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Doctoral School of Environmental Sciences

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INNOVATIVE APPROACHES OF PREDICTING SOIL PROPERTIES AND SOIL CLASSES IN THE EASTERN SLOPES OF MT. KENYA

By

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"The nation that destroys its soil destroys itself"
(Franklin Delano Roosevelt 1935)

"It is impossible to have a healthy and sound society without proper respect for the soil."
(Peter Maurin, 1933)

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1. INTRODUCTION

This chapter starts with the background and rationale of the study. It highlights the important soil functions and their linkages to the UN sustainable development goals. Efforts to provide soil information through development of soil information databases are discussed. An overview of the African context is provided. The research problem is then presented with objectives. The chapter ends with a justification of the study.

1.1 Background and rationale

Critical discussions and negotiations on soil resource have been on the international agenda and have elevated soil resources to a greater global awareness. Use of soil information to boost achievements of UN-Sustainable Development Goals (Keesstra et al., 2016) needs interdisciplinary approaches and active participation of soil scientists. Soil functions (listed below), defined by the European Commission (2006) have direct link to the ecosystem goods and services whose vigour guarantee provision of food, adequate and clean water, resilience to climate change shocks and an enhanced biodiversity. Environmental, social and economic challenges can be addressed if we follow the path to better management of soils (Brevik et al., 2015, McBratney et al., 2014). However, human interventions while utilizing soil resources and climate change impacts are having unanticipated consequences. Soil degradation processes like soil compaction (Jones et al., 2003), soil erosion (Cerdàr & Doerr, 2005), loss of organic carbon (Bellamy et al., 2005) are happening at unsustainable rate compared to soil formation processes (Verheijen et al., 2009). This has resulted in limited soil capacity to perform important soil functions like: biomass production, nutrients recycling, carbon and water regulation.

Soil functions as defined by the European Commission (2006).

1. Biomass production, including agriculture and forestry
2. Storing, filtering and transforming nutrients, substances and water
3. Biodiversity pool, such as habitats, species and genes
4. Physical and cultural environment for human and human activities
5. Source of raw material
6. Acting as carbon pool
7. Archive of geological and archaeological heritage

1.2 Links of soil to the UN-Sustainable Development Goals (SDGs)

Low soil fertility is currently a food security problem in many developing countries (UNDESA, 2013). Some of the causes of low soil fertility are the following: soil degradation (Vlek *et al.*, 2008), limited access to important agricultural inputs (Tittonell, 2014), climate change shocks (Thornton *et al.*, 2014) and competing demands for limited soil resources (Hooper *et al.*, 2005). Soils affect human health directly and indirectly. Direct contact of soils with pathogens may cause skin lessons (Franz *et al.*, 2008). Microbial communities are a useful source of antibiotics (Ling *et al.*, 2015). Soil microbial community have been found to affect soil structure (Young and Crawford, 2004). This in return affects soil functional properties like water infiltration. The data on soil–health relationships are scarce and very much incoherent. Protecting and enhancing the ability of the Earth's soils to provide clean water in sufficient quantities is a key element to the achievement of SDGs. *In situ* soil water influences ground and surface hydrology and besides it supports plants growth. An estimated 74% of freshwater sources come from soils (Hoekstra & Mekonnen, 2012). Soils are integral parts of several global nutrient cycles. Carbon and nitrogen in the soil are sources of green house gases. Soils contain three times as much carbon as the atmosphere (Smith, 2004). Small changes of soil carbon may have a huge impact on climate. This means of sequestering carbon into the soils is an important step to climate change mitigation. Soil biodiversity have been reported to increase resilience of soils to climate change (Bardgett & van der Putten, 2014). A study by Six *et al.* (2002) shows strong association between loss of biodiversity and poor soil physical properties. Global distribution of soil biodiversity is minimally understood due possibly to the inadequate global soil data inventories. The recently launched 'Global Biodiversity Atlas' (Orgiazzi *et al.*, 2016) shows the potential of biodiversity living in the soil based on some proxy soil datasets. For example, microbial soil carbon distribution data that was developed by Serna-Chavez *et al.* (2013) was used as a proxy to map the soil microbial diversity. In summary, efforts to restore soil productivity require thorough understanding of soil properties. This cannot be possible without adequate and reliable soil data inventories.

1.3 Some developments in soil information databases

The first attempt to prepare a soil map of world with a uniform legend was through a joint project by FAO and UNESCO (FAO-UNSECO, 1974). This map has enabled correlation of soil units and the comparison of soils on a global scale making it useful in many global studies on climate change, food production and land degradation. However it's low resolution (1:5M scale) is not suitable for land management decisions at field or catchment scales. Recognising the importance of soil as a non renewable resource, there is a definite return of soil on the political and global research agenda (Hatermink, 2008). Efforts have been put to explore new techniques and methodologies (Hartemink & McBratney, 2008) aimed to provide updated high resolution soil information. Some example of projects that focused on methodology development include: iSoil (van Egmond *et al.,* 2009), Digisoil (Grandjean, 2010), and e-SOTER (van Engelen, 2008). These developments resulted in the establishment of the Global Soil Partnership whose aim was to enhance use of knowledge of soil resources and also ensure standardization of methodologies. The GlobalSoilMap.net project (Sanchez *et al.*, 2009a) and e-SOTER (van Engelen, 2008) were initiated to address large-scale environmental issues. The development of the World Soil Information Service (WoSIS) was a follow-up to earlier compilations of soil legacy data coordinated by ISRIC such as WISE (Batjes, 2009a), SOTER (van Engelen & Dijkshoorn, 2013), and the Africa Soil Profiles database (Leenaars, 2013). The aim of WoSIS was to harmonise soil data (point, polygon and grids), from shared legacy data and soil spectral libraries (e.g. Viscarra Rossel *et al.*, 2016; Shepherd & Walsh, 2002). However, these global soil databases are incomplete and only indirectly relate to the dynamic soil properties that are sensitive to soil management at relevant scales (Vagen *et al.*, 2013). The limitation to most of these soil databases is the scale at which data is presented, lack of harmonized methodologies of data collection and laboratory analysis, that affect the accuracy and therefore fail to provide adequate information for soil management at farm or watershed scale.

1.4 Overview of the African context

Competing demand for natural resources result in overexploitation, making it a big challenge, yet very important to sustainably manage the natural resources for the survival of over one billion people (Jones *et al.,* 2013). Increased advocacy on the role of soils is essential in Africa, but important soil information on which policy and land management could be based is limited or even lacking in most areas. For this reason, the capacity of Africa to feed itself is held back by land degradation from both natural and anthropogenic causes. The available legacy soil information could not be well correlated between countries because of variable age, methologies and sometimes low quality. In view of this, the Joint Research Centre (JRC) of the European Commission and African experts worked together to produce the Soil Atlas of Africa (Jones *et al.,* 2013). The data sources were from the Harmonized World Soil Database (HWSD), FAO/Unesco Digital Soil Map of the World (FAO/Unesco 1971-1981; FAO, 2003), the Soil and

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Terrain database (SOTER) , from WISE databases (FAO/ISRIC, 2003; Batjes, 2007, 2008) and from national sources. The soil map of Africa (Figure 1.) demonstrates great soil diversity. The distribution of WRB reference soil groups (RSG) (IUSS Working Group, WRB, 2006) shows that over 60% of the soil types represent hot, arid or immature soil assemblages which include: Calcisols (5%), Leptosols (18%), Cambisols (11%), Arenosols (22%), Regosols (3%) and Solonchacks/Solonetz (2%). Then approximated 20% are soils of tropical or sub-tropical characteristics which include: Nitisols (2%), Plinthisols (5%), Ferralsols (10%), and Lixisols (4%). The distribution of soil forming factors has been noted to contribute to the distribution of soil types in Africa (Jones *et al.*, 2013). The occurrence of Chernozems, Kastanozems and Phaeozems which are developed under steppe conditions is limited in Africa.

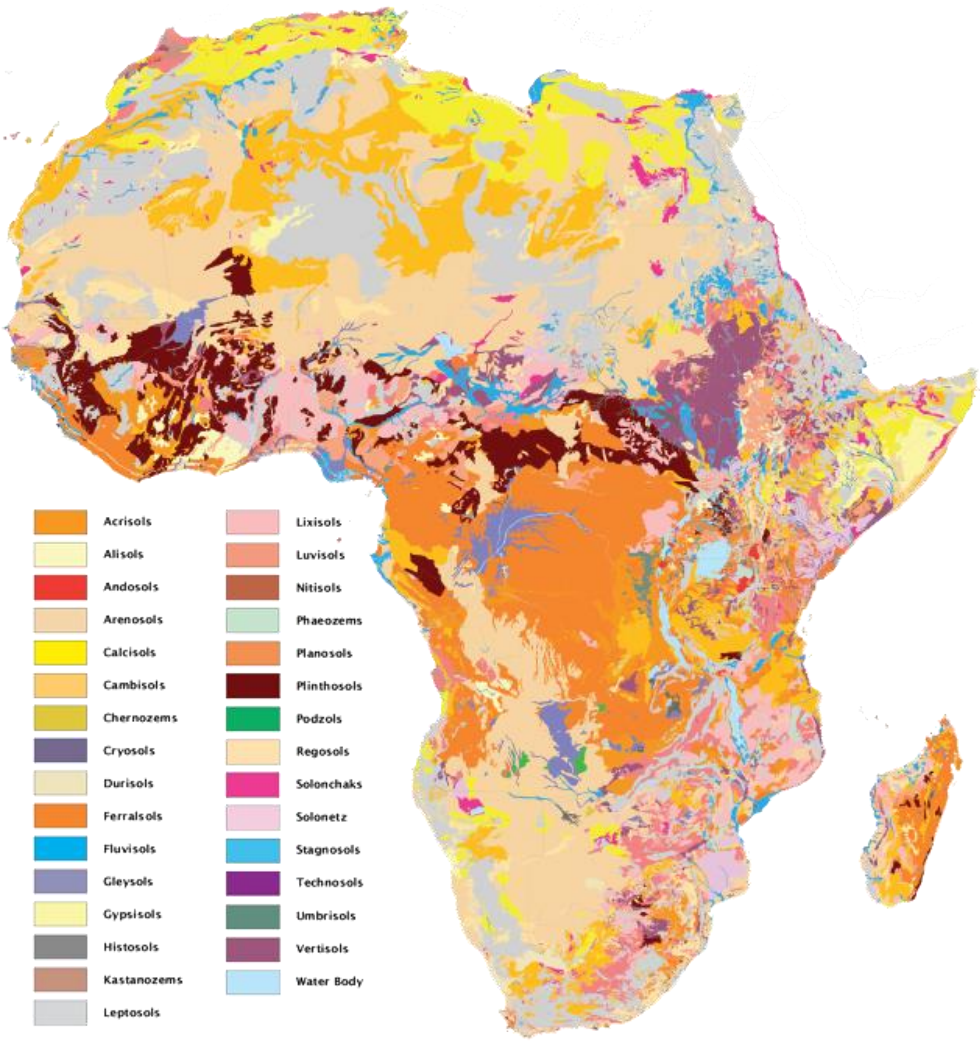

Figure 1. The major soil types in Africa (Jones et al., *2013)*

Natural causes like low cation exchange capacity (CEC) of the soils, climate change impacts and low soil organic matter partly explain the reasons of low productivity of soils in the sub-Saharan

Africa (Shepherd & Walsh, 2007). Further decline in productivity is anticipated (AfSIS, 2013; Nziguheba *et al.*, 2010; Shepherd & Walsh, 2007) because of limited investment into programs that can increase soil productivity. This worsens for small holder farmers who fully rely on what these poor soils can offer resulting in vicious poverty traps. The Alliance for a Green Revolution in Africa (AGRA) which was launched in 2007 scantly achieved its objectives. Inadequate soil data inventories for Africa that could support important decision making on soil resource management and increase agricultural productivity was identified as one of the major impediments (Nziguheba *et al.,* 2010). Integrated soil fertility management has been suggested by Vanlauwe *et al*. (2015) as a better soil management approach for sub-Saharan Africa. European African partnership projects like the PROIntensAfrica (www.IntenseAfrica.org) under the Horizon 2020 framework are looking at agro-ecological pathways to sustainable intensification of the agri-food systems. The situation in Kenya is not any better. Kenya's economy is agricultural based, currently contributing 24 percent to the Gross Domestic Product (GOK, 2009). Low soil fertility impedes productivity in many farming operations in Kenya (Okalebo *et al.,* 2006). This is worsened by lack of cost efficient soil fertility diagnostic tools (Bekunda *et al.,* 2010). To achieve the vision of the UN-SDGs 2015-2030, vision for Alliance for a Green Revolution in Africa (AGRA, 2013) and other ongoing and future projects will require up to date soil data inventories.

1.5 Research problem

The expected growth of population and the need of more food make the knowledge of soil properties essential to secure the successes of agricultural production on currently available land. Despite Kenya's economy being agricultural based, existing soil inventories (i.e Legacy data) do not capture dynamic soil properties at scales that are sensitive to management. The high costs of soil surveys and laboratory measurements have partly contributed to the scarcity of soil data as very little is done to update soil information inventories. The inventories also lack a harmonized sampling design that satisfies data quality checks of repeatability, reproducibility and accuracy. The commonly used plot experiments in the study area are expensive and do not capture the geographical variability of soil properties over a wide area. Unfortunately findings from plot experiments are used to make soil management recommendations for areas or regions away from the plot locations not withstanding soil properties variability in a very short distance. Lack of soil monitoring networks makes it impossible to recommend and prioritise site specific soil management practices increasing vulnerability of the soils to further degradation. Without a soil monitoring network it's difficult to report achievements made following any soil restoration activities. This has continually deprived the already nourished soils of the capacity to optimally provide the much needed ecosystem services. Rapid methods to quantify soil properties and support national soil health surveillance systems urgently need to be adopted.

1.6 Study objectives.

Based on the problem statement I have identified the following objectives which are represented in a summarized format:

1. To develop an optimized soil sampling scheme that preserves the natural distribution of soil forming factors in the study area, in the eastern slopes of Mt. Kenya.
2. To develop an ensemble model for predicting of important soil properties (i.e soil organic carbon, base cations, pH, aluminium and particle size distribution).
3. To demonstrate the usefulness of the derived database for mapping soil properties for the study area.
4. To classify the visited soils and validate the soil types in the KENSOTER soil units of the study area.
5. To compare differences of soil properties in different WRB Reference soil groups and the implications of applications for management purposes in the study area.

1.7 Justification of the study

Maintenance of soil fertility is an important supporting service as it is necessary for the overall productivity of the agricultural systems. But this is only possible if reliable soil property information is available and can be accessed in good time to enable timely decision making. Winoweick *et al.* (2016) have pointed the need to understand soil properties in view of identifying limitations that hinder increased agricultural production. Conventional soil laboratory analytical procedures are costly and consume a lot of time (Shepherd & Walsh, 2002; McBratney *et al.*, 2003). These cost prohibitive methods are ballooning the already existing soil data scarcity problem making it difficult for informative decisions on soil management. Traditional wet chemistry methods for quantifying soil properties are expensive because they take a long period of time and the chemicals required (Ludwig *et al.*, 2002). In addition, these analytical methods are associated with generation of toxic wastes that must be properly disposed. Over nearly three decades, reflectance spectroscopy, near and mid infrared (NIR & MIR) has been used as a dry chemistry analytical tool to provide quantitative and qualitative data of soil properties in a much faster, non destructive, cost efficient and less hazardous way to the environment because few chemicals are required compared to wet chemistry laboratory measurements (Nocita *et al.*, 2015, Madari *et al.,* 2006; Vagen *et al.,* 2016). MIR is integrative making it a good soil health diagnostic tool (Shepherd & Walsh, 2002). Traditionally, farmers in this study area consider fields as uniform pieces of land and thus, farm inputs like fertilizers are applied without taking into account spatial variations in field characteristics. Adoption of poor soil sampling methods makes it worse as they conceal soil properties variability within fields. This may lead to fertilizer wastage in parts of the field that are well endowed with nutrients and under application in parts of the field with high nutrient deficiency. The consequence is imbalance in field productivity. Thus, there was need to design a soil sampling scheme that can ensure the area of interest is covered uniformly. Site specific management systems are possible to achieve with the input of geostatistical approaches that enable spatial mapping soil properties in unsampled locations (Saito *et al.,* 2005; Behera & Shukla, 2015). This study targets to quantify soil properties using rapid and cost efficient MIR spectroscopy and predictive models to quantify soil properties. The predicted soil properties support development of spatial distribution maps using geostatistical techniques. This approach made it possible to provide the much needed spatial soil information at relevant management scales for the study area. The spatial information also forms a good basis to monitor soil fertility in the study area.

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6.

2. LITERATURE REVIEW

The basis of this thesis requires knowledge about soil, infrared spectroscopy, multivariate statistics and geostatistical approaches for mapping soil properties. A quick overview of available soil information for Kenya and the eastern of Mount Kenya region are presented. The commonly used soil sampling techniques discussed with more details on Latin Hypercube Sampling. Spectroscopy and Digital Soil Mapping are discussed. Gaps are identified that support the choice of methods used in this study.

2.1 Overview of some of available soil information for Kenya

The Exploratory Soil Map of Kenya (ESMK) (Figure 2.) at the scale of 1:1M dated 1980 was the fourth attempt to present the soils of Kenya in a more comprehensive manner by the Kenya Soil Survey under the supervision of W. Sombroek. (Ministry of Agriculture, 1980). The first provisional 1:2M soil map was included in the soil map of East Africa (Milnes, 1935). The second map at the scale of 1:3M was produced by Gethi Jones and Scott (1959) reprinted in 1962 (2^{nd} edition) and 1970 (3^{rd} edition). Scott used the same information from the East Africa soil map (Scott, 1971). In all these soil maps the soils were surveyed and presented following the catena concept developed by Milnes (1935b). This concept was taken further into the land system approach which resulted in the preparation of land system atlas for the western part of Kenya at the scale of 1:5M (Scott *et al.,* 1971). The compilation of the exploratory soil map of Kenya drew soil information from the Kenya Soil Survey (KSS) and exploratory pieces of fieldwork during the period 1973-1977. An inventory of all Kenya Soil Surveys that formed important source of data for the exploratory soil map of Kenya can be found in KSS publications (Siderius, 1979). The soil map of world (FAO-UNSECO, 1974) also derived soil information for Kenya from the KSS. The density of sampling or the number of profiles used during the compilations of the ESMK is however missing.

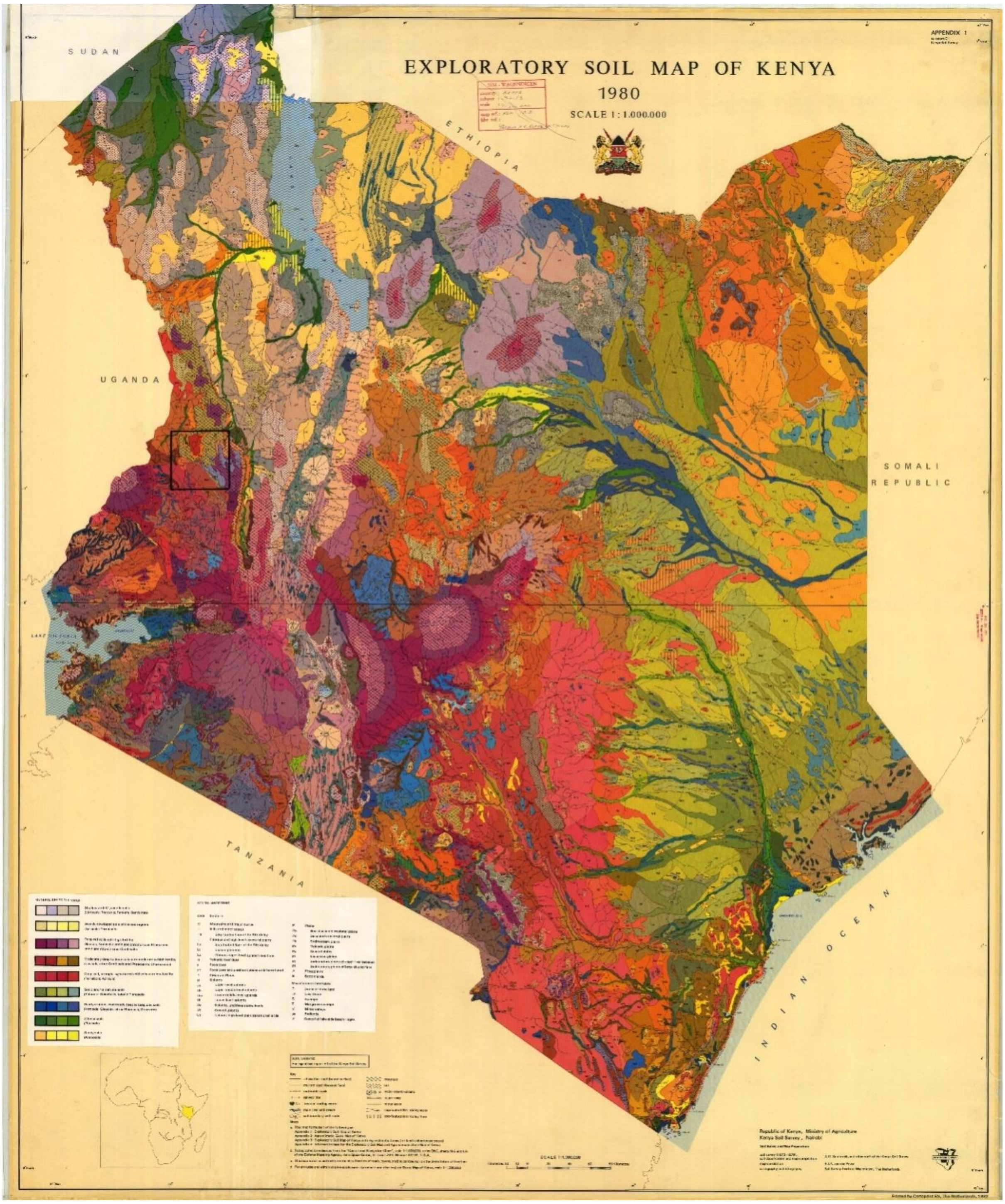

Figure 2. Exploratory soil Map of Kenya

(Ministry of Agriculture, Kenya Soil Survey, 1980)

Another important soil information source for Kenya is the KENSOTER database; it was developed by the Kenya Soil Survey (KSS) following the UNEP/ISRIC SOTER procedures (Kenya Soil Survey, 1996). The KENSOTER map is based on the ESMK at scale 1:1M (Ministry of Agriculture, Kenya Soil Survey, 1980). The delineations of the KENSOTER mapping units largely coincide with the unit boundaries of the ESMK. The land surface of the republic of Kenya, excluding lakes and towns was characterised using 397 unique SOTER units corresponding with 623 soil components. The major soils were described using 495 soil profiles which included 178 synthetic profiles selected as representative for the units (Batjes & Gicheru, 2004).

Regarding data quality of the KENSOTER the following general remarks can be made:

- Soil components in the KENSOTER are defined by a single reference profile. This makes information on soil variability scarcely available.
- The information of over 40% of the soil components was found to be incomplete (Van Waveren, 1995). This missing information was mostly on soil classification and soil texture.
- The total proportional area of the soil components in KENSOTER was not always 100% often due to undefined soil components (Van Waveren, 1995).
- The soil classification of a number of profiles is not in accordance with profile information.
- Classification of the parent material was inconsistent. For example basement system rocks were classified as granite instead of gneiss.

The Africa Soil Information Service (AfSIS) library is another source of soil information for Kenya. Soil data were collected at over 9,000 locations from 60, 10 X 10 km sentinel sites in Africa stratified by the major Koppen-Geiger climate zones of Africa (Peel *et al.,* 2007). This exercise excluded some of the African countries which were no-go zones due to security threats. The data were further combined with collated and harmonized soil legacy data from over 18,000 locations in Africa. Each sentinel site was subdivided into 16 sampling units (clusters), each cluster was further split into 10 smaller sampling units (plots). The sampling plot was designed to sample approximately 30 x 30 m area. Only three sentinel sites were visited in Kenya (western parts of Kenya, rift valley and the coastal region). The sampling design and density was clustered and therefore did not capture important soil resource and land use variability in Kenya. Mount Kenya region (my study area) for example was not part of the sentinel sites for AfSIS in Kenya.

The available data for eastern slopes of Mount Kenya is the Soil and Terrain (SOTER) database for the Upper Tana River catchment (SOTER_UT), at scale 1:250,000. This database was developed during the Green Water Credits (GWC) projects for hydrological studies in the Upper Tana catchment of Mount Kenya Region (Dijkshoorn *et al.,* 2010). The SOTER_UT data was extracted from the national KenSOTER database and updated with information from reconnaissance surveys (Kenya Soil Survey, 1975, 2000) at a scale of 1:1M and more detailed soil studies in the catchment (Kinyanjui, 1990; Njoroge & Kimani, 2000). The SOTER_UT provides data of 191 SOTER units using 109 representative soil profiles. It is evident that much of available soil data were compiled from the legacy soil data sources and little has been done to update these inventories.

2.2 Overview of soil sampling methods.

Reliable data sampling of spatially distributed data require use of appropriate statistical tools. It is a standard statistical procedure to use sampling techniques to improve the coverage of the sampling area, especially when the function being analysed is expensive like carrying out soil survey campaigns. There are two major types of sampling methods: probability sampling which utilizes some form of random selection.

2.2.1 Probability sampling methods

- Simple random sampling is the commonly used sampling method that provides independent estimates of the mean and variance but may require many samples to reduce prediction error. In addition, simple random sampling can sometimes leave large unsampled areas. Simple random sampling is not the most statistically efficient method of sampling because in many times it's difficult to achieve good representation of the total population (Leornard & Anselm, 1973).
- Systematic sampling is a statistical method involving the selection of elements from an ordered sampling frame. The most common form of systematic sampling is an equiprobability method. However, systematic sampling is only useful if the given sample population is logically homogeneous. Soil variability in a landscape is highly heterogeneous and therefore this method was not suitable for soil sampling in this study (Leornard & Anselm, 1973)
- Stratified random sampling is also called *proportional* or *quota* random sampling and involves dividing the sample population into homogeneous subgroups and then taking a simple random sample in each subgroup. The requirement is that the strata or subgroups should be homogeneous. However, stratified sampling may not capture the continuous natural distribution of ancillary data (soil forming factors) as stratification results in discrete polygons. An example of stratified random sampling is the use of *'catena'.* This approach describes a grouping of different soils that occur together in the landscape

based on differing topographic attributes. However, topography cannot be completely isolated from other soil forming factors like parent material, climate, organisms and time (Jenny, 1941). This is a difficult task to delineate homogeneous landscapes in a highly heterogeneous landscape like Mount Kenya region. A good soil sampling scheme should take cognisant of all the soil forming factors.

- Cluster sampling is a sampling plan used when mutually homogeneous yet internally heterogeneous groupings are evident in a statistical population. In this study the natural distribution of environmental variables that guided the sampling plan are continuous variables. Clustering continuous environmental variables may conceal information on its variability in the landscape (Paul & Stanely, 2011).
- Multistage sampling involves a combination of sampling methods. This may help to address complex sampling questions like uniformity of sampling and increase coverage of the area of interest while addressing the heterogeneity of the subgroups.
- Latin hypercube sampling (LHS) is an optimization procedure that picks sampling sites which can form a Latin hypercube in a feature space/landscape. The LHS method has so far been successfully applied in the design of soil sampling schemes (Worsham *et al.*, 2012; Taghizadeh-Mehrjardi *et al.*, 2014).
- Conditional Latin Hypercube Sampling is hybrid of LHS. The difference between CLHS and the LHS is the additional of field operation constraints to the objective function of LHS. Roudier *et al.* (2012) used CLHS to optimize the chances of sampling site accessibility. Mulder *et al.* (2013) successfully used CLHS in inaccessible field in Morocco to increase the probability of accessing sampling sites. CLHS was adopted for this study and is further explained in Chapter 3.

2.2.2 Non- probability sampling methods

- Convenience sampling is a sampling method that draws samples of the population that are close to hand or readily availability. This sampling is most useful for pilot testing. However, the results of convenience sampling cannot be generalized to the target population because of the potential bias (Bornstein *et al.*, 2013).
- Purposive sampling is a sampling technique in which researcher relies on own judgment when choosing samples of a population. This method is vulnerable to errors in judgment by the researcher, as low level of reliability, high levels of bias and inability to generalize research findings (Zhi, 2014).

- Quota sampling is based on the researcher's judgment. The selection is not random and therefore selection bias is a big problem that can result in unrepresentative samples of the population (Cochran , 1977).

2.3 Spectroscopy

In this section Near-infrared (NIR), Mid-Infrared (MIR) and multivariate calibration of spectra data are discussed.

2.3.1 Infrared spectroscopy (IR)

Infrared (IR) spectroscopy offers a non-destructive means of measurement of soil properties based on reflectance spectra of illuminated soils. Near infrared (NIR; 25000-4000 cm-1 and mid infrared (MIR; 4000-400cm-1) regions are tools currently in use by soil scientist for acquiring soil properties information rapidly and cheaply (Nocita *et al.*, 2015). Figure 3. shows different regions of the electromagnetic spectrum.

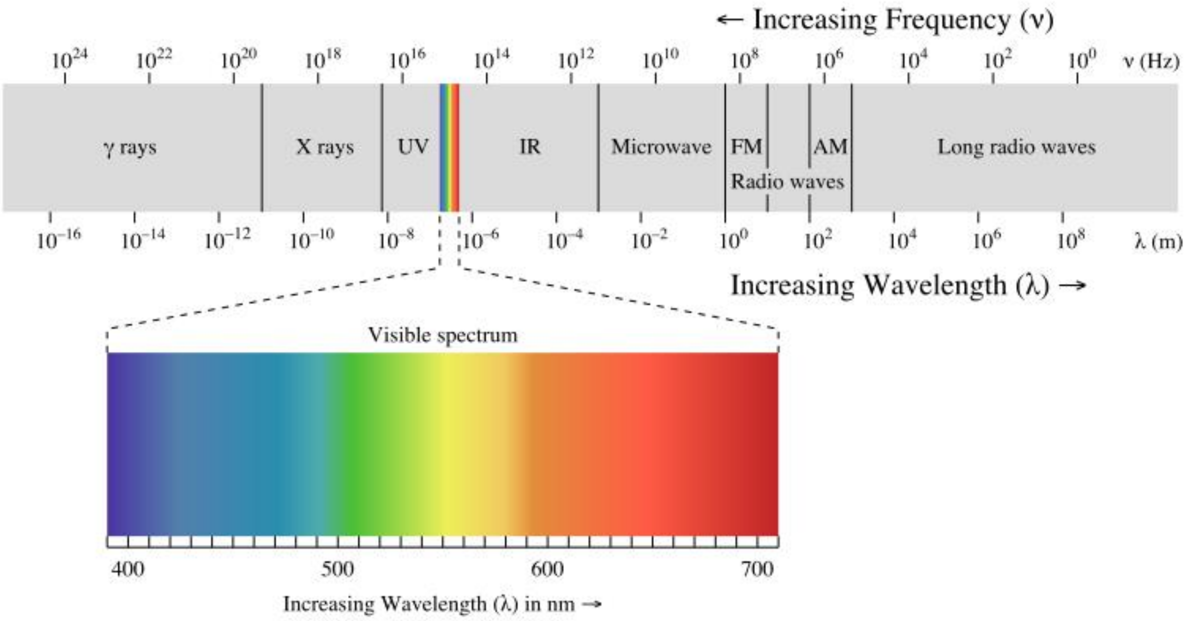

Figure 3. The Electromagnetic spectrum.

