HUNGARIAN UNIVERSITY OF AGRICULTURE AND LIFE SCIENCES

DOCTORAL SCHOOL OF ENVIRONMENTAL SCIENCES

THESIS OF THE DOCTORAL (PHD) DISSERTATION

ANALYSIS OF SOIL QUALITY, FARMERS' KNOWLEDGE AND MANAGEMENT PRACTICES IN MOUNT KENYA EAST REGION

By

AMOS WANJALA WAWIRE

GÖDÖLLŐ, HUNGARY

2021

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): Tormáné Dr. Kovács Eszter

Associate professor, PhD.

MATE, Institute for Wildlife Management and Nature Conservation

Department of Nature Conservation and Landscape Management

Dr. Csorba Ádám

Assistant professor, PhD.

MATE, Institute of Environmental Sciences

Department of Soil Science

Approval

....	....
Approval of the School Leader	Approval of the Supervisor (s)

1 INTRODUCTION

1.1 Background

Soil is admittedly the foundation of agriculture. It is the most valuable and widespread natural resource and the economic engine to the agricultural-based livelihoods. Soils can be considered as life enabler courtesy of the ecosystems services that they deliver on Earth. According to the Food and Agriculture Organization (FAO, 2015), soils provide the following ecosystem functions and services: i) provision of food, ii) fibre and fuel; iii) nutrient cycling; iv) water purification, soil contaminant reduction and fresh water storage; v) carbon sequestration; vi) foundation for human infrastructure; vii) flood regulation; viii) habitat for organisms; ix) provision of construction materials; x) cultural heritage and xi) climate regulation. The criticality of these ecosystem functions and services places soil (and of course agriculture) at the heart of sustainable development goals (SDGs) (Bouma & Montanarella, 2016; Tóth et al., 2018). But, for soil to deliver on most of these functions, it must be maintained in good health.

On the flipside however, there has been consistent decline in land productivity stemming from declining soil fertility (NAAIAP, 2014). The increase in global population and the resulting pressure on the natural resources (including water, land and nutrients), clearly puts soil on spot, calling for sustainable management of the resource to ensure supply of adequate food and achievement of SDG2 (zero hunger). Similarly, environmental issues including land degradation, soil erosion, and decline in soil organic carbon (SOC) are strongly connected with decline in environmental quality, thus putting the livelihoods of a significant global population at risk (Bouma et al., 2017).

Understanding of the problems affecting soil resources is a critical prerequisite in addressing these challenges and ensuring that soil effectively delivers its functions. In response to this reality, there is increasing interest at national, regional and international levels on the strategies to enhance and sustain healthy soils.

1.2 Problem Statement and Justification

There is increasing demand for accurate, consistent and comprehensive soil data at small-scale level. Informed farming decisions depend heavily on quality, reliable and up-to-date soil information. In response, soil resource inventories have been undergoing dramatic revolution from the use of traditional soil surveys to sophisticated digital techniques. Consequently, the quantity and quality of digital soil data sets at global, regional, national and local scales has increased tremendously (Dobos et al., 2001). However, access to soil information remains a major challenge. Many parts of the world including Kenya, lack or little survey information, or only scanty generalized small-scale soil maps and data are available. Similarly, there is lack of harmonized databases occasioned by unsystematized sampling design, rendering comparison of different surveys difficult, thus compromising the accuracy of soil data. Most of these databases are based on either regional or national scale (Dobos et al., 2001), thus highly generalized and unsuitable for decision-making at farm level (which are characterized by high variability of soil properties at very short distances). Most of the existing soil databases are outdated with little efforts being made to update the resources, largely due to high costs of survey and laboratory analyses (Mutuma, 2017). Fortunately, at the continental level, the Africa Soil Information Service (AfSIS) has actively been working on bridging this major gap in soil spatial information. The database generated by AfSIS has been the major input to digital soil mapping activities (AfSIS, 2013). Information on distribution and the nature of soil resources is critical in making decisions on efficient land use and management and to help deal with food security, global climate change and other looming environmental and economic issues.

1.3 Research Objectives

The purpose of this study is to evaluate the quality of soil Mount Kenya East region and determine management-induced changes in soil properties. To achieve this aim, the following objectives were defined.

1. To characterize and classify soils of the visited sites
2. To describe the farming systems and soil management practices and explore the socio-economic determinants of soil fertility management strategies.
3. To determine local indicators of soil fertility and compare scientific assessment and farmers' soil fertility perception.
4. To evaluate the influence of farmers' socio-economic characteristics and management practices on soil quality.

1.4 Research Questions

To achieve the stated objectives, the following research questions were formulated.

1. **Objective one**

i. What are the defining characteristics of the soils of Mount Kenya East region?
ii. How do these properties vary with the sampling depth intervals?
iii. What are the major reference soil groups (RSGs) of Mount Kenya East region?
iv. How do soil attributes vary across the identified RSGs?

2. **Objective two**

i. What are the socio-economic and demographic characteristics of farm households in Mount Kenya East region?
ii. What are the characteristics of farming systems in the study area?
iii. What are the soil fertility management practices (SFMP) used by farmers in the study region?
iv. What are the combination clusters of SFMP as used by farmers?
v. How do farm household socio-economic and demographic characteristics correlate with adoption of SFMP?

3. **Objective three**

i. What are the local indicators of fertile and infertile soils used by farmers?
ii. How important are the indicators in predicting soil fertility?
iii. How does farmers' soil fertility evaluation correlate to scientific measurements of soil attributes?

4. **Objective four**

i. How do management practices relate with soil characteristics?
ii. How can farm households be grouped (typologies) based on socio-economic, farm management practices and soil variability?
iii. How do soil characteristics vary across the identified farm household groups (typologies)?

2 MATERIALS AND METHODS

2.1 Description of the Study Area

The study was conducted in Mount Kenya East, a region encompassing Meru and Tharaka Nithi Counties (Figure 2.1) covering an area of 1,618 km^{2}within longitudes 37°53'38.4" E and 37°33'35.28" E and latitudes 0°4'26.4" N and 0°20'20.4." S. The counties are located almost in the middle of the country, on the eastern slopes of Mount Kenya, about 200 km north of the Kenyan capital, Nairobi. The primary land use is rainfed agriculture.

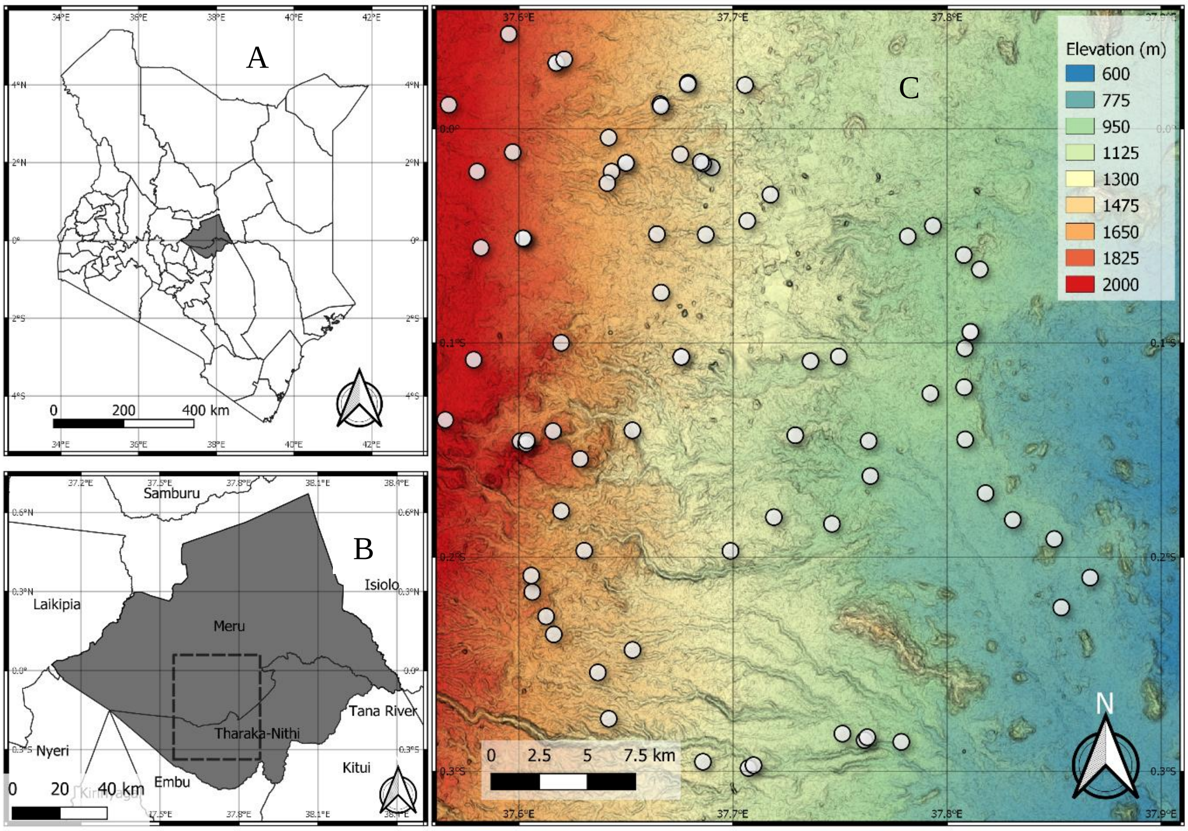

Figure 2.1. Map of Kenya (a) showing the Location of Meru and Tharaka Nithi Counties (b), and the distribution of sampling points within the study area (c)

The study area has a total population of 1,938,891 people (1,545, 714 in Meru and 393,177 in Tharaka Nithi). The total land area is about 6,936 and 2,662 km^2, with a population density of 221 and 153 persons per km^2 for Meru and Tharaka Nithi Counties, respectively. Family size in the region averages 3.6 person per household (KNBS, 2019).

The relatively dense population derives their livelihood from farming and has put a lot of pressure on land leading to overexploitation of natural resources and advanced land degradation. Agriculture dominates the region's economic activity and accounts for 80% of the economy, with more than 90% of the population directly or indirectly dependent on farming. Majority of the farmers are smallholders, constituting about 98.6% of farms. The average farm size is estimated at 2 acres (in Meru) and 2.9 acres (Tharaka Nithi), but this varies based on population density (County Government of Tharaka-Nithi, 2013; Meru County Government, 2014). Average farm size in densely populated areas is one acre, and five acres in more sparsely populated areas (Meru County Government, 2014). The region experiences shortage of farm labour and rising unemployment rate due to the youth's preference for white collar jobs in an otherwise predominantly agriculture-based economy (CIDP, 2018).

Climate

The region is characterised by a bi-modal rainfall pattern, with longer rains occurring between March-May, and the shorter rains between October-December. There is high variation in rainfall which increases from east to west, with the annual mean rainfall ranging from 300 mm to 2,500 mm. The region's altitude spans from 300 metres (low hills) to 5,199 metres (the peak of Mt. Kenya) above sea level. Temperatures range between 8°C and 32°C.

There are primarily two landforms in the area: uplands with gently undulating to rolling landscape (slope ranging from 2-16%), and minor valleys with 5-30% slopes (undulating to hilly). In some places, the valleys are deeply incised (Mason & Geological Survey of Kenya, 1955; Njoroge & Kimani, 2001)

Tharaka Nithi County is located in the Upper Midland Zone two (UM2) and Upper Midland Zone three (UM3) agro-ecological zones (AEZ) on the eastern slopes of Mount. Kenya. Meru comprises of about twenty different sub-Agro-ecozones (CIDP, 2018), falling into four main agro ecological zones (AEZs) ranging from the upper highlands-UH3 to lower midlands-LM6 (Jaetzold et.al., 2010).

The region's varied climatic and ecological zones is the basis for its diverse agricultural production, which is primarily rainfed (County Government of Tharaka-Nithi, 2013; Meru County Government, 2014).

Agriculture

The study area is characterized by a wide range of socio-economic and biophysical conditions, which is typical of highlands, midlands and lowlands where both mixed farming and agro-pastoralism are common.

The crops grown range from staples, cash and horticulture crops. Food crops grown include white corn (maize), beans, bananas, sweet potatoes, Irish potatoes (potatoes), peas, cowpeas, arrow roots, yams. Horticultural crops include fruits (such as mangoes, passion fruit, avocadoes, watermelon, nuts and pineapples), vegetables (such as snow peas and French beans) and flower farming (cut flowers). Coffee and tea are the main cash crops (CIDP, 2018; County Government of Tharaka-Nithi, 2013).

