CHARACTERISATION OF SMALLHOLDER FARMING SYSTEMS AND GREENHOUSE GAS EMISSIONS SIMULATION FROM MAIZE CROPPING SYSTEM IN THARAKA-NITHI COUNTY, KENYA

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DECLARATION

This thesis is my original work and has not been presented elsewhere for a degree or any other award.

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DEDICATION

To my dear mum Florence, daddy Musafiri, Siblings Tuli and Rehema.

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ABBREVIATION AND ACRONYMS

AEZs	:	Agro-Ecological Zones
ANOVA	:	Analysis of Variance
BMGF	:	Bill and Milenda Gate Foundation
CA	:	Clustering Analysis
CAM	:	Calibration Mode
CHK	:	Central Highlands of Kenya
DEM	:	Default Mode
DNDC	:	DeNitrification DeComposition
EFs	:	Emission Factors
FAO	:	Food and Agriculture organization
GC	:	Gas Chromatography
GHG	:	Greenhouse Gas
GoK	:	Government of Kenya
IPCC	:	Inter-Governmental Panel On Climate Change
ISFM	:	Integrated Soil Fertility Management
KPHC	:	Kenya Population Housing and Census
LH	:	Lower Highlands
LM	:	Lower Midlands
LR	:	Long Rains
ME	:	Mean Error
MEA	:	Model Absolute Error
ME	:	Modelling Efficiency
MNLR	:	Multinomial Logistic Regression
ODK	:	Open Data Kit
PC	:	Principal Component
PCA	:	Principal Component Analysis
R^2	:	Coefficient of Determination
RCBD	:	Randomised Complete Block Design
RSME	:	Root Mean Square Error
SOC	:	Soil Organic Carbon

SPSS	:	Statistical Package of Social Sciences
SSA	:	sub-Saharan Africa
UM	:	Upper Midlands
VAM	:	Validation Mode
YSE	:	Yield Scaled Emissions

ABSTRACT

The influence of soil fertility management technologies on crop production has widely been researched in Tharaka-Nithi County. However, data on their contribution towards national greenhouse gas budget is scanty. This study aimed at characterising smallholder farming systems and simulating greenhouse gas emissions, maize yields, yield scaled nitrous oxide (N_2O) emissions and N_2O emission factors from different soil fertility management technologies in Tharaka-Nithi County. Three hundred households were interviewed to obtain data for farming systems characterisation and evaluation of socio-economic factors influencing the diversity of farm typologies. Interview schedules were administered using open data kit collect mobile App. Multivariate analysis was done to characterise smallholder farming systems. To evaluate socio-economic factors influencing farm diversity, Chi-square, t-test, and multinomial regression analysis were carried out using the Statistical Package for Social Sciences (SPSS version 23). For calibration and validation of the DeNitrification DeComposition (DNDC) model, a one-year soil greenhouse gas quantification experiment data were used. The data were obtained from a field experiment conducted in Kigogo primary school. It was laid out in randomised complete block design under four soil fertility treatments as control (no external inputs), inorganic fertiliser (NP, 23.23, 120 kg N ha^{-1} yr^{-1}), animal manure (goat manure, 120 kg N ha^{-1} yr^{-1}) and animal manure + inorganic fertiliser (120 kg N ha^{-1} yr^{-1}) replicated thrice. Climate, soil properties, N_2O fluxes, maize yields and farm management data were used. The model was evaluated using modelling efficiency, mean error, coefficient of determination, mean absolute error, and root mean square error (RMSE). The experimental data were subjected to Analysis of Variance in SAS 9.4 software and mean separation done using least significance difference at $p = 0.05$. The results showed six farm types: Type 1, comprising cash crop and hybrid cattle farmers; Type 2, involving food crop farmers; Type 3, composed of coffee-maize farmers; Type 4, consisting of millet-livestock farmers; Type 5, comprising highly diversified farmers, and Type 6, had tobacco farmers. Land size, total tropical livestock unit, the proportion of land and amount of nitrogen applied to different cropping systems were significant in the construction of farm typologies. The DNDC model was fair in simulating daily N_2O fluxes (54% $\leq$ normalized RMSE (nRMSE) $\leq$ 68% and 0.26 $\leq$ modelling efficiency (ME_i) $\leq$ 0.49) and good to excellent performance in simulating cumulative annual soil N_2O fluxes (6.16 $\leq$ nRMSE $\leq$ 12.86 and 0.63 $\leq$ ME_i $\leq$ 0.86) across soil fertility treatments. The cumulative observed and simulated annual soil N_2O fluxes ranged between 0.21±0.01 and 0.38±0.02 kg N_2O-N ha^{-1} yr^{-1} and 0.20 kg N_2O-N ha^{-1} yr^{-1} (control) to 0.38 (fertiliser) kg N_2O-N ha^{-1} yr^{-1}. The simulated N_2O yield scaled emissions, and emission factors ranged from 0.022 to 0.029 g N Kg^{-1} grain yield and 0.03 % to 0.14% under manure and fertiliser treatments, respectively. Based on the low observed and simulated emission factors, using the Intergovernmental Panel on Climate Change (IPCC) Tier 1 default factor of 1% overestimates agricultural soils GHG emissions in the Central Highlands of Kenya. Manure and fertiliser combination should be promoted to enhance the three pillars of climate-smart-agriculture (CSA) as food security, climate change mitigation and adaptation.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The role of smallholder farming systems towards food security is indisputable at the global level (Guiomar *et al.,* 2018). These farming systems produce approximately 80% of the global food FAO (2014) and are vital in meeting dietary demand for the rural poor (Herrero *et al*., 2014). Smallholder farming systems face numerous challenges, including continuous population growth, climate change, declining soil fertility, land degradation and reduced land sizes (Chen *et al.,* 2018b). To meet dietary demands for the increasing population, smallholder farming systems have diversified and intensified on agricultural production (Ha, 2011; Chen *et al.,* 2018a). Over the last fifty years, sub-Saharan Africa (SSA) smallholder farming systems have played a vital role in feeding the ever-growing population (Moyo, 2016).

Despite the novel gain in grain production from smallholder farming systems in SSA, the agricultural sector remains flawed with a myriad of problems including technological shifts and unpredictable rains (IFAD, 2013; Myeni *et al.,* 2019). Further, agricultural productivity in SSA is constrained by limited institutional support, low public investment, dependence on rain-fed agriculture, under-irrigation and gender disparities thus hampering climate change adaptation (Shimeles *et al.*, 2018). Rain-fed agriculture is predominant in the Central Highlands of Kenya and Kenya at large, contributing approximately 80% of agricultural production and are vulnerable to climate change (Stefanović, 2015). Various agricultural intensification technologies have been developed in Tharaka-Nithi County to increase agricultural productivity (Ngetich *et al.,* 2014a; Kiboi *et al.,* 2017; Kiboi *et al.,* 2019). Agricultural intensification and diversification can increase heterogeneity of smallholder farming systems and greenhouse gas (GHG) emissions which are key drivers towards climatic variability (Ortiz-Gonzalo *et al.,* 2018; Macharia *et al.,* 2020).

The diversity of the smallholder farming systems constrains the implementation of governments' policies, interventions and mitigation measures directed towards enhancing agricultural and environmental sustainability (Daloğlu *et al*., 2014; Goswami *et al*., 2014) including GHG emissions quantification, accounting and reporting. To appropriately address the menace of low agricultural productivity, technological interventions should be designed to fit dynamic and spatially heterogeneous smallholder farming systems (Tittonell *et al.,* 2010). Typologies remain vital in guiding intervention measures directed to increase agricultural productivity and climate change adaptation (Tittonell *et al.*, 2020). Various socio-economic factors have been documented to influence farm typologies in SSA for instance population densities, farm size, production objectives and resources endowment (Sakané *et al.,* 2013; Kansiime *et al.,* 2018). Farming systems have been characterised to guide policymakers in recommending resilient agronomic management practices in Kenya (Tittonell *et al.,* 2010; Kamau *et al.,* 2018) and mapping spatial variability of farming systems (Van de Steeg *et al.,* 2010).

Soil fertility depletion has been widening yield gaps in SSA (Sanchez, 2002), and in particular the central highlands of Kenya (CHK) (Mugwe *et al.,* 2009; Mucheru-Muna *et al.,* 2014; Kiboi *et al*., 2017). Assorted soil nutrient management technologies have been developed, tested and reported to improve soil fertility, crop yields, and overall soil health (Mucheru-Muna *et al.,* 2014; Kiboi *et al.,* 2020). Further, the adoption of these technologies have been assessed (Mugwe *et al.,* 2009) and found to have a high cost-benefit ratio. Smallholder farmers are knowledgeable about the use of manure and inorganic fertiliser, but few farmers implement manure and inorganic fertiliser combination (Macharia *et al.,* 2014). Given the wide diversity of these soil fertility management technologies and their varying levels of intensification in smallholder farming systems, GHG emissions quantification, simulation, and mitigation are complicated. For instance, despite the novel gains in the adoption of integrated soil fertility management (ISFM), an agricultural production intensification mechanism (Ngetich *et al*., 2012; Mucheru-Muna *et al*., 2014; Vanlauwe *et al*., 2015), its contribution to GHG emissions amounts might be significant (FAO, 2014).

Agriculture contributes approximately 14-17% of the global anthropogenic GHG emissions (Vermeulen *et al.,* 2012; Ciais *et al.,* 2013). Fermentation and anaerobic decomposition of organic matter emit methane (CH_4), nitrification and denitrification of manure and nitrogenous fertiliser produce nitrous oxide (N_2O) while organic matter decomposition and microbial respiration emit carbon dioxide (CO_2) (Smith *et al.,* 2008; Butterbach-Bahl *et al.,* 2016). Nitrogen application increase agricultural productivity and GHG emissions (Hickman *et al.,* 2014; Tongwane *et al.,* 2016). Knowledge of agricultural soil GHG emissions is essential for national and regional GHG inventories. However, limited empirical data have been documented on GHG emissions under smallholder farming systems (Rosenstock *et al.,* 2016; Pelster *et al.,* 2017). Direct measurement of GHG emissions for national and regional inventories is not practical as it requires data to be collected over a large area and extended period (Giltrap *et al.*, 2010). Therefore, developing countries use the default IPCC default Tier 1 emission factors which tends to overestimates the GHG emissions resulting to poor targeting of mitigation and adaptation strategies (Richards *et al.,* 2016; Pelster *et al.,* 2017; Macharia et al., 2020).

Therefore, there is a need to explore the utilisation of cheaper and available means such as the use of biogeochemical models for GHG emissions quantifications for national GHG inventories. The biogeochemical models could simulate soil GHG emissions accurately, at a large spatial scale and a lower cost compared with experimentation (Giltrap *et al.,* 2010). A good example of such a model is the DeNitrification DeComposition (DNDC) developed by Li *et al.* (1992) for the simulation of N_2O emission from agricultural soils in the US. Since its development, it has been modified and used in various parts of the world to simulate N_2O, CO_2 and CH_4 emissions (Deng *et al.,* 2011; Zhang & Niu, 2016).

1.2 Statement of the Problem

Smallholder farming systems in Tharaka-Nithi County are faced with soil fertility decline, water stress, and declining agricultural production (Ngetich *et al*., 2014a; Kiboi *et al.*, 2019). To curb these vagaries, there have been concerted efforts to intensify and diversify the smallholder farming systems, thus, increasing application of external inputs their heterogeneity. This leads to increased atmospheric GHG emissions and their effects on climate variability and change that negatively affects agricultural productivity. To understand the contribution of different farming systems towards GHG emissions, there is a need to characterise smallholder farming systems based on soil external inputs such as inorganic and organic fertilisers and livestock enterprises in the farm. Assorted soil fertility management technologies have been developed, tested and reported to improve crop yields in Tharaka-Nithi County (Mucheru-Muna *et al.*, 2014; Ngetich *et al.*, 2014a; Kiboi *et al.*, 2017; Kiboi *et al.*, 2019). However, there is a huge data gap in the documentation of their individual contributions to GHG fluxes. Direct quantification of GHG emissions for national inventories is impractical and expensive as it would require many measurements to be made over large areas and for a long period compared to simulation. Biogeochemical models, including Denitrification Decomposition (DNDC), have been found to simulate crop yields and GHG emissions elsewhere accurately. Hence there is a need to test their applicability in simulating maize yield and N_2O emissions under different soil fertility management technologies in the Tharaka-Nithi County.

1.3 Justification

To attain sustainable agricultural production in Tharaka-Nithi County, there is a need to characterise existing farming systems and quantify GHG emissions under different soil fertility management technologies. Grouping smallholder farming systems to coherent farm types (smallholder farming systems typologies) has the potential to guide agricultural policies, interventions and mitigation measures implementation. This can also lead to the identification of GHG emissions hotspots that can inform their quantification and simulation. Simulating maize yields and GHG emissions from different soil fertility management technologies provides an insight on which technology increases crop yields with minimal increase or decrease in GHG emissions. Further, the model simulates soil GHG emissions in a cheaply providing an alternative to direct quantification in informing nationally determined contributions.

1.4 Research Questions

(i) What are the key characteristics of smallholder farming systems in Tharaka-Nithi County?

(ii) How do socioeconomic factors influence the diversity of smallholder farm typologies in Tharaka-Nithi County?

(iii) How well does the DeNitrification-DeComposition model simulate GHG?

(iv) How well does the DeNitrification-DeComposition model simulate maize production (yield and biomass), N_2O yield-scaled emissions and emission factors?

1.5 Research Objectives

1.5.1 Broad Objective

To characterise smallholder farming systems and simulate greenhouses gas fluxes from selected soil fertility technologies in Tharaka-Nithi County, Kenya.