Source: http://www.geo.mtu.edu/rs/back/spectrum/ (Accessed 2016, October, 13).

Infrared (IR) spectroscopy works based on absorption of electromagnetic waves in the infrared regions (Cécillon *et al.*, 2009). All bonds have specific vibrational frequencies, and IR absorption can be used to describe (i) the location of absorption in terms of wave numbers, (ii) the amplitude of the absorption peak (relative intensity), and (iii) the width of the peak describing its intensity-bandwidth (Cécillon *et al.*, 2009). Near infrared (NIR) spectra results from overtones and combination bands; they are complex and not easily interpretable compared to other spectra like ones from mid infrared regions (MIR), which are mostly fundamental bands (Workman Jr. & Mark, 2004). Compared to the MIR, the NIR region is dominated by broader signals, rather than sharp peaks due to additive effects of two or more bonds (combinations of absorbance) at each wavelength (Workman Jr. & Mark, 2004). The fundamental absorption is the most intense absorption of energy and occurs in the mid-infrared. Each higher overtone and combination band is typically 10-100 times weaker than the fundamental bands (Sandorfy *et al.*, 2006). Vibrations of atoms of a molecule involve change in bond length (stretching) or bond angle (bending*)* (Stuart, 2004). Stretching vibration consists of symmetric and asymmetric stretching, while bending vibration are a result of wagging, twisting, rocking and deformation. Symmetric vibration is generally weaker than asymmetric vibration, because symmetrical molecules have fewer “infrared active” vibrations than asymmetrical ones (Stuart, 2004).

Spectral pre-processing is important in spectra analysis. The goals of spectra data pre-processing are:

- To improve the robustness and accuracy of subsequent quantitative or classification analyses
- To improved interpretability: raw data transformed into formats that are better understandable
- To enable detection and removal of outliers
- To reduce dimensionality of the data
- To remove overlapping of data and redundant information.

A commonly used pre-processing method is Savitzky-Golay smoothing (Savirzky & Golay, 1964). In this method, a polynomial least-squares fit is performed on a spectral window. Savitzky-Golay filters are optimal in the sense that they minimize the least-squares error in fitting a polynomial to each frame of noisy data (Swierenga *et al.*, 1999).

2.3.2 Mid Infrared Spectroscopy (MIR) of soil properties

MIR identifies the kind of molecular motions and bonds or functional groups present in a sample, because each frequency match a certain quantity of energy and unique molecular motion (e.g. stretching and bending). This concept allows the characterization of complex soil components. MIR spectroscopy has frequently been applied to investigate soil properties and soil organic matter (Viscarra Rossel *et al.*, 2006). Currently, the combination of multivariate statistical methods used for the Fourier Transform IR (FTIR) spectra analysis is a powerful diagnostic tool for identification and quantification of soil components (Viscarra Rossel *et al.*, 2006; Sila *et al.*, 2016).

MIR spectra can be divided into four regions (e.g., Shepherd and Walsh, 2007): (i) fingerprint (O–Si–O stretching and bending) from 1500 to 600 cm−1, (ii) double bond (C=O, C=C, and C=N) from 2000 to 1500 cm−1, (iii) triple bond (C≡C, C≡N) from 2500 to 2000 cm−1, and (iv) X–H stretching (O–H stretching) from 4000 to 2500 cm−1. FTIR spectra have made it possible to distinguish clay minerals from each other through the bands assigned to OH and Si–O groups. Clays or aluminosilicates show two sharp peaks at 3695 and 3622 cm^{-1} due to OH stretching (Janik *et al.,* 2007b). Near 3400 cm^{-1} is a broad band associated with OH stretching (H bonded water); the strength and position of this band is affected by exchangeable cations. Its position decreases in the order $K^+ < Na^+ < Ca^{2+} < Mg^{2+}$. This is related to the increasing polarizing power (charge/radius) of the cations (Janik *et al.*, 2007b). Weak bands at 1980, 1870 and 1790 cm−1 are associated to quartz overtone (Janik *et al*., 2007b). Carbonates produce absorption at 2600 to 2500 cm−1 with little interference from other minerals (Janik *et al.*, 2007). Wavebands at 3683–3639; 2580–2306–; 2137–2098; 1709–1689; 1556–1400 cm−1 are important for pH predictions. These bands are associated with hydroxyl stretching vibrations, alumino-silicate lattice vibrations and Al-OH deformation vibrations (Yitayesu *et al.*, 2011). Wavebands at 2285–2025, 1751–174 and 1423 cm−1 are important for sand prediction (Sila *et al.*, 2016) and correspond to alumino-silicate lattice vibrations and Al-OH deformation vibrations (Yitayesu *et al.*, 2011). Soil organic matter produces features across the entire spectral range, for example contributing to the broad absorption features near 3400, 1600, and 1400 cm^{-1} and due to absorption by aromatic structures, alkyls, carbohydrates, carboxylic acid, cellulose, lignin, C=C skeletal structures, ketones, and phenolics (Janik *et al.*, 2007).

2.3.3 Multivariate calibration of soil MIR spectra data

Multivariate calibration is the collective term used for the development of quantitative models for prediction of soil properties. The goal of model calibration is to replace a measurement of the soil property by one that is cheaper, or faster, or better accessible, yet sufficiently accurate. Examples of multivariate methods include linear methods such as multiple linear regressions (MLR), principal component regression (PCR), partial least squares (PLS) and non- linear methods such as artificial neural networks (ANN), non-linear support vector machines (SVM) and random forest regression (RF). Principal Component Regression (PCR) and Partial least squares (PLS) regression are the most commonly used prediction methods in spectroscopy. A combination of multivariate calibration methods with spectroscopic data has allowed the analysis of complex spectra libraries. Linear and non-linear calibration methods are used for modelling soil spectra data. The utility of Random Forest regression (RF) for quantifying soil properties from MIR spectra data has not been widely used as compared to other multivariate statistics like multiple linear regression (MLR), partial least squares (PLS) and Principal Component Regressions (PCR). A study by Ghasemi and Tavakoli (2013) on application of RF for multivariate calibration of MIR spectra, compared performance of PLS and RF on four varied spectra data sets. The result indicated that RF had generally better performance than PLS on the noisy data set containing outliers which is a characteristic of soil spectra data measured using FTIR. McDowell *et al.* (2012) found no significant difference among PLS and RF ensemble regression trees to predict soil Total Carbon (TC) on Hawaiian soils. Minasny and McBratney (2008) and Minasny *et al.* (2009) used cubist regression approach and obtained excellent predictions for SOC. Vasques *et al.* (2010) identified SOC predictions made by ensemble regression trees as more accurate than those derived from PLS in an investigation in Florida. PLS and PCR are only useful in absence of non-linear variations (Brown *et al.,* 2006). Non-linear variations caused by temperature changes, light scattering, baseline drifts and multicollinearity are a common phenomenon in spectra data and have been reported in Fourier transform infrared spectroscopy (Hoffmann & Knözinger, 1987). The MLR model is simpler and easier to interpret, but is not capable of dealing with the multicollinearity of spectra data (Massart *et al.,* 1998). In practice, the presence of non-linear influence (such as temperature variation, baseline drifts, light scattering effect and multicollinearity) on the spectra decreases the accuracy of linear methods. Thus, non- linear methods like artificial neural networks (ANN), support vector machines (SVM) and random forest regression (RF) have better predictions than linear methods. However, ANN is not efficient in modelling high-dimensional data and requires a dimension reduction (Anderson, 2009). SVM is capable of handling high-dimensional data but is not robust in the presence of noisy data which is a characteristic of soil spectral data. Among various regression methods, tree structured models, so-called decision trees, can model linear as well as non-linear relationships (Svetnik *et al.,* 2003; Vega *et al.,* 2009; Tan *et al.,* 2010). They are easy to interpret, fast and non-parametric thus do not rely on assumptions about data distribution. However, they have low prediction accuracy especially for regression purposes (Lim *et al.,* 2000). Based on its robustness, RF was used as the calibration method in this study.

2.4 Digital soil mapping

Digital soil mapping (DSM) is an alternative to the conventional soil mapping (CSM) approach which has been found to have major limitations. Important limitation of CSM in large inaccessible areas is the dense sampling that is required for detailed soil maps (Bui *et al.*, 1999). Other limitations include: lack of quantified measures of accuracy (Kempen *et al.*, 2012) and lack of reproducibility because the mental soil landscape models used by surveyors are difficult to interpret. DSM offers a much flexible and quantitative approach to study soils and their relation to environmental factors (Pásztor *et al.,* 2006; Dobos *et al.,* 2006; Hartemink & McBratney, 2008). In DSM, field, laboratory and remotely sensed soil observations are integrated with multivariate statistics to infer spatial patterns of soils (Grunwald, 2011). The concept of pedometrics is applied in the state factor equation of soil formation (Jenny, 1941) in order to develop empirical models that relate observations of soil properties with environmental variables. This model is often known as CLORPT model. Refinements to CLORPT model include the SCORPAN (McBratney *et al.,* 2003) framework which is spatially explicit (Grunwald, 2011). The environmental variables are data layers from digitized geological and soil maps, satellite images, digital elevation models (DEMs) and its derivatives. The success of DSM depends on the spatial autocorrelation of soil observations in a landscape (Grunwald, 2011). The sample size and the sampled variability determine the accuracy of soil prediction models (Vasques *et al.,* 2012).

Some of the guiding considerations for successful DSM

- The choice of sampling method should be guided by how well the sampling procedure enhances coverage of the full extent of environmental variables needed as input data in the prediction models. Taking this conclusion into consideration, the Conditional Latin Hypercube Method (CLHS) was selected for this study. Details of CLHS are explained in Chapter 3.
- To optimize spatial prediction of soil properties, a good choice of geostatistical approach need to be considered. Details of how the geostatistical method was selected are also given in Chapter 3.
- The approach methods should be both time and cost efficient. Rapid methods of soil properties measurements and multivariate statistics have been adapted for this study and are explained in Chapter 3.

3. MATERIALS AND METHODS.

This chapter provides details of the study area, demographic and social economic activities design of the sampling frame, the methods used in the laboratory using conventional wet chemistry laboratory procedures and dry chemistry infrared spectroscopy techniques for soil analysis. The actual procedures for processing soil data and the applied multivariate models are discussed. Geostatistical approaches used to investigate the spatial dependence of data are discussed together with the spatial mapping of soil properties.

3.1 Study area

In this section, the location of the study area, soil forming factors, the dominant soils and the demographic and social economic characteristics are discussed.

3.1.1 Location

Soil sampling was conducted in Mt. Kenya region covering an area of 1200 km^2 within latitudes 37^0 36'E and 38^0 0' E and longitudes 0^0 6' N and 0^0 18' S (Figure 4.). The major land use is rainfed agriculture.

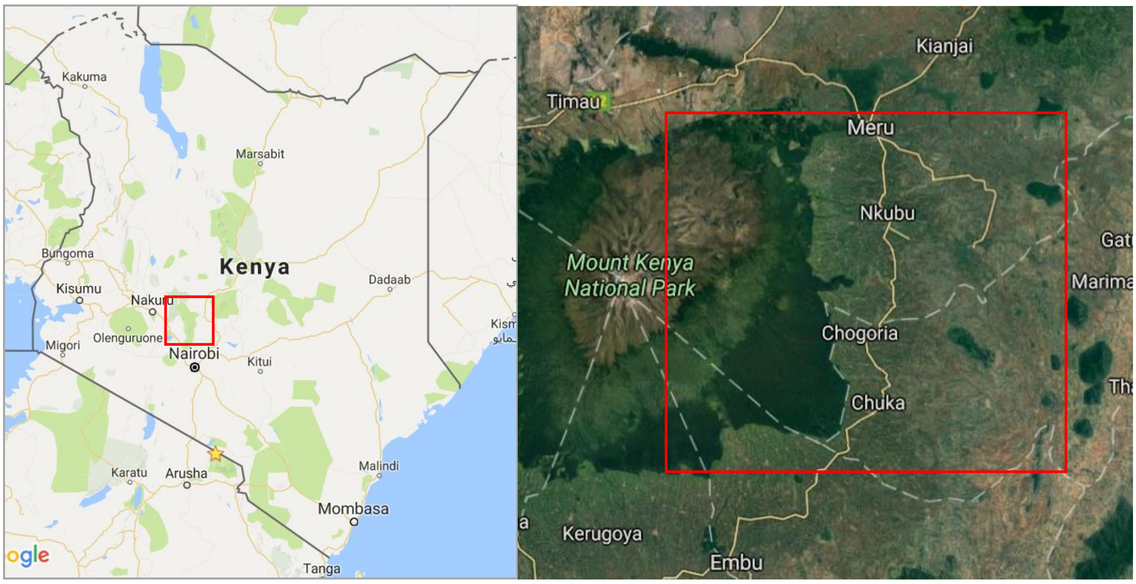

Figure 4. The locations of study area in the eastern slopes of Mt. Kenya.

3.1.2 Soil forming factors.

Soil forming factors; climate, topography and geology influence distribution of the soil types. The altitude range was 700 m to 2000 m. The agro-climatic zone is humid in high altitudes and semi-arid in the lower altitudes (Jaetzold *et al.*, 2007). The area has large rainfall differences, with rainfall gradient increasing from east towards west. Annual rainfall is distributed in two major seasons between March to May and October to December. Amount of rainfall is 1500 mm in upper humid zones and 600 mm in the lower semi-arid zones. Temperature is correlated with altitude, warm parts in the eastern lowlands and cooler zones high up towards western parts. The annual average temperature is 10 ^{0}C to 35 ^{0}C.

The geology is mainly volcanic rock and ash and some old metamorphic rocks (Schoeman, 1952). The volcanic rocks in the area are related to the Rift Valley development during the Pliocene time and dated from 3.5 to 2 million years. Three phases of deposition by this volcanism can be distinguished. The first phase was during the main activity of Mt. Kenya. This phase took place during the upper Pliocene time. In this period *phonolite* flows and *lahars* were deposited in the area. These form the plateau level in the area which borders the basement system area. The second phase was during the activity of the parasitic cones in the north eastern side of Mt. Kenya during the Plio-Pleistocene time. Parasitic cones are cone-shaped accumulation of volcanic material forming from fractures on the side of volcano because the sides of the volcano are unstable. The lava flows during this time consisted of *lahar* and *basalt*. The third, recent phase was during the Pleistocene time and is also related to the activity of the parasitic cones of Mt. Kenya. *Lahar, tuffs* and *volcanic ashes* were deposited during the time especially in the river valleys. Therefore the volcanic rocks related to the Mt. Kenya series are mainly *lahars, phonolites, tuffs, basalt and volcanic ashes.*

The rocks and/or rock groups were identified as the parent material of the soils in this study area from the digitized geology map of the study area. Figure 5. shows how these rocks are distributed in the study area. The presented geology map was derived from the ISRIC library KE. 2002.02 document for this study area. This document was scanned, georeferenced to the World Geodetic System 1984 (WGS 84) and then polygons were digitized using ArcMap 10.5 software as part of my research work.

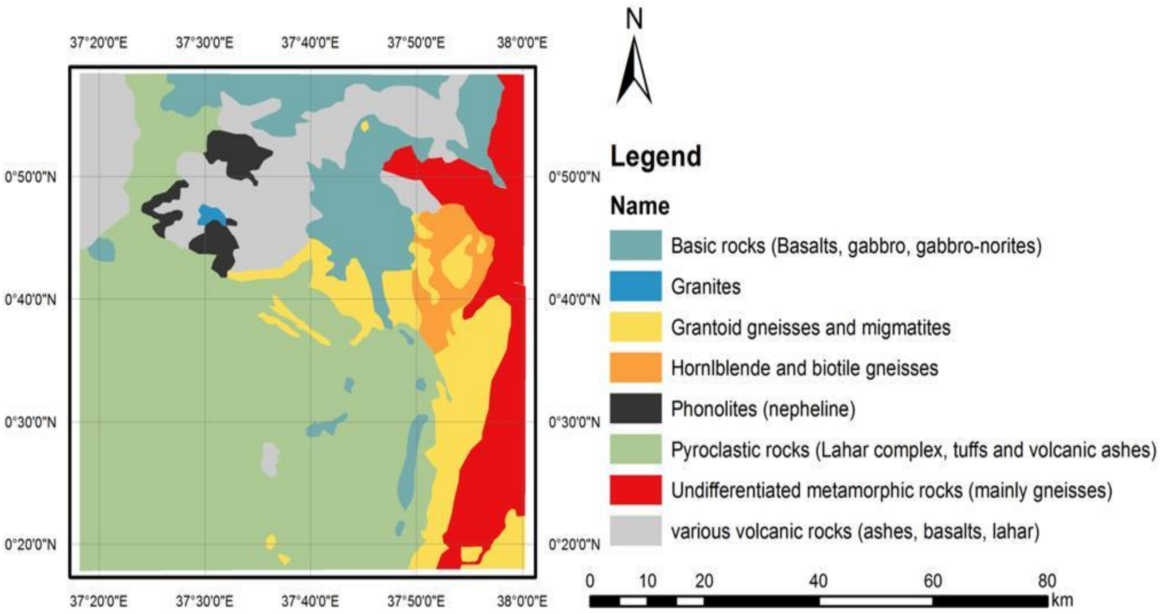

Figure 5. Spatial distribution of rocks identified as parent material of soils in the study area.

Another important soil formation factor is the anthropogenic influence. Human populations can knowingly, or unknowingly, manipulate land conditions to the extent that they affect soil formation. Human activities like excavation act as external modifiers to soil formation processes.

3.1.3 Dominant soil types of the study area

For this study area, the dominating WRB (IUSS Working Group WRB, 2015) Reference soil groups (RSG) are: Nitisols, Ferrasols, Regosols, Vertisols and Phaeozems (Figure 6.). This is according to the 1:1 M KENSOTER map and database (Dijkshoorn, 2007). Western part is relatively humid with lower temperatures. Low rate of mineralisation of organic matter, strong leaching and eluviation give rise to humic topsoils, and mostly acid soils with low base saturation like Andosols, Umbrisols and Alisols. Andosols which are mainly found in *high elevation, humid zones* of Mt. Kenya region are intermediary weathered compared to soil types in the middle and lower zones of the study area.

In the *middle elevation* the rainfall and temperatures are moderate. Hence less leaching and moderate organic matter decomposition resulting in well structured, drained and deep soils evidenced by presence of Nitisols. Nitisols are deep, well-drained red tropical soils with diffuse horizon boundaries and a sub-surface horizon with more than 30 % clay and moderate to strong angular blocky structure elements that easily fall apart into characteristic shiny, polyhedric (‘nutty’) elements. The genesis of Nitisols includes ferralization which result in loss of silica (Si), formation of kaolinite and accumulation of sesquioxides. The angular shinny peds are a result of nitidization caused by micro swelling and shrinking and pressure regulating clay particles in the form of ped faces. Bioturbation by ants and earth worms homogenises soils (Driessen *et al.,* 2001). Rejuvenation of Nitisols through deposition and enrichment of volcanic ashes has been reported (De Wispelaere *et al.,* 2015).

Ferrasols are associated with high rainfall and very old (Tertiary) land surfaces (Jones *et al.,* 2013). They are strongly leached soils that have lost nearly all weatherable minerals over time. As a result they are dominated by stable products such as aluminium oxides, iron oxides and kaolinite which give Ferralsols strong red and yellow colours. Ferrasols are mainly found in the middle zones of the study area. The effect of past climate, alternating of dry and wet spells give rise to pisolithic material as evidenced by presence of Plinthosols in the lower semi-arid zones.

Young soils like Cambisols show incipient subsurface soil formation on *alluvial plains* and shallow Leptosols are mainly found in areas with basement rock. Presence of Regosols in the eastern semi-arid zones is evident due to extensive erosion and accumulation especially in the mountainous terrain. Regosols are weakly developed mineral soils in unconsolidated medium and show only slight signs of soil development. They are commonly found in extensive eroding lands such as mountains or desert areas where soil formation is generally absent or moderate.

Vertisols are mainly found in *lower landscape* positions that are periodically wet in their natural state. Vertisols are clayey soils that exhibit wide crack which open and close periodically upon drying and wetting. This is caused by the presence of montmorillonite clay mineral, which takes up water when it becomes wet (swells) and releases the water again upon drying (shrinks).

Phaeozems have a thick dark coloured surface layer which is rich in organic matter. This soil type was found mainly in the north eastern part of the study area where rainfall is adequate and grass for grazing livestock is the main land use practice.

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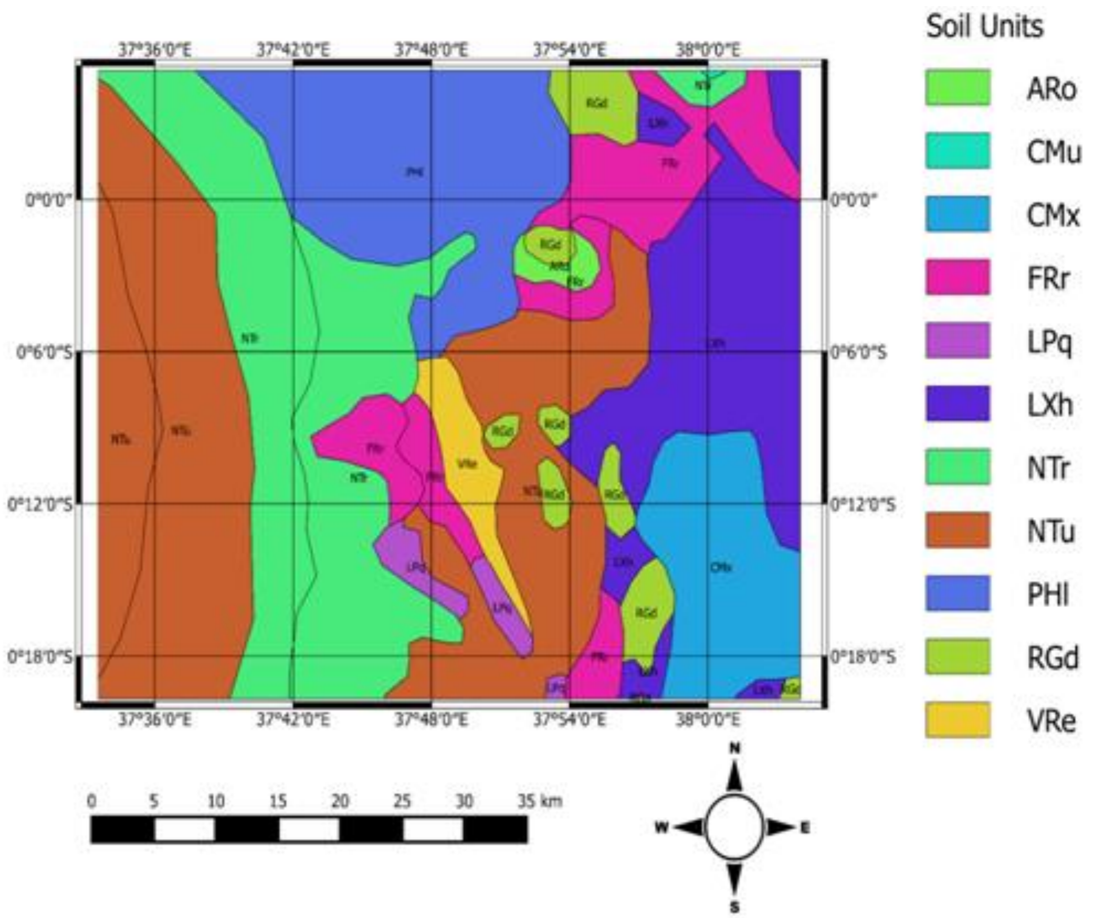

Figure 6. KENSOTER soil units for the study area.

KENSOTER soil units descriptions (indicated by the dominant soil types)

ARo = Ferralic Arenosols; CMu = Humic Cambisols; CMx = Chromic Cambisols; FRr = Rhodic FERRALSOLS; LPq = Lithic Leptosols; LXh = Haplic Lixisols; NTr = Rhodic Nitisols; NTu = Humic Nitisols; PHI = Luvic Phaeozems; RGd = Dystric Regosols; VRe = Eutric Vertisols.

3.1.4 Demographic and socioeconomic factors.

The population density estimate according to Kenya population and housing census basic report of 31st August 2010 was 424 persons/km^2. This huge population density derives their livelihoods from farming and has put a lot of pressure on land leading to overexploitation of natural resources and advanced land degradation. Rainfed agriculture is the major farming method. A variety of food crops that are grown in this region include: bananas, white corn, beans, potatoes, yams, arrow roots, sweet potatoes, peas cowpeas and a wide variety fruits and horticultural crops like avocadoes, mangoes, pineapples, flowers and vegetable farming. The region also produces the best coffee in Kenya and tea has the main cash crops. Livestock rearing includes dairy and beef cattle, sheep and goats and poultry. These are important for they provide a source of farm yard manure. Donkeys and oxens are important means of transport and for land preparation. Lumbering is also a source of income where trees such as *eucalyptus, cypress* and *gravillea robusta* are the commonly planted trees for timber, charcoal and fuelwood. Connection to electricity is still poor, but some major have electricity connection. Access to adequate drinking water in some areas is a challenge because surface water is not evenly distributed and connection to piped water systems is still at its low levels. Irrigation methods include furrow and overhead irrigation where water is conveyed in open canals and pipes, respectively. Due to inefficient methods of irrigation there is a lot of wastage of water. Soil degradation processes like soil erosion by water and water logging are exacerbated through poor irrigation methods. Water pollution through agrochemicals is also an issue as effluents are directed to waterways without pre-treatment in most areas. Wildlife and tourism is also a major income source for the county at the Meru National Park.

3.2 Soil sampling design

To define the soil sampling locations, Conditional Latin Hypercube Sampling (CLHS) was performed. The reason of using CLHS in sampling site selection were the foreseen constraints (inaccessibility due to poor weather roads, very steep slopes, possibility of having sampling locations coinciding with water bodies, national parks or built environment) and the need to reduce the sample size yet cover a wide geographical area with limited budget was put into consideration.

The need to input the distribution of environmental variables in our soil sampling scheme justified the use of CHLS. This method aims to pick sampling sites that form a Latin Hypercube feature space as demonstrated below:

- Assuming K variables X_i…………………X_K the array of each variable X is divided into *n* equal strata.
- In this case K variables are: the environmental covariates (soil forming factor derivatives)
- Then samples are picked randomly for every variable X_i…………………$X_{K.}$
- In total n samples covering n intervals are selected. [they can be randomly paired guided by some conditions (CLHS)]
- Use of conditions involved addition of constraints to the objective function formally formulated by Minasny & McBratney (2006).
- These constraints are based on field operation costs which are a function of time, sample size and accessibility to sampling locations.

- Finally addition of constraints to the objective function leads to equation (1)

$$J = W_1 * \sum_{i=1}^{n} \sum_{i=1}^{k} |n_{ij} - 1| + W_2 * \sum_{P=1}^{n} C_P \tag{1}$$

n=samples; k= variables; n_{ij} *=sampling frequency (where i= interval and j=variable); cp=cost associated with sampling. W1 & w2 are the weights.*

A comparison of CLHS and the commonly used Monte Carlo simple random sampling show that CHLS is superb in that it ensures a more even distribution of sampling points (Figure 7.).

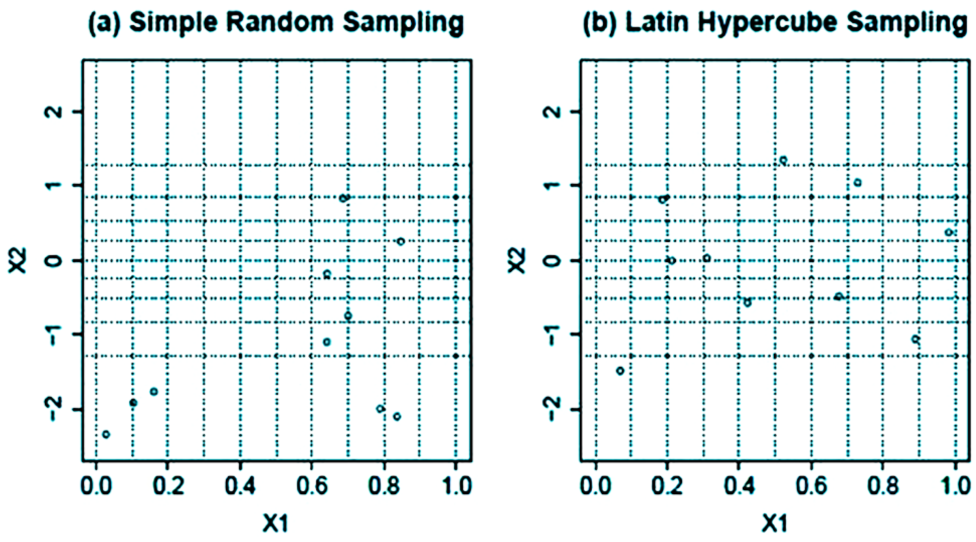

Figure 7. Comparison of the spread of sampling points in SRS & Latin Hypercube Sampling

(Source, Matthieu *et al.*, 2010).

3.2.1 Assembly of variables for input into CHLS algorithm

In this section environmental variable layers and operational cost layer were generated as input variables for the CHLS algorithm. Good expressions of soil forming factors in remote sensing data have been reported (Dobos *et al.*, 2000, Vagen *et al.*, 2013). Jenny's (1941) state equation for soil formation: S=f (cl, o, r, p, and t) clearly outlines the influence of each soil forming factor in the soil forming matrix. Climate (cl) is the surrogate of rainfall and temperature and influences the rate of soil forming processes like humification processes (McBratney *et al.*, 2003). Representatives of other soil forming factors and how they were generated are described below.

