representation, the number of respondents in each ward was distributed using proportionate sampling, which was informed by the number of active farming HHs in each village as of primary information gathered from agricultural extension officers and elders.

Table 1: Sample size and sampling design on the studied area

Districts	Wards	Agro-ecological zones	Ward area (km ²)	Sample size	Percentage
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Kyela	Bondeni	Mid-lands zone (800-1,500m)	108	40	19
Rungwe (Tukuyu)	Lufingo	High lands zone (1,500 - 2,400m)	102	43	21
Mbozi	Mlowo	Mid-lands zone (800-1,500m)	114	40	19
Mbarali	Lugelele	High lands zone (1,500 - 2,400m)	89	42	20
Mbeya urban	Iyunga	Mid-lands zone (800-1,500m)	83	41	21
Total			496	206	100

2.2.4 Data collection tools and data sources

The survey was administered using a face-to-face questionnaire survey between 12 January 2023 and 15 March 2023. Primary data was gathered through Key Informant Interviews and field observations in the research field to supplement data obtained from HH surveys and information that may have been missed in the HH questionnaires. Field observations were conducted at the farm level.

Semi-structured questionnaires were utilized to gather data from smallholder farmers. These questions were pre-tested on 20 farmers in the nearby Mwasanga village in Mbeya urban and modified as necessary. Furthermore, the questionnaires utilized in the study were developed by including both expert inputs, literature review and field observations, while reliability was ensured through applying a standardized procedure by asking similar questions to different respondents in same sequence and tone.

The Open Data Kit (ODK), a digital data collection tool, was used to develop questions. Under strict supervision, three qualified research assistants provided questionnaires to the farmers. The main topics of the questions in the questionnaires were smallholder farmers' demographic characteristics, site characteristics, pest control management, farming practices, weed control, soil conservation practices, farmers' awareness, and the adoption of IAPs.

2.2.5 Farming categories and conservation practices related to soil fertility

Farmers' answers to structured questionnaire topics about their primary agricultural activities, crop kinds, and livestock ownership were used to create farming categories (such as mixed farming, crop-only, and livestock-only). Through a mix of literature analysis and interaction with subject-matter experts, these categories were created before the survey and subsequently verified through pilot testing.

Farmers were asked to indicate which of a list of predetermined conservation activities they used in order to evaluate strategies for increasing soil fertility and organic content. These included crop rotation, the use of cover crops, mulching, little or zero tillage, applying compost or manure, and agroforestry techniques where the frequency and scope of these activities were measured and examined.

2.2.6 Data management, statistical analysis of questionnaire data

A score of 1 was assigned to the “yes” response, while a score of 0 was assigned to the “no” response. For the questions with multiple choices, a score of numbers from 1, 2, 3, 4, etc. were assigned. Microsoft Office Excel 2016 and STATA version 18 software were used to analyze the data obtained from the HH questionnaire, which was retrieved via the ONA web platform.

Descriptive and inferential statistics were used to analyze the socioeconomic, demographic information

and assess the performance of several agricultural practices in different districts on the farmers' awareness and adoption of improved agricultural practices (IAPs) at 5% significance level. Frequency counts, percentage, tables, and graphs were used to display the analysis' findings.

2.2.7 Estimation of factors influencing farmer's adoption of improved agricultural practices (IAPs).

The probit regression analysis technique was utilized to examine the factors influencing the adoption of IAPs. This entailed using probit model to analyze the linkage between a binary dependent variable and a set of independent variables, which typically consisted of binary variables. The probit model for the “K” explanatory variables, X_2, X_3, \dots, X_K) is represented by equation two below.

$$Prbit P(X) = \alpha + \sum_{i=1}^K \beta_i X_i \quad (2)$$

where Expectation (β_i) denotes the coefficient estimates for each respondent with the attributes i contrasted to another individual without the attributes. The probit regression coefficient is denoted by β_i and c the constant is denoted by α (Fosu-Mensah et al., 2012).

2.3 Soil sampling

2.3.1 Site selection, sample collection and sampling design

This study used a systematic random sampling design, following the Soils4Africa sampling protocol (Huisling & Mesele, 2021), to evaluate soil properties in agricultural fields in the Southern Highlands of Tanzania. The sampling took place at two standard depths: 0 to 20 cm and 20 to 50 cm. Soil samples were taken from four (4) different sites (Kyela, Mbalali, Mbozi and Tukuyu) chosen for their representation of land use and agro-ecological conditions. At each site, a total of 18 undisturbed soil samples were collected for bulk density (BD) analysis, resulting in 72 undisturbed soil samples across all sites. In addition, 60 composite soil samples were collected from each site, totaling 240 composite soil samples for the analysis of chemical and physical soil properties. Each composite sample was obtained by mixing four subsamples (aliquots) collected in a triangular pattern within a 5 m * 5 m area centered at the sampling point. Soil samples were taken at regular intervals of 100 meters across the agricultural fields (Figure 2). This ensured good coverage and reduced sampling bias.

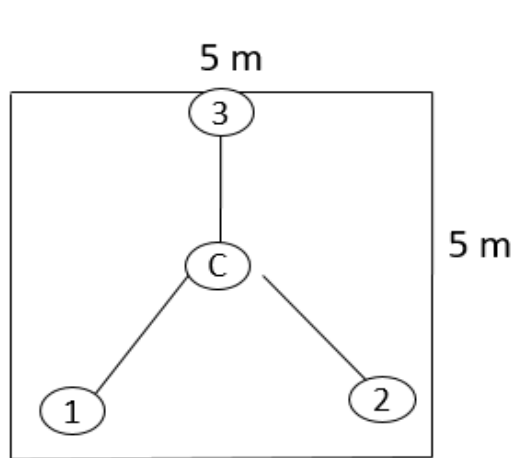


Figure 2: Schematic representation of composite soil sampling design. Each composite sample was formed by thoroughly mixing four soil aliquots collected from a triangular pattern within a 5 m × 5 m area surrounding the central sampling point.

Table 2: Sample size and sampling procedures

Districts	Agro-ecological zones	Ward area (km²)	Dominant Soil type	Undisturbed samples (bulk density analysis)	Composite soil samples	Reference soil data	MIR data	% distribution
Kyela	Mid-lands zone (800-1,500m)	108	Eutric Gleyic Fluvisol	18	60	18	42	25
Rungwe (Tukuyu)	High lands zone (1,500 - 2,400m)	102	Humic Umbric Nitisol	18	60	18	42	25
Mbozi	Mid-lands zone (800-1,500m)	114	Molic Andosol	18	60	18	42	25
Mbarali	High lands zone (1,500 - 2,400m)	89	Eutric Leptosol	18	60	18	42	25
Total		496		72	240	72	168	100

Wet chemistry samples (Reference soil samples): A subset of 72 composite soil samples was systematically selected for wet chemistry analysis to establish the reference dataset for calibrating and verifying spectral predictions (Table 2). To account for spatial variability across the agricultural sites, a systematic sampling approach was employed. A total of 18 soil samples were systematically collected from each of the four study sites, ensuring coverage of the entire area at each location. From an initial pool of 240 collected samples, a final set of 72 representative soil samples (18 per site) was selected for detailed analysis.

MIR spectroscopy analysis: The other 168 composite soil samples underwent analysis utilizing Mid-Infrared (MIR) Spectroscopy to estimate important soil characteristics based on the reference soil dataset.

Bulk density determination: Furthermore, 72 undisturbed soil samples were also collected from the same sampling sites as for reference soil samples to measure bulk density.

All the samples were air - dried for 2 - 4 days in Tanzania, packaged in labeled zip - loc plastic bags and shipped to the Hungarian University of Agriculture and Life Sciences (MATE) laboratory for

additional processing and analysis. Additional environmental attributes in the surveyed area were obtained from (Mlingano Agricultural Research Institute, 2006). The collected undisturbed soil samples were analyzed at the Mbeya University of Science and Technology (MUST) chemistry laboratory to determine bulky density. **Error! Reference source not found.** shows sample collection in Kyela, which involved taking topsoil samples, subsoil samples, and other related farm information.

2.3.2 Laboratory methods

Soil samples were gently crushed through a 2 mm sieve. The pH_{H2O} and pH_{KCl} of the soil were measured potentiometrically with a pH meter (VWR pH 1100L) in 1:2.5 Soil: Water and soil:1N KCl ratios, respectively.

2.3.2.1 Bulk density determination

All samples were oven-dried at 105 °C for 24h. Bulk density was calculated as dry weight divided by volume using the following formula

$$BD_g = M_{\text{dry soil}}/V_{\text{core}} \quad (3)$$

Whereas;

BD_g: gross bulk density (g/cm³)

M_{dry soil}: mass of oven-dried soil (g)

V_{core}: volume of the soil (100 cm³)

3.3.2.2 Soil texture measurements

Soil texture was determined by laser diffractometer Mastersizer 3000 (Malvern, UK) with Hydro LV dispersion unit as described by (Makó et al., 2017).

3.3.2.3 Soil organic carbon and nitrogen analysis

Vario Max Cube organic elemental analyzer was used to analyze soil samples for total carbon and nitrogen contents of the sieved and ground soils, by burning the sample with pure oxygen in a helium atmosphere (4.6 He), at 1150 C°. The concentration (%) of the carbon and nitrogen was determined separately by the TCD detector. The method is parallel with the Dumas burning method for carbon

measurement of a sample, whereby the sample is balanced with the inorganic carbon content (usually from carbonate), and multiplied by 1.714 to get the organic carbon content of the soil. Given that the pH levels of the sites varied from normal to acidic, it was inferred that the soil did not contain inorganic carbon. The lack of inorganic carbon was verified using an HCl test conducted on all samples, hence the total carbon content was regarded as SOC. The C: N ratio of the soil samples was determined using carbon and nitrogen concentrations obtained from CNS elemental analyzer.

2.3.2.4 SOC Stock calculations

The soil organic carbon stocks for each collected depth were determined by utilizing the SOC concentration, depth thickness and bulk density, as per the equation (4) below.

$$\text{SOC}_{\text{stock}(i)} = C_i \times \text{BD}_{\text{sample}} \times \text{depth}_{(i)} \quad (4)$$

Whereas: $\text{BD}_{\text{sample}}$ is the bulk density of the soil, $\text{SOC}_{\text{stock}(i)}$ is the SOC stock of the investigated soil layer (i) (Mg ha^{-1}), $C_{(i)}$ soil is the content of SOC in (%) and $\text{depth}_{(i)}$ is the depth of the respective soil layer (cm).

2.3.3 Statistical analysis on Soil Organic Carbon distribution

Pearson correlation was used to determine the relationship between different soil parameters in the studied sites. The lme4 package (Douglas Bates et al., 2015) was utilized in R software to enable the use of standardized/normalized residuals in residual plots, instead of raw residuals.

ANOVA and Tukey's HSD test were both applied to derive the letter designations in tables and figures at statistical significance levels $p < 0.05$.

The data from agricultural sites were analysed by using Linear Mixed-Effect Models (LMEM) to determine the influence different factors on SOC and SOC stock distribution. Additionally, the package permits more intricate combinations of random effects. In linear mixed-effects models (LMEM), R^2 comprises marginal and conditional R^2 , where marginal R^2 denotes the variance accounted for by fixed effects, and conditional R^2 encompasses both fixed and random effects, utilizing the MuMIn package (Bartoń, 2024). Model 1 is a linear mixed-effects model that includes the fixed effects of soil type, and the random effect of sites. Model 2 is analysis of variance (aov) that includes SOC concentrations as response and soil type as fixed effect for models that were singularly fitted. Model3 has crop type as a fixed factor.

SOC as response and sites as a random effect.

```
Model1 <- lmer(Response ~ soil type + (1 |Sites), data = Data)
```

```
Model3 <- aov(Response ~ soil_type ,data = Data)
```

```
Model2 <- lmer(Response ~ crop type + (1 |Sites), data = Data)
```

NOTE: Response = SOC concentration and SOC stocks

These models accounted for the influence of soil type, crop type and site variations on the distribution of SOC across the studied agricultural sites. Mean separations were determined using the random intercept model utilizing Tukey's post hoc HSD test with a significance level of $p = 0.05$. For SOC concentrations and stocks mean separation, the weighted mean was used. The study employed Pearson correlations to investigate the associations between soil parameters in different agricultural sites. The data were analyzed using R statistical program version 4.3.2.

2.4 Spectral measurements

2.4.1 Pre-processing, measurement and analysis

The preprocessing of absorbance spectra involved applying a moving average window with a width of 17 bands and utilizing the Savitzky-Golay filtering techniques developed by (Abraham Savitzky and Marcel Golay, 1964). Both approaches were utilized to reduce and eliminate noise, which refers to random variations in the signal's surroundings. The techniques of coning and quartering were utilized to get 20g samples of soil, which were then manually crushed to a particle size of less than 0.5um using an agate pestle and mortar. This resulted in a fine powdered particle size ranging between 20 and 53um. The samples were dried by exposure to air and then passed through a sieve with a maximum aperture size of 2mm to ensure uniformity. The fine soil samples were transferred into aluminum sample cups using a micro spatula, and then the loaded samples were positioned in the sample storage tray. Prior to measurement, the sample holder was aligned using a straight-edged tool and then positioned on the MIR Bruker. Every sample was prepared in triplicate to ensure the area being researched was accurately represented. The Bruker Alpha II, which has a spectral range of 2500 - 25000 nm ($4000 - 500\text{cm}^{-1}$), was employed to scan 240 soil samples. The measured spectrum reflectance was converted to an absorbance value using the equation: Absorbance = $\log(1/\text{Reflectance})$.

2.4.2 Model building, validation and prediction

Prior to model development, the mid-infrared spectral data and soil reference data were merged into a unified dataset.

Both Random forest (RF), XGBoost and the Partial Least Squares Regression (PLSR) approach were employed separately to establish the correlation between the measured soil spectra and soil properties in a multivariate regression analysis in R (version 4.2.2) using the caret package (version 2.5-0) and Ranger package for RF developed by Moritz Wright and Andreas Alfons ((Wright & Ziegler, 2017). The analysis involved centering the predictor variables within the approach. Wet chemistry data obtained from laboratory measurements were used as reference soil data to train the model for MIR spectral data. Partial Least Squares Regression (PLSR) method assesses the relationship between the soil spectra and its constituents by decomposing the spectra into a set of scores and eigenvectors. This process is described in detail by (Varmuza K & Filzmoser., 2016) and (Viscarra Rossel et al., 2006). The Partial Least Squares Regression (PLSR) equations can be expressed as:

$$X = TP^T + E \quad (5)$$

$$Y = UQ^T + F \quad (6)$$

Where: X = predictor variables, Y = response variables, T and U are score matrices, P and Q are loading matrices, E = matrix of residuals for X, and F = matrix of residuals for Y.

Thus, PLSR evaluates the correlation between the spectra and the soil constituents during the decomposition of the soil spectra into a collection of eigenvectors and scores. RF as ensemble learning method builds multiple decision trees during training and outputs the average or majority vote of the individual trees, leading to improved accuracy and generalization. As recommended by (Liaw & Wiener, 2002), the RF analysis was conducted using the following parameters: node size = 5, number of variables utilized in each tree (mtry) = 5, number of trees of the model (ntrees) = 500, and number of variables divided by 3. Additionally, RF gives the model's variables' significance, or how the prediction accuracy varies when one variable is removed while keeping the others in place. Accordingly, a variable is more significant for the model if it is eliminated and the prediction error rises (Breiman, 2001; Liaw & Wiener, 2002).

XGBoost (Extreme Gradient boosted) decision based on tree implementation. It is applicable to both classification and regression models. Similar to existing boosting techniques, it constructs the model step-by-step and expands on them by permitting optimization of an arbitrary differentiable loss function (Chen and Guestrin, 2016). XGBoost models utilized nrounds = 53, learning rate (η) = 2.7, lambda=0.1, and alpha=0.02. Depending on the sample size and to provide a robust in the models, 10-fold cross-validation technique was performed to separately provide an optimistic assessment of the model's actual performance (PLSR, RF, and XGBoost) (Dardenne et al., 2000). The technique involved randomly selecting K samples from datasets. One sample from each of the K subsamples is utilized to validate the results, while the remaining K-1 samples are either used as training data or to construct the classification model. The model with the most reduced RMSE and increased R^2 dependent on the validation set, the best fitted model was chosen.

2.4.3 Models performance and accuracy

The evaluation of soil attribute models involved a comparison between anticipated values (based on MIR spectral data) and observed values (based on reference soil data) utilizing many criteria. The model performance in PLSR, RF and XGBoost were evaluated by calculating the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The prediction accuracy of the regression model was categorized into three groups based on the ratio of performance to deviation values and the dependability of the prediction was determined based on the coefficient determination which are good prediction, average prediction and poor prediction accuracy

2.4.4 Statistical analyses on the performance of predictive models

Descriptive statistics, such as mean, minimum, maximum, standard deviation, median, count, skewness, kurtosis, and coefficient of variation, were calculated to describe the variability of soil properties for both reference soil data (conventional soil analyses, CNS elemental analyzer and Laser diffraction method), and the entire sample set (data on soil properties predicted by PLSR model). PCA was conducted on the preprocessed first derivative soil spectra to visually represent the variety of spectral signatures in the entire dataset of soil samples. All statistical analyses were performed using R software 4.3.2.

3. RESULTS AND DISCUSSIONS

3.1 Awareness and Adoption of Smallholder Farmers of IAPs

3.1.1 Demographic information characteristics of the interviewed respondents

A total of 206 respondents were interviewed from five locations(wards) in the Southern part of Tanzania (Table 3). The dominant age group was found to be 18–34 years, representing 40% of the studied group. About 64% of the study population was male, and primary school education accounted for 51%. The majority of the farmers (56%) were married, and this was consistent across all regions studied. Farming experience was dominated by 1 – 5 years (40%) while “more than 10 years” of experience came second with 30% of the interviewed farmers. The Mbozi district (Mlowo) stands out with a higher number of females, a notable absence of college education, a prevalence of smaller household sizes, and a considerable presence of individuals aged 45-64 (Table 3). Academic underachievement in secondary schools and the lack of employment opportunities in the region explain this phenomenon (Laizer et al., 2019; Mushi et al., 2022). In Mbozi districts, there was a higher participation of females in agricultural activities compared to males (NBS, 2022). This could be attributed to the fact that Mbozi district is predominantly inhabited by two prominent ethnic groups, namely the Wanyiha and Wanyamwanga (NBS, 2022). This could be further explained by the reason that men belonging to these tribes often marry and leave their families, migrating to other areas that provide better employment opportunities in non-agricultural sectors (Christopher & Helena, 2018).

While mono-cropping, mixed crops, and livestock keeping were the most common cropping systems observed across the field under study, the majority of farmers rely on rainfall as their primary source of water for irrigation. This study emphasizes that in underdeveloped nations, mixed crop-livestock systems are the main source of income. Additionally, the findings show that farms are not vulnerable

to flooding based on regional climate trends and topography as reported by (Ahmad & Ma, 2020; Tshenko, 2003).

This study emphasizes that in underdeveloped nations, mixed crop–livestock systems are the main source of income. Because they frequently rely on rainfall for their farming operations, farmers in these areas are vulnerable to climatic fluctuations.

Table 3: Demographic information of the studied population (n = 206)

Variable (%)		Data collection sites					Chi Square, p - value	
		Kyela	Mbalali	Mbeya Urban	Mbozi	Tukuyu	Mean(SD)	
Gender	Male	77.5	76.2	56	45	62.8	63.5(6.1)	$\chi^2=7.3$ $p = 0.007$
	Female	22.5	23.8	44	55	37.2	36.5(6.1)	
Marital status	Single	10	19	22.5	20	39.5	22.2 (10.8)	$\chi^2 = 457$ $p<0.0001$
	Married	87.5	78.6	77.5	77.5	55.8	75.4 (11.7)	
	Divorced or separated	2.5	2.4	0	2.5	4.7	2.4 (1.7)	
Education level	No formal education	2.4	2.4	7.3	12.5	3.9	3.9 (1.9)	
	Primary school	14.3	46.3	63.4	37.5	51.2	51.2(8.2)	
	Secondary school	50	48.8	21.9	50	32.6	32.6(5.7)	
	College	28.6	2.4	7.3	0	9.3	9.52(5.1)	
Household size	< 1Ha	27.5	30	41.5	77.5	41.9	41.9(8.9)	
	1 - 5 Ha	72.5	70	58.5	22.5	58.1	56.32(8.9)	
Age (years)	18-34	20	59.5	31.7	20	39.5	39.5 (7.3)	$\chi^2 = 25.5$ $p<0.0001$
	35-44	22.5	28.6	17.1	12.5	27.9	27.9(3.1)	
	45-64	45	11.9	39	45	27.9	27.9 (6.3)	
	>65	12.5	0	12.2	22.5	4.7	4.7 (3.8)	
Farming experience	<1year	2.5	9.5	34.1	2.5	9.3	11.6 (13.1)	$\chi^2 = 217.6$ $p<0.0001$
	1 – 5	42.5	61.9	29.3	50	16.3	40.0 (17.8)	
	10-Jun	14.6	7.1	7.3	30	30.2	17.8 (11.6)	
	>10	39	21.4	29.3	17.5	44.2	30.3 (11.3)	
Cropping system	Monocropping	14.7	29.4	23.5	6.6	25.7	20.0 (9.2)	$\chi^2 = 554.5$ $p < 0.0001$
	Mixed crops	17.7	29.0	20.8	25.0	6.3	19.8 (8.7)	
	Livestock keeping	13.5	45.9	2.7	37.8	18.9	23.8 (17.8)	
	Crop rotation	13.5	45.9	2.7	37.8	18.9	23.8 (17.8)	
	Polyculture system	80.0	20.0	0.0	0.0	0.0	20.0 (34.6)	
	Integrated culture system	1.0	0.0	0.0	0.0	0.0	0.2 (0.5)	
Water source	Irrigation	3.6	92.9	0.0	3.6	0.0	20.0 (40.8)	$\chi^2 = 333$ $p < 0.0001$
	Rainfall	21.4	15.1	21.9	20.8	21.4	20.1 (2.8)	

Following time	1-4 months	14.3	29.5	24.1	20.5	11.6	20.0 (7.3)	$\chi^2 = 206.9$ $p < 0.0001$
	5-6 months	10.2	0.0	28.6	24.5	36.7	20.0 (14.7)	
	Plough immediately	31.3	31.3	0.0	2.0	25.0	17.9 (15.7)	
	Less than one month	56.0	20.0	0.0	4.0	20.0		
Exposure to flood	Yes	74.2	19.4	3.2	0.0	3.2		
	No	10.3	21.3	22.4	23.0	23.0		
Manure Application	Cattle manure	12.4	22.1	18.6	14.2	32.7	20.0 (8.0)	$\chi^2 = 438$ $p < 0.0001$
	Poultry manure	6.1	9.1	57.6	9.0	0.0	16.4 (23.3)	
	Goat manure	0.0	25.0	50.0	25.0	0.0	20.0 (20.9)	
	Farm yard manure	31.8	13.6	4.5	9.1	40.9	20.0 (15.6)	
	Compost manure	28.1	0.0	0.0	6.3	59.4	18.8 (25.5)	
	Not applicable	32.9	23.7	22.4	21.1	0.0	20.0 (12.1)	
Top dressing	Yes	15.0	39.0	25.0	15.0	1.0		
	No	25.5	3.8	15.1	23.6	37.7		

The results in (Figure 3) depict that 59% of the female-headed households have better soil information on IAPs than men. According to studies, women are frequently in charge of overseeing small-scale farming and land resources in rural areas, which makes them more aware of both agricultural factors and environmental changes as reported by Meinzen-Dick. (2011). Furthermore, Women in Tanzania's southern highlands are more exposed to and dependent on local ecological knowledge since they are frequently in charge of crop selection, soil preparation, and residue management (Mnimbo et al., 2017). Never the less, women are regularly the focus of capacity-building interventions by NGOs and agricultural development programs in the area. This may help them become more aware of better agronomic practices, such as managing invasive alien plants (IAPs) and maintaining soil health (Agunga et al., 2018; URT, 2014).