1.5.2 Specific Objectives

(i) To characterise smallholder farming systems in Tharaka-Nithi County.

(ii) To evaluate socioeconomic factors influencing the diversity of smallholder farm typologies in Tharaka-Nithi County.

(iii) To calibrate, validate and evaluate the accuracy of the DeNitrification-DeComposition model in the quantification of greenhouse gas emissions in Tharaka-Nithi County.

(iv) To simulate maize production (yield and biomass), N_2O yield-scaled emissions and emission factors from maize cropping systems in Tharaka-Nithi County using DeNitrification-DeComposition model.

1.6 Conceptual Framework

Farming systems diversification and intensification leads to higher usage of external inputs in Tharaka-Nithi County. These increase GHG emissions leading to climate variability. Further, poor farming practices cause a decline in soil fertility. Reduced soil fertility and allied negative climate variability result in reduced agricultural production. Farming systems characterisation (Objectives 1 and 2) and GHG emissions simulation (Objectives 3 and 4) can be used to reverse this problem by promoting appropriate use of external inputs with the highest productivity but least GHG emissions. The interactions of these processes are as shown in (Figure 1.1).

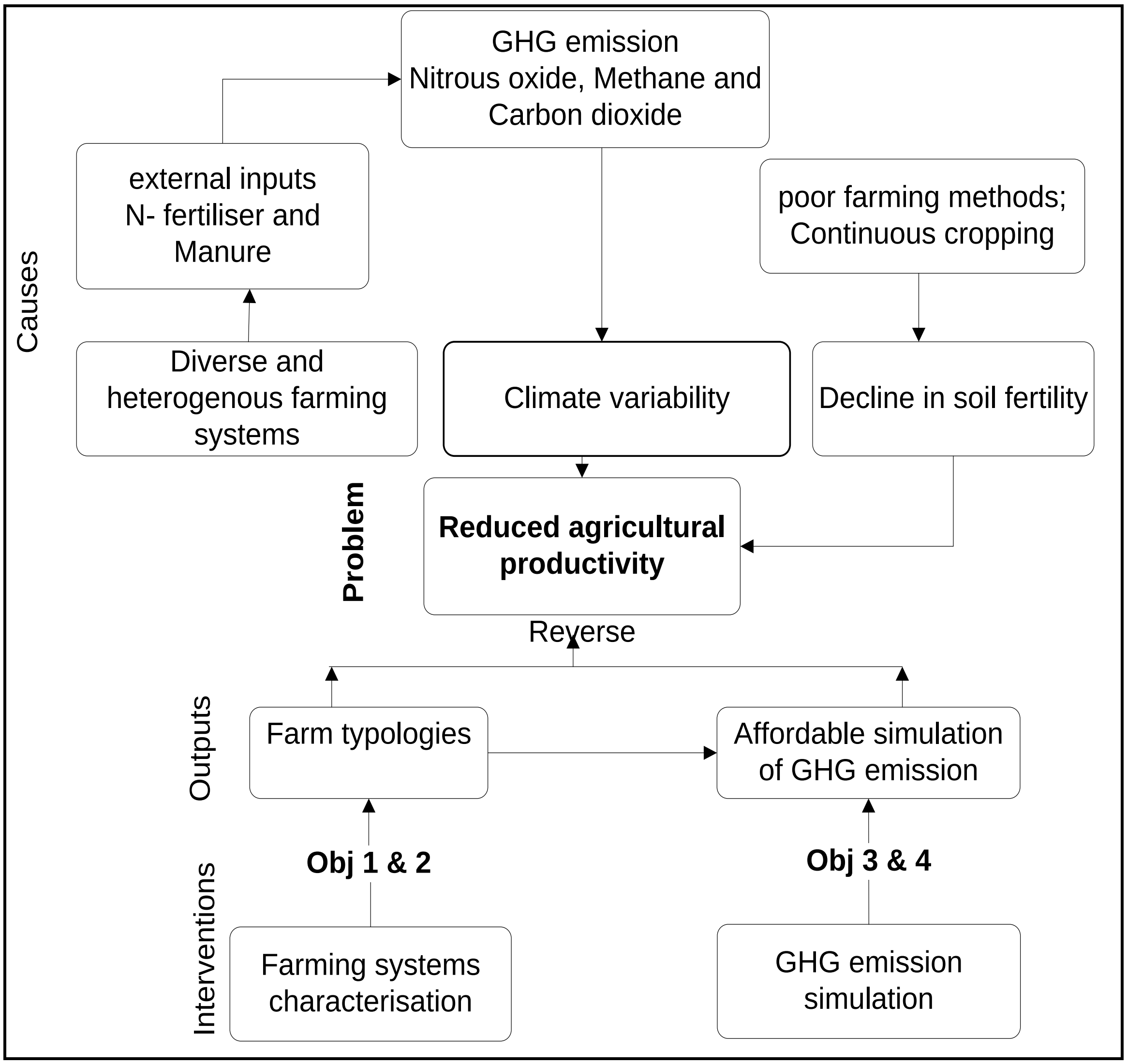

Figure 1.1 Conceptual framework

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

This chapter reviews the current state of knowledge and contribution of past studies on the researched subject matter. The thematic areas reviewed are farming systems characterisation, socio-economic factors influencing the diversity of farm typologies, GHG fluxes, the DNDC model calibration and validation.

2.2 Farming Systems Characterisation

There are about 570 million small farms worldwide Lowder *et al.* (2016), these farms are fundamental in meeting the global food demand (Guiomar *et al.,* 2018; Lopez-ridaura *et al.,* 2018). Smallholder farms produce approximately 80 per cent of the food consumed in SSA (IFAD, 2013), that heavily depend on family labour (Rapsomanikis, 2015). Despite the ability of smallholder farming systems to feed the bulk of world's population, they are constrained by numerous challenges encompassing limited governments' support, over-dependency on rain-fed agriculture, soil fertility decline, population pressure, land fragmentation, market shifts and climate change (Dillard, 2019; Martin-Shields & Stojetz, 2019). Climate discrepancy from the normal trends leads to severe cut of grain yields (Vogel *et al*., 2019). Agricultural interventions to increase food production are at risk as they might contribute significantly to GHG emissions (Tongwane *et al.,* 2016).

Smallholder farming systems are fundamental in promoting rural development, poverty alleviation and sustainable development in SSA (Moyo, 2015; Suttie & Benfica, 2016). These farms account for approximately 78% of food products consumed in Kenya and Tharaka-Nithi County (Word Bank, 2015) and are constantly affected by climate change and water stress (Vanlauwe *et al*., 2015; Kiboi *et al*., 2017; Kiboi *et al.,* 2019; Mugwe *et al*., 2019). Land and population pressure, limited government spending on agriculture, low access to extension services, limited credit assess, climate change, soil fertility decline and land degradation have been documented as a major hindrance to achieving food security in Kenya (Birch, 2018). Technological interventions to improve agricultural productivity and climate change mitigation are limited by both spatial and temporal diversity exhibited by smallholder farming systems (Haileslassie *et al.*, 2016; Guiomar *et al.,* 2018). Smallholder farming systems are diverse, and no single intervention measure fits all, each farm should receive a different intervention and is practical at a large scale level (Alvarez *et al.,* 2014). Due to their dynamism, farm typologies creation technique gains relevancy in addressing challenges facing these farms (Tittonell *et al*., 2010).

Smallholder farm typologies can be created based on structural or functional data variable that describes households assets or livelihood strategies, respectively (Alvarez *et al*., 2014; Lacoste *et al.,* 2018; Tittonell *et al.*, 2020). Variables involved in creating smallholder farm typologies are objectives based and yields typologies geared towards addressing the specific research problem, for example, Tittonell *et al*. (2020) were on drought risks, Kamau *et al*. (2018) were on organic farming, and Foguesatto *et al*. (2019) were on climate change. Characterising farming systems simplifies their diversity hence permitting policy formulation and establishment of area-specific interventions measures (Chatterjee *et al.,* 2015). Developing farm typologies guide farmers to adopt intervention mechanisms which are well suited to their challenges (Daloğlu *et al.,* 2014). These farm types are useful in designing intervention measures which are consistent with households' environmental, socio-economic climatic and agronomic challenges (Meylan *et al.,* 2013; Haileslassie *et al.,* 2016) thus informing best-fitted models for addressing specific problems. Further, farm typologies can guide policies implementation aimed at improving agricultural productivity, mitigating climate change and quantifying agricultural GHG emissions (Gelasakis *et al.,* 2012; Guiomar *et al.*, 2018).

Multivariate analysis, expert knowledge, participatory ranking and step by step comparison of farm functioning are the main methods used in categorising smallholder farming systems (Alvarez *et al*., 2014). Step by step comparison of farm functioning categorised farming systems based on household structure and then farmers strategies and orientation were identified (Capillon, 1993). This method is data-intensive as it needs a lot of data to be collected using a survey method from a stratified sample. Expert knowledge typologies construction techniques use farm clusters identified by farmers, local experts or key informants (Paccin *et al*., 2013) thus can be implemented over a shorter time. Participatory ranking techniques involve classification of households based on observable assets by knowledge experts (Knierim *et al*., 2019). Finally, the multivariate analysis uses statistical data analysis techniques including principal component analysis (PCA) and clustering analysis (CA) commonly referred as 'dimensional data reduction (Alvarez *et al*., 2018; Kamau *et al*., 2018). The multivariate technique is widely preferred over the three because of its reproducibility because of its integral statistical procedure (Paccin *et al*., 2013; Kamau *et al*., 2018). Since multivariate analysis is dominant in creating farm typologies, its applicability in farming systems typologies to guide GHG emissions quantification, simulation, and mitigation is accentuated.

2.3 Socio-economic Factors Influencing Farm Typologies

Smallholder farming systems are socially dissimilar and spatially heterogeneous (Tittonel *et al*., 2010). Due to their dynamism, farm typologies become out-dated with time and need regular modernisation. Several household variables such as assets, livelihood strategies, farm management, socio-economics, biophysical and economic resource, farm performance, farm inputs and dietary access have been used to construct farm typologies (Paccin *et al*., 2013; Sakané *et al.*, 2013; Kansiime *et al.*, 2018). Variables involved in farm typologies construction are chosen, objective-based and differs among studies (Tittonell *et al*., 2010; Alvarez *et al*., 2014; Alvarez *et al*., 2018; Tittonell *et al*., 2020). Therefore, the influence of socio-economic variables should be evaluated across farm typologies.

For intervention measures aimed at enhancing food security and GHG emissions mitigation to be accepted by society, they should match with societal socio-economic status (Chatterjee *et al.*, 2015). Socio-economic factors influence farmers' acceptance of any intervention measure example (Jena *et al.*, 2012; Ntshangase *et al*., 2018). Subsequently, developing farm typologies guides researchers, policymakers and extensions officers on farmers' best well-matched intervention mechanisms (Daloğlu *et* *al.,* 2014). Since most of the typologies are constructed using variables that have an immediate influence on the research theme, for example, Tittonell *et al*. (2010) were on soil fertility, Makate *et al*. (2018) was on climate-smart agriculture, and Aravindakshan *et al*. (2020) were on agrarian change, there is need to integrate them with households' socio-economic context to enhance their acceptability.

Smallholder farm typologies become obsolete with time because socio-economic eminences controlling them are vibrant (Alvarez *et al*., 2014). The constructed typologies represent an abstract of farming systems at that time. Therefore, a clear context of when the data used in typologies construction was collected is essential in predicting the appropriateness of some study variables (Giller *et al*., 2011). Data collection for several years example, land use land change can be used to create farmers' decision tree, and expert opinion can guide in projecting long term variations (Kuivanen *et al*., 2016a). Assessing socio-economic factors influencing the diversity of farm typologies provide a basis for monitoring advancements achieved through specified intervention measures.

2.4 Soil Greenhouse Gas Fluxes

Agriculture is the primary land use in SSA and East Africa producing a significant amount of GHG emissions; however, limited GHG quantification research has been implemented in the region (Rosenstock *et al.,* 2016; Ortiz-Gonzalo *et al*., 2018). Soil management practices such as manure management, nitrogen application, tillage, mulching influence soil GHG emissions (Ogle *et al.,* 2014; Skinner *et al*., 2014; Togwane *et al*., 2016). These soil management practices aimed at increasing agricultural productivity manipulates soil environment (soil substrate concentration, structure, cover) thus stimulating microbial activities accountable for tracer gas emissions (Powlson *et al*., 2011; Thomson *et al*., 2012). Agricultural soil acts as a source of CO_2; however, it can also be both source and sink of CH_4 and N_2O (Smith *et al.,* 2008). Agricultural ecosystems produce approximately 60% of the total global anthropogenic N_2O emissions (IPCC, 2014). Microbial nitrification and denitrification process is responsible for N_2O emissions from the soil (Butterbach-Bahl *et al*., 2013).

Soil GHG fluxes are driven by soil biogeochemistry process (Butterbach-Bahl *et al.*, 2016), which are catalysed by the interaction between climate, environment and soil management practices such as the addition of nitrogen and carbon to soil (Abdalla *et al.*, 2009). Further, atmospheric temperature, precipitation, solar radiation, and relative humidity sways soil GHG fluxes (Zona *et al*., 2013; Gilhespy *et al.,* 2014). Soil properties such as bulk density, moisture, pH, temperature, clay fraction and C to N ratio affects soil GHG fluxes (Powlson *et al*., 2011; Wiesmeier *et al*., 2013). Since soil GHG fluxes are highly controlled by carbon and nitrogen dynamics, effective management of carbon and nitrogen entry into agricultural land can mitigate GHG fluxes (Smith *et al.*, 2008).