3.2.2 Calculating NDVI from LANDSAT 8 satellite image.

Organisms (O) were represented using Normalized Difference Vegetation index (NDVI) derived from Landsat 8 satellite imagery with a resolution of 30 m for dry season from row/path 168/60 from 15 September 2014. The NDVI is a Normalized Difference Vegetation Index which is the ratio of the near infrared (NIR) and red bands of multispectral image. NDVI is one of the most widely used multispectral indices and its suitable for vegetation monitoring because it takes care of changing illumination conditions, surface slope and aspect (Lillesand, 2004). NDVI value for water is < 0; bare soils between 0- 0.1 and vegetation over 0.1. Increase in the positive NDVI value means greener vegetation. NDVI is calculated as shown in equation 2.

$$NDVI = \frac{NIR_{band} - RED}{NIR_{band} + RED} \tag{2}$$

*Where NIR =Band 5, wavelength 0.64-0.67 μm and RED=Band 4 wavelength 0.85-0.88 μm and a resolution of 30*30m.*

NDVI values ranged from 0.09 to 0.5 (Figure 8.). Increase in the positive NDVI value means greener vegetation. The value of 0.09 would mean almost bare soil especially towards the semi-arid lower zones of the study area. The spatial distribution of the NDVI values reflect rainfall gradient that increases from east to west of Mt. Kenya region. This was also an important input variable representing vegetation/organism factor which is important for humification process and surrogate for soil organic matter.

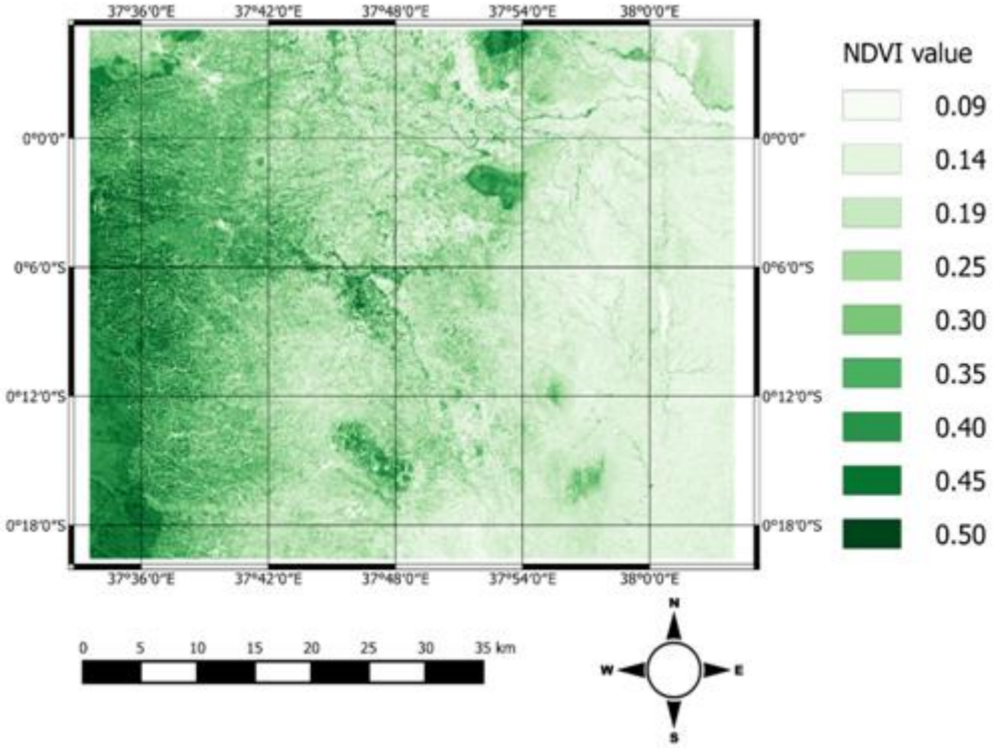

Figure 8. NDVI layer generated from Landsat 8 satellite imagery

3.2.3 Calculating terrain derivatives from DEM

Relief (*r*) was represented by terrain derivatives (slope and topographic wetness Index). These were calculated from Digital Elevation Model (DEM), Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) with a resolution of 30 m. SAGA GIS 2.0.6 was used to generate these terrain derivatives.

Topographic Wetness Index

The Topographic Wetness Index (TWI) is also called Compound Topographic Index (CTI). It is defined as a steady state wetness index which is a function of both the slope and the upstream contributing area per unit width orthogonal to the flow direction (Equation 3). It's also capable of predicting areas susceptible to saturated land surfaces and areas that carry the potential to produce overland flow.

$$TWI = ln\left({}^{A}/_{\tan\beta}\right) \tag{3}$$

Where A is the specific catchment area expressed as m^2 per unit width orthogonal to the flow direction, and β is the slope angle in radians (Gessler *et al.* 1995).

To create TWI grid from the DEM: go to SAGA GIS module > Terrain Analysis - Hydrology -> SAGA Wetness Index. The range of the TWI was 8.47 to 13.41(Figure 9.). TWI being a function of slope and the upstream contributing area perpendicular to the flow direction, it means that, the larger the value of TWI the higher the tendency of runoff. This fact has an important dimension on soil redistribution and soil water saturation in a landscape and therefore forms an important input variable into the CHLS algorithm.

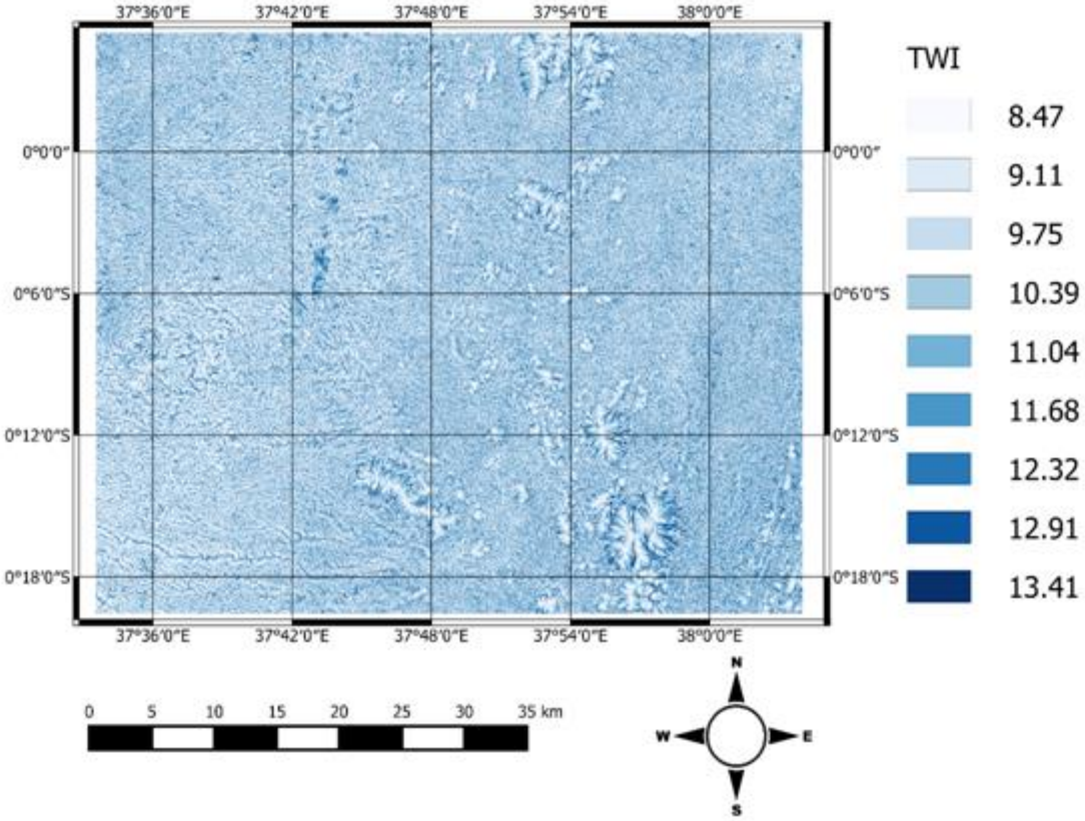

Figure 9. Topographic Wetness Index layer generated from DEM

Slope

For this study, slope was calculated as local slope around the pixel (Sorensen *et al.*, 2005). Slope shows the minimum, mean and maximum slope around the pixel. The slope function calculates the maximum rate of change from every cell to its neighbours. The function is calculated over a 3x3 set of cells and can provide the slope in angular degrees (0-90) or in percent, which is a measure of vertical rise over horizontal run. Local slope was generated from the DEM using SAGA GIS >Spatial Analyst tools > Surfaces > slope.

Slope percentage affects the amount of deposition or erosion of soil material and therefore an important input to the CHLS algorithm. A soil that is level is the most developed as there is no loss or gain of material to slow the soil forming processes. The slope for this study area ranged between 5% and 40% (Figure 10.).

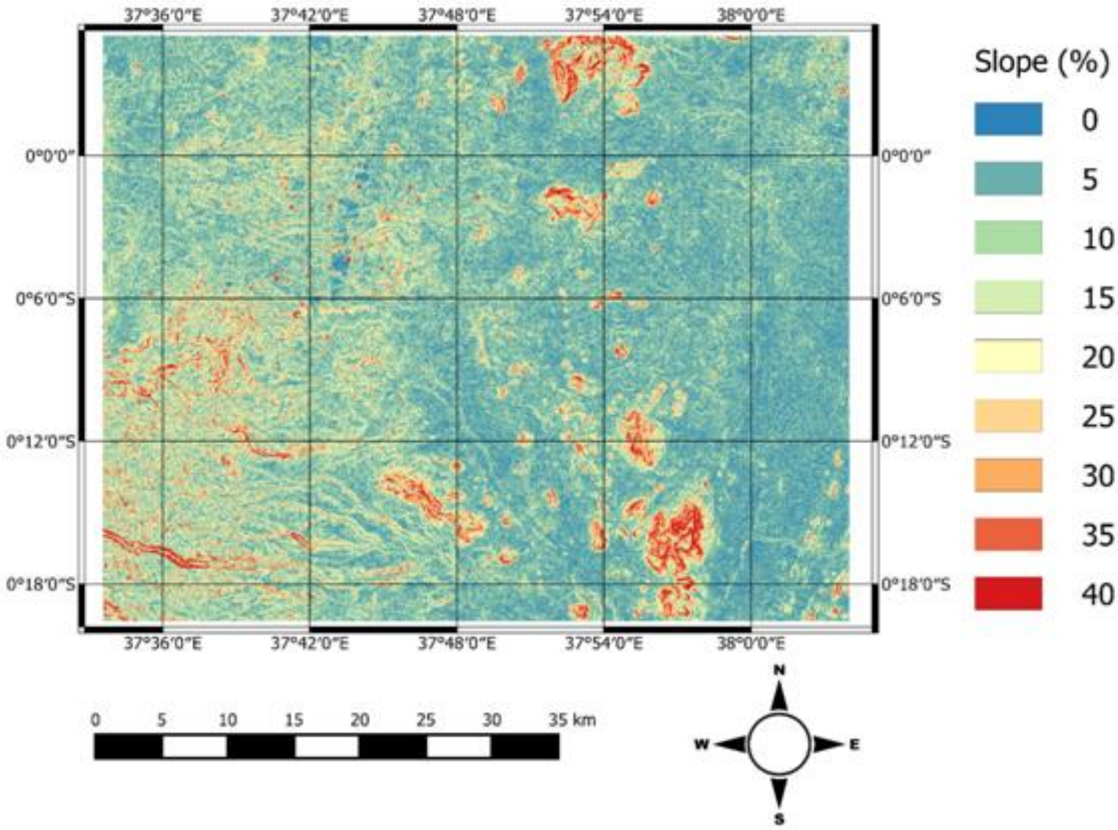

Figure 10. Slope percentage layer generated from DEM

3.2.4 Calculating the operational costs layer

From the practical point of view of a soil scientist, operational cost can usually be defined according to the question like: "how long it will take to reach every intended soil sampling point?" slope data and vectorized road map were used to generate a "friction map" that described areas relatively easier to traverse, areas relatively difficult traverse or inaccessible areas with impassable features. The 'ease of reach' was determined by generating an arbitrary 'cost of reach' layer. Distance from road network and slope percentage "*friction*" was integrated into a model of travel time and implemented using *r.walk* in GRASS GIS (Neteler *et al.,* 2012).The result of the friction map 'cost of reach layer' shows an arbitrary cost dependent on the distance from the road network (Figure 11.). This was an important input layer that aimed to ensure most of the sampling points were accessible at the least operational cost possible. Similar approach by Roudier *et al.* (2012) in Australia and Mulder *et al.* (2013) in Morocco reduced the working cost of soil survey significantly by identifying easy to reach points yet covering the sampling area more uniformly.

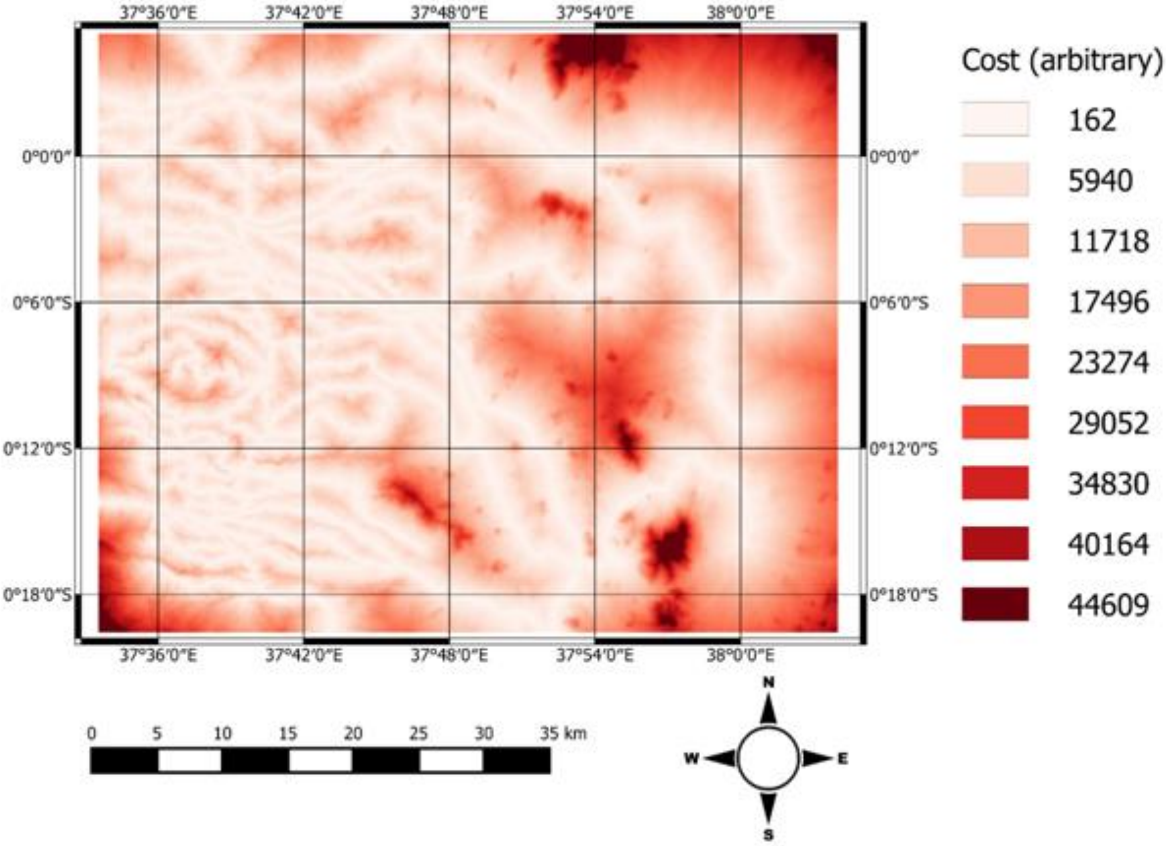

Figure 11. The cost of reach layer showing arbitrary cost units.

Figure 12. shows an example of bad weather road conditions that I had to walk through during the soil sampling campaign. This road is already difficult to traverse and even more difficult for sampling points away from such bad road network. This necessitated development of a 'cost of reach layer' to increase the chances of accessible sampling points.

Figure 12. Difficult weather roads during wet season (Photo by Mutuma, 2015)

KENSOTER soil units layer

Dominant soils of the polygons of the KENSOTER units (Dijkshoorn, 2007) were used as categorical data to ensure sampling was done in every dominant soil type. R 'CLHS' algorithm (R Core Team, 2013), and Quantum GIS processing were used to design the sampling frame.

Box plots were used for validation of the sampling scheme based on natural and sampled distribution of environmental variables. The spread of the sampling points in the study area (Figure 13.) satisfied the initial objective to preserve the natural distribution of environmental variables that were used as input layers for the CLHS algorithm. After evaluation of the sampling scheme I embarked on field work.

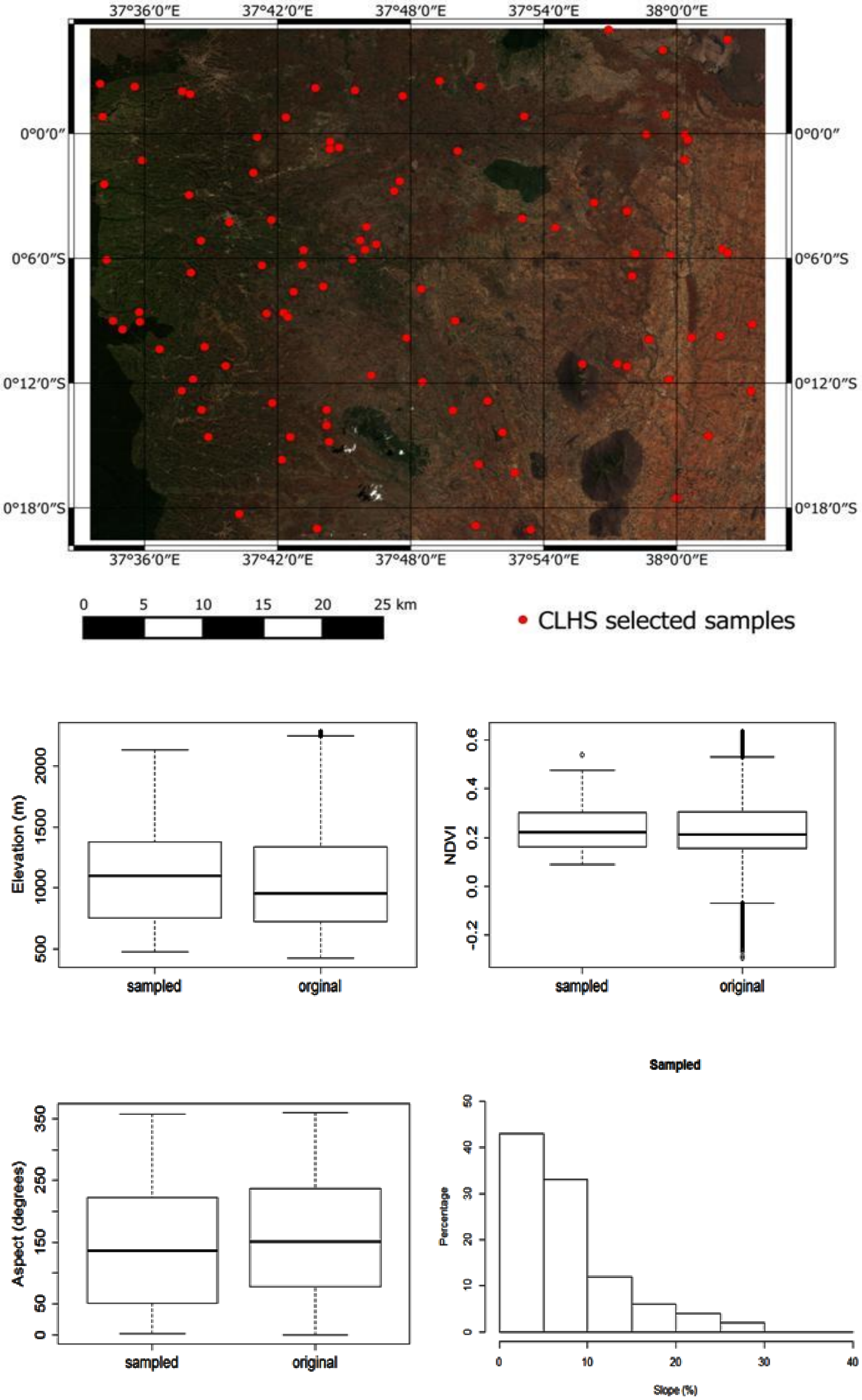

Figure 13. Comparison of the statistical distributions of the environmental covariates in the original GIS layers in selected sampling locations and sampled slope

3.3 Field work and soil description

The developed sampling plan guided the locations to be visited. The soil sampling campaign commenced on 5th December 2015 and ended on 15th Jan 2016. The field work tools included: a navigation Garmin GPS, Munsel color charts, pH meters, 10% hydrochloric acid, spade, soil augering equipment, plastic sampling bags, labelling pens and the FAO Soil Description Guideline (FAO, 2006) and WRB guidelines (IUSS Working Group WRB, 2015). On arrival at each sampling site the following preliminary information were recorded: GPS coordinates, location name and land use. The slope percentages were not recorded because they were already generated from the digital elevation models while developing the sampling plan. A total of 77 sampling sites were visited, out of this total, 28 were open profiles and 49 were augured profiles. The 28 open profiles were described based on genetic horizons. For each genetic horizon the following information was recorded: depth, pH, Munsell color, $CaCO_3$ and structure for each master horizon, also and presence or absence of coatings (i.e clay, iron, and manganese), volcanic glass and pressure surfaces in the relevant horizons. A preliminary definition of diagnostics and classification was performed based on the WRB 2015. Similar procedures were carried for the 49 augured profiles except for the depths of sampling which was based on 0-20 cm, 20-50 cm, 50-100 cm intervals. This choice of the sampling interval for this study was based on earlier sampling designs in Mount Kenya region (Gicheru & Kiome, 2000). All together a total of 269 soil samples were collected. Appendix 1 and 2 shows the data that was generated.

3.4 Laboratory soil measurements

This section explains methods used for analysing soil samples in the laboratory.

The laboratory measurements were performed for supporting my objectives related to prediction of soil properties and also the objectives related to soil classification. The section consists of two subsections for: (i) infrared measurements, and (ii) conventional measurements using wet chemistry methods. Sample pre-processing before analysis is explained.

3.4.1 Mid-infrared (MIR) spectral-reflectance measurements

The pre-processing of the total 269 samples involved air drying, crushing and sieving using a 2 mm sieve, further crushing (< 100 μm) using agate pestle and mortal. Loading into A 752-96, Bruker Optics, Karlsruhe aluminium micro titer plates with wells measuring 6-mm diameter was done into four replications. MIR soil spectra measurements for the 269 samples were performed using a Fourier-transform MIR spectrometer-FTIR. Tensor 27. Liquid N_2–cooled HgCdTe detector was used. Sample variability and differences in particle size and packing density were solved by averaging the four replicates. This work was performed at the soil-plant spectra laboratory of the World Agroforestry Centre (ICRAF) in Nairobi, Kenya. The first derivative of the reflectance spectra was computed based on Savitzky–Golay smoothing filters (Wand & Ripley, 2008). Figure 14. shows the absorbance spectra for all the 269 soil samples before (noisy spectra) and after pre-processing to 4000-400 cm^{-1}.

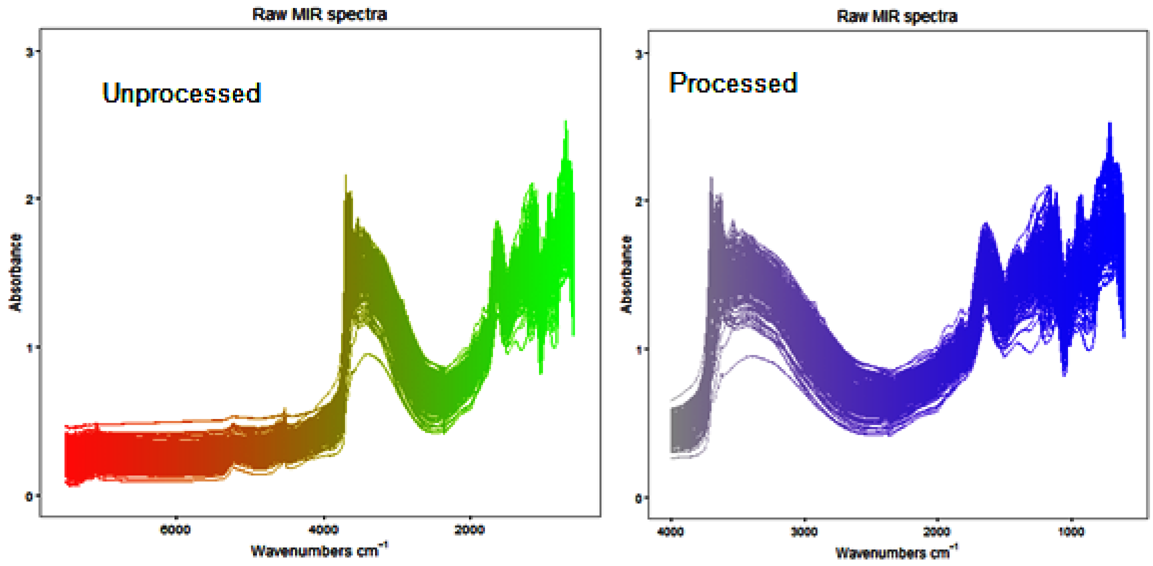

Figure 14. Unprocessed and processed MIR absorbance spectra to 4000-400 cm^{-1}

3.4.2 Calibration sample selection

Selection of calibration samples with normal distribution were avoided because results of subsequent analysis degenerate towards the mean. Kennard-Stone algorithm (Kennard & Stone, 1969) was a solution because it ensures that the selected calibration samples are uniformly distributed by choosing the samples that maximize the Euclidean distances between each other. This aspect complimented well with our sampling design (CLHS) that ensured the full range of sampling area was uniformly covered. Principal Component Analysis (PCA) that was computed on reflectance spectral matrix further reduced data overlap. The results of sample selection (Figure 15.) could explain 75.6% of the variations and the next step was to perform laboratory analysis of the calibration sample set as described in section 3.4.3. Out of the 269 samples, only 30 with tolerance of 2 were selected the tedious laboratory analysis.

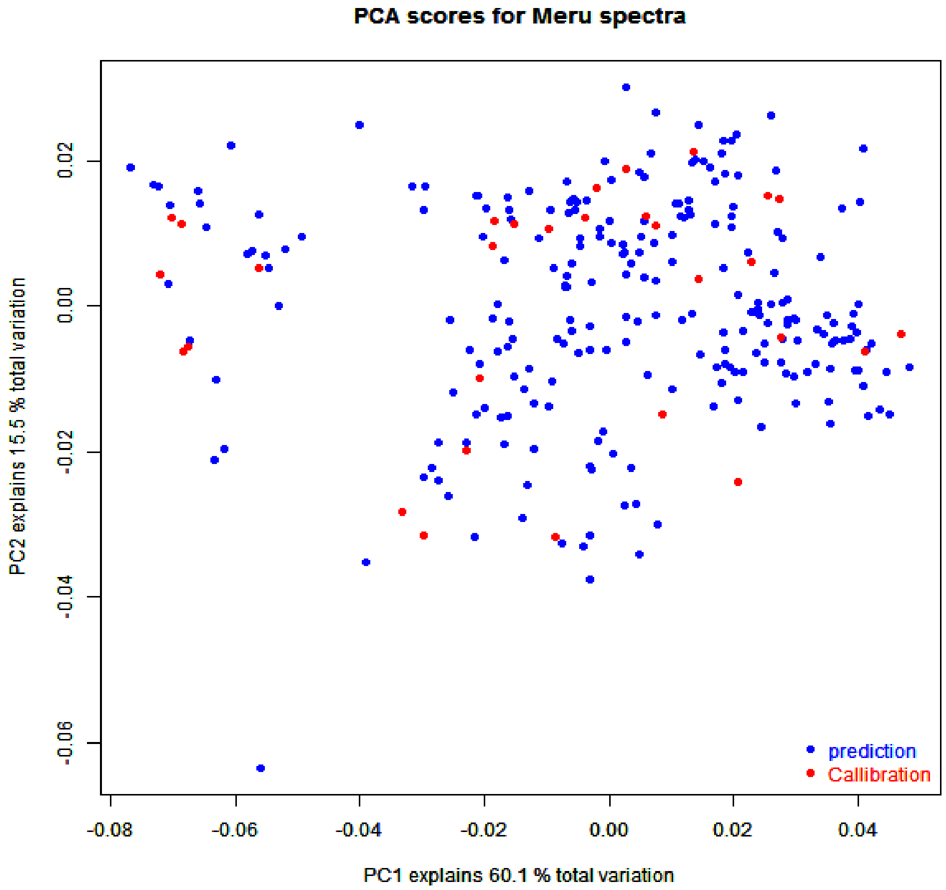

Figure 15. PCA for sample selection explains 75.6% of variations.

3.4.3 Soil analysis for the calibration samples

First all soil samples were air-dried then large clods were crushed and sieved using a 2 mm sieve. The samples were analysed for the following parameters with the respective methods following the recommendations of Van Reeuwijk, 2002.

- pH –potentiometrically measured in the supernatant suspension of a 1:2.5 soil: liquid (H_2O) mixture.
- Cation Exchange Capacity (CEC)-Ammonium acetate method (Van Reeuwijk, 2002)
- Na, K, Ca, Mg and Al following Mehlich 3 extraction (Mehlich, 1984).
- Soil organic Carbon (SOC) and total nitrogen (TN) following thermal oxidation (Skjemstad & Baldock, 2008)
- Particle size distribution (PSD) using Laser Diffraction Particle Size Analyzer (LDPSA).
- Free iron ($Fe_{dithionite}$) was analysed using the Holmgren procedure (Van Reeuwijk, 2002) and Active iron ($Fe_{oxalate}$) using acid ammonium oxalate solution (Van Reeuwijk, 2002).

The ($Fe_{dithionite}$) and ($Fe_{oxalate}$) were measured only for 5 selected samples from those that qualified the nitic horizon morphological characteristics (Appendix 3).

3.4.4 Calibration of LDPSA using pipette method

Conventionally, the PSD of soils is measured using sieve-sedimentation method (SSM). The sand fraction is separated first then a suspension is prepared from the finer fractions. After thorough mixing, the suspension is left for sedimentation. There are two major sedimentation based measurement methods: (1) Measuring the density of suspension using hydrometer (Molinaroli *et al.*, 2011) and (2) Use of pipette to measure dry mass of a sample at a given height in a cylinder (Kuznetsova & Motenko, 2014).