Higher (28%) soil information was observed among young household heads aged between 25-34 years (Figure 3). Similarly, household heads with primary education levels have higher soil information on IAPs, followed by those possessing a secondary level of education. Levine's test was conducted to assess the equality of variances between genders. The results indicated a significant difference ($p > 0.05$) in soil information about IAPs between male and female household headships.

However, the One-Way ANOVA analysis at $p > 0.05$ revealed no significant difference in the knowledge of both soil type and soil information towards IAPs based on household head age and education level.

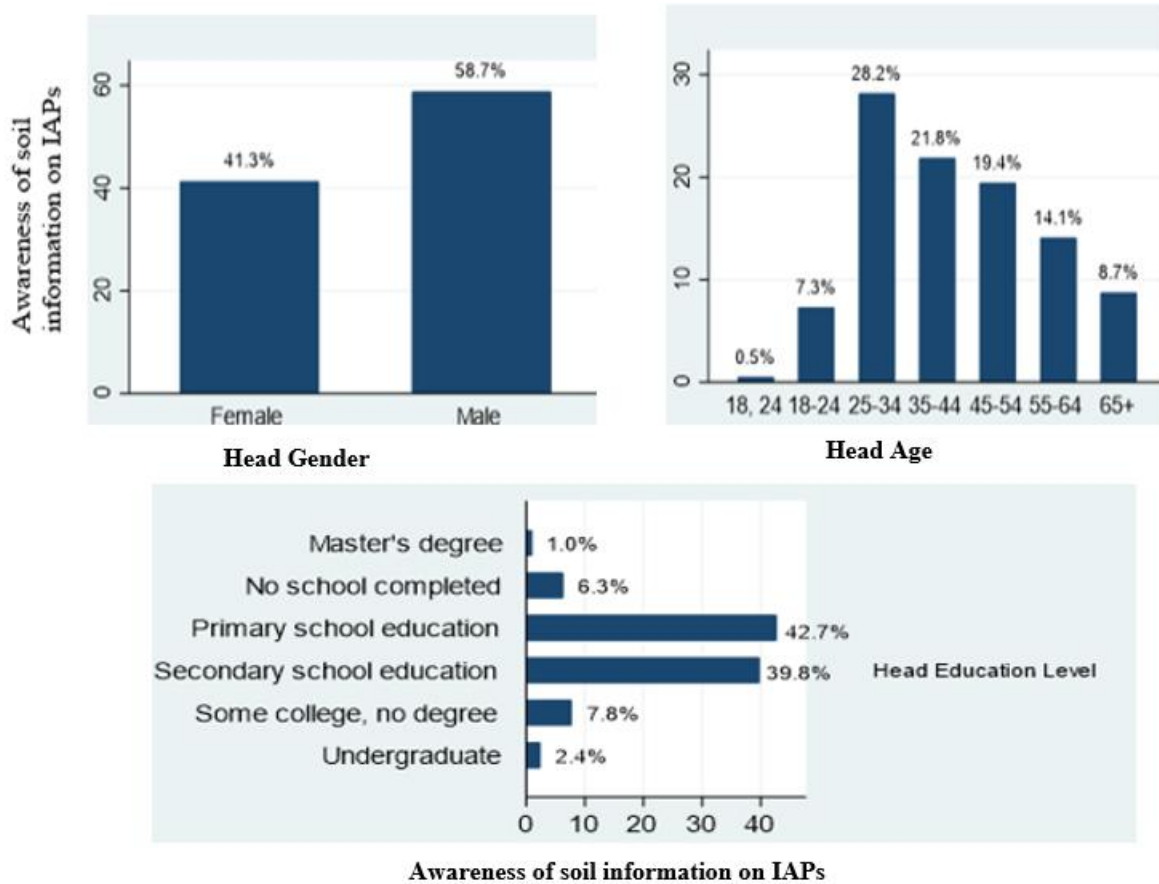


Figure 3: Awareness of Soil information on IAPs by gender, age, and education level

3.1.2 Soil conservation practices in the selected sites

Crop residues (Table 4) are utilized to feed livestock such as goats, cows, and sheep. Incorporating these residues into the soil, a practice passed down through generations enhances soil organic content and fertility for subsequent cultivation seasons (Mng'ong'o et al., 2021a; Rogers et al., 2022). Approximately 80% of farmers were actively engaged in soil conservation practices, with minimum tillage or no tillage (21%), crop rotation (19%), and strip cropping (18%) achieving high scores.

The methods used to control residue varied according to the type of agriculture. Crop wastes were frequently used as fodder on livestock farms ((Blummel, 2013)), while they were more often left in place (incorporated in situ) on non-livestock farms to enhance soil organic matter (Wilhelm et al.,

2004); (FAO, 2011)). Accurately determining residue presence on fields depends on understanding these differing priorities. About 20% of respondents were not involved in any conservation practices. Contour farming and terracing were the least practiced by smallholder farmers. Farmers used 36% of crop residues as fodder and integrated 32% into the soil (Table 4). The “none” response was observed with 19% of soil conservation practices.

Table 4: Conservation practices and residue management by smallholder farmers in the selected sites (n = 206)

Variable	Respondents	Respondents (%)	
Residue management	Burning	28	13.6
	Composted	35	17.0
	Incorporated in situ	66	32.0
	Used as fodder	74	35.9
	Used for fuel	3	1.5
Soil conservation practices	Contour farming	1	0.3
	Minimum tillage or no tillage	70	20.5
	Strip cropping	60	17.5
	Terracing	20	5.8
	Crop rotation	66	19.3
	Mulching	25	7.3
	Cover crops	0	0.0
	Tillage	35	10.2
	None	65	19.0

4.1.3 Awareness to improved agricultural practices (IAPs)

Our results revealed three-quarter of the studied population had no information about the use of IAPs in their farms, while more than 80% of the same population lacked information about soil type associated with their farmland (Figure 4). Majority of farmers (65%) reported to be unfamiliar with either of the agricultural experts, while only a quarter of the farmers identified extension service

officers as their source of knowledge. Only 24% of farmers relied on information from extension service officers whereas 65% of the respondents were not aware of these group of experts (Figure 4). This could be associated with insufficient agricultural extension services provided to the societies, as mentioned in some articles (Baloch & Thapa, 2019; Laizer et al., 2019; Srijna Jha, 2021). Encouraging more extension services to smallholder farmers regarding IAPs could augment the efforts of extension agents and enhance the crop yield.

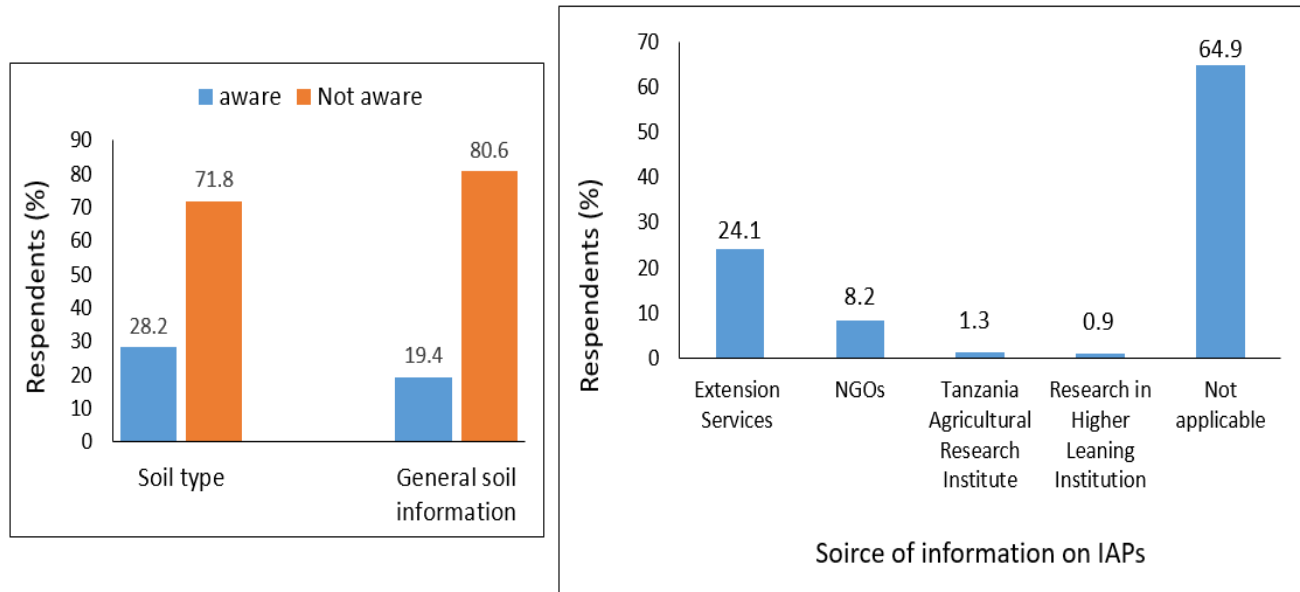


Figure 4: Awareness and adoption of IAPs (A), and the source of information on IAPs (B)

3.1.4 Farmers adoption to improved agricultural practices (IAPs)

About 72.5% of respondents were motivated to adopt various IAPs with the higher number of respondents being observed in “increase crop yield” as shown in (Figure 5A). As reported by (Abdul-Majid et al., 2024; Wordofa et al., 2021), smallholder farmers' adoption to IAPs is mostly driven by higher crop yields and increased household income. Our results are also in line with findings previously reported by (Ashrit & Joshi, 2024) on agricultural systems who discovered that farmers' acceptance of improved techniques and their understanding of sustainable agricultural practices were linked to higher yields. Apart from that, most of farmers (75.9%) adopted IAPs especially in fertilize type, land preparation methods and weed control practices (Figure 5B). Both agricultural experts and reduce pests and disease problems also plays important role in the farmers' adoption to IAPs.

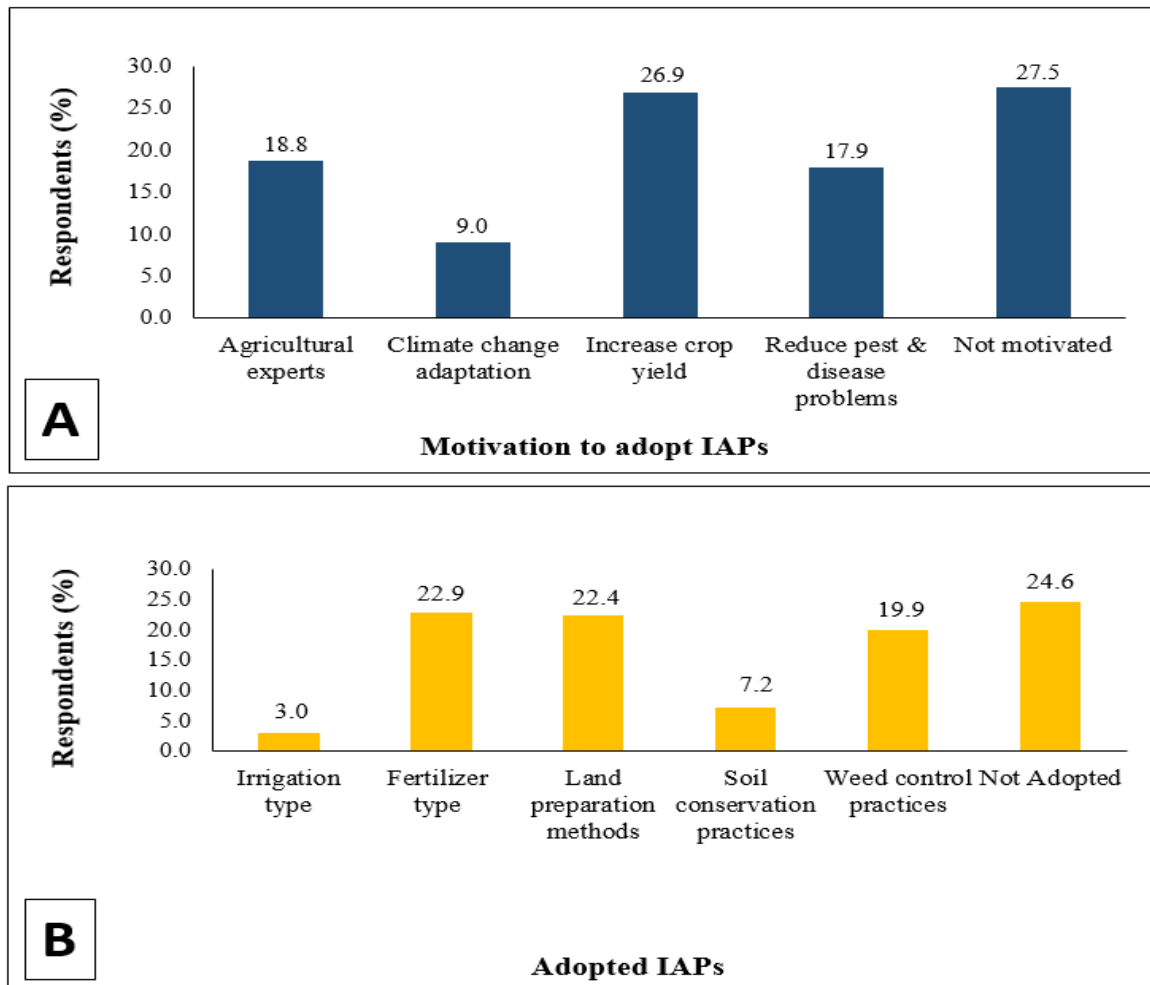


Figure 5: Motivation towards smallholder farmer's adoption to IAPs (A) and adopted IAPs (B)

3.1.5 Estimation of factors influencing farmer's adoption of IAPs

Table 5 shows the findings of the predicted Probit regression model coefficient estimates in column 2 and marginal effects in column 3. The sign and magnitude of the marginal effect indicate the direction of the independent variables' effect and the predicted effect of the dependent variable correspondingly (Baiyegunhi et al., 2022; Danso-Abbeam & Baiyegunhi, 2018). The likelihood ratio test value of -83.34 depicts that the utilized probit regression model and the selected determinant variables of adopting IAPs fits the data correctly. The pseudo-R² value (0.3471), with a significantly ($P=0.010<0.05$) larger LR Chi-square value (88.61) points out that the estimated probit model has significant explanatory power, thus the idealness of the model information.

Among the selected independent variables influencing adoption of IAPs, the marital status of the household head, farming period, flooding exposure, top dressing using inorganic fertilizer, following

time, soil information, and soil type of the farm were observed to be significant predictors of household IAPs adoption at 5% significance level. Specifically, household marital status has a negatively significant influence on household IAPs adoption ($\beta = -0.674$; $P < 0.05$). The marginal effect (see column 3) indicates that a positive change in household marital status by leads to a decline in the likelihood of adopting IAPs by 15.2% holding all other variables constant. These findings align with the observations made by (R. J. F. Burton, 2014) who observed that individual characteristics such as age, gender, and marital status influence the individual's decision-making process and behaviors, hence providing understanding on how certain group of farmers can respond to certain situations.

Additionally, the farming period has a significant negative influence on the household adoption of IAPs ($\beta = -0.308$; $P < 0.05$), with marginal effect indicating that an increase in the farming period by 1 year results in a decline in the adoption of IAPs by 7.0% at 5% confidence level. These findings are similar with the one observed by (Atari et al., 2009) that higher farming period and experiences reduces the likelihood of changing the agricultural production and conservation practices. Nevertheless, the findings contradict the observations made by (Coyne et al., 2021; Taylor & Van Grieken, 2015) who concluded that farmers with large experience and longer farming experience have a better understanding of the farm variability and operational efficiency, as most farmers learn through hands-on application and adoption of improved practices (Tey & Brindal, 2012).

Table 5: Results of probit regression for the IAPs adoption

Dependent Variable: IAPS Adoption	Coefficients	Marginal Effect
Constant	-1.301	
Household head age	-0.131	-0.030
Household head gender	-0.025	-0.006
Household head marital status	-0.674**	-0.152**
Household head education level	0.130	0.030
Farm size	-0.236	-0.053
Farming period	-0.308**	-0.070**
Cropping system	-0.007	-0.002
Flooding exposure	1.142**	0.258**
Water source	-1.108	-0.251
Top dressing	0.822**	0.186**
Manure usage	-0.394	-0.089
Pest control practices	0.913	0.207
Weed control	0.243	0.055
Crop residue management	0.122	0.028
The following time	0.281**	0.064**
Yields after IAPs adoption	0.325	0.073
Soil information	1.162**	0.263**
Soil type	0.374**	-0.085**
LR Chi ² (20)	88.61	
Prob >Chi ²	0.0000	
Pseudo R ²	0.3471	
Log likelihood	-83.34	
No. of observations	206	

Note: * $p < .1$; ** $p < .05$; * $p < .01$: Source: Author's Construction (2023)**

The findings also indicated a significant positive effect of flooding exposure, top dressing using inorganic fertilizer, fallowing time, reception of soil information and soil type on the farmer's adoption of IAPs in Tanzania at 5% confidence interval. Particularly, the coefficient of farmer's farm exposure to flooding during growing or harvesting period ($\beta = 1.142$; $P < 0.05$) and marginal effect of 0.288, implies that an increase in flooding exposure increases the household's likelihood

of adopting IAPs by 28.8% holding all other factors constant. These findings align with findings observed by previous studies that farmer's farm conservation awareness to natural catastrophes such as floods are effective in enhancing the likelihood of adopting improved agricultural skills and practices by inculcating additional and innovative skills (Ardoin et al., 2020; Du et al., 2019; T. Liu et al., 2018; Nilsson et al., 2020).

Similarly, top dressing using inorganic fertilizer increases the farmer's likelihood of adopting IAPs by 18.6% holding other factors constant. Allowing the land to fallow for a longer time increases the farmer's likelihood of adopting IAPs by 6.4% holding other factors constant. Furthermore, the results showed that farmers receiving soil information have a higher likelihood of adopting IAPs by 26.3%. These findings are in line with previous studies which concluded that farmers with access to information regarding their soil type and condition have a higher likelihood to adopt improved agricultural practices (IAPs) compared to those without access to soil information (Franco, 2020; Machingura et al., 2018; Mango et al., 2018). The soil type of the farm increases the likelihood of farmer's adoption of IAPs by 8.5% holding all other factors constant 5% confidence interval. To enhance direct agricultural strategy and policy interventions for smallholder farmers in Tanzania, it is necessary to have a systematic and concurrent understanding of sustainability, adoption restrictions, and scaling-up of agricultural extensions. (Jha et al., 2020).

3.2 Status of SOC and SOC stocks in different agricultural soil type

3.2.1 Soil characteristics on selected agricultural sites

Among the sites studied, silt loam and loam were the most frequently observed soil textures (Table 6). The predominant soil type in Kyela, at both soil depths, was silt loam. The soil texture detected in both the topsoil and subsurface of Mbarali was predominantly loam. Loam soil was found at a depth of 0 - 20 cm in both Mbozi and Tukuyu. Clay loam soil was found at a depth of 20 - 50 cm in Mbozi, while sandy loam soil was found at the same depth in Tukuyu. The occurrence of loam and sandy loam soils in both Kyela and Tukuyu was influenced by the presence of Eutric Glayeic Fluvisol and Humic Umbric Nitisol, respectively. This could potentially explain why these places are commonly used for cultivating tubers (Kashuliza, 1998; Mpogole, 2012).

Increased yield of crops, tubers, cash crops, vegetables, and fruits in Mbeya may be attributed to the presence of loam and silt loam soil textures, as demonstrated in our research. The soil textures

mentioned offer ideal circumstances for the growth of roots, the ability to retain water, and the availability of nutrients. These factors are crucial for the successful cultivation of a wide variety of crops.

Both sites exhibited nearly identical pH values, with a small variation observed between the topsoil and subsoil layers. The pH levels varied between 5.9 and 6.4, with the lowest recorded in Kyela and Tukuyu. Tukuyu had a statistically significant ($p < 0.05$) decrease in bulk density (BD) with values of 0.64 and 0.79 in the topsoil and subsoil, respectively. The pH levels in all the examined fields were somewhat acidic, ranging from 5.9 to 6.4. These findings are consistent with previous research conducted in various agricultural fields in Tanzania, as reported by (Hamadi Mohamed et al., 2021; Mhoro et al., 2015b; Steven Merumba et al., 2020).

The pH range measured in agriculture is optimal for the root environment, enabling the achievement of maximum or near maximum crop growth (Islam et al., 1980). The lack of statistically significant variations in soil pH at different depths, despite minor fluctuations, indicates a level of uniformity in the distribution of pH within the soil profile. This can be attributed to the regular mixing of soil through tillage in agricultural regions, which affects both the topsoil (0-20cm) and subsoil (20-50cm) depths (Blanco-Canqui & Ruis, 2018). Tillage practices such as ploughing potentially mixes soil layers, disrupts soil stratification and potentially homogenizing soil (Bauer et al., 2002; Blanco-Canqui & Ruis, 2018) which can mitigate potential differences in pH between surface (topsoil) and subsurface (subsoil) layers.