Strategies directed towards increasing global food production upsurge GHG emissions not unless appropriate mitigation measures are introduced (Majiwa *et al*., 2018). This mandates development of soil fertility management technologies responsible for improving agricultural productivity with minimal increase or reduction in agricultural GHG emissions (Agovino *et al*., 2019). Since various ISFM technologies for example (manure, fertiliser, fertiliser + manure) have been developed, tested and showed to be economically plausible in improving food output (Vanlauwe *et al*., 2015; Kiboi *et al*., 2019), there is need to document the contribution of such technologies to GHG emissions. This can guide in identifying the ISFM technologies that are economically proficient and environmentally sustainable.

Most developing countries use the Inter-Governmental Panel on Climate Change (IPCC) Tier 1 emission factor (EF) of 1% to report their agricultural contribution towards GHG emissions (Tubiello *et al*., 2013). These EFs were based on few studies and can either overestimate or underestimate agricultural soil GHG emission in different regions (Hickman *et al*., 2014). Therefore, the need for countries' specific emissions factors for accurate soil GHG emissions reporting, accounting and mitigation.

Nitrous oxide is a powerful ozone layer (O_3) depleting agent, a global warming potential of 298 times higher than that of carbon dioxide and over 150 years' time horizon (Shang *et al*., 2011). Numerous studies have assessed the influence of agricultural management on soil N_2O fluxes (Rosenstock *et al*., 2016; Pelster *et al*., 2017). The data documented on soil N_2O fluxes emitted is inadequate as it compares only emissions amounts among technologies. Therefore, the need for an integrated approach including yields-scaled N_2O emission (YSE) that provide the quantities emitted per unit of production (Pelster *et al*., 2017; Chen *et al*., 2019). The YSE provides a basis for comparing N_2O fluxes per grain productivity which is more informative as it combines food production and GHG emissions.

2.5 Nitrous Oxide and Maize Yields Modelling

Quantification of soil greenhouse gas emissions under different soil fertility management technologies is essential in choosing the best technology that improves crop yields while lowering or with an insignificant increase in the fluxes. However, direct quantification of the soil N_2O fluxes is impractical and expensive under national and regional scale (Giltrap *et al*., 2010). Therefore, process-based biogeochemical models may offer an alternative by simulating greenhouse gas emissions and maize yields from agricultural systems as influenced by different soil fertility management technologies. One of the commonly used biogeochemical models in simulating soil N_2O fluxes and maize yields is the DNDC model. The DNDC model was initially developed to simulate soil tracer emissions following rainfall event in the USA (Li *et al*., 1992; Li *et al*., 2010). Previous studies indicated the DNDC model performance in well in simulating soil N_2O fluxes, and maize yields elsewhere were acceptable (Cui *et al*., 2014; Uzoma *et al*., 2015). However, there is still limited information on the model performance in Kenya and SSA at large. Cognisant of the applicability of the DNDC model in simulating soil N_2O fluxes and maize yields elsewhere, there is a need for its calibration and validation in simulating maize yields and soil N_2O fluxes under different soil fertility management practices in Kenyan soils.

2.6 The DeNitrification DeComposition (DNDC) Model

The DNDC is a process-based biogeochemistry model developed by Li *et al.* (1992) to simulate C and N turnover in agricultural ecosystems. The DNDC model can predict crop yield, soil environmental factors, C sequestration and C and N trace gas fluxes. The model has six sub-models; soil climate, crop growth, decomposition, nitrification, denitrification and fermentation sub-models and can simulates trace gases (NO, N_2O, CH_4 and NH_3) fluxes, soil moisture, pH, temperature and substrate concentrations. A review conducted by Gilhespy *et al.* (2014), revealed that the DNDC model is widely used to simulate GHG emissions because its features are responsible for extensive uses

The latest DNDC model version (9.5) (http://www.dndc.sr.unh.edu/) can be implemented at both site and regional scale (Li *et al*., 1992, Li *et al.,* 2017). Soil properties, climatic condition, vegetation and farm management are the main input parameters for DNDC modelling. The climate input parameters include daily weather (relative humidity, solar radiation, maximum and minimum temperature, wind speed, and precipitation). The soil properties used in DNDC modelling include field capacity, texture, pH, clay fraction bulk density, C: N ratio, wilting point and initial SOC. Additionally, crop type, planting date, harvesting date, biomass components (grain, root, leaf and stem) and all farm agronomic managements ranging from the nitrogen application date, times and depth are used as DNDC input parameters (Gilhespy *et al.,* 2014; Li *et al*., 2017).

Various studies have used the DNDC model to predict crop production, trace gas emissions, soil temperature, moisture, and Nitrogen (Uzoma *et al*., 2015; Zhang & Niu, 2016; Li *et al*., 2017). Based on evaluations matrices used in different studies Abdalla *et al*. (2011), Wang *et al*., 2011 and Deng *et al*. (2016), the DNDC model performed well in predicting soil GHG emissions. According to Rafique *et al*. (2011), the DNDC model predicted annual and seasonal GHG fluxes well but failed to capture negative soil N_2O fluxes. Failure to predict the soil N_2O uptake could result in overestimation. Therefore, the carbon and nitrogen ratio can be lowered during the calibration process to enable the model to capture both peaks and nadirs (Rafique *et al*., 2011).

The DNDC model has widely been used over the last two decades to inform implication of management practices on agriculture and climate change (Giltrap *et al*., 2010, Rafique *et al*., 2011; Deng *et al*., 2016; Li *et al*., 2017; Cui & Wang, 2019). Since Li *et al*. (1992)

version 1.0 - 7.0, the model has been modified and updated to fit specific research situation to the current DNDC model version 9.5 (Gilhespy *et al.,* 2014). Further, various models such as online, manure, wetland, crop, forest, landscape, UK and Europe DNDC have been developed to fit different agro-ecosystems (Giltrap *et al*., 2010).

The model is comparatively easy to use as it has an attractive graphical user interface that has enhanced its widespread use across the globe (Gilhespy *et al.,* 2014). The DNDC model has various user-defined default parameters making it comprehensive and able to give diversified outputs for evaluation. Since the DNDC model is user friendly, it can be used by many inexperienced modellers. The DNDC model manual focuses on step by step application rather than technical mechanisms surrounding the inputs and outputs.

2.7 The Model Calibration and Validation

The DNDC model is calibrated by fitting the measured and user-defined local conditions (parameterisation) to simulate the underlying biogeochemistry processes (Ruser *et al.,* 2017). The DNDC model is calibrated by inputting measured and default values (Chen *et al.,* 2018b). The model is then run with the in-situ and default parameters to yield default mode (DEM) output (Rafique *et al*., 2011; Zhao *et al*., 2015). The input parameters that are responsible in simulating underlying processes in GHG emissions and crop yields such as soil moisture, bulk density, clay fraction, field capacity, pH, bulk density and C to N ratio are adjusted to give optimized range of parameters (Giltrap *et al*., 2010; Li *et al*., 2017). Finally, the model is then run with an optimised range of parameters to yield calibration mode (CAM) outputs (Grant *et al.,* 2015).

The model is validated by comparing simulated with experimental data to ensure the model predicts underlying biogeochemical processes (Giltrap *et al*., 2010). Validation is a confirmatory step in DNDC modelling that ascertains that the simulated and observed values are in agreement. During the validation stage, the model is run with input parameters from different treatments or site to yield validation mode (VAM) as described out by Rafique *et al*. (2011). Studies have revealed varying agreements between modelled and observed values Abdalla *et al*. (2011), Jiang *et al.* (2017) and Deng *et al*. (2016)

documenting good model agreement while according to Rafique *et al*. (2011) the model failed to capture negative N_2O fluxes. High C to N ratio increases the DNDC model N_2O fluxes; therefore, lowering the ratio can make the model predict soil N_2O uptake (Uzoma *et al*., 2015).

Model goodness of fit is implemented to describe disparities between observed and simulated (Giltrap *et al*., 2010; Deng *et al*., 2016). Statistical measures such as mean error (ME), root mean square error (RSME), coefficient of determination (R^2), mean absolute error (MAE) and modelling efficiency (ME_i) have been developed and widely used to statistically evaluate model performance (Smith *et al*., 1997; Wang *et al*., 2011; Gilhespy *et al.*, 2014; Uzoma *et al*., 2015; Li *et al*., 2017). These measures provide a researcher with a methodology to report how well the model predicts a set of measured values.

2.8 Summary and Research Gap Identified

Smallholder farming systems in SSA are both socially diverse, spatially heterogeneous and are faced with abundant challenges such as water stress, climate change shocks and soil fertility decline consequently lowering agricultural productivity (Tittonel *et al*., 2010; Alverez *et al*., 2014). The heterogeneity of these smallholder farming systems constrains technological interventions aimed at increasing food security, whereas mitigating GHG emissions. Smallholder farming systems typologies provide a novel entry point in addressing smallholder farming systems challenges. The variables used in characterising the smallholder farming systems are based on research objective hence they are not universally applicable (Giller *et al*., 2011; Kamau *et al*., 2018) thus the need to develop farm typologies aimed at GHG quantification, simulation and mitigation. Thus farm typologies aimed at addressing farmers challenges should be woven within the context of farm socio-economic characteristics. Information on farm typologies is scanty and inadequate to inform agricultural greenhouse gas emissions quantification, simulation and mitigation. Soil fertility decline is a significant peril to agricultural production in SSA and the Central Highlands of Kenya. The use of ISFM has contributed significantly to increasing agricultural productivity among smallholder farming systems. However, there is a dearth of information showing the nexus between agricultural productivity and climate change mitigation by reducing GHG emissions in Tharaka-Nithi County. This calls for smallholder farming systems in Tharaka-Nithi County to guide GHG emission quantification, simulation and mitigation. Since direct quantification of agricultural GHG is expensive and somewhat impractical for the national level, this demands the use of a biogeochemical model to simulate agricultural trace gas emissions. The model was purposively designed to simulate carbon and nitrogen dynamics from agricultural soils. The model has been modified over the last two decades to simulate crop growth, tracer gas emission, soil temperature, nutrients concentrations and moisture. Estimating N_2O YSE and EFs based on simulated N_2O emissions and grain crop provides integral data useful in identifying soil fertility management technology that can promote food security while mitigating GHG emissions.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study Area

The study was conducted in Maara, Chuka and Igamba Ng'ombe sub-counties in Tharaka-Nithi County. The study area experiences bi-modal rainfall with long rains (LR) occurring from March to June and short rains (SR) from October to December. The annual rainfall amount ranges from 600 mm to 2200 mm (Jaetzold *et al.*, 2007). The study area is within eight Agro-Ecological Zones (AEZs) namely: LH1 - tea diary zone, LH2 - wheat/maize pyrethrum zone, UM1 - coffee tea zone, UM2 - marginal coffee zone, UM4 - sunflower maize zone, LM3 - cotton zone, LM4 - marginal cotton zone and LM5 - millet Livestock Zone (Jaetzold *et al.*, 2007). The altitude ranges from 600 m at lowlands to 5200 m a.s.l at the peak of Mt. Kenya. Annual mean temperature ranges from 14 °C to 17 °C in the highlands and 22 °C to 27 °C in the lowlands with a long-term average temperature of 20 °C. The predominant soil type in the area is *Humic-nitisols* and has clay content of 78% (Ngetich *et al.,* 2014a). Major economic activities in the area are crop and livestock productions, especially maize cropping. During the 2019 census Igamba Ng'ombe, Maara and Chuka sub-counties recorded a population of 53,210, 114,894 and 91,080, respectively (Table 3.1), KPHC, 2019).

3.2 Study Design

The study employed a mixed-design approach to implementation. To characterise the prevailing farming systems and evaluate socio-economic factors influencing their diversity, a cross-sectional survey was carried out. For DNDC modelling, calibration, validation and accuracy evaluation, a one-year GHG quantification experiment was laid out in a randomised complete block design (RCBD).

3.3 Objectives 1 and 2: Farming Systems Characterisation and Socio-economic Factors Influencing Farm Typologies

3.3.1 Sampling Design

The sample size was calculated using the Cochran formula (Bartlett *et al*., 2001).

$$n=\frac{z^2pq}{E^2}=\frac{1.96^2\times0.5(1-0.5)}{0.0565^2}=300 \qquad \text{Equation 3.1}$$

Where: n= Sample size, z= z value (e.g. 1.96 for 95% confidence level), p= percentage picking a choice, expressed as decimal (0.5), q= 1-p and E = 5.65 % allowable error, expressed as decimal (0.0565).

The study design and implementation was a cross-sectional survey. The multi-stage sampling procedure was used to determine the interviewed households. First, Chuka, Igamba Ng'ombe, and Maara sub-counties in Tharaka-Nithi County were purposely selected based on previous ISFM studies conducted in the area that could influence GHG emissions. Secondly, total sampling was used to select all ten wards in the selected sub-counties, where primary data were collected at the household level (Table 3.1). Thirdly, probability proportionate to size sampling method was used to calculate the number of households (the sample size [n]) to be sampled in each ward using a sample frame obtained from respective agricultural offices at the ward level. The total number of farming households (N) in each ward was divided by the sample size to obtain the interval size (k). Finally, a simple systematic sampling procedure was used to collect data in each ward. The first household in each the ward was randomly selected; afterwards, each k^{th} farming household in the list was sampled. Sampled household spatial distribution is shown in Figure 3.1.