The LD method is based on measurements of the intensity of laser light scattered by high speed particles passing through a measuring cell; the smaller the particle, the larger the scatter angle. Mie or Fraunhofer approximation theory (Ma *et al.*, 2001) is used to convert the light intensity to a PSD. Fraunhofer approximation is inappropriate for soil particles because its utility is limited for particles with a smaller wavelength than 0.05mm (International Organization of Standardization, 2009b). As a result, Mie theory is used to overcome the Fraunhofer approximation inability. Mie theory describes the scattering of light at a specific angle and intensity relative to an incident laser beam as it illuminates a particle. Multiple particles illuminated at the same time provide a light pattern representative of the summation of all the contributions of intensity by each particle at each angle (Ma *et al.*, 2001). A study by Eshel *et al.* (2004), comparing PSD results of LDPA with pipette analysis reports an overestimation by LDPSA of the clay particles for samples of milled quartz as compared to the pipette method. Conversely, Loizeau *et al.* (1994) reported an underestimate of the clay particle fraction with an efficiency of detection of 36% to 70% proportional to the clay content resulting from pipette analysis. Additionally, Eshel *et al.* (2004) state that LD reports an underestimate of the clay fraction in 40 out of 42 samples when compared to pipette analysis. In this regard, Pipette method was superior but tedious and slow for measurement of large number of samples like in the case of this study.

3.4.5 X-Ray Diffraction (XRD)

XRD was performed to support soil classification (Appendix 3.). A total of 10 samples were selected based on the preliminary soil classification and soil color at the depth interval of 20-50 cm (to minimise the effects of organic matter in the surface horizon and also the effects of the parent material in the lower depths). XRD analysis was carried out to support the classification decisions, especially in case of soils with characteristic nitic horizons morphology. Mineral composition of selected soil samples was determined by X-ray powder diffraction (XRD) analysis at the Hungarian Academy of Sciences Institute of Geological and Geochemical Research. The equipment used was Rigaku Miniflex 600 diffractometer equipped with a graphite monochromator using Cu-Kα radiation at 45 kV and 35 mA with 1° divergence slit and 1° receiving slit. Scanning rate was 0,05°2Θ per minute from 3° to 70°. Rietveld refinement method of Siroquant V4.0 software quantified the mineral constituents of the selected soil samples.

The results of sampling scheme, the fieldwork, and MIR spectroscopic analysis provided input data for mapping and soil classification.

3.5 Mapping of soil properties

To allow estimation of soil properties at the unvisited locations, geostatistical approaches were used for spatial prediction. To decide the choice of the mapping method, the correlation between selected soil properties and the explanatory variables was analysed. Then the data was analysed for spatial autocorrelation. The selected soil properties were not significantly correlated with the input explanatory variables (Table 1.). The variables showed spatial autocorrelation using nugget to sill ratio (Table 2.). Based on the results of Table 1 and Table 2, Ordinary Kriging (OK) was selected as the appropriate method for the spatial prediction. These results (Table 2. and Table 3.) are presented in this chapter because they form part of the procedures that informed the selection of the mapping method.

10.14751/SZIE.2017.065

Table 1. Explanatory variables were not significantly correlated with test soil variables

Variables	TWI	SLOPE	NDVI	TN (%)	SOC (%)	P(mg/ kg)	pH H_2O
TWI	**1**						
SLOPE	**-0.492**	**1**					
NDVI	-0.117	**0.240**	**1**				
TN (%)	-0.024	0.110	-0.001	**1**			
SOC (%)	-0.021	0.117	-0.011	**0.980**	**1**		
P(mg/ kg)	-0.069	0.150	-0.107	**0.202**	**0.220**	**1**	
pH H_2O	0.060	-0.189	-0.308	**-0.413**	**-0.375**	**-0.239**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Table 2. Semivariogram parameters for the selected spherical model show moderate spatial dependence.

Soil property N=232	Model	Nugget Variance(C_0)	Sill variance (C_1)	Nugget/sill ratio C_0/ C_1	Range (Meters)	Remarks
SOC (%)	Spherical	0.098	0.21	0.46	13576	M
TN (%)	Spherical	0. 556	0.9	0.61	13737	M
Ph H2O	Spherical	0.226	0.72	0.31	2142	M
Extractable P (mg/kg)	Spherical	2.31	3.7	0.62	12590	M

M= Moderate spatial dependence, N= number of samples

3.5.1 Evaluation of the spatial structure of the data using semivariograms

Ordinary Kriging approach uses semivariogram to express spatial continuity of data (spatial autocorrelation).

Kriging estimate $z^*(x_o)$ was calculated as follows (Equation 4):

$$z^* \ (x_0) = \sum_{i=1}^{n} w_i \ z(x_i) \tag{4}$$

Where W_i is the weight and (x_0, x_i) are the corresponding distances (Agrawal *et al.*, 1995).

Semivariograms are useful for measuring data correlation as a function of distance. They evaluate the spatial structure of data. The common theoretical variogram models are outlined by Webster & Oliver (2001). The nugget is the value of the semivariogram as distance (h) approaches zero. The nugget effect is due to error in measurement, spatial variation that occurs within the sampling distance interval, and random events. Four parameters: range, sill, nugget and nugget to sill ratio are used to interpret a semivariogram. Range is defined by the distance beyond which data autocorrelation no longer exists. Sill is the value of the semivariogram beyond which no spatial dependence of data is exhibited.

A semivariogram is expressed as follows (Nielsen & Wendroth, 2003):

$$S(H) = \frac{1}{2N(H)} \sum_{i=1}^{N(H)} [Z(x_i) - Z(x_i + H)]^2 \tag{5}$$

S(H) is the semivariance, *N(H)* is the number of pairs of locations separated by a lag distance *H*, *h* is the lag distance, *Z* is the parameter of the soil properties, $Z(x_i)$, and $Z\ (x_i + H)$ are values of *Z* at positions x_i and $x_i + H$.

Spatial data dependence is defined by its Nugget to sill ratio. Three classifications of spatial dependence of data based on the nugget/sill ratios are described by Zuo *et al.* (2008). A nugget to sill ratio of < 25% means strong dependence, a proportion between 25% and 75% indicates a moderate spatial dependence and > 75% often signify weak spatial dependency of data. Usually high nugget to sill ratio is an indication that the spatial variability of data is not strongly influenced by the natural factors but rather by stochastic factors like land management practices. Low ratios of nugget to sill suggest that structural factors like soil forming factors influence spatial variability of data.

Two concerns are important in the analysis of semivariograms

1. Fitting the semivariogram to the experimental data requires careful choice of the total lag distance. This was addressed by setting conditions such that selection of the separation distance involved 95% pairs to fit the semivariogram model.

2. The choice of appropriate model to fit to the experimental semivariogram data is also a big concern. Spherical model was selected compared to exponential and Gaussian models based on analysis of our data (Table 2.).

3.6 Soil Classification

Soil classification systems help to identify differences among and between soils and their environments (Soil Survey Staff, 1999). Different classification systems have been applied. For example, Sanchez *et al.* (2003) used fertility capability classification system to help assess soil quality in the tropical Africa. Numerical approach to soil classification is evident following advances of computer aided techniques and multivariate statistics (Hughes *et al.*, 2014). Increasingly, use of soil classification in journals has been discussed by Hartemink, (2015). In this study the World Reference Base of soil resources (WRB) classification system (IUSS Working Group WRB, 2015) was applied to characterize and classify soils of the visited sites. The WRB is based on a diagnostic approach defined in terms of diagnostic horizons, diagnostic properties and materials, that are measurable to the greatest extent possible and observable in the field. On the highest level 32 reference soil groups (RSG) are defined by the classification key based on the presence/absence of combination of the diagnostics. Additional qualifiers are giving are added to the RSG name to provide further information on important soil properties.

3.6.1 Data analysis

Exploratory data analysis was performed using descriptive statistics and data normality testing using Shapiro-Wilk test at 5% significant level. Multiple pairwise comparisons using Dunn's procedure (Dunn's, 1964) was used to compare variability of soil properties in different WRB reference soil groups. Kennard- Stone algorithm (Kennard & Stone 1964) and Principal Component Analysis were used in the selection of calibration and prediction sample sets. Discriminant analysis (Carroll *et al.* 2006) was used to evaluate contribution of each soil property in the classification of reference soil groups. Random Forest (RF) Regression was used for the calibration of spectra data using the laboratory measurements of the calibration sample set. The utility of RF for regression and classification is described by Gislason *et al*. (2006). Cross validation was performed to evaluate the model performance based on the variations between the observed and the predicted values of soil properties. This was determined using coefficient of determination (r^2), the Mean Error (ME), Root Mean Square Error (RMSE) and the Standardized Root Mean Square Error (SRMSE) using equations (6), (7) and (8) respectively.

$$ME = 1/n \sum_{i=1}^{n} (Obs_i - Pred_i) \tag{6}$$

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (Obs_i - Pred_i)^2} \tag{7}$$

$$SRME = \sqrt{1/n \sum_{i=1}^{n} (Obs_i - Pred_i)/Pred\ var_i} \tag{8}$$

Where n is the sample size, Obs_i is observed values and $Pred_i$ is modelled values at place i. $Pred_{var}$ is the variance of the prediction. The best model is one that has ME nearest zero, the smallest RMSE and SRME nearest to 1. For good predictive model the RMSE values should be low (<0.3).

3.7 Summary of the research methodology

The first step of this study was to develop a sampling scheme that could capture as much as possible the variability of the soil types and soil properties in the area of study. Variability of soil types reflects the natural distribution of soil forming factors and the soil forming processes. It is for this reason that I sought to develop a sampling scheme that would preserved the natural distribution of the continuous and categorical soil forming factors.

The first step was to assemble the ancillary data for use in the sampling design process. The choice was based on Jenny’s (1941) state equation of soil formation.

Continuous variables

- Normalized Difference vegetation Index layer generated from Landsat 5 satellite image
- Terrain attributes layers (Aspect, Elevation, Slope and Topographic Wetness index) generated from the Digital Elevation Model.

Categorical variables

- Parent material layer (geology of the area) generated from a digitized ISRIC document of the study area.
- KENSOTER soil units layer (to make sure all polygons were visited during the soil sampling activity.
- The ancillary data formed the input layers for the conditional Latin Hypercube objective function equation in R programming platform and the result was visualized using GIS interface.
- The sampling plan was evaluated to check if it conformed to the natural distribution of the selected ancillary data using box plots.

The second step was field work and soil description. The field work was guided by the already developed sampling plan/scheme. Soil description was guided by the FAO 2006 guidelines for soil description. A total of 77 profiles were targeted with 28 open profiles, 2 in each KENSOTER polygon and 44 auguring distributed accordingly based on the designed sampling plan.

The third step was sample pre-processing and MIR spectra measurements for all the samples. Sample selection to identify the calibration and prediction set and laboratory chemical analysis of the calibration set samples

The fourth step was multivariate quantification of soil properties from MIR spectra using Random forest regression and the results of chemical laboratory analysis (calibration sample set). Validation of the results was done to check the accuracy of predictions using the coefficient of determination (r^2) and root mean square error (RMSE).

The fifth step was to develop a spatial distribution using geostatistical techniques. The process Involved selecting the model and selecting a semivariogram to use for the model.

The sixth and final step was soil classification using the WRB classification system. The quantified soil properties and the field observations were used during the classification. Variability of soil properties in different WRB reference soil groups were analysed using Dunn's pairwise comparison method.

Below (Figure 16.) is the schematic representation summarising the methodology.

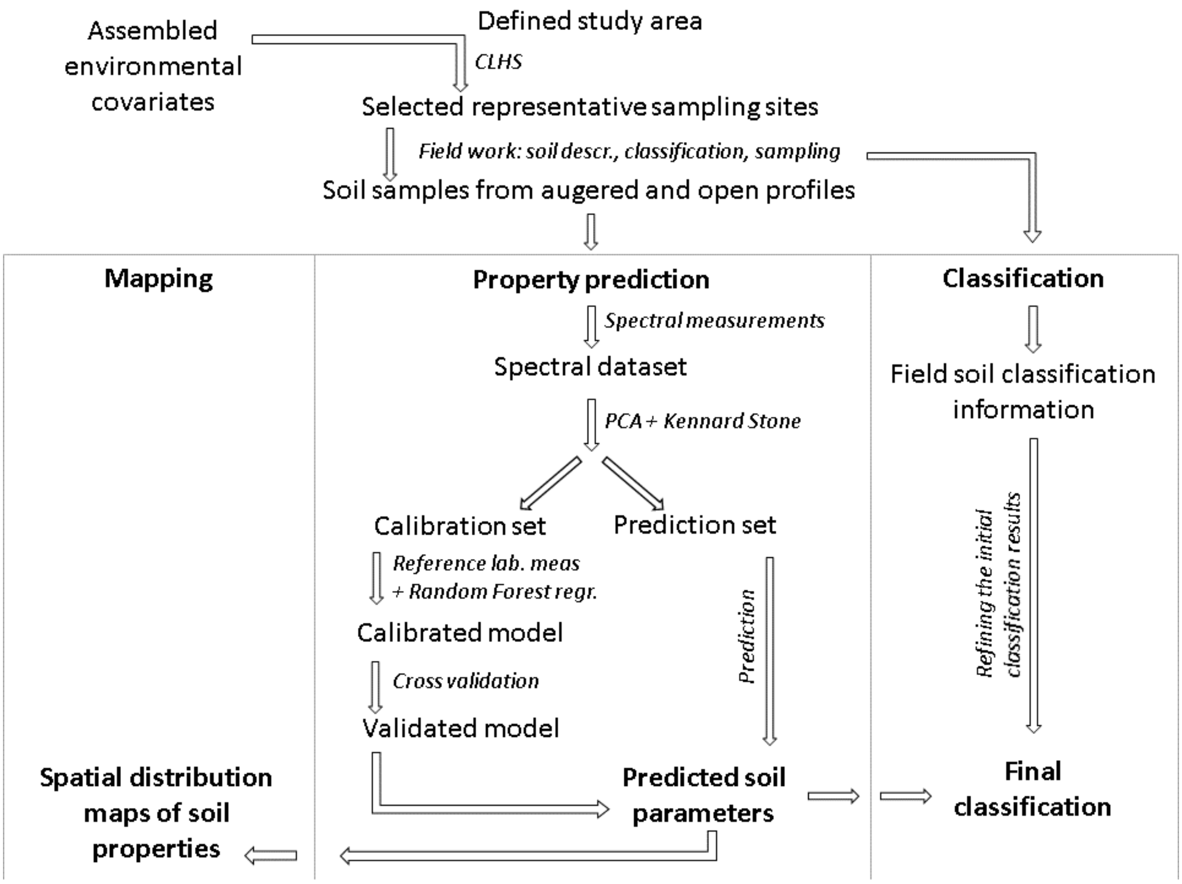

Figure 16. Methodology flowchart summarising this research work

4. RESULTS AND DISCUSSIONS

4.1 Accuracy of soil property predictions

In this section the accuracy of the soil properties predictions is presented (Table 3.) and discussed. The model performance was excellent when r^2>0.90, good when 0.81<r^2<0.90, moderately successful when 0.66<r^2<0.80 and unsuccessful when 0.50<r^2<0.65. This classification was adopted from Saeys *et al.* (2005).

Table 3: Validation results of soil properties predictions

Soil property	Coefficient of determination r^2	Root mean Square error (RMSE)
SOC (%)	0.78	1.64
pH H_2O	0.88	0.63
Exc Na cmol/kg	0.93	1.45
Exc Mg cmol/kg	0.88	1.60
Exc K cmol/kg	0.92	2.32
Exc Ca cmol/kg	0.92	189
Exc Al cmol/kg	0.85	71.25
Ext P mg/kg	0.78	0.51
Clay (%)	0.59	9.9
Silt (%)	0.63	7.3

Moderately successful predictions were achieved for SOC % at r^2=0.78 and RMSE=1.64 (Figure 17.). Comparable accuracy (r^2=0.77 and RMSE=1.64) for SOC has been reported by Terhoeven-Urselmans *et al.* (2010). But my coefficient of determination (r^2) was better. This can be associated to the use of different calibration statistics as the sample size and all other methods were similar. Terhoeven-Urselmans *et al.* (2010) used partial least squares regression (PLS) as the calibrating statistics while in my study I used random forest regression (RF) was used to calibrate the soil MIR spectra. This may be the source of the prediction accuracy differences. Higher accuracy of SOC prediction (r^2 = 0.96) was achieved by McDowell *et al.* (2012), this may be attributed to high and wide range of SOC (%) of the calibration set (0.24 to 55.29%) compared to narrower SOC range (0.56 to 10.83%) in my soil samples.

The accuracy for the calibration of pH was good (r^2 = 0.88 and RMSE = 0.48) and better in terms of r^2 and RMSE compared to those achieved by Terhoeven-Urselmans *et al.* (2010) (r^2 = 0.81, RMSE = 0.63) and Shepherd & Walsh (2002) (r^2 = 0.83, RMSE = 0.54) while analysing a spectral library of soils from Africa.

Calibrations for Mehlich extraction of Na, Mg, K and Ca were excellent (r^2=0.93 and RMSE=1.45; r^2=0.88 and RMSE=1.60; r^2=0.92 and RMSE=2.32 and r^2=0.92 and RMSE=189.16 respectively. The prediction of Ca was better than that of Sila *et al.* (2016) who reported r^2=0.91 for Ca. Again this could be associated with the efficiency of RF, a multivariate statistic that was used for the calibration of soil MIR spectra. The high RMSE values especially for Ca can be attributed to under prediction by MIR due to low calcium content in all my sampling locations. Calibration of Mehlich extraction of Al was good (r^2=0.85 and RMSE=0.51).Calibration of P was satisfactory (r^2=0.78 and RMSE=71.25).

Calibration for clay (r^2 = 0.59 and RMSE = 9.9); Silt (r^2 = 0.63 and RMSE = 7.3) were low compared to other soil properties. The low calibration accuracy for sand (r^2= 0.30 and RMSE=5) was because the soil samples were mainly clay dominated due to extreme weathering resulting in poor MIR absorbance. The percentage sand was calculated from of the cumulative percentages of clay and silt.

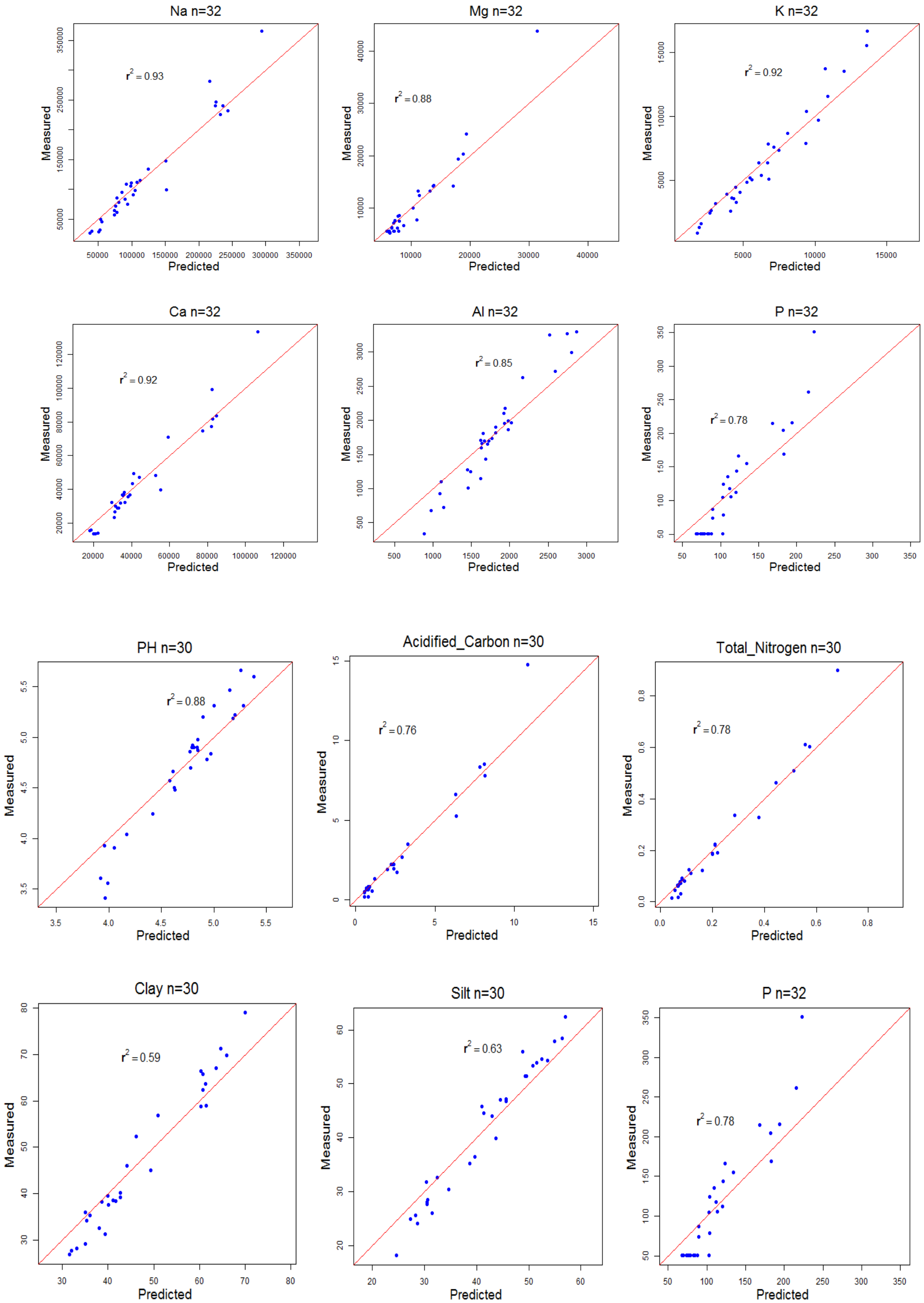

Figure 17. Linear regression of observed against predicted soil properties

4.2 Spatial interpolation of soil properties

SOC, TN, pH and P were selected for spatial interpolation because they present important agronomic soil properties that can be restored through good soil management practices. Moderate spatial dependence was exhibited by all the soil properties (Table 2.). Spherical model and OK resulted in spatial distribution maps (Figure 18.).

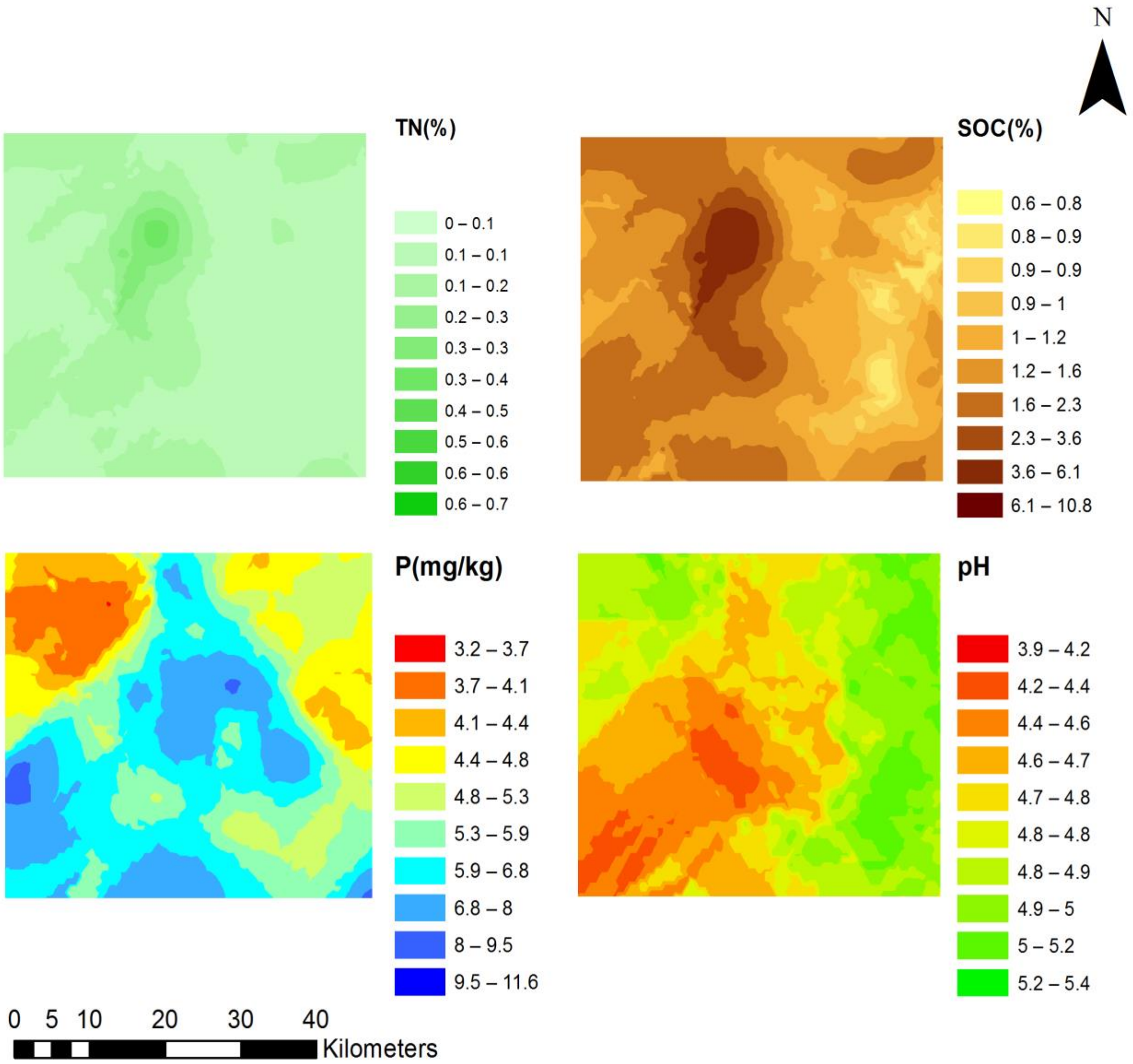

Figure 18. Maps of predicted spatial distribution of soil properties

The performance of spatial prediction for TN and pH was satisfactory based on the cross validation results (Table 4.). Low accuracy was registered for P (RMSE=1.1). Soil type data layers and land management practices were not used as explanatory variables during the prediction process yet they influence P availability. Inventories for land management practices were unfortunately not available and soil type data layers are only available in the KENSOTER database with limitations highlighted earlier.

Important trends are visible from the spatial distribution of soil properties. The region with high SOC contents coincides with the region with very low pH values. The low pH values are a result of intense leaching caused by heavy rainfall in this humid high altitude part of the study area. The soil type in humid, high altitude is dominated by Umbrisols (by default Umbrisols are Dystric and have high organic matter). Low pH slows down the activity of microbes responsible for mineralisation of SOC resulting in its stabilization and accumulation. Litter from the tea plantations provide input material for humification.

The trend for TN is similar to that of SOC because this is mainly organic nitrogen from soil organic matter. Therefore areas with high TN coincide with areas with high SOC. Fertilization using NPK resulted in high nitrogen in tea plantations.

The trends for P are determined by soil types, rainfall intensity and management. High P values in the middle zone of the study area can be associated with tea plantations due to addition of NPK fertilizers, mineralization of SOC resulting in addition of organic phosphorus and less P fixation by the dominant soil types in this section of the study which were Umbrisols and Nitisols. Towards the far east of the study P increase as the pH increase due to less reaching occasioned by decreasing rainfall amounts towards the east.

Table 4. Cross validation results of the prediction model.

Soil property	**ME**	**RMSE**	**SRMSE**
SOC (%)	0.001	0.81	0.76
TN (%)	0.0002	0.06	0.96
pH	-0.0006	0.13	0.98
P (mg/kg)	0.006	1.11	0.77

ME=Mean error, RMSE=Root Mean Square Error, SRMSE=Standardized Root Mean Square Error.

Prediction of SOC (RMSE=0.81) was not as accurate compared to results by Wen *et al.*(2015). Based on Zuo *et al.* (2008) earlier mentioned guidelines for classifying spatial structure of data, a nugget to sill ratio of 0.46 (Table 2.) for SOC means a moderate spatial dependency of data. According to Kravchenko *et al.* (2006a), strong dependency of spatial data is a prerequisite for good performance of a spatial prediction model. Kravchenko *et al.* (2006a) reported strong spatial structure of data for SOC. But in his research samples were collected only 100 m apart. In our study the total sampling area was 1200 km^2 and sampling distance was > 100 m. Differences in sampling distance affect the strength of association of soil properties between the sampling points and ultimately influence the spatial structure of data. Land management practices influence the spatial structure of SOC data (Kravchenko *et al.*, 2006a). Different land use practices were evident during the soil sampling campaign and these have strong influence on soil properties like SOC. Those areas with tea plantations had better nutrient management practices than in the areas on subsistence food crop farming. Absence of land management explanatory variables as an input to the model might have weakened our model for SOC spatial distribution prediction.

Table 5. Statistics of predicted soil properties

Variable	**Min**	**Max**	**Mean**	**STD**	**CV**	**Skewness**	**Shapiro-Wilk test**
TN (g/kg)	0.41	6.8	1.64	1.28	0.78	1.88	< 0.0001
SOC (g/kg)	3.60	57.2	10.34	7.57	0.73	3.49	< 0.0001
Clay (%)	36.37	58.71	46.26	3.04	0.07	0.43	< 0.0001
Silt (%)	32.64	52.42	42.35	2.69	0.06	0.18	0.002
Sand (%)	7.66	16.17	12.09	1.54	0.12	0.34	0.002
P (mg/kg)	3.15	11.63	5.82	1.88	0.32	0.87	< 0.0001
K (cmol/kg)	1.19	1.88	1.59	0.14	0.09	-0.56	0.000
Ca (cmol/kg)	5.32	18.09	8.03	1.44	0.18	1.98	< 0.0001
Mg (cmol/kg)	2.70	5.89	4.34	0.51	0.117	-0.265	0.174
Al (cmol/kg)	3.17	5.39	4.08	0.51	0.12	0.27	< 0.0001
Al (%)	42.9	73.1	55.0	6.87	0.12	0.26	< 0.0001
Na (cmol/kg)	0.07	0.17	0.13	0.02	0.13	-0.65	< 0.0001
pH H_2O	3.9	5.3	4.7	0.2	0.05	-0.5	

4.3 Inferences for management from predicted soil properties

The results of this study show the soils were acidic with pH range of 3.9 - 5.3 (Table 5.). The causes and effects of acidification on soils are well explained by Goulding (2016). Spatial distribution of pH values (low to high values) shows a west- east tendency (Figure 18.). High rainfall events in high altitudes in the west result in high leaching and extremely low pH. The spatial distribution map shows that areas with Andosol Reference soil group were associated with extreme low pH except within the tea management areas.