The bulk density (BD) of the topsoil was measured to be 0.98, 1.19, and 0.96 in Kyela, Mbarali, and Mbozi, respectively. With the exception of Tukuyu, there were no notable variations found in the bulk density (BD) of Kyela, Mbarali, and Mbozi at depths of 0 – 20 cm and 20 – 50 cm. The average clay concentration at a depth of 0-50 cm varied between 6.4 ± 0.7 and 23.9 ± 2.3 , while the silt content ranged from 36.5 ± 2.7 to 51.9 ± 2.9 , and the sand content ranged from 23.3 ± 2.7 to 57.4 ± 3.2 . Our research indicates that soil bulk density increased progressively from the topsoil to the subsurface. However, the measures of bulk density indicate that the soils in issue are not compacted, which may be attributed to a limited use of current technology (Shah et al., 2017). Intensive agriculture, machinery irrigation techniques, and high mechanical load are the main factors causing compaction in soils. On the other hand, less compacted soils have lower bulk density, increased porosity, better aggregate stability index, higher soil hydraulic conductivity, and nutrient availability, resulting in improved soil health. These findings are supported by (Shah et al. (2017) & Shaheb et al. (2021).

Mtama (2018) noted a comparable pattern in the investigation of pedology in the southern highland zone of Tanzania by employing traditional, step-by-step descriptions of soil samples. The soils in the areas he examined were characterized by significant depth, making them well-suited for cultivating crops with both long and shallow root systems. The chemical properties, pH, cation exchange capacity (CEC), base saturation (BS), soil organic matter (SOM), and nutrient balance studies demonstrated that these soils possess inherent health and fertility, making them suitable for the growth of various crops and the production of biomass and high crop yields. The samples obtained from Mbarali district exhibited elevated bulk density due to the prevalence of sandy silt clays and alluvial silt clays in the district's soil composition (Mbarali, 1980).

The bulk density of the Mbozi area was found to be higher than that of Kyela and Tukuyu. This can be attributed to the presence of valleys, volcanic soil, and a combination of clay soil, sand, alluvial loam, and silt soil. The bulk density values nearly correspond to those reported by (Mfaume et al., 2019). Tukuyu exhibited the lowest bulk density compared to the other three districts, perhaps due to the prevalence of Humic Umbric Nitisol as the predominant soil type. Humic Umbric Nitisol exhibits elevated levels of soil organic matter, which subsequently enhances soil porosity (Akinde et al., 2020; Chalise et al., 2019). The measured bulk densities suggest that the soils in question exhibit enhanced porosity, soil moisture, and hydraulic conductivity, all of which contribute to greater crop output. However, it is important to note that these soils may be susceptible to erosion as a result of ploughing. The references cited are (Bogunovic et al., 2018; Dam et al., 2005).

Table 6: Soil properties in four different sampling sites

Soil parameters	physical Depths	Sampling sites			
		Kyela	Mbarali	Mbozi	Tukuyu
pH (H ₂ O)	0 - 20	5.9±0.1 ^a	6.3±0.1 ^a	6.1±0.2 ^a	6.0±0.1 ^a
	20 - 50	6.3±0.1 ^a	6.4±0.0 ^a	6.3±0.1 ^a	6.2±0.1 ^a
	Mean±SE	6.2±0.1 ^a	6.4±0.2 ^a	6.2±0.2 ^a	6.1±0.1 ^a
Clay (%)	0 - 20	21.9±2.6 ^a	15.8±1.6 ^b	26.4±1.2 ^a	7.8±1.5 ^c
	20 - 50	25.9±2 ^a	14.8±2.2 ^b	32.4±1.8 ^a	4.9±0.8 ^c
	Mean±SE	23.9±2.3 ^a	15.3±1.9 ^b	29.4±1.5 ^a	6.4±0.7 ^c
Silt (%)	0 - 20	50±3.7 ^a	36.5±2.4 ^b	43.7±1.8 ^b	41±2.5 ^b
	20 - 50	53.8±2.1 ^a	25.2±2.4 ^b	42±3 ^c	32.1±2.7 ^d

	Mean±SE	51.9±2.9 ^a	30.8±2.4 ^b	42.8±2.4 ^a	36.5±2.7 ^b
Sand (%)	0 - 20	26.2±2.6 ^a	47.7±2 ^b	30±2.8 ^a	51.3±3.8 ^b
	20 - 50	20.3±2.7 ^a	59.1±4.2 ^b	26.1±4.3 ^a	63.4±2.8 ^b
	Mean±SE	23.25±2.7 ^a	53.4±3.6 ^b	28.5±3.5 ^a	57.4±3.2 ^b
Bulk density (g/cm ³)	0 - 20	0.98±0.04 ^a	1.19±0.02 ^a	0.96±0.1 ^a	0.64±0.03 ^b
	20 - 50	1.31±0.04 ^a	1.3±0.02 ^a	1.36±0.1 ^a	0.79±0.02 ^b
	Mean±SE	1.14±0.04 ^a	1.26±0.02 ^a	1.16±0.5 ^a	0.72±0.02 ^b
Soil texture	0 - 20	Silt loam	Loam	Loam	Loam
	20 - 50	Silt loam	Loam	Clay loam	Sandy loam

Note: Means with small letters in the same row with identical superscripts for different sampling sites do not show statistically significant differences at a significance level of $\alpha = 0.05$ based on Tukey's HSD test

3.2.2 Soil and crop types as predictors of SOC concentrations and stocks by Linear mixed effect model (LMEM)

We conducted a study to examine how different types of crops and soils affect the content and stock of soil organic carbon (SOC) in both the topsoil and subsoil. We used linear mixed-effects models (lme4 and lmerTest) to analyze the data, and the results are presented in (Table 7). The linear mixed models used to predict SOC concentration and stocks in the topsoil were individually fitted with soil types as fixed effects and site as random factors. The models were found to be singular, suggesting that one or more variances were extremely close to zero (Brown, 2021; Matuschek et al., 2017; Nobre & Da Motta Singer, 2007).

Consequently, each of those data sets were subjected to analysis of variance. The content and stocks of soil organic carbon (SOC) were significantly impacted by different soil types (p-value = $1.18e^{-8}$ for SOC content and p-value = 0.004 for stocks), with the maximum SOC content and stocks seen in the Humic Umbric Nitisol. The results highlight the crucial influence of soil type, particularly Humic Umbric Nitisol, in regulating levels of soil organic carbon (SOC) in agricultural areas in the Southern part of Tanzania. In the subsoil, the correlation between SOC content and soil type was even more pronounced, with soil type alone accounting for a substantial proportion of the variability, exceeding 50%. Cai et al, (2016) & Wiesmeier et al, (2012) highlighted that nitisols typically have higher SOC concentrations than other soil types in the study area. This might be caused by a number advantageous characteristics, such as stable aggregates that prevent erosion and preserve organic

matter, and clay content that strengthens organic matter stabilization through chemical bonding and physical protection. The finding is different from literature reviews which highlights Molic Andosol to have more SOC followed by Humic Umbric Nitisol, Eutric Leptosol and finally Eutric Gleyic Fluvisol in the studied soil type (Jakšić et al., 2021).

The overall model for soil organic carbon (SOC) content in the topsoil, considering different crop kinds, exhibited a strong explanatory ability (conditional $R^2 = 0.75$). Nevertheless, the crop kinds alone accounted for a minimal amount of the variation, with a marginal R^2 value of 0.04. The model for soil organic carbon (SOC) content in the subsoil, including crops, exhibited a substantial overall explanatory capacity (conditional $R^2 = 0.75$). However, crop types only accounted for a small proportion of this explanatory ability (marginal $R^2 = 0.05$), as indicated in (Table 7). The model elucidates that soil organic carbon (SOC) levels found among different sites were not significantly influenced by both agricultural practices and crop types. This suggests that inherent soil properties may overshadow the effects of agricultural practices and crop types on SOC levels.

Due to differences in soil type, climate, and management intensity, some studies have found minor or inconsistent effects of particular methods on SOC, while others have found large effects. For instance, the strength of these effects can differ, and they might not always result in statistically significant shifts in the overall levels of SOC (C. Liu et al., 2024). Never the less, numerous interrelated factors, including as geography, land-use history, and climate variability, affect SOC dynamics. These variables may interact in areas to mask the distinct impacts of crop kinds and agricultural techniques on SOC. Our findings seems to be contrary to number of studies which show that farming as well as crop types have significant influence on the SOC (Balkovič et al., 2020; Gocke et al., 2023; Söderström et al., 2014; Q. Wang et al., 2025).

Table 7: Impact of fixed effects (crop and soil types) and random effect (sites) on SOC concentrations and stocks on the topsoil (0 – 20cm) depth

Models	Fixed effect	Rando m factor	P value (Fixed effect)	P value (random effect)	Conditional R^2	Marginal R^2
SOC content						
Model1	Soil type	Sites	$1.18e^{-8}$	0.001		0.79

Model2	Soil type	-	1.18e ⁻⁸	0.001		
Model3	Crop type	Sites	0.63		0.75	0.04
SOC stocks						
Model1	Soil type	Sites	1.18e ⁻⁸	0.001		0.55
Model2	Soil type	-	1.18e ⁻⁸			

3.2.3 Soil organic carbon concentrations and stocks in different soil type

The Humic Umbric Nitisol exhibited a substantially ($p < 0.05$) greater concentration and stock of Soil Organic Carbon (SOC) in comparison to the other soil types mentioned in (Table 8). The amounts of SOC concentrations were assessed using the Booker tropical soil manual (Landon, 1985). With the exception of the Humic Umbric Nitisol, which had a moderate (4-10%) concentration of soil organic carbon (SOC), all the other three soil types had a low (<2%) SOC content in the topsoil.

Table 8: Distribution of SOC and SOC stocks based on soil type. Same letters (“a”) indicate no significant difference of SOC concentrations in the same column ($n = 72$)

Soil types	Topsoil (0 – 20cm)		Subsoil (20 – 50cm)	
	SOC conc (%)	SOC stocks (%)	SOC conc (%)	SOC stocks (%)
Eutric Leptosol	1.60a	39.30a	0.76a	20.60a
Eutric Glayeic Fluvisol	1.70a	35.90a	0.97a	27.20a
Molic Andosol	1.80a	34.20a	0.94a	25.10a
Humic Umbric Nitisol	4.40b	54.80b	3.25b	51.90b

Note: Means with small letters in the same row with identical superscripts for different sampling sites do not show statistically significant differences at a significance level of $\alpha = 0.05$ based on Tukey's HSD test

Soil types vary in their fertility and can affect the distribution of plants, characteristics of vegetation, and levels of soil organic carbon (SOC) (Paz et al., 2016).

Figure 6 and Figure 7 demonstrate that Humic Umbric Nitisol has a higher concentration of soil organic carbon (SOC) compared to other studied soil types. Furthermore, (Figure 6) reveals that maize has the highest SOC concentration in the topsoil, followed by banana among the different crop kinds. While the impact of different crop types on soil organic carbon (SOC) concentrations

was not statistically significant, it is worth noting that banana and mixed crop types exhibited greater SOC reserves in the subsoil. This is consistent with the findings presented by (Monroe et al., 2016), who emphasized a correlation between soil organic carbon (SOC) stocks and various agricultural systems.

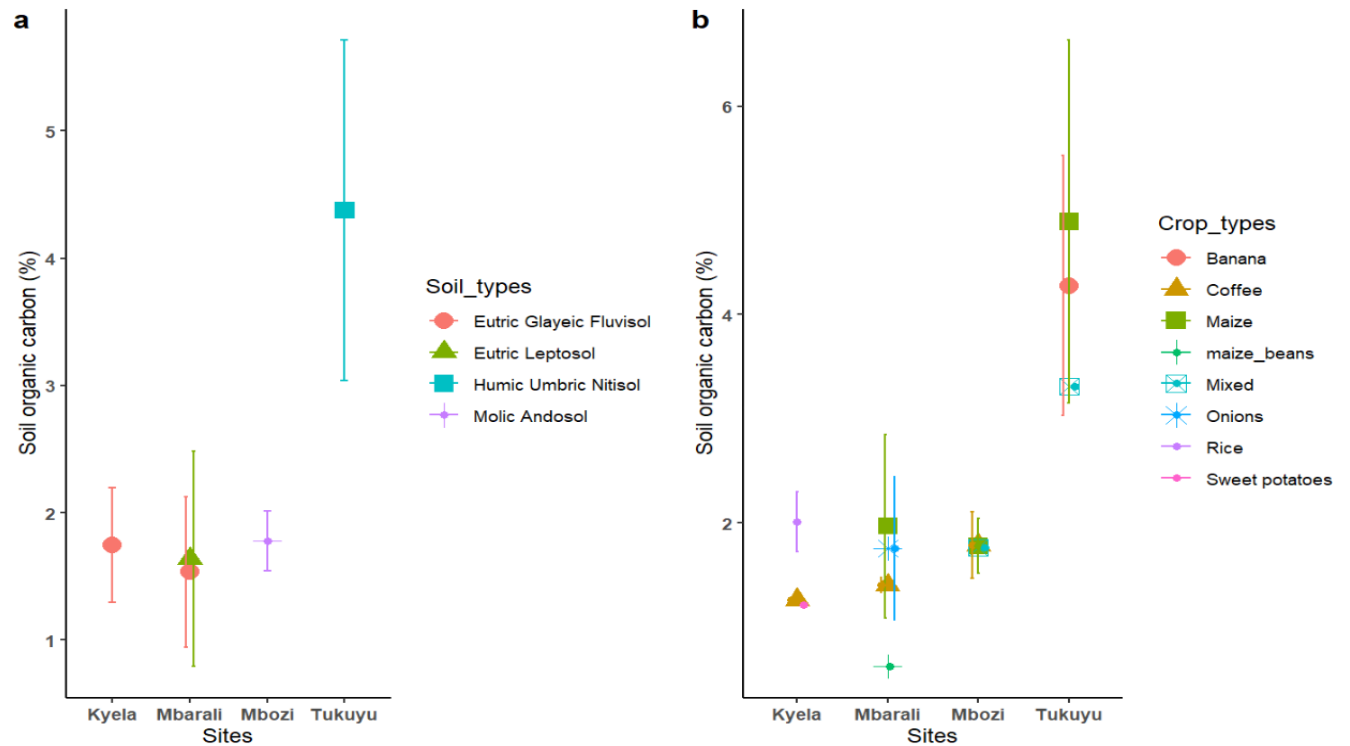


Figure 61: Distribution of SOC concentrations based on (a) soil type and (b) crop type (0 – 20 cm)

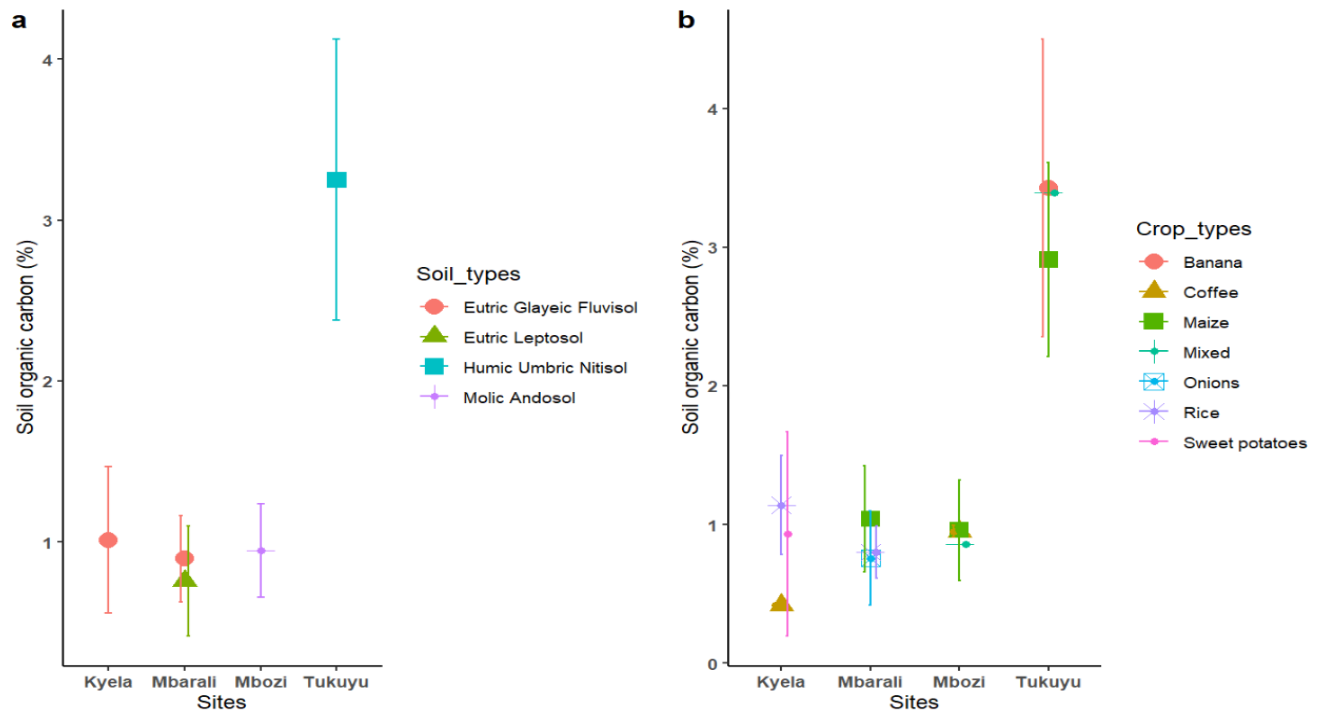


Figure 7: Distribution of SOC based on (a) soil type and (b) crop types (20 - 50 cm)

3.2.4 Soil organic carbon concentrations and stocks in different crop type

In the analysed crop type, the concentrations of SOC ranged from 0.76 to 4.27, while the stocks ranged from 20.60 to 55.36 Mg/Ha, as shown in (Table 9). Significant variations in the distribution of soil organic carbon (SOC) were identified in both the topsoil and subsoil. However, these differences did not reach statistical significance, as shown in (Table 9). Several studies have shown that different factors, such as tillage, fertilizer methods, residue management, irrigation, and pesticide use, have a notable influence on both crop productivity and the storage of carbon in soil within agroecosystems (Ratnayake et al., 2014), which explain the variations of SOC in the studied crop types.

Banana crops exhibited the largest concentrations and stocks of SOC (soil organic carbon) in both the topsoil and subsoil layers compared to other crop types. This is attributed to the fact that banana fields undergo less tillage, as reported by

Krauss et al., (2022). The concentrations and stocks of soil organic carbon (SOC) were greater in the uppermost layer of soil compared to the lower layer for all types of crops. This difference may be attributed to increased microbial activities in the uppermost layer of soil (Tian et al., 2016).

From Booker Tropical Soil Manual (Landon R. J, 1991), the concentrations of Soil Organic Carbon (SOC) in the topsoil of coffee, onions, and sweet potatoes are classified as extremely low, measuring less than 2%. Maize, mixed cropping, and rice have low SOC concentrations, ranging from 2% to 4%. On the other hand, banana has a medium SOC concentration, ranging from 2% to 10%. The subsoils included low quantities of soil organic carbon (SOC) in the banana and mixed cropping soils, but all other crop types showed extremely low SOC concentrations.

Table 9: Distribution of SOC and SOC stocks based on crop type. Same letters (“a”) indicate no significant difference of SOC concentrations in the same column

Crop types	Topsoil (0 - 20cm)		Subsoil (20 - 50cm)	
	SOC conc (%)	SOC stocks (%)	SOC conc (%)	SOC stocks (%)
Banana	4.27a	52.24a	3.40a	55.36a
Coffee	1.51a	32.13a	0.80a	21.03a
Maize	2.60a	44.95a	1.47a	31.22a
Mixed	2.53a	35.75a	2.12a	38.60a
Onions	1.76a	43.45a	0.76a	20.60a
Rice	2.01a	37.80a	1.03a	27.02a
Sweet potatoes	1.21a	33.45a	0.93a	34.95a

Note: Means with small letters in the same row with identical superscripts for different sampling sites do not show statistically significant differences at a significance level of $\alpha = 0.05$ based on Tukey's HSD test

3.3 Prediction of selected soil properties by PLSR, RF and XGBoost Models

3.3.1 Assessment of selected soil properties for calibration on MIR spectra

The sub-soil samples selected using the Kennard-Stone algorithm were used to calibrate and validate the predictive models. These samples were analysed using traditional laboratory procedures and covered a broad spectrum of soil fertility characteristics (Table 10). The soil attributes had a usually positive skewness in their distribution, with the exception of bulk density, clay, silt, and sand, which displayed a negative skewness, same range of the results were previously reported for top soil by

Viscarra Rossel et al. (2016) and J. Johnson et al. (2019). Except for pH and BD values, which have a coefficient of variation (CV) of less than 18%, the soil parameters (total SOC, SOC stocks, total N, clay, silt, and sand) showed substantial variance, with CV ranging from 31% to 71.9%. The significant range of variation in the sub-sample set is appropriate for the calibration and validation of the entire (Nduwamungu., 2009; J. M. Johnson et al., 2019; Mohammedzein et al., 2023).