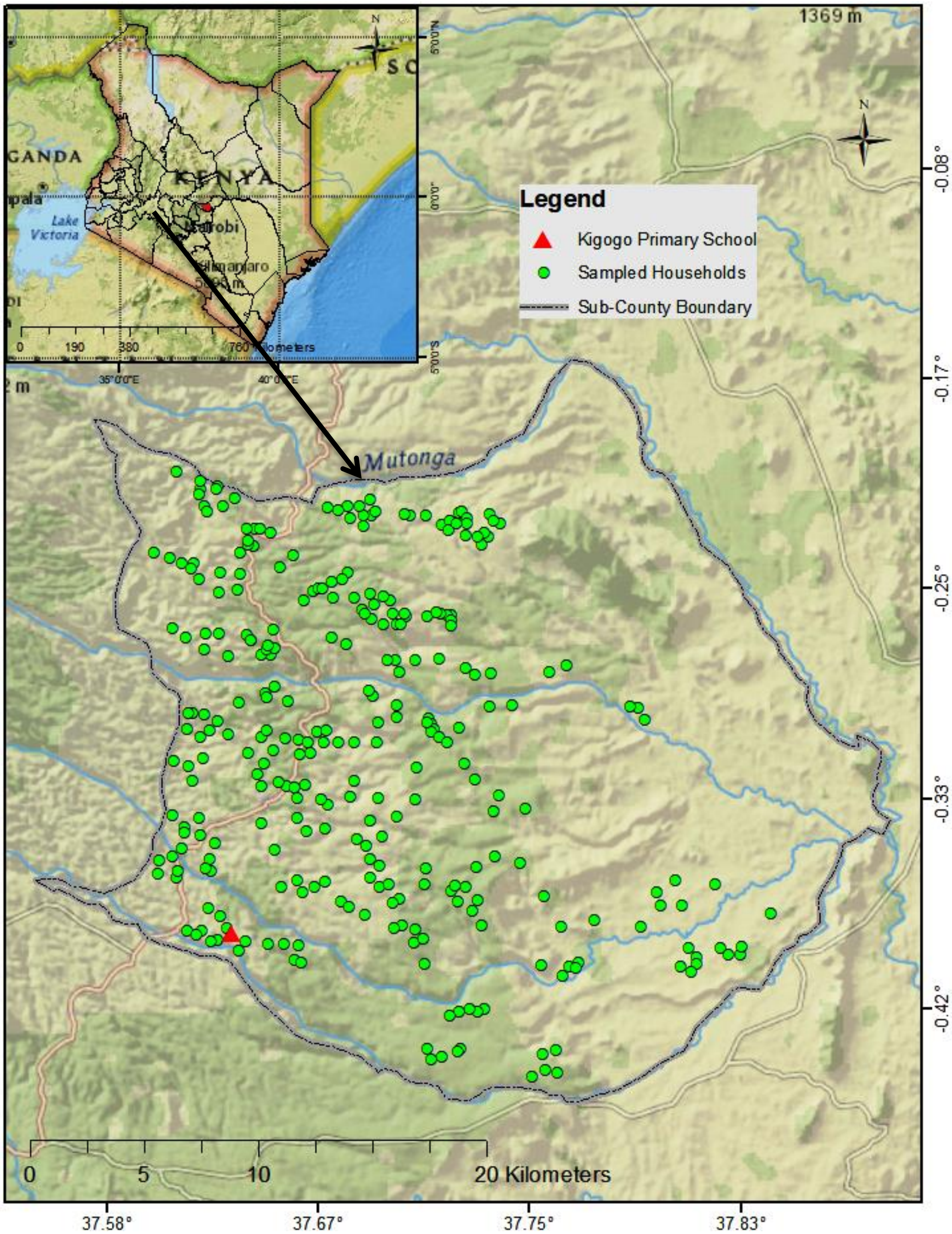

Figure 3.1 Map of the study area showing geo-referenced sampled households and Kigogo primary school experimental site.

Table 3.1 Population and sample size per ward in Maara, Chuka and Igamba Ng'ombe Sub-Counties

Sub-county	Ward	Population	Sample size
Maara	Mitheru	16,419	19
	Muthambi	20,778	24
	Ganga	18,784	22
	Mwimbi	24,598	28
	Chogoria	34,314	40
	Sub-total	**114,894**	**133**
Chuka	Karingani	25,145	29
	Magumoni	39,657	46
	Mugwe	26,278	30
	Sub-total	**91,080**	**105**
Igamba Ng'ombe	Igamba Ng'ombe	36,240	42
	Mariani	16,970	20
	Sub-total	**53,210**	**62**
	Total	**259184**	**300**

Source interpolation of wards' population GoK (2010) and sub-counties' population (KPHC, 2019)

3.3.2 Data Collection

The data were collected using a semi-structured interview schedule following prior pre-testing and appropriate modification. The study targeted to interview household heads or most senior family member in case of the absence of the family heads. The study relied on farmers' farm records and remembrance of preceding six cropping seasons and alterations at the plot level. Three years were considered satisfactory to elucidate on agricultural GHG emissions quantification and simulation. The interview schedule had questions on farm identity, socio-capital, cropping activities, soil management, livestock systems, demographics and wealth characteristics. The interview schedule was administered using Open Data Kit (ODK) mobile app by well-trained enumerators.

3.4 Multivariate Analysis

Basic conversions were executed for the survey variables to obtain standard values. Nitrogenous (N) fertiliser application rate was calculated from nutrient concentration ratio. Nitrogen applied from manure was converted based on 2.1% concentration (Kiboi *et al*., 2018). Total tropical livestock unit (TLU) was calculated for each livestock where

1 TLU is equal to 1 mature cow of 250 kg (FAO, 2003). The TLU for each livestock was determined following Jahnke (1982) and Chilonda & Otte (2006) whereby a cattle, sheep, goat, pig, chicken, duck, and rabbit have TLU units of 0.7, 0.1, 0.1, 0.2 and 0.01, 0.03, 0.02, respectively. Afterwards, the TLU was summed for each household. Household wealth asset index was determined using the Bill & Melinda Gates Foundation (BMGF), 2010) guide, which assigns a weight to each household asset. Finally, households' income generated from crops, livestock and remittance were converted to a percentage of the total estimated income.

The study variables were checked for accuracy and consistency, after which one incomplete response was eliminated from the sample; hence, a total of 299 respondents were subjected to statistical analysis. Farm typologies were constructed using the Principal component analysis (PCA) and cluster analysis (CA) in SPSS 23 software. Dimensional data reduction was performed using PCA after which the resultant non-related principal components (PCs) were used as inputs in the CA. The multivariate analysis method has been successfully used by other related studies to cluster smallholder farming systems (e.g. Kuivanen *et al*., 2016a; Kamau *et al*., 2018; Lopez-ridaura *et al.*, 2018).

Table 3.2 Description of the variables used in creating farm typologies in the study area

Variables description	Code	Unit
Total land size owned	Land size	Ha
Total land size under cultivation	Cultivated land	Ha
Proportion of land on Maize	Proportion Maize	Percentage (%)
Nitrogen applied to Maize	Nitrogen Maize	Kg N ha^{-1}
Proportion of land on Tea	Proportion Tea	Percentage (%)
Nitrogen applied to Tea	Nitrogen Tea	Kg N ha^{-1}
Proportion of land on Coffee	Proportion Coffee	Percentage (%)
Nitrogen applied to Coffee	Nitrogen Coffee	Kg N ha^{-1}
Proportion of land on Banana	Proportion Banana	Percentage (%)
Nitrogen applied to Banana	Nitrogen Banana	Kg N ha^{-1}
Proportion of land on Beans	Proportion Beans	Percentage (%)
Nitrogen applied to Beans	Nitrogen Beans	Kg N ha^{-1}
Proportion of land on Napier	Proportion Napier	Percentage (%)
Nitrogen applied to Napier	Nitrogen Napier	Kg N ha^{-1}
Proportion of land on Tobacco	Proportion Tobacco	Percentage (%)
Nitrogen applied to Tobacco	Nitrogen Tobacco	Kg N ha^{-1}
Proportion of land on Millet	Proportion Millet	Percentage (%)
Nitrogen applied to Millet	Nitrogen Millet	Kg N ha^{-1}
Tropical Livestock Unit	TLU	Numeric
Household Wealth Assets Index	WI	Numeric

Note; ha= hectares, kg N ha^{-}=kilogram Nitrogen per hectares

Kaiser Mayer-Olkin (KMO) and Bartlett's sphericity test was done to check data credibility for factoring, similar to the study of Mugi-Ngenga *et al*. (2016). Orthogonal rotation (Varimax method) was used to group study variables. All PCs exceeding an Eigenvalue of 1 were initially retained. Kaiser Normalization criterion is considered accurate for variables < 30 and sample size < 250 (Field, 2005). However, the sample size used in this study was greater than 250 household heads. Therefore, the study opted for further checks such as the explained cumulative variance of ≤ 60% Hair *et al*. (2006) and loading ≥ 0.50, which were considered for interpretation (Field, 2013).

The PCA retained factors were used in CA to construct farm types. A two-step clustering procedure was performed i) hierarchical agglomerative clustering algorithm using Ward's method to form the number of groups and ii) partitioning algorithm to separate the groups to a given number of clusters. The numbers of clusters retained in hierarchical agglomerative clustering were used in partitioning. A dendrogram was used to select the number of clusters used as farm types. The variables used to typify farming systems (Table 3.2) were subjected to one-way analysis of variance (ANOVA) in SPSS version 23 at p = 0.05 and mean separated using Tukey's honest significance difference (HSD) test. The data were subjected to ANOVA to identify socio-economic factors that were significant in constructing farm types similar to (Macharia *et al.*, 2014; Murage *et al.*, 2019), Table 3.3). A multinomial logistic regression model was run in SPSS version 23 to evaluate socio-economic factors that influenced farmers belonging to a specific farm typology.

Table 3.3 Definition of independent variables used in the multinomial logistic regression analysis

Variables	**Definition**
Dependent variable	
Farm typologies	1,2,3,4,5 & 6
Independent variables	
Household Head Gender	0 Female
	1 Male
Household Head Education	0 No formal Education
	1 Primary
	2 Secondary
	3 Tertiary
Hired Labour	0 No
	1 Yes
Group Member	0 No
	1 Yes
Credit Access	0 No
	1 Yes
Training Access	0 No
	1 Yes
Extension Access	0 No
	1 Yes
Household Head Age (years)	Continuous
Household Head Experience (years)	Continuous
Household size (number)	Continuous
Proportion of income from Crop (percentage)	Continuous
Proportion of income from Livestock (percentage)	Continuous
Proportion of income from Remittance (percentage)	Continuous

Note; Type 1, cash crop and hybrid cattle farmers; Type 2, food crop farmers; Type 3, coffee-maize farmers; Type 4, millet-livestock farmers; Type 5, highly diversified farmers, and Type 6, tobacco farmers

3.5 Objectives 3 and 4: The DNDC Modelling, Calibration, Validation and Evaluation

3.5.1 Experimental Set-Up and Agronomic Management

Nitrous oxide quantification experiment was laid out in randomised complete block design with four treatments replicated thrice. The treatments of interest were: i) control (No fertiliser input), ii) inorganic fertiliser (NP, 23.23, 120 kg N ha^{-1} yr^{-1}), iii) animal manure (goat manure, 120 kg N $ha^{-1}yr^{-1}$), and iv) animal manure + inorganic fertiliser (120 kg N $ha^{-1}yr^{-1}$). Maize (Zea may L.) HB 516 variety was used as test crop. Plot dimensions were 6 m by 4.5 m. The maize planting holes were spaced as 0.75 m between rows and 0.50 m within rows. Land and manure incorporation was manually done using hand hoe a week prior to planting. Nitrogen concentration of the locally acquired goat manure was done using a C/N analyser (Thermal Scientific, Flash 2000 Analyser, Waltham, MA 180 USA). The animal manure nitrogen content was 1.9 ± 0.2 %. Therefore, 3158 kg ha^{-1} and 1579 kg ha^{-1} of goat manure per season for animal manure and animal manure + inorganic fertiliser treatment was incorporated to meet the recommended N requirement. Planting coincided with fertiliser application and therefore, 260.8 kg ha^{-1} and 130.4 kg ha^{-1} per season of NP (23.23) for inorganic fertiliser and animal manure + inorganic fertiliser treatment was applied. To ensure weed-free plots, weeding was manually done using hand hoe twice a cropping season.

3.5.2 Soil N_2O Fluxes Measurement and Gas Chromatography

A total of 46 soil N_2O fluxes sampling campaigns were done from March 2018 through March 2019 using a static chamber technique. The chamber had two components a lid and a base. Three chambers were installed in each sampling plot to a depth of 7 cm. During each sampling event, four gas samples at chamber headspace closure of 30 min were collected. Gas pooling techniques following Arias-Navarro *et al*. (2013) was used to collect the gas samples at an interval of 10 min. The samples were analysed for the soil N_2O concentration using an SRI 8610C gas chromatography (GC), SRI Instruments, Torrance, CA, USA) fitted with a ^{63}Ni-electron capture detector (ECD. Hourly soil N_2O fluxes (μg N_2O-N m^{-2} h^{-1}) were calculated by converting the concentrations to mass per volume accounting for auxiliary measurements such as actual air temperature, chamber volume, and ambient pressure as per ideal gas law (Pelster *et al*., 2017). To determine daily soil N_2O fluxes (μg N_2O-N m^{-2} d^{-1}), the chamber soil N_2O hourly fluxes were multiplied by 24 hour period. Linear interpolation between sampling days based trapezoidal rule was used to calculate cumulative seasonal/annual cumulative soil N_2O fluxes from each sampling plot.

