HUNGARIAN UNIVERSITY OF AGRICULTURE AND LIFE SCIENCES

DOCTORAL SCHOOL OF ENVIRONMENTAL SCIENCES

DISSERTATION OF THE DOCTORAL (PH.D.)

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

By

PHENSON NSIMA JUSTINE

GÖDÖLLŐ, HUNGARY

2025

Discipline: Environmental Sciences

Name of Doctoral School: Environmental Sciences

Head: Csákiné Dr. Michéli Erika
Professor, DSc.
MATE, Institute of Environmental Sciences
Department of Soil Science

Supervisor(s): Csákiné Dr. Michéli Erika
Professor, DSc.
MATE, Institute of Environmental Sciences
Department of Soil Science

Dr. Csorba Ádám
Assistant professor, Ph. D
MATE, Institute of Environmental Sciences
Department of Soil Science

....

Approval of the Head of Doctoral School Approval of the Supervisor(s)

Approval of the Supervisor(s)

DECLARATION

This dissertation has not been submitted for a degree at any other university; it is my own unique work. Reproduction of any part of this dissertation is strictly prohibited without the author's and/or Hungarian University of Agriculture and Life Sciences' prior approval

DECLARATION BY SUPERVISORS

This dissertation has been submitted with our approval as supervisors.

___________________________________ Date_______________________________

ACKNOWLEDGEMENT

I desire to respectfully convey my sincere gratitude to all the people who have supported me in my endeavor and inspired my work in one way or the other. Clearly, without their active leadership, support, cooperation and encouragement, the completion of this project would have remained a mirage. I am profoundly obliged to my two recognised supervisors: Prof. Erika Micheli and Dr. Adam Csorba for their scientific and life support in the course of my study and dissertation writing. Their professionalism, dynamism, devotion, motivation, sincerity, friendship and empathy truly encouraged me to finish this project. I am incredibly grateful to Dr. Adam for the huge support in establishing the sampling strategy, the implementation of soil sampling. My heartfelt gratitude to Prof Erika Micheli, the head doctorate school of Environmental Sciences for fostering a very cordial, her full knowledge on soil science especially in Africa and accepting culture at the doctorate school. Her insights during the preliminary brainstorming were essential in the formulation of this study. The essential supervision of Dr. Caleb in methodology and whole write-up of my manuscripts has tremendously sharpened my capacity to think logically and to communicate the study work as simply as possible. Special thanks to Dr. Yuri Gelsleichter for his knowledge on the application of statistical software in the field of envinmental sciences. Without his help I wouldn't been able to successful run codes efficiently. Many thanks for facilitating my research work. I truly appreciate Kárász Ildikó, the institute administrator for being helpful as far as administrative matters are concerned. I am grateful to the instructors and all the people in the department of Environmental Sciences for their important participation in my PhD studies. It was great to work with you.

Special gratitude to my co-worker crew Azaria Stephano Lameck, a PhD student for his academic and non – academic advices during my PhD studies. My special thanks also goes to Edger Isdory, working as field assistant during sample collection in the selected agricultural sites. I am equally appreciative to village chairpersons from each location I collected soil sample for their cooperation. My classmate, Brian Rotich, a PhD student in the department of Soil Science, your availability throughout my PhD carrier is well appreciated. Many thanks also to agricultural extension officers especially in Mbeya and Songwe regions who gave us the much needed insights on the state of agricultural activities and soil fertility efforts and challenges in their respective jurisdictions. I'm grateful to the staff from various laboratories of the institution. Gergely Ildikó from the soil science lab, thank you for the guidance all through the analyses and translating the protocols from Hungarian to English. Dr. Andras Sebok from Environmental chemistry lab, thank you for the analysis of macronutrient elements and soil texture by CNS elemental analyzer and Laser diffraction respectively. To Mbeya University of Science and Technology (MUST) management, I say a very large thank you especially to the Vice Chancellor, Professor Aloyce Mvuma, for granting me a four-year study leave (with an extension) to pursue my PhD. My excitement knows no boundaries in presenting my joyful gratitude to the Hungarian government for granting me the PhD scholarship through the Stipendium Hungaricum scholarship scheme. Many gratitude to the entire management of Hungarian University of Agriculture and Life Sciences (MATE) for establishing a suitable environment for the international student community. Special appreciation to Ms. Tassy Zsuzsanna and Edit Dolanyi Simane, the coordinator of international students (then and now) for the overwhelming support and motherly love and care to the international student community. I am thankful to the Doctoral, Habilitation and Science Organization Office for their excellent services and support to PhD students. I am really grateful to all my friends and family who (directly/indirectly) supported me to withstand all the stress and to achieve this project. I acknowledge with a deep sense of reverence, my thanks towards my family for their moral support in either way. Any omission in this acknowledgement does not in any way reflect lack of gratitude.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION AND ACRONYMS

AfSIS	African Soil Information Systems
BD	Bulk Density
BS	Base Saturation
C/N	Carbon to Nitrogen Ratio
CEC	Cation Exchange Capacity
CNS	Carbon Nitrogen Sulfur
CV	Coefficient of Variation
ECEC	Effective Cation Exchange Capacity
EM	Electromagnetic
ESO	Extension Service Officers
GDP	Gross Domestic Product
HSD	Honestly Significant Difference
IAPs	Improved Agricultural Practices
IPM	Integrated Pest Management
iSDA	Innovative Solutions for Decision Agriculture
ISRIC	International Soil Reference and Information Center
MARS	Multivariate Adaptive Regression Splines
MATE	Hungarian University of Agriculture and Life Sciences
MIR	Mid Infrared
MIR-PLS	Mid Infrared - Partial Least Square
MRA	Multiple Regression Analysis
MUST	Mbeya University of Science and Technology
NBS	National Bureau of Standards
NEON	National Ecological Observatory Network
NGO	Non - Governmental Organizations
NIR	Near Infrared
PCR	Principal Component Regression
PLSR	Partial Least Square Regression
PSI	Phosphorous Sorption Index

RF	Random Forest
RHLI	Researches from Higher Learning Institutions
RMSE	Root Mean Square Error
RMSEP	Root Mean Square Error of Prediction
RPD	Ratio Performance to Deviation
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SPSS	Statistical Package for the Social Sciences
SSA	Sub Saharan Africa
SVR	Support Vector Regression
TARI	Tanzania Agricultural Research Institute
URT	United Republic of Tanzania
VNIR - SWIR	Visible Near Infrared – Shortwave Infrared
XRF	X-Ray Fluorescence

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 is a crucial agricultural area in Tanzania, considered one of the 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 Southern part of Tanzania, 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 in Mbeya agricultural fields 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 the 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

1^st^ 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?

2^nd^ 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. LITERATURE REVIEW

2.1 Awareness and adoption of smallholder farmers to improved agricultural practices (IAPs) in the selected sites

Sustainable farming techniques known as "improved agricultural practices" (IAPs) aim to increase output, preserve natural resources, and strengthen climate change resilience. These methods include integrated nutrient management, organic matter management, agroforestry, and conservation agriculture. The many advantages of IAPs are highlighted by recent research. For example, regenerative agricultural techniques like composting and cover crops can greatly raise soil organic carbon (SOC) levels, enhancing soil health and sequestering carbon, according to a systematic analysis by Capetz et al. (2024). In a similar way, Wanger et al. (2024)) showed how agricultural diversification techniques like organic farming and intercropping improve biodiversity, ecosystem services, and long-term profitability may greatly raise the amounts of soil organic carbon (SOC), which will improve soil health and sequester carbon although IAP adoption is not without its difficulties.

Some of these technologies are more efficient in adopting to limited production resources compared to modern technology. Modern academics should aim to comprehend the reasoning underlying traditional smallholder farmer conduct in technology. Enhanced agricultural productivity, technology adoption rates, and household food security and nutrition can be attained by implementing better agricultural practices, expanding rural financial markets, increasing capital and equipment ownership by rural households, and establishing research and extension linkages (Theis et al., 2018; Von Braun et al., 1999). Kinyondo & Magashi (2017) also reported that the government needs to provide farmers with quality and affordable seeds, fertilizer, agricultural infrastructure, subsidies, extension services, markets, information alerts, reasonable loans, and pastures to enhance farmers' lives. Low adoption to agricultural technology is a key factor contributing to low farm production and high levels of poverty and food insecurity in sub-Saharan nations, such as Tanzania (Kaliba et al., 2018). In the Southern part of Tanzania, farmers have commercialized the production of lucrative food crops. Smallholder farmers in the selected sites are involved in different agricultural practices including livestock keeping (Anania et al., 2020). Various research findings have reported that households' decision to accept new technology is influenced by socio-economic, demographic, and institutional aspects. Adoption of new technology may be influenced by factors such as attitude, awareness of current technology, and knowledge of the new technology (Kassie et al., 2013; Peter David Kulyakwave1 et al., 2023). Training farmers in improved agricultural practices (IAPs) is crucial for enhancing agricultural output. Some studies recommend a comprehensive strategy that takes into account both farm-related and non-farm-related elements (George Marechera and Joseph Ndwiga, 2015; Katambara, 2020; Mgendi et al., 2021), which include demographics, management techniques, and extension services. Farmer training workshops and seminars, enforcement of village by-laws on animal grazing, and facilitating farmers' access to financing as the primary methods to increase technology adoption (Matata et al., 2010). Researches have mentioned a strong complementarity between adoption to new technology and rate of productivity to smallholder farmers (Arslan et al., 2017). Nakano et al., (2018) pointed out that technology diffusion among smallholder rice producers in a rural irrigation scheme in Tanzania is influenced by key and intermediate farmers, highlighting the importance of providing training to all farmers. It is true that research findings have been conducted in different parts of Tanzania, yet clear documentation on the awareness and adoption of smallholder farmers to IAPs in the selected sites is still missing and thus need to be further investigated.

2.2 Conventional Soil Analysis

Conventional laboratory techniques involve the use of chemicals to extract and determine the concentration of the target component. It provides a very accurate examination of the chemistry of soil (L. Burton et al., 2020). Various conventional methods are employed to characterize the correlation among various soil qualities including physical, chemical, and primary soil components (Mohamed et al., 2018). Conventional soil analytical techniques have been used to assess soil properties and provide actual information on a particular agricultural field although they are costly and time-consuming and therefore not considered suitable for large-scale estates (Angelopoulou et al., 2020; Nocita et al., 2015). Analytical methods has been used for the analysis of soil properties in different parts of Tanzania for so many years (Funakawa et al., 2012). Studies were undertaken in specific physiographic units in the Southern part of Tanzania, to examine the impact of soil macro- and micronutrient levels on enhancing crop yields where the soil analysis was carried out through conventional methods (Mhoro et al., 2015a).

In Tanzania's Morogoro and Mbeya areas, a study was conducted to categorize and describe the soi ls in each area using FAO principles that clarified morphological traits, physico chemical properties, and origin (Hamadi et al., 2021; Msanya et al., 2016). Never the less, assessment of the nutrient level and soil health has been conducted in the North - East Landscape, Arusha, Tanzania (Kalonga et al., 2024).

The morphology, genesis, physico-chemical characteristics, and classification of soils formed from volcanic parent materials in Tanzania's Mbeya Region have all been established by Msanya et al. (2016). Another study was carried out in Mount Rungwe Forest Reserve in Mbeya, Tanzania, East Africa, to look into how vegetation type and height gradients affected soil organic carbon (Kilonzo et al., 2023). Nevertheless, another study was performed in Usangu agro-ecosystem in Southern Highland Tanzania by Mng'ong'o et al. (2021a) to evaluate the soil fertility status whereby soil samples were collected at 0 - 30 cm depth then analyzed for organic carbon, soil pH, N, P, Ca, K, Mg, S, and Al, as well as micronutrients including Zn, Mn, Cu, Fe, and Cr. Although several studies have highlighted the applications of conventional analysis in various parts of Tanzania including the southern highlands, yet updated soil information on SOC contents and SOC stocks from different agricultural fields are lacking and thus need to be further investigated.

2.3 Soil Reflectance Spectroscopy

Reflectance spectroscopy is a proximal sensing method that relies on the detection of electromagnetic radiation that is reflected by the soil material in the visible (Vis: 400–700 nm), near-infrared (NIR: 701–1100 nm), and short-wave infrared (SWIR: 1100–2500 nm) regions of the electromagnetic spectrum have enabled the quantification of mineralogical, chemical, and physical properties. (Stenberg et al., 2010) (Figure 1).

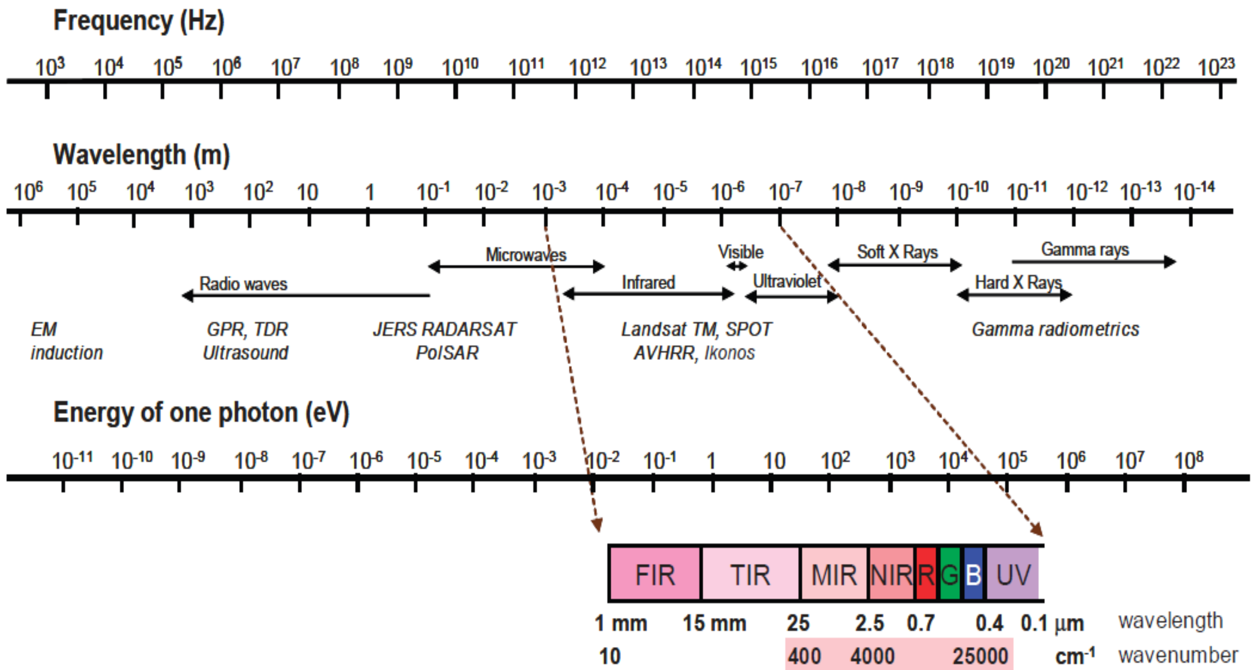


Figure 1: *The electromagnetic (EM) spectrum highlights visible and infrared portions (McBratney et al., 2003; Viscarra Rossel et al., 2006)*

Soil reflectance has been investigated since (Bowers & Hanks, 1965), and there is a solid foundation for its interpretation. The technique was first applied by (Zheng & Schreier, 1988) to predict field fertility and soil patterns via spectral reflection. Another early approach on proximal spectroscopy was by (Ben-Dor & Banin, 1995) to examine the possibility of investigating soil attributes by the reflectance curves in the near-infrared area in Israel's arid and semiarid soils. These researches were the breakthrough for predicting soil properties worldwide. The use of soil reflectance spectroscopy (visible – near-infrared reflectance or visible – mid-infrared reflectance) and XRF spectroscopy has gained much attention in soil analysis over recent decades (Viscarra Rossel et al., 2006). On the other hand, visible and infrared spectroscopy in some cases, is more straightforward than usual soil analysis, and sometimes, more precise. (Viscarra Rossel et al., 2001) proposed that the prediction precision of the MIR-PLS approach for lime requirement and pH is higher than traditional analysis. Infrared spectroscopy techniques are highly sensitive to both organic and inorganic phases of soil, making them particularly useful in agricultural and environmental studies (Viscarra Rossel et al., 2006).

Diffuse reflectance spectroscopies require the least or no sample preparation which avoids the use of environmentally destructive digestants in the laboratory (Soriano-Disla et al., 2014; Viscarra

Rossel et al., 2011). A material's molecular composition and form influence how it reflects, absorbs, scatters, and emits electromagnetic radiation, resulting in a distinct spectral signature (Haas & Mizaikoff, 2016). Nondestructive properties of spectral techniques enable repeatable and simultaneous measurements to be made, giving it a substantial advantage over wet chemistry laboratories (Pasquini, 2018). Proximal soil sensors can be used to detect both subsurface and surface soil properties. However, a full description of either fine or coarse variation in soil properties has been difficult and costly to manage (Viscarra Rossel et al., 2009).

In address the need for increasing information about soil condition, while reducing the cost of soil measurements (Nocita et al., 2015; Soriano-Disla et al., 2014) Spectroscopy in the VNIR-SWIR region (400–2500 nm) has been a possible alternative method for observing soil factors. MIR spectroscopy has been deemed to be appropriate for the prediction of soil organic and inorganic carbon contents at large-scale soil inventories (Grinand et al., 2012)

In both laboratory and field, there is undeniable potential for using proximal soil sensing techniques, such as Vis-NIR and MIR, to predict soil physical, chemical, and biological properties quickly and cost-effectively (Soriano-Disla et al., 2014). The most commonly studied soil properties in field conditions using portable Vis-NIR and NIR devices are extractable P, clay cohesion, macronutrients (Ca, K, and P), the water content in the soil, TOC, SOM, pH, and total C and N (Christy, 2008; Gomez et al., 2008; Mouazen et al., 2005; Nocita et al., 2011; Rossel & Behrens, 2010).

Some studies have reported a moderate prediction of gravimetric water content, cation exchange capacity (CEC), soil organic carbon stock, and elemental analysis (both macro and micro) with small variations for both MIR, NIR, and vis-NIR spectroscopy (Cambou et al., 2016; Soriano-Disla et al., 2014). NIR and Vis-NIR have been reported to give a better prediction for particle size analysis, electrical conductivity, microbial biomass, microbial respiration, and microbial groups (Kodaira & Shibusawa, 2013; McBratney et al., 2006; Soriano-Disla et al., 2014). Some studies have reported a better prediction of soil properties observations from MIR spectroscopy including (inorganic carbon, total organic carbon, soil organic matter), micronutrient prediction, pH and lime requirements, soil contaminants, CEC, and C/N ratio (McBratney et al., 2006).

The development of reflectance spectral libraries to describe soil properties in African Countries has been performed for fast and easy predictions (Shepherd, 2010; Shepherd & Walsh, 2002). Both near-infrared, mid-infrared, or combined diffuse reflectance spectroscopy have been applied to assess the soil fertility in rice fields in sub-Saharan Africa and also to determine various soil properties in several soil groups (Brunet et al., 2007; Johnson et al., 2019).