Strong soil acidity in Kenya has been associated with high leaching as a result of heavy rainfall amount, high aluminium (Al^{3+}) ions, H^+, iron (Fe) and manganese (Mn) saturation (Opala *et al.*, 2010). The soil pH affects the bioavailability of plant nutrients and so indirectly, crop plant growth. Low pH conditions reduce base saturation by replacing (Ca^{2+}, Mg^{2+}, K^+ and Na^+) from exchange sites with H^+ and Al^{3+} ions. Al^{3+} ions > 2.0 $cmol_c$ /kg are considered toxic for many crops (Landon, 1984) while % Al saturation > 20% cannot be tolerated by most maize (*Zea mays*) germplasm in Kenya (Opala *et al.*, 2010).

There was no clear spatial tendency of P (Figure 18). The range for P (Table 5.) was 3.15 mg/kg and 11.63 mg/kg, where 43.7% of total samples did not meet the threshold of 5mg/kg (Okalebo *et al.,* 2006). The high phosphate retention may be due to the existence of andic material occasioned by presence of Andosol reference soil groups in higher altitudes.

There was a west-east tendency of SOC and TN distribution in the study area (Figure 18.). Land management had significant contribution to the variations of SOC and TN with highest values in tea plantations. The minimum and maximum values were 3.6 g/kg and 57.2 g/kg (Table 5.) and 93.07% did not meet the threshold of 20 g/kg using the assessment of Loveland & Webb (2003). TN results show a minimum 0.4 g/kg and Max 6.8 g/kg but only 15% of the total sampling area met the threshold of 2.0 g/kg based on suggestions from Ndakidemi & Semoka (2006).

In general for all the soil observations, the textural classes were mainly clay, silt clay and silty clay loam. The ratio of sand in all the observations was less than 20 % while clay and silt were 36-58 % and 32-52% respectively as shown in the ternary diagram (Figure 19.).

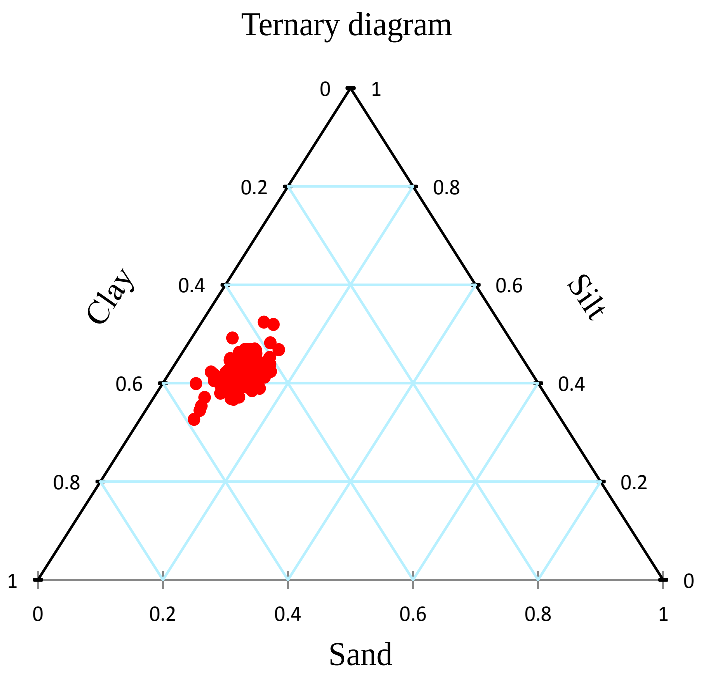

Figure 19. Ternary diagram for particle size distribution of the samples

4.4 Results of soil classification

The detailed results of soil classification show high variability of soil types in the study area (Appendix 1.). Figure 20 shows the most common diagnostic horizons that were identified. The Umbric horizon is a surface horizon which is relatively thick, dark-coloured with low base saturation and moderate to high content of organic matter Cambic horizon is a sub-surface horizon showing evidence of pedogenetic alteration from weak to moderate. Mollic horizon just like the Umbric horizon is a surface horizon that is relatively thick, dark coloured but the different is that it has a high base saturation unlike the Umbric horizon. An Argic horizon is a subsurface horizon with distinctly higher clay content than the overlying horizon, either caused by illuvial accumulation of clay, predominant pedogenetic formation of clay, selective surface erosion of clay, upward movement of coarser particles due to swelling and shrinking, biological activity or a combination of two or more of these processes. Plinthic horizon is a subsurface horizon that is rich in Fe (in some cases also Mn) oxides or hydroxides. This is caused by repeated wetting and drying that result in irreversibly hard concretions or nodules (IUSS Working Group WRB, 2015).

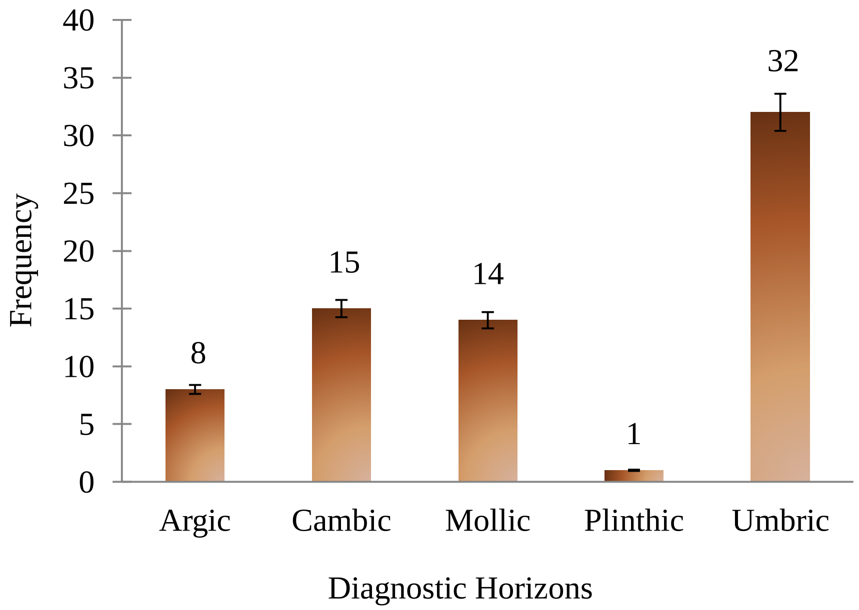

Figure 20. The frequency of the identified diagnostic horizons

The distribution of eight reference soil groups based on the identified diagnostic horizons was: Umbrisols > Cambisols >Andosols > Alisols > Phaeozems > Plinthsols > Regosols > Leptosols (Figure 21.). Umbrisols were characterised because of the presence of umbric horizon, Cambisols because of the presence of cambic horizon, Andosols were characterised on the basis of andic or/and vitric properties often in combination with the presence of a mollic or umbric horizons. Phaeozems were characterised on the basis of having a mollic horizon and high base throughout. Alisols are soils with argic horizon with low base saturation. Plinthosols were characterised on the basis of having a plinthic horizon. Leptosols are shallow soils with hard rock or coarse fragments close to surface, while Regosols are very weakly developed mineral soils in unconsolidated materials (IUSS Working Group WRB, 2015).

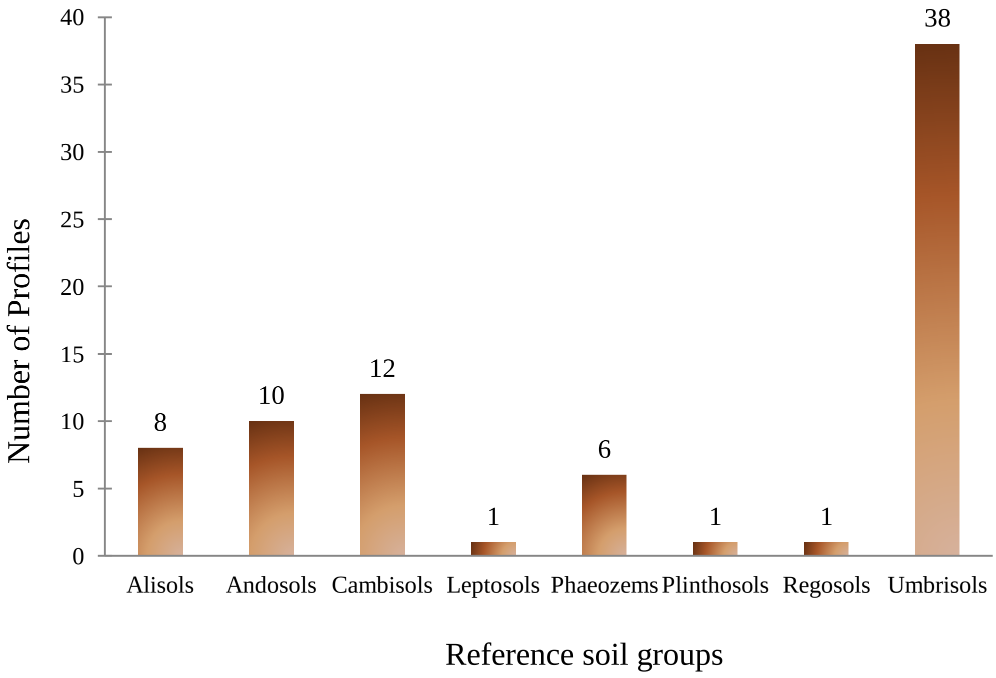

Figure 21. Representation of classified reference soil groups for the 77 soil profiles.

The qulifiers identified for the studied soils are presented in Figure 22. Identification of all applying qualifiers is very important as they provide information that is added to the reference soil groups (either as principal or supplimentary). They give very specific information that can support soil resource management.

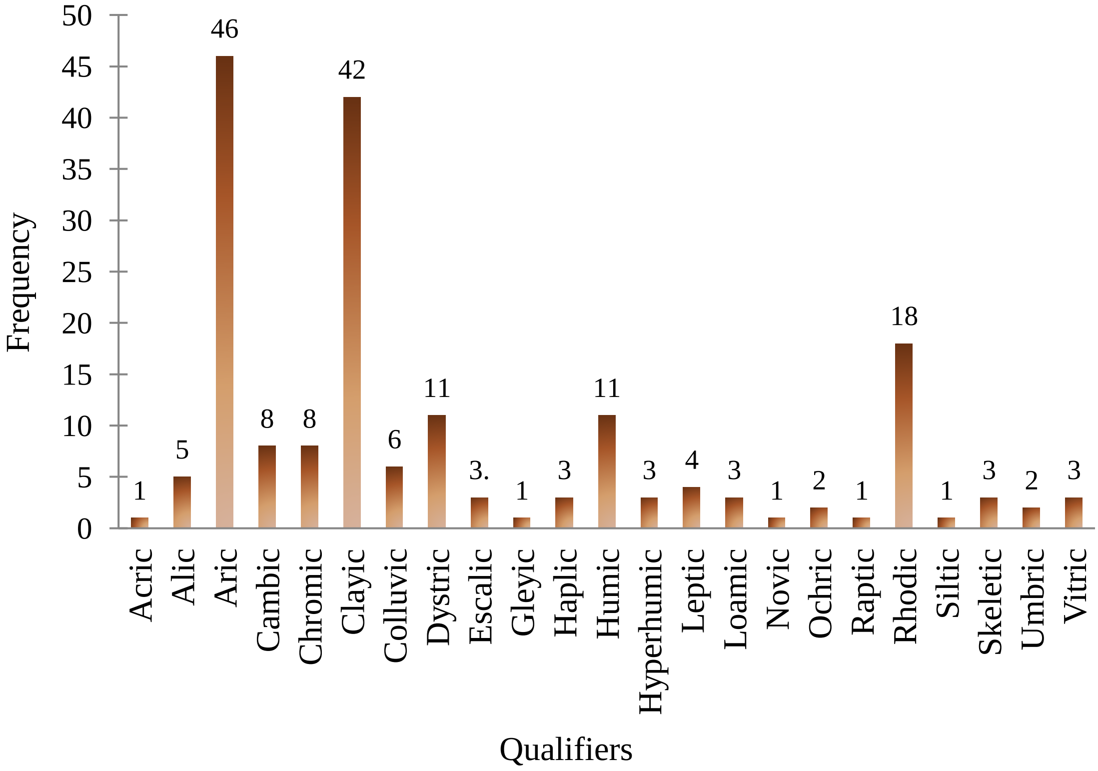

Figure 22. The frequency of qualifiers in the visited sites

My classification results at the RSG level were not fully matching the soil types of the associations of the relevant soil mapping units of the KENSOTER map units (polygons) (Table 6).

The polygons are indicated by the dominant soil, associations within the polygons are given in brackets with the proportions (Table 6.).

It is apparent from Table 6. that there was gross mismatch at the reference soil group level. Even with dense sampling (28 profiles) at the Nitisols polygons, no profile was classified as a Nitisols. The KENSOTER humic Nitisols polygon had the majority number of the visited profiles and diverse soil classes. Based on the KENSOTER map units, Humic Nitisols have the highest association (60), followed by humic Andosols (16) and humic Cambisols (14). Matching associations with classified profiles in this polygon were identified. The 10 profiles classified as Andosols matched the humic Andosol association and 1 profile classified as Cambisol matched the humic Cambisol association in the humic Nitisol polygon. Umbrisols were represented by 10 profiles, Alisols 5 profiles and Regosols by 1 profile.

Table 6. Matrix representation of soil classes in KENSOTER polygons.

KENSOTER Polygons	**The classification of the profiles in the map unit (polygon)**								**Profiles**
	AN	**UM**	**Al**	**RG**	**CM**	**LP**	**PH**	**PT**	
Humic Nitisols (NTu70:ANu16:CMu14)	10	10	5	1	2	0	0	0	28
Rhodic Nitisols (NTr60:NTu30:FRr10)	0	19	2	0	5	1	0	0	27
Luvic Phaeozems (PHl40:NTh30:CMx30)	0	8	0	0	3	0	5	0	16
Eutric Vertisols (VRe70:CMe30)	0	0	0	0	0	0	1	1	2
Lithic Leptosols (LPq60:PHl40)	0	1	0	0	0	0	0	0	1
Rhodic Ferrasols (FRr90:LXh5:ACh5)	0	0	1	0	1	0	0	0	2
Total RSGs	10	38	8	1	11	1	6	1	76
Share of the RSG in the study area (%)	13.3	50	10.5	1.3	14.4	1.3	7,9	1,3	100

Where PH=Phaeozems, LP=Leptosols, AN=Andosols, UM=Umbrisols, CM=Cambisols, AL=Alisols, PT=Plinthosols, RG= Regosols, HS=Histosols, NT=Nitisols, VR=Vertisols, FR=Ferrasols, CMu=Humic Cambisols, NTu=Humic Nitisols, NTr=Rhodic Nitisols, FRr=Rhodic Ferralsols, VRe=Eutric Vertisols, LXh=Humic Lixisols, Ach=Humic Acrisols, LPq=Lithic Leptosols, CMx = Chromic Cambisols.

The Rhodic Nitisol polygon had 27 profiles. The associations in this polygon based on the KENSOTER map units were Rhodic Nitisols (60), Humic Nitisols (30) and Rhodic Ferralsols (10). Cumulatively in this polygon Nitisols were 90% of all the associations in this polygon. No profile was classified as a Nitisol even with dense sampling and the high chance (90%) of having a profile classified as Nitisols. Out of the 27 visited profiles, 19 profiles were classified as Umbrisols, 2 as Alisols, 5 Cambisols and 1 Leptosol. There were no matching associations with classified profiles in this polygon.

The Luvic Phaeozem polygon had three associations based on KENSOTER map units as follows: Luvic Phaeozems (40), Humic Nitisols (30) and humic Cambisols (30) PHl40:NTh30:CMu30. Matching associations with 5 profiles classified as Phaeozems were identified. Umbrisols were represented by 8 profiles and Cambisols by 3 profiles out of the total 16 profiles in the Luvic Phaeozem polygon.

The Eutric Vertisols polygon had two associations, Eutric Vertisols (70) and Eutric Cambisols (30). Two profiles were visited in this polygon. One profile was classified as Phaoezem and another as Plinthosols. No matching associations with classified profiles was identified may be because this polygon was sparsely sampled.

The Lithic Leptosol polygon has two associations based on the KENSOTER map units. Lithic Leptosols (60) and Luvic Phaeozems (40). Only one profile was visited and classified as Umbrisols.

Two profiles were visited in the Rhodic Ferralsols polygon and classified as Alisols and Cambisols. This polygon had three association based on KENSOTER map units. Rhodic Ferralsos (90), Humic Lixisols (5), Humic Acrisols (5). This polygon was sparsely sampled reducing the chances for matching associations with classified profiles.

Based on the KENSOTER map units (Dijkshoorn, 2000) and a soil survey by the Kenya Soil Survey report (Gicheru & Kiome, 2000) this is a Nitisol rich region (Figure 23.). Soil profiles of my study that satisfied the morphological characteristics of nitic horizon however failed the silt/clay ratio of <0.4 diagnostic criterion for the nitic horizon (Appendix 3.). Results of two sample soil profiles are provided to demonstrate the problem with Nitisols classification in the eastern slopes of Mount Kenya.

10.14751/SZIE.2017.065

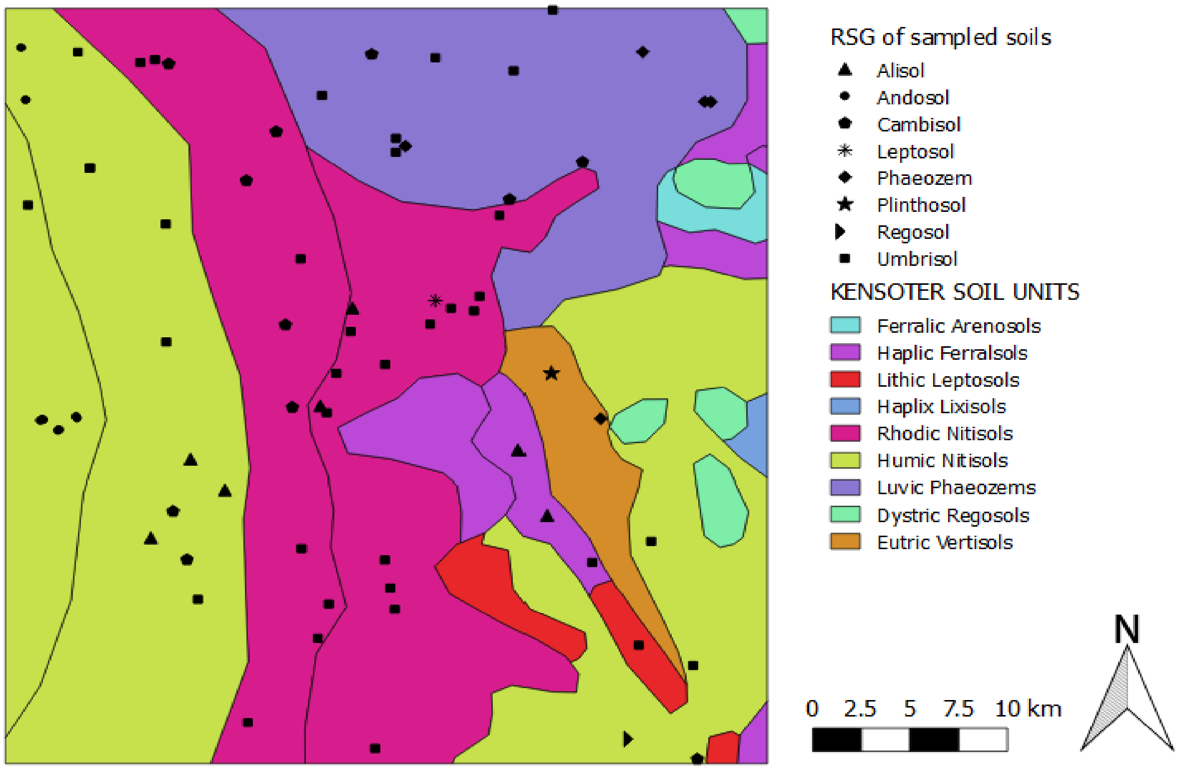

Figure 23. KENSOTER soil units and classified RSG of sampled soils

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4.4.1 Example profiles showing the classification problem of the nitic horizon and Nitisols

Profiles ID M5 and 14 are presented to discuss the classification problem. Climatic

Profile ID M 5
Location: Nguruma
GPS readings: latitudes 4188018,468 longitudes 3585, 04439
KENSOTER map unit: NTU
Climatic zone: Humid, Temperature regime: udic (DU)
Parent material: Pyroclastic rocks (IP3) and Basalts (IB2)
Macro relief: Plains (these are flat land forms), LP.
Percentage slope: 13,7%
Vegetation and land use: Agriculture= AA4, AP1 (Maize =CeMa, Bananas =FrBa, Coffee =LUCO, Agroforestry =MF)

Ap 0-20 cm, 2.5YR 3/3 moist
SiC, SBK, sticky when wet.

AB 20-50 cm, diffuse boudary
2.5YR3/3 moist
SiC, SBK, pressure faces
sticky when wet

B 50- cm, diffuse boudary
2.5YR 3/4 moist
SiC, SBK,
Pressure faces
sticky when wet

horizon	depth	OC	pH	CEC	B	Fe$_{dith}$	Fe$_{ox}$	Silt	Clay
	cm	%		cmol/kg	%	%	%	%	%
A	20	2,3	4,8	19,2	48,3			40,8	47,8
AB	30	1,6	4,9	18,2	48,2	8,44	1,8	46,0	42,1
Bw	50	1,1	4,9	17,5	47,5			41,4	47,7

Additional data: Mineralogy of AB: Kaolinite dominated (see Figure 24.).
(Kaolinite/halloysite>>goethite, hematite>quartz>smectite, k-feldspar, gibbsite)

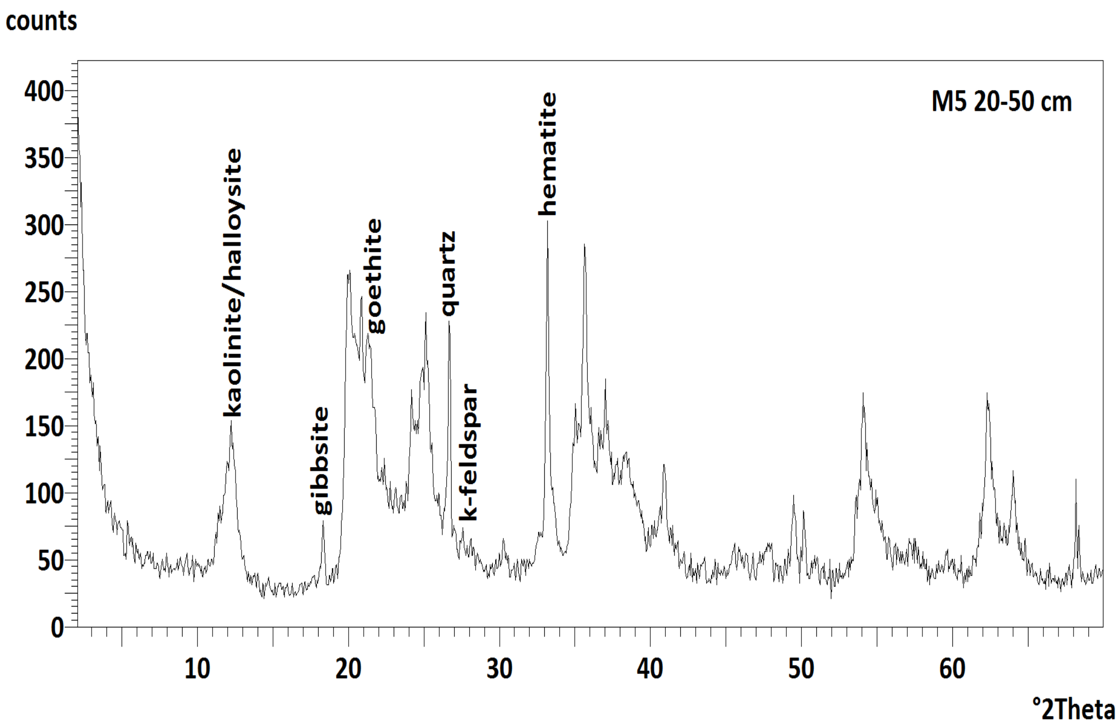

Figure 24. XRD diffractogram for sample M14 shows 1:1 kaolinite dominance

Diagnostic horizon: cambic and umbric

Reference Soil Group: Umbrisols

Principal qualifiers: Cambic

Supplementary qualifiers: Aric, Clayic

Soil name: Cambic Umbrisols (Aric, Clayic)

Based on the WRB, 2015 classification system, the profile descriptions qualify the diagnostic criteria for ‘nitic horizon’ (Appendix 3.), except the silt to clay ratio which was >0.4. Without the silt to clay ratio of <0.4 diagnostic criteria, this profile would be classified as Dystric Rhodic Nitisol (Aric, Humic). Although the WRB RSGs are different, the full classifications of the two versions capture similar soil information (Table 7.).

Table 7: The full classification of Profile M5 as function of the criteria silt/clay ratio <0.4

With the current criteria silt/clay ratio <0.4	Without the current criteria silt/clay ratio <0.4
Cambic **Umbrisols** (Aric, Clayic) The default of Umbrisols → Dystric and Umbric	Dystric Umbric **Nitisol** (Aric, Humic) The default of Nitisol → Clayic

The default information of the required diagnostics for the Reference Soil Group and qualifiers are building blocks that carry the information on the major soil properties that are important for management. As exemplified on profile M5, the low base (expressed in the Dystric qualifier), the clayey texture (expressed in the Nitisol RSG or the Clayic qualifier), the high OC status (expressed in Humic qualifier), are captured in both alternatives for the ploughed (Aric) M5 profile, given in Table 7.

10.14751/SZIE.2017.065

Profile ID M 14

Location: Giaki

GPS readings: latitudes 4203190.201 longitudes 3860.189111

KENSOTER map unit: PHI

Climatic zone: Sub-Humid, temperature regime: udic, FAO code: DU

Parent material: Basalts, FAO Code (IB2)

Macro relief: Plains (these are flat land forms), FAO Code: LP

Percentage slope: 4.2%

Vegetation and land use: Agriculture (Corn and coffee), FAO code: AA4, AP1, LuCo.

Ap — 0-20 cm, 5YR 2.5/4 moist
SiC, GR, sticky when wet.

AB — 20-50 cm, diffuse boudary
2.5YR2.5/4 moist
SiC, SBK, shiny peds,
pressurefaces
sticky when wet

Bw — 50- cm, diffuse boudary
2.5YR 2.5/6 moist
SiC, SBK, shiny peds
Pressure faces
sticky when wet

horizon	**depth**	**OC**	**pH**	**CEC**	**B**	**Fe_{dith}**	**Fe_{ox}**	**Silt**	**Clay**
	cm	**%**		**cmol/kg**	**%**	**%**	**%**	**%**	**%**
A	20	2,0	4,8	16,8	48,7			41,6	46,8
AB	30	1,2	4,9	16,9	48,7	8,69	1,17	41,7	45,8
Bw	50	1,0	4,9	17,2	48,7			43,8	45,5

Additional data: Mineralogy of AB: Kaolinite dominated (see Figure 25.).
(Kaolinite/halloysite>>goethite, hematite>quartz>smectite, k-feldspar, gibbsite)

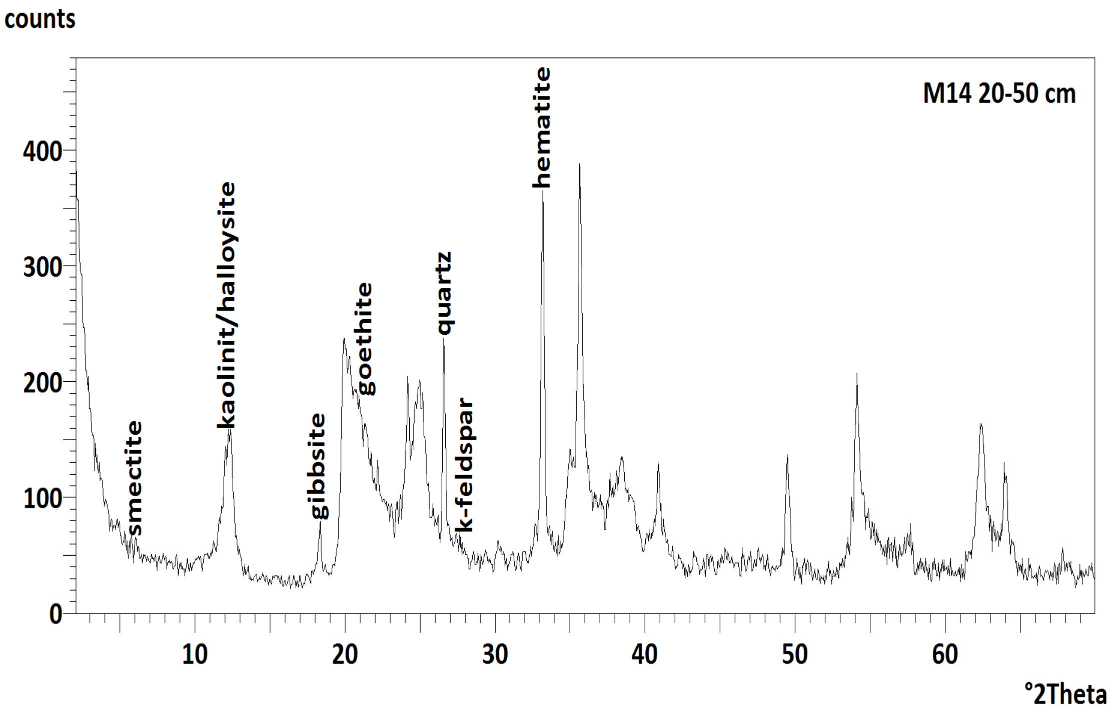

Figure 25. XRD diffractogram for sample M14 shows 1:1 kaolinite dominance

Diagnostic horizon: Cambic

Reference Soil Group: Cambisol

Principal qualifiers: Rhodic, Dystric

Supplementary qualifiers: Aric, Clayic, Humic

Soil name: Dystric Rhodic Cambisols (Aric, Clayic, Humic).

Based on the WRB, 2015 classification system, the profile descriptions qualify the diagnostic criteria for 'nitic horizon' (Annex 3.), except the silt to clay ratio which was >0.4. Without the silt to clay ratio of <0.4 diagnostic criteria, this profile would be classified as Dystric Rhodic Nitisol (Aric, Humic). Although the WRB RSGs are different, the full classifications of the two versions capture similar soil information (Table 8.).

Table 8: The full classification of Profile M14 as function of the criteria silt/clay ratio <0.4

With the current criteria silt/clay ratio <0.4	Without the current criteria silt/clay ratio <0.4
Dystric Rhodic **Cambisol** (Aric, Clayic, Humic)	Dystric Rhodic **Nitisol** (Aric, Humic) The default of Nitisol → Clayic

The default information of the required diagnostics for the reference soil group and qualifiers are building blocks that carry the information on the major soil properties that are important for the management. As exemplified on profile M14, the low base (expressed in the Dystric qualifier), the clayey texture (expressed in the Nitisol RSG or the Clayic qualifier), the high OC status (expressed in Humic qualifier), the highly weathered, iron rich status (expressed in the Rhodic qualifier) are captured in both alternatives for the ploughed (Aric) M14 profile, given in Table 8.