Livestock farming is equally an important means of livelihood, with exotic dairy cattle (Meru-114,251, Tharaka Nithi- 32,634), exotic beef cattle (Meru-24,656, Tharaka Nithi-5,137),indigenous cattle (Meru-173,277, Tharaka Nithi-52,935), goats (Meru-342,198, Tharaka Nithi-214,217) andsheep (Meru-138,771, Tharaka Nithi-53,816) being the most important livestock in the region. Chicken, both indigenous (Meru-1,006,744, Tharaka Nithi-418,193) and exotic (Meru-210,034, Tharaka Nithi-42.661) are the most common poultry (KNBS, 2019). Livestock is also an important source of manure. The community also derives livelihood from lumbering. *eucalyptus, cypress* and *Grevillea robusta* are the major trees used for timber, fuel and charcoal (CIDP, 2018; County Government of Tharaka-Nithi, 2013). .

Geology and geomorphology

The geology in the area is primarily volcanic rock, ash and old metamorphic rocks (Schoeman, 1952). The Mount Kenya volcanics consist of basalts, rhomb porphyries, phonolites, kenytes and trachytes which make up the main period of eruption. The plug of the volcano consists of nepheline syenite and phonolite in the form of a ring structure. Satellite activity from fissures resulted in the eruption of further phonolites, basalts, trachytes and mugearites, and the activity on the mountain was brought to a close by further satellite eruptions of trachytes, pyroclastics, basalts, and basaltic pumice from various vents on the slopes of the original volcano. The Mt. Kenya volcanics are believed to be mainly of Pleistocene age (Baker, 1967). The soils around the area are mainly developed from basalts of Mount Kenya volcanics (Njoroge & Kimani, 2001).

Major soil types of study area

There are two major predominant Reference soil groups based on WRB (IUSS Working Group, WRB, 2015), namely, Nitisols and Acrisols, occuring in the uplands and lowlands, respectively. Other common soils include Andosols, Umbrisols, Cambisols and Leptosols (Figure 2).

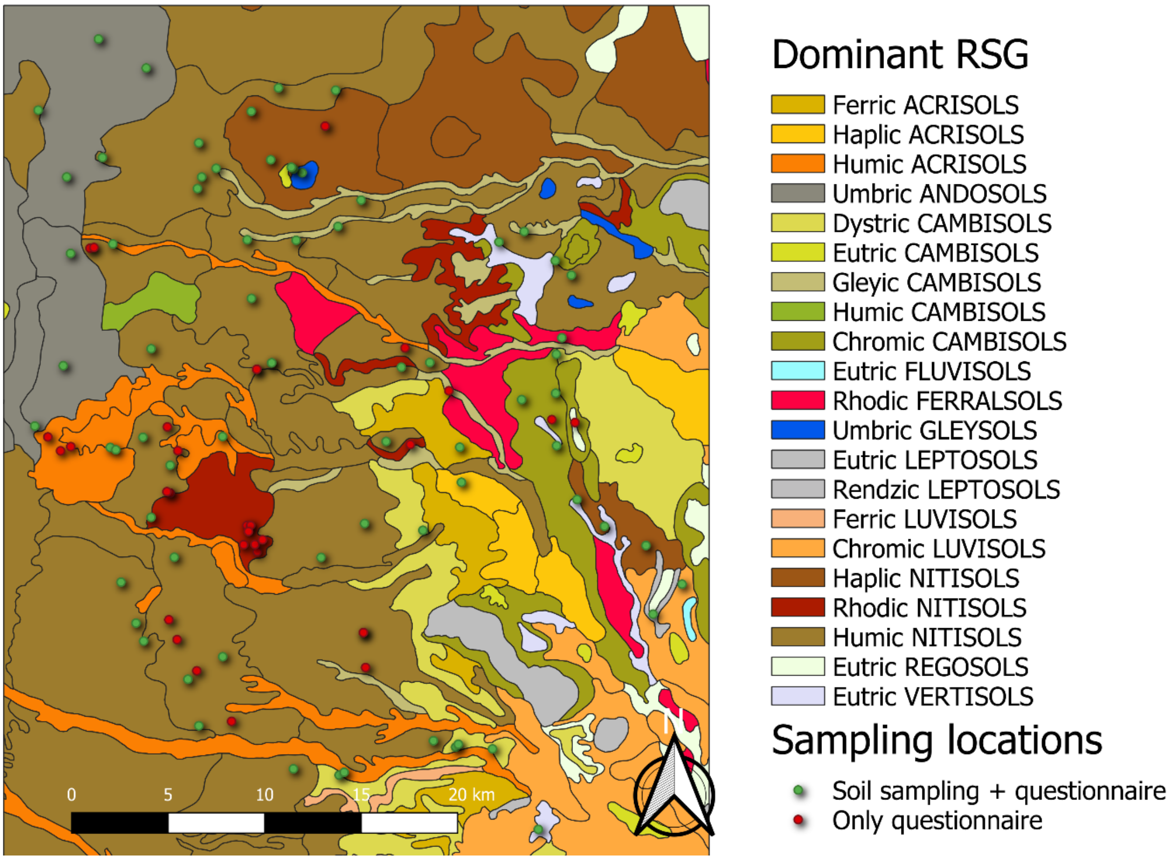

Figure 2. Major Reference Soil Groups of the study sites. (Source: Dijkshoorn et al., 2011)

The soils in the lowlands (Tharaka-Nithi) are predominantly sandy loam and shallow, thus the need for moisture conservation measures (Muriu-Ng'ang'a et al., 2017).

The study site was mapped using SOTER_UT and ISRIC-WISE, based on 186 unique SOTER units. SOTER_UT, at scale 1:100,000, which is more detailed compared to SOTER databases edition II and I, at scale 1:250,000 and 1:1 M, respectively (Dijkshoorn et al., 2011). Individual map units comprising of up to four different soil compinents were characterized by a regionally representative profile, identified and classified by national experts. Characterization was based on 144 profiles (108 real profiles, and 36 synthetic profiles), and taxotransfer procedures used to fill the gaps in the analytical data to facilitate modelling (Batjes, 2010). Soil property was estimated for 18 soil variables by soil unit for a fixed depth interval of 20 cm to 100 cm depth. The properties include organic carbon, pH(H2O), content of sand, silt and clay, coarse fragments content (>2 mm), base saturation, soil cation exchange capacity(CEC_{soil}), clay cation exchange capacity (CEC_{clay}), effective CEC, total nitrogen, aluminium saturation, exchangeable sodium percentage (ESP), CaCO3 content, gypsum content, electrical conductivity (ECe), volumetric water content. These attributes are considered critical for agro-ecological zoning, land evaluation, simulation of crop growth, carbon stocks modelling, and studies of global environmental change (Batjes, 2010).

2.2 Soil sampling design

Mapping of soil properties and fertility management practices made use of: (a) systematic and unbiased field surveys to collate soil data and other ecological parameters (following Conditioned Latin Hypercube Sampling or cLHS); (b) laboratory analyses using IR spectroscopy and wet chemistry, and (c) remote sensing information (Vagen, Winowiecki, Abegaz, & Hadgu, 2013). Developing a sampling scheme that as much as possible takes into account variations in soil types and soil properties in the study area was first undertaken.

Variation in soil types reflects the natural distribution of soil forming factors and the soil forming processes. The proposed sampling scheme preserves the natural distribution of both the continuous and categorical soil forming factors. To achieve this end, the ancillary data to be used in the sampling design process were assembled. This was guided by SCORPAN model of soil formation state equation (.McBratney et al., 2003).

For continuous variables, elevation data derived from Advanced Land Observation Satellite (ALOS) data. The slope was calculated from the elevation, topographic position index, and Topographic Wetness index. These methods are the most often used due to their efficiency, detail and availability (Weih & Mattson, 2004).

Categorical variables: i) the Parent material layer (geology of the area) generated from a digitized ISRIC document of the study area, was used; ii) SOTER_UT (at scale 1:100,000) polygons soil unit layer were used because of their higher resolution (Dijkshoorn et al., 2011) ensuring the inclusion of all polygons in the sampling exercise. ; iii) the ancillary data was the base for input layers for the conditional Latin Hypercube objective function equation in R programming platform, and GIS interface used to visualize output; iv) The sampling scheme was evaluated to confirm congruence to the natural distribution of the selected ancillary data by use of boxplots.

Conditioned Latin Hypercube Sampling

Latin hypercube sampling (LHS) is a stratified random procedure that provides an efficient way of sampling variables based on their multivariate distribution. For Conditioned (or constrained) Latin Hypercube Sampling (cLHS), as the name suggests, an additional criteria (condition is imposed on the model. cLHS aims at creating a dataset that covers the covariate space, while taking unforeseen constraints (such as poor road network, very steep slopes 'unsampleable" or forbidden areas like parks and water bodies) into consideration, and minimizing costs in relation to the sample size, time required for sampling, and accessibility of sampling sites. Covariate space can be defined as the space covered by the covariates utilized by the cLHS (Mulder et al., 2012). For model details including the equation, refer to Minasny & McBratney (2006).

2.3 Designing of Farm Household survey and interviews

Quantitative and qualitative social data were obtained through farm household questionnaire survey and interviews. Questionnaires were administered to 106 pre-selected purposively sampled farmers. The sample size of participant farmers for questionnaire survey was determined using Slovin's sampling formula (Stephanie, 2013).

Interviews were administered to strengthen the quality of questionnaire data (Patton, 2002). This was achieved by interviewing seven (7) extension providers and nine (9) farmers. Five of the seven extension staff were drawn from County government agricultural officers. The other two were Tea Extension Service Assistants from Kinoro and Imenti tea factory. Purposive sampling method was used for the selection of interviewees. While selection of extension personnel was based on availability, the choice of farmers for interview was based on the recommendation of the extension workers within their jurisdiction.

2.4 Field Work and Data Collection

Field work involved soil sampling and collection of social data (through administration of questionnairre and interviews (Figure 3).

Figure 3. Soil sampling (A) and questionnaire administration (B). Credit: Adam Csorba, 2019

Soil samples were obtained from 69 fields (identified by conditioned Latin hypercube sampling design) in January 2019. Three samples were obtained from each sampling point at three depth intervals, namely 0-20 cm, 20-50 cm and 50-100 cm, by hand auguring. In total, about 207 samples were collected. This design conforms to the approach recommended by the Africa Soil Information Service (AfSIS) of 0-20 and 20-50 cm depth. An additional subsoil sample (50-100 cm) was obtained following the previous sampling designs (Gicheru & Kiome, 2000; Mutuma, 2017). A preliminary field diagnostic and definition of soil properties was performed based on WRB 2014.

The samples were packed in labelled zip-loc plastic bags and delivered to the laboratory of the Hungarian University of Agriculture and Life Sciences (MATE) for further processing and analysis.

Questionnaire and interviews were administered through face-to-face survey. Farm household data collected include demographic and socio-economic characteristics (such as education, household farm size), type of farming, the kind of cultivated crops, types and quantity of each livestock, soil fertility management strategies, data concerning fertilizer and manure use (type and sources, frequency of application, beneficiary crops). Based on a list of predetermined indicators from literature review, data on farmer's description of fertile and infertile soils were collected. These indicators included soil colour, soil workability or tilth, water holding capacity, crop yield, crop growth rate, leaf colour, earthworm presence, indicator weeds, and topography. First, farmers described what they perceived as a fertile or infertile soil based on each of the indicators. Farmers then ranked fertility of their fields using a Likert scale ranging from 1-5 (Poor to excellent soil quality) for each of the indictors.

2.5 Laboratory measurements

Prior to laboratory analysis, the soil samples were air-dried and passed through a 2mm-mesh sieve (USDA, 2018). Soil samples were then subjected to laboratory analyses using standard methods for various soil properties, including soil organic carbon (SOC), pH, particle size distribution (clay, silt, sand), cation exchange capacity (CEC), exchangeable cations (Ca, K, Mg, Na,) and base saturation (BS). Available soil nutrients were also determined, including phosphorus (P), potassium (K) and available nitrogen.

Except for SOC and pH (which were analyzed for all samples), all the Laboratory soil analyses were performed using 40 representative samples (out of approximately 207 samples), determined based on multivariate calibration techniques (chemometrics). Partial Least Squares Regression (PLSR) with leave-one-out cross validation was used to calibrate the MIR spectral data with the reference laboratory soil data.

Soil organic carbon was determined following the Walkley-Black procedure (van Reeuwijk, 2002). Soil CEC and base saturation were determined following the $BaCl_2$ Compulsive Exchange Method (Gillman & Sumpter, 1986; Ross & Ketterings, 2011). Exchangeable cations (K, Ca, Mg, and Na) were determined following Mehlich 3 extraction method (Mehlich, 1984). Soil pH in H_2O was potentiometrically measured in the supernatant suspension of a 1:2.5 soil: extractant mixture (Carter & Gregorich, 2008). Soil N was determined using the Parnas-Wagner apparatus, with NaOH as the extraction reagent and Boric acid as an indicator solution using the micro Kjeldhal method (Bremmer and Mulvaney, 1982). Soil available K and P were determined using ammonium lactate acetate solution method (Egnér et al., 1960). The distribution of clay, silt and sand particles was determined by mechanical analysis using the pipette method (Haluschak, 2006).