Soil matrix includes a variety of low-concentration parameters with overlapping absorptions that affect spectroscopic detection (Angelopoulou et al., 2020). Thus, spectral analysis necessitates the application of multivariate approaches to extract hidden data.

Spectral data analysis is achieved with the use of multivariate statistical methods, in which the success is highly dependent on the selected calibration method (Geladi, 2003). Because of its interpretability and fast computation time, PLSR is the most widely used linear method for describing the relationship between spectral data and soil properties (Stenberg et al., 2010; Vibhute et al., 2018). In general, a model's accuracy can be measured using several methods and metrics.

Quantitatively, the accuracy of PLSR predictions in each of the spectral regions varies significantly between attributes; however, predictions

using the MIR has been observed to be better (Viscarra Rossel et al., 2006). Another study was carried out in the United States by collecting 1167 soil datasets from National Ecological Observatory Network (NEON) domains, with the findings indicating that soil MIR spectra could be used to characterize and categorize soil layers and orders when the soils have different spectral properties (Zhang et al., 2021). Despite the fact that reflectance spectroscopy has been used in Tanzania and other parts of the world, its use, especially in the agricultural field, is still not well reported.

2.4 Models for prediction of soil properties

Quantitative spectral study of soil employing visible and infrared reflectance spectroscopy necessitates sophisticated statistical techniques to distinguish the response of soil properties from spectral features (Deiss et al., 2020; Viscarra Rossel et al., 2006). Methods have been developed to link soil spectra to soil characteristics. The most prevalent strategies for spectrum calibration and prediction are principal components regression (PCR) by Chang et al, (2001) and partial least squares regression (PLSR) (McCarty et al., 2002). The soil information is utilized by PLSR during the breakdown process whereas PLSR exploits the association between spectra and soil, resulting in spectral vectors that are directly related to soil attributes (Nanni et al., 2018). PLSR has been used in both in situ and laboratory soil spectroscopy to predict soil properties in either NIR or MIR region of the electromagnetic spectrum (Hutengs et al., 2019; Ludwig et al., 2019; Xu et al., 2018). For instance, (Ben-Dor & and Banin, 1995) used multiple regression analysis (MRA) to link certain NIR bands to soil parameters. Four multivariate approaches; partial least-squares regression (PLSR), support vector regression (SVR), random forest (RF), and multivariate adaptive regression splines (MARS)) were applied to predict SOC from MIR spectra (Seema et al., 2022). Both of these multivariate regression approaches have been applied in different places to establish a relationship between soil properties and spectral features from different places and perspectives (Karray et al., 2023; Khuntia et al., 2015; Sun et al., 2012; Zhao et al., 2021). Employing chemometric methods in the prediction of soil properties in the selected agricultural sites, will help soil monitoring and thus draw attention to precise mitigation measures in order to maintain the level of SOC and SOC stocks.

2.5 Soil Organic Carbon (SOC) and Soil Organic Matter (SOM)

The mixture of degraded plant and animal waste, living soil organisms, and the materials they create is known as soil organic matter, or SOM (Rocci et al., 2024). A vital component of soil organic matter (SOM), soil organic carbon (SOC) is essential for soil fertility, structure, water retention, and carbon sequestration (Gao et al., 2024). Land usage, climate, and agricultural techniques all have an impact on SOC levels. Particularly in topsoil, techniques like organic amendments, cover crops, and reduced tillage aid in raising and stabilizing SOC, albeit stability over the long run may differ.

SOC is a measurable part of soil organic matter; organic matter makes up only 2–10% of the mass of most agricultural soils. It influences the biological activity of the soil, determines its physical and chemical qualities, and serves as a gauge of soil productivity (Rossi et al., 2009). Also identified for maintaining several functions. It is a significant part of soil organic matter (SOM), on the one hand. It is widely known for keeping up several functions. It is the primary component of soil organic matter (SOM) (Reeves, 1997; Rossi et al., 2009). Only the carbon portion of organic compounds is referred to as "soil organic carbon" (SOC). Since it is challenging to directly quantify soil organic matter (SOM), laboratories often measure and report SOC. It has been reported in several research findings, good agricultural farming methods led to increased SOC and crop yields (Alavaisha et al., 2019, 2022; Mkonda & He, 2023) Studies have been conducted in Tanzania to provide national carbon stock maps and topsoil organic carbon concentration by using soil carbon datasets (Kempen et al., 2019; Winowiecki et al., 2014). SOC stocks in some parts of Tanzania forests are characterized by poorly crystallized Fe- and Al-oxides due to variations in the soil chemical parameters governing SOC stability (Kirsten et al., 2016; Rossi et al., 2009). Another research finding which was carried out in the southern part of Tanzania, results showed that after 25 years of maize farming, native SOM dropped by an average of 50%. There is only a small contribution from cereal residues to SOM under the current residue management system, with the majority of them being grazed and burned (McDonagh et al., 2001). Although the significance of these services is widely acknowledged, little is known about the factors that influence soil organic carbon (SOC) dynamics across different land uses in the selected agricultural sites (Winowiecki et al., 2014).

2.6 Application of Soil Reflectance Spectroscopy in Tanzania

Tanzania as a tropical Sub-Saharan country experiences a rapid change in land use from forestry to agricultural vegetation (Food and Agriculture Organization, 2016; Henry et al., 2009; Smith et al., 2016). The distribution of SOC in soil profiles under distinct land uses has been predicted in situ by using Vis-NIR spectroscopy at Mount Kilimanjaro (Tanzania) as shown in (
Table 1). According to this discovery, it was possible to predict soil organic carbon by incorporating spectral characteristics from a new site and in-situ features into the model (Kühnel & Bogner, 2017). Near-infrared spectra have been used as a quick tool for assessing soil health indicators for sustainable food production systems in Tanzania where the research findings had promising results (Recha et al., 2021). Another research finding conducted in East Africa including Tanzania highlighted that most soil properties (pH, SOC, total nitrogen, and exchangeable K) were potentially predicted by spectral techniques for fertilizer recommendations (Asrat et al., 2023; Deiss et al., 2020).

Studies have been done in Tanzania to estimate SOC stocks ($kg\,m^{-2}$) in different soil depths, predict SOC concentrations ($g\,kg^{-1}$), evaluate the impact of erosion and land cover on SOC, and examine the link between dynamic and inherent soil qualities under various land uses. Results show that the mapping of SOC stocks using reflectance spectroscopy has promising potential with good R^2 values whereby the produced maps are extremely useful for strategic land management initiatives to emphasize ecosystem services (Kempen et al., 2019; Winowiecki et al., 2014). Overall, reflectance spectroscopy provides useful information, but it can be expensive to set up and operate and does require specialized resources. The cost is increased by the equipment, which includes spectrometers, fiber optic probes, and light sources. A study on reflectance spectroscopy also found that the cost can be further increased by maintaining the equipment repairs and even hiring expert staff for analysis (Wallace et al., 2009). Even though several research works have been carried out in different parts of the world about the use of MIR and NIR reflectance spectroscopy to predict soil properties, yet their applications in Tanzania are limited.

Table 1: Application of Diffuse reflectance spectroscopy in the prediction of soil properties in some parts of Tanzania

SN	Land use	Soil properties	Spectroscopic technique and chemometric methods	Prediction accuracy	References
1.	Forests	SOC concentration g cm^{-3}, SOC stock (kg m^{-2}) Bulk density	Kriging model	R^2= 0.60 in 0 – 30cm cross-validation	(Kempen et al., 2019)
2.	Agricultural fields	clay, sand, pH, total organic carbon, and permanganate oxidizable carbon	SVM, PLSR. mid- DRIFTS. Training sets = 75%, Test set = 25%	SVM>PLSR	(Deiss et al., 2020)
3.	Forest, woodland, shrubland, grassland and cropland	SOC stocks	MIR. Random forests =	R^2 of > 0.95 and RMSEP of 4.3 g kg^{-1} independent validation datasets n=2052	(Winowiecki et al., 2016)
4.	Croplands, Forests AfSIS project	organic carbon, pH, sand, silt and clay fractions, bulk density, cation-exchange capacity, total nitrogen, exchangeable acidity, Al content and exchangeable bases (Ca, K, Mg, Na).	MIR. Random forests and linear regression, 5-fold cross-validation	Random forests algorithm consistently outperforms the linear regression algorithm, with average decreases of 15–75% in Root Mean Squared Error (RMSE)	(Hengl et al., 2015)

5.	Sub-Saharan Africa Agricultural fields	exchangeable Ca, exchangeable Mg, sum of exchangeable cations, CEC, ECEC, , total N, total organic C, clay content.	MIR and NIR, NIR-MIR. PLRS, CV	($0.75 < R2 \leq 0.86$ and $1.36 \leq RPIQ \leq 3.78$) were obtained for 13 soil properties. combined MIR-NIR had a better prediction	(Johnson et al., 2019)

3. MATERIALS AND METHODS

3.1 Study area description

The research was carried out in five different sites within the Mbeya and Songwe Regions located in southwestern Tanzania (Figure 2): Mbozi, Kyela, Tukuyu (Rungwe), Mbarali, and Mbeya Urban. 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).

.

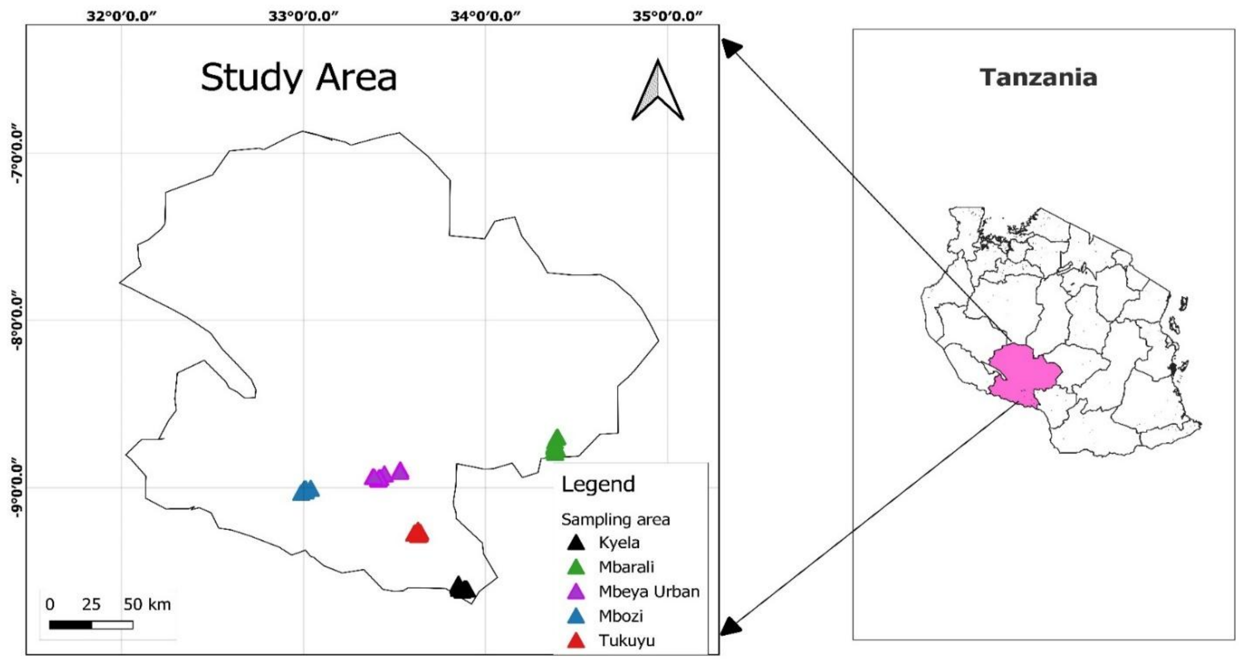


Figure 2: *Selected study sites in the southern part of Tanzania*

3.1.1 Climate

The climate in the Southern part of Tanzania is heavily impacted by physiology and altitude. It is mainly tropical, with distinct seasonal and 14 altitudinal temperature fluctuations, as well as distinct dry and rainy seasons. The average temperature in the highlands is 16^{0}C, whereas in the lowlands it is 25^{0}C. Rainfall is plentiful and consistent in the region. Annual rainfall ranges from 650 mm in the Usangu plains and Chunya to 2600 mm on Lake Nyasa's northern coasts and in the highlands. Rains usually begin in October and last until May, followed by a dry and chilly time between June and September (Mbeya district council, 2015; URT, 2017) (Hamadi Mohamed et al., 2021).

3.1.2 Agro-economics of the selected agricultural sites

The agro-economic zone in the selected sites is divided into major three categories, namely, the high potential zones, medium potential zones and low potential zones. The high potential zones are locations with a lot of agricultural production and a lot of rainfall (1,200mm in the lowlands and 2,600mm in the highlands). Central Mbeya Plain, South Usangu Plains, Poroto and Ilembo Highlands, West Rungwe Plain, East Ileje, East and Central Rungwe, North Kyela/South Rungwe, and South Kyela are the densely inhabited areas lowlands (URT, 2017). The medium potential zones receive moderate rainfall and include the Mbozi/Ileje Plateau, the Rukwa Valley and the North Usangu Plain. Low potential zones (650mm - 1,200mm) include the Msangaji Plateau and parts of central Chunya. In this zones, rainfall is usually inconsistent and soils are less productive (Mbeya district council, 2015).

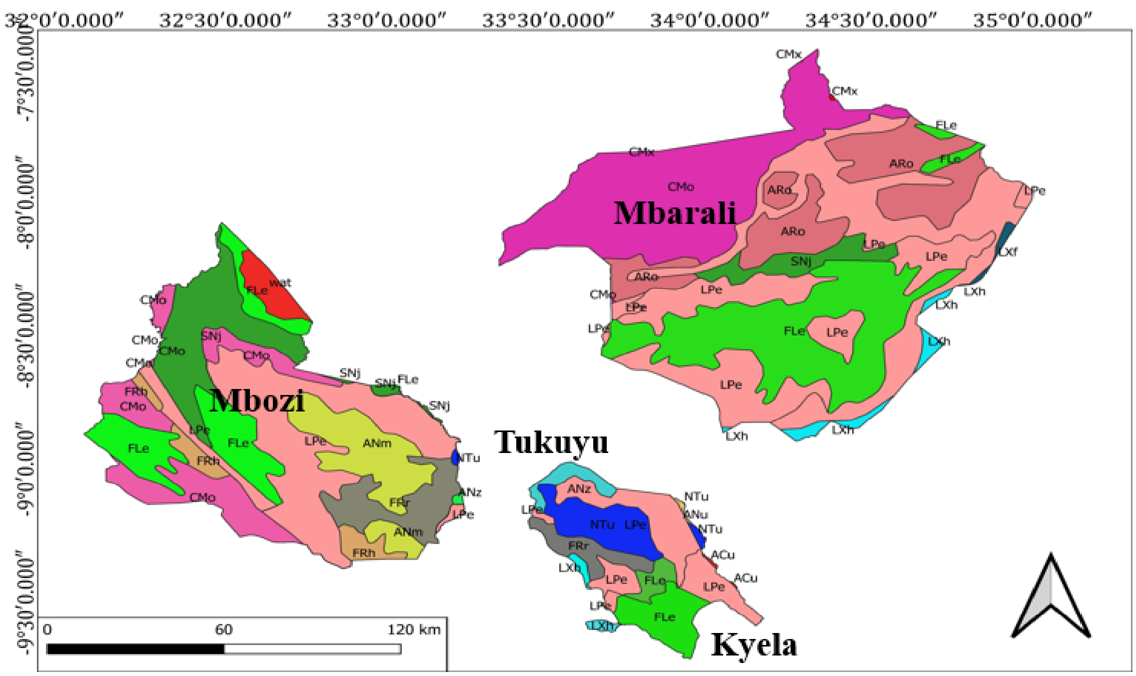
3.1.3 Agriculture

Mbeya is one of Tanzania's primary food surplus regions. The region spans 6,362,200 ha, with 3,960,000 ha suitable for agricultural and animal rearing. However, only about 1.3 million hectares of land are cultivated annually for both food and income generation crops. Agriculture provides a living for around 80% of the population. The region also produces surplus food (bananas, paddy, tomatoes, maize, onions, potatoes, wheat, groundnuts, sunflower, sorghum, beans, cassava, green vegetables, and lentils) to the tune of 350,000 tons per year, which is mostly sent to neighboring regions such as Dar es Salaam, Singida, Dodoma and the Lake Regions. Southern part of Tanzania also produces cash crops including cocoa, tea, and coffee as shown in (Figure 3) (Mbeya district council, 2015).

Figure 3: *Some crops cultivated in the Southern part of Tanzania (URT, 2017)*

3.1.4 Major soil types and vegetation

Major soil types across the selected sites are shown in (**Error! Reference source not found.**). Soils in most arable land are typically of moderate fertility, coarse to medium texture, and range from sandy loams to alluvial solids. Even though the land is heavily cultivated, huge areas are still uncultivated with natural vegetation such as "Miombo" woods. Areas with an annual rainfall of 800-1200 mm favor Miombo woodland growth, whilst areas with lower rainfall, particularly in the region's north, support the growth of dense thickets of acacias, forested grasslands, and thorny trees. Forests, frequently evergreen and bamboo trickers, grow in locations with higher rainfall, such as Rungwe, Kyela, and South-East Ileje, except at the highest elevations, where afro-alpine grasslands exist. Eutric Gleyic Fluvisol, Eutric Leptosol, Molic Andosol, and Humic Umbric Nitisol soil types are common soil type in the selected sites are as shown in (Figure 4).



ANa	Andic Andosols	CMo	Humic/Ochric Cambisols
ANz	Andosols	FRh	Hplic Ferralsols
LPe	Eutric Leptosols	SNj	Gelic Solonetz
FLe	Eutric Fluvisols	wat	Water bodies
FRr	Rhodic Ferralsols	ARx	Chromic/Xanthic Arenosols
LXh	Haplic Lixisols	CMx	Chromic/Xanthic Cambisols
NTu	Umbric Nitisols	LXf	Ferric Lixisols
ANm	Molic Andosols	ACu	Umbric Acrisols

Figure 4: *Common soil types on the studied sites (Mlingano Agricultural Research Institue, 2006)*

3.2 Farm household questionnaires

3.2.1 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.

3.2.2 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.

3. 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 2).

Slovin's sampling formula (Ismail et al., 2022), was applied to determine the sample size of participating active smallholder farmers for the questionnaire survey.

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

Where:

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

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

n = 206.06 ≈ 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 2: *Sample size and sampling design on the studied area*

Districts	Wards	Agro-ecological zones	Ward area (km^2)	Sample size	Percentage
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

3.2.4 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.

3.2.5 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.

3.2.6 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.

3.2.6 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, $\mathrm{X}_2, \mathrm{X}_3, \ldots, \mathrm{X}_K$) is represented by equation two below.

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

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).