In both the two profiles, the WRB reference soil groups are different but the qualifiers are preserved in both cases. This demonstrates the applicability of the WRB classification elements (building blocks) to provide important information for soil management.

However the Nitisol classification remains a problem, as Nitisols with their stable structure and high clay content are considered the best soils among highly weathered soils. It is important that on the highest level (RSG) soils with the nitic horizon are acknowledged.

For further investigations of the problem, the ISRIC WISE (Batjes, 2009a) database was revisited. In the data base 5054 profiles are classified as Nitisols (mostly Humic and Rhodic) .Although the silt to clay ratio of < 0.4 requirement for nitic horizon was introduced in 1998 (FAO-ISRIC-ISSS, 1998) and some of the soils were surveyed before, a large number of the legacy profiles do not satisfy the criteria. (Figure 26.).

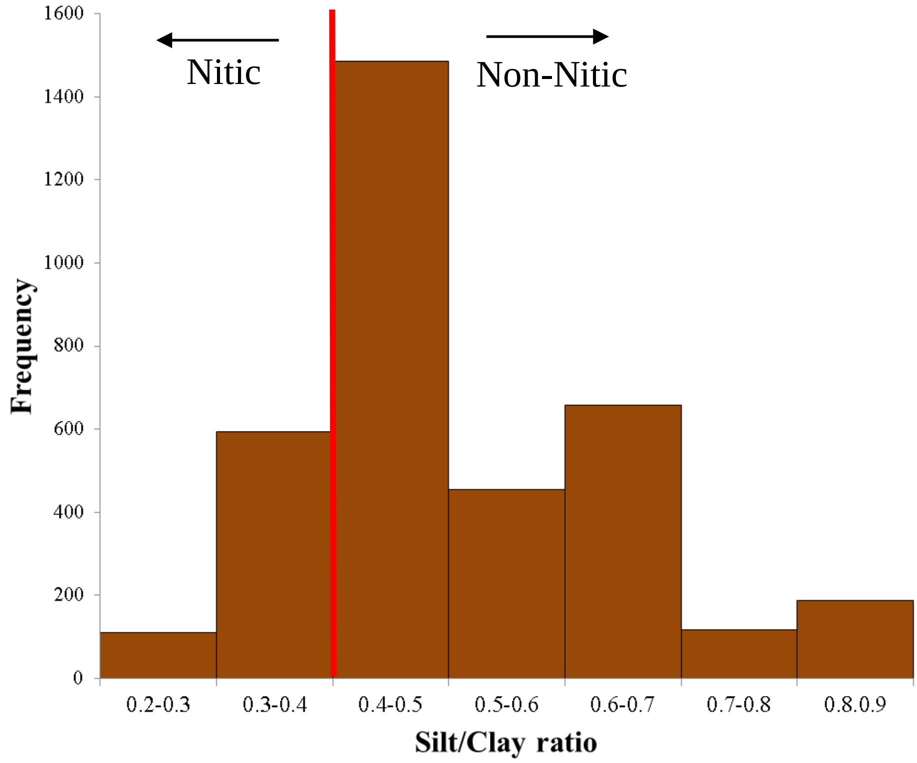

Figure 26. Evaluation of ISRIC WISE database for Nitisols classification

The higher silt ratio might be related to rejuvenation of the Nitisols during Pleistocene eruption in the Mt. Kenya region or even in larger distance. Similar suggestions were made by De Wispelaere *et al.* (2015) based on observations in Ethiopia. Regardless of the cause, the current criterion makes soil with nitic horizon morphology excluded from the Nitisols, and also makes confusion in legacy data bases. Based on these conclusion suggestions have been made to the IUSS WRB Working Group to skip this criteria from the nitic horizon diagnostic criteria.

4.4.2 Discriminant analysis results

In view of the differences from earlier classifications (Figure 23.), I sought to evaluate the classification results based on the known soil types in the KENSOTER database for the same study area. Discriminant analysis (DA) provided results that showed the contribution of each soil property in the classification of WRB reference soil groups in the form of factor components (Table 9.). The first factor (F1) showed high loadings for SOC and Al showing a negative correlation with F1. Base saturation (BS) and pH were positively correlated with F1. The second factor (F2) was associated strongly with Ca. The third factor (F3) loadings were mainly associated with silt, clay, sand, Fe and CEC.

Table 9. Loadings of the first 5 factors for elemental compositions in the soil

	F1	F2	F3	F4	F5
SOC (%)	**-0.726**	0.289	0.373	0.049	0.086
Clay (%)	-0.123	0.173	**-0.406**	0.192	0.189
Silt (%)	0.305	0.007	**0.443**	-0.069	0.076
Sand (%)	-0.259	-0.175	0.243	-0.071	-0.227
silt/clay	0.238	-0.111	**0.477**	-0.217	-0.067
P (mg/kg)	0.045	**-0.478**	**0.521**	0.288	-0.141
Ca (cmol/kg)	0.262	**0.528**	0.050	-0.016	0.365
Mg (cmol/kg)	0.056	-0.105	-0.042	0.385	-0.170
Al (cmol/kg)	**-0.596**	**-0.403**	0.241	0.157	-0.289
CEC (cmol/kg)	-0.359	0.038	**0.421**	0.214	0.011
BS (%)	**0.544**	**0.535**	-0.077	-0.019	0.195
pH	**0.704**	0.257	-0.051	-0.084	0.569
Eigen value	1.300	0.538	0.249	0.147	0.073
Discrimination (%)	55.446	22.945	10.626	6.261	3.113
Cumulative (%)	55.446	78.391	89.018	95.280	98.393

Calculated centroids for the WRB reference soil groups (Table 10.) of all the visited sites show that the values of silt to clay ratio were greater than the requirement of <0.4 for 'nitic horizon' and this was the major reason why no profile was classified as a Nitisols.

Table 10. Calculated centroids for classified WRB reference soil groups.

RSGs	SOC	C	Si	S	Si/C	P	Ca	Mg	Al	CEC	BS	pH
	%	%	%	%		mg/kg	cmol/kg	cmol/kg	cmol/kg	cmol/kg	%	
AL	1.2	45.1	42.5	12.3	0.9	6.2	7.9	4.32	17.7	18.0	43.1	4.6
AN	3.5	46.6	41.4	12.7	0.8	5.6	7.5	4.26	19.8	20.6	40.7	4.4
CM	1.2	46.1	42.3	12.2	0.9	6.4	7.7	4.45	17.8	19.1	44.4	4.7
PH	1.3	46.8	43.1	11.1	0.9	4.5	9.2	4.37	13.8	18.1	53.8	5.0
PT	1.4	43.5	45.4	12.1	1.0	9.5	7.6	4.64	18.4	19.8	43.2	4.8
RG	0.6	42.5	47.2	12.1	1.1	6.3	10.8	3.90	12.6	18.2	55.4	5.3
UM	1.3	46.5	42.1	11.9	0.9	5.5	8.0	4.32	16.2	18.7	45.3	4.8

Important variables for the classification of Phaeozems were pH and BS (Figure 26). Phaeozems must have a mollic horizon with a base saturation ≥ 50% through out to the depth of 100 cm (IUSS Working Group WRB, 2015). Characterisation of Andosols (AN) was based on high SOC, clay and CEC. Stabilization of SOC in AN has been attributed to formation of organo-mineral complexes Al/Fe–humus (Neculman *et al.*, 2013). Michéli *et al.* (2014) have demonstrated the importance of SOC as a major differentiation criterion in soil classification systems. Clay-size particles have been recognized as protecting SOC from microbial decomposition (Barré *et al.*, 2014). Plinthosols (PT) are characterised by formation of (piso) Plinthic horizons containing concretions or nodules that are strongly cemented with Fe and in some cases with Mn hydroxides. Their formation is related to the past climate (alternating wet and dry conditions). Discriminant analysis identified Regosols (RG) on the basis of the pH, silt and silt/clay ratio. These are very weakly developed mineral soils forming on eroding and accumulation zones, most probably losing their buffering capacity. They are associated with incipient soil formation such as Entisols in the US Soil Taxonomy. Umbrisols, Cambisols and Alisols were characterised on the basis of silt and silt/clay ratios. However, the silt to clay ratio is a diagnostic criterion for nitic horizon.

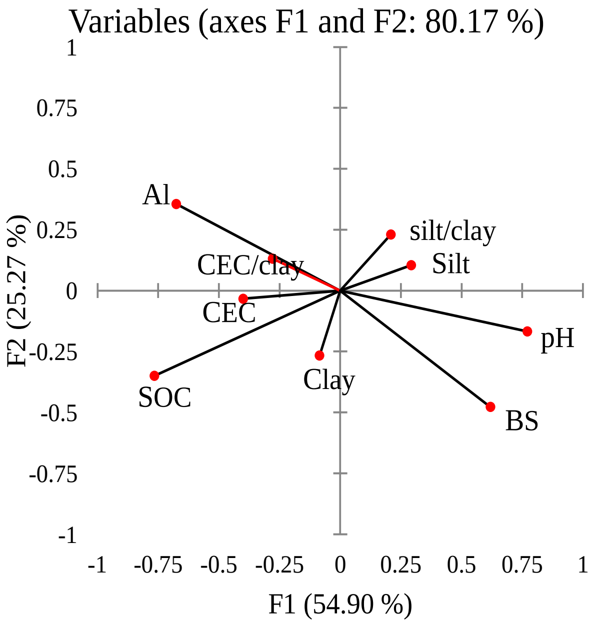

Figure 27. Principal components (F1 versus F2) show contribution of soil properties in classification of RSGs.

Overlap of soil properties in all the observations was evident (Figure 27.). Outliers were observed mainly due to high SOC in the case of Andosols and Alisols mainly due to high contents of silt. Overlap of centroids for Alisols, Umbrisols and Cambisols was also evident. Umbrisols observations dominated in all the centroids. This supports the classification results in Figure 21. that Umbrisols had the highest coverage based on the visited sites.

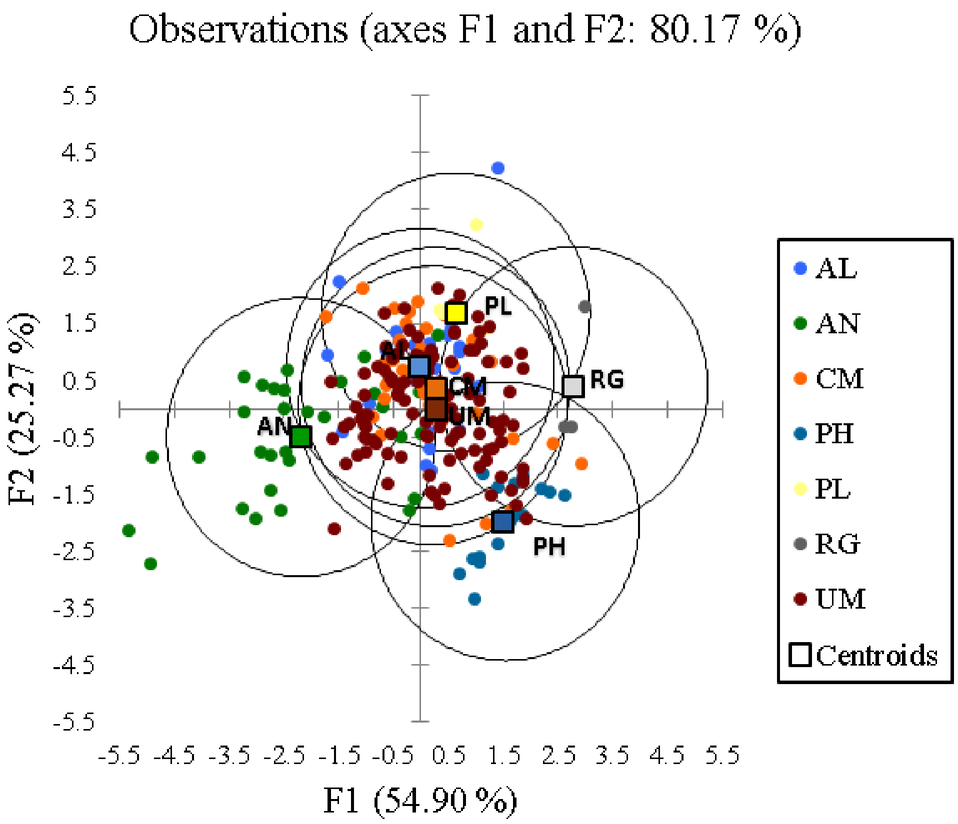

Figure 27. Principal components (F1 versus F2) show the distribution of the actual RSG profiles "around" the centroids of their RSGs.

4.5 Differences of soil properties in different RSGs and implications for management

Selected soil properties that can be managed either by adding organic or inorganic inputs were considered. These included: SOC, TN, P, Ca, Mg, pH and K. Soil organic carbon (SOC) is fairly reliable and field-based soil quality indicator for assessing soil and ecosystem health (Lal, 2006; Vagen *et al.*, 2005, Winowieck *et al.*, 2016). Comparison of SOC (%) in all the RSGs reveals three distinct groups 'A, AB and B' (Table 12a.). Plinthosols at the transition and Andosols completely isolated from the other RSGs. The calculated centroids (Table 10.) show that Andosols had the highest value of SOC (%). This is explained by Andosols ability to stabilize SOC through formation of SOC in organo mineral (Al/Fe) complexes (Rumpel *et al.*, 2012), low activity of soil microorganisms due to extremely low pH, Al toxicity as indicated by high values of Al in the soil samples and low base saturation (Tonneijck *et al.*, 2010). Physical protection of the SOC in stable microaggregates has been reported (Huygens *et al.*, 2005). If the pH of Andosols is controlled, these soils can be very fertile and perform most of the important soil functions. This could be the case in Plinthosols where SOC can be protected in the hard Fe or Mn concretions and nodules. In terms of management for SOC three clusters can be targeted: A, AB and B (Table 11a.).

Table 11a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for SOC

RSG	**Frequency**	**Sum of ranks**	**Mean of ranks**	**Groups**	
RG	3	62.0	20.7	A	
AL	25	2428.0	97.1	A	
CM	34	3423.0	100.6	A	
PH	16	1612.0	100.7	A	
UM	116	12623.0	108.8	A	
PT	5	567.0	113.4	A	B
AN	32	6081.0	190.0		B

Comparison of means within the RSGs for SOC (%) revealed similar information (Table 11b.). There was a significant difference between Andosols and all other RSGs except Plinthosols.

Table 12b. Evaluation of the significant differences between RSGs for SOC

RSG	**AN**	**UM**	**CM**	**AL**	**PH**	**PT**	**RG**
AN	No	**Yes**	**Yes**	**Yes**	**Yes**	No	**Yes**
UM	**Yes**	No	No	No	No	No	No
CM	**Yes**	No	No	No	No	No	No
AL	**Yes**	No	No	No	No	No	No
PH	**Yes**	No	No	No	No	No	No
PT	No	No	No	No	No	No	No
RG	**Yes**	No	No	No	No	No	No

Significant level P<0.05

Nitrogen (N) is the nutrient most often deficient for crop production in SSA and its use can result in substantial economic return for farmers (Chianu *et al.* 2012). However, when N inputs to the soil system exceed crop needs, there is a possibility that excessive amounts of nitrate (NO_{3-}) may enter either ground or surface water. Managing N inputs to achieve a balance between profitable crop production and environmentally tolerable levels should be every farmer's goal. The results of N were similar to those of SOC with three distinct groups 'A, AB and B' (Table 12a.). This is because SOC and TN were highly correlated (0.98) in the earlier results (Table 1.). Gains in SOC go along with increases in other elements including N (Hessen *et al.,* 2004). Like SOC, three clusters can be used for N management.

Table 12a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for TN

RSG	**Frequency**	**Sum of ranks**	**Mean of ranks**	**Groups**	
RG	3	56.0	18.6	A	
PH	16	1530.0	95.6	A	
UM	116	11993.0	103.3	A	
CM	34	3647.0	107.2	A	
AL	25	2699.0	107.9	A	
PT	5	646.0	129.2	A	B
AN	32	6225.0	194.5		B

There was significant difference between Andosols and all other RSGs except Plinthosols with regard to TN (Table 12b.).

Table 12b. Evaluation of the significant differences between RSGs for TN.

RSG	**AN**	**UM**	**CM**	**AL**	**PH**	**PT**	**RG**
AN	No	**Yes**	**Yes**	**Yes**	**Yes**	No	**Yes**
UM	**Yes**	No	No	No	No	No	No
CM	**Yes**	No	No	No	No	No	No
AL	**Yes**	No	No	No	No	No	No
PH	**Yes**	No	No	No	No	No	No
PT	No	No	No	No	No	No	No
RG	**Yes**	No	No	No	No	No	No

Significant level $P<0.05$

Kenyan soils, similar to other agricultural soils of the tropics, are generally low in available P attributable to low soil pH and oxides or/ and hydroxides of Al and / or Fe with high P-fixation capacities (Opala *et al.*, 2010). Five distinct clusters A, AB, ABC, BC and C were generated and form important management zones for P (Table 13a.). The cluster with least mean of ranks was associated with Phaoezems. Phaeozems are soils with high base saturation and high pH thus with low P fixing capacity. The cluster with highest mean of ranks was C associated with Plinthosols. Plinthosols usually have has high Fe and Mn concentrations thus have high capacity of P fixing. Liming to reduce soil acidity can reduce P fixation and fertilization with phosphorus fertilizers like NPK can increase available P for the plants.

Table 13a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for P

RSG	Frequency	Sum of ranks	Mean of ranks	Groups		
PH	16	1090.0	68.1	A		
UM	116	12757.0	109.9	A	B	
AN	32	3524.0	110.1	A	B	
AL	25	3130.0	125.2	A	B	C
CM	34	4750.0	139.7		B	C
RG	3	457.0	152.3		B	C
PT	5	1088.0	217.6			C

Significant differences are observable between the following RSGs: PT & AN; PT & UM; PT & PH and PH & CM (Table 13b.). This may be explained by the variations of elements that enhance phosphorus fixation in different RSGs.

Table 13b. Evaluation of the significant differences between RSGs for P

RSG	AN	UM	CM	AL	PH	PT	RG
AN	No	No	No	No	No	**Yes**	No
UM	No	No	No	No	No	**Yes**	No
CM	No	No	No	No	**Yes**	No	No
AL	No	No	No	No	No	No	No
PH	No	No	**Yes**	No	No	**Yes**	No
PT	**Yes**	**Yes**	No	No	**Yes**	No	No
RG	No	No	No	No	No	No	No

Significant level P<0.05

Calcium plays a very important role in plant growth and nutrition. It is found in many minerals in the soil, but is relatively insoluble in this state. High levels of other cations such as magnesium, iron, aluminium and especially potassium, will reduce the calcium uptake in some crops. The differences in the mean of ranks (Table 14a.) may be explained by the variability of Ca^{2+} among the RSGs. Andosols have the least mean of ranks; this can be explained by the fact that Andosols had the highest content of exchangeable Al . Al^{3+} replaces Ca^{2+} as the dominant exchangeable cations on the negatively charged surfaces of clay minerals and organic matter. Conversely, high mean of ranks of Ca for Phaoezems and Regosols are associated with low Al^{3+} and higher pH values in these RSGs. Four distinct zones can be identified for management A, AB, B and C. Addition of lime into the soil can increase lower increase Ph and at the same time increase calcium into the soil and fertilization with Calcium Ammonium Nitrate (CAN)

Table 14a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for Ca

RSG	**Frequency**	**Sum of ranks**	**Mean of ranks**	**Groups**		
AN	32	2565.0	80.2	A		
AL	25	2102.0	84.1	A	B	
PT	5	449.0	89.8	A	B	
CM	34	3562.0	104.8	A	B	
UM	116	14216.0	122.6		B	
PH	16	3243.0	202.7			C
RG	3	659.0	219.7			C

Significant differences existed between RSGs with regard to Ca content. Observable differences were as follows: AN & UM; AN & PH; AN & RG; UM & PH; CM & PH; AL & PH; PT & PH and RG & AL (Table 14b.).

Table 14b. Evaluation of the significant differences between RSGs for Ca

RSG	**AN**	**UM**	**CM**	**AL**	**PH**	**PT**	**RG**
AN	No	**Yes**	No	No	**Yes**	No	**Yes**
UM	**Yes**	No	No	No	**Yes**	No	No
CM	No	No	No	No	**Yes**	No	No
AL	No	No	No	No	**Yes**	No	**Yes**
PH	**Yes**	**Yes**	**Yes**	**Yes**	No	**Yes**	No
PT	No	No	No	No	**Yes**	No	No
RG	**Yes**	No	No	**Yes**	No	No	No

Significant level P<0.05

Magnesium (Mg) is the central atom of the chlorophyll molecule and is an important enzyme. It is very mobile in plants. Magnesium deficiency in plants causes yellowing between leaf veins. Low soil pH decreases the availability of magnesium to plants. The availability of Mg to plants depends on various factors: the distribution and chemical properties of the source parent material and its grade of weathering, site specific climatic and anthropogenic factors. The mean rank for Plinthosols was highest (Table 15a.). This can be explained by the fact that PT is associated with high Mn and Fe. High Mn has been reported to directly reduce Mg uptake resulting in increased Mg content in Plinthosols. In addition, in acidic soils, elements such as manganese and aluminium become more soluble and result in reduced magnesium uptake. Addition of liming material (i.e dolomitic lime) can reduce soil acidity and increase available magnesium. Dolomitic lime is calcium magnesium carbonate. It has about 50% calcium carbonate and 40% magnesium carbonate, giving approximately 22% calcium and at least 11% magnesium (Okalebo *et al.*, 2006)

Table 15a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for Mg

Sample	Frequency	Sum of ranks	Mean of ranks	Groups
RG	3	147.0	49.0	A
AN	32	3213.0	100.4	A
AL	25	2730.0	109.2	A
UM	116	13425.0	115.7	A
PH	16	1921.0	120.1	A
CM	34	4556.0	134.0	A
PT	5	804.0	160.8	A

There was no significant difference between RSGs with regard to magnesium content (Table 15b.).

Table 15b. Evaluation of the significant differences between RSGs for Mg.

RSG	AN	UM	CM	AL	PH	PT	RG
AN	No	No	No	No	No	No	No
UM	No	No	No	No	No	No	No
CM	No	No	No	No	No	No	No
AL	No	No	No	No	No	No	No
PH	No	No	No	No	No	No	No
PT	No	No	No	No	No	No	No
RG	No	No	No	No	No	No	No

Significant level P<0.05

Soil pH is a useful indicator of the relative acidity or alkalinity of a soil. All the soil samples were generally acidic. However, the severity of acidity differed in different RSGs forming five distinct management zones A, AB, B, BC and C (Table 16a.). However, it should be noted that this is just indicative as pH can change within a short span of time. Andosols had the least mean of ranks value based while Phaeozems and Regosols had higher mean of rank values. This was based on the variability of pH from low to high respectively. Liming to increase pH and availability of other important nutrients is necessary.

Table 16a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for pH.

RSG	**Frequency**	**Sum of ranks**	**Mean of ranks**	**Groups**		
AN	32	1990.0	62.1	A		
AL	25	2205.0	88.2	A	B	
CM	34	3360.0	98.8	A	B	
UM	116	14651.0	126.3		B	
PT	5	744.0	148.8		B	C
PH	16	3159.0	197.4			C
RG	3	687.0	229.0			C

Significant differences existed between RSGs with regard to pH content. These included: AN & UM; AN & PH; AN & RG, CM & PH; AL & PH; RG & CM and RG & AL (Table 16b.).

Table 16b. Evaluation of the significant differences between RSGs for pH

	AN	**UM**	**CM**	**AL**	**PH**	**PT**	**RG**
AN	No	**Yes**	No	No	**Yes**	No	**Yes**
UM	**Yes**	No	No	No	**Yes**	No	No
CM	No	No	No	No	**Yes**	No	**Yes**
AL	No	No	No	No	**Yes**	No	**Yes**
PH	**Yes**	**Yes**	**Yes**	**Yes**	No	No	No
PT	No	No	No	No	No	No	No
RG	**Yes**	No	**Yes**	**Yes**	No	No	No

Significant level P<0.05

Potassium (K) is highly mobile and is easily leached from leaves to be taken up in high quantities by soil microorganisms and roots. In soil, potassium may be found in minerals such as micas and feldspars, secondary aluminium silicates (e.g. illite). Potassium is available when attached to clay and humus colloids and easily available when in solution. Potassium dissolved in soil solution as an ion is highly leachable, although loses of potassium from runoff and erosion is not a significant problem. There were no differences in all the RSGs with regard K contents and one management group (A) could be considered (Table 17a.).

Table 17a. Multiple pairwise comparisons using Dunn's procedure / Two-tailed test for K.

RSG	Frequency	Sum of ranks	Mean of ranks	Groups
RG	3	246.0	82.0	A
AN	32	3483.0	108.8	A
PH	16	1794.0	112.1	A
UM	116	13372.0	115.2	A
AL	25	2884.0	115.3	A
PT	5	628.0	125.6	A
CM	34	4389.0	129.0	A

There was no significant difference between RSGs with regard to K content (Table 17b.).

Table 17b. Evaluation of the significant differences between RSGs for K

	AN	UM	CM	AL	PH	PT	RG
AN	No	No	No	No	No	No	No
UM	No	No	No	No	No	No	No
CM	No	No	No	No	No	No	No
AL	No	No	No	No	No	No	No
PH	No	No	No	No	No	No	No
PT	No	No	No	No	No	No	No
RG	No	No	No	No	No	No	No

Significant level P<0.05

4.6 Summary of the suggested management options

Soil erosion control and addition of soil organic matter into the soil.

Colluvic qualifier (Figure 22.) is an indication of movement of soil material through erosion. Measures of erosion control like terraces, increasing cover crops, mulching, improving the soil structure through addition of soil organic matter need to be emphasized in this study area. Farm yard manure (FYM) is a good source of organic matter. A major challenge remains as these FYM are usually insufficiently available to provide the nutrients needed to maintain agricultural production at a desirable level. Composting and use of biochar technologies may also increase availability of OMs for soil amendments.

Liming and use of P fertilizers

The Dystric qualifier (Figure 22.) show that the soils are mainly acidic with base saturation of <50%. Andic and Vitric qualifiers (refer Appendix1. and Appendix 2.) which were present in some of the sampling sites are good agents of P fixation. Application of agricultural lime containing Ca and/or Mg compounds increase Ca^{2+} and/or Mg^{2+} ions and reduces Al^{3+}, H^{+}, Mn^{4+}, and Fe^{3+} ions. This leads to increase in soil pH and available P due to reduction in P fixation (Connor *et al.,* 2011). Liming also increases earthworm activity and therefore macro porosity (Bolan *et al.,* 2003). Bennett *et al.,* (2014) found that lime applied at 5t/ha was improving aggregate stability, hydraulic conductivity, vegetation cover, total carbon and Nitrogen and respiration 12 years after application. However, high cost and inaccessibility of liming and fertilization inputs have been reported as key constraints in Kenya (Okalebo *et al.,* 2006). Due to these challenges, alternative management options need be explored to provide a bigger matrix of options to the famers.

Use of acid tolerant crops

Using germplasm that is tolerant to low pH and Al toxicity (i.e tea, sorghum). Although the use of tolerant plant germplasm does not reverse soil acidity conditions, it minimizes the problems experienced by farmers, especially those who do not use lime.

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5. CONCLUSION AND RECOMMENDATIONS

Combining Conditional Latin Hypercube Sampling, Mid Infrared spectroscopy, and Random Forest Regression (RF), soil properties were satisfactorily predicted. The results of the linear regression show a strong relationship between the measured values and the predicted. Out of the 269 samples, only 30 to 32 samples were selected for calibration and analysed through tedious and costly laboratory procedures. Laboratory measurements were calibrated to MIR spectra using RF regression and soil properties were simultaneously predicted with satisfactorily results. This supports the fact that our methodology is rapid, cost effective and environmentally friendly as compared to the dense sampling and intense wet chemistry laboratory procedures. Geostatistical analysis of our data revealed spherical model as the best fit for the semivariogram. Cross validations result show that TN and pH had excellent results compared to SOC and P. The low accuracy for SOC and P spatial predictions can be explained by lack of important input variables like land use/land management practices. Also the available KENSOTER database that represented soil types had its share of limitations that were discussed earlier in the introduction section and this may have affected the accuracy of the model. The maps of the predicted spatial distribution of the soil properties are a good demonstration of how a rapid and an accurate methodology of predicting soil properties can provide data to update legacy maps and databases in the study area. The scale for these developed maps can inform land management at watershed and farm level (resolution is 30 m by 30 m). Moreover, they form a good monitoring network that was not there before for planning, prioritizing and assessing soil management activities.

The second part of my research involved soil classification using the predicted soil properties and morphological field observations. The results show that the difficulties of Nitisols classification were primarily caused by the failure of the profiles data to qualify the nitic diagnostic criterion of silt to clay ratio of < 0.4. Modification of the criteria was suggested by the author during the European Geosciences Union 2017 general assembly in Vienna on 28th April 2014. This was through an oral presentation that I delivered '*Classification problems of Mount Kenya soils with reference to Nitisols'* in the presence of IUSS WRB working Group. The diagnostic elements, principal and supplementary qualifiers made it possible not to loose soil information even when the reference soil groups were different. The building blocks of the system capture specific information important for soil management.

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5.1 Recommendations

- More intense soil survey and soil classification is suggested for this study area and other similar environments to validate the results of this study. This will help IUSS WRB Working Group to make an informed decision on whether or not to modify the silt to clay ratio criterion for nitic horizon.
- Further work is required to understand the silt forming processes in the study area and similar environments.
- Development of land management inventories is required to enhance predictions of soil properties for more informed land use decision making.

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6. KEY SCIENCTIFIC FINDINGS AND IMPORTANT OUTPUT OF THIS RESEARCH

1. In my doctoral research I have applied Conditional Latin Hypercube Sampling for optimising the sample size; Mid Infrared Spectroscopy for rapid scanning of soil samples to generate a soil spectra library and Random Forest Regression to calibrate the soil MIR spectra using reference soil properties. This combination was 1st time and successfully used in the eastern slopes of Mt. Kenya to generate soil properties data. I achieved better coefficient of determination (r^2) for the prediction of SOC (r^2=0.78 and RMSE=1.64) than (r^2=0.77 and RMSE=1.64) by Terhoeven-Urselmans *et al.* (2010). My accuracy for the pH was (r^2 = 0.88 and RMSE = 0.48) and better in terms of r^2 and RMSE compared to those achieved by Terhoeven-Urselmans *et al.* (2010) (r^2 = 0.81, RMSE = 0.63) and Shepherd & Walsh (2002) (r^2 = 0.83, RMSE = 0.54). Excellent calibrations of Mehlich III extraction of Na, Mg, K and Ca were excellent (r^2=0.93 and RMSE=1.45; r^2=0.88 and RMSE=1.60; r^2=0.92 and RMSE=2.32 and r^2=0.92 and RMSE=189.16 respectively better than Sila *et al.* (2016) with regard to Ca (r^2=0.91). Calibration for clay (r^2 = 0.59 and RMSE = 9.9); Silt (r^2 = 0.63 and RMSE = 7.3) were low compared to other soil properties.