2.6 Methods of Data Analysis

2.6.1 Characterization and classification of soils of the study area

Descriptive statistics for soil data were generated in SPSS. The means were generated for the numerical soil properties for the measured soil attributes). Categorical data (such as texture and Munsell colour), were summarized using “frequency distributions” analysis.

Analysis of variance (ANOVA) in SPSS was used to determine the relationship between soil properties and the three sampling depth intervals, namely 0-20 cm, 20-50 cm and 50-100 cm.

Soil classification of the visited sites was conducted based on World Reference Base of soil resources (WRB) 2014 soil classification guideline (IUSS Working Group WRB, 2015). To determine the relationship between soil properties and RSGS, ANOVA was conducted using the R statistical environment (Roudier & Hedley; R Core Team, 2013).

Principal component analysis (PCA) and multiple correspondence analysis (MCA) were performed for soil properties (numeric) and RSGs (categorical), respectively, to compare variability of soil properties. These procedures were implemented using a mixed PCA procedure that integrates numeric and categorical variables (Chavent et al., 2015). The soil diagnostic properties were described using the approach in terms of their physical and chemical characteristics. Farming systems, soil fertility management practices (SFMP), and determinants of SFMP adoption.

Descriptive statistics using frequency distributions (for categorical variables) and means (continuous variables) were generated in IBM SPSS to answer the research questions relating to: 1) Socio-economic and demographic characteristics of farm households; 2) Characteristics of farming systems; and 3) the SFMP used by farming households.

Prior to empirial analyses, clusters were generated using Ward's method of hierarchical clustering in SPSS to identify combination patterns of soil SFMP. Ward's method of hierarchical clustering was used to separate soil fertility management practices into classes (Cornish, 2007). Technology clustering is a product of maximum variance for SFMP usage across farming households (IBM, 2013).

2.6.2 Analysis of socio-economic data and soil fertility indicators

Farmers' description of fertile and infertile soils was subjected to descriptive analysis to determine frequencies and percentages of responses for each indicator. ANOVAs were conducted to compare soil fertility scores between high and low fertility soil categories using LSD (*R agricolae* package) while mean plots were displayed using R *sciplot* package. Contrasts controlling for the mean likert scales were determined using the R *emmeans* package to determine differences between fertile and infertile soils for descriptive soil indicators.

Qualitative data from interviews were analysed using thematic analysis. This is an independent descriptive method generally described as a technique for identifying, analysing and reporting patterns (or themes) contained within the dataset. Thematic analysis (TA) presents a theoretically flexible technique of analysing qualitative data (Braun & Clarke, 2006) and aid in validation of responses from questionnaires. Information generated from interviews was used to complement questionnaire data and enhance interpretation of statistical analysis results.

Factor Analysis was used to analyze soil fertility indicator scores generated by farmers to determine the major soil quality dimensions within farmers' fields in the study sites. A Varimax rotation procedure with Kaiser Normalization (which essentially 'cleans up factors") was used because it generates an independent factor pattern which loads highly significant variables into one factor. This was considered a plausible and acceptable interpretation of the resultant factors. Each given factor loads highly (has high correlation) with a limited number of variables, while loading very low with the rest of the variables, which eases interpretation (Pituch & Stevens, 2016). The study assumed that the resultant factors were uncorrelated, thus the choice of orthogonal factor rotation (IBM, 2013).

2.6.3 Local indicators of soil fertility, and comparison of farmers' and scientific soil fertility measurements.

2.6.3.1 Description of farmers' soil fertility indicators

Descriptive statistics of soil fertility indicators used by farmers to classify fertile and infertile soils, were generated in SPSS. Frequencies and percentages of farmers' perception of fertile and infertile soils based on the 9 parameters provided in the questionnaire, namely soil colour, soil earthworms, indicator weeds, topography, water holding capacity, soil workability (tilth), crop yields, crop growth and leaf colour, were determined. The comparison in soil fertility measures between high and low fertile plots was undertaken using ANOVA.

Farmers rated the importance of each indicator in evaluating soil fertility using a 5-point Likert scale (1=not important to 5= very important). Means for importance ratings were analysed using descriptive techniques in SPSS and bar charts were generated. Similarly, based on soil fertility descriptions in relation to the various indicators, farmers rated the quality of their fields in terms of each indicator using a 5-point Likert scale (1=poor to 5=excellent).

The subsequent subsections describe how soil quality thresholds (both scientific and farmer-based) were determined.

2.6.3.2 Farmer-descriptive soil quality index (SQI)

After describing fertile and infertile soils, farmers evaluated fertility of their fields in respect to each of the indicators by giving a score of 1-5 (poor to excellent soil quality). The farmer descriptive SQI was generated by averaging the sums of the 9 indicator scores for each farm, resulting into an aggregated farmer criterion for soil quality assessment. Based on the average fertility score, the soils were classified as either infertile (<3.5) or fertile (>3.5).

2.6.3.3 Indicator selection and determination of scientific soil quality indices (SQIs)

Two methods were used to develop scientific soil quality indices based on measured soil properties, including a simple additive soil quality index (A-SQI) and mathematically developed soil quality index using multivariate analysis (Factor Analysis or FA-SQI). The simple additive-SQI was estimated following procedures outlined by Amacher et al. (2007) and Vlek et al. (2010). In this method, soil parameters were given threshold values based on the literature review. For threshold levels, interpretations, and associated dimensionless soil quality index score values, see Table 1 (p3) in Amacher et al. (2007).

The individual index values for the physical, chemical and biological soil properties were summed to give the additive SQI (A-SQI). The maximum SQI score was 17 when all the parameters were included and assumed to have received a maximal score value. The parameters selected for the A-SQI scale included sand (coarse fraction) (physical), soil pH (chemical), soil organic carbon (biological), CEC (chemical), potassium (chemical), magnesium (chemical), calcium (chemical), and available P (chemical).

In the FA-SQI score (Li Q et al., 2013; Masto et al., 2008), a multivariate model was used to reduce the indicator load and minimize data redundancy, using SPSS version 25 procedures. Factors were derived using a Kaiser-Varimax rotation procedure. Each of the extracted factors explained a given amount of variance in the model (see Table 7). The percentage variance for each factor was divided by the cumulative variance to derive a weight for each factor (PC), which was multiplied by the factor scores for each sampled field (Andrews et al., 2002). The weighted multivariate soil quality indicator was derived as follows:

*FA-SQI = w1*Component 1 score+ w2*Component 2 score+ w3*Component 3 score*

Where: w1-w3 are the factor weights

2.6.3.4 Measuring relations between the different soil quality indices

The two scientific SQIs (A-SQI and FA- SQI) were regressed against FD-SQI using the *lm* procedure in the R statistical environment and linear model facets for high and low fertility plots produced R *base* plotting procedures.

2.6.4 Examining the relationship among soil properties, farm management practices and farm household characteristics

To examine the influence of household and farm management characteristics, farm typology was developed using Categorical Principal Analysis (CATPCA) and Factor Analysis (FA), followed by cluster analysis (CA) using Two-Step and hierarchical clustering methods. After clustering, ANOVA and Fisher's Exact Test (FET) analyses were used to compare socio-economic attributes, farm management parameters and soil characteristics between clusters.

3 RESULTS AND DISCUSSION

3.1 Soil Characterization of Sampled Farms

3.1.1 Results of descriptive statistics of soil properties

The overall mean soil pH in the study area was 5.4 (strongly acid) with the lowest pH of 3.9 (extremely acid) and a high of 7.0 (neutral) (Table 1). Soils classified as fertile by farmers had a mean pH of 5.7 (medium acid) while the infertile soils had a pH of 5.1 (strongly acid). Spatial variations in soil properties are anticipated due variations in landscape (topography, relief), geology (parent materials) and climate (Muchena & Gachene, 1988). The topography of the area displays significant terrain diversity (ranging from 300 to 5,199 m), resulting in extremely varied climatic conditions including precipitation (300-2,500 mm, and decreases from the west to east) and temperature (8°C to 32°C). The study area consists of a variety of rocks ranging from teriary volcanics to unconsolidated sediments. These topographic, geological and climatic diversity result in the formation of a wide range of soils (Wanjogu et al., 2001).

Table 1. . Overall descriptive statistics of laboratory measurements of soil properties and across the three depths

Depth	**20**			**50**			**100**			**Total**		
Variable	Mean	N	Std. Dev	Mean	N	Std. Dev	Mean	N	Std. Dev	Mean	N	Std. Dev
Sand	25.48	69	7.65	22.44	66	7.02	20.61	65	5.98	22.89	200	7.19
Silt.	38.33	69	4.5	40.1	66	4.16	41.26	65	3.53	39.87	200	4.25
Clay	36.19	69	3.15	37.46	66	2.86	38.13	65	2.66	37.24	200	3
Bs	17.26	69	4.66	16.86	67	4.74	17.07	66	4.32	17.07	202	4.56
K.	0.81	68	0.1	0.81	67	0.13	0.82	64	0.12	0.81	199	0.12
Mg.	0.67	69	0.18	0.65	67	0.18	0.66	66	0.16	0.66	202	0.17
Ca	1.89	69	0.42	1.88	67	0.42	1.87	66	0.47	1.88	202	0.43
Na.	0.04	67	0.05	0.05	64	0.05	0.06	64	0.06	0.05	195	0.05
CEC.	8.47	69	1.44	8.39	67	1.82	8.39	65	1.73	8.42	201	1.66
AL-K2O	781.84	69	117.28	742.04	66	118.61	718.33	64	103.91	748.21	199	116.08
AL.P2O5.	11.32	69	7.7	13.14	67	9.33	12.77	63	9.73	12.39	199	8.92
pH.H2O.	5.49	69	0.74	5.31	68	0.98	5.4	65	0.89	5.4	202	0.88
OC.	0.97	68	0.52	1.16	67	0.86	1.1	63	0.69	1.08	198	0.71
Moisture	4.54	69	2.17	4.59	67	2.42	4.32	64	2.4	4.48	200	2.32
N (mg/Kg)	24.46	55	22.56							24.46	55	22.56

The strongly acid nature of most of the soils in the area is attributed to strong weathering and leaching, especially in the lower regions. The avilability of plant nutrients is highly determined by pH, and tend to be optimal for most agricultural crops (such as maize) within the neutral range of 6.0 to 7.0 value (Oshunsanya, 2019), with the exception of equally essential micronutrients including iron, zinc, manganese and copper which are readily available at pH 5.5 and below. However, too acidic soil hinders root growth and copper may become too toxic (Wanjogu et al., 2001).

The average SOC in the study area for topsoil (0-20 cm) was 1.34% with a range of 0.5%-5.9%. Farms in uplands had generally higher SOC (1.6) than lowland fields. The amount of SOC is positively correlated to elevation. The accumulation of SOC in highland areas varies greatly due to diverse environmental conditions (Arunrat et al., 2020). There was more SOC in fertile soils (1.6) compared to infertile soils (1.1).

Figure 4 and Figure 5 shows the patterns in soil properties across the sampling sites.