3.3 Soil sampling procedures

3.3.1 Site selection, sample collection and sampling design

This study used a systematic random sampling design, following the Soils4Africa sampling protocol (Huising & 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 (Figure 5). Soil samples were taken at regular intervals of 100 meters across the agricultural fields. This ensured good coverage and reduced sampling bias.

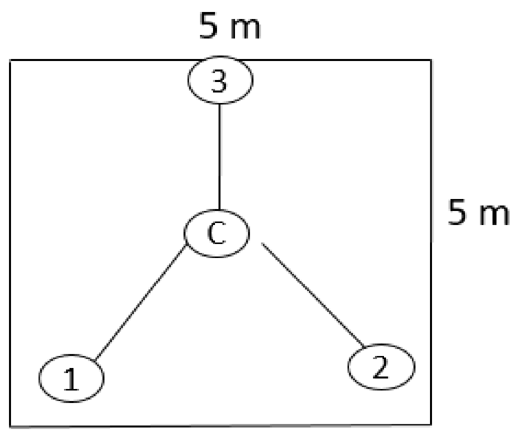


Figure 5: *Schematic representation of composite soil sampling design. Each composite sample was formed by thoroughly mixing four soil aliquots collected from a triangular pattern within a 5 m × 5 m area surrounding the central sampling point.*

Table 3: *Sample size and sampling procedures*

Districts	Agro-ecological zones	Ward area (km^2)	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. 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 (Table 3).

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. Figure 6 shows sample collection in Kyela, which involved taking topsoil samples, subsoil samples, and other related farm information.

Figure 6: *Soil sample collection in Kyela rice farms*

3.3.2 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.

3.3.2.1 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

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

Whereas;

BD_g: gross bulk density (g/cm^3)

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

V_{core}: volume of the soil (100 cm^3)

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.

3.3.2.4 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.

$$SOC_{stock(i)} = C_i \times BD_{sample} \times depth_{(i)} \tag{4}$$

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

3.3.3 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 th e 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 fig ures 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.

3.4 Spectral measurements

3.4.1 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 - 500cm^{-1}), was employed to scan 240 soil samples. The measured spectrum reflectance was converted to an absorbance value using the equation: Absorbance = log (1/Reflectance).

3.4.2 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:

$$X = TP^T + E \tag{5}$$

$$Y = UQ^T + F \tag{6}$$

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.

3.4.3 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

3.4.4 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.

4. RESULTS AND DISCUSSIONS

4.1 Awareness and Adoption of Smallholder Farmers of IAPs

4.1.1 Demographic information characteristics of the interviewed respondents

A total of 206 respondents were interviewed from five locations in the Southern part of Tanzania (Table 2). 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 4). 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; Tsheko, 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 4: Demographic information of the studied population (n = 206)

Variable (%)		Data collection sites						
		Kyela	Mbalali	Mbeya Urban	Mbozi	Tukuyu	Mean(SD)	Chi Square, p - value
Gender	Male	77.5	76.2	56	45	62.8	63.5(6.1)	x^2=7.3
	Female	22.5	23.8	44	55	37.2	36.5(6.1)	*p = 0.007*
Marital status	Single	10	19	22.5	20	39.5	22.2 (10.8)	
	Married	87.5	78.6	77.5	77.5	55.8	75.4 (11.7)	$x^2 = 457$
	Divorced or separated	2.5	2.4	0	2.5	4.7	2.4 (1.7)	$p<0.0001$
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)	$x^2 = 25.5$
	35-44	22.5	28.6	17.1	12.5	27.9	27.9(3.1))	$p<0.0001$
	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)	
	1 – 5	42.5	61.9	29.3	50	16.3	40.0 (17.8)	$x^2 = 217.6$
	10-Jun	14.6	7.1	7.3	30	30.2	17.8 (11.6)	$p<0.0001$
	>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)	
	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)	$\chi^2 = 554.5$
	Crop rotation	13.5	45.9	2.7	37.8	18.9	23.8 (17.8)	$p <0.0001$
	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)	$\chi^2 = 333$
	Rainfall	21.4	15.1	21.9	20.8	21.4	20.1 (2.8)	$p <0.0001$

Fallowing time	1-4 months	14.3	29.5	24.1	20.5	11.6	20.0 (7.3)	χ^2 = 206.9
	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)	$p < 0.0001$
	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)	
	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)	χ^2 = 438
	Farm yard manure	31.8	13.6	4.5	9.1	40.9	20.0 (15.6)	$p < 0.0001$
	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 7) 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 7). 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.

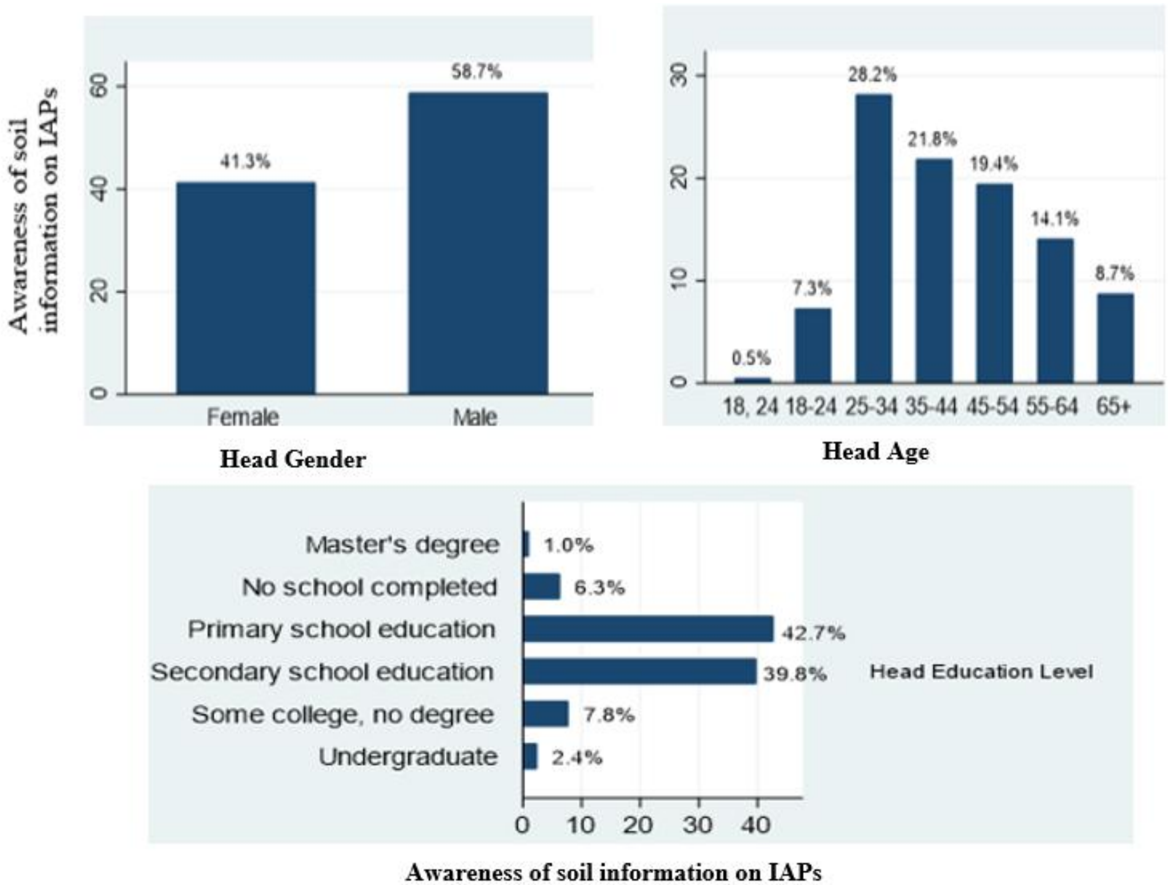


Figure 7: *Awareness of Soil information on IAPs by gender, age, and education level*

4.1.2 Farming practices

In the surveyed areas, crop farming dominated, with the participation of 92%, 95%, 92%, 80%, and 93% in Kyela, Mbarali, Mbeya Urban, Mbozi, and Tukuyu, respectively. Mixed farming ranked second, notably prevalent in Mbeya Urban (51%) and Mbozi (48%), whereas it was less pronounced in Mbarali (3%), Kyela (5%), and Tukuyu (2%). This might be due to nature of crops grown such as rice and banana (Justine et al., 2025). The following observation is because crop farming can be attributed to the dual purpose of crop cultivation, which serves both as a means of sustenance for families and as a source of marketable goods (Meemken & Bellemare, 2020). Prevalence also arises from the intergenerational transmission of commerce and expertise from older generations and is reinforced by various farming techniques such as crop rotation, intercropping, and monoculture. The most common method of intercropping is to plant maize and beans together in the same field (Banjarnahor et al., 2015; Nassary et al., 2020). Beans, maize, rice, and cocoa are the common crop types grown in Mbeya's arable land. Livestock farming emerged as the third most adopted practice, with rates of 43% in Mbarali, 30% in Kyela, and 19% in Tukuyu. Irrigated farming practices were absent in Tukuyu, Kyela, Mbeya Urban, and Mbozi, contrasting with the Mbarali region, where 41% of farmers were actively involved in irrigation agriculture (Figure 8). A number of reasons, such as the development of irrigation infrastructure, the availability of water supplies, and farmers' perceptions of risk, could be to blame for this. The higher adoption rate in Mbarali points to a more conducive irrigation environment, possibly with more water available or easier access to irrigation technologies (Justine et al., 2025). Root crop farming was less observed in all the surveyed area. Smallholder farmers in the selected sites have been engaged in livestock production for many years where by the incorporate crop residues and fodder use as the most common residue management (Marchant, 2006).

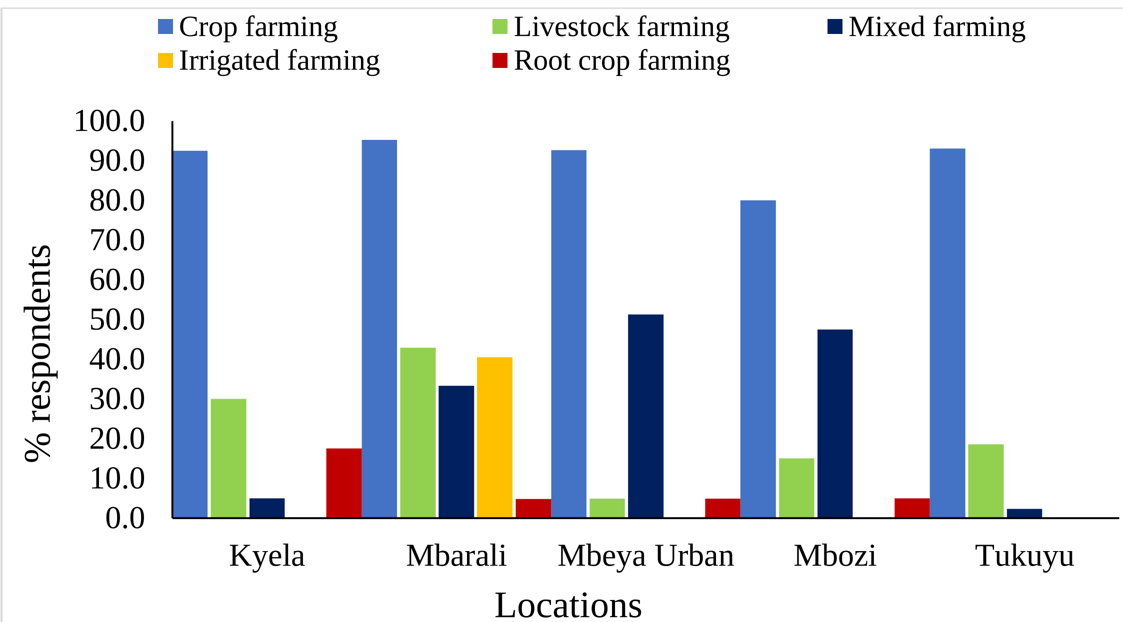


Figure 8: *Farming practices reported by smallholder farmers in the selected sites*

4.1.3 Pest control

Three-quarters of the farmers interviewed were using chemical control to eliminate pests, with higher scores of 88% in Mbeya urban and 74% in Mbarali areas. The second-highest score method was the "none" response, representing 73% in Kyela, 40% in Mbozi, and 35% in Tukuyu. Farmers in Mbeya Urban barely experienced Integrated Pest Management (IPM) and were not engaged in biological control at all (Figure 9). The following observation may be the result of farmers' perception that regular pesticide use is an efficient method to management pests (Dinham, 2003; Ngowi et al., 2007). Lack of agricultural extension services makes farmers resort to various methods, including pesticide use, to address pest issues. However, a constraint arises due to inadequate knowledge of pesticide application (Laizer et al., 2019; Ngowi, 2003). Biological and IPM management activities were not observed in our study area since they are expensive and require expertise to implement, thus smallholder farmers do not attempt to use it (Brewer & Goodell, n.d.; Grasswitz, 2019). The observed discrepancies among different study sites are probably caused by variances in crop types, farmers' economic capacity, input access, and level of extension services. While rural areas may rely more on traditional ways due to limited resources, urban areas have better access to agrochemicals and support (Midega et al., 2018; Mwangi & Kariuki, 2015).

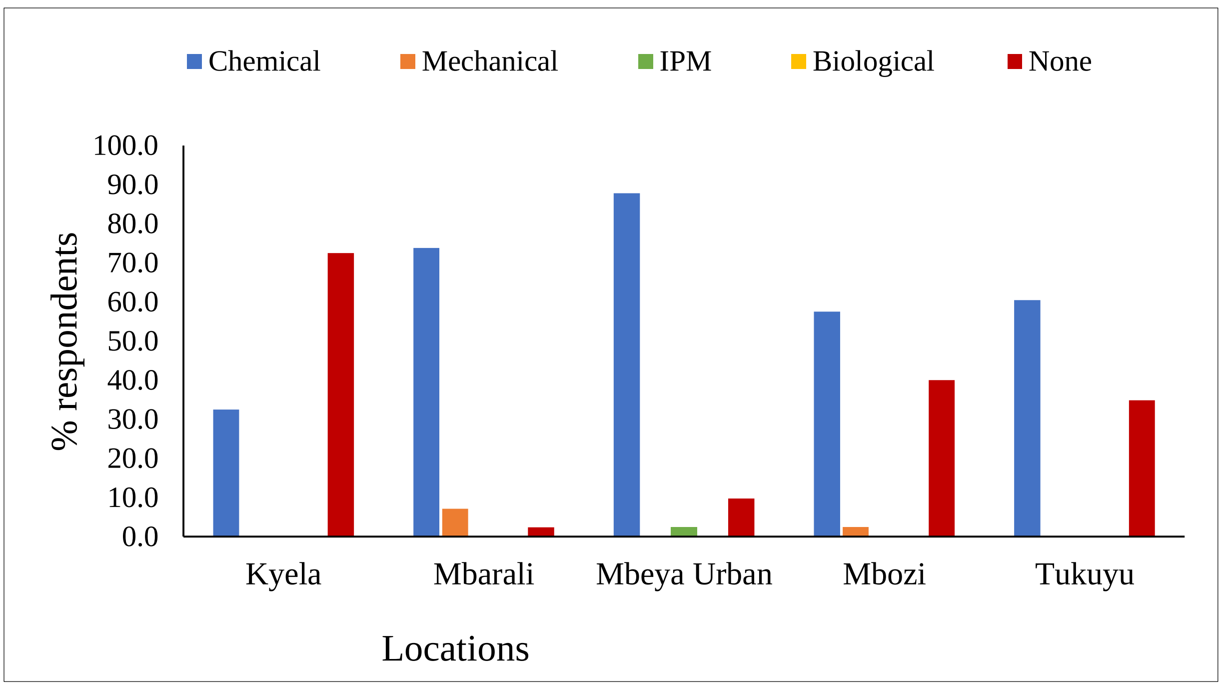


Figure 9: *Pest control methods reported by smallholder farmers*

4.1.4 Weed control management

Hand weeding was carried out by majority of smallholder farmers in the Mbarali areas (95%), Kyela (90%), and Mbozi (50%). The observed result is because hand weeding is determined to be a prevalent method of weed control due to financial constraints faced by local farmers, who opt to minimize the use of herbicides. The predominance of hand weeding could be due to its cost-effectiveness and accessibility to the workforce during periods of high demand thus farmers are selfmotivated to apply the procedure (Hussain et al., 2018; Sims et al., 2018). The highest rate of herbicide application was observed in Mbarali (81%), Mbeya Urban (71%), and Mbozi (50%) as shown in Figure 5. This could be explained by the reason that farmers from Mbarali area believe spraying is a major tool to eliminate weeds. Some studies have shown that smallholder farmers spray herbicides to control weeds (Frederick et al., 2020; Ngailo S. et al., 2016), which aligns with our findings. Mulching was found to be prevalent in Kyela (38%) and Tukuyu (47%), while no such response was recorded in Mbeya Urban. Smallholder farmers believe keeping the surface covered helps conserve soil surface water and aid regular infiltration (Jhariya et al., 2021), which could also be the reason for the minimal application of insecticides and herbicides observed in some parts of the studied areas (Figure 10). Furthermore, some researches have reported that mulching is routinely implemented on farms to improve productivity and control weeds. (Anantha et al., 2021; Chuma et al., 2022; Kimaro, 2019).

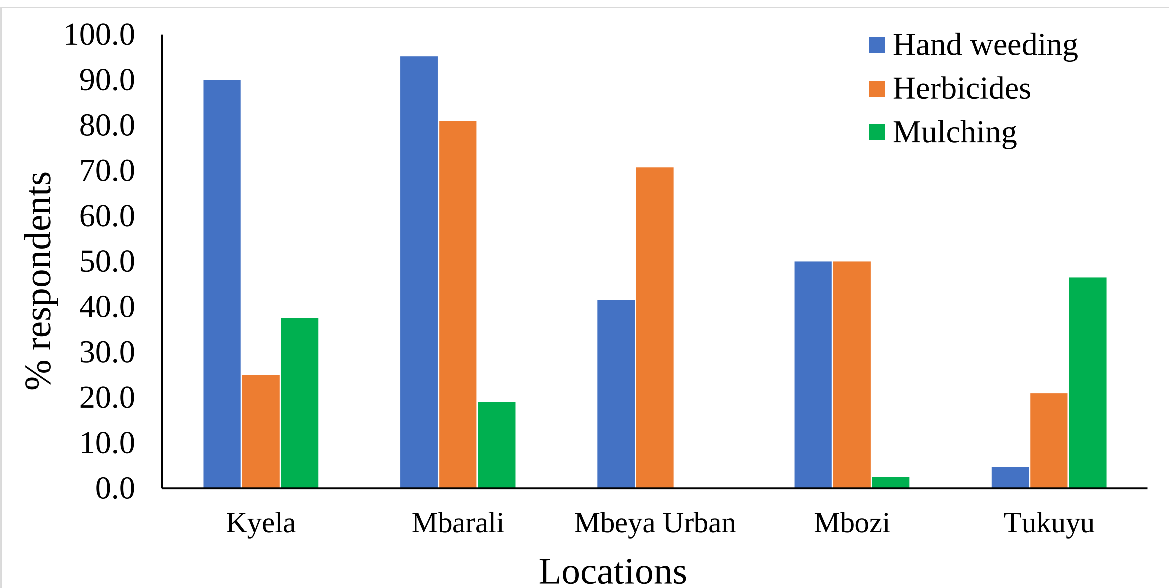


Figure 10: *Weed control methods reported by smallholder farmers in the selected sites*

4.1.5 Soil conservation practices in the selected sites

Crop residues (Table 5) 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 (Table 5).