2. Based on the results of the Conditional Latin Hypercube Sampling I have developed the first spectral library representing the spectral variability of the Eastern Mt. Kenya soils. This database contributes to future soil sampling campaigns, and enables the efficient soil property prediction.

3. The spatial density of available soils data in my study area is very low. The 77 georeferenced and fully described and analyzed profiles contribute to the understating of soil resources of the area. The investigated representative locations can serve for future monitoring of the determined soil parameters. Beside the point data I have compiled the spatial prediction map of the properties, which can support farmers in making soil management decisions in the area.

4. In earlier surveys extended areas were mapped as Nitisols on Mt. Kenya. In my study I have not classified any of my profiles as Nitisols, although they satisfied the important morphological

criteria of Nitisols, the silt/clay ratio < 0.4 diagnostic criterion for nitic horizon (introduced in 1998) was not satisfied. Nitisols that undergo rejuvenation, may lose this criterion but still fulfil all other requirements and the concept of the Nitisols. As shown in the thesis, the introduction of this criterion is creating confusion in legacy databases as well. My finding is that this criteria is not useful and should be removed from the diagnostic criteria of the nitic horizon in updated versions of the WRB. (This proposal was accepted by the IUSS WG WRB)

5.The WRB proved to be a proper system to be applied for soil classification and soil characterization in the study area. It was well demonstrated that the building blocks (diagnostic horizons properties, materials and the qualifiers) do carry the important information for management purposes on soils of the studied area. Although my profiles did not closely match the soil associations of the KENSOTER polygons on the highest level, the information content derived from the associations provided a better match with the classification building blocks of my profiles in the relevant polygons. This underlines the importance of the diagnostic approach in soil classification, mapping and validation processes.

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7. SUMMARY

The expected growth of population and the need of more food make the knowledge of soil properties essential to secure the successes of agricultural production on currently available land. The high costs of soil surveys and laboratory measurements, however have partly contributed to the scarcity of soil data. In this study a rapid, cost efficient method was experimented to produce the necessary soil data for proper land management on the Eastern slopes of Mt. Kenya. The full coverage of the input variables was enhanced by the application of Conditional Latin Hypercube Sampling (CLHS) approach. Terrain attributes, Normalized Difference Vegetation Index (NDVI) and soil types were derived from Digital Elevation Model (DEM), Landsat 8 imagery and the KENSOTER database respectively. An ensemble of QGIS and CLHS were used to define the *'ease of reach'* of each location in the landscape. The resulting soil sampling design preserved the distribution of environmental predictors. Reflectance spectra of the Mid-Infrared (4000–400 cm^{-1}) were recorded for 269 samples. Principal Component Analysis (PCA) and Kennard stone algorithm were used for calibration sample selection. Laboratory measurements were calibrated to first derivative spectra using Random Forest (RF) regression. Good predictions were achieved for SOC and N (r^2 = 0.76 and RMSE=1.64 and r^2=0.81 and RMSE= 0.09) as well for soil pH (r^2 = 0.88 and RMSE = 0.48). Mehlich extracted Na, Mg, Al, P, K and Ca were satisfactorily calibrated. Geostatistical analysis show moderate spatial dependency. Soil properties were quantified and now can support soil management decisions.

The second part of the research involved soil classification using the predicted soil properties and morphological field observations. Soil classification was performed based on the World Reference Base (WRB) for Soil Resources 2014. Based on the earlier surveys, geological and environmental setting, Nitisols were expected to be the dominant soils of the sampled area. However, this was not the case. The major difference to earlier survey data (KENSOTER database) is the high silt content (range 32.6 % - 52.4 %) and silt/clay ratio (range of 0.6 - 1.4) that invalidates the silt to clay ratio criterion of < 0.4 in the WRB 2014 classification system. There was good accordance in the morphological features with the earlier survey but failed the silt/clay ratio criteria for Nitisols. This observation calls for attention to set new classification criteria for Nitisols and other soils of warm, humid regions with variable rate of weathering to avoid difficulties in interpretation. However, most of the diagnostic horizons, properties and materials (Table 7) represent useful information for land use and management.

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8. ÖSSZEFOGLALÁS

A várható népességnövekedés és élelmiszerigény szükségessé teszi a megfelelő talaj információ megteremtését a rendelkezésre álló mezőgazdasági területeken történő gazdálkodás sikerének biztosítására. A jelenlegi adathiányt a hagyományos módszerekkel történő adatgyűjtés költség és időigénye nagyrészt magyarázza. Munkám során új, gyors költséghatékony adatgyűjtési módszert dolgoztam ki, mely támogatja a gazdálkodást a Mt. Kenya keleti lejtőin.

Input változók széles körét alkalmaztam a "Conditional Latin Hypercube Sampling (CLHS)" mintavételezési tervezés során. Domborzati adatok, NDVI, és talajadatok szerepeltek bemeneti adatokként, melyeket digitális domborzati modellből (DEM), Landsat 8 műholdképekből és a KENSOTER adatbázisból származtattam.

A 77 mintavételi ponton gyűjtött, összesen 269 talajminta alapján a középső infravörös tartományban (4000 – 400 cm^{-1}) végeztem spektrális méréseket. Főkomponens és Kennard-Stone analízis alapján választottam ki a – talajparaméterek spektrális alapú becslését lehetővé tevő – többváltozós modellek létrehozásához szükséges kalibrációs mintákat. A többváltozós kalibrációt Random Forest algoritmussal végeztem el a laboratóriumi referencia és spektrális mérési eredmények első deriváltjai alapján. Jó statisztikai mutatókkal rendelkező prediktív modellt kaptam a szerves szén (r^2=0.76, RMSE=1.64), nitrogén (r^2=0.81, RMSE=0.09), valamint a pH (r^2=0.88, RMSE=0.48) esetében. Kielégítő mutatókat kaptam a kicserélhető Na, Mg, Al, P, K és K értékekre is. A geostatisztikai vizsgálatok e talajtulajdonság-értékek közepes mértékű térbeli függőségét mutatják. Ezek a számszerűsített talajtulajdonságok jelentős szerepet játszanak a területet talajhasználatát érintő döntéshozatali eljárásokban.

A munka második része talajosztályozáshoz kapcsolódott a terepei felvételezési és a mért illetve becsült talajparaméterek alapján. A talajosztályozás alapjául a Világ Talajreferencia Bázis (World Reference Base (WRB) for Soil Resources) 2015-ös kiadása szolgált. A megelőző térképezési munkálatok alapján, a területen Nitisolok a várható domináns talajok. Saját felvételezésem más eredményeket hozott. Az osztályozási eredmény fő különbségét a (KENSOTER-hez képest) a nagy por frakció (32.6 % - 52.4 %) és por/agyag arány (0.6 - 1.4) okozta, amely nem felel meg a WRB (2015) jelenlegi por/agyag < 0.4 diagnosztikai követelménynek. A problémás talajok morfológiai és további tulajdonságai teljesen megfelelnek a Nitisolok koncepciójának, a fenti ok alapján kerültek más referencia csoportokba. A magas por arány e talajok szálló por frakció dúsulásával magyarázható. A tapasztalatok alapján szükséges felülvizsgálni a meleg, nedves területek mállott talajainak, különösen Nitisolok osztályozását és megszüntetni az tárgyalt diagnosztikai követelményt, a további besorolási és értelmezési nehézségek, valamint az archív adatok megőrzése érdekében. A Nitisol problémán túl, azonban a WRB kitűnően volt alkalmazható a területen. A diagnosztikai egységek és a minősítők hasznos és gyakorlat számára is értelmezhető információt hordoznak.

9. RELATED PUBLICATIONS

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12. APPENDICES

Appendix 1. Location, land use, slope and management data of the visited sites.

ID/plot Code	X_latitudes	Y_Longitude	SLOPE (%)	Land use	Location Name	Manure use
M1	4181879,198	4450,182538	6	Forest&grass	Nkunga	No
M2	4182107,218	1472,756876	4	Nappier grass, corn/Maize	Kathiranga/Munyeene	Yes
M3	4184798,552	4195,631911	6	Corn, Potatoes	Mworoga	No
M4	4188761,897	3747,570873	3	Agroforestry, napier grass, corn	Ngurumo	NO
M5	4188018,468	3585,04439	14	Corn Bananas, Coffee, Agroforestry	Ngurumo	NO
M6	4189471,93	3514,17097	19	Corn Beans, Bananas, Coff)	Ruiga Gatimbi	NO
M7	4195003,395	-334,51507	10	Coffee, Beans Corn, Banan)	kirigara/ Gatimbi	No
M8	4193469,227	-3138,65317	1	Tea, Potatoes)	Kamurita	YES
M9	4185420,457	-2421,384515	7	Tea, Mcadamia, Avocadoes & Agroforestry	Uruku/Mwinkithia	Charcoal Burining
M10	4185403,388	-2436,59818	7	Coffee, Bananas	Uruku/Kirumeene	NO
M10b	4182235,792	-4534,414307	8	Agroforestry	Uruku/Kirumeene	NO
M11p	4189322,761	-5608,833267	11	Tea	Nyayo Tea Zone	NO
M12	4189347,623	-12332,16641	22	Tea and agroforestry	Ngongo	NO
M13	4199912,77	4063,718286	4	Coffee and Maize	Gitimeene/Gaatia	YES
M14	4203190,201	3860,189111	4	Maize and Beans	Giaki	NO
M15	4207216,998	3119,357789	3	Maize/Corn	Giaki/Kirimamuthua	YES
M16	4217274,529	1351,418628	12	Maize and Groundnuts	Giaki/Thaamira	YES
M17	4216957,454	1357,726733	4	Water melons	Kiorimba/ Giaki	YES
M17b	4213771,119	4198,229366	5	Furrow	Kiorimba/Giaki	NO
M18	4209145,052	6597,536331	8	Beans and Maize	Mulika Mikinduri	NO
M19	4195478,173	-11361,27324	16	Beans and Maize	Mbeu	NO

M19p	4198820,169	-11741,05886	4	Beans and Maize	Mbeu	NO
M20	4198925,366	-10403,73869	2	Bananas, Yams	Mukuu/Baranga	NO
M21	4203995,783	-10422,29196	4	Bananas, Tea	Nkumari/Gaturi. Nkuene division	
M22	4203185,934	-9988,516459	7	Maize and Agroforestry	Ndemeene/Kirimene/Mitunguu	NO
M23	4205454,996	-9739,346034	17	Beans, Maize	Mitunguu	NO
M23p	4205170,019	-10570,53262	4	Maize and Beans	Kiagu/Kiroone/Mitunguu	NO
M24	4205174,019	-10573,53262	4	Beans, Maize		NO
M25	4210678,478	-2069,800435	10	Forest/ Shrubland/Thickets	Kiija farm/Mitunguu	NO
M26	4206485,258	-5121,624789	14	Napier grass, Agroforestry	Mitunguu/Thingithu river	YES
M27p	4207004,378	-4215,298358	4	Maize, Beans Sorghum	Kathagarene/ Mitunguu	NO
M28	4201647,684	-1155,496321	6	Maize	Chaaria/ Nkandone/Ndurumo	NO
M29	4201167,526	-715,4132623	7	Mangoes	Muti Fram, Ndurumo/ Chaaria	NO/ mulching was observed
M30	4201161,96	-1508,008049	1	Maize and Beans	Chaaria/Mwiti farm	NO
M31	4197359,658	1718,958491	12	Maize and Beans	Chaaria	NO
M32	4209075,292	-14116,99275	7	Maize and Beans	Runyeene/ Chaaria/ Gaitu	NO
M33	4211608,923	-16713,89854	5	Miaze, Beans Mangoes	Kimate/ Gaitu	NO
M34	4214200,998	-23624,46189	5	Maize, Beans, Peas, Agroforestry	Mati Road/Kamunandene	YES/ terracing/ mulching observed
M35p	4216575,814	-36041,73228	8	Corn, Beans & Sorghum	Kaurone/Mitunguu	NO
M36	4213257,38	-34895,49487	6	Maize, Mangoes, Beans	Tunyai Tharaka	YES
M37	4216357,442	-30701,10645	5	Agroforestry, Maize Beans	Twambonki/Tunyai/Tharaka	NO
M38	4213555,716	-29547,82366	7	Agroforestry, Maize Beans	Ciakariga/Tharaka	NO
M39	4211165,501	-24819,48524	3	Agroforestry	Mutino/Igambany'ombe/ Chuka	NO
M40	4208859,332	-22151,32447	2	Maize, Beans	Marindi/Igambany'ombe Chuka	NO
M41p	4207429,804	-18488,15245	0	Maize, Beans Magoes	Mutonga/Tharaka	NO
M42	4195829,386	-16069,17103	5	Beans, Milliet, Blackbeans, Maize(katumani type)	Gacheera/Nyakinjeru/River Mutonga/Tharaka	YES
M43	4197270,973	-15983,08368	9	Beans, Milliet, Blackbeans, Maize(katumani type)	Kamujua/Tunyai/Tharaka	NO
M44	4197603,447	-16377,71255	4	Beans Maize	Ngauru/Tharaka south	NO

M45	4198094,737	-14113,65316	26	Beans and Maize	Tharaka South	NO
M46	4200602,394	-13615,12619	2	Bananas coffee, Maize Beans	Kangamari/ Kanyakine	NO
M47	4196265,572	-7590,506804	13	Bananas coffee, Maize Beans	Kiringa/ Imenti South/ Abogeta	YES & Fertilizer
M48	4193537,132	-33952,41951	22	Bananas Maize Beans, Coffee	Kanyakine/ Abogeta East	YES
M49	4200095,52	-35433,54725	7	Bananas Maize Beans, Coffee	Kithakanaro/Abogeta East	YES
M50p	4197140,915	-29156,16044	7	Bananas Maize Beans,	Mutiokiama/ Abogeta East	YES
M51p	4197698,996	-27182,26108	6	Bananas, Maize, Beans	Mwanganthia/ Abothuguchi west	NO
M52	4190971,403	-26913,60762	13	Maize and Beans	Karingani/Chuka/Tungu River	NO
M53p	4201094,612	-27490,43337	1	Beans, Maize Agroforestry	Igandani/Karingani/Chuka	NO
M54	4200869,19	-26278,33887	1	Beans, Coffee, Maize, Agroforestry	Kangani/ Chogoria	YES/ Fertilizer
M55	4200592,376	-24681,2625	4	Dairy Farming, Maize Benas	Chogoria/ Igwanjau/Kiromi	YES/FYM
M56	4196309,544	-24038,01668	6	Beans, Maize, Coffee	Kathiru/Chogoria	NO
M57	4182968,459	-16754,34476	12	Maize, Beans, Coffee	Ndigia/Mwimbi/Tharaka nithi	YES
M58	4183006,865	-16771,41381	15	Maize, Beans Coffee	Magutuni/Mwimbi	NO
M59	4182862,891	-16810,74683	10	Beans, Maize	Magutuni/ Mwimbi	YES
M61	4183774,784	-17375,88081	5	Tea	Nyayo Tea zones/kiamweru/igoji	NO
M61b	4184752,354	-16676,23532	14	Tea	Nyayo Tea zones/kiamweru/igoji	NO
M61c	4184702,075	-16592,55988	12	Tea	Nyayo Tea zones/kiamweru/igoji	NO
M62	4189695,867	-21917,92321	2	Tea	Kiamweri/Igoji	NO
M62p	4188555,585	-23416,84963	8	Tea	Kamweri/Igoji	NO
M63	4190412,394	-24659,3695	9	Tea	Kiamweri/Igoji	NO
M63p	4192366,607	-20683,38317	10	Tea	Kiamweri/Igoji West	NO
M64	4190596,627	-19012,09845	13	Coffee and Maize	Karia/ Igoji west	NO
M65p	4168759,64	-18312,82353	5	Coffee, Maize, Beans	Karia/Igoji West	NO
M66	4169066,139	-18684,26112	11	Maize, Beans	Thigaa/ Chogoria	NO
M67	4170118,479	-19653,4872	13	Maize Beans Coffee	Koiri/Igoji East	YES
M68p	4170388,244	-20240,70039	15		Rwathene/ Igoji West	YES

Appendix 2. Generated soil properties and classification database.

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings or PF	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M1	0	20	3.3	50.4	39.4	12.3	C	22.9	54.7	5.1	5YR 3/3	GR	>5%		A	Mollic	ANDOSOL	Eurtic Mollic Vitric ANDOSOL (Clayic)
M1	20	50	2.2	47.0	41.7	12.4	SiC	21.5	55.0	4.9	5YR 3/3	SB		Clay	B	Vitric		
M1	50	100	1.5	50.0	40.1	10.9	SiC	20.2	53.0	4.8	2.5YR2.5/3	SB		Fe	Bt			
M2	0	20	2.4	44.7	46.3	10.9	SiC	18.6	48.1	5.1	7.5 YR 3/3	GR	>5%		Ap	Umbric	ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic)
M2	20	50	1.5	48.3	40.3	13.5	SiC	18.4	48.9	5.1	5YR 3/3	GR			B	Mollic		
M2	50	100	1.3	47.6	41.5	10.9	SiC	18.1	47.0	5.2	5YR 4/3	GR			CD			
M3	0	20	2.2	49.2	39.9	11.1	C	21.9	50.6	4.7	2.5 YR 3/3	SB			Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic)
M3	20	50	1.8	46.2	40.3	13.3	SiC	21.0	52.0	4.7	2.5 YR 2.5/3	SB			AB	Cambic		
M3	50	100	1.7	46.1	40.5	13.8	SiC	21.5	49.2	4.8	2.5 YR 2.5/3	SB			2B2			
M4	0	20	2.0	47.0	41.8	11.2	SiC	20.2	44.0	4.7	5YR 3/4	SB			AP	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M4	20	50	1.9	44.5	44.5	11.7	SiC	19.3	40.7	4.6	2.5 YR 3/6	SB			AB			
M4	50	100	1.2	42.4	45.5	11.7	SiC	19.6	42.2	4.7	2.5 YR 3/4	SB			B			
M5	0	20	2.3	47.8	40.8	12.5	SiC	19.2	48.3	5.1	2.5 YR 3/3	SB			AP	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic)
M5	20	50	1.6	42.1	46.0	13.4	SiC	18.2	48.2	5.1	2.5YR 3/3	SB			AB	Cambic		
M5	50	100	1.1	47.7	41.4	11.4	SiC	17.5	47.5	5.1	2.5 YR 3/4	SB		Clay	B			
M6	0	20	1.9	50.5	39.8	11.0	C	20.1	44.0	4.5	2.5 YR 3/4	SB			Ap	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M6	20	50	1.2	46.7	41.9	11.8	SiC	19.4	43.7	4.6	2.5 YR 3/6	SB			B			
M6	0	100	0.9	49.1	39.7	10.9	C	19.8	43.4	4.7	2.5 YR 3/6	SB			B1			
M7	0	20	1.8	46.4	41.5	12.0	SiC	20.8	44.6	4.6	2.5 YR 3/6	GR			A	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M7	20	50	0.7	48.4	41.3	11.3	SiC	20.1	46.6	4.8	2.5 YR 3/6	SB			B1			
M7	50	100	0.6	45.0	43.4	12.2	SiC	20.8	47.8	4.8	2.5YR3/6	SB			B2			
M8	0	20	2.4	46.9	41.2	11.4	SiC	17.7	39.6	4.5	5 YR 3/3	GR			AP	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic, Colluvic, Hyperhumic, Rhodic)
M8	20	50	2.5	46.5	42.2	12.0	SiC	16.4	36.3	4.4	2.5 YR 2.5/3	GR			A2	Cambic		
M8	50	100	1.5	45.6	42.6	11.9	SiC	17.7	44.1	4.7	5YR 3/4	GR			2A	Lithic discontinuity		
M9	0	20	4.0	43.4	43.9	12.3	SiC	19.1	41.3	4.7	2.5 YR 3/3	GR			Ap	Cambic	UMBRISOL	Cambic UMBRISOL (Aric, Escaric, Hyperhumic, Siltic)
M9	20	50	2.5	48.3	41.1	11.5	SiC	18.0	41.1	4.7	7.5 YR 3/3	GR			AB			
M9	50	100	2.0	47.5	41.0	11.6	SiC	17.2	42.2	4.7	2.5 YR 2.5/3	GR			BC			
M10	0	20	1.6	45.9	44.9	10.7	SiC	17.1	45.9	4.9	2.5YR 2.5/3	GR		clay	AP	Umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic)
M10	20	50	1.6	44.2	45.8	11.2	SiC	18.0	47.8	4.9	2.5 YR 3/3	GR		clay	A2	Argic		
M10	50	100	1.8	50.8	39.0	11.2	C	18.5	49.6	4.8	2.5 YR 3/3	GR			BC			

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ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M10b	0	40	1.9	43.1	41.9	11.7	SiC	17.9	48.0	4.8	2.5YR 3/3	SB		Clay	Ap		ALISOLS	Rhodic ALISOL (Aric, Clayic, Humic)
M10b	40	90	1.1	44.2	43.8	11.5	SiC	18.9	49.5	4.8	5 YR 3/3	AB			Bt1	Argic		
M10b	90	120	1.0	47.4	40.6	11.8	SiC	18.1	49.1	4.8	2.5 YR 2.5/3	AB			Bt2			
M10b	120	160	1.1	43.9	45.3	12.3	SiC	19.1	48.5	4.7	2.5 YR 2.5/3	AB			Bt3			
M11p	0	10	10.8	43.8	45.7	12.5	SiC	30.9	47.2	4.6	organic		<5		O	Andic	ANDOSOL	Umbric ANDOSOL (Aric, Clayic)
M11p	10	40	8.7	46.4	42.0	11.7	SiC	29.1	47.6	4.6	5YR 3/2	SB			Ap	Umbric		
M11p	40	80	7.1	45.8	41.6	12.1	SiC	19.5	36.7	4.7	7.5 YR 3/2	SB			B			
M11p	80	140	6.0	43.9	44.7	12.0	SiC	18.0	38.0	4.8	2.5 YR 3/2	SB			BC			
M11p	140	160	5.6	48.3	42.0	13.0	SiC	17.7	38.5	4.9	2.5 YR 3/2	SB			C			
M12	0	20	2.9	46.5	42.2	12.9	SiC	14.3	31.0	4.0	5 YR 3/3	GR		Clay	Ap	Umbric	UMBRISOL	Acric UMBRISOL (Aric, Chromic, Clayic, Hyperhumic)
M12	20	50	2.5	45.6	42.6	13.0	SiC	13.8	31.0	4.3	2.5YR2.5/3	SB			B	Argic		
M12	50	100	1.4	43.9	43.2	12.5	SiC	17.4	35.5	4.6	2.5 YR 2.5/3	SB			B2			
M13	0	20	1.9	42.7	44.6	13.4	SiC	20.2	46.0	4.6	5 YR 2.5/3	GR			Ap	umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic, Rhodic)
M13	20	50	1.5	44.1	44.1	12.3	SiC	19.6	51.8	4.7	2.5 YR 3/3	GR			AB			
M13	50	100	1.1	44.2	43.8	12.1	SiC	19.8	51.3	4.7	2.5 YR 2.5/3	SB		Clay	Bt	Argic		
M14	0	20	2.0	46.5	41.6	13.1	SiC	16.8	48.7	4.8	2.5 YR 2.5/4	GR			AP	Cambic	CAMBISOL	Dystric Rhodic CAMBISOL (Aric, Humic)
M14	20	50	1.2	45.8	41.7	13.6	SiC	16.9	48.7	4.9	2.5 YR 2.5/4	SB		Clay PF	AB			
M14	50	100	1.0	45.5	43.8	11.1	SiC	17.2	48.7	4.9	2.5 YR 2.5/6	SB		Clay PF	Bw			
M15	0	20	2.5	42.2	45.8	11.3	SiC	16.7	46.9	4.8	2.5 YR 2.5/2	GR			Ap	Umbric	UMBRISOL	Cambic Alic UMBRISOL (Aric, Clayic)
M15	20	50	2.2	45.5	44.3	11.1	SiC	16.0	43.7	4.8	2.5 YR 2.5/2	GR			A	Argic		
M15	50	100	2.7	44.8	45.0	11.3	SiC	20.7	47.1	4.8	2.5YR 2.5/3	SB			ABt			
M16	0	20	1.1	43.4	46.6	11.4	SiC	16.9	47.5	4.9	2.5YR 2.5/2	GR			Ap	Umbric	UMBRISOL	Acric UMBRISOL (Aric, Clayic, Rhodic)
M16	20	50	2.3	46.9	43.0	11.6	SiC	20.9	46.5	4.7	2.5 YR 2.5/2	SB			B	Argic		
M16	50	100	1.5	49.2	41.4	11.1	SiC	16.6	41.3	4.7	2.5YR 2.5/2	SB		Clay	Bt			
M17	0	20	1.0	47.3	41.4	12.8	SiC	18.3	54.4	5.0	2.5YR 2.5/3	GR			Ap	Mollic	PHAEOZEM	Haplic PHAEOZEM (Aric, Clayic, Rhodic)
M17	20	50	0.8	48.0	41.4	12.7	SiC	18.2	54.3	5.0	2.5 YR 2.5/3	SB		Clay Skins	B1			
M17	50	100	0.8	44.7	44.7	10.7	SiC	18.7	54.8	5.0	2.5 YR 2.5/3	SB			B2			
M17b	0	20	2.3	42.8	45.7	11.5	SiC	18.6	55.4	5.0	2.5 YR 2.5/3	SB		PF	Aph	Mollic	PHAEOZEM	Vertic Gleyic PHAEOZEM (Aric, Clayic, Pachic)
M17b	20	50	2.3	46.4	44.4	10.6	SiC	17.8	53.7	4.9	5YR 2.5/2	SB			B			
M17b	50	100	2.3	47.0	44.7	10.8	SiC	18.1	52.8	4.9	5YR 2.5/2	SB			Bl			

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M18	0	20	1.0	46.5	44.5	10.7	SiC	18.3	51.7	5.0	5YR 2.5/2	GR		Clay	Ap	Mollic	PHAEOZEM	Leptic PHAEOZEM (Aric, Clayic)
M18	20	50	0.8	46.7	45.0	11.0	SiC	18.7	55.7	5.2	5 YR 2.5/2	AB		Pressure surfaces	B			
M18	50	65	0.6	49.8	40.6	10.0	SiC	18.5	55.7	5.2	5 YR 3/2	AB			C			
M19	0	20	2.1	49.3	41.7	10.0	SiC	21.0	48.5	4.8	5 YR 3/2	WSB		Clay	Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Chromic, Clayic)
M19	20	50	1.0	47.9	42.1	10.5	SiC	19.7	44.6	4.8	7.5 YR 3/3	SB			AB	Cambic		
M19	50	100	0.6	46.3	43.6	11.1	SiC	20.3	48.2	4.8	5 YR 3/4	SB			B			
M19p	0	40	1.6	49.0	39.9	10.8	SiC	18.9	43.1	4.8	2.5 YR 3/2	WSB		Clay	Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Chromic, Clayic)
M19p	40	60	1.5	48.3	40.0	11.1	SiC	20.6	45.7	4.7	5 YR 3/3	SB			AB	Cambic		
M19p	60	100	0.8	49.6	39.9	11.6	SiC	20.6	47.5	4.8	5YR 3/4	SB			B			
M20	0	20	1.6	48.0	39.4	11.9	C	20.1	47.1	4.6	5YR 3/4	SB		Clay Skins	AP	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M20	20	50	1.1	47.0	42.6	11.0	SiC	19.9	45.4	4.7	5YR 3/4	SB			B1			
M20	50	100	1.7	46.7	43.4	11.3	SiC	19.9	42.6	4.7	2.5 YR 3/4	SB			B2			
M21	0	20	2.3	46.1	40.2	10.0	SiC	19.6	46.0	4.6	2.5 YR 3/3	SB			AP	Umbric	UMBRISOL	Acric UMBRISOL (Aric, Chromic, Clayic)
M21	20	50	0.8	50.7	40.7	10.2	SiC	19.8	49.7	4.7	5 YR 4/3	AB			ABt	Argic		
M21	50	100	0.7	42.8	46.5	11.8	SiC	19.3	49.5	4.8	5 YR 4/4	AB		Clay	B			
M22	0	20	0.9	42.5	46.9	11.9	SiC	18.7	41.7	4.6	2.5 YR 3/3	SB		Clay	Ap		ALISOLS	Rhodic ALISOL (Aric, Clayic, Humic)
M22	20	50	0.7	43.9	46.0	11.1	SiC	18.5	43.6	4.6	2.5YR 3/6	AB			Bt1	Argic		
M22	50	100	0.8	43.3	46.9	11.2	SiC	18.5	43.0	4.7	2.5 YR 3/6	AB			Bt2			
M23	0	20	1.2	43.8	45.8	11.7	SiC	16.4	46.7	5.1	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Skeletic Leptic UMBRISOL (Aric,Calyic)
M23	20	50	0.8	42.7	46.2	12.0	SiC	17.6	47.5	5.1	5YR 3/3	GR			A/D			
M23	50	100	0.6	43.1	46.6	11.5	SiC	17.3	48.9	5.2	5YR 3/3	GR			D/A			
M23p	0	20	1.0	44.4	45.2	11.3	SiC	16.8	50.9	5.1	5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Loamic)
M23p	20	30	1.0	49.8	40.3	11.6	SiC	18.0	52.1	5.1	2.5 YR 3/3	GR			B			
M23p	30	50	0.8	49.2	39.1	12.9	C	17.1	47.5	5.1	2.5 YR 3/4				D			
M24	0	20	0.9	48.4	41.9	10.4	5.0	5.0	46.1	5.1	2.YR 3/3	GR			Ap/D	Umbric	LEPTOSOL	Dystric Umbric LEPTOSOL (Aric, Clayic, Humic)
M25	0	20	0.9	46.6	43.3	10.9	SiC	17.3	49.2	5.2	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Leptic skeletic UMBRISOL (Aric, Loamic)
M25	20	50	0.9	44.2	46.1	11.0	SiC	17.8	46.7	5.2	2.5 YR 3/3	GR			A/D			
M25	50	100	0.8	45.1	44.3	11.0	SiC	18.4	48.5	5.3	2.5 YR 3/3	GR			D/A			
M26	0	20	3.1	44.5	45.8	11.1	SiC	20.0	48.8	4.9	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Gleyic UMBRISOL (Aric, Clayic, Rhodic)
M26	20	50	2.3	43.4	46.5	12.0	SiC	18.3	48.9	5.0	5YR 4/2	GR			A2			