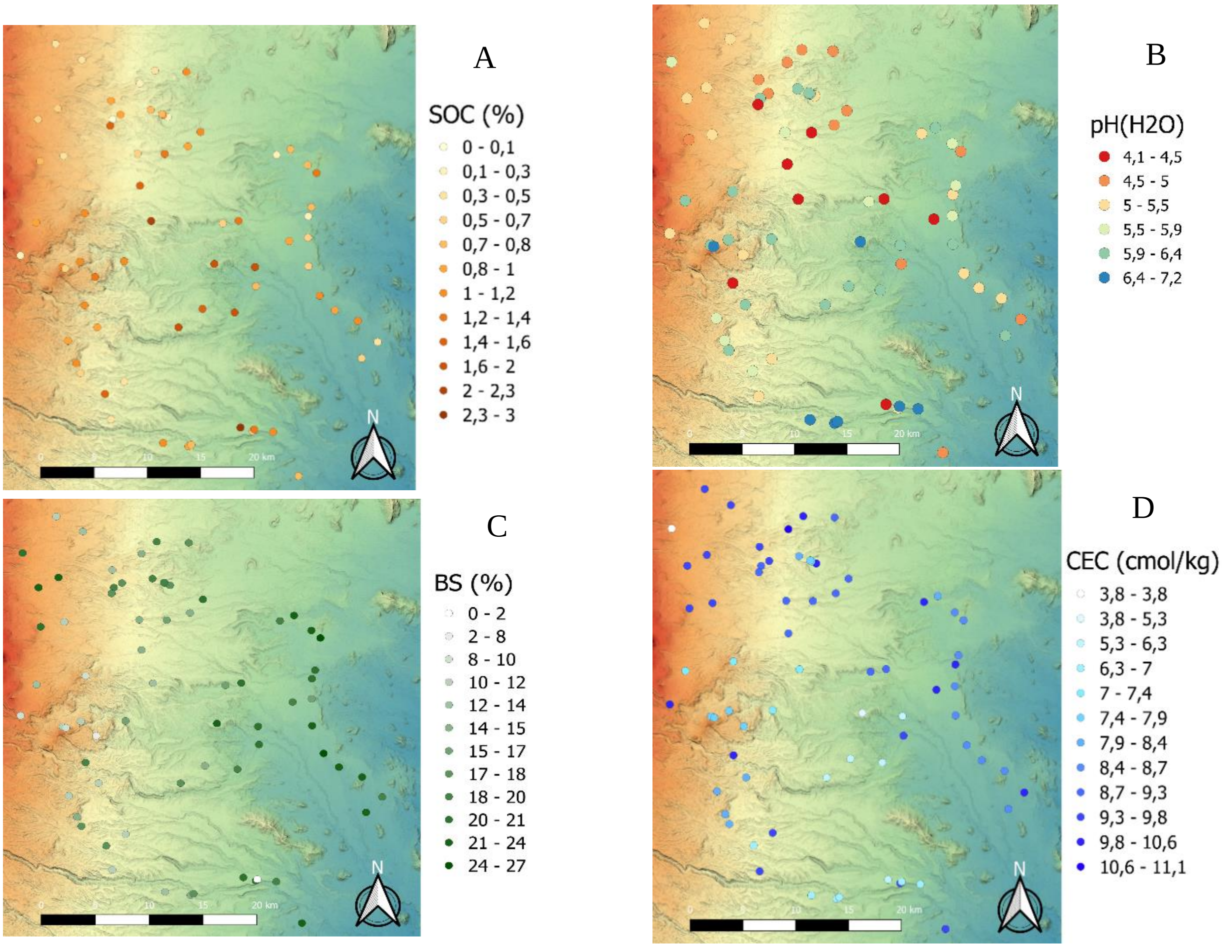

Figure 4. Soil property maps for selectected attributes: soil organic carbon (A), pH (B), Base saturation (C) and Cation exchange capacity (D)

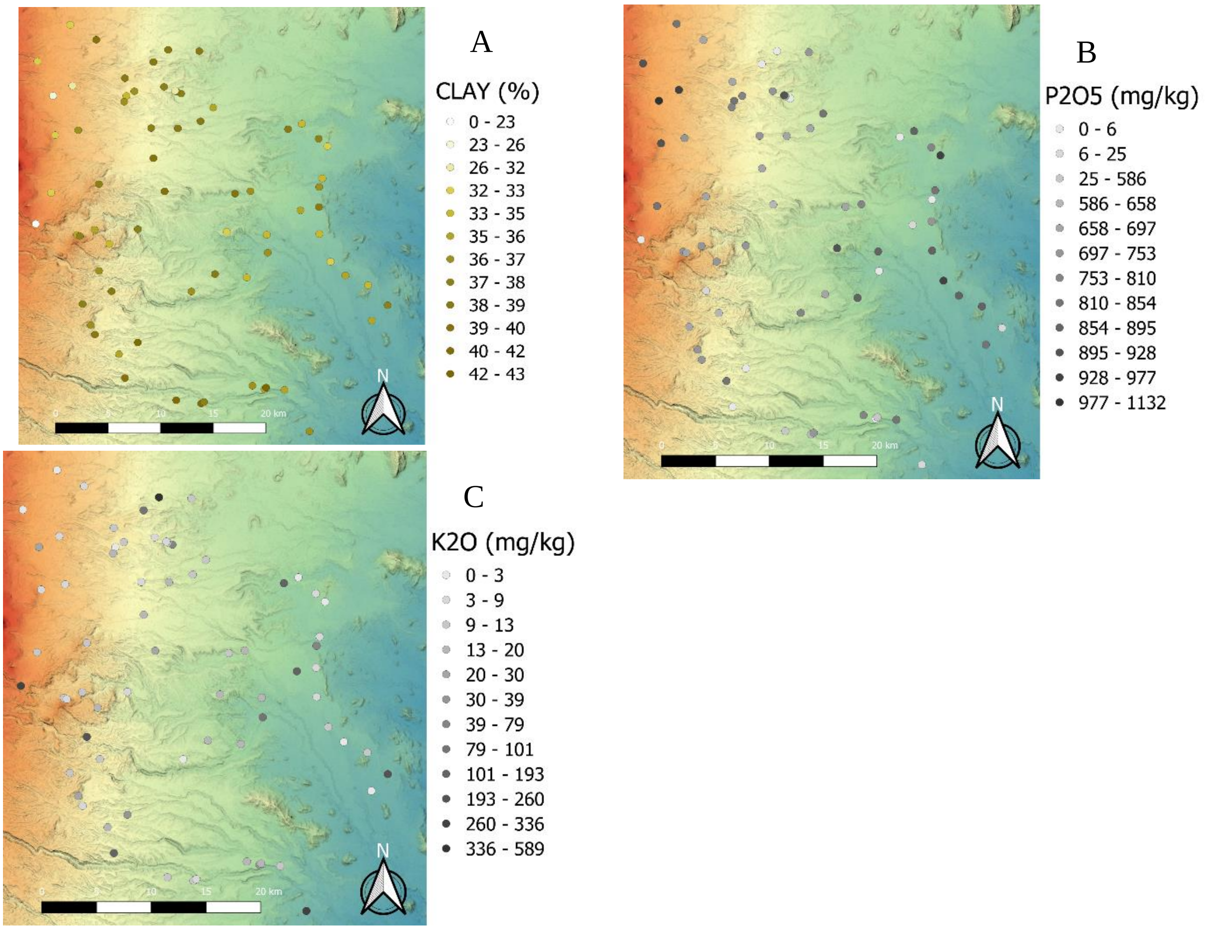

Figure 5. Soil property maps for selectected attributes: Clay (A), Available P (B) and extractable K

Clay content was higher in uplands fields (sites near the slope of Mount Kenya) and decreased towards the east. CEC was higher in the northern parts of the survey area compared to the lowlands in the south. Base saturation was lower in the uplands and highest in the eastern part of the study area. SOC was higher in the Upper Midlands with lowland areas recording low levels. There was no clear predictable pattern in the soil mineral nutrient properties, namely extractable K and available P.

There were significant differences for the three textural proportions across the depths (Table 2). There was more sand in the topsoil. Silt was higher at 0-50 cm depth. Clay was higher below 50 cm depth. The overall average pH (with water) was 5.4, and was fairly homogenous across the depths. The mean OC was 1% and ranged between 0.1 and 5%. The mean Base saturation was 17% (ranging between 2% and 27%) and was homogenous across the depths. The overall mean CEC was 8.4 cmol/kg, with a low of 0.7 and a high of 13 cmol/kg without significant differences across depth. The mean for basic cations was 0.8, 0.7, 1.9 and 0.05 cmol/kg for K, Mg, Ca and Na respectively. There were no variations across depth intervals. These soils are generally acidic and highly leached, thus the exchangeable bases are almost absent. The overall mean for extractable K, available P and N were 748, 12 and 24.5 mg/kg respectively. There were high variations in K across depths with the topsoil recording higher amount. The amount of K across all the sampling depths ranged between 371 and 1132 mg/kg.

Table 2. Results of ANOVA showing tendencies of soil properties across the three sampling depths (0-20, 20-50, 50-100cm)

Property	df	F	Sig.
Sand	2	8.485	0.000***
Silt	2	8.777	0.000***
Clay	2	7.74	0.001***
BS	2	0.131	0.878
Exch. K	2	0.064	0.938
Exch. Mg	2	0.131	0.878
Exch. Ca	2	0.022	0.979
Exch. Na	2	1.651	0.194
CEC	2	0.044	0.957
AL-K2O	2	5.333	0.006**
AL.P2O5	2	0.792	0.455
pH.H2O	2	0.784	0.458
OC.	2	1.224	0.296
Moisture	2	0.243	0.785

***, ***, significant at 5% and 1%, respectively*

3.1.2 Reference soil groups of the study area

A total of eight Reference soil groups were determined (based on WRB 2014 soil classification guideline), namely Nitisols (35), Acrisols (17), Andosols (2), Cambisols (6), Gleysols (2), Leptosols (3), Plinthisols (2) and Umbrisols (2). The most common RSG was Nitisols (mostly dystric Nitisols), occuring mainly in the areas on the slopes of Mount Kenya (Figure 6) due to low leaching and moderate organic matter.

The lower region was generally characterized by Acrisols (mostly dystric Acrisols) due to climatic conditions favourable to leaching and intense weathering. The lower areas (on flat or gently slopes) receive already weathered materials from adjacent uplands.

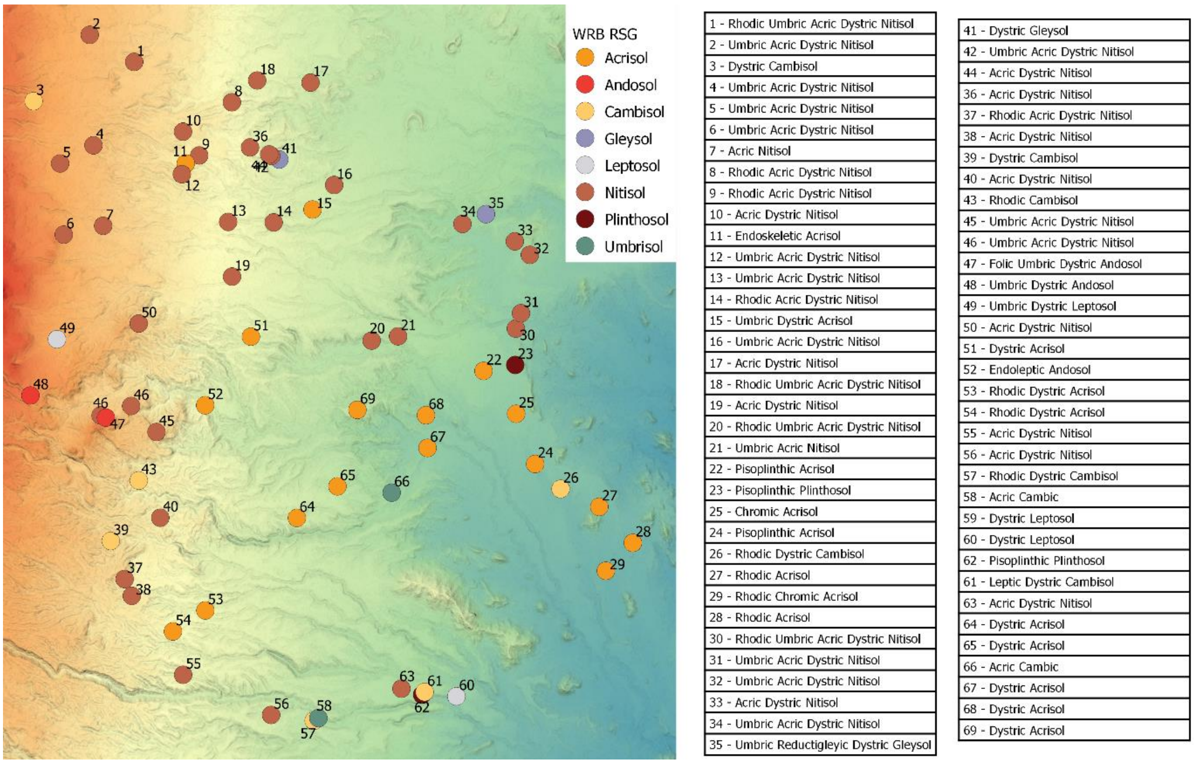

Figure 6. Distribution of Reference soil groups in the study sites

The overall mean soil pH in the study area was 5.4 (strongly acid) with the lowest pH of 3.9 (extremely acid) and a high of 7.0 (neutral). Soils classified as fertile by farmers had a mean pH of 5.7 (medium acid) while the infertile soils had a pH of 5.1 (strongly acid). Spatial variations in soil properties are anticipated due variations in landscape (topography, relief), geology (parent materials) and climate (Muchena & Gachene, 1988). The topography of the area displays significant terrain diversity (ranging from 300 to 5,199 m), resulting in extremely varied climatic conditions including precipitation (300-2,500 mm, and decreases from the west to east) and temperature (8°C to 32°C). The study area consists of a variety of rocks ranging from teriary volcanics to unconsolidated sediments. These topographic, geological and climatic diversity result in the formation of a wide range of soils (Wanjogu et al., 2001).