Table 10: Descriptive statistics of soil properties of the reference (cross-validation) soil samples

Soil properties	Soil depth	Descriptive statistics							
		Mean	n	Max	Min	Range	Std. Dev	Skewness	CV (%)
pH	0 - 20 cm	6.1	40	6.90	5.50	1.40	0.32	0.70	
	20 - 50 cm	6.2	40	6.80	5.90	0.90	0.22	0.37	5.25
BD (g/cm ³)	0 - 20 cm	0.94	40	1.30	0.50	0.75	0.23	-0.22	3.55
	20 - 50 cm	1.22	40	1.45	0.71	0.74	0.22	-1.30	24.47
Clay (%)	0 - 20 cm	17.97	40	32.80	3.10	29.70	8.50	-0.01	18.03
	20 - 50 cm	19.5	40	37.00	2.10	34.80	11.70	-0.06	47.30
Silt (%)	0 - 20 cm	42.8	40	61.30	27.80	33.40	8.70	0.34	60.00
	20 - 50 cm	38.2	40	56.80	15.50	41.30	12.20	-0.02	20.33
Sand (%)	0 - 20 cm	39.25	40	65.70	10.90	54.80	14.90	-0.34	31.94
	20 - 50 cm	42.2	40	79.10	11.50	67.50	21.60	0.04	37.96
Total [SOC]%	0 - 20 cm	2.36	40	6.54	0.62	5.90	1.36	1.50	51.18
	20 - 50 cm	1.53	40	5.20	0.37	4.80	1.10	1.70	57.63
Total [N]%	0 - 20 cm	0.2	40	0.54	0.06	0.48	0.10	1.60	71.90
	20 - 50 cm	0.13	40	0.43	0.04	0.39	0.09	1.50	50.00
SOC stock (mg/Ha)	0 - 20 cm	40.22	40	83.70	15.50	68.17	14.80	1.10	69.23
	20 - 50 cm	32.8	40	83.80	10.30	73.50	17.40	1.20	36.80

3.3.2 Spectral pre-processing and spectral assessment

The spectral characteristics of all the soil samples exhibited a high degree of similarity, as depicted in (Figure 8). The absorbance values observed in this investigation varied from 0.5 to 2.8 which is consistent with the range reported in prior studies (Towett et al., 2015). Nevertheless, there are modest variations compared to other research that examined different agricultural soils and documented absorbance values ranging from 0 to 1.2 (Johnson et al., 2019; Michel et al., 2009; Terra et al., 2015; Viscarra Rossel et al., 2006). As anticipated and previously demonstrated by (Kim et al., 2022; MohammedZein et al., 2023; Santos et al., 2015), moving average (5nm) was applied as a preprocessing (smoothing tool) to accurately increase prediction features (Figure 8B and Figure 9B). The MIR region is distinguished by its overall and powerful absorption, mostly driven by intense fundamental vibrations. This finding aligns with the observations made by (Johnson et al., 2019; Viscarra Rossel et al., 2006). Due to the complexity of soil, which consists of several mixed molecules, the absorption of various mineral and organic characteristics may occur simultaneously, making interpretation of individual component important. The scores and eigenvectors obtained from the principal component analysis (PCA) of the preprocessed MIR spectra were used to visually represent the distribution of the soil samples as shown in (Figure 10A). Three dominant PCA accounted for 61% of the spectral variance (Figure 10B). The Mahalanobis application indicated the absence of any outlier samples as in (Figure 10B).

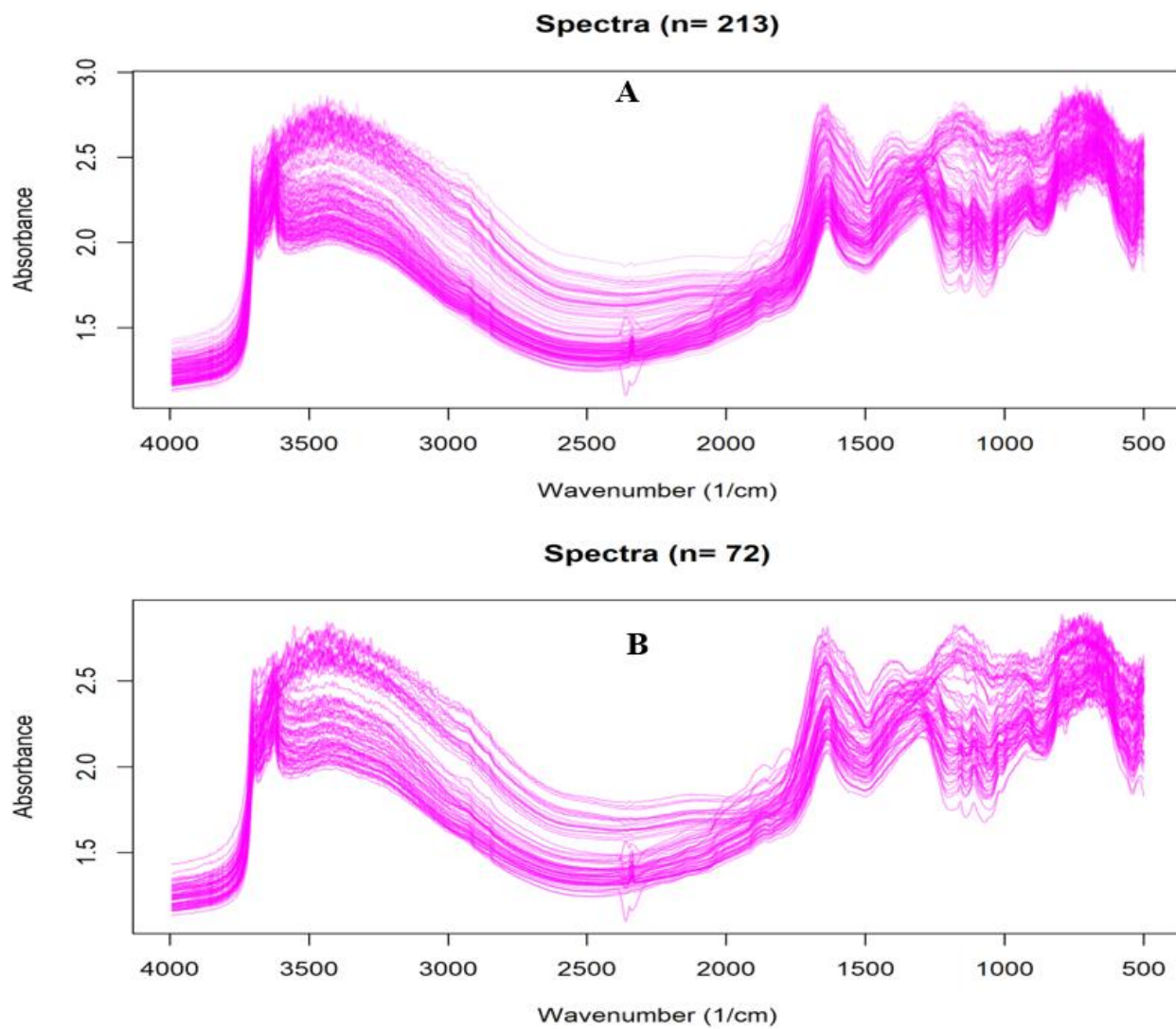


Figure 8: Absorbance spectra (pre-treatment) of the whole soil samples dataset in (A) and only reference soil datasets in (B) Mid-Infrared Reflectance spectroscopy (MIR) 4000 - 500 cm^{-1}

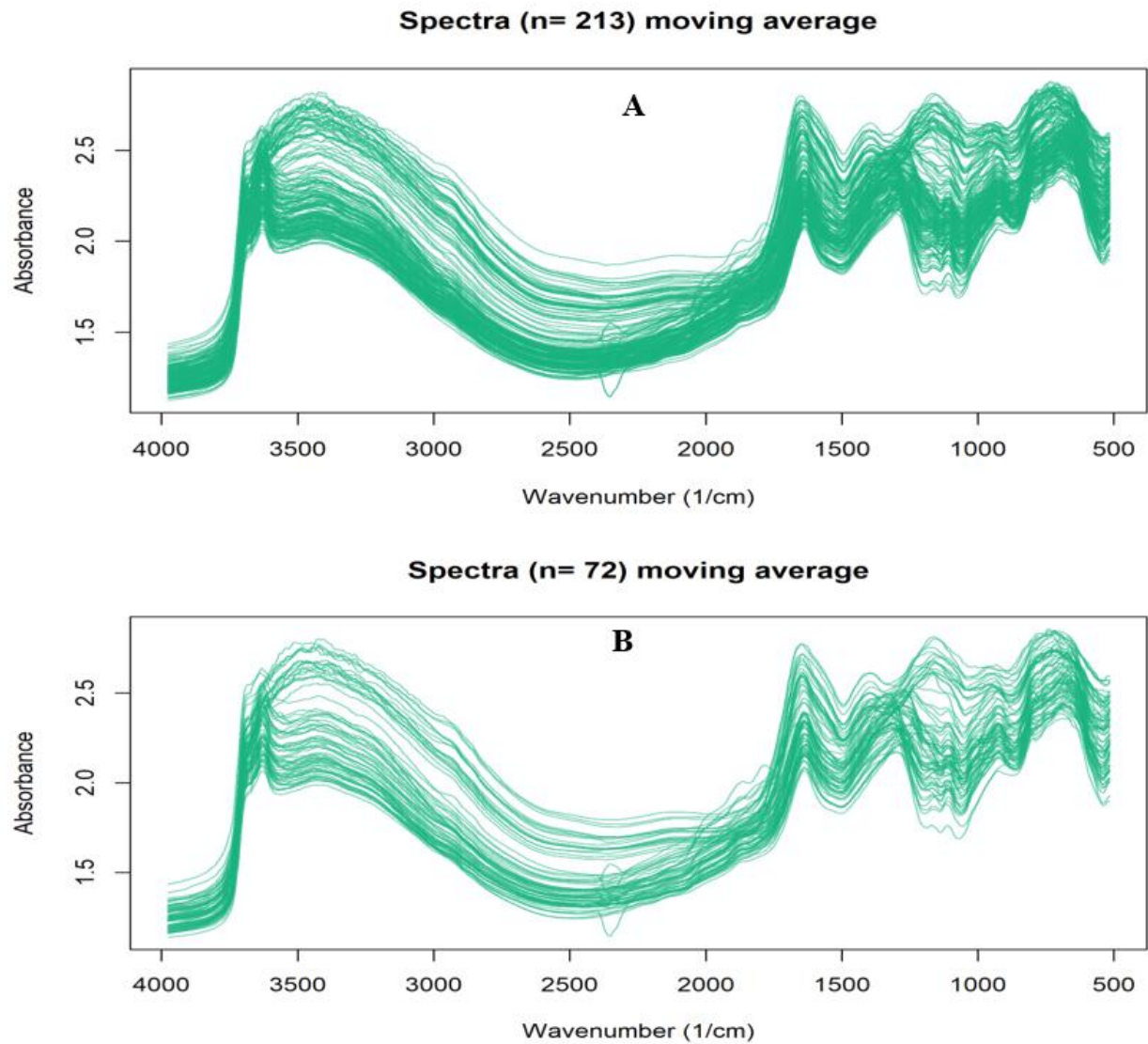


Figure 9: Absorbance spectra (processed by moving average) of the whole soil samples dataset (A), and reference soil dataset (B) in Mid-Infrared Reflectance spectroscopy (MIR) $4000\text{--}500\text{ cm}^{-1}$

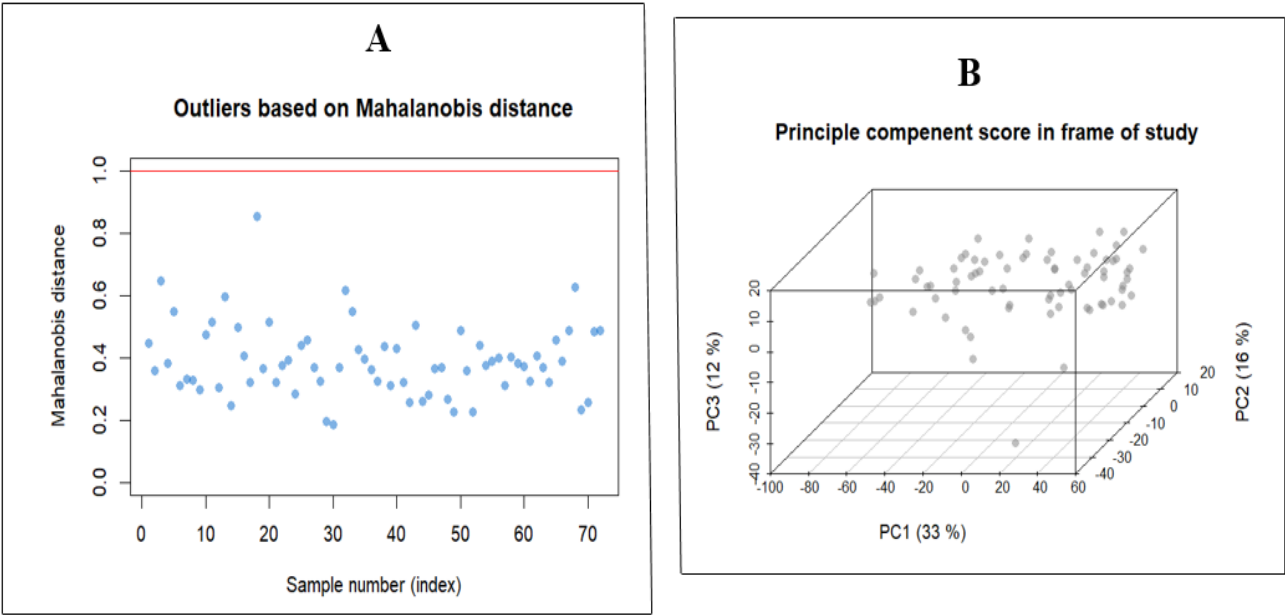


Figure 10: Outliers based on Mahalanobis (6A) and principal component analysis (PCA) showing scores and eigenvectors of the preprocessed MIR spectra (6B) on reference soil data ($n = 72$)

3.3.3 Assessment of 10-fold cross-validation models on PLSR

Only 10-fold cross-validation models for PLSR are included in this part due to their good performance over RF and XGBoost models. PLSR is a widely used, straightforward, and user-friendly multivariate regression technique that has proven to be effective in estimating the physical and chemical characteristics of the soil (Adeline et al., 2017; Sila et al., 2017a; Terhoeven-urselmans et al., 2010). Partial-least-squares regression (PLSR) cross-validation methods were created for each soil attribute using mid infrared spectral data and soil reference data, which made up around 28% of the entire sample. Good cross-validation models for PLSR were observed on total SOC ($R^2 = 0.83$, RMSE = 0.70), total nitrogen ($R^2 = 0.81$, RMSE = 0.06), clay contents ($R^2 = 0.77$, RMSE = 5.20) and bulk density ($R^2 = 0.71$, RMSE = 0.15) according to the classification selected for the appraisal of the predictive models. In general, satisfactory to good models ($0.56 \leq R^2 \leq 0.97$) were recorded for bulk density, total nitrogen, total SOC, SOC stock, and clay contents. The rest of soil properties were predicted with low cross-validation metrics ($R^2 < 0.56$) as shown in (Table 2). Overall, the range of R^2 values observed in this study is comparable to other studies (Johnson et al., 2019; Soriano-disla et al., 2017; Terhoeven-urselmans et al., 2010; Viscarra Rossel et al., 2016). Despite soil samples being collected from different agricultural fields (soil types), PLSR models in our findings obtained good metrics which implies that PLSR models can accurately represent the variability across diverse

soil types (Shi et al., 2023). Nevertheless, Shi et al. (2023) identified soil organic matter (SOM) as the primary factor affecting spectral soil BD models and a good prediction in SOC can lead to better prediction in bulk density. A good model performance of clay content could be explained by the idea that these soil properties are labelled as first order predictions as it is directly visible by diffuse reflectance spectroscopy (Johnson et al., 2019).

The observed cross-validation metrics in soil pH_{H2O} 1:2.5 ($R^2 = 0.25$, RMSE = 0.65) was the lowest model accuracy recorded in MIR - PLSR modelling. Our result is similar to the one documented by Terra et al. (2015) who recorded low prediction accuracy since pH is denoted as a second order prediction, but also different from (J. M. Johnson et al., 2019; Sila et al., 2017b; Terhoeven-urselmans et al., 2010) who both reported a good R^2 result on pH. Poor prediction in silt and sand contents could be related to the reason that texture is usually not constant over a certain agricultural field, and varies in space and with soil depths as documented by Augusto et al. (2020).

3.3.4 Comparison of 10-fold cross-validation prediction statistics of various soil properties using PLSR, RF and XGBoost models from first derivative MIR spectra

PLSR, RF and XGBoost prediction models were employed to estimate various soil properties on soil samples collected from Mbeya. Our results underlined a better prediction performance in PLSR models compared to RF and XGBoost models (Table 11) in all investigated soil properties except pH, silt and sand. A better performance of PLSR models over random forests (RF) and XGBoost in predicting soil properties like soil organic carbon (SOC), total nitrogen, bulk density (BD), and clay content is due to ability of PLSR to handle collinear and high-dimensional data, like spectral inputs from soil analysis (Thabit et al., 2024; Wold et al., 2001). PLSR concentrates on pertinent predictors and efficiently utilizing linear relationships. Nevertheless, PLSR lowers noise and dimensionality. On the other hand, RF and XGBoost perform well on more intricate, nonlinear patterns, but they could overfit datasets that are smaller or less varied. According to studies, the simplicity of PLSR frequently results in reliable, understandable forecasts for soil properties. Our findings are also in line with earlier research by J. Yang et al. (2023), which found that PLSR performs well on small to moderately sized datasets, whereas RF and XGBoost may struggle to generalize on these types of datasets due to their reliance on more complex decision-making and susceptibility to overfitting when there is insufficient data diversity.

Table 11: A 10-fold cross-validation results of MIR spectroscopy on PLSR, RF and XGBoost models

Soil properties			PLSR		RF		XGBoost	
	Unit	n	R ²	RMSE	R ²	RMSE	R ²	RMSE
pH water (1:2.5)	-	62	0.25	0.65	0.17	0.24	0.18	0.35
Bulk density	g/cm ³	62	0.71	0.15	0.64	0.30	0.59	0.17
Clay	%	62	0.77	5.20	0.71	5.8	0.62	6.76
Silt	%	62	0.33	10.15	0.28	9.65	0.24	11.07
Sand	%	62	0.50	14.03	0.47	14.05	0.39	15.28
Total N	%	62	0.81	0.06	0.73	0.06	0.67	0.07
Total SOC	%	62	0.83	0.70	0.78	0.79	0.66	0.98
SOC stock	Mg C/Ha	62	0.62	10.87	0.53	12.18	0.46	12.93
SOC stock								

3.3.5 External validation model performance on PLSR, RF and XGBoost

Some of external validation models provided average performance, this could be associated with small number of soil samples undertaken in this study for external validation. PLSR model provided a satisfactory result on Sand ($R^2 = 0.60$, $RMSE = 11.59$) and Silt ($R^2 = 0.54$, $RMSE = 7.18$). These findings imply that the PLSR model was able to create moderate correlations between spectral data and the components of soil texture (sand and silt), even with the limited sample size as previously reported by Nocita et al. (2014 and Stenberg et al. (2010). External validation models for bulk density, pH, clay, total nitrogen, total SOC and SOC stocks were all found to have poor performance (R^2 ranging from 0.37 to 0.01). This scenario could be explained by the limited number of soil samples in the study, nevertheless, these small datasets frequently makes the models less representative, by failing to capture the diversity in soil characteristics including texture, mineralogy, and organic content (Barra et al., 2023). This in turn results in predictions that are skewed or

untrustworthy as reported by Viscarra Rossel et al., (2006) and McBratney et al., (2003). According to Grinand et al., (2008), making strong predictions regarding soil properties is hampered by small datasets, which frequently lead to weaker correlations and less accurate parameter estimates.

4.3.6 Predictions of soil properties of agricultural soils by PLSR- MIR techniques.

RF had a good validation models on bulk density ($R^2 = 0.79$, RMSE = 0.10) and satisfactory validation model on clay contents ($R^2 = 0.64$, RMSE = 4.66). Similar result were observed by (Wadouxx B. et al. (2021) indicating an excellent association of RF on different soil properties to reach an R^2 of 0.77 for bulk density predictions. Other soil properties were, including SOC, total nitrogen and SOC stock showed a poor validation models. Wadouxx B et al. (2021) pointed out that while ensemble models such as RF work well for simpler soil characteristics, they have trouble capturing the intricacies and interconnections of SOC and TN. XGBoost had an average validation models on bulk density ($R^2 = 0.69$, RMSE = 0.13) and clay contents ($R^2 = 0.65$, RMSE = 5.04) while other soil properties in this study showed a poor result. According to (Padarian et al. (2020), XGBoost did well in predicting texture and bulk density, but because biological processes interact in a complicated way, its accuracy declined for SOC. Poor validation model recorded for total nitrogen and total SOC using XGBoost was also reported by Hengl et al. (2021) who pointed out that predicting SOC and TN necessitates integrating a variety of variables, such as climate, vegetation indices, and terrain models. External validation models discussed are all attached in the (supplementary materials).

Based on the best prediction models (n = 141) dataset, a PCA of all soil samples was forecasted in order to evaluate the trends of the soil attributes in the chosen agricultural areas in the Southern part of Tanzania. The dataset's intricate structure is demonstrated by this PCA, which shows that the two main principle components explained 61% of the variation. The descriptive data of the anticipated soil samples from four distinct sites in the Southern part of Tanzania are summarized in (Table 12). Most soil parameters had a non-normal distribution characterized by positive skewness, with the exception of clay content, pH, silt and bulk density (Table 12). Similar case was documented by Viscarra Rossel et al. (2006) who reported minor enhancements in the predictions of clay, silt, and sand utilizing data from the integrated VIS–NIR–MIR spectra. Excluding soil pH_{water} , the majority of soil variables exhibited moderate to high variability (CV = 17-72%) (

). Low CV observed in pH could be explained by fact that both soil samples collected from different agricultural sites where associated with almost similar fertilizer applications, cropping systems, management practices, irrigation methods and pesticide applications (Fageria & Baligar, 2008; Gikonyo et al., 2022; Lal, 2015).

Table 12: Descriptive statistics of the predicted soil fertility for the whole set of samples ($n = 128$) using PLSR on MIR spectra

Soil properties	Soil depth (cm)	Descriptive statistics									
		n	Mean	Std Error	Std Dev	Kurtosis	Skewness	Range	Min	Max	CV (%)
pH	0 - 20	67	6.12	0.03	0.28	0.53	0.08	1.63	5.30	6.93	4.53
	20 - 50	61	6.16	0.03	0.27	2.31	-0.03	1.78	5.30	7.08	4.42
BD (g/cm ³)	0 - 20	67	1.08	0.02	0.20	-0.53	-0.59	0.83	0.65	1.48	18.23
	20 - 50	61	1.13	0.03	0.20	0.10	-0.95	0.81	0.67	1.48	17.77
Clay (%)	0 - 20	67	18.22	0.79	8.07	-0.85	-0.03	36.44	-0.58	35.86	44.27
	20 - 50	61	19.82	1.04	8.11	-0.88	-0.16	30.93	3.08	34.00	40.93
Silt (%)	0 - 20	67	39.61	0.67	6.85	-0.10	0.45	31.51	27.92	59.44	17.30
	20 - 50	61	39.78	0.97	7.59	-0.67	0.25	31.06	24.63	55.70	19.09
Sand (%)	0 - 20	67	40.39	1.27	13.04	-1.26	-0.18	49.68	11.98	61.66	32.29
	20 - 50	61	39.88	1.71	13.32	-1.18	0.03	50.13	14.26	64.39	33.41
Total [SOC]%	0 - 20	67	1.91	0.11	1.12	0.05	1.10	4.41	0.43	4.84	58.89
	20 - 50	61	1.55	0.14	1.12	1.02	1.49	4.20	0.38	4.58	72.43
Total [N]%	0 - 20	67	0.16	0.01	0.09	-0.44	0.91	0.33	0.04	0.37	55.48
	20 - 50	61	0.13	0.01	0.09	0.47	1.28	0.33	0.04	0.37	65.54

3.3.6 Applicability of the models

PLSR typically produced the best forecasts compared to RF and XGBoost models and the range of expected soil parameters includes the values reported in different literatures for agricultural soils. The total SOC, SOC stock, total nitrogen, bulk density, clay, silt and sand contents in soil samples taken at 0 – 50 cm depth could be predicted using the models created here especially in agricultural sites. Various studies should be carried out for soils under various land uses (planted pastures, coffee, cocoa etc.), to predict more soil properties as the models created in this work only included soil samples which were mostly dominated by maize, onions and rice agricultural fields. The PLSR models developed in this work could be used to predict several soil fertilities in the agricultural fields because 10-fold cross-validation models resulted in more accurate predictions as stated previously by Guio Blanco et al. (2018). MIR spectroscopy exhibited great promise as a method for quickly evaluating such soil properties in addition to cutting down on the time and quantity of chemical waste produced by traditional laboratory analyses especially for large sample dataset, even though site variations in soil type may necessitate localized modelling in different agricultural sites with varying soil types.