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M27p	0	15	1.0	47.8	39.3	12.9	C	19.2	46.9	4.8	2.5 YR 2.5/2	GR			AP	Umbric	UMBRISOL	UMBRISOL (Aric,Clayic, Rhodic)
M27p	15	60	0.7	44.9	42.8	12.3	SiC	16.7	47.0	4.9	2.5 YR 2.5/2	SB		FE, Mg	Bt	Argic		
M27p	60	90	0.7	45.7	44.4	11.4	SiC	18.9	46.7	4.8	2.5 YR 3/3	SB			Bc			
M27p	90	150	0.7	44.7	45.3	11.1	SiC	17.1	46.0	4.8	2.5 YR 3/3	AB			Bc1			
M28	0	20	0.9	47.2	43.1	11.1	SiC	20.1	48.4	4.7	2.5 YR 3/4	GR		Clay	Ap		CAMBISOL	Dystric Rhodic CAMBISOL (Aric, Clayic, Humic)
M28	20	50	0.7	48.2	40.2	13.5	SiC	19.6	47.9	4.7	2.5 YR 3/4	WSB			AB			
M28	50	100	0.7	49.5	40.7	10.3	SiC	19.4	47.3	4.8	2.5 YR 3/4	SWB			B1			
M29	0	20	1.5	47.5	42.2	10.8	SiC	21.0	47.7	4.8	2.5 YR 3/2	GR			Ap/C	Umbric	UMBRISOL	Skeletic Leptic UMBRISOL (Aric, Clayic)
M29	20	50	0.9	47.3	42.4	11.1	SiC	21.3	48.8	4.8	2.5 YR 3/3	SB			C/A			
M29	50	100	0.6	44.5	44.3	11.9	SiC	19.1	48.3	5.3	5YR4/3				D			
M30	0	20	1.5	47.7	42.3	10.9	SiC	18.1	51.0	4.9	5YR 4/3	WSB			A	Cambic	CAMBISOL	Dystric Leptic CAMBISOL (Aric, Clayic, Humic)
M30	20	50	0.8	46.4	43.6	11.0	SiC	19.9	47.0	4.9	5 YR 3/3	SB			AB			
M31p	0	20	1.4	48.4	41.3	11.0	SiC	17.6	53.3	5.0	2.5 YR 3/2	GR			Ap	Mollic	PHAEOZEM	Luvic PHAEOZEM (Aric, Clayic, Rhodic)
M31p	20	50	0.7	47.1	43.3	10.9	SiC	17.5	51.1	5.0	2.5 YR 3/2	AB		clay	B1	Argic		
M31p	50	80	0.7	49.2	39.9	10.4	SiC	17.6	51.5	5.0	2.5 YR 3/2	AB			B2			
M31p	80	120	0.7	46.9	42.6	11.1	SiC	18.4	51.1	4.9	2.5 YR 2.5/3	AB			B3			
M32	0	20	0.9	50.7	39.1	10.2	C	15.9	42.9	4.9	2.5 YR 2.5/3	GR			Ap	Umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic, Rhodic)
M32	20	50	0.8	56.2	35.4	9.6	C	17.9	48.8	4.8	2.5 yr 3/3	SB			Bt	Argic		
M32	50	100	0.7	47.3	42.9	11.5	SiC	19.3	52.1	4.9	2.5 yr 3/3	SB		Clay	B			
M33	0	20	1.4	45.1	44.1	12.0	SiC	16.6	47.4	5.0	2.5 yr 3/2	GR			Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, loamic, Rhodic)
M33	20	50	0.8	50.1	39.8	10.6	C	16.6	49.0	4.9	2.5 YR 3/4	SB			BW	Cambic		
M33	50	100	0.7	46.8	43.0	11.2	SiC	17.4	51.3	5.0	5 YR 3/4	SB			BC			
M34	0	20	1.0	46.2	44.4	11.5	SiC	19.2	53.8	5.1	2.5YR 3/2	GR			Ap	Mollic	UMBRISOL	Cambic UMBRISOL (Aric, Clayic, Colluvic, Raptic)
M34	20	50	1.3	45.6	43.2	12.4	SiC	21.4	51.1	4.9	2.5 YR 3/4	SB			2B	Cambic		
M34	50	100	2.1	43.3	45.9	12.6	SiC	21.5	48.3	4.9	2.5 YR 3/3	SB			3A			
M35p	0	20	2.3	41.9	47.0	12.0	SiC	20.4	46.6	4.8	2.5 YR 3/4	GR			Ap	Plinthic	PLINTHOSOL	Umbric PLINTHISOL (Aric, Clayic, Dystric, Humic)
M35p	20	30	2.0	42.3	46.8	12.5	SiC	19.9	42.4	4.9	2.5 YR 3/4	GR			B			
M35p	30	90	1.0	44.1	44.8	12.4	SiC	19.8	40.0	5.0	2.5 YR 3/4	SB			B/C			
M35p	90	110	0.8	41.8	46.7	12.8	SiC	19.1	44.4	4.7	2.5 YR 3/4	SB			C/B			
M35p	110	150	0.8	47.8	41.9	10.8	SiC	19.7	42.9	4.8	2.5 YR 3/6	SB			C			
M36	0	20	1.7	44.3	45.1	11.5	SiC	19.0	56.1	5.2	2.5 YR 3/3	WSB			Ap	Mollic	PHAEOZEM	Haplic PHAEOZEM (Aric, Clayic, Colluvic, Novic, Rhodic)
M36	20	50	2.2	48.3	42.6	10.6	SiC	19.0	55.2	5.1	2.5YR 3/2	SB			2A			
M36	50	100	2.2	46.6	42.8	11.5	SiC	18.7	54.8	5.1	5YR 3/2	SB			2AB			

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ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M37	0	20	1.2	50.1	40.3	10.1	SiC	19.3	57.0	5.2	5YR 3/2	GR			Ap	Mollic	UMBRISOL	Cambic UMBRISOL (Aric, Chromic, Clayic)
M37	20	50	1.8	44.6	43.7	11.6	SiC	20.6	46.7	4.8	5YR 3/2	SB			AB	Cambic		
M37	50	100	0.9	51.0	39.7	10.1	C	19.1	42.1	4.7	2.5 YR 2.5/4	SB			B			
M38	0	20	1.0	45.7	44.3	11.1	SiC	19.5	42.2	4.7	2.5 YR3/4	GR			Ap	Cambic	CAMBISOL	Leptic, Chromic, EpiDystric, EndoEutric CAMBISOL (Aric, Clayic, Colluvic, Escalic, Ochric)
M38	20	50	0.9	46.3	42.8	11.2	SiC	21.7	54.4	5.0	2.5 YR 3/4				B/C1			
M38	50	100	0.7	43.9	44.6	12.0	SiC	21.1	55.7	5.0	2.5 YR 3/4				B/C2			
M39	0	20	0.9	48.3	41.5	10.9	SiC	18.8	54.9	5.4	2.5YR 3/4	GR			A	Cambic	CAMBISOL	Eutric Rhodic Leptic CAMBISOL (Aric, Clayic, Colluvic, Escalic, Ochric)
M39	20	50	0.7	43.5	46.0	12.2	SiC	18.7	56.1	5.2	2.5 YR 3/4	SB			B			
M40	0	20	0.6	44.9	44.2	12.0	SiC	19.2	55.6	5.3	2.5 YR 3/4				C		REGOSOL	Eutric Regosol (Aric, Clayic)
M40	20	50	0.6	45.1	45.2	11.8	SiC	18.8	55.5	5.4	2.5YR 3/4	GR			Ap			
M40	50	100	0.8	37.7	52.4	12.7	SiCL	18.5	55.2	5.3	5 YR 3/4				AB			
M41p	0	25	1.8	40.9	43.9	15.9	SiC	20.9	49.1	5.0	2.5YR 3/3	GR			A/C	Umbric	UMBRISOL	Skeletic , Leptic UMBRISOL (Aric, Chromic, Chromic)
M41p	25	40	1.0	46.2	40.0	13.9	C	20.0	45.5	4.9	5YR 3/4				AB/C			
M41p	40	70	1.0	45.9	40.3	13.9	SiC	20.0	42.7	4.9	2.5 YR 3/3				B/C			
M41p	70	90	0.7	43.1	41.7	15.7	SiC	20.1	46.7	4.9	2.5 YR 3/3				C/B			
M42	0	20	1.4	42.3	43.5	16.1	SiC	20.0	44.7	4.9	2.5YR3/3	GR			A/C	Umbric	UMBRISOL	Skeletic Leptic UMBRISOL (Aric, Calyic, Chromic)
M42	20	50	1.1	43.4	42.9	15.4	SiC	19.9	43.2	4.9	2.5 YR3/4				AB/C	Cambic		
M42	50	80	0.8	44.6	42.0	14.1	SiC	19.4	42.6	4.9	2.5YR 3/6				D			
M43	0	20	1.5	49.8	41.3	9.9	SiC	17.7	39.8	4.6	5YR 3/3	GR			Ap	Umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic)
M43	20	50	1.1	45.5	40.2	12.9	SiC	18.0	40.8	4.6	5YR 3/3	SB			A2	Argic		
M43	50	100	1.0	50.7	36.9	11.6	C	17.4	39.0	4.7	5 YR 3/3	SB			Bt			
M44	0	20	1.1	45.1	41.2	13.7	C	18.4	44.4	4.8	5YR 3/3	SB		Clay	A	Argic	ALISOLS	Chromic ALISOL (Aric, Clayic,Vitric)
M44	20	50	0.9	48.2	39.5	12.4	C	17.5	41.7	4.7	5YR 3/4	SB			Bt			
M44	50	100	0.9	47.5	40.8	11.8	SiC	17.5	39.7	4.7	2.5YR 2.5/4	SB			B2			
M45	0	20	1.8	43.1	41.2	14.8	SiC	18.5	42.3	4.6	2.5 YR 2.5/4	SG			Ap	Argic	ALISOLS	Chromic ALISOL (Aric, Clayic)
M45	20	50	1.2	45.1	43.4	11.6	SiC	16.6	36.4	4.6	2.5 YR 2.5/4	GR			ABt1			
M45	50	100	0.9	45.6	40.3	13.8	SiC	18.2	40.9	4.7	2.5 YR 2.5/4	SB		Clay	Bt2			
M46	0	20	1.2	44.3	41.3	13.8	SiC	17.0	34.2	4.5	2.5 YR 2.5/4	GR			Ap	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M46	20	50	1.3	47.0	41.2	13.4	SiC	17.5	35.6	4.5	2.5 YR 3/4	SB			B1			
M46	50	100	1.1	45.9	41.0	13.9	SiC	16.4	33.7	4.5	2.5 YR 3/4	SB			B2			

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M47	0	20	1.3	44.2	43.3	12.8	SiC	19.0	44.8	4.8	2.5 YR 3/3	SB			A		ALISOLS	Rhodic ALISOL (Aric, Clayic, Humic)
M47	20	50	0.8	45.9	43.3	10.2	SiC	18.3	42.0	4.8	2.5 YR 3/3	SB		Clay	AB	Argic		
M47	50	100	0.8	36.4	51.9	12.2	SiCL	18.7	43.4	4.8	2.5 YR 3/4	AB			B	Umbric		
M48	0	20	2.0	47.1	41.8	10.8	SiC	20.0	44.3	4.6	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic, Rhodic)
M48	20	50	1.7	43.4	44.6	11.8	SiC	19.7	45.1	4.6	2.5 YR 3/3	SB			A2			
M48	50	100	2.7	50.2	39.8	9.7	C	21.3	46.1	4.7	2.5 YR 3/2	AB			AB	Cambic		
M49	0	20	1.9	50.1	40.5	10.5	SiC	19.4	41.2	4.5	2.5 YR 3/3	AB		Clay	Ap	Umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic, Rhodic)
M49	20	50	0.8	45.4	41.4	13.8	SiC	18.1	41.1	4.7	2.5 YR 2.5/3	AB			AB	Argic		
M49	50	100	0.8	48.1	39.0	12.0	C	18.4	42.3	4.7	2.5YR 2.5/4	AB			Bt			
M50p	0	15	1.9	41.6	42.4	16.0	SiC	21.9	52.6	4.9	2.5 YR 3/2	SB		Clay	Ap/D	Argic	UMBRISOL	Skeletic Alic Leptic UMBRISOL (Aric, Clayic Rhodic)
M50p	15	50	0.8	42.7	46.3	13.2	SiC	13.7	40.2	5.0	2.5 YR 3/3	SB			AB/C	Mollic		
M50p	50	70	1.0	47.9	39.2	13.6	C	14.9	39.9	5.0	2.5 YR 3/3	SB			C/Bt			
M51p	0	35	0.9	43.5	46.8	11.9	SiC	13.5	37.7	4.9	5YR 3/2	GR		Clay	Ap	Umbric	UMBRISOL	Alic UMBRISOL (Aric, Clayic)
M51p	35	60	1.6	48.3	40.2	12.6	SiC	13.5	37.4	4.9	5YR3/3				ABt	Argic		
M51p	60	80	0.8	47.5	42.8	11.6	SiC	15.7	44.5	4.9	5YR 3/3				Bt/C			
M51p	80	100	0.7	50.1	37.4	12.8	C	16.7	46.8	4.9	5YR/3/4				C/Bt			
M52	0	20	0.7	46.9	39.2	13.2	C	16.8	47.0	5.0	5 YR 3/3	SB		Clay	Ap	Argic	UMBRISOL	Alic UMBRISOL (Aric, Chromic, Clayic, Colluvic)
M52	20	50	0.7	44.3	49.2	7.7	SiC	16.3	42.1	4.9	5 YR 4/4	AB		Clay	AB	Umbric		
M52	50	100	0.9	56.9	34.5	8.0	C	15.7	37.0	4.9	5YR 4/4	AB		Clay	Bt			
M53p	0	15	0.8	54.8	39.9	9.1	C	18.3	52.2	4.9	2.5 YR 3/2	GR		Clay	Ap	Mollic	UMBRISOL	Alic UMBRISOL (Aric ,Chromic, Clayic)
M53p	15	40	0.7	54.8	37.1	8.9	C	20.2	49.3	4.8	2.5 YR 3/4	AB			B1	Argic		
M53p	40	100	0.7	48.9	42.1	10.2	SiC	18.0	50.1	4.9	2.5 YR 3/4	AB			B2			
M54	0	20	1.8	45.8	41.0	11.4	SiC	20.3	41.7	4.5	5 YR 3/3	SB			Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic, Rhodic)
M54	20	50	1.9	46.3	40.4	12.3	SiC	20.4	46.6	4.6	2.5 YR 3/3	AB			AB1			
M54	50	100	1.6	45.6	41.6	13.6	SiC	19.8	46.5	4.6	2.5 YR 3/3	AB			AB2			
M55	0	20	1.3	46.9	40.7	12.6	SiC	18.8	37.7	4.6	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Cambic UMBRISOL (Aric, Clayic Rhodic)
M55	20	50	1.1	47.3	43.2	9.1	SiC	18.9	41.0	4.6	2.5 YR 3/3	SB			AB1			
M55	50	100	1.2	48.1	40.0	10.7	SiC	17.3	36.0	4.5	2.5 YR 2.5/3	SB			B2			
M56	0	20	1.9	51.2	42.3	9.2	C	16.4	30.6	4.4	2.5 YR 3/3	GR			Ap	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Clayic, Rhodic)
M56	20	50	0.9	51.0	41.8	9.9	C	19.7	45.7	4.7	2.5 YR 3/4	SB			B1			
M56	50	100	1.2	45.9	41.4	13.6	SiC	17.2	34.8	4.5	2.5 YR 3/6	SB			B2			

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M57	0	20	1.2	47.1	40.5	14.0	SiC	19.9	45.6	4.6	2.5 YR 2.5/3	GR			Ap	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Clayic, Rhodic)
M57	20	50	1.1	46.7	42.1	10.4	SiC	20.2	51.4	4.7	2.5 YR 2.5/3	SB			AB			
M57	50	100	0.9	48.3	39.9	11.6	C	20.0	48.8	4.7	2.5 YR 2.5/3	SB			B			
M58	0	10	0.9	50.1	37.5	12.2	C	19.5	45.5	4.7	2.5 YR 2.5/3	AB		Clay, PF	A	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Chromic, Clayic)
M58	10	60	0.8	43.2	42.1	15.2	SiC	19.7	47.9	4.7	2.5 YR 2.5/4	AB			B1			
M58	60	100	0.9	38.1	46.8	15.3	SiCL	19.6	47.0	4.7	2.5 YR 2.5/4	AB			B2			
M59	0	20	1.5	40.3	45.2	15.1	SiC	19.8	43.8	4.5	2.5 YR 2.5/2	SB			Ap	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Clayic, Rhodic)
M59	20	50	1.3	45.9	41.0	13.3	SiC	19.0	40.5	4.6	2.5 YR 2.5/3	AB			AB1			
M59	50	100	0.9	45.7	40.7	13.9	SiC	19.1	42.0	4.6	2.5 YR 2.5/3	AB			AB2			
M60	0	20	1.0	46.9	41.4	13.4	SiC	19.3	43.9	4.7	2.5YR 2.5/2	SB			Ap	Umbric	UMBRISOL	Haplic UMBRISOL (Aric, Clayic, Rhodic)
M60	20	50	1.4	46.4	41.5	13.5	SiC	19.3	41.4	4.5	2.5YR 2.5/2	SB			AB			
M60	50	100	0.8	46.3	41.4	13.4	SiC	19.4	44.5	4.7	2.5YR 2.5/2	SB			B1			
M61	0	20	3.2	46.6	41.0	13.1	SiC	19.1	33.5	4.2	5YR 2.5/2	GR	>5		Aph	Mollic	ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic, Hyperhumic)
M61	20	50	2.6	47.7	39.2	12.5	SiC	19.2	36.7	4.2	5YR 2.5/2	GR			B1	Umbric		
M61	50	100	2.2	43.1	43.1	13.7	SiC	19.6	37.5	4.2	5YR 2.5/2	WSB			B2			
M61b	0	20	6.3	50.1	39.7	10.8	C	19.0	31.2	4.0	5YR 3/2	GR	>5		Aph	Umbric	ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic, Hyperhumic)
M61b	20	50	3.1	42.9	44.0	13.6	SiC	18.9	33.5	4.1	5YR 3/2	GR			B1			
M61b	50	100	2.3	49.7	39.5	13.0	C	19.6	37.9	3.9	5YR 2.5/2	WSB			B2			
M61c	0	20	6.8	48.4	39.8	13.9	C	21.6	34.8	4.4	5YR 2.5/2	GR	>5		Ap		ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic, Hyperhumic)
M61c	20	50	3.4	47.9	40.9	13.3	SiC	19.9	34.3	4.2	5YR 3/3	GR			AB1	Umbric		
M61c	50	100	2.3	46.7	41.7	13.1	SiC	20.0	38.5	4.0	5YR 2.5/2	WSB			B2			
M62	0	20	4.6	43.2	42.6	14.2	SiC	20.7	35.1	4.2	5 YR 2.5/2	GR	>5		A	Umbric	ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic, Hyperhumic)
M62	20	50	4.2	43.8	42.5	13.7	SiC	20.9	37.5	4.1	5YR 3/2	SB			AB1			
M62	50	100	2.4	47.6	41.1	12.1	SiC	20.5	40.9	4.1	5YR 3/2				B2			
M62p	0	20	2.1	48.8	39.9	11.9	C	20.4	42.8	4.4	2.5YR 2.5/3	GR	>5		A	Umbric	ANDOSOL	Dystric Umbric Vitric ANDOSOL (Aric, Clayic)
M62p	20	50	0.8	47.0	39.9	12.9	C	19.5	44.2	4.4	2.5 YR 2.5/3	GR			AB1			
M62p	50	100	0.7	45.0	44.0	10.7	SiC	19.7	44.0	4.7	2.5 YR 3/3	WSB			B2			
M63	0	20	3.0	48.3	39.9	11.5	C	19.5	33.3	4.1	2.5 YR 3/2	GR	5		O	Umbric	ANDOSOL	Dystric Umbric Follic ANDOSOL (Aric, Clayic, Hyperhumic)
M63	20	50	2.4	45.1	39.0	16.2	C	19.4	35.2	4.2	2.5 YR 3/3	GR			A			
M63	50	100	1.6	45.1	41.7	14.7	SiC	18.9	38.8	4.5	5 YR 3/2	WSB			B			
M63p	0	30	5.2	42.9	42.3	15.8	SiC	20.3	35.3	4.2	5YR 3/3	SB	5		Ap	Umbric	ANDOSOL	Dystric Umbric ANDOSOL (Aric, Clayic, Hyperhumic)
M63p	30	60	2.5	51.8	38.0	11.5	C	20.6	40.0	4.2	2.5 YR 3/3	SB			AB			
M63p	60	100	1.6	43.4	42.3	14.7	SiC	19.6	42.7	4.5	2.5 YR 3/3	SB			B1			

ID /plot code	Depth from	Depth to	SOC	Clay	Silt	Sand	Tex-ture	Actual CEC	BS	pH	Munsell Color	Stucture	Volcanic glass	Coatings	Genetic horizon	WRB Diagn.	WRB RGS	WRB Soil Name
	cm	cm	%	%	%	%		cmol/kg	%		moist		%			list		
M64	0	20	2.3	42.8	44.4	15.2	SiC	17.9	32.6	4.3	2.5 YR 3/6	SB			Ap	Cambic	CAMBISOL	Dystric CAMBISOL (Aric, Clayic, Humic)
M64	20	50	1.3	49.3	37.2	12.8	C	18.3	39.9	4.6	2.5 YR 3/6	SB			AB			
M64	50	100	0.9	43.6	44.4	14.4	SiC	18.4	39.7	4.6	2.5 YR 2.5/4	SB			B1			
M65p	0	20	1.2	43.1	44.7	14.6	SiC	18.8	41.8	4.7	2.5 YR 3/4	GR			O		ALISOLS	Rhodic ALISOL (Aric, Clayic)
M65p	20	80	0.7	42.5	43.5	15.8	SiC	18.6	44.7	4.7	2.5 YR 3/4	WSB		Clay	A	Argic		
M65p	80	120	0.6	43.9	43.6	14.2	SiC	17.9	45.7	4.8	2.5 YR 3/4	WSB			B			
M66	0	20	1.8	41.0	44.6	15.5	SiC	17.6	33.4	4.4	2.5 YR 3/4	GR			Ap	Cambic	CAMBISOL	Dystric Rhodic CAMBISOL (Aric, Clayic, Humic)
M66	20	50	1.1	43.8	44.2	14.3	SiC	17.7	36.8	4.6	2.5 YR 3/4	WSB			B1			
M66	50	100	1.0	44.9	41.6	14.4	SiC	17.8	37.5	4.6	5 YR 3/3	SB			B2			
M67	0	20	2.1	50.4	36.7	12.9	C	21.6	49.2	4.6	5YR 3/3	SB			Ap	Argic	ALISOLS	Chromic ALISOL (Aric, Clayic, Humic)
M67	20	50	1.0	51.6	40.5	10.3	SiC	19.2	46.8	4.7	5 YR 3/3	AB		Clay	Bt1			
M67	50	100	0.9	58.7	32.6	8.2	C	19.2	46.3	4.7	2.5 YR 3/4	AB			Bt2			
M68p	0	30	2.4	38.7	48.2	12.4	SiCL	17.0	32.2	4.2	2.5 YR 3/4	GR			AP	Argic	ALISOLS	Chromic ALISOL (Aric, Clayic, Humic)
M68p	30	70	1.3	46.5	38.5	12.7	C	17.3	35.9	4.5	2.5 YR 3/4	SB		Clay	Bt			
M68p	70	120	3.1	45.0	39.7	13.4	C	20.2	36.6	4.5	2.5 YR 3/6	SB			BC			

Appendix 3. Additional Soil data (Fe, XRD)

ID/plot Code	**Depth from**	**Depth to**	FeO dith	FeO Ox	FeO dith/FeO ox	XRD
	cm	cm	(%)	(%)	Ratio	
M1	20	50	18,4	84,4	0,22	Kaolinite/halloysite>>goethite>illite>quartz, k-feldspar>smectite, hematite
M5	20	50				Kaolinite/halloysite>>goethite>hematite, quartz>k-feldspar, gibbsite
M10	20	50				Kaolinite/halloysite>>goethite>k-feldspar, quartz>illite, gibbsite, hematite>smectite
M14	20	50	11,7	86,9	0,13	Kaolinite/halloysite>>goethite, hematite>quartz>smectite, k-feldspar, gibbsite
M25	20	50	2,5	13,3	0,19	
M44	20	50	4,3	71,2	0,06	Kaolinite/halloysite>goethite, quartz>hematite>k-feldspar>gibbsite, plagioclase
M48	20	50				Kaolinite/halloysite>goethite>hematite>quartz>k-feldspar
M49	20	50	6	84,4	0,07	Kaolinite/halloysite>>goethite>hematite>quartz, smetcite, k-feldspar
M59	20	50				Kaolinite/halloysite>goethite>quartz>hematite, k-feldspar
M61	20	50				Kaolinite/halloysite>>goethite>illite>smectite, gibbsite, quartz, k-feldspar, hematite

Appendix 4. Changes in the definition of the Nitisols and the related nitic horizon.

4.1. Soil map of the World, Revised Legend (FAO/UNESCO, 1988)

NITISOLS (NT)

Soils having an argic B horizon showing a clay distribution which does not show a relative decrease from its maximum of more than 20 percent within 150 cm of the surface; showing gradual to diffuse horizon boundaries between A and B horizons; *having nitic properties in some subhorizon within 125 cm* of the surface; lacking the tonguing which is diagnostic for Podzoluvisols; lacking ferric or vertic properties; lacking plinthite within 125 cm of the surface.

Haplic Nitisols (NTh) Nitisols which are not strongly humic and have an argic B horizon that is not red to dusky red'.

Rhodic Nitisols (NTr) Nitisols which are not strongly humic and have a red to dusky red' argic B horizon.

Humic Nitisols (NTu) Nitisols having an umbric or a mollic A horizon, and which are strongly humic.

NITIC PROPERTIES

The term 'nitic properties' applies to soil material that has 30 percent or more clay, has a moderately strong or strong angular blocky structure which falls easily apart into flat edged ('polyhedric' or 'nutty') elements which show shiny ped faces that are either thin clay coatings or pressure faces. This soil structure is apparently associated with the presence of significant amounts of active iron oxides and is indicative of a high effective moisture storage and favourable phosphate sorption - desorption properties.

Laboratory facilities permitting, the characterization of 'nitic properties' can be enhanced by the determination of Fe_20_3 extractable from the fine earth by acid oxalate (AO iron) and the $Fe_e\ 0_3$ extractable from the fine earth by dithionate-citrate-bicarbonate (DCB iron). Soil materials with nitic properties have more than 0.2 percent AO iron which moreover is at least 5 percent of the DCB iron.

4.2.World Reference Base for Soil Resources, FAO-ISRIC-ISSS, 1998)

NITISOLS (NT)
Diagnostic Criteria: 1. an *argic* horizon, which has a cation exchange capacity (by 1 *M* NH4OAc) of less than 24 cmolc kg-1 clay in some part, either starting within 100 cm from the soil surface, or within 200 cm from the soil surface if the argic horizon is overlain by loamy sand or coarser textures throughout, ***and***
2. a base saturation (by 1M NH4OAc) of less than 50 percent in the major part between 25 and 100 cm.

Nitic horizon
General description. The nitic horizon (from L. ***nitidus***, shiny) is a clay-rich subsurface horizon with as its main feature a moderately to strongly developed polyhedric or nutty structure with many shiny ped faces, which cannot or can only partially be attributed to clay illuviation.

Diagnostic criteria. A nitic horizon must have:

1. diffuse to gradual transitions to horizons immediately above and below (less than 20 percent change in clay content, over at least 12 cm; no abrupt colour change); ***and***

2.

a. more than 30 percent clay; ***and***

b. water-dispersible clay/total clay ratio less than 0.10 (unless there is more than 0.6 percent organic carbon); ***and***

c. silt/clay ratio is less than 0.40; ***and***

3. moderate to strong, nutty or polyhedric structure, with many shiny pedfaces, which cannot or can only partially be associated with illuviation argillans in thin sections; ***and***

4. Munsell colour value of 5 or less, and chrome of 4 or less, but no mottling of hydromorphic nature (*gleyic* or *stagnic* properties); ***and***

5.

a. 4.0 percent or more citrate-dithionite extractable iron ("free" iron) in the fine earth fraction; ***and***

b. more than 0.20 percent acid oxalate (pH 3) extractable iron ("active" iron) in the fine earth fraction; ***and***

c. ratio between "active" and "free" iron of 0.05 or more; ***and***

6. minimum thickness of 30 cm, with gradual to diffuse transitions to horizons immediately above and below the nitic horizon.

10.14751/SZIE.2017.065

3.3 World reference base for soil resources 2006 and 2015 (IUSS Working Group WRB. 2006, 2015)

NITISOLS (NT)

Diagnostic Criteria:

1. a *nitic* horizon starting ≤ 100 cm from the soil surface; *and*

2. no *petroplinthic*, *pisoplinthic, plinthic* or *vertic* horizon starting ≤ 100 cm from the soil surface; *and*

3. no layers with *reducing conditions* above or within the *nitic* horizon.

Nitic horizon

General description

A nitic horizon (from Latin *nitidus*, shiny) is a clay-rich subsurface horizon. It has moderately to strongly developed blocky structure breaking to polyhedral, flat-edged or nutty elements with many shiny soil aggregate faces, which cannot or can only partially be attributed to clay illuviation.

Diagnostic criteria

A nitic horizon consists of *mineral* material and:

1. has both of the following:

a. ≥ 30% clay; ***and***

b. a silt to clay ratio < 0.4; ***and***

2. has < 20% difference (relative) in clay content over 15 cm to layers directly

above and below; ***and***

3. has moderate to strong blocky structure breaking into polyhedral or flat-edged or nut-shaped elements with, in moist state, shiny soil aggregate faces. The shiny faces are not, or are only partially, associated with clay coatings; ***and***

4. has all of the following:

a. ≥ 4% Fedith (*free* iron) in the fine earth fraction; ***and***

b. ≥ 0.2% Feox (*active* iron) in the fine earth fraction; ***and***

c. a ratio between *active* and *free* iron of ≥ 0.05; ***and***

5. does not form part of a *plinthic* horizon; ***and***

6. has a thickness of ≥ 30 cm.