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 5). The "none" response was observed with 19% of soil conservation practices.

Table 5: *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

4.1.6 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 11). 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 11). 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.

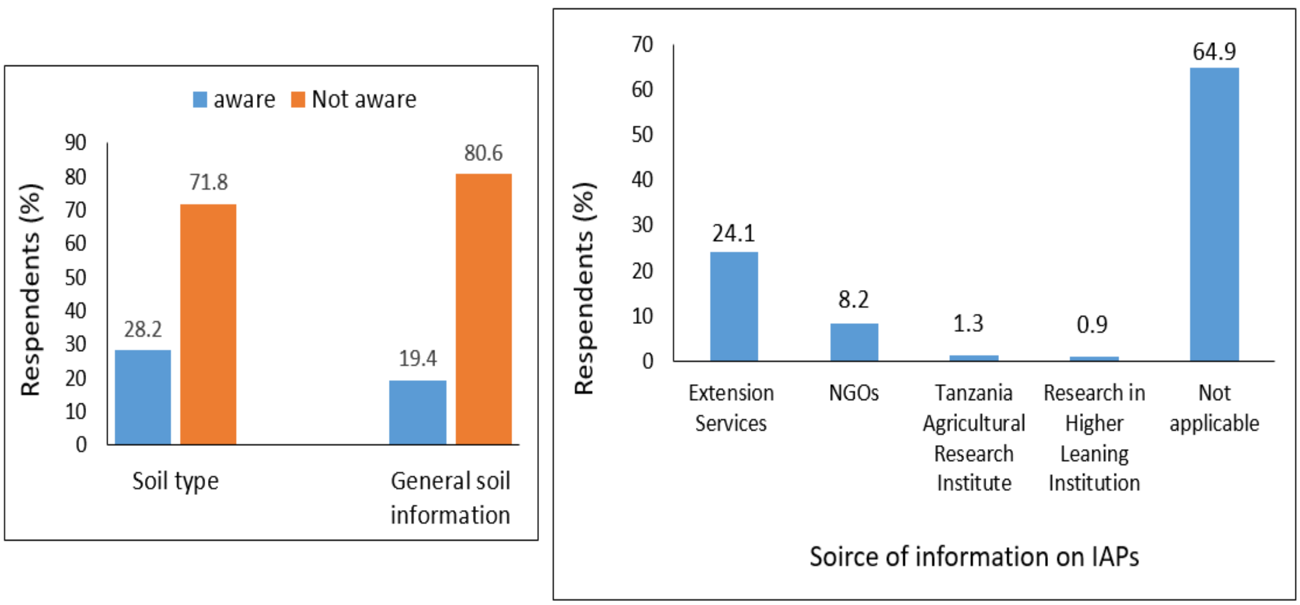


Figure 11: *Awareness and adoption of IAPs (A), and the source of information on IAPs (B)*

4.1.7 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 12A). 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 12B). Both agricultural experts and reduce pests and disease problems also plays important role in the farmers' adoption to IAPs.

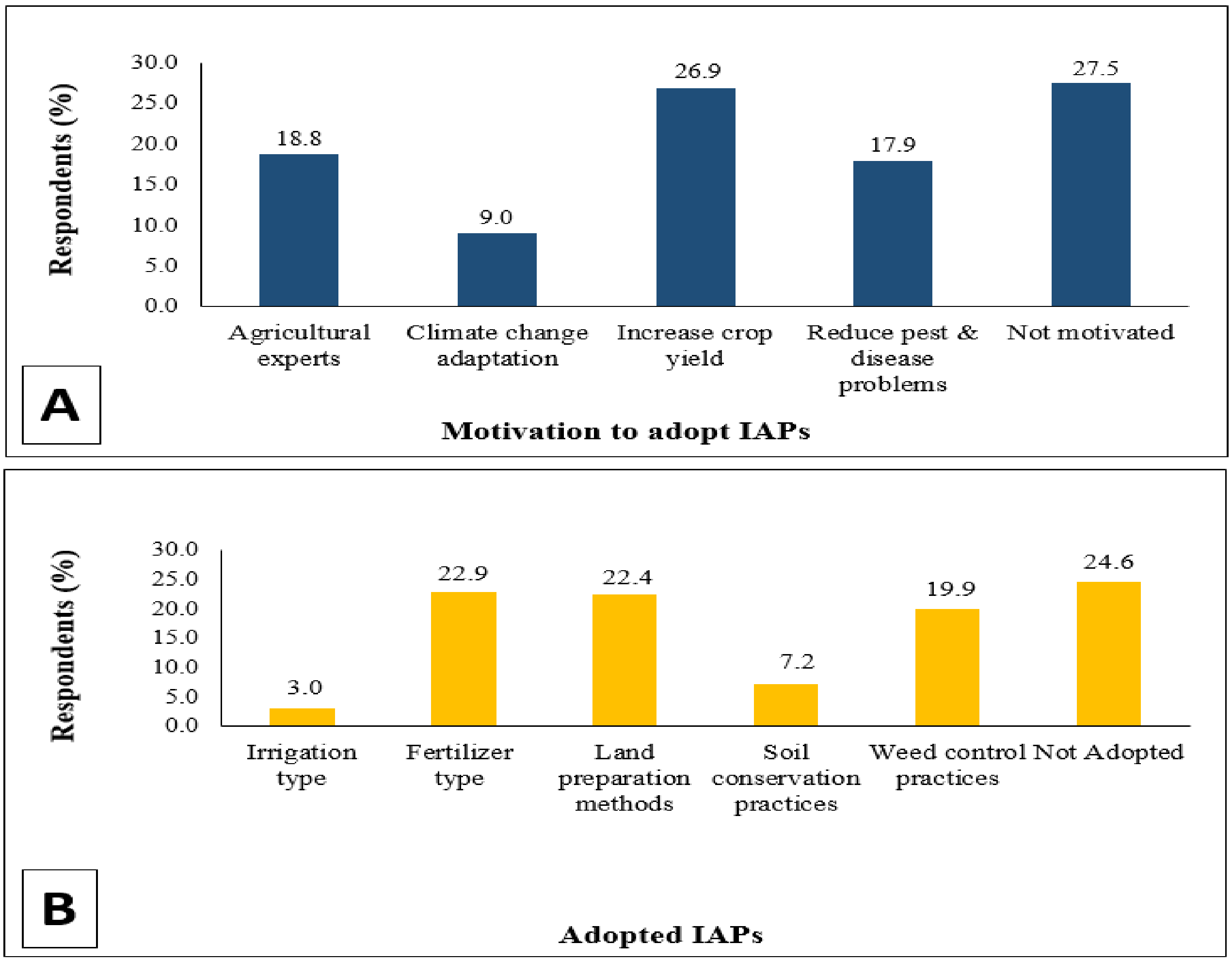


Figure 12: *Motivation towards smallholder farmer's adoption to IAPs (A) and adopted IAPs (B)*

4.1.8 Farmer's perception of yield after they have Adopted to IAPs

More than 50% of the respondents reported positive perfection there will be an increase in yield after they have adopted to IAPs, with 97% in Mbeya urban, 60% in Mbozi, and 52% in Mbarali (Figure 13A). Farmers in these areas believe applying IAPs will improve productivity which could be explained by farmers' interaction with agricultural experts or their understanding on improved agricultural techniques as reported by (Oo & Usami, 2020). Smallholder farmers in Kyela, and Tukuyu were not confident with what will happen after they have implemented IAPs in their farms.

This scenario may be caused by lack of extension services or farmers see it as expensive to adopt the techniques (Asiedu – Darko, 2014).

Respondents (56%) in this study showed that there was a "normal increase in yield" after they adopted IAPs, while only 5% observed a double in crop yield and the rest of respondents reported no increase in yield at all (Figure 13B). A low observation in crop yield could be accounted by the reason that precision and consistency of IAPs implementation determine their efficacy. Practices may be partially or improperly adopted by farmers, producing less than ideal outcomes. According to a study on the adoption of better agricultural technology in eastern Ethiopia, incomplete adoption may result in low crop yield, while proper implementation has a substantial impact on farm household income (Wordofa et al., 2021). Nevertheless, local environmental conditions, like soil fertility, climate, and water availability, could have impacted success on IAPs (Berg, 2013). Additionally, the potential advantages of IAPs may be hampered by limited access to high-quality seeds, fertilizer, and other essential inputs (Aman et al., 2024).

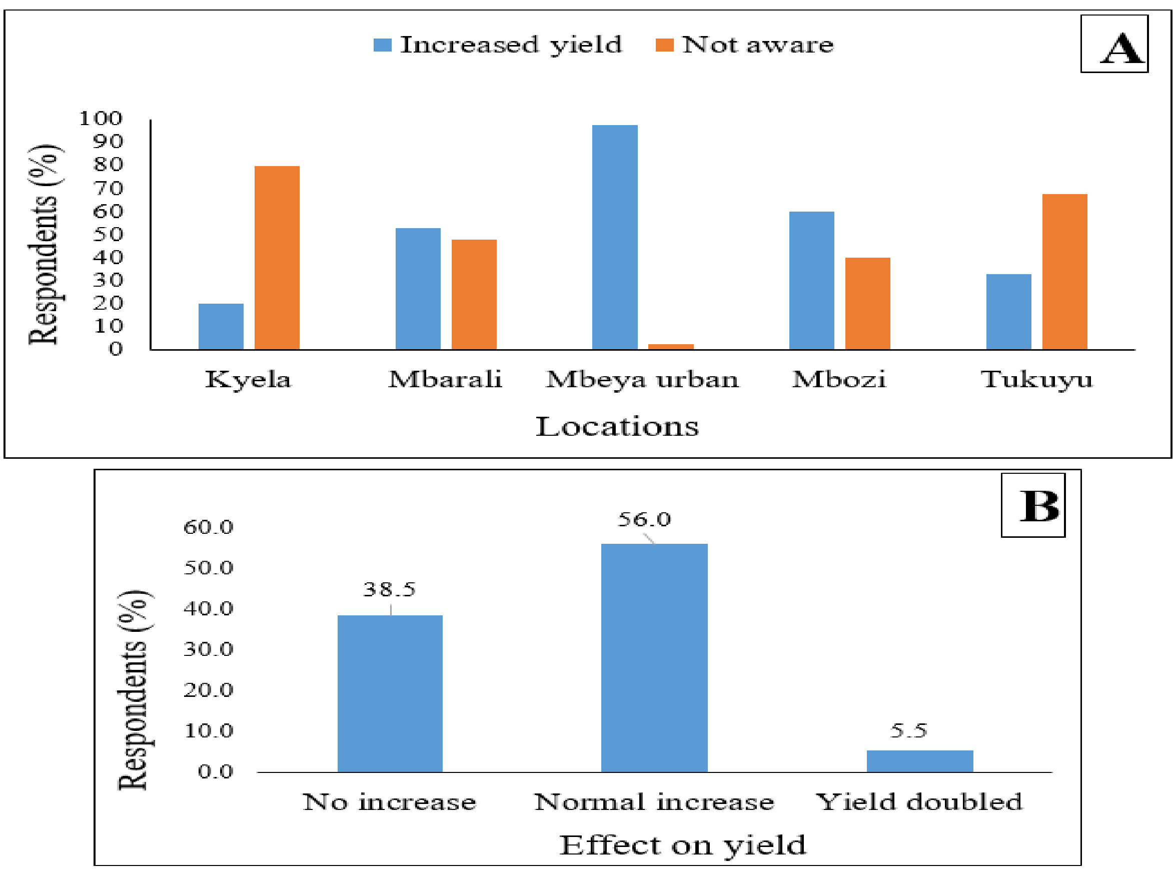


Figure 13: *Status of IAPs on the yield (A) and effects of IAPs on yield (B)*

4.1.9 Estimation of factors influencing farmer's adoption of IAPs

Table 6 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-R^2 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, fallowing time, soil information, and soil type of the fam 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 (β= -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 (β= -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 6: *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).

4.1.10 A proposed framework to help increase yield and improve the livelihood of smallholder farmers

Our findings highpoint farm-specific elements such as availability of high-quality seeds, fertilizer, irrigation, soil type, control of pests and diseases, and appropriate IAP application. When paired with non-farm elements such as efficient pest and disease control methods, precise information on soil type, defined farming methods for a specific crop type, soil testing practices, and crop rotation techniques can greatly boost yields, increase productivity and enhance crop resistance to environmental problems (Jayne et al., 2019). The findings also highlight that, even though both farm and non-farm influences are complex, agricultural specialists and extension services play a crucial role in combining and putting these elements into practice for the benefit of smallholder farmers.

Agricultural experts in these areas are essential in providing smallholder farmers with context-specific, scientifically supported answers. For example, they assist farmers in implementing climate-smart farming methods that are crucial to reducing the effects of climate change, such as conservation tillage and drought-tolerant crop types (FAO, 2018). By bridging the gap between farmers and research institutions, extension agents promote sustainable agricultural practices by converting intricate agronomic information into practical actions (Davis et al., 2012). Furthermore, this study has presented a simple framework that can be adopted by small-scale farmers in Tanzania (Figure 14).

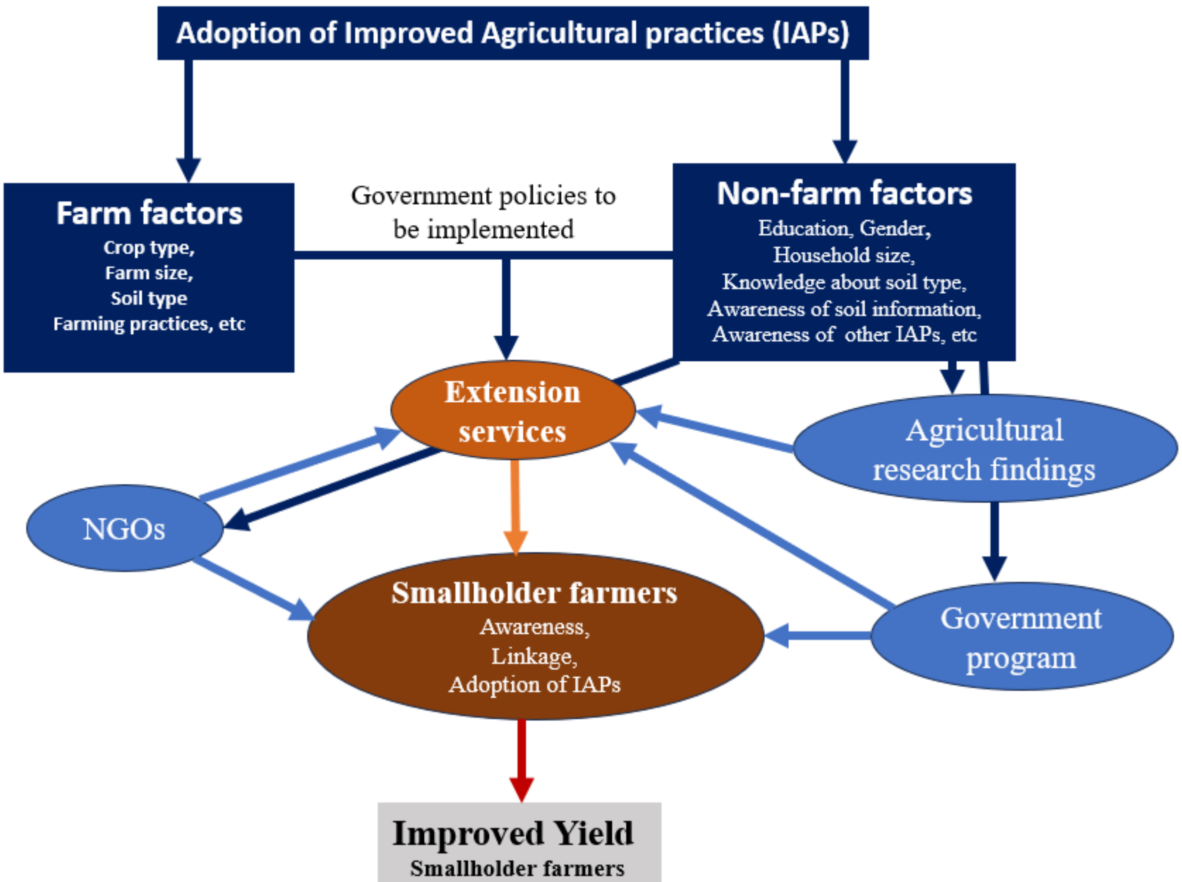


Figure 14: *A proposed framework to help increase yield and improve the livelihood of smallholder farmers in the Southern part of Tanzania*

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

4.2.1 Soil characteristics on selected agricultural sites

Among the sites studied, silt loam and loam were the most frequently observed soil textures (Table 7). 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 7: *Soil properties in four different sampling sites*

Soil physical parameters	Depths	Sampling sites			
		Kyela	Mbarali	Mbozi	Tukuyu
pH (H_2O)	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 α = 0.05 based on Tukey's HSD test*

4.2.2 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 8). 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).

In the subsoil SOC content model had a significantly greater correlation with soil type alone, accounting for approximately 79% of the variation (marginal R^2 = 0.79). The subsoil samples successfully created a strong model that gave accurate predicted values, regardless of the actual data, which closely aligned with the observed data (Buscemi & Plaia, 2020). 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 8). 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.

There is a complicated and multifaceted link between crop varieties, agricultural techniques, and soil organic carbon (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 8: *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	Random 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	-	$1.18e^{-8}$			

4.2.3 Soil organic carbon (SOC) concentrations and stocks across sites

The soil organic carbon (SOC) concentration varied between 1.6±0.03 and 4.3±0.5 in the 0 – 20 cm depth, and between 0.83±0.2 and 3.31±0.6 in the 20 – 50 cm depth. The soil organic carbon (SOC) stock ranges from 33.4±2.1 to 53.9±4.7 Mg/ha at a depth of 0 - 20cm, and from 21.7±1.7 to 49.9±5.2 Mg/ha at a depth of 20-50cm. There was a notable disparity in the observed SOC stock between topsoil and subsoil samples, with a significance level of $p<0.05$ for SOC stock (Mg/ha), as depicted in (Figure 15).

Mbozi area had the lowest soil organic carbon (SOC) stock at 57.7 Mg/ha in the 0-50 cm depth, while the Tukuyu region had the highest SOC stock at 103.8 Mg/ha (Figure 15). The observed tendency can be attributed to the reality that different agricultural areas in the studied sites display unique agricultural activities, management strategies, and kind of crops, all of which contribute to variability in soil organic carbon (SOC) stocks (Follett & Kimble, 2009).