3.2 Farming Systems and Soil Fertility Management Strategies

3.2.1 Demographic and socio-economic characteristics

The largest proportion of farmers included those in the age cohort (31-40 years), while 20-30 age group represented less than 10% of the sample (Table 3). There were few farmers who did not attain formal education (3%) across the sample. Most of the farmers were primary (45%) and high school graduates (43%). In relation to agricultural income contribution, 35% of the farms experienced 51-75% income contribution. Agricultural income contributed more than half of house-hold income among 86% of all farmers. Most farmers practiced mixed crop-livestock farming (94%). The house-hold size averaged 5 members, while approximately 3 members were involved in farming activity per household. The mean annual income averaged Ksh 203,149.

Table 3. Major socio-demographic characteristics of farms in Mount Kenya East

Variable	Categories	Frequency (%)
Age categories	20-30	10(9.4)
	31-40	32(30.2)
	41-50	24(22.6)
	51-60	21(19.8)
	60+	19(17.9)
Education	None	3(2.8)
	Primary dropout	48(45.3)
	High school dropout	45(42.5)
	Middle level Graduate	7(6.6)
	Tertiary	3(2.8)
Gender	Male	57 (53.8)
	Female	49 (46.2)
Farming Income contribution	0-10%	1(0.9)
	11-25%	6(5.7)
	26-50%	8(7.5)
	51-75%	37(34.9)
	76-100%	54(50.9)
Farming type	Crop Farming	6(5.7)
	Both crop and livestock farming	100(94.3)
Farming experience (years)	<20	54(50.9)
	>20	52(49.1)
Family size		5.1
Members active in farming		2.7
Farm size (Ha)		1.3
Crop income/ year		197044.6
Livestock income/ year (Ksh*)		106208.9
Employment income		320000
Wages		124000
Business income		240000
Total income		271668.6

Values are presented as number of farmers and column percentages calculated within county (parentheses) for categorical variables. For numeric variables, values are means.

**1 Kenya shilling (Ksh) = 0.0101 USD based on the average exchange rate at the time of data collection (March 2019)*

3.2.2 Determinants of soil fertility management strategy

T-tests statistics were performed to determine the drivers of adoption of soil fertility management strategies. The results obtained from the Fisher's exact test (Table 4) and Welch's t test models (Table 5) are presented.

Table 4A. Fisher's Exact test of significance of explanatory variables

Variables	Slash-no-burn		Residue burn		Residue app		Agroforestry	
	Coef	**P>|z|**	**Coef**	**P>|z|**	**Coef**	**P>|z|**	**Coef**	**P>|z|**
Gender	0.105	0.403	-0.019	0.586	0.109	0.314	0.03	0.781
Age	0.218	**0.043****	-0.052	0.679	0.074	0.451	-0.031	0.495
Education	-0.205	**0.05****	-0.009	0.624	0.042	0.801	0.126	0.254
Farming as primary occupation	0.027	0.627	0.075	0.579	0.122	0.201	-0.119	0.603
Years in farming	0.089	0.413	-0.077	0.679	-0.083	0.454	-0.007	0.583
Location (County)	-0.169	0.109	-0.14	0.332	-0.134	0.237	0.158	0.18
Contact with extension	-0.246	**0.012****	-0.132	0.23	-0.137	0.204	-0.164	0.146
Access to soil information	-0.138	0.357	-0.083	0.509	-0.083	0.411	-0.05	0.637
Soil fertility info	-0.112	0.458	-0.111	0.587	-0.051	0.736	-0.12	0.251
Credit info	0.038	0.571	0.079	0.543	0.017	0.568	-0.16	0.126
Crop info	-0.148	0.182	-0.129	0.336	0.052	-0.554	0.2	**0.049****
Livestock info	0.202	**0.038****	0.019	0.66	-0.138	0.202	-0.156	0.146
Agribusiness info	0.08	0.538	0.049	0.789	0.093	0.448	0.077	0.562
Agribusiness info	0.053	0.758	0.053	0.758	0.154	0.295	0.058	0.617

*Note: ***, **,*, Significant correlation at 1%, 5% and 10%, respectively.*

Table 4B. Fisher's Exact test of significance of explanatory variables (Continuation)

Variables	Manure app		Fertilizer		Minimum tillage		Fallowing	
	Coef	**P>|z|**	**Coef**	**P>|z|**	**Coef**	**P>|z|**	**Coef**	**P>|z|**
Gender	0.134	0.245	0.058	0.701	0.137	0.167	0.101	0.318
Age	0.095	0.431	0.018	0.576	0.046	0.685	0.083	0.416
Education	0.048	0.709	0.048	0.709	0.146	0.162	-0.107	0.314
Farming as primary occupation	-0.081	0.527	-0.081	0.527	0.112	0.293	-0.125	0.277
Years in farming	0.033	0.521	0.033	0.521	0.024	0.843	-0.025	0.841
Location (County)	0.152	0.19	0.152	0.19	0.127	0.246	-0.06	0.641
Contact with extension	-0.15	0.235	-0.15	0.125	0.235	0.524	-0.178	**0.051****
Access to soil information	-0.034	0.547	-0.034	0.547	0.201	**0.049****	-0.125	0.321
Soil fertility info	-0.082	0.339	0.019	0.661	0.041	0.793	-0.076	0.591
Credit info	-0.174	0.131	0.044	0.511	0.015	0.565	0.107	0.325
Crop info	-0.136	0.172	-0.136	0.172	0.127	0.231	-0.107	0.331
Livestock info	0.154	0.138	0.154	0.138	-0.004	0.579	0.026	0.5
Agribusiness info	0.053	0.758	0.053	0.758	0.154	0.295	0.058	0.617

*Note: *, **, Significant at 5% and 1% significance level, respectively*

Table 5. Welch t test of significance of determinants of soil fertility management practices (continuous variables)

Welch t-test p-values								
Variables	Slash-no-burn	Residue burn	Residue app	Agroforestry	Manure app	Fertilizer	Minimum tillage	Fallowing
On-farm labour	0.832	0.019**	0.237	0.022**	0.006**	0.012**	0.4	0.818
Household size	0.204	0.356	0.427	0.032**	0.032**	0.004**	0.642	0.366
Farm size	0.037**	0.000***	0.375	0.765	0.52	0.688	0.453	0.065
Household income	0.374	0.003**	0.139	0.827	0.839	0.824	0.818	0.815
TLU	0.176	0.548	0.876	0.000***	0.011**	0.143	0.012**	0.142

*Note: *, **, ***, statistically significant at 10%, 5% and 1% signigificance level respectively*

Fertilizer and manure application and agroforestry were the most common practices employed by farmers. Correlations between the various ISFM practices, suggests that households often adopt a bundle of practices based on their needs as well as resource capacities. The decision to invest in fertility practices was significantly correlated with several farmers' socio-economic, farm-related factors and institutional characteristics. The relationship points to the need to adapt the fertility management techniques to the local environment.

3.3 Farmers' soil fertility knowledge and scientific evaluation

3.3.1 Farmers' indicators of soil fertility

Descriptive statistics of soil fertility indicators used by farmers to classify fertile and infertile soils, are presented (Table 6).

High fertility plots were characterised by dark coloured soils (94%), while they were light coloured in poor sites. Most farmers also recognised earthworms as key indicators of fertile soils (86%) while indicator weeds were shown by 91% of farmers. In terms of topography, valley bottoms indicated fertile fields (90%), while upper slopes were mostly infertile sites. Fertile soils were also characterized by high water holding capacity and good soil workability. For infertile plots, the most important indicators included low yield, yellow leaves, slow growth, light coloured soils, soils with low water-holding capacity, and tilling difficulty.

Table 6. Descriptive soil quality indicators among farmers for high and low fertility fields

Indicator /characteristic		High fertility		Low fertility	
		Frequency	Percentage	Frequency	Percentage
Colour	Brown	2	2.9	13	18.8
	Dark	65	94.2	2	2.9

Indicator /characteristic		High fertility		Low fertility	
		Frequency	Percentage	Frequency	Percentage
	White/pale/light	2	2.9	43	62.3
	Red			11	15.9
Earthworms	Numerous worm casts	59	85.5	1	1.4
	Moderate worm casts	8	11.6	1	1.4
	Fewer worm casts	2	2.9	67	97.1
Indicator weeds	Present	63	91.3	51	73.9
	Not present	6	8.7	18	26.1
Topography	Valley bottom slopes	62	89.9	6	8.7
	Lower middle slope	3	4.3	6	8.7
	Upper slopes	4	5.8	57	82.6
Water holding capacity	High	63	91.3	3	4.3
	Moderate	2	2.9	1	1.4
	Low	4	5.8	65	94.2
Workability	Very easy to till	40	58	9	13
	Moderately easy to till	22	31.9	4	5.8
	Difficult to till	7	10.1	56	81.2
High yields	High yields	69	100	-	-
Leaf colour	Green leaf colour	69	100	-	-
	Yellow leaves	-	-	69	100
Growth	Fast growth	69	100	-	-
	Stunted growth	-		69	100

3.3.2 Linkage between farmer and measured soil quality indicators

Regarding the regression between additive soil quality index and the farmer-descriptive SQI, there was a positive relationship indicating that the additive SQI increased with farmer-descriptive SQI in both high (y=1.94+0.29x, R^2=25%) and low fertility plots (y=3.7+0.082x, R^2=4%), though this relationship was stronger in high quality soils compared to low quality soils, as shown by their regression functions (Figure 7A). In fertile fields, increasing the additive SQI by one unit was associated with an average increase of 0.29 units in the farmer-descriptive SQI. The pooled regression model was positively significant. The farmer-descriptive SQI was significantly and positively related with the FA-SQI (y=3.6***+0.82x***, rsq=90%) (Figure 7A). In regard to the FA-SQI, a unit increase in the multivariate index led to an average increase of 1.2 units in the farmer-descriptive SQI (Figure 7B).

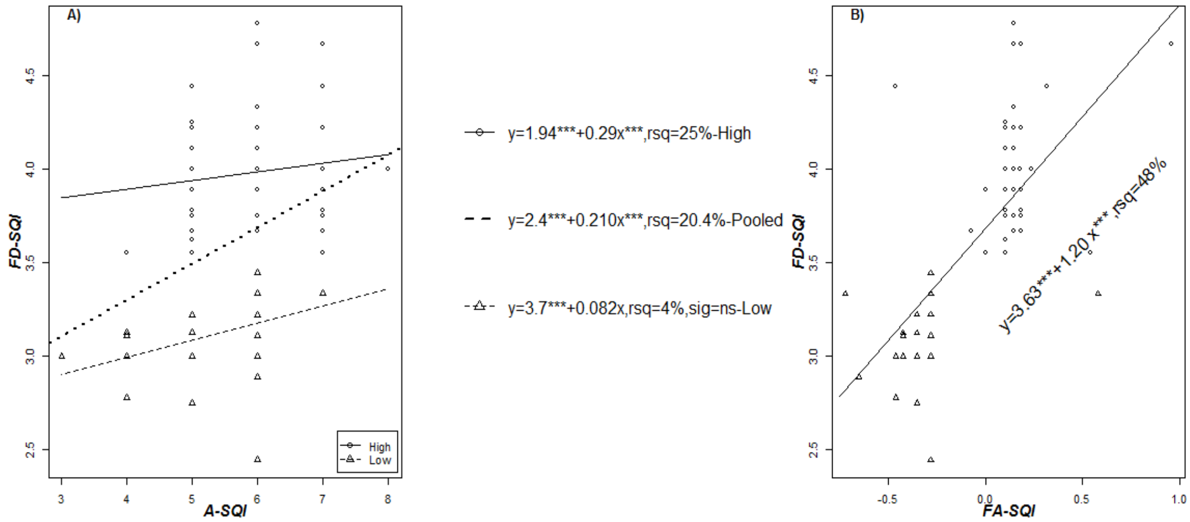

Figure 7. Relationship between quantitative and qualitative soil quality indices in the study area (0-20 cm depth). Farmer-descriptive SQI is correlated against additive SQI (A) and Factor analysis-generated SQI (B).

The comparison between farmer and scientific soil fertility assessment suggests a linkage between F-SQI and the two scientific systems, implying that farmers' knowledge provided a consistent and logical classification of soil quality. The linkage between the two soil fertility assessment paradigms calls for closer examination of farmer soil knowledge systems and better collaboration between farmer soil knowledge and technical soil knowledge systems.

3.3.3 Farm typologies based on clustering

Farm typology is the systematic classification of farms into groups that have common characteristics, using several methods, including multivariate methods. Ideally, farm types should reflect the potential access of different households to resources for managing their soils (Makate et al., 2018).

Soil variables with the highest loading as revealed by PCA were selected for inclusion in the cluster analysis. Non-hierarchical Two-step clustering approach was used. Two clusters were automatically determined based on Bayesian Information Criterion (BIC). However, upon close examination of the retained clusters with respect to the field observations (Goswami et al., 2014), the classification was not very meaningful. The solution was repeated with 3 clusters which seemed representative of the farm households in the study sites (Figure 8).