3.5.3 Soil Sampling and Maize Crop Production

At the beginning of the experiment (March 2018), soil samples for determination of baseline soil properties determination were collected. At each sampling plot, three samples at 0 to 20 cm depth were taken using an Eijkelkamp Gouge auger (Eijkelkamp Agrisearch Equipment, Giesbeek, The Netherlands) and pooled together in a labelled ziplock bag. The samples were oven-dried at 40 °C for 72 h, ground using a ball mill (Retsch ball mill, Haan, Germany), and sieved through a 2 mm sieve. A sub-sample of 1:2 soil: water ratio and a glass probe pH meter (Crison Instruments, Barcelona, Spain) was used for pH determination. Soil nitrogen and carbon were determined using a C/N analyser (Thermal Scientific, Flash 2000 Analyser, Waltham, MA USA). At each sampling plot, three soil bulk density samples (0 - 5 cm depth) were collected using a 100 cm^3 core rings (Eijkelkamp Agrisearch Equipment, Giesbeek, The Netherlands). The samples were oven-dried at 105 °C for a day then soil bulk density determined following Okalebo *et al*. (2002), Table 3.4).

During harvesting, maize yields were separated into grain, leaf, stem, and root. The leaf, stem, and root were harvested at plot dimensions of 1.5 m^2 (eight plants) while grain at the net plot (21 m^2). Both wet and dry weight were recorded and extrapolated to 10,000 m^2. Maize grain yields were adjusted to 12.5 % moisture content following Ngetich *et al*. (2014a). Meteorological data (daily precipitation, solar radiation, air pressure, maximum and minimum air temperature, humidity and wind speed) were obtained from an automatic weather station mounted within the experimental site at (1434 m a.s.l, 00°23’12.5’’ S and 037°37’37.6’’ E).

Table 3.4 Mean (± 1 standard error of the mean) baseline soil physicochemical characteristic Tharaka-Nithi County

Treatment [1]	**Bulk density ($g\ cm^{-3}$)**	**pH**	**Total Nitrogen (%)**	**SOC (%)**	**C/N Ratio**
Control	0.98±0.01	5.06^{a2}±0.02	0.20±0.01	2.26±0.09	11.12±0.07
Fertiliser	0.96±0.01	5.04^{a}± 0.08	0.21±0.01	2.33± 0.13	11.28±0.17
Manure	0.97±0.01	4.70^{b}±0.04	0.20±0.01	2.48±0.31	12.59±1.41
Man+Fert	0.97±0.01	4.73^{b}± 0.06	0.25±0.03	2.79±0.30	11.17±0.23
P value	0.3	0.002	0.2	0.4	0.5

[1] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NP. 23.23, 120 kg N ha−1 yr-1), Manure= (animal manure, 120 kg N ha−1 yr-1) and Man + Fert= (animal manure+ inorganic fertiliser, 120 kg N ha−1 yr-1).

[2] Same superscript letters in the same column denote no significant difference between the treatments means at P ≤0.05.

3.5.4 DNDC Modelling

The DNDC model version 9.5; http://www.dndc.sr.unh.edu, was downloaded in August 2019 to simulate crop production and N_2O fluxes. The input parameters used in simulating treatment-specific tracer N_2O fluxes and crop yields were categorised into the soil, weather, vegetation, and farm management data. Initial in situ and default soil data used were; texture, bulk density, hydraulic conductivity, SOC, field capacity, C to N ratio, wilting point, and porosity. The observed soil data were obtained from a baseline soil samples analysis using standard laboratory procedure (Ryan *et al*., 2001). Daily weather data such as solar radiation, wind velocity, precipitation, minimum and maximum air temperature, and relative humidity used were obtained from adjacent 0.5 km automated weather station. Farm management data such as manure amendments, fertilization, tillage, planting and harvesting dates were obtained from the experimental set-up.

3.5.5 Model Calibration and Validation

The DNDC model was calibrated with measured N_2O fluxes from the control treatment. The model was first run with observed parameters to obtain default mode (DEM) following (Rafique *et al*., 2011). Further, the DNDC model was calibrated using the soil parameters from control treatment to give simulated soil N_2O fluxes that agree well to the measured values that are calibration mode (CAM). During calibration, the following soil data was used bulk density, clay content, SOC, C to N ratio, and soil pH. The calibration was run to evaluate the effects of a range of parameters to the observed soil N_2O fluxes. This helped to construct an optimised set of parameters that resulted in the best fit for the soil N_2O to the measured value. The model was then validated using an optimised set of parameters in simulating N_2O fluxes and maize production for the other three treatments.

3.5.6 Model Evaluation

The model goodness of fit was measured using a coefficient of determination (R^2), mean error (ME), modelling efficiency (ME_i), mean absolute error (MAE), and root mean squared error (RMSE), (Rafique *et al*., 2011; Moriasi *et al*., 2007):

$$ME=\frac{\sum i(O_{i-}P_i)}{n} \qquad \text{Equation 3.2}$$

$$RMSE=\frac{\sqrt{\sum_{i-1}^{n}(P_i\text{-}O_i)^2}}{n} \qquad \text{Equation 3.3}$$

$$nRMSE(\%) = \frac{100}{\bar{o}}\sqrt{\frac{\sum_{i-1}^{n}(P_i\text{-}O_i)^2}{n}} \qquad \text{Equation 3.4}$$

$$R^2=\frac{\sum_{i-1}^{n}(O_{i-}O)(P_i\text{-}P)}{\sqrt{\sum_{i-1}^{n}(O_{i-}O)^2\sum_{i-1}^{n}(P_i\text{-}P)^2}} \qquad \text{Equation 3.5}$$

$$ME_i=1\text{-}\frac{\sum_{i-1}^{n}(O_{i-}\bar{O})^2\text{-}(S_i\text{-}O_i)^2}{\sum_{i-1}^{n}(O_{i-}\bar{O})^2} \qquad \text{Equation 3.6}$$

S_i and 0_i represent simulated values from the DNDC model and measured values from field trials, $_i$ one observation, *n* total observations and $\bar{O}$ = the mean value of the observed data. P_i and p represents $_i{}^{th}$ and mean prediction, respectively. Observed and simulated data were fitted in zero to intercept linear regression. The observed and simulated data were subjected to Analysis of Variance in SAS 9.4 software and mean differences between treatments separated using least significant difference at $p \leq 0.05$.

3.5.7 Model Sensitivity Analysis

A sensitivity assessment is done to test model performance when various input parameters are changed (Giltrap *et al.,* 2015). This helps to identify which input parameters have a high influence on simulating emissions. The following parameters were altered to determine their influence in predicting GHG emissions: soil properties, crop, climate and farm management. The model revealed that soil clay content, pH, SOC, bulk density, and inorganic nitrogen were more sensitive in simulating soil N_2O fluxes.

3.6. Estimation of Yield Scaled N_2O Emissions and Emission Factors

The yield scaled N_2O emission in g N_2O-N Kg^{-1} was calculated by dividing cumulative annual fluxes to air-dried grain yield eq. 3.7.

$$YSE=\frac{N_2O}{GY} \qquad \text{Equation 3.7}$$

Where YSE = N_2O yield scaled emission in g N_2O-N Kg^{-1}, N_2O = N_2O emission and GY = air-dried grain yield.

Emission factor were determined following equation. 3.8 (Giltrap *et al*., 2013).

$$EF = \frac{N_2O\ emission\ with\ N\ applied\ - N_2O\ emission\ with\ 0\ N\ applied}{N\ applied} \qquad \text{Equation 3.8}$$

Where EF = emission factor, N_2O emission with N applied treatments = N_2O emission from the nitrogen fertilised treatments, N_2O emission with 0 N applied = N_2O emission from control and N applied = Nitrogen application rate per year.

CHAPTER FOUR

RESULTS

4.1 Overview

This chapter presents the extracted principal components, the characterised smallholder farm typologies and socioeconomic factor that influenced the diversity of farm typologies. Further, the DNDC calibration, validation and accuracy assessment resulted are presented. Finally, the simulated and observed maize yield (grain, stem, leaf and root), soil N_2O fluxes, yield scaled N_2O emission, and emission factor results are reported.

4.2 Smallholder farming systems characterisation

4.2.1 Extracted Principal Components

The PCA results revealed a KMO of 0.57, and Bartlett's sphericity test was significant at $p<0.001$. The reported KMO was greater than 0.50; hence PCA was considered appropriate. The first PC had high positive loadings in the proportion of land on maize (0.922) and nitrogen applied on maize (0.924) which explained variance of 11.2%, and therefore, identified as maize cropping system (Table 4.1). The second PC that had high positive loadings in the proportion of land on millet (0.863) and nitrogen applied on millet (0.730) explained 9.4% of the variance, consequently, identified as millet cropping system. The third PC had high positive loadings in the proportion of land under tobacco (0.892) and nitrogen applied on tobacco (0.889), explaining 8.7% of the variance and thus identified as tobacco cropping system. The fourth PC that had high positive loading in the proportion of land on tea (0.818) and nitrogen applied on tea (0.850) which explained 8.5% of the variance, therefore, identified as tea cropping system.

The fifth PC had high positive loading in land size (0.831), and farm size (0.865) explaining 8.14% of the variance thus identified as land size characteristics. The sixth PC had high positive loadings in the proportion of land on Napier (0.819) and nitrogen applied on Napier (0.734) which explained 7.74% of the variance, therefore, categorised as Napier cropping system. Lastly, the seventh PC had high positive loading in TLU, and

WI, which explained 7.69% of the variance and therefore identified as livestock systems and household wealth assets index.

Table 4.1 Extracted principal components (PCs) from smallholder farmers in Tharaka-Nithi County

Independent Variables	Principal Components						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Proportion Maize	**0.922**	-0.160	-0.009	-0.241	-0.106	-0.128	-0.022
Nitrogen Maize	**0.924**	-0.149	-0.005	-0.250	-0.096	-0.118	0.006
Proportion Millet	-0.115	**0.863**	-0.028	-0.080	0.111	-0.054	0.080
Nitrogen Millet	-0.095	**0.730**	-0.061	-0.103	-0.091	-0.103	-0.063
Proportion tobacco	0.002	-0.070	**0.892**	-0.075	-0.031	-0.069	-0.052
Nitrogen tobacco	0.023	0.008	**0.889**	-0.066	-0.026	-0.047	0.076
Proportion Tea	-0.286	-0.120	-0.096	**0.818**	-0.035	-0.058	0.002
Nitrogen Tea	-0.139	-0.056	-0.063	**0.850**	-0.109	0.134	0.075
Land size	-0.029	0.098	-0.034	-0.094	**0.831**	-0.062	0.162
Farm size	-0.093	-0.020	-0.020	-0.040	**0.865**	-0.046	-0.007
Proportion Napier	-0.210	-0.086	-0.070	-0.101	-0.042	**0.819**	-0.092
Nitrogen Napier	0.017	-0.028	-0.068	0.257	-0.082	**0.734**	0.271
TLU	-0.044	0.503	0.036	0.073	0.226	0.215	**0.535**
WI	0.008	-0.012	0.042	0.049	0.101	0.031	**0.838**
Proportion Coffee	-0.460	-0.364	-0.260	-0.112	-0.152	-0.169	0.413
Nitrogen Coffee	-0.314	-0.324	-0.211	-0.050	-0.141	0.158	0.302
Proportion Beans	0.197	-0.105	0.057	-0.183	0.019	0-.110	-0.341
Nitrogen Beans	-0.050	-0.075	-0.023	-0.104	-0.061	-0.068	0.181
Proportion banana	-0.013	-0.110	-0.078	-0.008	-0.126	-0.090	0.037
Nitrogen banana	-0.086	-0.059	-0.024	-0.061	-0.046	0.367	-0.032
Eigenvalue	2.242	1.888	1.740	1.696	1.628	1.549	1.535
% explained variance	11.2	9.4	8.7	8.5	8.1	7.7	7.7
%cumulative Variance	11.2	20.7	29.4	37.8	46.0	53.7	61.4

Bold Number referred to loadings higher than 0.50. KMO (0.57, p<0.001), PC 1= Maize cropping system, PC 2 = Millet cropping system, PC 3= Tobacco cropping system, PC 4= Tea cropping system, PC 5= Land size characteristics, PC 6= Napier cropping system, PC 7= livestock systems and household wealth assets index

4.2.2 Smallholder Farming Systems Typologies

The dendrogram from the cluster analysis illustrates how the nested clusters were cut to identify farm types (Figure 4.1). The cut tree point was at C to obtain six farm types.

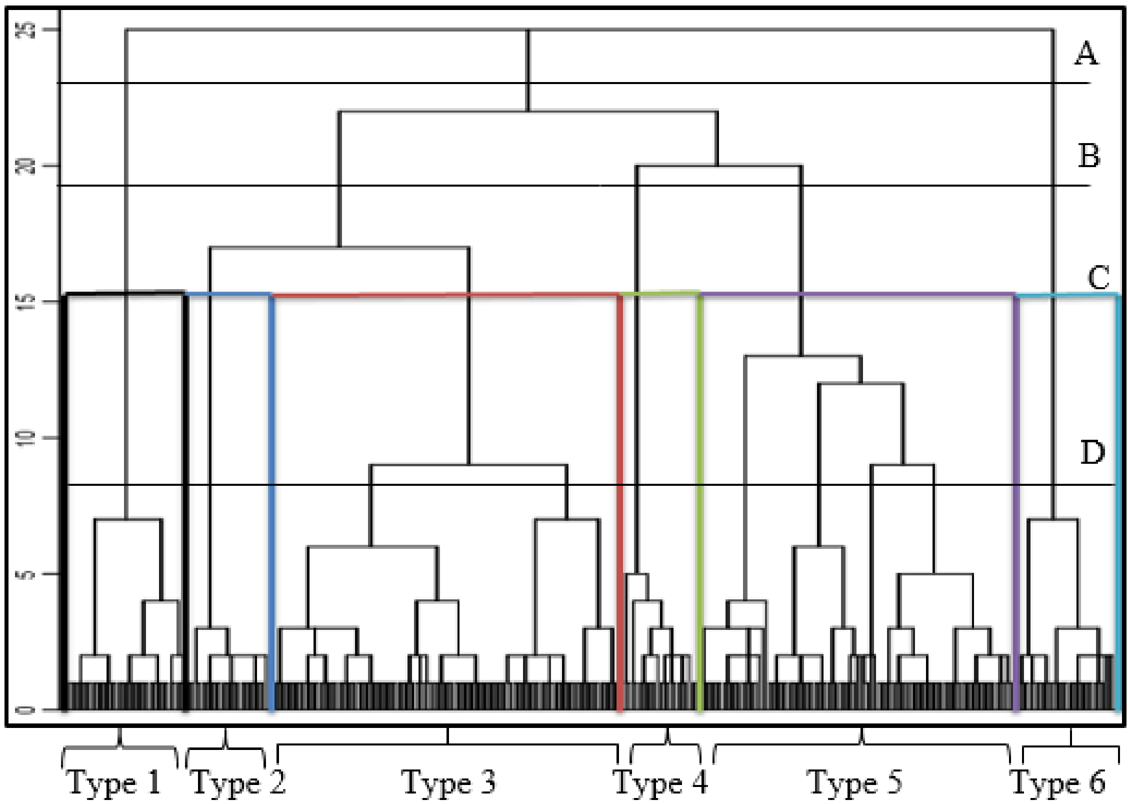

Figure 4.1 Dendrogram with four cut tree points A, B, C and D The dendrogram was cut at C, and six farm typologies were identified. Type 1, cash crop and hybrid cattle system; Type 2, food crop system; Type 3, coffee-maize system; Type 4, millet-livestock system; Type 5, highly diversified system, and Type 6, tobacco system.