Agricultural fields with Humic Umbric Nitisol soil type have greater stocks of soil organic carbon (SOC) in both the topsoil and subsoil, as illustrated in (Figure 16 and Figure 17). Among the different crop types, maize contributes to a higher SOC stock in the topsoil, but banana and mixed crop types are predominant in the sub-surface. The observed low soil organic carbon (SOC) levels in Kyela, Mbarali, and Mbozi may be attributed to the insufficient implementation of integrated soil fertility management, as reported by (Mhoro et al., 2015a; Ngailo., 2016). The limited quantities of soil organic carbon (SOC) in Mbarali can be ascribed to the decline in soil fertility in those fields (Mng'ong'o et al., (2021), resulting in a drop in soil productivity (Adiyah et al., 2022). The high concentrations of soil organic carbon (SOC) and SOC stocks in Tukuyu agricultural fields can be attributed to the presence of volcanic parent materials, including dense pumice and ash. These materials originated from various volcanoes in and around the Rift Valley of Southwestern Tanzania, as documented by (Funakawa et al., 2012; Msanya et al., 2007), could explain the level of soil organic carbon concentrations and SOC stocks, especially in Tukuyu agricultural fields but also the existing climatic condition of the area which observed to be quite different to the rest of the study areas.

Besides that, Tukuyu was found dominated by banana cultivation and the use banana waste as mulch. Dorel et al. (2010) reported that the application of both banana mulch and fertigation results in elevated levels of soil organic carbon (SOC) concentrations.

Applying organic fertilisers in Tukuyu can act as an extra source, resulting in an increase in soil organic carbon in the uppermost layer of soil (Schneider et al., 2021).

The high levels of SOC in these places can also be ascribed to the rugged topography. The soil samples we collected primarily originated from low-lying areas, where there is a possibility of gathering a significant amount of organic matter from the adjacent higher slopes. Furthermore, the significantly elevated soil organic carbon (SOC) levels seen in Tukuyu can be related to the cool climate in the region. This cool environment slows down the breakdown of organic matter, leading to a greater capacity for storing carbon in the soil (Miller et al., 2004). The observed soil organic carbon (SOC) concentrations in Tukuyu can be attributed to agronomic practices such as mulching, crop rotations, intercropping, or the cultivation of crops with extensive root systems (Bationo et al., 2007; Laub et al., 2023). In general, the type of soil had a greater impact on explaining the distribution and amount of soil organic carbon (SOC) than the kind of crop, especially in the lower layers of the soil. In addition to soil type, the impact of crop types was rather minimal, this could be attributed by the fact that all the studied areas were dominated by cereal crops except Tukuyu which was dominated by banana (Akida et al., 2020). It is essential to comprehend the specific differences in soil organic carbon (SOC) levels and quantities in different locations, especially in connection to different types of soil.

Tillage practices, fertilizer application, land-use changes, and erosion can all modify the organic matter inputs and rates of decomposition in the topsoil. This might possibly obscure the underlying impact of soil and crop types on soil organic carbon (SOC). Constant addition of organic matter to the topsoil layer, such as plant residuals, turnover of fine roots, fallen leaves, and decomposition, can have a greater impact on the distribution of soil organic carbon (SOC) in the topsoil compared to the subsoil. This has been supported by studies conducted by (Adiyah et al., 2022; Emiru & Gebrekidan, 2013; Godlove Mtama, 2018; Kunlanit et al., 2019).

On the other hand, subsoils demonstrate a certain level of stability that enables the fundamental characteristics of the soil, such as the amount of clay or the ability to drain water, to have a more significant impact on the accumulation and breakdown of soil organic carbon (SOC). Please cite references if available. Further work is required to explore the higher correlation between soil types and soil organic carbon (SOC) in the subsurface as opposed to the topsoil. The model incorporating soil types in the subsurface exhibited a significant level of explanatory ability (conditional R^2 = 0.55), with a considerable proportion of the variability being accounted for just by soil types (marginal $R^2 = 0.53$). The various sites did not have a significant effect ($p > 0.05$) on the content and stock of soil organic carbon (SOC) in the different soil types. The majority (70%) of the differences in the amount of organic carbon (SOC) in the topsoil and subsoil, with respect to different crop types, may be attributed to the specific locations where the samples were taken. This relationship was statistically significant, with p-values of 0.0003 for the topsoil and 0.0002 for the subsoil. In general, the changes in SOC levels and stocks at specific sites were more strongly associated with soil types rather than crop types.

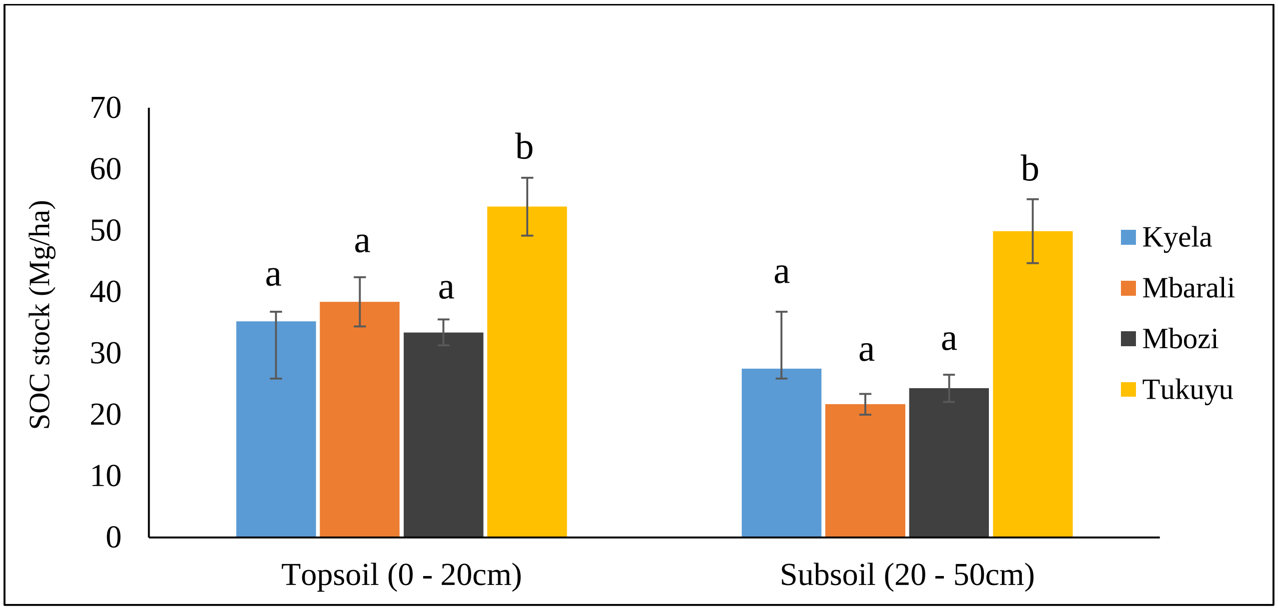


Figure 15: *Soil Organic Carbon stocks (Mg/ha) in topsoil and subsoil from the selected sites. Means in the same soil depth with the same superscripts show no significant differences for distinct sampling sites at α = 0.05 using Tukey's HSD test*

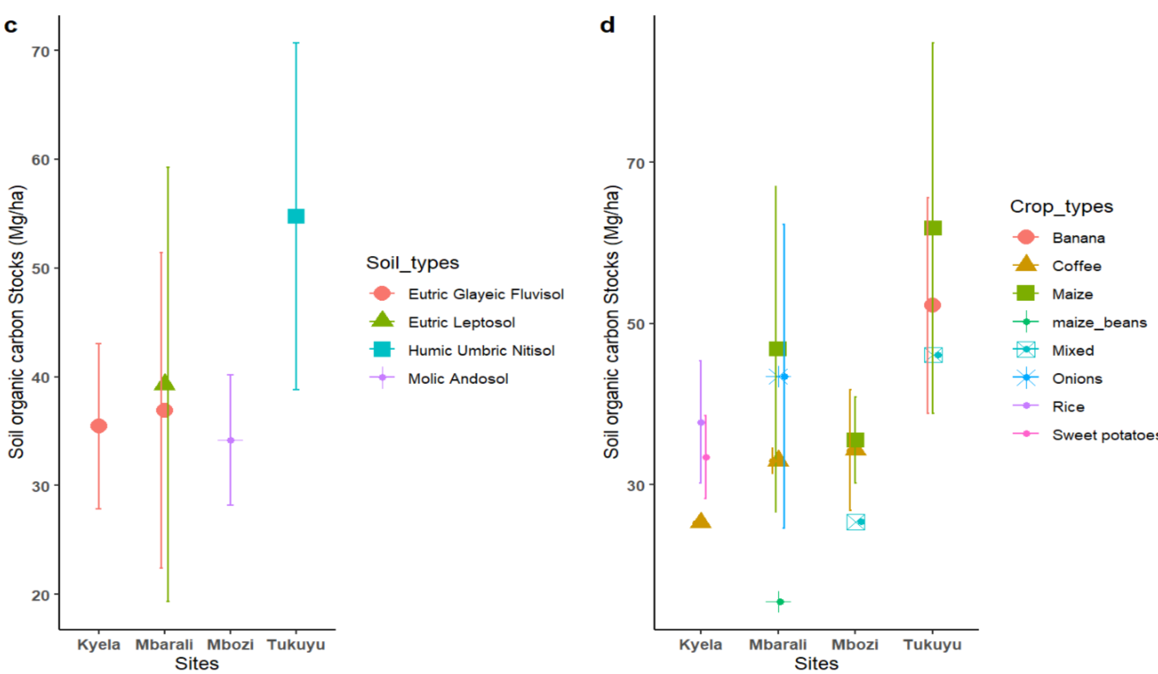


Figure 16: *Distribution of SOC stocks based on (c) soil type and (d) crop type (0 – 20 cm)*

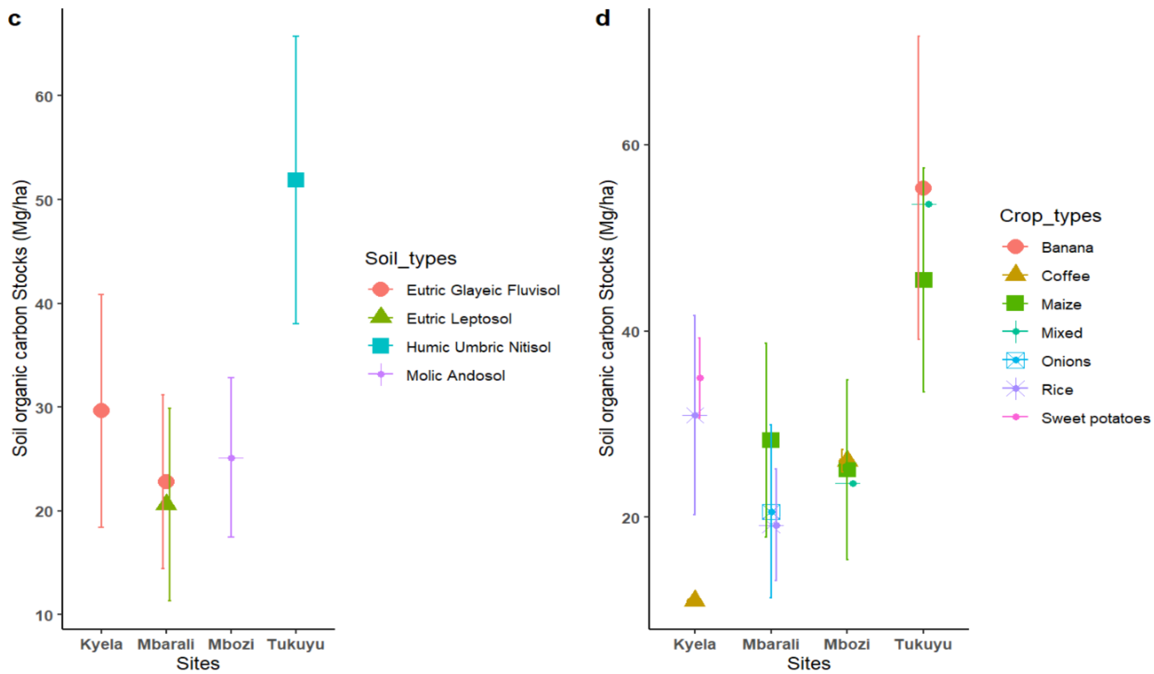


Figure 17: *Distribution of Soil Organic Carbon stocks based on (c) soil type and (d) crop type (20 – 50 cm)*

4.2.4 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 9). 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 9: *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)*

	Topsoil (0 – 20cm)		Subsoil (20 – 50cm)	
Soil types	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 α = 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 18 and Figure 19 demonstrate that Humic Umbric Nitisol has a higher concentration of soil organic carbon (SOC) compared to other studied soil types. Furthermore, (Figure 18) 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.

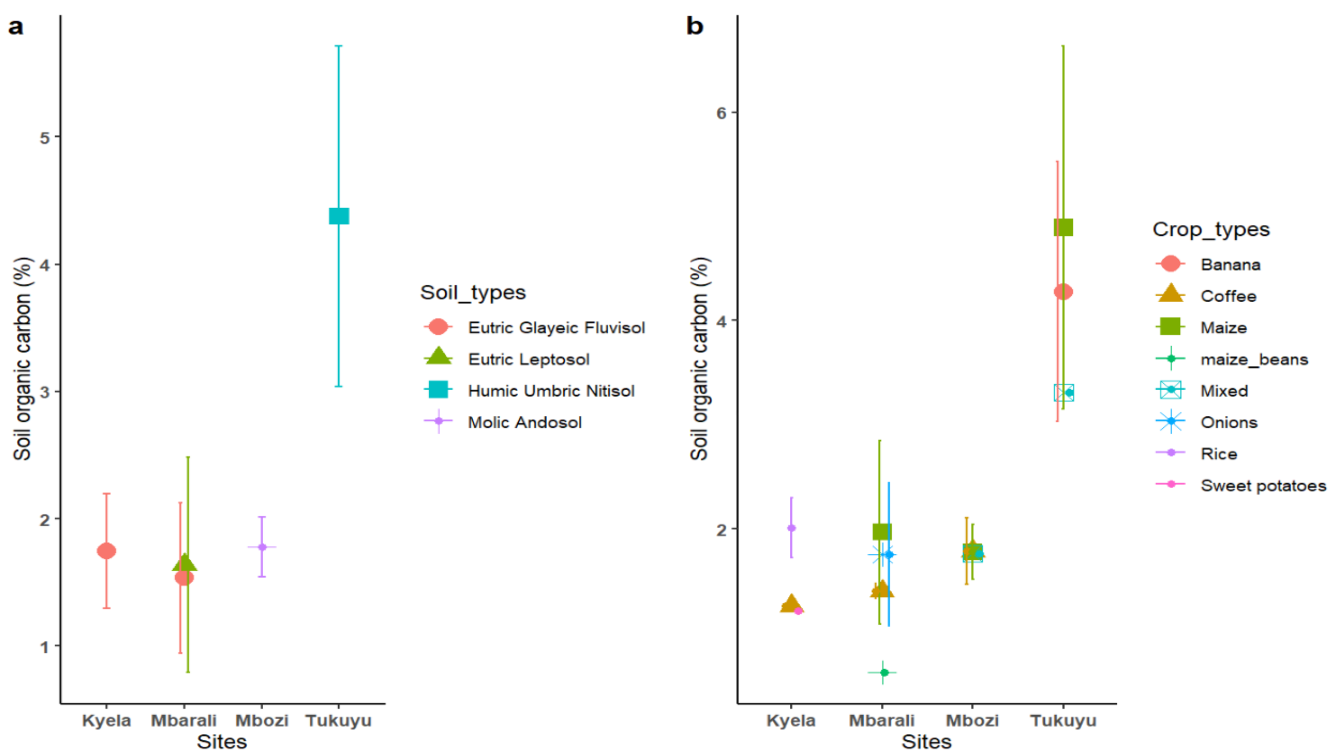


Figure 18: *Distribution of SOC concentrations based on (a) soil type and (b) crop type (0 – 20 cm)*

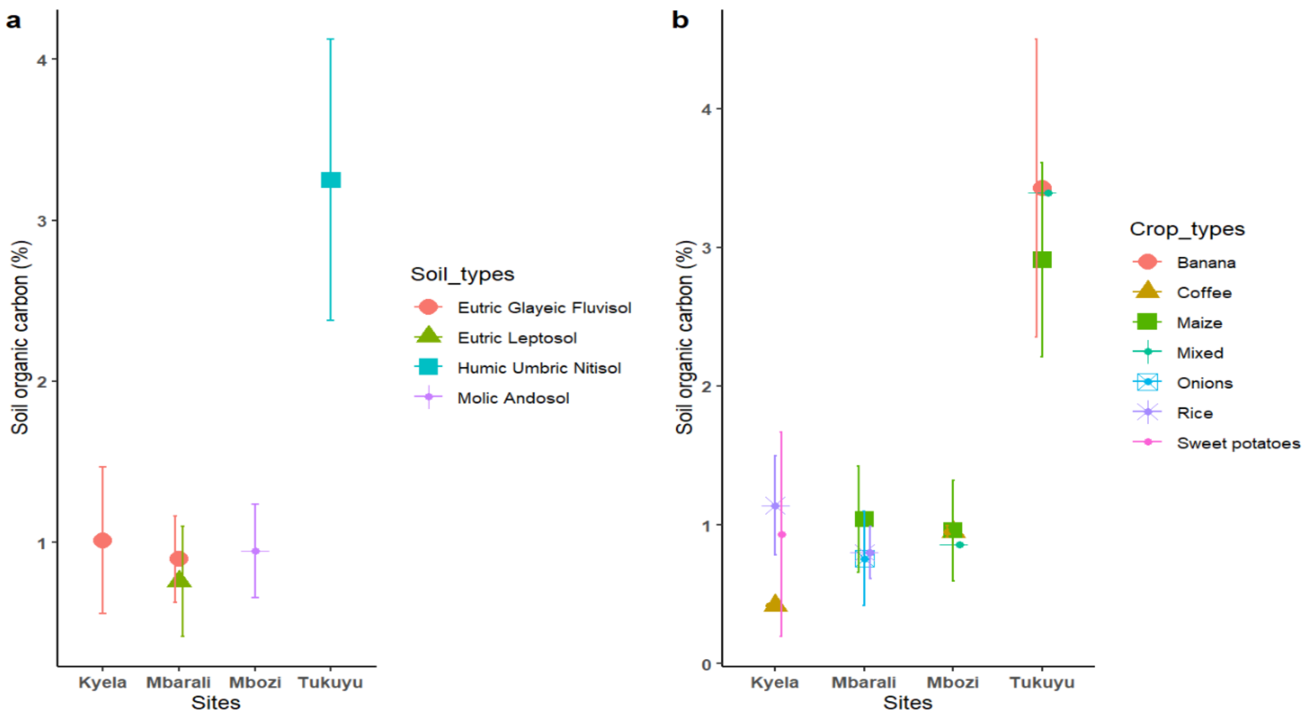


Figure 19: *Distribution of SOC based on (a) soil type and (b) crop types (20 - 50 cm)*

4.2.5 Soil organic carbon concentrations and stocks in different crop type

In the analysed crop type, the concentrations of SOC (Soil Organic Carbon) ranged from 0.76 to 4.27, while the stocks ranged from 20.60 to 55.36 Mg/Ha, as shown in (Table 10). 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 10). 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.