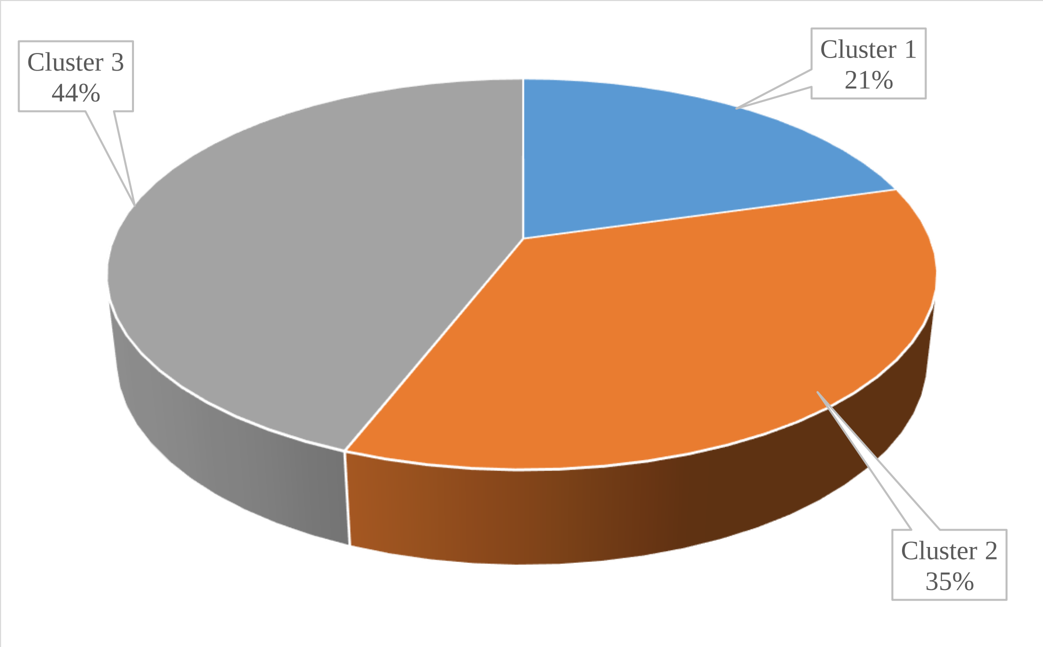

Figure 8. Farm household's membership across the clusters

Cluster membership was 14 (20.6%), 24 (35.3%) and 30 (44.1%) households for clusters 1, 2 and 3, respectively. The size ratio between the smallest and largest cluster was 2.14 (a fairly commendable ratio). The overall silhouette measure of cluster cohesion and separation value was 0.5, indicating a fair assignment of data points to cluster centres (Jain & Koronios, 2008). The final clusters obtained were profiled and assigned names: Farm type (FT) 1, 2 and 3.

Figure 9 shows household cluster membership across the study sites. Cluster 3 membership is more concentrated close to the slopes of Mount Kenya (Eastern parts of the survey area). Cluster 2 farms seem to be evenly distributed within the study area while cluster 1 fields are more spread towards the east (lower slopes).

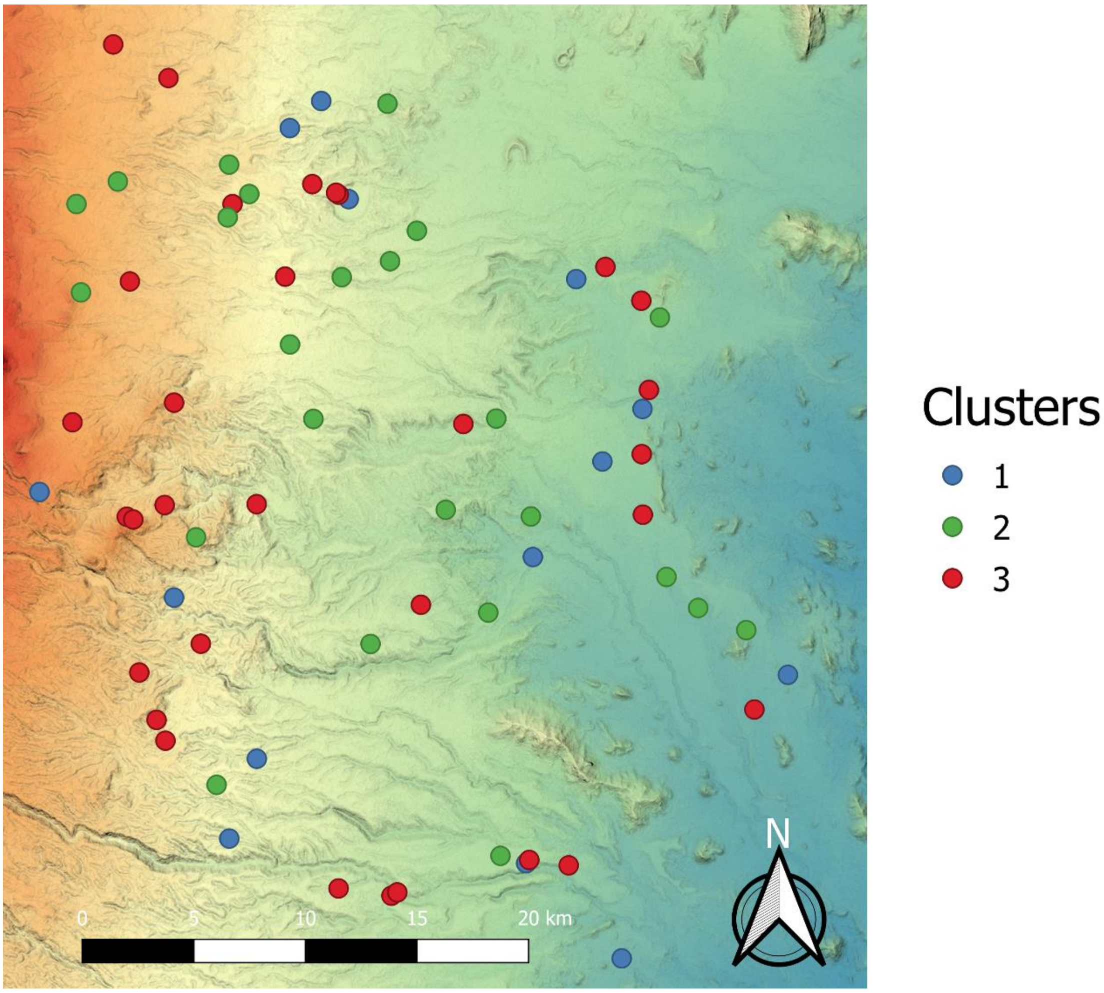

Figure 9. Distribution of cluster membership in the study area

Fisher's Exact Test (and Pearson Chi-square where applicable) and one-way ANOVA were conducted for each group of variables to determine factors that were significant in discriminating between the 3 clusters (farm types).

Characterization of identified farm types based soil properties

Farm typology based on soil characteristics clustered farm households in Mount Kenya east into 3 farm types. The most important variables (soil characteristics) that discriminated between farm types include pH, soil organic carbon (SOC), cation exchange capacity (CEC), available P, extractable K and exchangeable bases (Table 7), typifying farms as infertile (Farm type 1), moderately fertile (FT 2) and fertile farms (FT 3).

Table 7. Characterization of identified farm types based on p-value of one-way analysis of variance (equality of mean) of soil properties.

Variable	**Cluster (Farm types)**			**Total**	**F**	**Sig.**
	1 (n=14)	2 (n=24)	3 (n=30)			

Exch.K	**0.388b**	1.000a	1.000a	0.874	168.183	**0.000**
Exch.Mg	**0.512b**	0.958a	0.733ab	0.767	4.995	**0.010**
Exch. Na	**0.059a**	0.000b	0.000b	0.013	26.188	**0.000**
CEC	**16.448a**	8.167b	8.033b	9.813	65.407	**0.000**
BS%.	18.73	19.083	15.633	17.488	2.074	0.132
Sand	27.857	27.958	23.333	25.897	2.159	0.124
AL-P2O5	**5.286c**	**828.717a**	**740.510b**	620.272	348.851	**0.000**
AL-K2O	**195.357a**	13.125b	9.233b	48.926	42.199	**0.000**
pH.H2O	4.879b	5.083b	**6.103a**	5.491	38.743	**0.000**
SOC	0.543bc	**1.398a**	0.835b	0.974	22.797	**0.000**
SQI	**4.286b**	5.291a	5.233a	5.059	3.468	**0.037**

The bold values are significantly different across the row (clusters). Similar letters indicate absence of significance difference.

Discriminatory farm characteristics included fertilizer application intensity and fallowing (Table 8).

Table 8. Frequency distribution of farm management characteristics across clusters (farm types) in Upper Eastern Kenya.

Variable		**Cluster (Farm types)**						**Total**	**P-value**
		1 (n=14)		**2 (n=24)**		**3(n= 30)**			
		freq	**%**	**freq**	**%**	**freq**	**%**		
Pure stand	No	9a	64.3	14a	58.3	21^{a}	70.0	44	0.606
	Yes	5a	35.7	10a	41.7	9a	30.0	24	
Mixed cropping	No	3a	21.4	11a	45.8	10a	33.3	24	0.308
	Yes	11a	78.6	13a	54.2	20a	66.7	44	
Agroforestry	No	10a	71.4	18a	75.0	16a	53.3	44	0.255
	Yes	4a	28.6	6a	25.0	14a	46.7	24	
Intercropping	No	12a	85.7	21a	87.5	28a	93.3	61	0.667
	Yes	2a	14.3	3a	12.5	2a	6.7	7	
Residue application	No	2a	14.3	5a	20.8	6a	20.0	13	
	Yes	12a	85.7	19a	79.2	24a	80.0	55	0.856
Fallowing	No	8ab	57.1	13b	54.2	24a	80.0	45	**0.05**
	Yes	6ab	42.9	11b	45.8	6a	20.0	23	
Residue incorporation	No	6a	42.9	15a	62.5	17a	56.7	38	0.538
	Yes	8a	57.1	9a	37.5	13a	43.3	30	
Fertilizer Planting rate	Low	7a	50.0	6a	25.0	7a	23.3	20	**0.043**
	Moderate	1ab	7.1	4b	16.7	0a	0.0	5	
	High	6a	42.9	14ab	58.3	23b	76.7	43	
Fertilizer top dressing rate	Low	7a	50.0	6a	25.0	7a	23.3	20	**0.043**
	Moderate	1ab	7.1	4b	16.7	0a	0.0	5	
	High	6a	42.9	14ab	58.3	23b	76.7	43	
Residue composting	No	13a	92.9	19a	79.2	23a	76.7	55	0.526
	Yes	1a	7.1	5a	20.8	7a	23.3	13	

Residue for fodder	No	2a	14.3	5a	20.8	5a	16.7	12	0.921
	Yes	12a	85.7	19a	79.2	25a	83.3	56	
Residue for fuel	No	9ab	64.3	18b	75.0	14a	46.7	41	**0.11**
	Yes	5ab	35.7	6b	25.0	16a	53.3	27	

Each letter denotes a subset of TwoStep Cluster Number categories whose column proportions do not differ significantly (p<0.05). Fertilizer application rates: low= less than 25kg, moderate =25-50kg, High= >50kg/acre.

Socio-economic variables that distinguished farm types include farm size (Table 9) and household income (Table 10).

Table 9. Characterization of identified farm types based on p-value of one-way analysis of variance (equality of mean) of socio-economic characteristics.