4.0 CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

The study offers an understanding of the agricultural environment of small-scale farmers in Tanzania. Above 70% of the surveyed population, demonstrated a lack of understanding regarding IAPs. Nevertheless, more than 80% of the surveyed population had no information regarding the specific soil type linked with their farmland. This highlights a crucial knowledge gap that has to be addressed by the government. The findings on demographic trends indicate that men, namely in the age range of 25-34, who have attained primary or secondary school, are more inclined to participate in agricultural activities. The implementation of management practices, such as the use of chemicals and the spraying of herbicides, differs among districts, indicating the impact of site factors. While extension service officers are acknowledged as a primary source of knowledge for smallholder farmers, the quality of service they deliver remains inadequate. This strongly underlines the need for the government to expand its programs in order to significantly enhance farmers' productivity. The probit regression analysis shows several significant predictors of IAPs adoption, such as marital status, farming period, flooding exposure, top dressing with inorganic fertilizer, fallowing time, soil

information, and soil type. Therefore, it is essential for government policies to take into account the aforementioned predictors in order to improve the productivity of small-scale farmers in the area under study. Our findings also revealed that female-headed households (59%) possess much more comprehensive soil information on IAPs, suggesting that women possess knowledge of enhanced farming practices to a greater extent than males. Based on our research, we have determined that smallholder farmers can successfully implement improved agricultural practices (IAPs) by taking into account both on-farm and off-farm factors. Our findings highlight the need for increased extension services specifically targeted towards the Kyela and Tukuyu areas, as farmers in these regions are not fully aware of the benefits of IAPs.

Based on objective two, it was observed that soil type and soil depths have a significant influence on soil physico-chemical properties, especially SOC contents. Silt loam and loam were the predominant soil textures in the studied sites. A strong positive correlations were observed between SOC and nitrogen concentrations, as well as a negative correlation between SOC with bulk density. The study also highlighted the influence of soil physical and chemical properties, such as clay content, sand, silt, and pH, on SOC distribution.

Our work also demonstrated the potential of Mid Infrared Reflectance (MIR) spectroscopy on objective three to predict soil properties through PLSR, RF, XGBoost models. Moving average preprocessing techniques were utilized to produce precise predictions of the mentioned soil parameters. Although most of soil parameters used for modelling (reference soil data) were not normal distributed, they still showed a positive skewness. Both RF, PLSR and XGBoost models were able to predict selected soil properties, however PLSR models had an overall better performance in cross-validation and external validation metrics followed by RF and XGBoost in most of soil properties (bulk density, total SOC, total Nitrogen, clay contents). Despite of few soil samples collected, yet our result demonstrates a potential application of different modelling techniques on MIR spectra data to predict various soil properties in agricultural sites. Subsequent research will expand upon this study by integrating spatial environmental variables and incorporating additional soil samples into the modelling framework.

4.2 Recommendations

- Although the study estimated the factors controlling awareness, linkage and adoption of smallholder farmers to IAPs, yet our study suggests that agricultural extension services, NGOs, and research institutions should collaboratively work together to improve the efficient spread of information, increase awareness, and promote the use of advanced agricultural methods to improve the livelihoods of smallholder farmers in Tanzania. This can be achieved by focusing on education, policy assistance, and specific interventions that address the unique needs of farming communities.
- Despite many policies performed by the government to help smallholder farmers gain access to IAPs, our research findings highlighted extension services as the key information provider to farmers. Nevertheless, the study emphasizes the necessity of implementing specific policies to encourage the adoption of enhanced agricultural practices (IAPs). Policymakers in the Southern part of Tanzania should prioritize implementing strategies to improve access to agricultural extension services, specifically in regards to the dissemination of information regarding soil conditions.
- Our study demonstrates that SOC contents are dependent on soil type. This work suggests understanding site-specific variations in SOC distribution is crucial to increase SOC contents and stocks in a particular agricultural site in the selected sites. This could be implemented by adoption of sustainable agricultural practices including organic matter management and crop selection is encouraged to improve soil organic carbon in the region. Our study underpins soil type as the core determinant of SOC in the studied sites, yet more research work should focus to investigate the influence of other factors including climate, crop type, depth, altitude, agricultural practices, management practices, forming factors and forming processes.
- Although this work provided a better prediction of SOC and other selected soil properties based on small sample size by PLSR and RF methods. The study suggests a subsequent modelling should expand upon this finding by involving large number of soil samples and integrating spatial environmental variables into the chemometric modelling framework.
- Our research work documented the social factors controlling farmer's adoption to IAPs and on the other hand the key factor that determines the level of distribution of SOC contents in the selected agricultural sites. Further research could improve our study by modelling social

factors with more soil parameters including biological parameters and identifying the major combination associated with high and/or low SOC contents.

5. NEW SCIENTIFIC RESULTS

1. This study confirmed that, in cases involving a limited number of samples, Partial Least Squares Regression (PLSR) can outperform more complex machine learning models in predicting soil properties. Contrary to the prevailing trend, where algorithms such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost) typically demonstrate superior performance in mid-infrared (MIR) spectroscopy-based predictions of soil organic carbon (SOC), nitrogen, and soil texture, PLSR delivered more robust and reliable models in this context.
2. A complementary socio-economic survey conducted among smallholder farmers in the Southern part of Tanzania identified several factors that significantly influence the adoption of Improved Agricultural Practices (IAPs). Key determinants included farming experience, frequency of flooding, use of inorganic fertilizers for top dressing, fallowing duration, access to soil information, self-reported awareness of soil type, and, unexpectedly, marital status. Despite the potential benefits of IAPs, the survey revealed that only 25% of farmers were aware of these practices, and approximately 65% reported having no interaction with agricultural extension officers. These findings suggest that social and informational barriers are major constraints to the diffusion of sustainable farming practices in the region. These relationships were revealed through the application of a Linear Mixed Effects Model (LMEM), a statistical modelling technique.
3. This study established a regional spectral library for the Southern part of Tanzania, along with the development of a comprehensive framework linking soil information, extension services, and farmer adoption for improved yields.
4. This study was the first to apply the Vario MAX Cube CNS elemental analyzer and a laser-diffraction particle size analyzer in the Southern part of Tanzania for agricultural soil analysis. The successful application of these technologies establishes and proposes new standard methods for SOC analysis via combustion and for soil texture determination using laser diffraction in agricultural soil studies.

6. LIST OF PUBLICATIONS

1. **Justine, P. N.**, Csorba, Á., Ocansey, C.M. *et al.* Awareness and adoption strategies for improved agricultural practices (IAPs) by smallholder farmers in the Mbeya Region, Tanzania. *Discov Sustain* 6, 198 (2025). <https://doi.org/10.1007/s43621-025-00970-y> (Q1)
2. Rotich, B., Maket, I., Kipkulei, H. K. Ocansey, C.M., **Justine, P.N.**, MohammedZein, M.A., Csorba, Á., & Michéli, E. (2024). Determinants of soil and water conservation practices adoption by smallholder farmers in the Central Highlands of Kenya. *Farming System*. <https://doi.org/10.1016/j.farsys.2024.100081>. (Q1)
3. Mohammedzein, M. A., Csorba, A., Rotich, B., **Justin, P. N.**, Melenya, C., Andrei, Y., & Micheli, E. (2023). Development of Hungarian spectral library: Prediction of soil properties and applications. *Eurasian Journal of Soil Science*, 12(3), 244-256. <https://doi.org/10.18393/ejss.1275149>. (Q3).
4. Mohammedzein, M. A., Csorba, A., Rotich, B., **Justin, P. N.**, Mohamed, H. T., & Micheli, E. (2023). Prediction of some selected soil properties using the Hungarian Mid-infrared spectral library. *Eurasian Journal of Soil Science*, 12(4), 300-309. <https://doi.org/10.18393/ejss.1309753> (Q3).
5. MohammedZein, M. A., Micheli, E., Rotich, B., **Justine, P. N.**, Ahmed, A. E. E., Tharwat, H., & Csorba, Á. (2023). Rapid Detection of Soil Texture Attribute based on Mid-Infrared Spectral Library in Salt Affected Soils of Hungary. *Hungarian Agricultural Engineering*, 42, 5–13. <https://www.doi.org/10.17676/HAE.2023.42.5>.
6. Lameck, A. S., Saeed, O., **Justine, P. N.**, Mwakagile, D., Akos, P., & Boros, E. (2024). Hydrochemical properties and heavy metal concentrations (ecological and human risk) of lake Rukwa. *Environmental Challenges*, 15(March), 100940. <https://doi.org/10.1016/j.envc.2024.100940> (Q1)
7. Simon, B., Boziné Pullai, K., Selmeczi, D., Sebök, A., Tóthné Bogdányi, F., Weldmichael, T. G., **Justine, P. N.**, ... & Tóth, F. (2022). Green corridors may sustain habitats for

earthworms in a partially converted grassland. *Agronomy*, 12(4), 793.

<https://doi.org/10.3390/agronomy12040793> (Q1)

8. Stephano, A., Mnyawi, S. R., **Justine, P. N.**, & Lufingo, M. (2022). Major ions and Nutrients loading by atmospheric wet deposition in Mbeya Urban, Tanzania.
<https://doi.org/10.21203/rs.3.rs-1933223/v1>
9. **Justine, P. N.**, Csorba, A., & Micheli, E. (2022). A Review on Irrigation Techniques and their Performance in Tanzania Agricultural Sector. *5th International Scientific Conference on Water*: Szarvas, Hungary.

BIBLIOGRAPHY

Abdul-Majid, M., Zahari, S. A., Othman, N., & Nadzri, S. (2024). Influence of technology adoption on farmers' well-being: Systematic literature review and bibliometric analysis.

Heliyon, 10(2), e24316. <https://doi.org/10.1016/j.heliyon.2024.e24316>

Abraham Savitzky and Marcel Golay. (1964). Smoothing and Differentiation of by Simplified Least Squares Pro, Cedures. *Analytical Chemistry*, 36(8), 1639–1643.

<https://doi.org/10.1021/ac60214a048>

Adeline, K. R. M., Gomez, C., Gorretta, N., & Roger, J. M. (2017). Predictive ability of soil properties to spectral degradation from laboratory Vis-NIR spectroscopy data. *Geoderma*, 288, 143–153. <https://doi.org/10.1016/j.geoderma.2016.11.010>

Adiyah, F., Michéli, E., Csorba, A., Gebremeskel Weldmichael, T., Gyuricza, C., Ocansey, C. M., Dawoe, E., Owusu, S., & Fuchs, M. (2022). Effects of landuse change and topography on the quantity and distribution of soil organic carbon stocks on Acrisol catenas in tropical small-scale shade cocoa systems of the Ashanti region of Ghana. *Catena*, 216(May).

<https://doi.org/10.1016/j.catena.2022.106366>

- Agunga, R., Sanga, C. A., & Isaya, E. (2018). Empowering Women Farmers in Tanzania Through Communication for Development. *World Journal of Social Science*, 5(2), 8.
<https://doi.org/10.5430/wjss.v5n2p8>
- Ahmad, M. I., & Ma, H. (2020). Climate change and livelihood vulnerability in mixed crop-livestock areas: The case of Province Punjab, Pakistan. *Sustainability (Switzerland)*, 12(2), 12–16. <https://doi.org/10.3390/su12020586>
- Akida I. Meya, Patrick A. Ndakidemi, Kelvin M. Mtei, Rony Swennen, R. M. (2020). Optimizing Soil Fertility Management Strategies to Enhance Banana Production in Volcanic Soils of the. *Agronomy*.
- Akinde, B. P., Olakayode, A. O., Oyedele, D. J., & Tijani, F. O. (2020). Selected physical and chemical properties of soil under different agricultural land-use types in Ile-Ife, Nigeria. *Heliyon*, 6(9), e05090. <https://doi.org/10.1016/j.heliyon.2020.e05090>
- Alavaisha, E., Manzoni, S., & Lindborg, R. (2019). Different agricultural practices affect soil carbon, nitrogen and phosphorous in Kilombero -Tanzania. *Journal of Environmental Management*, 234(January), 159–166. <https://doi.org/10.1016/j.jenvman.2018.12.039>
- Alavaisha, E., Tumbo, M., Senyangwa, J., & Mourice, S. (2022). Influence of Water Management Farming Practices on Soil Organic Carbon and Nutrients: A Case Study of Rice Farming in Kilombero Valley, Tanzania. *Agronomy*, 12(5). <https://doi.org/10.3390/agronomy12051148>
- Alphonse, R. (2017). Ending rural hunger: The Case of Tanzania. *Africa Growth Initiative at Brookings*, 51.
https://assets.ctfassets.net/5faekfvmlu40/ZV2xshpSScu6Ym0iakqCG/b54fbc84169d77f8f203025fecc37fc5/Tanzania_ERH_FINAL_v1.pdf
- Aman, R., Nyanda, S., & Massawe, G. (2024). *Factors Influence the Adoption of Improved Agricultural Practices among Smallholder Farmers in the Ripat Program : A Case of Morogoro*. 24(11), 491–502.
- Anania, A. S., Malongo, R. S., & Vang, M. (2020). *Assessment of livelihoods of smallholder pig keepers in Mbeya rural and Mbozi districts , Mbeya region , Tanzania*. 3(2014), 260–267.
- Anantha, K. H., Garg, K. K., Barron, J., Dixit, S., Venkataradha, A., Singh, R., & Whitbread, A. M. (2021). Impact of best management practices on sustainable crop production and climate resilience in smallholder farming systems of South Asia. *Agricultural Systems*, 194, 103276. <https://doi.org/10.1016/j.agsy.2021.103276>

- Anderson, J., Leach, C. E., & Gardner, S. T. (2016). National Survey and Segmentation of Smallholder Households in Bangladesh: Understanding Their Demand for Financial, agricultural and digital solutions. *CGAP Working Paper, April*, 101.
- Angelopoulou, T., Balafoutis, A., Zalidis, G., & Bochtis, D. (2020). From laboratory to proximal sensing spectroscopy for soil organic carbon estimation-A review. *Sustainability (Switzerland)*, *12*(2), 1–24. <https://doi.org/10.3390/su12020443>
- Ardoin, N. M., Bowers, A. W., & Gaillard, E. (2020). Environmental education outcomes for conservation: A systematic review. *Biological Conservation*, *241*(April 2019), 108224. <https://doi.org/10.1016/j.biocon.2019.108224>
- Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, *69*, 68–81. <https://doi.org/10.1016/j.foodpol.2017.03.005>
- Ashrit, R. R., & Joshi, S. (2024). Farmer’s understanding and adoption of agricultural practices in southern part of India. *Discover Agriculture*, *2*(1). <https://doi.org/10.1007/s44279-024-00017-2>
- Asiedu – Darko, E. (2014). Farmers’ Perception on Agricultural Technologies a Case of Some Improved Crop Varieties in Ghana. *Agriculture, Forestry and Fisheries*, *3*(1), 13. <https://doi.org/10.11648/j.aff.20140301.13>
- Asrat, T. G., Sakrabani, R., Corstanje, R., Breure, T., Hassall, K. L., Kebede, F., & Haefele, S. M. (2023). Spectral soil analysis for fertilizer recommendations by coupling with QUEFTS for maize in East Africa: A sensitivity analysis. *Geoderma*, *432*(November 2022), 116397. <https://doi.org/10.1016/j.geoderma.2023.116397>
- Atari, D. O. A., Yiridoe, E. K., Smale, S., & Duinker, P. N. (2009). What motivates farmers to participate in the Nova Scotia environmental farm plan program? Evidence and environmental policy implications. *Journal of Environmental Management*, *90*(2), 1269–1279. <https://doi.org/10.1016/j.jenvman.2008.07.006>
- Augusto, J., Giasson, É., Demattê, J. A. M., Carnieletto, A., Janderson, J., Costa, F., & Va, R. (2020). *Catena Prediction of soil texture classes through different wavelength regions of reflectance spectroscopy at various soil depths*. *189*(July 2019). <https://doi.org/10.1016/j.catena.2020.104485>
- Baiyegunhi, L. J. S., Akinbosoye, F., & Bello, L. O. (2022). Welfare impact of improved maize

- varieties adoption and crop diversification practices among smallholder maize farmers in Ogun State, Nigeria. *Heliyon*, 8(5), e09338. <https://doi.org/10.1016/j.heliyon.2022.e09338>
- Balkovič, J., Madaras, M., Skalský, R., Folberth, C., Smatanová, M., Schmid, E., van der Velde, M., Kraxner, F., & Obersteiner, M. (2020). Verifiable soil organic carbon modelling to facilitate regional reporting of cropland carbon change: A test case in the Czech Republic. *Journal of Environmental Management*, 274. <https://doi.org/10.1016/j.jenvman.2020.111206>
- Baloch, M. A., & Thapa, G. B. (2019). Review of the agricultural extension modes and services with the focus to Balochistan, Pakistan. *Journal of the Saudi Society of Agricultural Sciences*, 18(2), 188–194. <https://doi.org/10.1016/j.jssas.2017.05.001>
- Banjarnahor, D., Kristen, U., & Wacana, S. (2015). *Adoption and adaptation of conservation agriculture in Tanzanian southern highlands Adoption and adaptation of conservation agriculture in Tanzanian southern highlands : lessons learned from Mshewe ward Mbeya region*. June. <https://doi.org/10.13140/RG.2.1.5139.4726>
- Barra, I., El Moatassef, T., & Kebede, F. (2023). Soil Particle Size Thresholds in Soil Spectroscopy and Its Effect on the Multivariate Models for the Analysis of Soil Properties. *Sensors*, 23(22). <https://doi.org/10.3390/s23229171>
- Bartoń, K. (2024). *MuMIn: Multi-Model Inference*. R package version 1.48.4.
- Bationo, A., Kihara, J., Vanlauwe, B., Waswa, B., & Kimetu, J. (2007). Soil organic carbon dynamics, functions and management in West African agro-ecosystems. *Agricultural Systems*, 94(1), 13–25. <https://doi.org/10.1016/j.agsy.2005.08.011>
- Batjes, N. H. (1996). Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science*, 47(June), 151–163. <https://doi.org/10.2134/agronmonogr9.2.c38>
- Bauer, P. J., Frederick, J. R., & Busscher, W. J. (2002). Tillage effect on nutrient stratification in narrow- and wide-row cropping systems. *Soil and Tillage Research*, 66(2), 175–182. [https://doi.org/10.1016/S0167-1987\(02\)00025-9](https://doi.org/10.1016/S0167-1987(02)00025-9)
- Behrman, Julia & Beintema, Nienke & Biermayr-Jenzano, Patricia & Meinzen-Dick, Ruth & Noordeloos, Marco & Quisumbing, Agnes & Ragasa, C. & W., & 重庆市设计院. (2011). *Engendering agricultural research, development, and extension: Research reports* ruthmeitzen-dick, International Food Policy Research Institute (IFPRI). *הגות עליון*, 66(July), 6–17.
- Ben-Dor, E., & Banin, A. (1995). Near-Infrared Analysis as a Rapid Method to Simultaneously

- Evaluate Several Soil Properties. *Soil Science Society of America Journal*, 59(2), 364–372.
<https://doi.org/10.2136/sssaj1995.03615995005900020014x>
- Benefoh, D. T. (2018). *Assessing land-use dynamics in a Ghanaian cocoa landscape*. 1–182.
<https://bonndoc.ulb.uni-bonn.de/xmlui/handle/20.500.11811/7357%0Ahttps://bonndoc.ulb.uni-bonn.de/xmlui/bitstream/handle/20.500.11811/7357/5142.pdf?sequence=1>
- Berg, J. Van den. (2013). Socio-economic factors affecting adoption of improved agricultural practices by small scale farmers in South Africa. *African Journal of Agricultural Research*, 8(35), 4490–4500. <https://doi.org/10.5897/ajar12.1025>
- Blanco-Canqui, H., & Ruis, S. J. (2018). No-tillage and soil physical environment. *Geoderma*, 326(April), 164–200. <https://doi.org/10.1016/j.geoderma.2018.03.011>
- Blummel, M. (2013). looking for Opportunities from Second Generation Bio-fuel Technologies for Upgrading lignocellulosic Biomass for livestock Feed. *Deconstruction of Lignocellulosic Feeds*.
- Bogunovic, I., Pereira, P., Kisic, I., Sajko, K., & Sraka, M. (2018). Tillage management impacts on soil compaction, erosion and crop yield in Stagnosols (Croatia). *Catena*, 160(June 2017), 376–384. <https://doi.org/10.1016/j.catena.2017.10.009>
- Bowers, S. A., & Hanks, R. J. (1965). Reflection of radiant energy from soils. *Soil Science*, 100(2), 130–138. <https://doi.org/10.1097/00010694-196508000-00009>
- Breiman, L. E. O. (2001). *Random Forests*. 5–32.
- Brewer, M. J., & Goodell, P. B. (n.d.). *Approaches and Incentives to Implement Integrated Pest Management that Addresses Regional and Environmental Issues*.
<https://doi.org/10.1146/annurev-ento-120709-144748>
- Brown, V. A. (2021). An Introduction to Linear Mixed-Effects Modeling in R. *Advances in Methods and Practices in Psychological Science*, 4(1).
<https://doi.org/10.1177/2515245920960351>
- Brunet, D., Barthès, B. G., Chotte, J. L., & Feller, C. (2007). Determination of carbon and nitrogen contents in Alfisols, Oxisols and Ultisols from Africa and Brazil using NIRS analysis: Effects of sample grinding and set heterogeneity. *Geoderma*, 139(1–2), 106–117.
<https://doi.org/10.1016/j.geoderma.2007.01.007>
- Burton, L., Jayachandran, K., & Bhansali, S. (2020). Review—The “Real-Time” Revolution for In