According to (Table 10), 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 10: *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*

4.2.6 Soil organic carbon, nitrogen concentrations and C: N ratio

The average SOC at a depth of 0-50cm were determined to be 1.5±0.6, 1.2±0.6, 1.3±0.5, and 3.8±1.2 in the locations of Kyela, Mbarali, Mbozi, and Tukuyu, respectively. Our research indicates that implementing sustainable agricultural methods that are tailored to the unique characteristics of each site, including soil type and crop type, is crucial for increasing the sequestration of soil organic carbon (SOC) and improving soil health in agricultural areas of Tanzania. Tukuyu exhibited a statistically significant increase ($p<0.05$) in soil organic carbon (SOC) concentration (Figure 20), with a value of 4.28, as well as nitrogen (N) concentration, with a value of 0.35, in comparison to other places in the topsoil.

The C: N ratio is a crucial component that has a substantial impact on the rate at which organic matter breaks down (Batjes, 1996). Furthermore, the balance of this ratio has consequences for the carbon and nitrogen cycles. The C: N ratio exhibited no significant variation among places at the same depth, which can be attributed to the predominance of conventional agricultural operations and management techniques. The agricultural ecosystems had comparable C: N ratios, all below 20, suggesting the presence of organic components of high quality in the soils that release nitrogen during decomposition (Swangjang, 2015) who states that in order to promote the mineralization of organic matter in agricultural soils, it is recommended to maintain a C: N ratio of ≤ 20.

The study revealed a decrease in the C: N ratio as the soil depth grew, suggesting a reduction in the amount of organic compounds, plant residues, and microbial population with greater depth.

(Ostrowska & Porębska, 2015). The absence of a strong correlation between soil organic carbon (SOC) and carbon-to-nitrogen (C:N) ratios indicates that the observed C:N ratios in the fields were not solely influenced by the process of soil organic matter (SOM) mineralization. Other factors, such as the uneven distribution of carbon and nitrogen in the soil profile and the amount of dissolved carbon and nitrogen released from SOM decomposition, may have also played a role in shaping these ratios (Ostrowska & Porębska, 2015). The levels of soil organic carbon (SOC) and nitrogen are mostly governed by the pace of decomposition, which is predominantly regulated by microorganisms (Adiyah et al., 2022; Yan et al., 2021).

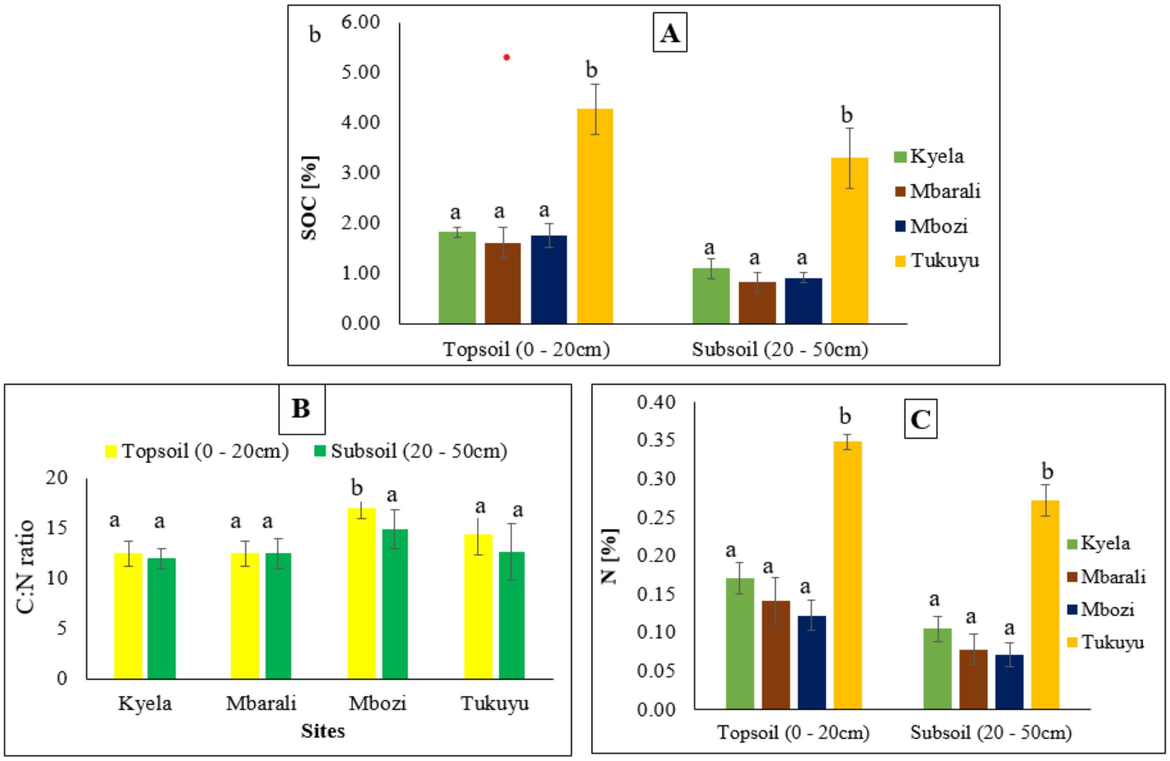


Figure 20: *SOC concentrations (A), C: N ratio (B) and Nitrogen concentrations (C), on topsoil (0 – 20 cm) and subsoil (20 – 50 cm) depths in four different sites. Means in the same row with identical superscripts for different sampling sites do not show statistically significant differences at a significance level of α = 0.05 based on Tukey's HSD test*

4.2.7 The relation between SOC distribution and other soil properties

The correlation coefficients between the analysed parameters are presented in (Table 11). Several research (Benefoh, 2018; Gami et al., 2009; Liu et al., 2013; McLauchlan, 2006) have investigated the associations between soil physical and specific chemical features, and have shown statistically significant connections that are consistent with the results of our study.

The study found a significant and positive relationship between the concentrations of soil organic carbon (SOC), nitrogen, and SOC stocks at soil depths of 0 - 20 cm and 20 - 50 cm. The soil organic carbon (SOC) showed a robust positive association with nitrogen (N) and SOC stock. This can be attributed to the collinearity observed between these two measures, as documented by Adiyah et al., (2022).

Furthermore, the data presented in (Table 11) demonstrates a significant inverse relationship between SOC and both bulk density (BD) and clay content. The association between silt and pH and

SOC concentrations was found to be negative, but quite weak. An evident inverse association exists between soil organic carbon (SOC) and bulk density (BD), indicating the substantial impact of SOC levels on BD.

Previous studies (Ramasamy & Ramalingam, 2019; Walter et al., 2016; T. Wang et al., 2016) have reported a major negative relationship between SOC/SOC stock and BD, which is consistent with our own findings. It is noteworthy to notice that there was a negative link between SOC (soil organic carbon) and clay, while there was a positive correlation between SOC with sand. This contradicts previous research findings. The contradictory findings could be confirmed by the findings (Six et al., 2004), who proposed that sand is a more accurate predictor of soil organic carbon (SOC) distribution than clay. This is due to the fact that clay's influence can be modified significantly by their involvement in the creation of soil aggregates. The lower negative correlation of silt and pH that was reported with SOC can be explained by the variability in soil physical and chemical characteristics across agricultural fields. This variability is dependent on a number of factors, including the type of soil, the climatic conditions, the type of crop, and the management strategies that farmers employ.

Table 11: *Pearson correlation of SOC with selected soil properties (0 - 50cm depth). The correlation was significant to some properties*

	Topsoil (0 - 20cm)								
	Clay(%)	Silt(%)	Sand (%)	pH	BD(g/cm3	SOC[%]	N[%]	SOC_ Stock (g/MG)	C:N
Clay(%)	1								
Silt(%)	0.45	1							
Sand(%)	-0.85	-0.82	1						
pH	-0.01	-0.05	0.07	1					
BD(g/cm3	0.38	-0.17	-0.15	0.31	1				
SOC[%]	-0.57	-0.01	0.37	-0.14	-0.72	1			
N[%]	-0.58	0.01	0.36	-0.13	-0.66	0.95	1		

SOC_ Stock (g/MG)	-0.43	-0.14	0.35	-0.05	-0.35	0.86	0.86	1	
C:N	0.21	-0.13	-0.06	-0.05	-0.22	0.03	-0.18	-0.04	1
	Subsoil (20 - 50cm)								
	clay(%)	silt(%)	sand (%)	pH	BD(g/c m3	SOC[%]	N[%]	SOC_st ock(g/ MG)	C:N
clay(%)	1								
silt(%)	0.62	1							
sand(%)	-0.87	-0.88	1						
pH	-0.01	0.00	-0.05	1					
BD(g/cm 3	0.61	0.19	-0.41	0.09	1				
SOC[%]	-0.63	-0.15	0.44	-0.08	-0.85	1			
N[%]	-0.65	-0.13	0.45	-0.08	-0.84	0.99	1		
SOC _stock (g/MG)	-0.50	0.01	0.27	-0.10	-0.73	0.94	0.92	1	
C:N	0.14	-0.06	-0.08	-0.12	0.09	0.00	-0.08	0.06	C:N

4.2.8 Policy implications of findings in the Southern part of Tanzania

This study help farmers to adopt sustainable land management and agricultural development policies.

For smallholder farmers; Adopt practices specific to the soil where by farmers should concentrate on enhancing soil health by applying organic amendments (such as compost, farmyard manure, and green manure) that are suited to particular soil conditions, as SOC is more influenced by soil t ype than crop choice, reduce the amount of soil disturbance, promote mulching and cover crops:

For those who make policy; Create agricultural programs that are informed by both soil type and site management practices, encourage the management of sustainable land (SLM) by use results-based incentives (such as carbon farming or SLM grants) to incentivize methods that increase SOC in a variety of soil types and remote long-term diversification:

For the community of scientists and researchers; Monitor SOC over an extended period of time to gain a deeper comprehension of climate variability and temporal shifts under smallholder manage ment, examine the effects of elevation and microclimate, create recommendations for site-specific SOC management, close the gap between research and extension, and work together with regional organizations to disseminate soil focused SOC results in regional languages via farmer field schools, radio, and training.

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

4.3.1 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 12*: 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/cm3)	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

4.3.2 Spectral pre-processing and spectral assessment

The spectral characteristics of all the soil samples exhibited a high degree of similarity, as depicted in (Figure 21). 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 21B and Figure 22B). 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 23B). Three dominant PCA accounted for 61% of the spectral variance (Figure 23B). The Mahalanobis application indicated the absence of any outlier samples as in (Figure 23B).

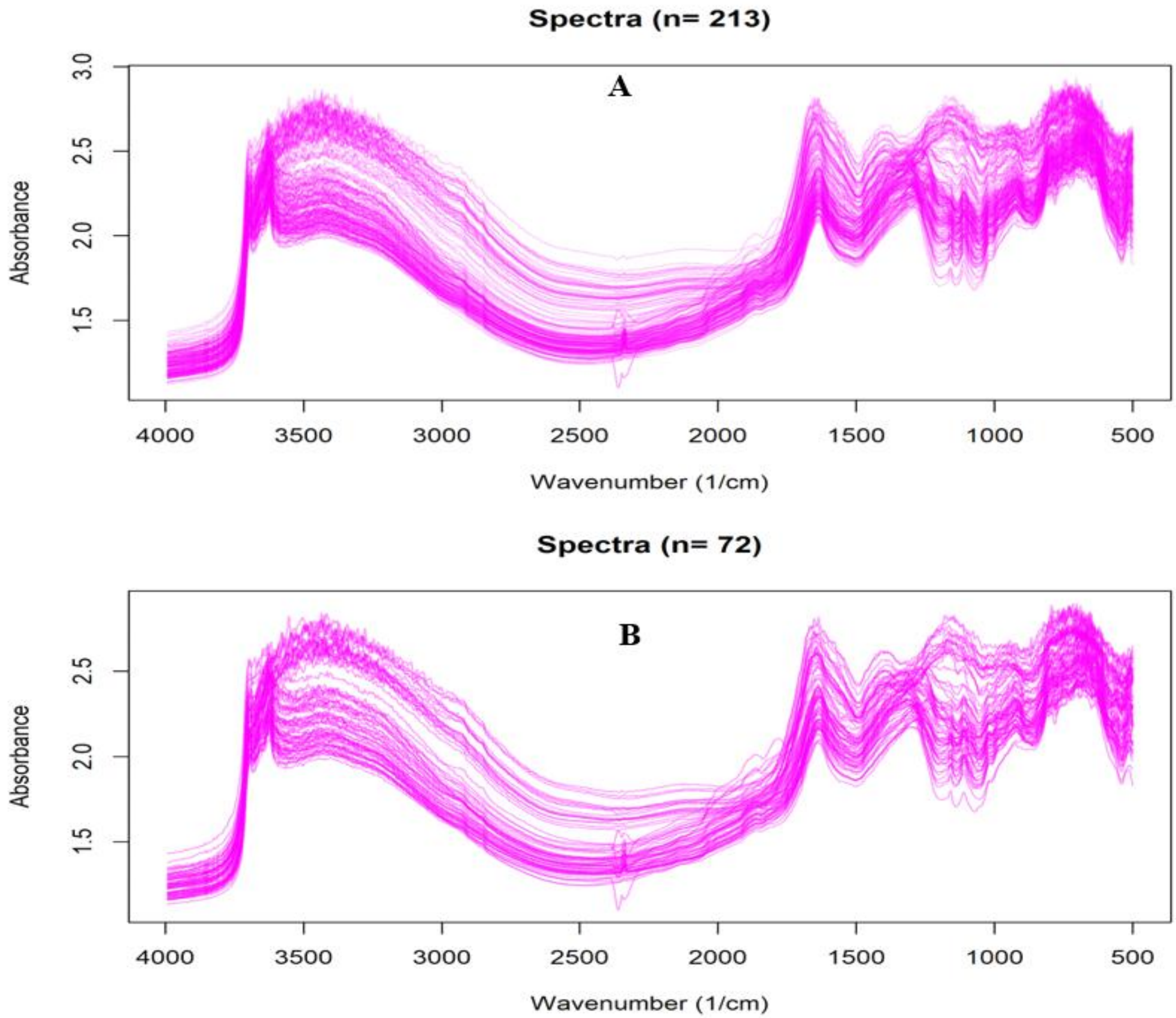


Figure 21: *Absorbance spectra (pre-treatment) of the whole soil samples dataset in (A) and only reference soil datasets in (B) Mid-Infrared Reflectance spectroscopy (MIR) 4000 - 500 cm*$^{-1}$

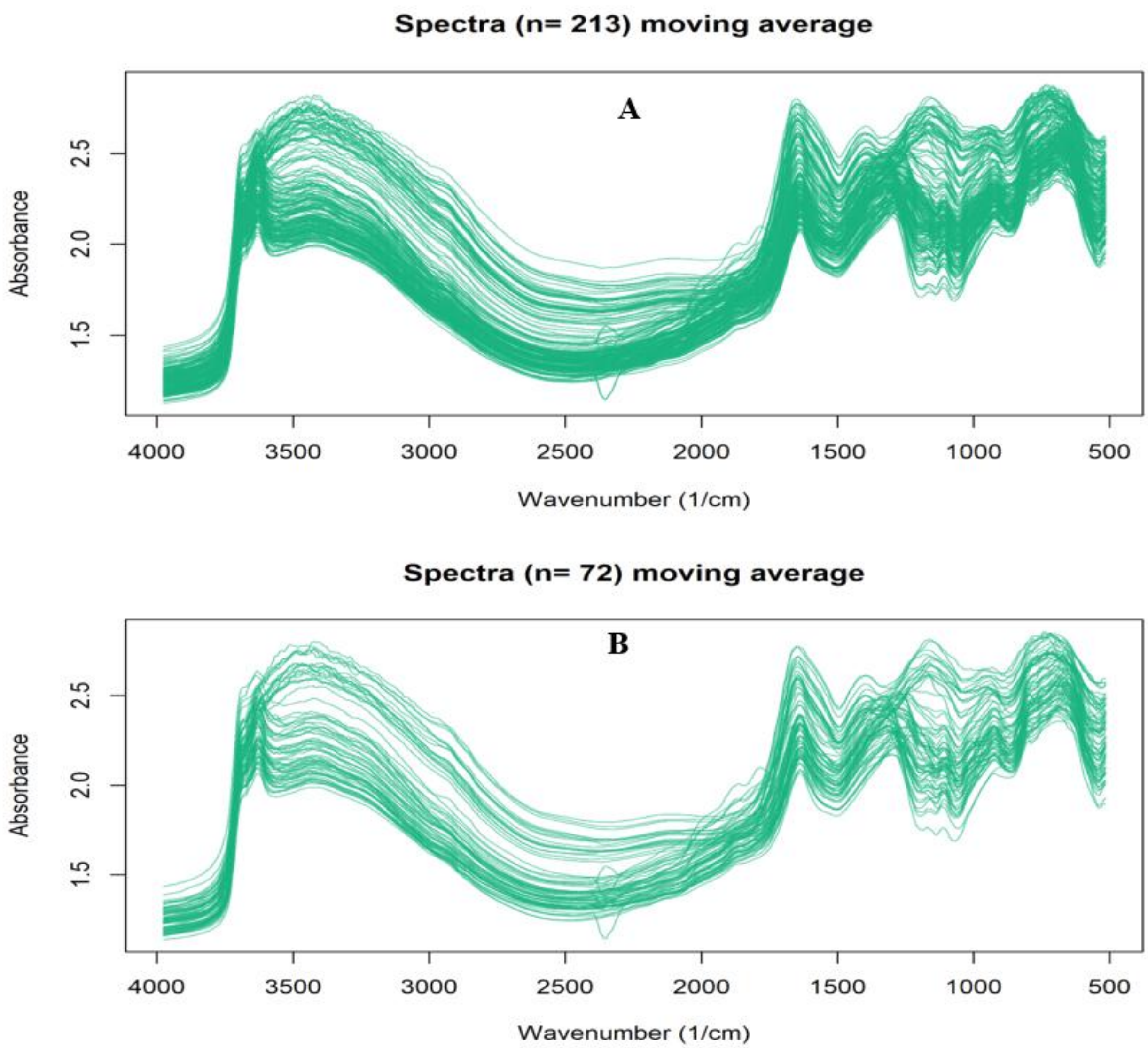


Figure 22: *Absorbance spectra (processed by moving average) of the whole soil samples dataset (A), and reference soil dataset (B) in Mid-Infrared Reflectance spectroscopy (MIR) 4000–500 cm*$^{-1}$

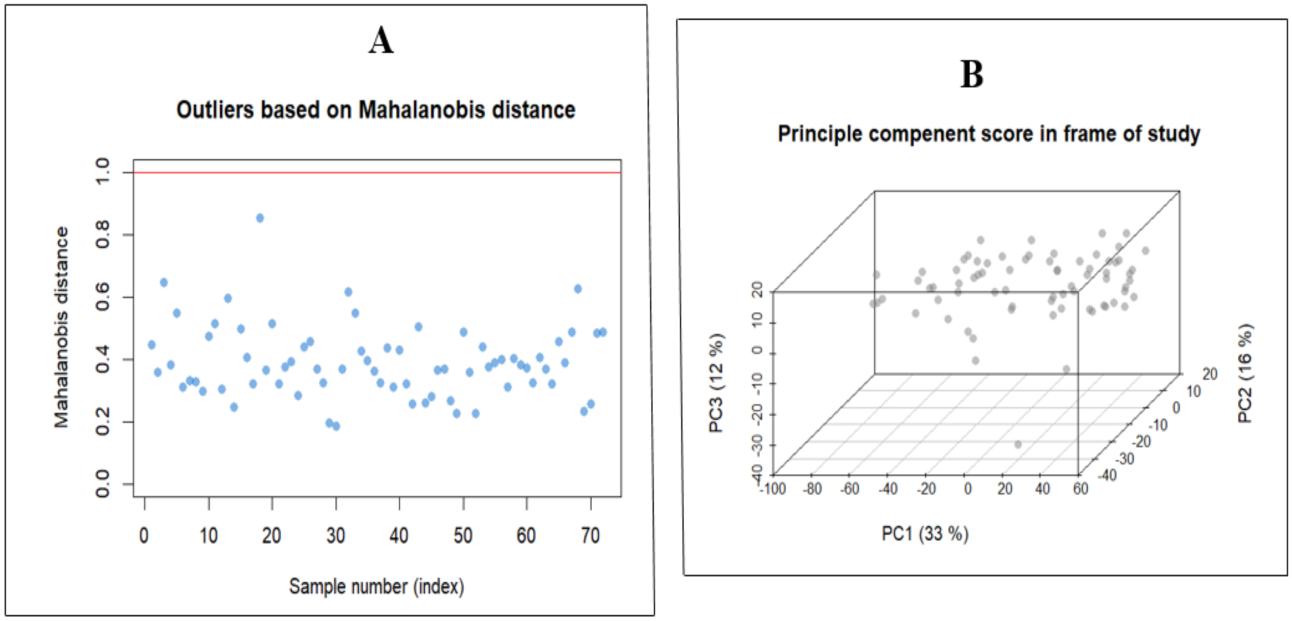


Figure 23: *Outliers based on Mahalanobis (6A) and principal component analysis (PCA) showing scores and eigenvectors of the preprocessed MIR spectra (6B) on reference soil data (n = 72)*

4.3.3 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).