Variable	Cluster	N	Mean	Std. Dev	Min	Max	F	Sig.
Family size	1	14	4.714	1.326	3	7	0.958	0.389
	2	24	5.125	1.676	1	8		
	3	30	5.433	1.695	2	11		
	Total	**68**	**5.176**	**1.62**	**1**	**11**		
Farm size	1	14	2.482bc	2.202	0.25	6	3.692	**0.03***
	2	24	2.813b	2.329	0.25	10		
	3	30	4.598a	3.512	0.5	10		
	Total	**68**	**3.532**	**3.011**	**0.25**	**10**		
TLU	1	14	1.565	1.083	0.62	4.85	1.497	0.232
	2	24	1.455	1.259	0	5.2		
	3	30	2.133	1.845	0	7.07		
	Total	**68**	**1.777**	**1.532**	**0**	**7.07**		
Workforce	1	14	3.071	1.385	1	5	0.862	0.427
	2	24	2.667	1.494	1	6		
	3	30	3.167	1.392	1	6		
	Total	**68**	**2.971**	**1.424**	**1**	**6**		
Age	1	14	41.071	17.022	20	73	1.617	0.206
	2	24	49.125	12.081	26	75		
	3	30	47.867	13.627	30	74		
	Total	**68**	**46.912**	**14**	**20**	**75**		

* *Significant at 5% level (P<0.05)*

Table 10. Comparison of households' socioeconomic characteristics across the identified farm types in upper Eastern Kenya

Variable	Category	Farm type (Cluster)						Total	%	Coeff	Sig
		1 (n=14)		2 (n=24)		3(n=30)					
		Freq	%	Freq	%	Freq	%				
Gender	Female	5	35.7	11	45.8	12	40	28	41	0.077	0.855
	Male	9	64.3	13	54.2	18	60	40	59		

Income (Ksh, '000)	<75	7	53.8	10	52.6	11	42.3	28	48.3		**0.13**
	75-150	1	7.7	4	21.1	6	23.1	11	19		
	150-225	5	38.5	4	21.1	3	11.5	12	20.7		
	>225	0	0	1	5.3	6	23.1	7	12.1		
Education	Primary & below	5	35.7	14	58.3	19	63.3	38	56	0.207	0.218
	High sc.& above	9	64.3	10	41.7	11	36.7	30	44		
Farm occupation	No	1	7.1	2	8.3	2	6.7	5	7	0.029	0.973
	Yes	13	92.9	22	91.7	28	93.3	63	93		
Farming experience	<20	7	50	8	33.3	16	53.3	31	46	0.18	0.318
	>20	7	50	16	66.7	14	46.7	37	54		
Ext Contact	No	10	71.4	13	54.2	19	63.3	42	62	0.13	0.557
	Yes	4	28.6	11	45.8	11	36.7	26	38		
Soil info	No	13	92.9	22	91.7	26	86.7	61	90	0.09	0.759
	Yes	1	7.1	2	8.3	4	13.3	7	10		
Siol TEST	No	12	85.7	8	33.3	26	86.7	46	68	0.141	0.500
	Yes	2	14.3	6	25	4	13.3	12	18		
Credit INFO	No	14	100	21	87.5	28	93.3	63	93	0.172	0.356
	Yes	0	0	3	12.5	2	6.7	5	7		
Crop Husbandry	No	12	85.7	20	83.3	24	80	56	82	0.059	0.887
	Yes	2	14.3	4	16.7	6	20	12	18		
Animal husbandry	No	14	100	21	87.5	24	80	59	87	0.216	0.188
	Yes	0	0	3	12.5	6	20	9	13		
Agribiz	No	14	100	24	100	29	96.7	67	99	0.136	0.526
	Yes	0	0	0	0	1	3.3	1	1		

* *Significant at 5% level (P<0.05).*

Delineation of farms based on the various parameters including resource endowment underlines imbalanced farm resource flows suggesting a need to address the inequality in farm resource availability to reduce high soil quality variability and enhance the productivity and sustainability among smallholder farming systems.

4 CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

Characterisation of soils on farms indicate that soils in study area were generally moderately fertile. Specifically, these soils are characterized by low pH (5.4), low organic carbon, low exchangeable bases, and inadequate plant minerals. Deficiencies in exchangeable cations, partly contributes to soil acidity. Moderate levels of SOC in the region could be attributed to reasonable utilization of organic soil fertility resources as well as topological and climatic factors. In terms of soil nutrients, available P was low while extractable K was high. Available N ranged from low to moderate, and this could be explained by the nature of farm management practices, namely use of manure (which was applied in small amount). As part of interventions, there is a need for increased application of both organic and inorganic resources to ameliorate conditions unfavourable for crop production. The wide range variation in soils as identified by this study is largely influenced by variations in parent material (geology), relief and climate. These soil resources range from sandy to clayey, shallow to very deep and low high fertility.

The second objective was to identify soil fertility management practices, and to determine drivers of adoption of these practices. Fertilizer and manure application and agroforestry were the most common practices employed by farmers. Correlations between the various ISFM practices, suggests that households often adopt a bundle of technologies (which complement or substitute each other) as opposed to the entire ISFM package, based on their needs as well as resource constraints. The decision to invest in fertility practices was significantly correlated with several farmers' socio-economic, farm-related factors and institutional characteristics. On-farm labour and household size influenced manure and fertilizer adoption. Livestock quantity had a bearing on manure use. The relationship implies on the need to adapt the ISFM techniques to the local environment. Farmers have different assets which determine how they can apply techniques of their choice, and therefore exploring which practices make more sense depends on farmer's assets such as capital and labour.

Evaluation of farmers' soil fertility perception showed that farmers' knowledge provided a consistent and logical classification of soil quality. Fertile fields were associated with darker soil colour, numerous earthworms, indicator weeds, and plot locations in valley bottoms. Farmers' soil knowledge was substantiated using laboratory soil tests whereby soil pH, soil carbon, silt, sand and available -N were significantly different between soil fertility categories, implying that there was a qualitative difference in soils that had been characterized as different by farmers.

There was a correlation between farmer-descriptive SQI (F-SQI) and the two scientific SQIs, namely additive SQI (A-SQI) and the multivariate (Factor analysis) soil quality index (FA-SQI). There was a stronger relationship between F-SQI and the A-SQI in fertile than infertile plots. The soil quality indices derived from farmers' and scientific soil fertility assessments showed that there was a significant linkage between the two soil fertility assessment paradigms, thus calling for closer examination of farmers' soil knowledge systems and better collaboration between farmers' soil knowledge and technical soil knowledge systems.

Using cluster analysis, three farm types (typologies) were identified, suggesting a significant level of farm households' heterogeneity in regard to socioeconomic characteristics, farm management practices and soil fertility. Delineation of farms based on the various parameters including resource endowment underlines imbalanced farm resource flows suggesting a need to address the inequality in farm resource availability to reduce high soil quality variability and enhance the productivity and sustainability among smallholder farming systems.

4.2 Recommendations

Based on the findings, this study proposes the following recommendations

- Smallholder farmers in Mount Kenya East, and by extension, in Kenya, should be encouraged to embrace the use of both organic and inorganic resources to improve soil fertility and agricultural productivity. Increasing the use of organic resources such as manure to 60 kg N ha^{-1} has the potential to increase maize yields from the current 0.5 to 1.5 t ha up to 4 to 6 t ha^{-1}
- It is imperative for the Kenya's County governments to strengthen extension services to enhance dissemination of information on the use of ISFM practices. The significant relationship between access to extension and adoption of some ISFM practices, point to the continued importance of agricultural extension. Capacity building of extension providers by equipping them with skills on soil fertility management is crucial. Establishment of demonstration sites and organizing of field days can increase adoption of the desired farm practices.
- Policymakers should formulate innovative financing opportunities to provide credit to farmers and promote profitable start-up projects especially among the youthful farmers, whom their participation in agriculture is often constrained by lack of capital. Creating

an enabling environment can facilitate their investment capacities in soil fertility management practices. This intervention will also resolve the challenge of labour shortage as observed in this study.

- The correlation between farmers' soil knowledge and scientific soil systems suggests for more collaboration between scientists and farmers. Innovative soil fertility assessment and shared communication between scientists and farmers are needed to improve soil fertility management in low-input-low-output farming systems of the SSA. Integrated soil fertility assessment methodologies within similar agro-ecological zones and socio-economic settings may enhance communication between multiple stakeholders and improve soil fertility management among smallholder farming systems.
- There is a need to address the inequality in farm resource availability to reduce high soil quality variability (as demonstrated by farm typology) and enhance the productivity and sustainability in the farm system. Resource endowment was a significant discriminant between farm types and thus in reinforcing the cycle of imbalanced farm resource flows. Again, this emphasizes on the importance of capital in agriculture

Further research

- While the current study has achieved general conclusions regarding how farmer and scientific soil measurements were related, more innovative, comprehensive and systematic studies are needed to clarify the integration of soil knowledge between local and technical paradigms in diverse farming systems. Additionally, future research could also explore the local terminology in the study area for soil names based on the key indicators, namely texture and colour, to enhance a two-way communication between the extension providers and farmers.
- While this study made great strides in discriminating farm types based on fertility status, more research should be targeted towards smallholder farming systems to improve understanding of soil fertility dynamics in these farm types. This study suggests for the inclusion of additional relevant parameters in the initial model (PCA) and with a larger sample size (which can yield a potentially realistic number of clusters/farm types that reflect the general reality observed during field survey). Considering that in the current study, variable selection for cluster analysis was achieved strictly by methodological approach based on PCA (CATPA and FA), incorporation of expert opinion is suggested for future studies.

- In regard to comparing farmers' and scientific soil fertility assessment, further research could improve our study by modelling with more soil parameters including biological parameters and identifying the specific weed species associated with high and low soil fertility.
- Both extensive and intensive within-farm soil sampling is recommended for future research on soil fertility. In this study, samples were obtained from only one sampling point per farm. Within-farm soil fertility gradient (arising from preferential application of soil fertility resources based on perceived field's soil quality) is a common phenomenon among smallholder farming systems in SSA and thus should be taken into consideration as it is important in facilitating resource allocation in these farms. Control environment is recommended for quality data

5 KEY SCIENTIFIC FINDINGS AND IMPORTANT OUTPUT

1. Properties of soils in the study area were determined, and this facilitated the estimation of the general soil fertility status in the region based on the measured laboratory data and published SQI indicators. Similarly, the identified RSGs were correlated with soil properties to determine variation in their fertility status. A connection was drawn between reference soil groups and soil fertility in a local context (larger scale), making this study, the first one to investigate fertility variation across RSGs in the area of study.
2. Through clustering, farmers' combination patterns of soil fertility management practices were determined. This study used multivariate analyses, which are critical in capturing the true picture among smallholder farmers. This is useful in identifying areas of policy intervention.
3. In this research a Farmer-descriptive SQI was systematically developed and used to classify soils (as either fertile or infertile). Most of (if not all) the previous studies that have investigated the relationship between farmers' and scientific soil assessment, simply asked farmers to identify fertile and infertile fields. In this study, farmers rated the fertility of their soils based on the various indicators. The scores were summed and then averaged to give the final soil fertility rating (from the farmer's perspective).
4. By comparing farmers' perception of soil fertility against scientific assessment, this study validated local soil fertility classification system. Farmer-descriptive SQI and two scientific fertility assessment methods (FA-SQI and additive SQI) were compared. Local knowledge was largely consistent with substantial scientific attributes. A substantial attempt to quantify qualitative soil parameters was made.This study lays a good base for an integrated location-specific soil management guideline.
5. Farm households were classified into 3 farm types, following a systematic methodological typology approach, based on soil variability and the identified clusters characterized based on farm management practices and socio-economic factors. The farm typology methodology (grouping of farms/households into common or similar groups) used in relating farm characteristics was key in understanding and dealing with variability and diversity and appreciating of both the farm management and household characteristics that explain the variation in soil fertility. Multivariate analysis (CATPCA, FA and CA) were used. This approach is useful in identifying resources allocation patterns. It provides a good framework for futher studies focusing on

exploring differences in challenges, opportunities, efficiencies in resource allocation and dissemination of innovation as well as identifying potential areas of collaboration.

REFERENCES

AfSIS. (2013). *Africa Soil Information Service*. www.africasoils.net

Andrews, S. S., Karlen, D. L., & Mitchell, J. P. (2002). A comparison of soil quality indexing methods for vegetable production systems in Northern California. *Agriculture, Ecosystems and Environment*, *90*(1), 25–45. https://doi.org/10.1016/S0167-8809(01)00174-8

Arunrat, N., Pumijumnong, N., Sereenonchai, S., & Chareonwong, U. (2020). Factors Controlling Soil Organic Carbon Sequestration of Highland Agricultural Areas in the Mae Chaem Basin, Northern Thailand. *Agronomy*, *10*(2). https://doi.org/http://dx.doi.org/10.3390/agronomy10020305

Baker, B. H. (1967). *Geology of the Mount Kenya area*.

Batjes, N. H. (2010). *Report 2010/07 Soil property estimates for the Upper Tana, Kenya, derived from SOTER and WISE (Version 1.0)*. www.isric.org

Bouma, J., Keesstra, S., & Cerdà, A. (2017). “The importance of Soil Science to understand and remediate Land Degradation and Desertification processes.” EGU General Assembly 2017, 19. *EGU General Assembly 2017*.

Bouma, J., & Montanarella, L. (2016). Facing policy challenges with inter- and transdisciplinary soil research focused on the un Sustainable Development Goals. *Soil*, *2*(2), 135–145. https://doi.org/10.5194/soil-2-135-2016

Carter, M. R., & Gregorich, E. G. (2008). Soil Sampling and Methods of Analysis Second Edition Edited by. In E. G. Carter, M.R., Gregorich (Ed.), *Canadian Society of Soil Science*. CRC Press.