Farm Type 1 comprised of cash crop and hybrid cattle system (N=36 (12%), Table 4.2). This farm type varied from the rest by the proportion of land and nitrogen applied on tea, coffee and Napier. This farm type had the least proportion of land and nitrogen applied to maize. Further, farmers in this category neither grew tobacco nor grew millet and had the least proportion of land and nitrogen applied on beans. The farmers in this category also owned the least total land size. More so, they had moderate total TLU, the proportion of land and nitrogen applied on bananas.

Table 4.2 Smallholder farming systems' descriptive characteristics based on nitrogen application rates in Tharaka-Nithi County

Independent Variable	**Cash crop and hybrid cattle system** ***N=36***	**Food crop system** ***N=21***	**Coffee-maize system** ***N=102***	**Millet-livestock system** ***N=19***	**Highly diversified system** ***N=92***	**Tobacco system** ***N=29***	**P value**
Land size	0.58^{b}	0.66^{b}	0.75^{ab}	**1.17**$^{\mathbf{a}}$	**0.89**$^{\mathbf{ab}}$	0.69^{b}	0.016
Cultivated land	0.51	0.54	0.65	0.93	0.83	0.59	NS
Proportion Maize	4.89^{d}	29.91^{b}	**43.12**$^{\mathbf{a}}$	12.42^{cd}	20.61^{bc}	30.10^{b}	0.001
Nitrogen Maize	2.69^{d}	15.91^{b}	**22.42**$^{\mathbf{a}}$	7.21^{cd}	10.80^{bc}	15.72^{b}	0.001
Proportion Tea	**2.69**$^{\mathbf{a}}$	0.00^{b}	1.86^{b}	0.00^{b}	7.45^{b}	0.00^{b}	0.001
Nitrogen Tea	**146.04**$^{\mathbf{a}}$	0.00^{b}	4.43^{b}	0.00^{b}	6.52^{b}	0.00^{b}	0.001
Proportion Coffee	**22.84**$^{\mathbf{a}}$	7.17^{bcd}	**14.40**$^{\mathbf{abc}}$	0.66^{d}	**17.13**$^{\mathbf{ab}}$	2.71^{cd}	0.001
Nitrogen Coffee	**157.18**$^{\mathbf{a}}$	26.53^{b}	**76.42**$^{\mathbf{ab}}$	11.92^{b}	**77.42**$^{\mathbf{ab}}$	13.51^{b}	0.001
Proportion Banana	4.19^{b}	1.95^{b}	2.59^{b}	0.00^{b}	**20.09**$^{\mathbf{a}}$	4.03^{b}	0.001
Nitrogen Banana	29.67^{ab}	14.90^{ab}	13.96^{b}	0.00^{b}	**120.03**$^{\mathbf{a}}$	23.45^{ab}	0.001
Proportion Beans	0.44^{c}	**34.38**$^{\mathbf{a}}$	18.16^{b}	4.53^{c}	3.63^{c}	18.24^{b}	0.001
Nitrogen Beans	0.13^{c}	**97.57**$^{\mathbf{a}}$	2.68^{bc}	0.47^{c}	1.59^{bc}	16.65^{b}	0.001
Proportion Napier	**13.74**$^{\mathbf{a}}$	5.27^{ab}	6.09^{ab}	2.13^{b}	14.07^{a}	3.85^{ab}	0.001
Nitrogen Napier	**124.51**$^{\mathbf{a}}$	21.00^{b}	40.42^{b}	27.30^{b}	39.57^{b}	14.71^{b}	0.001
Proportion Tobacco	0.00^{b}	0.00^{b}	1.06^{b}	0.00^{b}	0.00^{b}	**33.30**$^{\mathbf{a}}$	0.001
Nitrogen Tobacco	0.00^{b}	0.00^{b}	2.04^{b}	0.00^{b}	0.00^{b}	**125.55**$^{\mathbf{a}}$	0.001
Proportion Millet	0.00^{b}	1.19^{b}	0.17^{b}	**35.15**$^{\mathbf{a}}$	0.66^{b}	1.24^{b}	0.001
Nitrogen Millet	0.00^{b}	0.09^{b}	0.00	**30.21**$^{\mathbf{a}}$	0.17^{b}	0.89^{b}	0.001
TLU	2.36^{b}	1.91^{b}	1.73^{b}	**6.16**$^{\mathbf{a}}$	1.51^{b}	1.70^{b}	0.001
Wealth Index	39.64	38.57	31.88	31.94	28.49	29.79	NS

The same superscript in the same row shows no significant difference between treatment means at p=0.05, N= number of household heads in a farm type, NS=Not significant at P=0.05, bold numbers indicate the most relevant explanatory variable(s) per farm type, land size and cultivated land = acres, the proportion of land allotted to different crops = percentage, nitrogen application on a crop = kg N ha^{-1}, TLU = tropical livestock unit.

Farm Type 2 was composed of food crop system (N=21 (7%), Table 4.2). The key aspect that isolated this farm type from the others is that they primarily grew beans but did not grow either tea or tobacco. This farm type was also composed of farmers who had a low proportion of land and nitrogen applied on coffee, banana, Napier and millet. Total TLU and total land size owned were equally small (Table 4.2).

In farm Type 3, most of the households were coffee and maize system (N=102 (34%), Table 4.2). These households had a moderate proportion of land and nitrogen applied to maize and coffee. These farmers had limited proportion of land and nitrogen applied on tea, banana, beans, tobacco and millet. Additionally, they had moderate total land size owned and nitrogen applied to Napier but low proportion of land on Napier and relatively low total TLU (Table 4.2).

Under farm Type 4, most of the households were Millet-livestock system (N=19 (6%), Table 4.2). These households were distinct from the rest by owning the largest tracks of land and highest TLU. They had the highest proportion of land and nitrogen applied to millet. These farmers were not tea, coffee or tobacco growers. They had a low proportion of land and nitrogen applied on maize, coffee and beans (Table 4.2).

Farm Type 5 comprised of a highly diversified system (N=92 (31%), Table 4.2). Farmers in this category had a high proportion of land and nitrogen applied to banana and coffee. They owned high to moderate land sizes and had moderate to low land and nitrogen used on maize. Additionally, they had a modest proportion of land and nitrogen applied to tea. These farmers had a small portion of land and nitrogen applied to beans and millet. Further, they had a high proportion of land on napier, but moderate nitrogen used on it and the lowest total TLU.

Farm Type 6 comprised of tobacco system (N=29 (10%), Table 4.2). These farmers had the highest proportion of land and nitrogen applied to tobacco. They had a moderate proportion of land and nitrogen applied on maize, bananas, beans, napier, millet and coffee but low TLU (Table 4.2).

4.3 Socio-Economic Characteristics Influencing the Diversity of Smallholder Farm Typologies

4.3.1 Univariate Analysis of Socio-Economic Factors Influencing Farm Typologies

The univariate analysis results showed that household head level of education, group membership, hired labour, the proportion of income from cropping activities, and access to extension services were the significant socio-economic factors that influenced farmers belonging to a specific farm typology (Table 4.3).

Table 4.3 Univariate analysis of socio-economic factors influencing farm types in Tharaka-Nithi County

Independent variables	**Definition**	**Cash crop and hybrid cattle system**	**Food crop system**	**Coffee-maize system**	**Millet-livestock system**	**Highly diversified system**	**Tobacco system**	**χ2 Value**
HHH Gender	Female	7(13.5)	2(3.8)	21(40.4)	5(9.6)	15(28.8)	2(3.8)	NS
	Male	29(11.7)	19(7.7)	81(32.8)	14(5.7)	77(31.2	27(10.9)	
HHH Education	No education	3(18.8)	1(6.3)	4(25.0)	4(25.0)	4(25.0)	0(0.0)	0.032
	Primary	15(9.3)	7(4.3)	56(34.8)	13(8.1)	50(31.1)	20(12.4)	
	Secondary	11(14.5)	8(10.5)	30(39.5)	1(1.3)	21(27.6)	5(6.6)	
	Tertiary	7(15.2)	5(10.9)	12(26.1)	1(2.2)	17(37.0)	4(8.7)	
Hired Labour	No	7(7.6)	6(6.5)	26(28.3)	10(10.9)	36(39.1)	7(7.6)	0.043
	Yes	29(14.4)	15(7.2)	76(36.7)	9(4.3)	56(27.1)	22(10.6)	
Group Members	No	20(9.7)	13(6.3)	78(37.9)	17(8.3)	58(28.2)	20(9.7)	0.044
	Yes	16(17.2)	8(8.6)	24(25.8)	2(2.2)	34(36.6)	9(9.7)	
Credit Access	No	30(11.7)	18(7.0)	90(35.0)	18(7.0)	75(29.2)	26(10.1)	NS
	Yes	6(14.3)	3(7.1)	12(28.6)	1(2.4)	17(40.5)	3(7.1)	
Training access	No	20(10.9)	12(6.5)	63(34.2)	17(9.2)	57(31.0)	15(8.2)	NS
	Yes	16(13.9)	9(7.8)	39(33.9)	2(1.7)	35(30.4)	14(12.2)	
Extension Access	No	21(9.1)	18(7.8)	83(35.9)	16(6.9)	73(31.6)	20(8.7)	0.050
	Yes	15(22.1)	3(4.4)	19(27.9)	3(4.4)	19(27.9)	9(13.2)	
Mean								**p value**
HHH Age		55.18	49.48	53.04	54.16	55.49	49.38	NS
HHH Experience		28.39	21.57	23.92	28.11	25.43	22.21	NS
HH Size		3.94	4.55	4.34	4.60	4.18	4.06	NS
Proportion of income from Crops (%)		43.56	16.45	30.26	32.55	32.63	45.14	0.01
Proportion of income from Livestock (%)		23.70	19.83	19.59	32.82	21.12	16.87	NS
Proportion of income from Remittance (%)		3.50	4.92	4.52	1.05	3.67	1.47	NS

Association significant at α = 0.05, HHH=Household head, HH= Household, χ2 = chi square value

4.3.2 Socio-Economic Factors Influencing the Diversity of Farm Typologies

Type 1: The multinomial logistic regression (MNLR) model identified six predictor variables: household head age, access to agricultural training, group membership, access to extension services, household head experience in agriculture, and proportion of income from cropping activities, as significant factors influencing farm Type 1 (Table 4.4). **Type 2**: The MNLR model indicated that access to agricultural training, the proportion of income on cropping activities, and access to extension services were significant variables in explaining whether a farmer belonging to Type 2 (Table 4.4). **Type 3**: The MNRL model showed that access to credit, household head gender, and access to the agricultural extension was important in explaining farmers who belonged to farm Type 3 (Table 4.4). **Type 4**: The MNLR model revealed five predictor variables: household size, hired labour, household head level of education, the proportion of income from cropping activities, and proportion of income from livestock activities were significant in explaining farmers who belonged to Type 4 (Table 4.4). **Type 5**: The MNLR model showed four predictor variables: hired labour, household head age, household head level of education, and proportion of income from livestock activities were significant in explaining farmer who belonged to Type 5 (Table 4.4).

Table 4.4 Multinomial logistic regression analysis of socio-economic factors influencing farmers belonging to farm typologies

Variables	**Cash crop and hybrid cattle system**	**Food crop system**	**Coffee-maize system**	**Millet-livestock system**	**Highly diversified system**
Constant	-2.811	-0.033	1.693	2.427	0.182
HHH Gender	-1.566	-0.706	-2.181*	-0.972	-0.978
HHH Education	0.357	0.603	0.444	-1.027*	0.526*
Hired labour	0.652	-0.800	-0.099	-0.978*	0.978*
Group Membership	1.713**	0.201	-0.530	-0.944	0.049
Credit Access	0.083	0.930	-0.730*	0.184	0.907
Training Access	-1.439**	0.046*	-0.793	-0.793	-0.439
Extension Access	0.523*	-1.328*	1.127*	-0.769	-0.769
HHH Age	0.049*	0.006	0.010	0.018	0.042**
HHH Experience	0.065*	-0.064	-0.014	0.038	-0.016
HH size	-0.027	0.292	0.153	0.381*	0.078
Proportion of income from Crops (%)	0.010*	-0.031**	-0.017	-0.019**	-0.012
Proportion of income from Livestock (%)	0.023	0.002	-0.007	0.020**	-0.014*
Proportion of income from Remittance (%)	0.065	0.039	0.083	-0.053	0.018

**, * significance at 5% and 10%, respectively, HHH=Household head, HH= Household, the presented values are model coefficients of each independent variable

4.4 The DNDC Model Calibration, Validation and Accuracy Assessment

The DNDC model accurately simulated cumulative seasonal/ annual soil N_2O fluxes based on its R^2 ranging from 0.78 to 0.88 and slope ranging between 0.95 and 1.1 across soil fertility management technologies (Figure 4.2). The DNDC model explained 78 to 88 % of the observed N_2O fluxes.