4.3.4 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 13) 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 13:__ 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								

4.3.5 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 selected agricultural areas. 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 14). Most soil parameters had a non-normal distribution characterized by positive skewness, with the exception of clay content, pH, silt and bulk density (Table 14). 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 14: *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/cm3)	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

4.3.7 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). Lastly, MIR spectroscopy exhibits 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.

). 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 12: 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/cm3)	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

4.3.2 Spectral pre-processing and spectral assessment

The spectral characteristics of all the soil samples exhibited a high degree of similarity, as depicted in (Figure 21). 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 21B and Figure 22B). 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 23B). Three dominant PCA accounted for 61% of the spectral variance (Figure 23B). The Mahalanobis application indicated the absence of any outlier samples as in (Figure 23B).

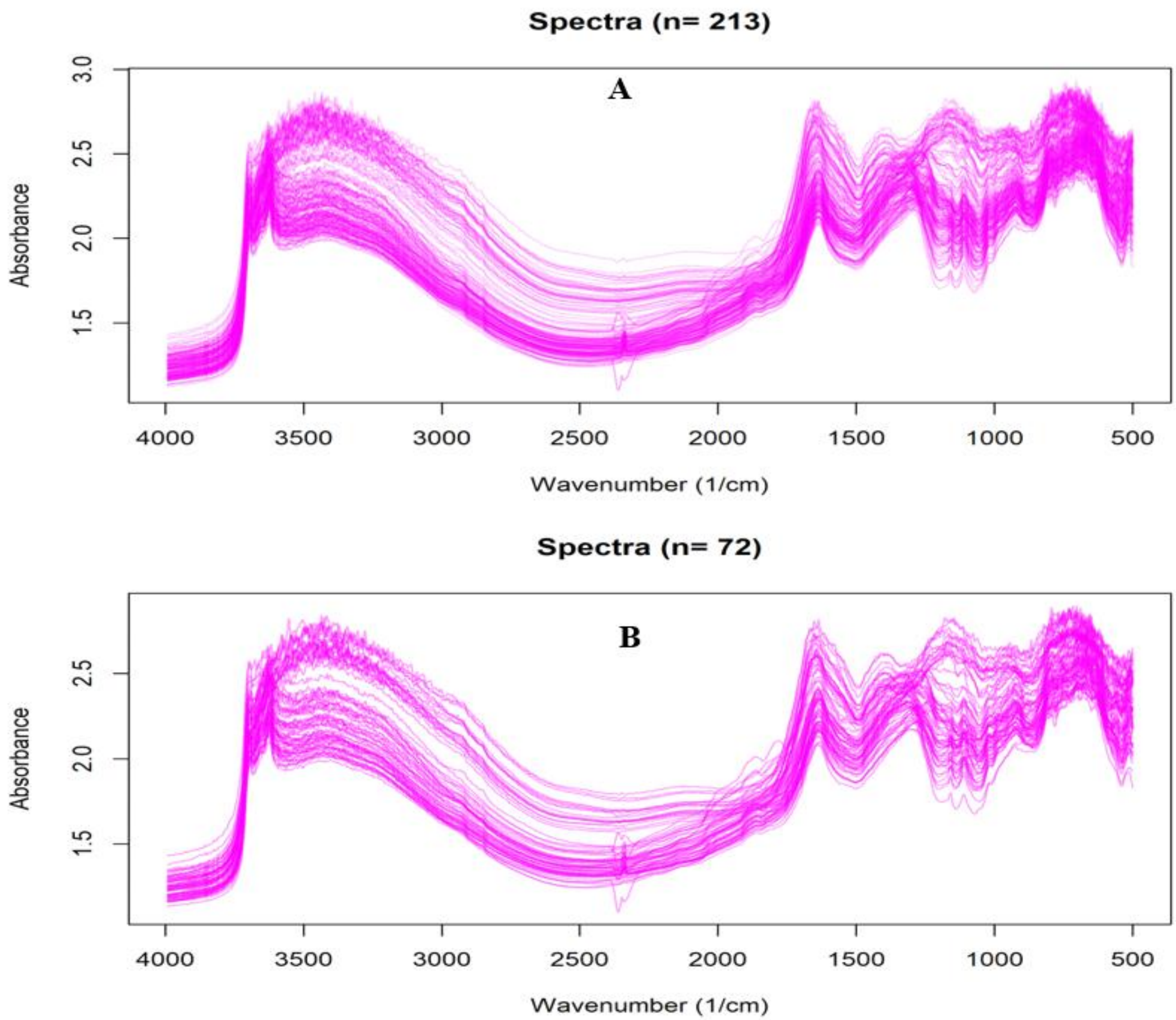
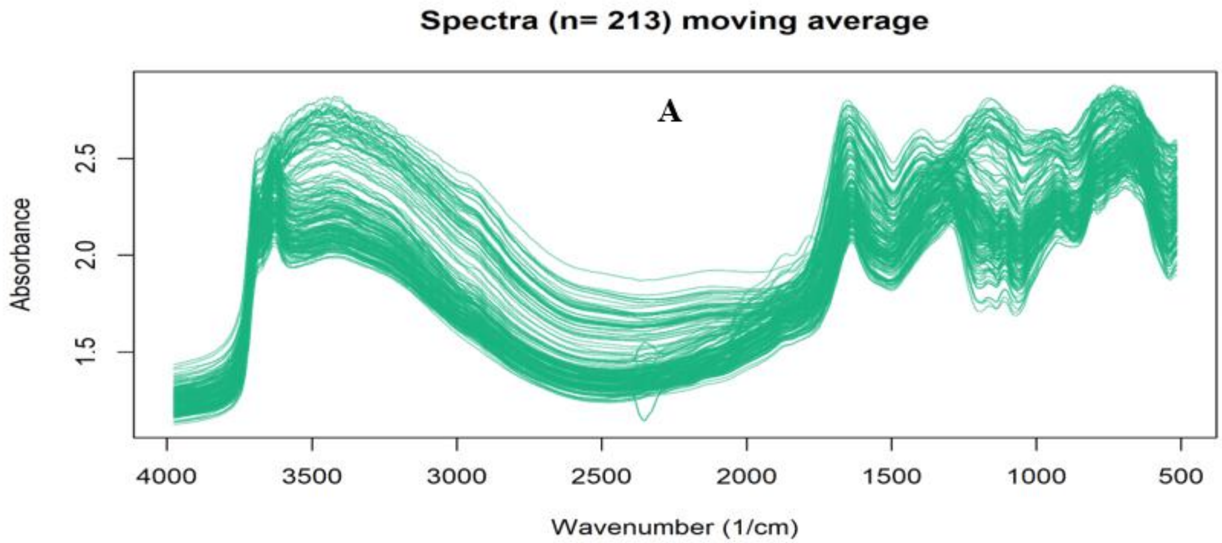


Figure 21: *Absorbance spectra (pre-treatment) of the whole soil samples dataset in (A) and only reference soil datasets in (B) Mid-Infrared Reflectance spectroscopy (MIR) 4000 - 500 cm*$^{-1}$



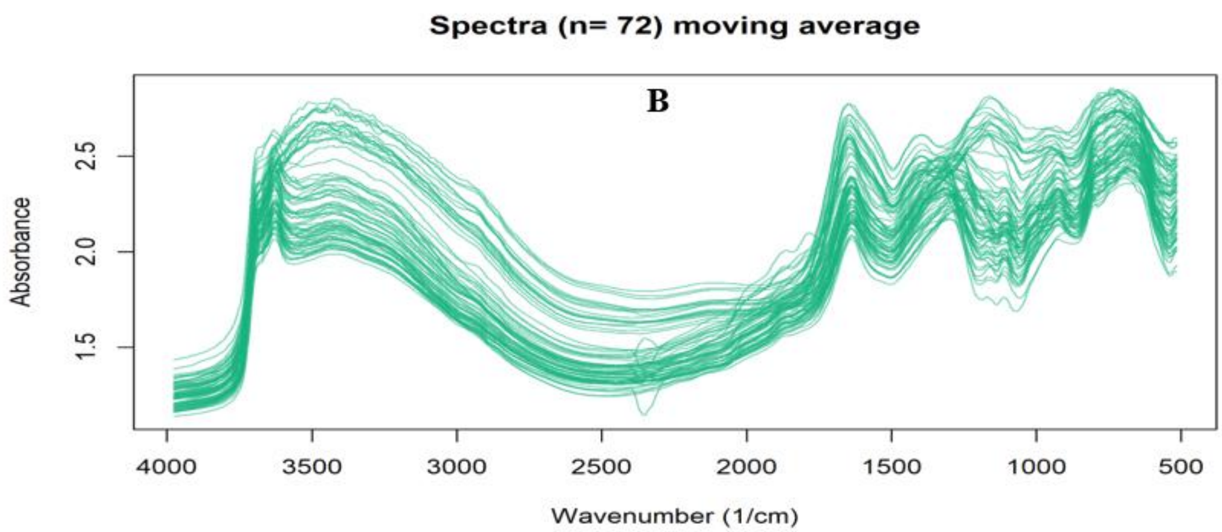


Figure 22: *Absorbance spectra (processed by moving average) of the whole soil samples dataset (A), and reference soil dataset (B) in Mid-Infrared Reflectance spectroscopy (MIR) 4000–500 cm*$^{-1}$

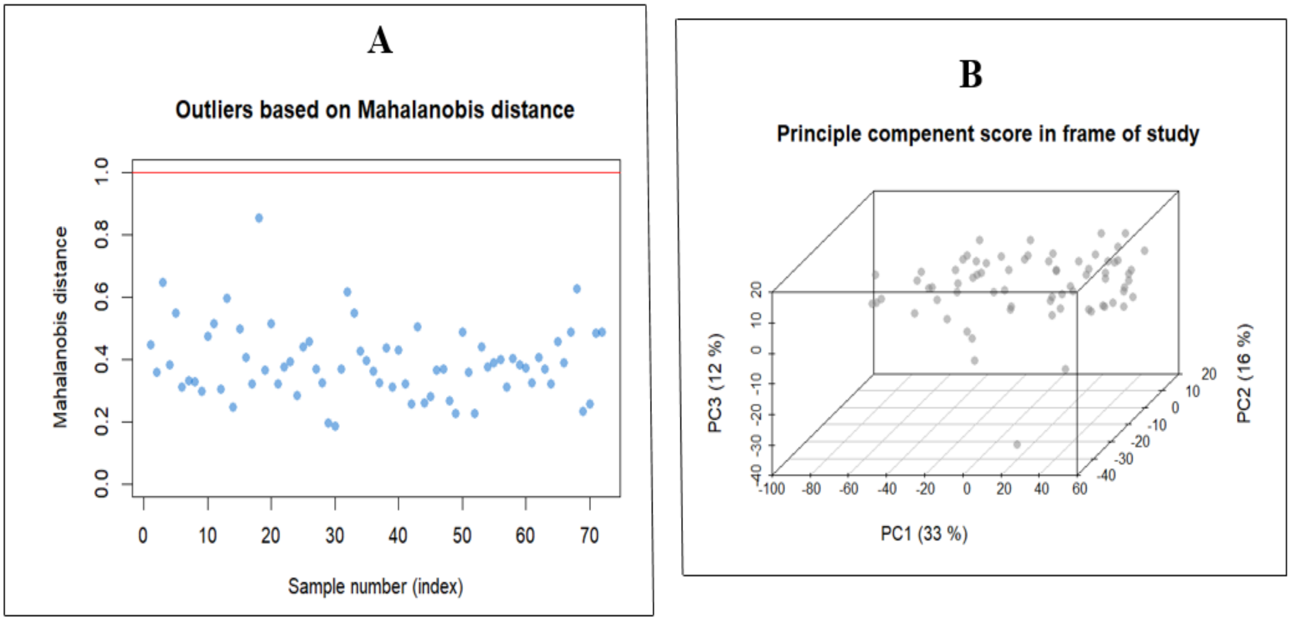


Figure 23: *Outliers based on Mahalanobis (6A) and principal component analysis (PCA) showing scores and eigenvectors of the preprocessed MIR spectra (6B) on reference soil data (n = 72)*

4.3.3 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).

4.3.4 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 13) 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 13: *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								

4.3.5 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 selected agricultural areas. 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 14). Most soil parameters had a non-normal distribution characterized by positive skewness, with the exception of clay content, pH, silt and bulk density (Table 14). 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 14: *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/cm3)	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

4.3.7 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). Lastly, MIR spectroscopy exhibits 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.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 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 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.

5.2 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 the selected agricultural 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 agricultural sites in the Southern part of Tanzania. 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.

6. 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.

7. SUMMARY

Soil organic carbon (SOC) status is a crucial metric for assessing soil quality and fertility. Linkage, awareness and adoption of farmers to management strategies and IAPs can affect soil organic carbon and soil fertility in general. In recent years, different chemometric methods have been applied to determine various soil properties including SOC. The objectives of this work were as follows; (i) To assess smallholder farmers' awareness, linkage and adoption on the application of improved agricultural practices (IAPs), (ii) To determine the status of SOC and SOC stock in different agricultural sites by modern measurements in the Southern part of Tanzania, and (iii) To predict total

SOC, total nitrogen, BD, pH, and soil texture by MIR - RF and MIR - PLSR models, and assess the accuracy of prediction. To achieve the following objectives, both natural and social science approaches were applied.

The study was conducted in Kyela, Mbarali, Mbozi and Tukuyu in the Southern part of Tanzania. The criteria for site selection under this study were governed by high yield per year thus making these sites food basket in Tanzania at large, although they experience different climatic conditions, agricultural practices and altitude.

The questionnaire data used in this work were obtained through well-structured questionnaires and soil samples collected between July to August 2023, involving 206 smallholder farmers interviewed. On soil samples, 240 undisturbed soil samples were collected using a 5cm*5cm core sampler ring (98.125 cm^3), at 0 - 20 cm and 20 - 50 cm soil depths from Kyela, Mbarali, Mbozi, and Tukuyu agricultural sites. From the same sampling point as for undisturbed samples, 240 composite soil samples were also collected at 0 - 20 cm depth and 20 - 50 cm depth. Undisturbed soil samples were used to determine bulk density. Laboratory soil analysis was performed on 72 representative composite soil samples through wet chemistry, laser diffraction and CNS elemental analyzer. Soil data based on 72 soil samples were used to determine the status of total SOC but also utilized as reference soil data during RF and PLSR modelling on MIR spectral data. About 200 composite soil samples were scanned by MIR spectral region for prediction. The preprocessing of MIR spectra entailed the implementation of a moving average spectrum by utilizing Savitzky-Golay filtering procedures.

In relation to objective one and two, collected questionnaires were analysed using R statistical software through probit regression model to determine significant factors hindering adoption of farmers to IAPs. For objective three, LMEM was employed to determine significant fixed and random factor affection SOC contents. Chemometric methods (PLSR and RF) approaches were employed separately to establish the correlation between the measured soil spectra and soil properties in a multivariate regression analysis.

To achieve objective four, chemometric methods (PLSR and RF) approaches were employed separately to establish the correlation between the measured soil spectra and soil properties in a multivariate regression analysis.

Results on questionnaires under probit regression model revealed that household head marital status, flooding exposure, top dressing, farming period, soil information and soil type indicated significant positive effect on farmer's adoption of IAPs in Tanzania at 5% confidence interval.
Based on linear mixed effect model (LMEM) soil type and soil depths are significant predictors ($p<0.001$) of SOC contents in different agricultural sites.

Apart from that our findings also revealed that agricultural practices need sustainable agricultural techniques tailored to specific soil type to improve soil organic contents. Our study also demonstrated the potential of diffuse reflectance spectroscopy, using the MIR spectra on predicting soil properties using different chemometric methods. PLSR models had a better performance compared to RF and XGBoost models on soil pH, bulk density, total SOC, total Nitrogen, clay, silt and sand contents.

8. APPENDICES

A1: 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., Learch, 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 di ff erent wavelength regions of re fl ectance 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 Moatassem, 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

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 ruthmeinzen-dick, International Food Policy Research Institute (IFPRI). *הנוטע עלון*, *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 re fl ectance spectroscopy (VNIRS) in the fi eld. *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., & Bielders, 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., & Zougmore, 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. *ARPN: 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

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., Hobley, 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=IwAR0owWkHXsrPeaEzNPlniyffHqW2G0gK4VgRXJqp2MA6NlUbwTDgsdEVzqc

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.0000000061

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 Tanza-nia : 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

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-al1.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., Mhoro, 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. *Issn*, *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 fi eld 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 Kulyakwave1, 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

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, δ13C and δ15N 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

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

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/IPCBEE

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.