- situ Soil Nutrient Sensing. *Journal of The Electrochemical Society*, 167(3), 037569.
<https://doi.org/10.1149/1945-7111/ab6f5d>
- Burton, R. J. F. (2014). The influence of farmer demographic characteristics on environmental behaviour: A review. *Journal of Environmental Management*, 135, 19–26.
<https://doi.org/10.1016/j.jenvman.2013.12.005>
- Buscemi, S., & Plaia, A. (2020). Model selection in linear mixed-effect models. *AStA Advances in Statistical Analysis*, 104(4), 529–575. <https://doi.org/10.1007/s10182-019-00359-z>
- Cai, A., Feng, W., Zhang, W., & Xu, M. (2016). Climate, soil texture, and soil types affect the contributions of fine-fraction-stabilized carbon to total soil organic carbon in different land uses across China. *Journal of Environmental Management*, 172, 2–9.
<https://doi.org/10.1016/j.jenvman.2016.02.009>
- Cambou, A., Cardinael, R., Kouakoua, E., Villeneuve, M., Durand, C., & Barthès, B. G. (2016). Geoderma Prediction of soil organic carbon stock using visible and near infrared reflectance spectroscopy (VNIRS) in the field. *Geoderma*, 261, 151–159.
<https://doi.org/10.1016/j.geoderma.2015.07.007>
- Capetz, M., Padilha, R., Olsen, P., Wolk, J., & Chandra, R. (n.d.). *Enabling Adoption of Regenerative Agriculture through Soil Carbon Copilots*. 2022.
- Cargele Nduwamungu, Noura Ziadi, Leon Etienne Parent, and G. F. T. (2009). *Mehlich 3 extractable nutrients as determined by near-infrared reflectance spectroscopy*. D.
- Chalise, K. S., Singh, S., Wegner, B. R., Kumar, S., Pérez-Gutiérrez, J. D., Osborne, S. L., Nleya, T., Guzman, J., & Rohila, J. S. (2019). Cover crops and returning residue impact on soil organic carbon, bulk density, penetration resistance, water retention, infiltration, and soybean yield. *Agronomy Journal*, 111(1), 99–108. <https://doi.org/10.2134/agronj2018.03.0213>
- Chang, C.-W., Laird, D. A., Mausbach, M. J., & Hurburgh, C. R. (2001). Near-Infrared Reflectance Spectroscopy–Principal Components Regression Analyses of Soil Properties. *Soil Science Society of America Journal*, 65(2), 480–490.
<https://doi.org/10.2136/sssaj2001.652480x>
- Chen, H., Tan, C., & Lin, Z. (2025). Application of subspace ensemble radical basis function networks to quantitative analysis of near-infrared and mid-infrared spectroscopy. *Microchemical Journal*, 212, 113354.
<https://doi.org/https://doi.org/10.1016/j.microc.2025.113354>

- Christopher, A. M., & Helena, E. M. (2018). Survival strategies and livelihood diversification of Ileje Migrants in Mbozi District, Southern Tanzania. *Journal of African Studies and Development*, 10(4), 43–50. <https://doi.org/10.5897/jasd2018.0490>
- Christy, C. D. (2008). Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy. *Computers and Electronics in Agriculture*, 61(1), 10–19. <https://doi.org/10.1016/j.compag.2007.02.010>
- Chuma, G. B., Mondo, J. M., Ndeko, A. B., Bagula, E. M., Lucungu, P. B., Bora, F. S., Karume, K., Mushagalusa, G. N., Schmitz, S., & Biolders, C. L. (2022). Farmers' knowledge and Practices of Soil Conservation Techniques in Smallholder Farming Systems of Northern Kabare, East of D.R. Congo. *Environmental Challenges*, 7(April). <https://doi.org/10.1016/j.envc.2022.100516>
- Coyne, L., Kendall, H., Hansda, R., Reed, M. S., & Williams, D. J. L. (2021). Identifying economic and societal drivers of engagement in agri-environmental schemes for English dairy producers. *Land Use Policy*, 101(November 2020), 105174. <https://doi.org/10.1016/j.landusepol.2020.105174>
- Dam, R. F., Mehdi, B. B., Burgess, M. S. E., Madramootoo, C. A., Mehuys, G. R., & Callum, I. R. (2005). Soil bulk density and crop yield under eleven consecutive years of corn with different tillage and residue practices in a sandy loam soil in central Canada. *Soil and Tillage Research*, 84(1), 41–53. <https://doi.org/10.1016/j.still.2004.08.006>
- Danso-Abbeam, G., & Baiyegunhi, L. J. S. (2018). Welfare impact of pesticides management practices among smallholder cocoa farmers in Ghana. *Technology in Society*, 54, 10–19. <https://doi.org/10.1016/j.techsoc.2018.01.011>
- Dardenne, P., Sinnaeve, G., & Baeten, V. (2000). Multivariate calibration and chemometrics for near infrared spectroscopy: Which method? *Journal of Near Infrared Spectroscopy*, 8(4), 229–237. <https://doi.org/10.1255/jnirs.283>
- Davis, K., Nkonya, E., Kato, E., Mekonnen, D. A., Odendo, M., Miiro, R., & Nkuba, J. (2012). Impact of Farmer Field Schools on Agricultural Productivity and Poverty in East Africa. *World Development*, 40(2), 402–413. <https://doi.org/10.1016/j.worlddev.2011.05.019>
- Deiss, L., Margenot, A. J., Culman, S. W., & Demyan, M. S. (2020). Tuning support vector machines regression models improves prediction accuracy of soil properties in MIR spectroscopy. *Geoderma*, 365(February 2020), 114227.

- <https://doi.org/10.1016/j.geoderma.2020.114227>
- Derksen-schrock, K., Anderson, C. L., Mary, A., & Gugerty, K. (2011). *Tanzania: Agricultural Sector Overview*. 133, 1–18. <http://10.10.11.7/fulltext/doc-37>
- Dewitte, O., Jones, A., Spaargaren, O., Breuning-Madsen, H., Brossard, M., Dampha, A., Deckers, J., Gallali, T., Hallett, S., Jones, R., Kilasara, M., Le Roux, P., Michéli, E., Montanarella, L., Thiombiano, L., Van Ranst, E., Yemefack, M., & Zougmou, R. (2013). Harmonisation of the soil map of africa at the continental scale. *Geoderma*, 211–212, 138–153. <https://doi.org/10.1016/j.geoderma.2013.07.007>
- Dinham, B. (2003). Growing vegetables in developing countries for local urban populations and export markets: Problems confronting small-scale producers. *Pest Management Science*, 59(5), 575–582. <https://doi.org/10.1002/ps.654>
- Dorel, M., Lakhia, S., Pététin, C., Bouamer, S., & Risède, J. M. (2010). No-till banana planting on crop residue mulch: Effect on soil quality and crop functioning. *Fruits*, 65(2), 55–68. <https://doi.org/10.1051/fruits/20010001>
- Douglas Bates, M., Maechler, B. B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, 67(1), 1–48.
- Du, Y., Wang, X., Zhang, L., Feger, K. H., Popp, J., & Sharpley, A. (2019). Multi-stakeholders' preference for best management practices based on environmental awareness. *Journal of Cleaner Production*, 236. <https://doi.org/10.1016/j.jclepro.2019.117682>
- E. Jeroen Huising & Samuel A. Mesele. (2021). *Soils4Africa Sampling Design* (Issue 869200).
- Emiru, N., & Gebrekidan, H. (2013). Effect of Land Use Changes and Soil Depth on Soil Organic Matter, Total Nitrogen and Available Phosphorus Contents of Soils in Senbat Watershed, Western Ethiopia. *ARPJ: Journal of Agricultural and Biological Science*, 8(3), 206–212. www.arpnjournals.com
- Ewing, P. M., TerAvest, D., Tu, X., & Snapp, S. S. (2021). Accessible, affordable, fine-scale estimates of soil carbon for sustainable management in sub-Saharan Africa. *Soil Science Society of America Journal*, 85(5), 1814–1826. <https://doi.org/10.1002/saj2.20263>
- Fageria, N. K., & Baligar, V. C. (2008). Chapter 7 Ameliorating Soil Acidity of Tropical Oxisols by Liming For Sustainable Crop Production. *Advances in Agronomy*, 99(08), 345–399. [https://doi.org/10.1016/S0065-2113\(08\)00407-0](https://doi.org/10.1016/S0065-2113(08)00407-0)
- FAO. (2011). Save and Grow: A policymaker's guide to the sustainable intensification of

- smallholder crop production. In *Food and Agriculture Organization of the United Nations*. (Vol. 11, Issue 1). http://scioteca.caf.com/bitstream/handle/123456789/1091/RED2017-Eng-8ene.pdf?sequence=12&isAllowed=y%0Ahttp://dx.doi.org/10.1016/j.regsciurbeco.2008.06.005%0Ahttps://www.researchgate.net/publication/305320484_SISTEM_PEMBETUNGAN_TERPUSAT_STRATEGI_MELESTARI
- FAO. (2018). *Climate-Smart Agriculture Successful approaches from different regions*.
- Focken, D., Michael, S., & Mlozi, M. (2004). *Urban agriculture in Tanzania. Issues of sustainability. African Studies Centre. Research Report Number 75*. 195.
- Follett, R. F., & Kimble, J. M. (2009). *Conversion of native*. 53711.
- Food and Agriculture Organization. (2016). State of the World 's Forests. In *Food and Agriculture Organization of the United Nations*.
- Fosu-Mensah, B. Y., Vlek, P. L. G., & MacCarthy, D. S. (2012). Farmers' perception and adaptation to climate change: A case study of Sekyedumase district in Ghana. *Environment, Development and Sustainability, 14*(4), 495–505. <https://doi.org/10.1007/s10668-012-9339-7>
- Franco, J. C. (2020). *Integrated Pest Management: Sustainable Approach to Crop Protection*. August, 1–9. https://doi.org/10.1007/978-3-319-71065-5_84-1
- Frederick, B., Sabula, L., Mruma, S., Mzee, F., Mtoka, E., Masigo, J., Ndunguru, A., & Swai, E. (2020). Maize production manual for smallholder farmers in Tanzania. *International Institute of Tropical Agriculture, 32*.
- Funakawa, S., Yoshida, H., Watanabe, T., Sugihara, S., Kilasara, M., & Kosaki, T. (2012). Soil Fertility Status and Its Determining Factors in Tanzania. *Soil Health and Land Use Management*. <https://doi.org/10.5772/29199>
- Gami, S. K., Lauren, J. G., & Duxbury, J. M. (2009). Influence of soil texture and cultivation on carbon and nitrogen levels in soils of the eastern Indo-Gangetic Plains. *Geoderma, 153*(3–4), 304–311. <https://doi.org/10.1016/j.geoderma.2009.08.003>
- Gao, G., Li, G., Liu, M., Liu, J., Ma, S., Li, D., Liang, X., Wu, M., & Li, Z. (2024). Microbial carbon metabolic activity and bacterial cross-profile network in paddy soils of different fertility. *Applied Soil Ecology, 195*, 105233. <https://doi.org/https://doi.org/10.1016/j.apsoil.2023.105233>
- Geladi, P. (2003). *Chemometrics in spectroscopy . Part 1 . Classical chemometrics*. 58, 767–782.
- George Marechera and Joseph Ndwiga. (2015). This document is discoverable and free to

researchers across the globe due to the work of AgEcon Search . Help ensure our sustainability . **a c t o r s I n f l u e n c i n g P r i c e o f A g r i c u l t u r a l P r o d u c t s a n d S t a b i l i t y C o u n t e .** *AgEcon Search*, 18.

- Gikonyo, F. N., Dong, X., Mosongo, P. S., Guo, K., & Liu, X. (2022). Long-Term Impacts of Different Cropping Patterns on Soil Physico-Chemical Properties and Enzyme Activities in the Low Land Plain of North China. *Agronomy*, *12*(2), 1–18.
<https://doi.org/10.3390/agronomy12020471>
- Gocke, M. I., Guigue, J., Bauke, S. L., Barkusky, D., Baumecker, M., Berns, A. E., Hobbey, E., Honermeier, B., Kögel-Knabner, I., Koszinski, S., Sandhage-Hofmann, A., Schmidhalter, U., Schneider, F., Schweitzer, K., Seidel, S., Siebert, S., Skadell, L. E., Sommer, M., von Tucher, S., ... Amelung, W. (2023). Interactive effects of agricultural management on soil organic carbon accrual: A synthesis of long-term field experiments in Germany. *Geoderma*, *438*, 116616. <https://doi.org/https://doi.org/10.1016/j.geoderma.2023.116616>
- Godlove Mtama, J. (2018). Pedology at Four Representative Sites of Southern Highland Zone of Tanzania. *American Journal of Agriculture and Forestry*, *6*(5), 111.
<https://doi.org/10.11648/j.ajaf.20180605.11>
- Gomez, C., Viscarra Rossel, R. A., & McBratney, A. B. (2008). Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study. *Geoderma*, *146*(3–4), 403–411. <https://doi.org/10.1016/j.geoderma.2008.06.011>
- Grasswitz, T. R. (2019). *Integrated Pest Management (IPM) for Small-Scale Farms in Developed Economies : Challenges and Opportunities*.
- Grinand, C., Arrouays, D., Laroche, B., & Martin, M. P. (2008). Extrapolating regional soil landscapes from an existing soil map: Sampling intensity, validation procedures, and integration of spatial context. *Geoderma*, *143*(1–2), 180–190.
<https://doi.org/10.1016/j.geoderma.2007.11.004>
- Grinand, C., Barthès, B. G., Brunet, D., Kouakoua, E., Arrouays, D., Jolivet, C., Caria, G., & Bernoux, M. (2012). Prediction of soil organic and inorganic carbon contents at a national scale (France) using mid-infrared reflectance spectroscopy (MIRS). *European Journal of Soil Science*, *63*(2), 141–151. <https://doi.org/10.1111/j.1365-2389.2012.01429.x>
- Gruszczyński, S., & Gruszczyński, W. (2022). Assessing the Information Potential of MIR

- Spectral Signatures for Prediction of Multiple Soil Properties Based on Data from the AfSIS Phase I Project. *International Journal of Environmental Research and Public Health*, 19(22). <https://doi.org/10.3390/ijerph192215210>
- Guio Blanco, C. M., Brito Gomez, V. M., Crespo, P., & Ließ, M. (2018). Spatial prediction of soil water retention in a Páramo landscape: Methodological insight into machine learning using random forest. *Geoderma*, 316, 100–114. <https://doi.org/https://doi.org/10.1016/j.geoderma.2017.12.002>
- Haas, J., & Mizaikoff, B. (2016). *Advances in Mid-Infrared Spectroscopy for Chemical Analysis*. 45–68. <https://doi.org/10.1146/annurev-anchem-071015-041507>
- Hamadi Mohamed, S., Michael Msanya, B., Juma Tindwa, H., & Semu, E. (2021). Pedological Characterization and Classification of Selected Soils of Morogoro and Mbeya Regions of Tanzania. *International Journal of Natural Resource Ecology and Management*, 6(2), 79. <https://doi.org/10.11648/j.ijnrem.20210602.17>
- Han, E., Ines, A. V. M., & Koo, J. (2019). Development of a 10-km resolution global soil profile dataset for crop modeling applications. *Environmental Modelling and Software*, 119(May), 70–83. <https://doi.org/10.1016/j.envsoft.2019.05.012>
- Hengl, T., Heuvelink, G. B. M., Kempen, B., Leenaars, J. G. B., Walsh, M. G., Shepherd, K. D., Sila, A., MacMillan, R. A., De Jesus, J. M., Tamene, L., & Tondoh, J. E. (2015). Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. *PLoS ONE*, 10(6), 1–26. <https://doi.org/10.1371/journal.pone.0125814>
- Hengl, T., Miller, M. A. E., Križan, J., Shepherd, K. D., Sila, A., Kilibarda, M., Antonijević, O., Glušica, L., Dobermann, A., Haefele, S. M., McGrath, S. P., Acquah, G. E., Collinson, J., Parente, L., Sheykhmousa, M., Saito, K., Johnson, J. M., Chamberlin, J., Silatsa, F. B. T., ... Crouch, J. (2021). African soil properties and nutrients mapped at 30 m spatial resolution using two-scale ensemble machine learning. *Scientific Reports*, 11(1), 1–18. <https://doi.org/10.1038/s41598-021-85639-y>
- Henry, M., Valentini, R., & Bernoux, M. (2009). Soil carbon stocks in ecoregions of Africa. *Biogeosciences Discussions*, 6(1), 797–823. <http://www.biogeosciences-discuss.net/6/797/2009/>
- Hussain, M., Farooq, S., Merfield, C., & Jabran, K. (2018). Mechanical weed control. In *Non-Chemical Weed Control*. Elsevier Inc. <https://doi.org/10.1016/B978-0-12-809881-3.00008-5>

- Hutengs, C., Seidel, M., Oertel, F., Ludwig, B., & Vohland, M. (2019). In situ and laboratory soil spectroscopy with portable visible-to-near-infrared and mid-infrared instruments for the assessment of organic carbon in soils. *Geoderma*, 355(August), 113900. <https://doi.org/10.1016/j.geoderma.2019.113900>
- Islam, A. K. M. S., Edwards, D. G., & Asher, C. J. (1980). pH optima for crop growth. *Plant and Soil*, 54(3), 339–357. <https://doi.org/10.1007/bf02181830>
- Ismail, I. A., Pernadi, N. L., & Febriyanti, A. (2022). How to Grab And Determine the Size of The Sample For. *International Journal of Academic and Applied Research*, 6(9), 88–92.
- Jakšić, S., Ninkov, J., Milić, S., Vasin, J., Banjac, D., Jakšić, D., & Živanov, M. (2021). The state of soil organic carbon in vineyards as affected by soil types and fertilization strategies (Tri Morave Region, Serbia). *Agronomy*, 11(1). <https://doi.org/10.3390/agronomy11010009>
- Jayne, T. S., Muyanga, M., Wineman, A., Ghebru, H., Stevens, C., Stickler, M., Chapoto, A., Anseeuw, W., van der Westhuizen, D., & Nyange, D. (2019). Are medium-scale farms driving agricultural transformation in sub-Saharan Africa? *Agricultural Economics (United Kingdom)*, 50(S1), 75–95. <https://doi.org/10.1111/agec.12535>
- Jha, S., Kaechele, H., Lana, M., Amjath-Babu, T. S., & Sieber, S. (2020). Exploring farmers' perceptions of agricultural technologies: A case study from Tanzania. *Sustainability (Switzerland)*, 12(3), 1–21. <https://doi.org/10.3390/su12030998>
- Jhariya, M. K., Meena, R. S., & Banerjee, A. (2021). Ecological Intensification of Natural Resources Towards Sustainable Productive System. In *Ecological Intensification of Natural Resources for Sustainable Agriculture*. https://doi.org/10.1007/978-981-33-4203-3_1
- Johnson, J. M., Vandamme, E., Senthilkumar, K., Sila, A., Shepherd, K. D., & Saito, K. (2019). Near-infrared, mid-infrared or combined diffuse reflectance spectroscopy for assessing soil fertility in rice fields in sub-Saharan Africa. *Geoderma*, 354(July). <https://doi.org/10.1016/j.geoderma.2019.06.043>
- Johnson, J., Vandamme, E., Senthilkumar, K., Sila, A., Shepherd, K. D., & Saito, K. (2019). *Geoderma Near-infrared , mid-infrared or combined di ff use re fl ectance spectroscopy for assessing soil fertility in rice fi elds in sub-Saharan Africa*. 354(February). <https://doi.org/10.1016/j.geoderma.2019.06.043>
- Justine, P., Csorba, Á., Ocansey, C. M., Rotich, B., Maket, I., Lameck, A. S., Abdulkadir, M., MohammedZein, M. A., Michéli, E., & Gelsleichter, Y. A. (2025). Awareness and adoption

- strategies for improved agricultural practices (IAPs) by smallholder farmers in the Mbeya Region, Tanzania. *Discover Sustainability*, 6(1). <https://doi.org/10.1007/s43621-025-00970-y>
- Kaaria, S., & Osorio, M. (2018). The gender gap in land rights. *Research Program on Policies, Institutions, and Markets, Social Pol*, 4.
<http://www.fao.org/3/I8796EN/i8796en.pdf?fbclid=IwAR0owWkHXsrPeaEzNPlniyffHqW2G0gK4VgRXJqp2MA6NIUbwTDgsdEVzqc>
- Kaliba, A. R., Mazvimavi, K., Gregory, T. L., Mgonja, F. M., & Mgonja, M. (2018). Factors affecting adoption of improved sorghum varieties in Tanzania under information and capital constraints. *Agricultural and Food Economics*, 6(1). <https://doi.org/10.1186/s40100-018-0114-4>
- Kalonga, J., Mtei, K., Massawe, B., Kimaro, A., & Winowiecki, L. A. (2024). Characterization of soil health and nutrient content status across the North-East Maasai Landscape, Arusha Tanzania. *Environmental Challenges*, 14(September 2023), 100847.
<https://doi.org/10.1016/j.envc.2024.100847>
- Karoui, R., Antonio, J., & Pierna, F. (2008). *Technique : Spectroscopies*.
- Karray, E., Elmannai, H., Toumi, E., Gharbia, M. H., Meshoul, S., Aichi, H., & Rabah, Z. Ben. (2023). Evaluating the Potentials of PLSR and SVR Models for Soil Properties Prediction Using Field Imaging, Laboratory VNIR Spectroscopy and Their Combination. *CMES - Computer Modeling in Engineering and Sciences*, 136(2), 1399–1425.
<https://doi.org/10.32604/cmes.2023.023164>
- Kashuliza, A. S. . M. and A. K. (1998). *Impact of structural adjustment policies in Tanzania.pdf*.
- Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Technological Forecasting & Social Change Adoption of interrelated sustainable agricultural practices in smallholder systems : Evidence from rural Tanzania. *Technological Forecasting & Social Change*, 80(3), 525–540. <https://doi.org/10.1016/j.techfore.2012.08.007>
- Katambara, A. M. and Z. (2020). 1 +255755306466, 2 +255756662009. 1(2), 145–159.
- Kempen, B., Dalsgaard, S., Kaaya, A. K., Chamuya, N., Ruipérez-González, M., Pekkarinen, A., & Walsh, M. G. (2019). Mapping topsoil organic carbon concentrations and stocks for Tanzania. *Geoderma*, 337(June 2016), 164–180.
<https://doi.org/10.1016/j.geoderma.2018.09.011>
- Khuntia, S., Mujtaba, H., Patra, C., Farooq, K., Sivakugan, N., & Das, B. M. (2015). Prediction of