Chavent, M., Kuentz, V., Labenne, A., Liquet, B., & Saracco, J. (2015). *Multivariate analysis of mixed data:PCAmixdata R package*. https://pdfs.semanticscholar.org/d78e/560eaf64d29b61fd78ce5025e12f86710c67.pdf

CIDP. (2018). *Meru County Integrated Development Plan*. 2018–2022. http://devolutionhub.or.ke/kwale-county-integrated-development-plan/

Cornish, R. (2007). *Statistics: Cluster analysis*. Mathematics Learning support centre. http://www.statstutor.ac.uk/resources/uploaded/clusteranalysis.pdf

County Government of Tharaka-Nithi. (2013). Tharaka Nithi County Integrated Development Plan. In *County Intergrated Development Plan (2013-2017)*.

Dijkshoorn, J., Macharia, P., Huting, J., Maingi, P., & Njoroge, C. (2011). *Soil and and terrain conditions for the Upper Tana river catchment, Kenya (Ver. 1.1), ISRIC Report 2010/09b*. https://isric.org/sites/default/files//isric_report_2010_09b.pdf

Dobos, E., Montanarella, L., Negre, T., & Micheli, E. (2001). A regional scale soil mapping approach using integrated AVHRR and DEM data. *JAG*, *3*(1), 1–13.

Egnér, H., Riehm, H., & Domingo, W. R. (1960). Untersuchungen uber die chemische Bodenanalyse als Grundlage fur die Beurteilung des Nährstoffzustandes der Böden. II. Chemische Extraktionsmethoden zur Phosphor- und Kaliumbestimmung. *Kungliga Lantbrukshögskolans Annaler*, *26*, 199–215.

FAO. (2015). *Soil functions*. Food and Agriculture Organization (FAO) of the United Nations.

Gicheru, P., & Kiome, R. (2000). *Reconnaissance soil survey of Chuka-Nkubu area (quarter degree sheet No. 122)*.

Gillman, G. P., & Sumpter, E. A. (1986). Modification to the compulsive exchange method for measuring exchange characteristics of soils. *Aust. J. Soil Res*, *24*, 61–66.

Goswami, R., Chatterjee, S., & Prasad, B. (2014). Farm types and their economic characterization in complex agro-ecosystems for informed extension intervention: Study from coastal West Bengal, India. *Agricultural and Food Economics*, *2*(1), 1–24. https://doi.org/10.1186/s40100-014-0005-2

Haluschak, P. (2006). *Laboratory Methods Of Soil Analysis Canada-Manitoba Soil Survey*.

IBM. (2013). *IBM SPSS Statistics for Windows, version 22.* IBM Corp.

Jain, R., & Koronios, R. (2008). Innovation in the cluster validating techniques. *Fuzzy Optimization and Decision Making*, *7*(3), 233–241.

Li Q, X. M., Liu, G., Zhao, Y., & Tuo, D. (2013). Cumulative effects of a 17- year chemical fertilization on the soil quality of cropping system in the Loess Hilly Region, China. *Journal of Plant Nutrition and Soil Science*, *176*, 249–259.

Makate, C., Makate, M., & Mango, N. (2018). Farm household typology and adoption of climate-smart agriculture practices in smallholder farming systems of southern Africa Farm household typology and adoption of climate- smart agriculture practices in smallholder farming systems of southern Africa. *African Journal of Science, Technology, Innovation and Development*, *0*(0), 1–19. https://doi.org/10.1080/20421338.2018.1471027

Mason, P., & Geological Survey of Kenya. (1955). *Geology of the Meru-Isiolo area (with coloured geological map)*. Printed by the Govt. Printer.

Masto, R., Chhonkar, P., Singh, D., & Patra, A. (2008). Alternative soil quality indices for evaluating the effect of intensive cropping, fertilisation and manuring for 31 years in the semi-arid soils of India. *Environmental Monitoring and Assessment*, *136*, 419–435.

Mehlich, A. (1984). Mehlich-3 soil test extractant: a modification of Mehlich-2 extractant. *Communications in Soil Science and Plant Analysis*. https://doi.org/ht10.1080/00103628409367568.

Meru County Government. (2014). *The Report: Meru County 2014 Kenya*. http://meru.go.ke/image/Oxford report.pdf

Minasny, B., & McBratney, A. B. (2006). A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Geosciences, Computers &*, *32*(9), 1378–1388.

Muchena, F. N., & Gachene, C. K. K. (1988). Soils of highland and mountainous areas of Kenya with special emphasis on agricultural soils. *Mountain Research & Development*, *8*(2–3), 183–191. https://doi.org/10.2307/3673446

Mulder, V. L., Bruin, S. de, & Schaepman, M. . (2012). Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *21*(1), 301–310. https://doi.org/10.1016/j.jag.2012.07.004

Mutuma, E. (2017). *Innovative Approaches of Predicting Soil Properties and Soil Classes In The Eastern Slopes of Mt. Kenya* [Szent István University]. https://szie.hu/file/tti/archivum/Evans_Mutuma_dissertation.pdf

NAAIAP. (2014). *Soil suitability evaluation for maize production in Kenya:A Report by National Accelerated Agricultural Inputs Access Programme (NAAIAP) in collaboration with Kenya Agricultural Research Institute (KARI) Department of Kenya Soil Survey, February 2014*. *February*, 150–215.

Njoroge, C. R. K., & Kimani, P. K. (2001). *The Soils of Muguna Igoki Irrigation, Meru District*.

Oshunsanya, S. O. (2019). Introductory Chapter: Relevance of Soil pH to Agriculture. *Soil PH for Nutrient Availability and Crop Performance*, *January*. https://doi.org/10.5772/intechopen.82551

Patton, M. Q. (2002). *Qualitative research and evaluation methods (3rd ed.). Thousand Oaks, CA.* Sage Publications.

Pituch, K. A., & Stevens, J. P. (2016). Applied multivariate statistics for the social sciences: Analyses with SAS and IBM's SPSS. In *Routledge* (6th ed.). Routledge. https://doi.org/10.1017/CBO9781107415324.004

Ross, D. S., & Ketterings, Q. (2011). Recommended Methods for Determining Soil Cation Exchange Capacity. In A. Wolf & J. McGrath (Eds.), *" Recommended Soil Testing Procedures for the Northeastern United States* (3rd ed.).

Tóth, G., Hermann, T., da Silva, M. R., & Montanarella, L. (2018). Monitoring soil for sustainable development and land degradation neutrality. *Environmental Monitoring and Assessment*, *190*(2), 57. https://doi.org/10.1007/s10661-017-6415-3

USDA. (2018). *Sampling Soils for Nutrient Management*. https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs141p2_036444.pdf

van Reeuwijk, L. . (2002). *Procedures for soil analysis* (L. . van Reeuwijk (ed.); 6th ed.). International Soil Reference and Information Centre (ISRIC).

Vlek, P. L. G., Le, Q. B., & Temene, L. (2010). Assessment of land degradation, Its possible causes and threat to food security in Sub-Saharan Africa. In L. Rattan & B. A. Stewart (Eds.), *Advances in Soil Science: Food Security and soil quality* (pp. 57–86). CRC Press. https://doi.org/10.1201/EBK1439800577-c4

Wanjogu, S. N., Gicheru, P. T., Maingi, P. M., & Nyamai, M. (2001). *SALINE AND SODIC SOILS IN THE DRYLANDS OF KENYA*. http://www.fao.org/fileadmin/user_upload/spush_upload/Kenya-_extent.pdf

LIST OF PUBLICATIONS

JOURNAL ARTICLES AND CONFERENCE FULL PAPERS

1. **Wawire, A. W**., Csorba, A., Toth, J. A., & Michéli, E. (2020). Integration of manure and mineral fertilizers among smallholder farmers in Kenya: a pathway to sustainable soil fertility management and agricultural intensification. International Journal of Agricultural Extension and Rural Development Studies, 7(2), 1–20. https://www.eajournals.org/wp-content/uploads/Integration-of-manure-andmineral-fertilizers-among-smallholder-farmers-in-Kenya.pdf

2. **Wawire, A. W.,** Csorba, A., Toth, J., A., Michéli, E., Szalai, M., Mutuma, E., & Kovács, E. (2020). Soil fertility management among smallholder farmers in Mount Kenya East Region. Heliyon. https://www.sciencedirect.com/journal/heliyon (Accepted).

3. **Wawire, A. W.**, Csorba, A., Kovács, E., Mairura, F., & Michéli, E. (2020). Comparing farmers' soil fertility knowledge systems and scientific assessment in Upper Eastern Kenya. Geoderma. (Accepted).

4. **Wawire, A.**, Michéli, E., Csorba, A. (2018). The Centrality of Soil Information in the Realization of Sustainable Food Security in Kenya (paper presented at 3rd International *Young Researcher Scientific Conference on "Sustainable Regional Development- Challenges of space & Society in the 21st Century*", Godollo, Hungary, April 26, 2018. http://rtdi.gtk.szie.hu/sites/default/files/files/2018_SRD-Conference-Proceedings_April-26%20k%C3%B6nyv.pdf 76-82.

5. Salik, A. W., Csorba, A., **Wawire, A. W**., Alvarez, P. A., & Aung, W. (2018). Key Barriers Toward Sustainable Agriculture Development in Arid And Semi Arid Area: Case Study Afghanistan. 3rd International Young Researcher Scientific Conference on "Sustainable Regional Development Challenges of Space & Society in the 21st Century", Godollo, Hungary, April 26, 2018, 64–70. http://rtdi.gtk.szie.hu/sites/default/files/files/2018_SRD-Conference-Proceedings_April-26%20k%C3%B6nyv.pdf 64-70

6. **Wawire, A.,** Wangia, S. & Okello, J. (2017). Determinants of Use of Kenya Agricultural Commodity Exchange Information Communication Technologies: the case of Smallholder Farmers in Bungoma County, Kenya. 10.5539/jas.v9n3p128. p.128-137

7. **Wawire, A. W.,** Michéli, E., & Csorba, A. (2018). Sustainable Water Resource Management: Prerequisite for Realizing Kenya's Vision 2030. In G. habil Jakab, A. Tóth, & E. Csengeri (Eds.), International Conference on Water Sciences, Szent Istvan University, Szarvas, Hungary, March 22, 2018 (pp. 224–229). Szent Istvan University. http://intelszak.szarvas.szie.hu/sites/default/files/uploads/444_compressed.pdf

CONFERENCE ABSTRACTS

1. **Wawire, A. W.**, Csorba, A., & Michéli, E. (2020). Scientific Evaluation of farmer soil fertility knowledge in Meru and Tharaka Counties in Kenya. Geneva Eurosoil 2020, August 24-28 (Postponed to August 23-27, 2021). https://eurosoil2020.com/ (Abstract accepted)
2. **Wawire, A. W**., Csorba, A., & Kovács, E. (2019). Assessing soil fertility challenges and accessibility to inorganic fertilizer and manure resources by smallholder farmers in the Central Highlands of Kenya. In K. Zoltán (Ed.), the 19th Alps-Adria Scientific Workshop, 26th April – 1st May 2021, Wisla -Poland (p. 47). http://www.alpsadria.hu/ (conference postponed to 25th - 30th April 2021. Abstract published) http://www.alpsadria.hu/19thAASW/19thAASW_Abstract_book.pdf
3. Mutuma, E., Csorba, Á., **Wawire, A. W**., Dobos, E., & Michéli, E. (2017). Classification problems of Mount Kenya soils. European Geosciences Union (EGU) General Assembly 2017, Vienna, Austria, 23–28 April 2017. https://meetingorganizer.copernicus.org/EGU2017/EGU2017-16230.pdf
4. **Wawire, A. W**., Michéli, E., & Csorba, A. (2018). The Centrality of Soil Information in the Realization of Sustainable Food Security in Kenya. In B. Horváth, A. Khademi-Vidra, & I. M. Bakos (Eds.), 3rd International Young Researcher Scientific Conference on "Sustainable Regional Development-Challenges of space & Society in the 21st Century", Godollo, Hungary, April 26, 2018 (pp. 76–82). Szent Istvan University. http://rtdi.gtk.szie.hu/sites/default/files/files/2018_SRDConference-Proceedings_April-26 könyv.pdf
5. Salik, A. W., Csorba, A., **Wawire, A. W**., Alvarez, P. A., & Aung, W. (2018). Key Barriers toward Sustainable Agriculture Development in Arid and Semi Arid Area: Case Study Afghanistan. 3rd International Young Researcher Scientific Conference on "Sustainable Regional Development Challenges of Space & Society in the 21st Century", Godollo, Hungary, April 26, 2018, 64–70.
6. **Wawire, A. W**., Michéli, E., & Csorba, A. (2018). Sustainable Water Resource Management: Prerequisite for Realizing Kenya's Vision 2030. In G. habil Jakab, A. Tóth, & E. Csengeri (Eds.), International Conference on Water Sciences, Szent Istvan University, Szarvas, Hungary, March 22, 2018 (pp. 224–229). Szent Istvan University. http://intelszak.szarvas.szie.hu/sites/default/files/uploads/444_compressed.pdf