Wadouxx Brendannmalonee·, A. J., Marioofajardoo·, B., & Mcbratney, A. (2021). *Progress in Soil Science Soil Spectral Inference withhR Analysing Digital Soil Spectra using theeR 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

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

A2: Supplementary Materials

A2.1 Reference soil data for MIR prediction

S/N	X	Y	Site	Sample_ID	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	pH	BD (g/cm3)	[Total SOC]	[Total N]	SOC_stock mg/Ha)
1	-8.91651	33.48751	Kyela	K_20_1	0 - 20	21.46	61.31	17.23	5.9	0.8	1.97	0.15	31.5
2	-8.91651	33.48751	Kyela	K_50_1	20 - 50	29.88	56.81	13.32	5.9	1.24	1.4	0.12	36.7
3	-9.57533	33.87929	Kyela	K_20_4	0 - 20	27.68	56.91	15.41	6	0.85	1.77	0.18	30.1
4	-9.57533	33.87929	Kyela	K_50_4	20 - 50	30.13	54.02	15.84	6.5	1.31	1.19	0.12	32.6
5	-9.5756	33.87563	Kyela	K_20_8	0 - 20	32.03	57.09	10.89	5.9	0.95	2.25	0.21	42.8
6	-9.5756	33.87563	Kyela	K_50_8	20 - 50	26.05	55.52	18.42	6.2	1.37	0.84	0.08	21.7
7	-9.63403	33.90325	Kyela	K_20_12	0 - 20	28.9	58.06	13.03	6.1	0.98	1.89	0.17	36.9
8	-9.63403	33.90325	Kyela	K_50_12	20 - 50	33.33	55.15	11.52	6.4	1.29	1.58	0.15	45.8
9	-9.63808	33.90598	Kyela	K_20_16	0 - 20	13.06	32.01	54.93	6.1	1.03	1.71	0.17	35.1
10	-9.63808	33.90598	Kyela	K_50_16	20 - 50	15.18	49.13	35.69	5.9	1.45	1.22	0.12	32.9
11	-9.63278	33.90628	Kyela	K_20_20	0 - 20	12.02	42.43	45.55	6.3	1.03	2.45	0.25	50.4
12	-9.63278	33.90628	Kyela	K_50_20	20 - 50	23.89	55.59	20.52	6.5	1.35	0.61	0.06	16
13	-9.5854	33.84878	Kyela	K_20_24	0 - 20	17.02	40.43	42.6	6	1	1.26	0.13	25.3
14	-9.5854	33.84878	Kyela	K_50_24	20 - 50	27	50.6	22.4	6.2	1.31	0.42	0.05	11
15	-9.58775	33.84704	Kyela	K_20_28	0 - 20	23.02	51.91	25.1	5.9	1.24	1.2	0.11	29.8
16	-9.58775	33.84704	Kyela	K_50_28	20 - 50	22.05	53.6	24.3	6.6	1.28	1.45	0.14	38
17	-9.58651	33.84496	Kyela	K_20_30	0 - 20	20.02	44.43	22.1	5.8	1.16	1.22	0.13	37.1
18	-8.74365	34.37875	Kyela	K_50_30	20 - 50	18.05	47.6	21.3	6.5	1.24	0.41	0.05	31.9
19	-8.7536	34.37764	Mbarali	I_20_1	0 - 20	13.65	42.71	43.65	5.9	1.13	2.42	0.24	54.8
20	-8.7536	34.37764	Mbarali	I_50_1	20 - 50	9.88	21.31	68.81	6.1	1.31	1.06	0.1	28.8
21	-8.76019	34.37954	Mbarali	I_20_4	0 - 20	14.61	35.33	50.06	5.8	1.25	0.62	0.06	15.5
22	-8.76019	34.37954	Mbarali	I_50_4	20 - 50	15.47	32.38	52.15	6.4	1.36	1.03	0.1	28
23	-8.77729	34.37791	Mbarali	I_20_8	0 - 20	12.82	39.83	47.35	6.2	1.19	1.27	0.1	30.1
24	-8.77729	34.37791	Mbarali	I_50_8	20 - 50	5.4	15.54	79.06	6.2	1.39	0.37	0.04	10.1
25	-8.69537	34.39633	Mbarali	I_20_12	0 - 20	24.64	31.21	44.14	6.1	1.27	2.24	0.19	56.8
26	-8.69537	34.39633	Mbarali	I_50_12	20 - 50	24.24	30.6	45.16	6.8	1.27	0.57	0.06	15.5
27	-8.75921	34.38885	Mbarali	I_20_16	0 - 20	14.83	27.87	57.3	6.3	1.22	2.53	0.2	61.8
28	-8.75921	34.38885	Mbarali	I_50_16	20 - 50	14.99	30.36	54.65	6.2	1.3	0.77	0.06	20.9
29	-8.77185	34.37958	Mbarali	I_20_20	0 - 20	11.19	48.3	40.51	6.8	1.26	0.95	0.1	23.9
30	-8.77185	34.37958	Mbarali	I_50_20	20 - 50	11.83	25.37	62.8	6.1	1.4	1.31	0.13	35.6
31	-8.78764	34.3809	Mbarali	I_20_24	0 - 20	20.64	34.21	45.2	6.4	1.15	1.42	0.13	32.6
32	-8.78764	34.3809	Mbarali	I_50_24	20 - 50	22.24	20.6	55.2	6.5	1.28	0.59	0.06	16
33	-8.7891	34.3819	Mbarali	I_20_28	0 - 20	14.1	32.7	53.2	6.5	1.08	1.46	0.11	31.6
34	-8.7891	34.3819	Mbarali	I_50_28	20 - 50	15.01	29.78	55.21	6.3	1.32	0.96	0.08	26.1
35	-8.7871	34.38167	Mbarali	I_20_30	0 - 20	16.1	31.7	51.4	6.2	1.12	1.32	0.13	34.7
36	-8.7871	34.38167	Mbarali	I_50_30	20 - 50	13.21	27.4	48.11	6.6	1.3	0.85	0.07	15.4
37	-9.00849	33.00307	Mbozi	M_20_1	0 - 20	32.83	52.58	14.59	6.2	0.95	1.57	0.11	29.8
38	-9.00849	33.00307	Mbozi	M_50_1	20 - 50	33.31	41.56	25.13	6.2	1.36	0.58	0.06	15.9
39	-9.00441	33.007	Mbozi	M_20_4	0 - 20	26.13	41.5	32.38	6.9	1	1.55	0.11	31
40	-9.00441	33.007	Mbozi	M_50_4	20 - 50	35.51	42.3	22.19	6.4	1.31	0.56	0.05	15.3
41	-9.00507	33.01145	Mbozi	M_20_8	0 - 20	27.68	39.83	32.5	6.4	1.27	1.56	0.11	39.6
42	-9.00507	33.01145	Mbozi	M_50_8	20 - 50	34.2	48.53	17.27	6	1.42	0.92	0.07	25.2
43	-9.00581	33.00744	Mbozi	M_20_12	0 - 20	26.99	49.07	23.94	5.8	1.05	1.52	0.1	32
44	-9.00581	33.00744	Mbozi	M_50_12	20 - 50	34.71	49.35	15.94	6.2	1.29	1.52	0.1	41.6
45	-9.02889	32.98663	Mbozi	M_20_16	0 - 20	25.94	46.91	27.15	5.7	1.01	2.11	0.16	42.5
46	-9.02889	32.98663	Mbozi	M_50_16	20 - 50	20.76	26.27	52.97	6.1	1.33	0.9	0.07	24.7
47	-9.02757	32.9897	Mbozi	M_20_20	0 - 20	21.1	41.72	37.19	5.9	0.72	2.01	0.14	29
48	-9.02757	32.9897	Mbozi	M_50_20	20 - 50	36.99	47.52	15.49	6.3	1.37	0.98	0.08	26.9
49	-9.02054	33.00964	Mbozi	M_20_24	0 - 20	26.21	38.99	34.81	5.6	0.72	1.76	0.12	25.4
50	-9.02054	33.00964	Mbozi	M_50_24	20 - 50	31.83	37.8	30.36	6	1.22	0.86	0.06	23.6
51	-9.01197	33.00925	Mbozi	M_20_28	0 - 20	23.96	39.12	36.92	5.8	0.94	2.01	0.13	37.6
52	-9.01197	33.00925	Mbozi	M_50_28	20 - 50	31.85	38.63	29.51	5.9	1.26	1.05	0.08	28.8
53	-9.01275	33.00906	Mbozi	M_20_30	0 - 20	20.96	35.12	33.2	5.7	0.97	1.92	0.12	40.5
54	-9.01275	33.00906	Mbozi	M_50_30	20 - 50	28.6	37.3	16.77	6.3	1.17	1.14	0.06	24.2
55	-9.25805	33.65471	Tukuyu	T_20_1	0 - 20	6.85	44.31	48.84	6.4	0.52	3.61	0.24	37.2
56	-9.25805	33.65471	Tukuyu	T_50_1	20 - 50	2.44	24.47	73.09	6.6	1.24	3.37	0.25	53.2
57	-9.25689	33.65592	Tukuyu	T_20_4	0 - 20	4.03	31.03	64.95	5.9	0.7	3.31	0.22	46.1
58	-9.25689	33.65592	Tukuyu	T_50_4	20 - 50	2.1	29.72	68.17	6.2	0.85	3.39	0.26	53.6
59	-9.25374	33.65508	Tukuyu	T_20_8	0 - 20	7.58	40.3	52.12	5.8	0.8	3.01	0.27	48
60	-9.25374	33.65508	Tukuyu	T_50_8	20 - 50	3.42	36.79	59.78	6.3	0.72	5.2	0.43	82.2
61	-9.24998	33.65988	Tukuyu	T_20_12	0 - 20	8.2	42.65	49.15	5.7	0.59	6	0.45	70.2
62	-9.24998	33.65988	Tukuyu	T_50_12	20 - 50	8	39.55	52.45	6.2	0.77	3.36	0.28	53.1
63	-9.24926	33.65667	Tukuyu	T_20_16	0 - 20	3.16	31.13	65.71	5.5	0.61	3.61	0.35	44.3
64	-9.24926	33.65667	Tukuyu	T_50_16	20 - 50	5.22	20.69	74.2	5.9	0.92	2.4	0.22	37.9
65	-9.26108	33.65845	Tukuyu	T_20_20	0 - 20	16.84	51.6	31.56	5.9	0.62	3.07	0.27	37.9
66	-9.26108	33.65845	Tukuyu	T_50_20	20 - 50	7.54	36.75	55.71	6.3	0.87	2.1	0.19	31.6
67	-9.26329	33.65794	Tukuyu	T_20_24	0 - 20	7.2	46.3	46.5	6.3	0.64	6.54	0.54	83.7
68	-9.26329	33.65794	Tukuyu	T_50_24	20 - 50	6.42	36.79	59.78	6	0.71	3.32	0.29	52.5
69	-9.25944	33.65956	Tukuyu	T_20_28	0 - 20	8.8	40.6	51.6	6.2	0.63	5.07	0.45	63.9
70	-9.25944	33.65956	Tukuyu	T_50_28	20 - 50	4.42	31.6	64.05	6.3	0.79	3.31	0.26	52.3
71	-9.25806	33.65529	Tukuyu	T_20_30	0 - 20	7.5	43.1	52.61	5.9	0.75	5.16	0.3	61.5
72	-9.25806	33.65529	Tukuyu	T_50_30	20 - 50	5.3	34.44	40.6	6.3	0.8	2.8	0.2	50.4

A2: 2. Farm household questionnaire

INTRODUCTION

This questionnaire survey seeks to collect data on-farm management practices for purposes of Ph.D. research. The information collected shall be treated with the utmost confidentiality and will not be disclosed to a third party unless where consent is sought and granted.

I would be glad if you would help in responding to the questions in this questionnaire. Feel free to skip any question that you are uncomfortable providing a response to. Answering this questionnaire would take you about 30 minutes.

Farm ID………………. Coordinates ………………. Date……………………

County…………………. Sub – County……………. Ward…………………

A. BASIC FARM INFORMATION

1. What is the total size of your farm in acres?...............
2. For how long have you been in farming?.............
3. What was the previous land use/cover before farming?

   A. Forest land ☐ B. Grassland ☐ C. Bareland ☐ D. Wetland ☐ E. ☐ Shrubland

   F. Other……………...(specify)

4. What type of farming are you engaged in?

   A. Crop farming ☐ B. Livestock farming ☐ C. Mixed farming ☐

5. Which crops do you grow on your farm?
6. During which season do you grow the specific crops?

   (Use Table 1 to respond to questions 5 and 6)

Table 1: Crops grown and seasons of cultivation

S/N	Crops grown	Season		
		Long season (LS)	Short season (SS)	Both
1	Maize			
2	Rice			
3	Tea			
4	Coffee			
5	Vegetables			
6	Legumes			
7	Potatoes			
8	Fruit crops			
9	Sugarcane			
10	Bananas			
11	Pasture			
12	Beans			
13	Other (specify).…			

7. What cropping system do you practice on your farm?

A. Mono-cropping ☐ B. mixed cropping ☐ C. Agroforestry ☐

D. Other……………. (specify)

8. Which type of livestock do you keep on your farm? (*Please fill in the table 2 below, if NA skip to section B)*

Table 2: Livestock data

S/N	Livestock	Approximate Number
1	Exotic dairy cattle	
2	Indigenous dairy cattle	
3	Beef cattle	
4	Goats	
5	Sheep	
6	Poultry	
7	Fish farming	

S/N	Livestock	Approximate Number
8	Other (Specify)………………………	

B. FARM MANAGEMENT PRACTICES

i. Land preparation methods

9. Which of the following land preparation methods do you practice on your farm (you can select more than one, as applicable)

Table 3. land preparation practices

S.NO.	Land preparation method	YES	NO
1	Minimum tillage		
2	Hand cultivation		
3	Ox-plough		
4	Tractor		
5	Other (specify)………………		

ii. Source of water for agriculture

10. What is the source of water for agriculture in your farm?

A. Rainfall ☐ B. Irrigation ☐

11. If the answer is irrigation, what type of irrigation do you practice in your farm?

(Use table 4 to respond to question 11 above)

Table 4. Irrigation type

S.NO.	Irrigation type	YES	NO
1	Surface (Flood/ Furrow/border)		

S.NO.	Irrigation type	YES	NO
2	Sprinkler		
3	Drip		
4	Sub-surface		
5	Other (specify)………………		

iii. Inorganic fertilizers use on the farm

(Use Table 5 for responses to questions 12 -15)

Table 5. Inorganic fertilizer use

QN	Activity	Response	Choices
12	a. Do you use fertilizer during planting of crops?		0=No, 1=Yes
	b. If yes, which brand of fertilizer do you use during planting		
	c. What is the application rate/acre?		
13	How often do you use fertilizer when planting your crops?		A. Every planting seasons B. Only during main planting season C. sometimes (irregular)
14	a. Do you top-dress your crops with inorganic fertilizers?		0=No, 1=Yes
	b. If yes, which brand of fertilizer do you use for top dressing?		
	c. What is the application rate/ acre?		

15 How often do you top-dress your crops with inorganic fertilizer?

A. Every growing season
B. Only during main growing season
C. sometimes (irregular)
D. Rarely top dress
E. Never

iv. Manure

16. Do you use manure on your farm? 1. Yes ☐ 0. No ☐

(*If yes, proceed to subsequent questions, otherwise jump to question 20).*

17. Please indicate the type of manure used on your farm (Table 6).
18. What is the source of manure? *(You can indicate more than one, as applicable)*
19. What quantity of manure (Kgs) do you apply in your farm?

(Use Table 6 for questions 17 -19 above)

Table 6. Types and sources of manure

S/N	Form of manure	0 = No, 1 = Yes	Source	Quantity (kg)		
				SS	LS	Total
1.	Farm yard manure					
2.	Poultry manure					
3.	Biogas slurry					
4.	Green manure					
5.	Compost manure					
6.	Fish pond manure					
7.	Goat manure					
8.	Cattle manure					

S/N	Form of manure	0 = No, 1 = Yes	Source	Quantity (kg)		
				SS	LS	Total
9	Other(specify)……………					

Sources: 1. Own farm 2. Free From neighbour 3. Purchase from neighbour 4. Purchase from next village 5. Purchase from market centre 6. Others (specify)……

SS = Short season, LS = Long season

v. Pest Management practices

20. Do you practice pest control in your farm?................. 1. Yes ☐ 0. No ☐

21. If yes, what type of pest control do you practice?

22. What is the reason for the choice of the pest control method?

(Use Table 7 for questions 21 and 22)

Table 7: Pest management practices

S/N	Pest management Practices	Types	Reason
1.	Biological	Use of predators	
2.	Chemical	Pesticides	
3.	Mechanical	Traps, Tillage, fire,	
4.	Cultural	Crop rotation	
5	Integrated Pest Management (IPM)	Combined practices If yes, which combination do you use? _______________	

vi. Weed control practices

23. Do you practice weed control in your farm?................. 1. Yes ☐ 0. No ☐

24. If yes, what type of weed control do you practice?
25. What is the reason for the choice of the weed control method?

(Use table 8 to answer question 24 and 25)

Table 8: weed control practices

S/N	Weed control	Yes	No	Reason
1.	Hand weeding			
2.	Slashing			
3.	Mulching			
4.	Cover crops			
5.	Herbicides			
6.	Other ………………			

vii. post-harvest practices

26. How do you manage crop residues after harvesting your crop? *(You can choose more than one, as applicable)*

A. Burning ☐ B. Composted ☐ C. incorporated in situ ☐

D. Used as fodder ☐ E. Used for fuel ☐ F. Other…………...(specify)

27. How long do you leave your farm fallow after harvesting crops?

A. I plough it immediately ☐ B. less than one month ☐ C. 1-4 months ☐
D.5-6 months ☐ E. Other………… (specify)

viii. Soil conservation practices

28. Do you practice soil conservation?

1. Yes ☐ 0. No ☐

29. If yes, which of the below soil conservation practices do you carry out in your farm

A. Contour farming ☐ B. Conservation tillage ☐ C. Strip cropping ☐

A. Terracing ☐ E. Crop rotation ☐ F. Mulching ☐ G. Cover crops ☐

H. Other…………(specify)

ix. Soil Information on Improved agricultural practices (IAPs)

30. Do you receive soil information about IAPs?

1. Yes ☐ 0. No ☐

31. If yes, where do you receive information from?

A. NGOs

B. Extension service officers (ESO)

C. Tanzania Agricultural Research Institute (TARI)

D. Research from Higher Learning Institution (RHLI)

E. Not aware of either method

END

THANK YOU FOR YOUR TIME AND COOPERATION