- compaction parameters of coarse grained soil using multivariate adaptive regression splines (MARS). *International Journal of Geotechnical Engineering*, 9(1), 79–88.
<https://doi.org/10.1179/1939787914Y.00000000061>
- Kilonzo, M., Richard, U., & Mauki, D. (2023). Influence of elevation gradient and plant species composition on soil organic carbon in Mount Rungwe Forest Reserve, Tanzania. *Environmental and Sustainability Indicators*, 19(April), 100291.
<https://doi.org/10.1016/j.indic.2023.100291>
- Kim, M. J., Lee, H. I., Choi, J. H., Lim, K. J., & Mo, C. (2022). Development of a Soil Organic Matter Content Prediction Model Based on Supervised Learning Using Vis-NIR/SWIR Spectroscopy. *Sensors*, 22(14). <https://doi.org/10.3390/s22145129>
- Kimaro, J. (2019). A Review on Managing Agroecosystems for Improved Water Use Efficiency in the Face of Changing Climate in Tanzania. *Advances in Meteorology*, 2019.
<https://doi.org/10.1155/2019/9178136>
- Kinyondo, A., & Magashi, J. (2017). Enhancing rural livelihoods in Tanzania : A small-holder farmers' perspective. *International Journal of Accounting and Economics Studies*, 5(2), 68.
<https://doi.org/10.14419/ijaes.v5i2.7672>
- Kirsten, M., Kaaya, A., Klinger, T., & Feger, K. H. (2016). Stocks of soil organic carbon in forest ecosystems of the Eastern Usambara Mountains, Tanzania. *Catena*, 137, 651–659.
<https://doi.org/10.1016/j.catena.2014.12.027>
- Kodaira, M., & Shibusawa, S. (2013). Geoderma Using a mobile real-time soil visible-near infrared sensor for high resolution soil property mapping. *Geoderma*, 199, 64–79.
<https://doi.org/10.1016/j.geoderma.2012.09.007>
- Krauss, M., Wiesmeier, M., Don, A., Cuperus, F., Gattinger, A., Gruber, S., Haagsma, K., Peign, J., Palazzoli, M. C., Schulz, F., Heijden, M. G. A. Van Der, Vincent-caboud, L., Wittwer, R. A., Zikeli, S., & Steffens, M. (2022). *Soil & Tillage Research Reduced tillage in organic farming affects soil organic carbon stocks in temperate Europe*. 216.
<https://doi.org/10.1016/j.still.2021.105262>
- Krone, M., Dannenberg, P., & Nduru, G. (2016). The use of modern information and communication technologies in smallholder agriculture: Examples from Kenya and Tanzania. *Information Development*, 32(5), 1503–1512. <https://doi.org/10.1177/0266666915611195>
- Kühnel, A., & Bogner, C. (2017). In-situ prediction of soil organic carbon by vis–NIR

- spectroscopy: an efficient use of limited field data. *European Journal of Soil Science*, 68(5), 689–702. <https://doi.org/10.1111/ejss.12448>
- Kunlanit, B., Butnan, S., & Vityakon, P. (2019). Land-use changes influencing C sequestration and quality in topsoil and subsoil. *Agronomy*, 9(9), 1–16. <https://doi.org/10.3390/agronomy9090520>
- Laizer, H. C., Chacha, M. N., & Ndakidemi, P. A. (2019). Farmers’ knowledge, perceptions and practices in managing weeds and insect pests of common bean in northern Tanzania. *Sustainability (Switzerland)*, 11(15), 1–11. <https://doi.org/10.3390/su11154076>
- Lal, R. (2015). Restoring soil quality to mitigate soil degradation. *Sustainability (Switzerland)*, 7(5), 5875–5895. <https://doi.org/10.3390/su7055875>
- Landon, J. (1985). Booker Tropical Soil Manual: a Handbook for Soil Survey and Agricultural Land Evaluation in the Tropics and Subtropics. *Experimental Agriculture*, 21(1985), 1985. <https://doi.org/10.1017/S0014479700012655>
- Landon, J. R. (1991). *Booker tropical soil manual: a handbook for soil survey and agricultural land evaluation in the tropics and subtropics*. 532.
- Laub, M., Corbeels, M., Couëdel, A., Ndungu, S. M., Mucheru-Muna, M. W., Mugendi, D., Necpalova, M., Waswa, W., Van De Broek, M., Vanlauwe, B., & Six, J. (2023). Managing soil organic carbon in tropical agroecosystems: evidence from four long-term experiments in Kenya. *Soil*, 9(1), 301–323. <https://doi.org/10.5194/soil-9-301-2023>
- Liaw, A., & Wiener, M. (2002). The R Journal: Classification and regression by randomForest. *R Journal*, 2(3), 18–22. <http://www.stat.berkeley.edu/>
- Liu, C., He, C., Chang, S. X., Chen, X., An, S., Wang, D., Yan, J., Zhang, Y., & Li, P. (2024). Fertilization and tillage influence on soil organic carbon fractions: A global meta-analysis. *CATENA*, 246, 108404. <https://doi.org/https://doi.org/10.1016/j.catena.2024.108404>
- Liu, T., Bruins, R. J. F., & Heberling, M. T. (2018). Factors influencing farmers’ adoption of best management practices: A review and synthesis. *Sustainability (Switzerland)*, 10(2), 1–26. <https://doi.org/10.3390/su10020432>
- Liu, Z. P., Shao, M. A., & Wang, Y. Q. (2013). Spatial patterns of soil total nitrogen and soil total phosphorus across the entire Loess Plateau region of China. *Geoderma*, 197–198, 67–78. <https://doi.org/10.1016/j.geoderma.2012.12.011>
- Longnan, S., O’Rourke, S., de Santana, F. B., & Daly, K. (2023). Prediction of soil bulk density in

- agricultural soils using mid-infrared spectroscopy. *Geoderma*, 434(April), 116487.
<https://doi.org/10.1016/j.geoderma.2023.116487>
- LUCAS. (2018). *LUCAS Soil , the largest expandable soil dataset for Europe : a review. January*, 140–153. <https://doi.org/10.1111/ejss.12499>
- Ludwig, B., Murugan, R., Parama, V. R. R., & Vohland, M. (2019). Accuracy of Estimating Soil Properties with Mid-Infrared Spectroscopy: Implications of Different Chemometric Approaches and Software Packages Related to Calibration Sample Size. *Soil Science Society of America Journal*, 83(5), 1542–1552. <https://doi.org/10.2136/sssaj2018.11.0413>
- Machingura, F., Nyamwanza, A., Hulme, D., & Stuart, E. (2018). Correction to: Climate information services, integrated knowledge systems and the 2030 agenda for sustainable development. *Sustainable Earth*, 1(1), 1–7. <https://doi.org/10.1186/s42055-018-0006-1>
- Makó, A., Tóth, G., Weynants, M., Rajkai, K., Hermann, T., & Tóth, B. (2017). Pedotransfer functions for converting laser diffraction particle-size data to conventional values. *European Journal of Soil Science*, 68(5), 769–782. <https://doi.org/10.1111/ejss.12456>
- Mango, N., Makate, C., Tamene, L., Mponela, P., & Ndengu, G. (2018). Adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on household income in the Chinyanja Triangle, Southern Africa. *Land*, 7(2), 1–19.
<https://doi.org/10.3390/land7020049>
- Marchant, R. (2006). This document is discoverable and free to researchers across the globe due to the work of AgEcon Search . Help ensure our sustainability. *AgEcon Search*, 1(3), 11.
- Matata, P. Z., Ajay, O. C., Oduol, P. A., & Agumya, A. (2010). Socio-economic factors influencing adoption of improved fallow practices among smallholder farmers in western Tanzania. *African Journal of Agricultural Research*, 5(9), 818–823.
- Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., & Bates, D. (2017). Balancing Type I error and power in linear mixed models. *Journal of Memory and Language*, 94, 305–315.
<https://doi.org/10.1016/j.jml.2017.01.001>
- Mbarali, N. (1980). Ministry of Finance and Planning, National Bureau of Statistics and Mbarali District Council - Tanzania. *Population Policy Compendium*, 1–6.
<https://doi.org/10.1201/9781003307785-198>
- Mbeya district council. (2015). *The United Republic of Tanzania Mbeya District socio-economic profile*. 1–149.

- McBratney, A. B., Mendonça Santos, M. L., & Minasny, B. (2003). On digital soil mapping. In *Geoderma* (Vol. 117, Issues 1–2). [https://doi.org/10.1016/S0016-7061\(03\)00223-4](https://doi.org/10.1016/S0016-7061(03)00223-4)
- McBratney, A. B., Minasny, B., & Viscarra Rossel, R. (2006). Spectral soil analysis and inference systems: A powerful combination for solving the soil data crisis. *Geoderma*, *136*(1–2), 272–278. <https://doi.org/10.1016/j.geoderma.2006.03.051>
- McCarty, G. W., Reeves, J. B., Reeves, V. B., Follett, R. F., & Kimble, J. M. (2002). Mid-Infrared and Near-Infrared Diffuse Reflectance Spectroscopy for Soil Carbon Measurement. *Soil Science Society of America Journal*, *66*(2), 640–646. <https://doi.org/10.2136/sssaj2002.6400a>
- McDonagh, J. F., Birch Thomsen, T., & Magid, J. (2001). Soil organic matter decline and compositional change associated with cereal cropping in Southern Tanzania. *Land Degradation and Development*, *12*(1), 13–26. <https://doi.org/10.1002/ldr.419>
- McLauchlan, K. K. (2006). Effects of soil texture on soil carbon and nitrogen dynamics after cessation of agriculture. *Geoderma*, *136*(1–2), 289–299. <https://doi.org/10.1016/j.geoderma.2006.03.053>
- Mdegela, R. H., Mwakapeje, E. R., Rubegwa, B., Gebeyehu, D. T., Niyigena, S., Msambichaka, V., Nonga, H. E., Antoine-Moussiaux, N., & Fasina, F. O. (2021). Antimicrobial use, residues, resistance and governance in the food and agriculture sectors, tanzania. *Antibiotics*, *10*(4), 1–23. <https://doi.org/10.3390/antibiotics10040454>
- Meemken, E. M., & Bellemare, M. F. (2020). Smallholder farmers and contract farming in developing countries. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(1), 259–264. <https://doi.org/10.1073/pnas.1909501116>
- Mfaume, D. P., Msanya, B. M., & Msaky, J. J. (2019). Pedological Characterization and Fertility Assessment of Mbimba Substation Soils Under Coffee Production in Mbozi District, Tanzania. *International Journal of Advances in Scientific Research and Engineering*, *05*(10), 221–236. <https://doi.org/10.31695/ijasre.2019.33540>
- Mgendi, G., Mao, S., & Qiao, F. (2021). Is a training program sufficient to improve the smallholder farmers' productivity in Africa? Empirical evidence from a Chinese agricultural technology demonstration center in Tanzania. *Sustainability (Switzerland)*, *13*(3), 1–23. <https://doi.org/10.3390/su13031527>
- Mhoro, L., Semu, E., Amuri, N., Msanya, B., Munishi, J. A., & Malley, Z. (2015a). Growth and yield responses of rice, wheat and beans to Zn and Cu fertilizers in soils of Mbeya region,

- Tanzania. *International Journal of Agricultural Policy and Research*, 3(11), 402–411.
<http://journalissues.org/wp-content/uploads/2015/11/Mhoro-et-all.pdf>
- Mhoro, L., Semu, E., Amuri, N., Msanya, B., Munishi, J. A., & Malley, Z. (2015b). Growth and yield responses of rice, wheat and beans to Zn and Cu fertilizers in soils of Mbeya region, Tanzania. *International Journal of Agricultural Policy and Research*, 3(11), 402–411.
<https://doi.org/10.15739/IJAPR.067>
- Michel, K., Terhoeven-Urselmans, T., Nitschke, R., Steffan, P., & Ludwig, B. (2009). Use of near-And mid-infrared spectroscopy to distinguish carbon and nitrogen originating from char and forest-floor material in soils. *Journal of Plant Nutrition and Soil Science*, 172(1), 63–70.
<https://doi.org/10.1002/jpln.200700246>
- Midega, C. A. O., Pittchar, J. O., Pickett, J. A., Hailu, G. W., & Khan, Z. R. (2018). A climate-adapted push-pull system effectively controls fall armyworm, *Spodoptera frugiperda* (J E Smith), in maize in East Africa. *Crop Protection*, 105, 10–15.
<https://doi.org/https://doi.org/10.1016/j.cropro.2017.11.003>
- Miller, A. J., Amundson, R., Burke, I. C., & Yonker, C. (2004). The effect of climate and cultivation on soil organic C and N. *Biogeochemistry*, 67(1), 57–72.
<https://doi.org/10.1023/B:BIOG.0000015302.16640.a5>
- Miller, M. A. E., Shepherd, K. D., Kisitu, B., & Collinson, J. (2021). iSDAsoil: The first continent-scale soil property map at 30 m resolution provides a soil information revolution for Africa. *PLoS Biology*, 19(11), 2–5. <https://doi.org/10.1371/journal.pbio.3001441>
- Misaki, E., Apiola, M., & Gaiani, S. (2016). Technology for small scale farmers in tanzania: A design science research approach. *Electronic Journal of Information Systems in Developing Countries*, 74(1), 1–15. <https://doi.org/10.1002/j.1681-4835.2016.tb00538.x>
- Mkonda, M. Y., & He, X. (2023). The Influence of Soil Organic Carbon and Climate Variability on Crop Yields in Kongwa District, Tanzania. *Environmental Management*, 71(1), 170–178.
<https://doi.org/10.1007/s00267-022-01592-0>
- Mlingano Agricultural Research Institue. (2006). *Soils of Tanzania Potential for Agriculture Development*. November, 1–36.
- Mng'ong'o, M., Munishi, L. K., Blake, W., Comber, S., Hutchinson, T. H., & Ndakidemi, P. A. (2021a). Soil fertility and land sustainability in Usangu Basin-Tanzania. *Heliyon*, 7(8).
<https://doi.org/10.1016/j.heliyon.2021.e07745>

- Mng'ong'o, M., Munishi, L. K., Blake, W., Comber, S., Hutchinson, T. H., & Ndakidemi, P. A. (2021b). Soil fertility and land sustainability in Usangu Basin-Tanzania. *Heliyon*, 7(8), e07745. <https://doi.org/10.1016/j.heliyon.2021.e07745>
- Mnimbo, T. S., Lyimo-Macha, J., Urassa, J. K., Mahoo, H. F., Tumbo, S. D., & Graef, F. (2017). Influence of gender on roles, choices of crop types and value chain upgrading strategies in semi-arid and sub-humid Tanzania. *Food Security*, 9(6), 1173–1187. <https://doi.org/10.1007/s12571-017-0682-2>
- Mohamed, E. S., Saleh, A. M., Belal, A. B., & Gad, A. A. (2018). Application of near-infrared reflectance for quantitative assessment of soil properties. *Egyptian Journal of Remote Sensing and Space Science*, 21(1), 1–14. <https://doi.org/10.1016/j.ejrs.2017.02.001>
- Mohammedzein, M. A., Csorba, A., Rotich, B., Justin, P. N., Melenya, C., Andrei, Y., & Micheli, E. (2023). Development of Hungarian spectral library: Prediction of soil properties and applications. *Eurasian Journal of Soil Science*, 12(3), 244–256. <https://doi.org/10.18393/ejss.1275149>
- MohammedZein, M. A., Micheli, E., Rotich, B., Justine, P. N., Ahmed, A. E. E., Tharwat, H., & Csorba, Á. (2023). Rapid Detection of Soil Texture Attribute based on Mid-Infrared Spectral Library In Salt Affected Soils of Hungary. *Hungarian Agricultural Engineering*, 7410(42), 5–13. <https://doi.org/10.17676/hae.2023.42.5>
- Monroe, P. H. M., Gama-Rodrigues, E. F., Gama-Rodrigues, A. C., & Marques, J. R. B. (2016). Soil carbon stocks and origin under different cacao agroforestry systems in Southern Bahia, Brazil. *Agriculture, Ecosystems and Environment*, 221, 99–108. <https://doi.org/10.1016/j.agee.2016.01.022>
- Mouazen, A. M., De Baerdemaeker, J., & Ramon, H. (2005). Towards development of on-line soil moisture content sensor using a fibre-type NIR spectrophotometer. *Soil and Tillage Research*, 80(1–2), 171–183. <https://doi.org/10.1016/j.still.2004.03.022>
- Mpogole, H. (2012). Round potato (*Solanum tuberosum*) production in southern highlands of Tanzania: Are smallholder farmers becoming commercial? *Journal of Agricultural Extension and Rural Development*, 4(14). <https://doi.org/10.5897/jaerd12.067>
- Msanya, B. M., Otsuka, H., Araki, S., & Fujitake, N. (2007). *Organic Matter and Humus Characteristics of Some*.
- Msanya, B., Munishi, J., Amuri, N., Semu, E., Mhoru, L., & Malley, Z. (2016). Morphology,

- Genesis, Physico-chemical Properties, Classification and Potential of Soils Derived from Volcanic Parent Materials in Selected Districts of Mbeya Region, Tanzania. *International Journal of Plant & Soil Science*, 10(4), 1–19. <https://doi.org/10.9734/ijpss/2016/24855>
- Mushi, G. E., Serugendo, G. D. M., & Burgi, P. Y. (2022). Digital Technology and Services for Sustainable Agriculture in Tanzania: A Literature Review. *Sustainability (Switzerland)*, 14(4), 1–17. <https://doi.org/10.3390/su14042415>
- Mwangi, M., & Kariuki, S. (2015). Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. *Iiste*, 6(5), 2222–1700. www.iiste.org
- Mwema, E., Mukiri, J., Nzogela, B., Paul, B. K., & Notenbaert, A. M. O. (2021). *Assessing the environmental impacts of smallholder dairy intensification through improved feeding strategies in the Southern Highlands of Tanzania*. <https://cgspace.cgiar.org/handle/10568/115055>
- Nakano, Y., Tsusaka, T. W., Aida, T., & Pede, V. O. (2018). Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. *World Development*, 105, 336–351. <https://doi.org/10.1016/j.worlddev.2017.12.013>
- Nanni, M. R., Cezar, E., Silva Junior, C. A. da, Silva, G. F. C., & da Silva Gualberto, A. A. (2018). Partial least squares regression (PLSR) associated with spectral response to predict soil attributes in transitional lithologies. *Archives of Agronomy and Soil Science*, 64(5), 682–695. <https://doi.org/10.1080/03650340.2017.1373185>
- Nassary, E. K., Baijukya, F., & Ndakidemi, P. A. (2020). Productivity of intercropping with maize and common bean over five cropping seasons on smallholder farms of Tanzania. *European Journal of Agronomy*, 113(May 2019), 125964. <https://doi.org/10.1016/j.eja.2019.125964>
- NBS. (2019). Tanzania in Figures 2018 National Bureau of Statistics Dodoma. *United Republic of Tanzania, June*, 103. https://www.nbs.go.tz/nbs/takwimu/references/Tanzania_in_Figures_2018.pdf
- NBS. (2022). Administrative Units Population Distribution Report. *National Population and House Census of Tanzania. National Bureau of Statistics, Dar Es Salaam, Tanzania*.
- Ndimbo, G. K., Yu, L., & Ndi Buma, A. A. (2023). ICTs, smallholder agriculture and farmers' livelihood improvement in developing countries: Evidence from Tanzania. *Information Development*, 02666669231165272. <https://doi.org/10.1177/02666669231165272>

- Ngailo, J. A. (2016). *RICE FARMING IN THE SOUTHERN HIGHLANDS OF TANZANIA: MANAGEMENT PRACTICES, SOCIO-ECONOMIC ROLES AND PRODUCTION CONSTRAINTS Preparing African Rice Farmers Against Parasitic Weeds in a Changing Environment (PARASITE) View project ECAPAPA project View project*. 4(4), 28–39. <https://www.researchgate.net/publication/317185270>
- Ngailo, S., Shimelis, H. A., Sibiya, J., & Mtunda, K. (2016). Assessment of sweetpotato farming systems, production constraints and breeding priorities in eastern Tanzania. *South African Journal of Plant and Soil*, 33(2), 105–112. <https://doi.org/10.1080/02571862.2015.1079933>
- Ngowi, A. V. F. (2003). *A study of farmers' knowledge, attitude and experience in the use of pesticides in coffee farming*.
- Ngowi, A. V. F., Mbise, T. J., Ijani, A. S. M., London, L., & Ajayi, O. C. (2007). Pesticides use by smallholder farmers in vegetable production in Northern Tanzania. *Crop Protection (Guildford, Surrey)*, 26(11), 1617–1624. <https://doi.org/10.1016/j.cropro.2007.01.008>
- Nilsson, D., Fielding, K., & Dean, A. J. (2020). Achieving conservation impact by shifting focus from human attitudes to behaviors. *Conservation Biology*, 34(1), 93–102. <https://doi.org/10.1111/cobi.13363>
- Nobre, J. S., & Da Motta Singer, J. (2007). Residual analysis for linear mixed models. *Biometrical Journal*, 49(6), 863–875. <https://doi.org/10.1002/bimj.200610341>
- Nocita, M., Kooistra, L., Bachmann, M., Müller, A., Powell, M., & Weel, S. (2011). Geoderma Predictions of soil surface and topsoil organic carbon content through the use of laboratory and field spectroscopy in the Albany Thicket Biome of Eastern Cape Province of South Africa. *Geoderma*, 167–168, 295–302. <https://doi.org/10.1016/j.geoderma.2011.09.018>
- Nocita, M., Stevens, A., Toth, G., Panagos, P., van Wesemael, B., & Montanarella, L. (2014). Prediction of soil organic carbon content by diffuse reflectance spectroscopy using a local partial least square regression approach. *Soil Biology and Biochemistry*, 68, 337–347. <https://doi.org/10.1016/j.soilbio.2013.10.022>
- Nocita, M., Stevens, A., van Wesemael, B., Aitkenhead, M., Bachmann, M., Barthès, B., Dor, E., Ben, Brown, D. J., Clairotte, M., Csorba, A., Dardenne, P., Demattê, J. A. M., Genot, V., Guerrero, C., Knadel, M., Montanarella, L., Noon, C., Ramirez-Lopez, L., Robertson, J., ... Wetterlind, J. (2015). Soil Spectroscopy: An Alternative to Wet Chemistry for Soil Monitoring. *Advances in Agronomy*, 132, 139–159.