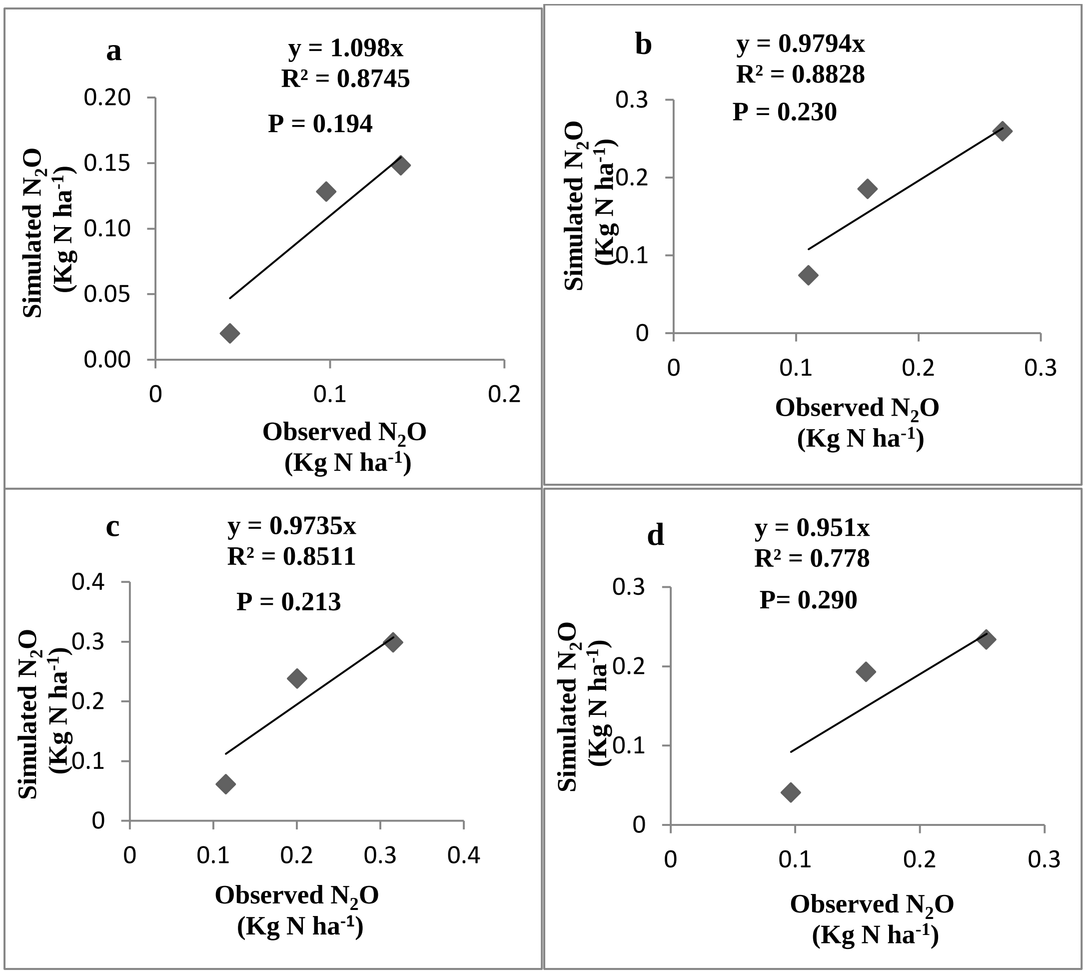

Figure 4.2 The Zero to intercept linear regression between observed and simulated cumulative seasonal/ annual N_2O fluxes a) = control (no external input), b) = inorganic fertiliser (NP 23.23, 120 kg N ha^{-1} yr^{-1}), c) = animal manure (goat manure, 120 kg N ha^{-1} yr^{-1}), and d) = animal manure + inorganic fertiliser (120 kg N ha^{-1} yr^{-1}).

The time series observed and simulated daily soil N_2O fluxes across the four treatments from March 2018 through March 2019 are shown in Figure 4.3

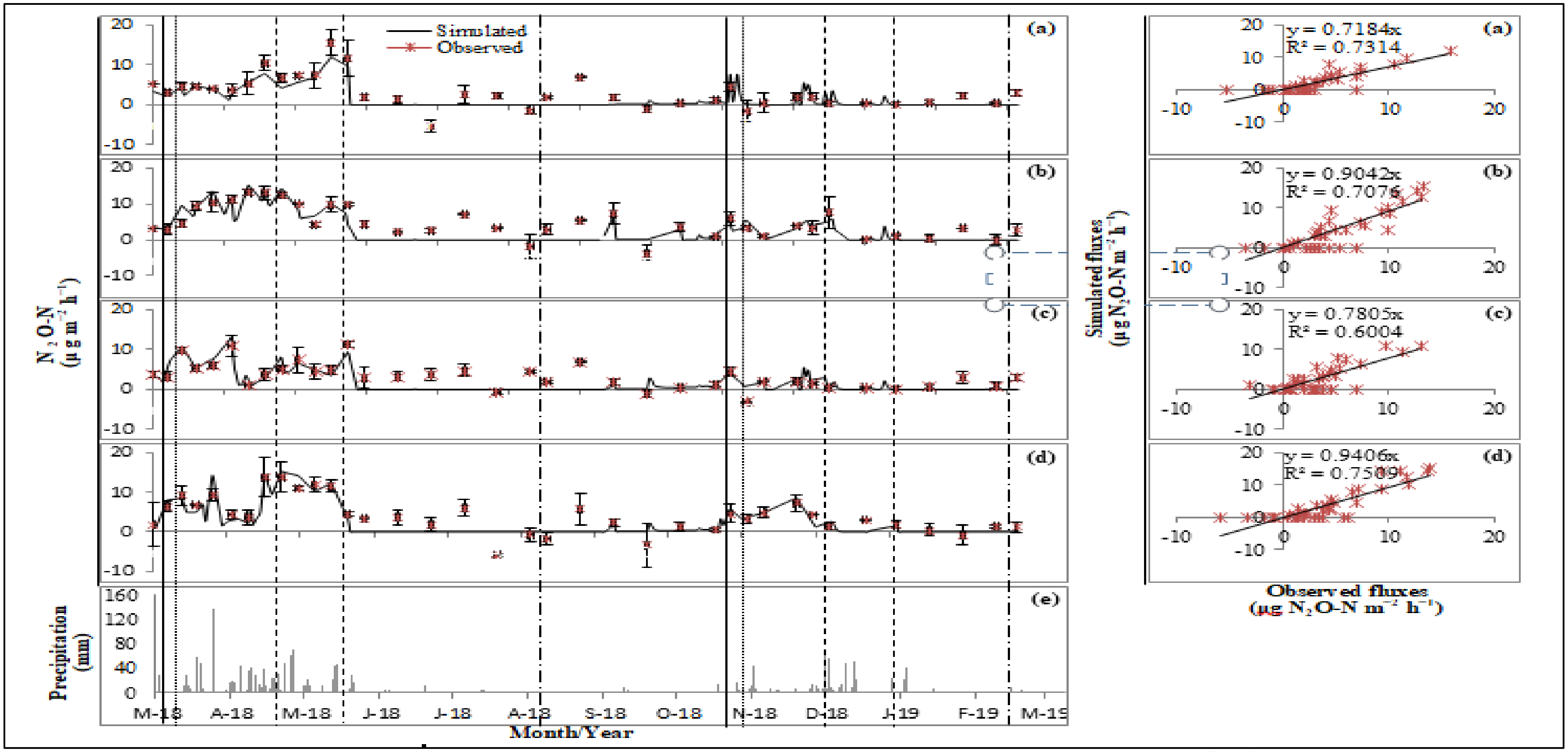

Figure 4.3 The comparison between instantaneous observed and simulated daily N_2O fluxes ($\mu g\ N_2O$-N $m^{-2}\ h^{-1}$) from a) = control (no external input), b) = inorganic fertiliser (NP 23.23, 120 kg N $ha^{-1}\ yr^{-1}$), c) = animal manure (goat manure, 120 kg N $ha^{-1}\ yr^{-1}$), and d) = animal manure + inorganic fertiliser (120 kg N $ha^{-1}\ yr^{-1}$). The vertical lines correspond to land preparation and manure application (continuous), planting and fertiliser application (dotted), weeding (dashed), and harvesting (long dashed). The Zero to intercept linear regression and R^2 are shown.

The measured daily soil N_2O ranged across soil fertility technologies ranged between −5.83 and 13.18 μg N_2O-N m^{-2} h^{-1}. The negative and positive soil N_2O fluxes mean that the soil acted as a sink or source of the emissions, respectively. The simulated daily N_2O fluxes ranged between 0 and 15.25 μg N_2O-N m^{-2} h^{-1} across soil fertility treatments. The DNDC model captured both timing and magnitude of the soil N_2O fluxes peaks across treatments except control. The model underestimated soil N_2O peak on 16th May 2018. Additionally, the model did not capture the negative daily soil N_2O fluxes across soil fertility management technologies.

The comparison between simulated and observed daily soil N_2O fluxes using zero to intercept regression resulted to a slope that ranged from 0.72 to 0.94, and R^2 ranged from 0.60 to 0.75 across treatments (Figure 4.3). The model was not able to accurately capture the temporal trends in soil N_2O fluxes as shown by high nRMSE ranging between 54 and 68 % across all treatments. The comparison between simulated and observed daily soil N_2O fluxes using zero to intercept regression resulted in a slope that ranged from 0.72 to 0.94, and R^2 ranged from 0.60 to 0.75 across treatments (Figure 4.3). Across all the four treatments, the model performance resulted in calculated matrices that ranged between E = -0.80 and -0.28 μg N_2O-N m^{-2} h^{-1}, RMSE = 2.17 and 2.65 μg N_2O-N m^{-2} h^{-1}, and $0.26 \leq ME_i \leq 0.49$ (Table 4.5).

The site received a cumulative annual rainfall amount of 1815 mm. The LR 2018 and SR 2018 season had 1193.5 mm and 621.5 mm, respectively (Figure 4.3, e). The highest daily rainfall amount recorded in LR and SR season 2018 was 138 mm and 69 mm, respectively.

Table 4.5 The model evaluation matrices comparing between simulated and measured daily and cumulative seasonal/ annual soil N_2O fluxes Tharaka-Nithi County

Season[1]	**Treatment**[2]	**ME**	**RMSE**	**nRMSE (%)**	**ME_i**
Daily	Control	-0.80	2.17	68.43	0.26
(µg N2O-N m^{-2} h^{-1})	Fertiliser	-0.68	2.65	53.56	0.45
	Manure	-0.69	2.29	63.34	0.32
	Man+Fert	-0.28	2.48	59.37	0.49
LR 2018	Control	1.95	22.58	15.05	0.92
(g N_2O-N ha^{-1})	Fertiliser	-12.13	15.42	6.18	0.89
	Manure	-22.55	33.53	16.89	0.96
	Man+Fert	-18.09	25.91	11.88	0.81
SR 2018	Control	-8.14	8.89	13.44	0.97
(g N_2O-N ha^{-1})	Fertiliser	19.72	28.96	22.94	0.94
	Manure	-5.46	7.12	9.79	0.71
	Man+Fert	18.47	26.31	28.74	0.89
Annual	Control	-6.19	21.77	10.07	0.86
(g N_2O-N ha^{-1} yr^{-1})	Fertiliser	7.59	31.49	8.38	0.71
	Manure	-28.01	34.89	12.86	0.63
	Man+Fert	0.39	19.07	6.16	0.76

[1] Daily is the sampling events, LR 2018 is the long rain 2018 season, SR 2018 is the short rain 2018 season and annual is the two cropping season March 2018 through March 2019.

[2] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NP. 23.23, 120 kg N ha−1 yr-1), Manure= (animal manure, 120 kg N ha−1 yr-1) and Man + Fert= (animal manure+ inorganic fertiliser, 120 kg N ha−1 yr-1). E is mean error and RSME root mean square error in µg N_2O-N m^{-2} h^{-1} for daily and g N_2O-N ha^{-1} for cumulative seasonal/annual N_2O fluxes, nRSME is the normalised root means square error in %, and ME_i is the Model efficiency.

4.5 The DNDC Model Simulation

The cumulative observed and simulated annual soil N_2O fluxes ranged between 0.21±0.01 and 0.38±0.02 kg N_2O-N ha^{-1} yr^{-1} and 0.20 to 0.38 kg N_2O-N ha^{-1} yr^{-1}, respectively (Table 4.6). The DNDC model was capable of capturing the magnitude of cumulative soil N_2O fluxes across the soil fertility management technologies (Table 4.5). Simulated and observed cumulative annual soil N_2O fluxes greatly varied across treatment (Table 4.6). The highest soil N_2O fluxes were observed under fertiliser treatment and the lowest under control treatment similar to the field experiment (Table 4.6). Though the observed and simulated soil N_2O fluxes were similar, the DNDC model underestimated the fluxes (E = -6.19 and -28.01 g N_2O-N ha^{-1} yr^{-1}) in control and manure treatments while overestimating (E = 7.59 and 0.39 g N_2O-N ha^{-1} yr^{-1}) in fertiliser and manure + fertiliser treatments, respectively (Table 4.5). The overall model performance was as slope = 1.01, R^2 = 0.80, RMSE ranged from 19.07 to 34.89 g N_2O-N ha^{-1}, $6.16 \leq$ nRMSE ≤ 12.86, and $0.63 \leq ME_i \leq 0.86$ (Table 4.5).