- <https://doi.org/10.1016/bs.agron.2015.02.002>
- Oo, S. P., & Usami, K. (2020). Farmers' perception of good agricultural practices in rice production in Myanmar: A case study of Myaungmya District, Ayeyarwady Region. *Agriculture (Switzerland)*, *10*(7), 1–20. <https://doi.org/10.3390/agriculture10070249>
- Ostrowska, A., & Porębska, G. (2015). Assessment of the C/N ratio as an indicator of the decomposability of organic matter in forest soils. *Ecological Indicators*, *49*, 104–109. <https://doi.org/10.1016/j.ecolind.2014.09.044>
- Padarian, J., Minasny, B., & McBratney, A. B. (2020). Machine learning and soil sciences: A review aided by machine learning tools. *Soil*, *6*(1), 35–52. <https://doi.org/10.5194/soil-6-35-2020>
- Pasquini, C. (2018). Near infrared spectroscopy: A mature analytical technique with new perspectives – A review. *Analytica Chimica Acta*, *1026*, 8–36. <https://doi.org/10.1016/j.aca.2018.04.004>
- Paz, C. P., Goosem, M., Bird, M., Preece, N., Goosem, S., Fensham, R., & Laurance, S. (2016). Soil types influence predictions of soil carbon stock recovery in tropical secondary forests. *Forest Ecology and Management*, *376*, 74–83. <https://doi.org/10.1016/j.foreco.2016.06.007>
- Peter David Kulyakwave^{1, 2*}, Shiwei¹, X., & Wen¹, Y. (2023). *Climate and Socio-economic Factors Affecting the Adoption of Irrigation Practices for Improved Rice Yield in Mbeya Region , Tanzania*. *11*(June), 1–11.
- Ramasamy, J., & Ramalingam, K. (2019). Influence of soil organic matter on bulk density in Coimbatore soils Taxonomy of Lymantriinae in Tamil Nadu View project Farm Level Fertility Mapping View project. *International Journal of Chemical Studies*, *7*(3), 3520–3523. <https://www.researchgate.net/publication/336059088>
- Ratnayake, R. R., Kugendren, T., & Gnanavelrajah, N. (2014). Changes in soil carbon stocks under different agricultural management practices in North Sri Lanka. *Journal of the National Science Foundation of Sri Lanka*, *42*(1), 37–44. <https://doi.org/10.4038/jnsfsr.v42i1.6679>
- Recha, J. W., Olale, K. O., Sila, A., Ambaw, G., Radeny, M., & Solomon, D. (2021). Ensemble modeling on near-infrared spectra as rapid tool for assessment of soil health indicators for sustainable food production systems. *Soil Systems*, *5*(4), 1–15. <https://doi.org/10.3390/soilsystems5040069>
- Reeves, D. W. (1997). The role of soil organic matter in maintaining soil quality in continuous

- cropping systems. *Soil and Tillage Research*, 43(1–2), 131–167.
[https://doi.org/10.1016/S0167-1987\(97\)00038-X](https://doi.org/10.1016/S0167-1987(97)00038-X)
- Rocci, K. S., Cotrufo, M. F., Ernakovich, J., Foster, E., Frey, S., Georgiou, K., Grandy, A. S., Malhotra, A., Reich, P. B., Schlerman, E. P., & Wieder, W. R. (2024). *Special Collection : Bridging 20 Years of Soil Organic Matter Frameworks : Empirical Support , Model Representation , and Next Steps*. <https://doi.org/10.1029/2023JG007964>
- Rogers, P. M., Yanda, P. Z., Pauline, N. M., Haikola, S., Hansson, A., & Fridahl, M. (2022). Effects of Biochar on Soil Fertility and Crop Yields: Experience from the Southern Highlands of Tanzania. *Tanzania Journal of Science*, 48(2), 256–267. <https://doi.org/10.4314/tjs.v48i2.3>
- Rossel, R. A. V., & Behrens, T. (2010). Using data mining to model and interpret soil diffuse reflectance spectra. *Geoderma*, 158(1–2), 46–54.
<https://doi.org/10.1016/j.geoderma.2009.12.025>
- Rossi, J., Govaerts, A., De Vos, B., Verbist, B., Vervoort, A., Poesen, J., Muys, B., & Deckers, J. (2009). Spatial structures of soil organic carbon in tropical forests-A case study of Southeastern Tanzania. *Catena*, 77(1), 19–27. <https://doi.org/10.1016/j.catena.2008.12.003>
- Sanogo, K., Touré, I., Arinloye, D. D. A. A., Dossou-Yovo, E. R., & Bayala, J. (2023). Factors affecting the adoption of climate-smart agriculture technologies in rice farming systems in Mali, West Africa. *Smart Agricultural Technology*, 5(March).
<https://doi.org/10.1016/j.atech.2023.100283>
- Santos, U. J. dos, José Alexandre de Melo Demattê, R. S. C. M., Dotto, Clécia Cristina Barbosa Guimarães, B. J. R. A., & Dário Costa Primo, and E. V. de S. B. S. (2015). Predicting carbon and nitrogen by visible near-infrared (Vis-NIR) and mid-infrared (MIR) spectroscopy in soils of Northeast Brazil. *Angewandte Chemie International Edition*, 6(11), 951–952., 1(April).
- Schneider, F., Amelung, W., & Don, A. (2021). Origin of carbon in agricultural soil profiles deduced from depth gradients of C:N ratios, carbon fractions, $\delta^{13}\text{C}$ and $\delta^{15}\text{N}$ values. *Plant and Soil*, 460(1–2), 123–148. <https://doi.org/10.1007/s11104-020-04769-w>
- Seema, Ghosh, A. K., Mouli Hati, K., Kumar Sinha, N., Mridha, N., & Sahu, B. (2022). Regional soil organic carbon prediction models based on a multivariate analysis of the Mid-infrared hyperspectral data in the middle Indo-Gangetic plains of India. *Infrared Physics and Technology*, 127(October), 104372. <https://doi.org/10.1016/j.infrared.2022.104372>
- Shah, A. N., Tanveer, M., Shahzad, B., Yang, G., Fahad, S., Ali, S., Bukhari, M. A., Tung, S. A.,

- Hafeez, A., & Souliyanonh, B. (2017). Soil compaction effects on soil health and cropproductivity: an overview. *Environmental Science and Pollution Research*, 24(11), 10056–10067. <https://doi.org/10.1007/s11356-017-8421-y>
- Shaheb, M. R., Venkatesh, R., & Shearer, S. A. (2021). A Review on the Effect of Soil Compaction and its Management for Sustainable Crop Production. *Journal of Biosystems Engineering*, 46(4), 417–439. <https://doi.org/10.1007/s42853-021-00117-7>
- Shepherd. (2010). *Soil spectral diagnostics – infrared , x-ray and laser diffraction spectroscopy for rapid soil characterization in the Africa Soil Information Service*. August, 24–27.
- Shepherd, K. D., & Walsh, M. G. (2002). Development of Reflectance Spectral Libraries for Characterization of Soil Properties. *Soil Science Society of America Journal*, 66(3), 988–998. <https://doi.org/10.2136/sssaj2002.9880>
- Shi, L., Rourke, S. O., Bachion, F., Santana, D., & Daly, K. (2023). Geoderma Prediction of soil bulk density in agricultural soils using mid-infrared spectroscopy. *Geoderma*, 434(April), 116487. <https://doi.org/10.1016/j.geoderma.2023.116487>
- Sila, A., Pokhariyal, G., & Shepherd, K. (2017a). Evaluating regression-kriging for mid-infrared spectroscopy prediction of soil properties in western Kenya. *Geoderma Regional*, 10, 39–47. <https://doi.org/10.1016/j.geodrs.2017.04.003>
- Sila, A., Pokhariyal, G., & Shepherd, K. (2017b). *Evaluating regression-kriging for mid-infrared spectroscopy prediction of soil properties in western Kenya*. 10, 93.
- Sims, B., Corsi, S., Gbehounou, G., Kienzle, J., Taguchi, M., & Friedrich, T. (2018). Sustainable weed management for conservation agriculture: Options for smallholder farmers. *Agriculture (Switzerland)*, 8(8), 1–20. <https://doi.org/10.3390/agriculture8080000>
- Six, J., Bossuyt, H., Degryze, S., & Denef, K. (2004). A history of research on the link between (micro)aggregates, soil biota, and soil organic matter dynamics. *Soil and Tillage Research*, 79(1), 7–31. <https://doi.org/10.1016/j.still.2004.03.008>
- Smaling, E. M. A., & Fresco, L. O. (1993). A decision-support model for monitoring nutrient balances under agricultural land use (NUTMON). *Geoderma*, 60(1–4), 235–256. [https://doi.org/10.1016/0016-7061\(93\)90029-K](https://doi.org/10.1016/0016-7061(93)90029-K)
- Smith, P., House, J. I., Bustamante, M., Sobocká, J., Harper, R., Pan, G., West, P. C., Clark, J. M., Adhya, T., Rumpel, C., Paustian, K., Kuikman, P., Cotrufo, M. F., Elliott, J. A., Mcdowell, R., Griffiths, R. I., Asakawa, S., Bondeau, A., Jain, A. K., ... Pugh, T. A. M. (2016). Global

- change pressures on soils from land use and management. *Global Change Biology*, 22(3), 1008–1028. <https://doi.org/10.1111/gcb.13068>
- Söderström, B., Hedlund, K., Jackson, L. E., Kätterer, T., Lugato, E., Thomsen, I. K., & Jørgensen, H. B. (2014). *What-are-the-effects-of-agricultural-management-on-soil-organic-carbon-(SOC)-stocks_2014_Environmental-Evidence*. 1–8.
- Soriano-Disla, J. M., Janik, L. J., Viscarra Rossel, R. A., MacDonald, L. M., & McLaughlin, M. J. (2014). The performance of visible, near-, and mid-infrared reflectance spectroscopy for prediction of soil physical, chemical, and biological properties. *Applied Spectroscopy Reviews*, 49(2), 139–186. <https://doi.org/10.1080/05704928.2013.811081>
- Soriano-disla, M., Janik, L. J., Allen, D. J., & Mclaughlin, M. J. (2017). *ScienceDirect Evaluation of the performance of portable visible-infrared instruments for the prediction of soil properties. 1*. <https://doi.org/10.1016/j.biosystemseng.2017.06.017>
- Srijna Jha, H. K. and S. S. (2021). *Factors influencing the adoption of agroforestry by smallholder farmer households in Tanzania: Case studies from Morogoro and Dodoma*. Elsevier.
- Stenberg, B., Viscarra Rossel, R. A., Mouazen, A. M., & Wetterlind, J. (2010). Visible and Near Infrared Spectroscopy in Soil Science. In *Advances in Agronomy* (1st ed., Vol. 107, Issue C). Elsevier Inc. [https://doi.org/10.1016/S0065-2113\(10\)07005-7](https://doi.org/10.1016/S0065-2113(10)07005-7)
- Steven Merumba, M., Semu, E., Mashambo Semoka, J., & Michael Msanya, B. (2020). Soil Fertility Status in Bukoba, Missenyi and Biharamulo Districts in Kagera Region, Tanzania. *International Journal of Applied Agricultural Sciences*, 6(5), 96. <https://doi.org/10.11648/j.ijaas.20200605.12>
- Sun, W., Minasny, B., & McBratney, A. (2012). Analysis and prediction of soil properties using local regression-kriging. *Geoderma*, 171–172(m), 16–23. <https://doi.org/10.1016/j.geoderma.2011.02.010>
- Swangjang, K. (2015). Soil Carbon and Nitrogen Ratio in Different Land Use. *International Conference on Advances in Environment Research*, 87, 7. <https://doi.org/10.7763/IPCBEETaylor>
- Taylor, B. M., & Van Grieken, M. (2015). Local institutions and farmer participation in agri-environmental schemes. *Journal of Rural Studies*, 37, 10–19. <https://doi.org/10.1016/j.jrurstud.2014.11.011>
- Terhoeven-urselmans, T., Vagen, T., & Shepherd, K. D. (2010). *Prediction of Soil Fertility Properties from a Globally Distributed Soil Mid-Infrared Spectral Library*. 74(5).

<https://doi.org/10.2136/sssaj2009.0218>

- Terra, F. S., Demattê, J. A. M., & Viscarra Rossel, R. A. (2015). Spectral libraries for quantitative analyses of tropical Brazilian soils: Comparing vis-NIR and mid-IR reflectance data. *Geoderma*, 255–256, 81–93. <https://doi.org/10.1016/j.geoderma.2015.04.017>
- Tey, Y. S., & Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: A review for policy implications. *Precision Agriculture*, 13(6), 713–730. <https://doi.org/10.1007/s11119-012-9273-6>
- Thabit, F. N., Negim, O. I. A., AbdelRahman, M. A. E., Scopa, A., & Moursy, A. R. A. (2024). Using Various Models for Predicting Soil Organic Carbon Based on DRIFT-FTIR and Chemical Analysis. *Soil Systems*, 8(1). <https://doi.org/10.3390/soilsystems8010022>
- Theis, S., Lefore, N., Meinzen-Dick, R., & Bryan, E. (2018). What happens after technology adoption? Gendered aspects of small-scale irrigation technologies in Ethiopia, Ghana, and Tanzania. *Agriculture and Human Values*, 35(3), 671–684. <https://doi.org/10.1007/s10460-018-9862-8>
- Tian, Q., Yang, X., Wang, X., Liao, C., Li, Q., Wang, M., Wu, Y., & Liu, F. (2016). Microbial community mediated response of organic carbon mineralization to labile carbon and nitrogen addition in topsoil and subsoil. *Biogeochemistry*, 128(1–2), 125–139. <https://doi.org/10.1007/s10533-016-0198-4>
- Towett, E. K., Shepherd, K. D., Sila, A., Aynekulu, E., & 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. <https://doi.org/10.2136/sssaj2014.11.0458>
- Tsheko, R. (2003). Rainfall reliability, drought and flood vulnerability in Botswana. *Water SA*, 29(4), 389–392. <https://doi.org/10.4314/wsa.v29i4.5043>
- URT. (2014). *The United Republic of Tanzania Agriculture Climate Resilience Plan. September*, 1–76. <http://extwprlegs1.fao.org/docs/pdf/tan152483.pdf>
- URT. (2017). *The United Republic of Tanzania (URT), President's Office, Regional Administration and Local Government. Mbeya Region Investment Opportunities*. 1–70.
- URT. (2022). *The United Republic of Tanzania, President's Office Regional Administration and Local Government. Mbeya Regional Secretariat Strategic Plan for the Financial Year 2018 / 19 – 2022 / 23 Table of Contents List of Tables and Figures*

- Varmuza, K., & Filzmoser, P. (2016). Introduction to multivariate statistical analysis in chemometrics. *CRC Press*, 2016.
- Vibhute, A. D., Kale, K. V, Mehrotra, S. C., Dhumal, R. K., & Nagne, A. D. (2018). *Determination of soil physicochemical attributes in farming sites through visible , near-infrared diffuse reflectance spectroscopy and PLSR modeling.*
- Viscarra Rossel, R. A., Behrens, T., Ben-Dor, E., Brown, D. J., Demattê, J. A. M., Shepherd, K. D., Shi, Z., Stenberg, B., Stevens, A., Adamchuk, V., Aïchi, H., Barthès, B. G., Bartholomeus, H. M., Bayer, A. D., Bernoux, M., Böttcher, K., Brodský, L., Du, C. W., Chappell, A., ... Ji, W. (2016). A global spectral library to characterize the world's soil. *Earth-Science Reviews*, 155(February), 198–230. <https://doi.org/10.1016/j.earscirev.2016.01.012>
- Viscarra Rossel, R. A., Cattle, S. R., Ortega, A., & Fouad, Y. (2009). In situ measurements of soil colour, mineral composition and clay content by vis-NIR spectroscopy. *Geoderma*, 150(3–4), 253–266. <https://doi.org/10.1016/j.geoderma.2009.01.025>
- Viscarra Rossel, R. A., Chappell, A., De Caritat, P., & Mckenzie, N. J. (2011). On the soil information content of visible-near infrared reflectance spectra. *European Journal of Soil Science*, 62(3), 442–453. <https://doi.org/10.1111/j.1365-2389.2011.01372.x>
- Viscarra Rossel, R. A., Goovaerts, P., & McBratney, A. B. (2001). Assessment of the production and economic risks of site-specific liming using geostatistical uncertainty modelling. *Environmetrics*, 12(8), 699–711. <https://doi.org/10.1002/env.471>
- Viscarra Rossel, R. A., Walvoort, D. J. J., McBratney, A. B., Janik, L. J., & Skjemstad, J. O. (2006). Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma*, 131(1–2), 59–75. <https://doi.org/10.1016/j.geoderma.2005.03.007>
- Von Braun, J., Teklu, T., & Webb, P. (1999). *Famine in Africa: Causes, responses, and prevention.* Intl Food Policy Res Inst.
- Wadoux, B., Brennan, A. J., Marioofajardoo, B., & Mcbratney, A. (2021). *Progress in Soil Science Soil Spectral Inference with R Analysing Digital Soil Spectra using the R Programming Environment.* <http://www.springer.com/series/8746>
- Wallace, M. B., Wax, A., Roberts, D. N., & Graf, R. N. (2009). Reflectance Spectroscopy. *Gastrointestinal Endoscopy Clinics of North America*, 19(2), 233–242.

<https://doi.org/10.1016/j.giec.2009.02.008>

- Walter, K., Don, A., Tiemeyer, B., & Freibauer, A. (2016). Determining Soil Bulk Density for Carbon Stock Calculations: A Systematic Method Comparison. *Soil Science Society of America Journal*, *80*(3), 579–591. <https://doi.org/10.2136/sssaj2015.11.0407>
- Wang, Q., Xu, Y., Zhu, G., Lu, S., Qiu, D., Jiao, Y., Meng, G., Chen, L., Li, R., Zhang, W., Zhao, L., Qi, X., Wang, Y., Huang, E., & Li, W. (2025). Agricultural activities increased soil organic carbon in Shiyang River Basin, a typical inland river basin in China. *Scientific Reports*, *15*(1), 1–13. <https://doi.org/10.1038/s41598-025-90424-2>
- Wang, T., Kang, F., Cheng, X., Han, H., & Ji, W. (2016). Soil organic carbon and total nitrogen stocks under different land uses in a hilly ecological restoration area of North China. *Soil and Tillage Research*, *163*, 176–184. <https://doi.org/10.1016/j.still.2016.05.015>
- Wanger, T. C., Systems, S. A., & Network, G. A. (2024). *Decades matter: Agricultural diversification increases financial profitability, biodiversity, and ecosystem services over time.*
- Wiesmeier, M., Spörlein, P., Geuß, U., Hangen, E., Haug, S., Reischl, A., Schilling, B., von Lützow, M., & Kögel-Knabner, I. (2012). Soil organic carbon stocks in southeast Germany (Bavaria) as affected by land use, soil type and sampling depth. *Global Change Biology*, *18*(7), 2233–2245. <https://doi.org/10.1111/j.1365-2486.2012.02699.x>
- Wilhelm, W. W., Johnson, J. M. F., Hatfield, J. L., Voorhees, W. B., & Linden, D. R. (2004). Crop and Soil Productivity Response to Corn Residue Removal: A Literature Review. *Agronomy Journal*, *96*(1), 1–17.
- Winowiecki, L., Vågen, T. G., & Huising, J. (2014). Effects of land cover on ecosystem services in Tanzania: A spatial assessment of soil organic carbon. *Geoderma*, *263*, 274–283. <https://doi.org/10.1016/j.geoderma.2015.03.010>
- Winowiecki, L., Vågen, T. G., Massawe, B., Jelinski, N. A., Lyamchai, C., Sayula, G., & Msoka, E. (2016). Landscape-scale variability of soil health indicators: effects of cultivation on soil organic carbon in the Usambara Mountains of Tanzania. *Nutrient Cycling in Agroecosystems*, *105*(3), 263–274. <https://doi.org/10.1007/s10705-015-9750-1>
- Wold, S., Sjostrom, M., & Eriksson, L. (2001). PLS-regression: A Basic Tool of Chemometrics. *Chemometrics and Intelligent Laboratory Systems*, *58*, 109–130. [https://doi.org/10.1016/S0169-7439\(01\)00155-1](https://doi.org/10.1016/S0169-7439(01)00155-1)

- Wordofa, M. G., Hassen, J. Y., Endris, G. S., Aweke, C. S., Moges, D. K., & Rorisa, D. T. (2021). Adoption of improved agricultural technology and its impact on household income: a propensity score matching estimation in eastern Ethiopia. *Agriculture and Food Security, 10*(1), 1–12. <https://doi.org/10.1186/s40066-020-00278-2>
- Wright, M. N., & Ziegler, A. (2017). Ranger: A fast implementation of random forests for high dimensional data in C++ and R. *Journal of Statistical Software, 77*(1). <https://doi.org/10.18637/jss.v077.i01>
- Xu, D., Ma, W., Chen, S., Jiang, Q., He, K., & Shi, Z. (2018). Assessment of important soil properties related to Chinese Soil Taxonomy based on vis–NIR reflectance spectroscopy. *Computers and Electronics in Agriculture, 144*(November 2017), 1–8. <https://doi.org/10.1016/j.compag.2017.11.029>
- Yan, X., Yang, W., Muneer, M. A., Zhang, S., Wang, M., & Wu, L. (2021). Land-use change affects stoichiometric patterns of soil organic carbon, nitrogen, and phosphorus in the red soil of Southeast China. *Journal of Soils and Sediments, 21*(7), 2639–2649. <https://doi.org/10.1007/s11368-021-02953-8>
- Yang, J., Li, X., & Ma, X. (2023). Improving the Accuracy of Soil Organic Carbon Estimation: CWT-Random Frog-XGBoost as a Prerequisite Technique for In Situ Hyperspectral Analysis. *Remote Sensing, 15*(22). <https://doi.org/10.3390/rs15225294>
- Zhang, Y., Hartemink, A. E., & Huang, J. (2021). Spectral signatures of soil horizons and soil orders – An exploratory study of 270 soil profiles. *Geoderma, 389*(August 2020), 114961. <https://doi.org/10.1016/j.geoderma.2021.114961>
- Zhao, D., Arshad, M., Li, N., & Triantafilis, J. (2021). Predicting soil physical and chemical properties using vis-NIR in Australian cotton areas. *Catena, 196*(December 2019), 104938. <https://doi.org/10.1016/j.catena.2020.104938>
- Zheng, F., & Schreier, H. (1988). Quantification of soil patterns and field soil fertility using spectral reflection and digital processing of aerial photographs. *Fertilizer Research, 16*(1), 15–30. <https://doi.org/10.1007/BF01053311>