With the exception of roots yields which were overestimated the DNDC model accurately simulating maize yields (grain, leaf, and stem) across soil fertility management technologies (Table 4.6). The highest grain yields were observed under fertiliser treatment and the lowest under control treatments. The DNDC model accurately captured both magnitude and treatment effects on maize yields.

Table 4.6 Mean (±1 standard error of the mean) observed and simulated soil N_2O fluxes and Maize production (grain, stems, leaves and roots) under different soil fertility management technologies in Tharaka-Nithi County

Treatment [1]	**kg N_2O-N ha^{-1} yr^{-1}**		**Grain Mg ha^{-1} yr^{-1}**		**Stem Mg ha^{-1} yr^{-1}**		**Leaf Mg ha^{-1} yr^{-1}**		**Root Mg ha^{-1} yr^{-1}**	
	Observed	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**
Control	0.21^{c2}±0.01	0.20^{d}	8.2^{c}±0.11	7.7^{c}	4.1^{c}±0.16	4.1^{d}	5.7^{c}±0.15	6.7^{bc}	1.0^{b}±0.01	1.1^{b}
Fertiliser	0.38^{a}±0.02	0.38^{a}	13.7^{a}±0.27	13.4^{a}	5.8^{a}±0.10	5.8^{a}	7.5^{a} ±0.23	7.6^{a}	1.4^{a}±0.02	1.5^{a}
Manure	0.27^{b}±0.01	0.24^{c}	11.3^{b}±0.25	11.1^{b}	4.5^{b}±0.15	4.4^{c}	6.7^{b}±0.29	6.8^{b}	1.1b±0.02	1.2^{b}
Man+Fert	0.31^{b}±0.03	0.31^{b}	13.0^{a}±0.23	12.6^{a}	5.0^{ab}±.09	4.7^{b}	6.6^{b}±0.19	6.5^{c}	1.2b±0.01	1.2^{b}
P value	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**0.004**	**0.002**	**0.020**	**0.031**

[1] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NP. 23.23, 120 kg N ha−1 yr-1), Manure= (animal manure, 120 kg N ha−1 yr-1) and Man + Fert= (animal manure+ inorganic fertiliser, 120 kg N ha−1 yr-1).

[2] Mean maize yields followed by the same superscript in a column for the same season are not significantly different at p=0.05.

The observed N_2O YSE and N_2O EFs ranged from 0.024 to 0.028 g N Kg^{-1} grain yield and 0.05 to 0.14 %, respectively (Table 4.7). The highest and lowest N_2O YSE was in fertiliser and control treatments, respectively. The simulated N_2O YSE and EFs ranged from 0.022 to 0.029 g N Kg^{-1} grain yield and 0.03 to 0.14 %, respectively.

Table 4.7 Mean (±1 standard error of the mean) observed and simulated yield-scaled N_2O emissions and N_2O emission factors under different soil fertility management technologies in Tharaka-Nithi County

Treatment[1]	**Yield-scaled N_2O emission**[2] **(g N_2O-N kg^{-1} grain yield)**		**N_2O Emission factors**[3] **(%)**	
	Observed	**Simulated**	**Observed**	**Simulated**
Control	0.027 ± 0.001	0.028±0.001	-	-
Fertiliser	0.028 ± 0.003	0.029±0.001	0.14^{a4}±0.02	0.14^{a}±0.01
Manure	0.024 ± 0.002	0.022±0.001	0.05^{b}±0.01	0.03^{c}±0.01
Man+Fert	0.024 ± 0.001	0.025±0.001	0.08^{b}±0.02	0.08^{b}±0.01
P value	0.4	0.2	<0.001	0.001

[1] Treatments Control = (No external input), fertiliser = (inorganic fertiliser NP. 23.23, 120 kg N ha−1 yr-1), Manure= (animal manure, 120 kg N ha−1 yr-1) and Man + Fert= (animal manure+ inorganic fertiliser, 120 kg N ha−1 yr-1)
[2] Yield-scaled N_2O emission calculated by dividing maize grain yield with cumulative annual N_2O emissions
[3] N_2O emission factors calculated by subtracting N_2O emissions control treatment from N_2O emissions in N applied treatments then dividing by annual N application rate (120 kg N ha^{-1} yr^{-1}).
[4] mean N_2O emission factors followed by the same superscript in the same column show no significant difference between treatments at $p \leq 0.05$

CHAPTER FIVE

DISCUSSIONS

5.1 Overview

This chapter presents the discussions for smallholder farming systems characterisation and socio-economic factors influencing the diversity of farm typologies. The DNDC calibration, validation and accuracy assessment results are linked to the existing body of knowledge. The DNDC model simulated results for soil N_2O fluxes, and yield scaled N_2O emission, emission factors and maize productions are also discussed.

5.2 Smallholder Farming Systems Characterisation

The study revealed a KMO 0.57 and Bartlett's sphericity test significance at $p<0.001$ (Table 4.1). The observed KMO was greater than 0.50; hence PCA was considered appropriate (Gelasakis *et al*., 2017). The nitrogen application rate, land size owned by smallholder farmers and TLU were significant variables in typifying farming systems (Table 4.2). The ISFM techniques such as fertilisers and manure application shrink yield gaps (Vanlauwe *et al*., 2010; Vanlauwe *et al*., 2015). However, these practices might have an adverse effect on atmospheric GHG (CO_2, CH_4, N_2O) emissions (Tongwane *et al*., 2016). Attempts directed towards agricultural GHG emissions measurements should consider farm-level nitrogen application rate. These farm typologies depicted different cropping systems and their average nitrogen application rates.

In reference to GHG emissions, farm Types 1, 5 & 6 are expected to be hotspots of GHG emissions because of their high nitrogen application rates (Table 4.2). Type 2 & 3 are probable to contribute towards GHG emissions moderately. Though farm Type 4 is predicted to contribute least GHG emissions from cropping activities, high total TLU might contribute a significant amount of GHG emissions through manure production and enteric fermentation (Ortiz-Gonzalo *et al*., 2017). The results showed that smallholder farms in Tharaka-Nithi County had a range of categories from cash crop-hybrid cattle, food crop, coffee-maize, millet livestock, highly diversified and tobacco farmers. Total land size owned, total tropical livestock unit, the proportion of land and nitrogen applied to different cropping systems were significant variables in constructing farm typologies. These classification variables were capable of differentiating farming systems. Dissimilar cropping systems and livestock intensities contribute differently to GHG inventories. Furthermore, nitrogen application rates might play a significant role in influencing these emissions. Therefore, nitrogen application in cropping systems can be an entry point for quantifying and simulating GHG emissions from individual cropping systems or whole farm emissions.

Total TLU was a significant variable in categorising farming systems similar to studies by Sakané *et al*. (2013) and Kuivanen *et al*. (2016b). Studies have demonstrated that livestock densities have been increasing in Africa and are sources of GHG emissions with significant amounts emanating from ruminants (e.g. Herrero *et al*., 2008). The highest TLU was recorded in farm Type 4 that is concentrated in dry zones of the study area (LM5) that can be ascribed to their large land sizes (Table 4.2) which can be used for livestock production. Livestock act as GHG emissions source and is projected to increase over time O'Mara, (2011) through enteric fermentation and use of manure. Manure production increases with an increase in TLU, and its decomposition and management lead to GHG emissions (Ortiz-Gonzalo *et al*., 2017).

Total and proportion of land allotted to each cropping system were important variables in capturing farms' diversity. These results collaborate with the findings by Mutoko *et al*. (2014) and Kansiime *et al*. (2018). The smallest land size was in Type 1, which was identified as cash-crop (tea and coffee) and hybrid cattle farmers while the largest in Type 4 as millet-livestock. Coffee and tea farmers owned small tracks of land as opposed to millet livestock farmers (Mwaura & Muku, 2008). The population density in coffee tea zones is high compared to the dry zone of millet-livestock hence this can account for the small land size in Type 1.

5.3 Socio-Economic Factors Influencing the Diversity of Farm Typologies

Group membership positively predicted whether the farmer belonged to farm Type 1 (Table 4.4). This implied that farmers who belonged to agricultural groups were more likely to belong to farm Type 1. Majority of these farmers grew coffee and tea as cash crops and reared hybrid cattle under high intensive management since they had small parcels of land (Table 4.3). These farmers marketed their coffee, tea and milk through farmers' cooperatives. Farmers in cooperatives are capable of improving their bargaining power hence gaining more from their agricultural products (Mugwe *et al*., 2009; Macharia *et al*., 2014). This could explain the positive prediction by the proportion of income from cropping activities which was the highest in this farm typology (Table 4.4). Belonging to cooperatives also increase access to agricultural information, inputs and other agricultural services that boost their agricultural production (Odendo *et al*., 2006).

Farmers who belonged to this farm type were among the oldest in the study area and had the highest farming experience (Table 4.4). Household head age and farming experience positively influenced farmers belonging to this farm type. This implies that older and relatively more experienced farmers were more likely to belong to farm Type 1 than any other. Older and experienced farmers tend to trust traditional methods of technology transfer (i.e. extension officers) more than other types of agricultural training and could probably miss out new agricultural innovations. These findings agree with Macharia *et al*. (2014). They reported that older farmers might fail to utilise information on new technologies because they are risk-averse and less flexible than their young counterparts. Therefore, this could be the reason why access to agricultural extension positively predicted whether a farmer belonged to this farm typology (Table 4.4). The higher the farmer had access to agricultural extension, the higher the likelihood of belonging to farm Type 1 and which would result in higher incomes (Bowe & Van der Horst, 2015). According to Mugi-Ngenga *et al*. (2016), older farmers have less access to new information and trust the traditional extension officers. Further, this could also be explained by the negative prediction of access to agricultural training on whether a farmer belonged to farm Type 1 (Table 4.4). It could be that the farmers in this farm typology either lacked access to formal training or were resistant to new knowledge and could be they believed they knew based on their many years of experience.

Access to agricultural training positively predicted whether farmers belonged to Type 2, which was food crop systems (Table 4.4). The results inferred that the higher the access to agricultural training a farmer had, the more chances of that farmer belonging to farm type 2. Farmers in this group were younger with short farming experience (Table 4.4) implying that they had high access to modern technologies, more willing to learn, innovative and are lower risk-averse with longer planning horizons (Mapiye *et al*., 2006; Murage *et al*., 2019). According to Macharia *et al*. (2014), training is an important component of instilling knowledge and skills and hence builds the capacity of the target group. However, farm type 2 farmers had less access to extension services as specified by the negative prediction on access to extension services towards whether farmer belonged to this farm type (Table 4.4). This implies that the farmers in this farm type had less contact with extension services a factor that could have highly contributed towards the low proportion of income from crops (Table 4.4). The low proportion of income from cropping can be ascribed to inadequate information as these farmers had limited access to extension services. Farmers who access extension services reduce externalities increase profit and improve production efficiency for all agricultural products (Bowe & van der Horst, 2015). The proportion of income from cropping activities negatively predicted whether a farmer belonged to Type 2 (Table 4.4). Farmers who recorded low crop income were more likely to belong to this farm type. The limited earning from cropping in this farm type could be attributed to the lower years of farming experience and age. According to Akinola & Adeyemo (2013), high experienced farmers are more likely to increase agricultural productivity.

Household head gender negatively predicted whether farmer belonged to farm Type 3 (Table 4.4). The results exposed that female-headed households were more likely to belong to this farm typology than households headed by their male counterparts. According to Mugwe *et al*. (2009), males are the make most of the farming decisions, including access to extension services. This might make them access more knowledge on agriculture management than their female counterparts (Nambiro *et al*., 2006).

Access to extension services positively predicted whether farmers belonged to this farm type. This implies that access to extension services had a high chance of predicting farmers belonging to this farm type. However, there were more females not having access to extension services than the males (Table 4.4) which could be attributed to cultural norms and traditions Habtemariam and Düvel (2004) or lack of appropriate time schedules for the extension for females (Al-Shadiadeh, 2007). According to Mudege *et al*. (2017), stereotyping women limits their access to the extension. Access to credit facilities negatively predicted belonging to this farm typology (Table 4.4). This implies that this farm type was composed of farmers with a low likelihood of accessing credit. With most of the land and property ownership belonging to males in the study area, including some of the properties belonging to female-headed households, the female-headed households with limited assets do not have access to credit as they may lack loan collateral. This lowers the agricultural production and profitability Awotide *et al*. (2015) partly by limiting access to agricultural inputs (Ekwere & Edem, 2014).

Household head education level negatively predicted farmers who belonged to farm Type 4 (Table 4.4). This implies that farmers who belonged to this farm type had low levels of education with the majority of the household heads having no formal education (Table 4.4). Low education depicted in this farm type can be attributed to either marginalisation or lack of parents' will power to supports their children's education (Mucee *et al*., 2014). Further, household size positively influenced farmers who belonged to this typology (Table 4.4). This implied that farmers with large household size were more likely to belong to Type 4. Additionally, hired labour was a negative predictor in explaining whether farmers who belonged to Type 4 (Table 4.4). This implied that farmers who had no hired labour were more likely to belong to farm Type 4 since these households had adequate labour based on the large household sizes (Table 4.4). According to Odendo *et al*. (2006), household sizes reflect the amount of labour available for agricultural activities. According to Bassey *et al*. (2014), large households prefer using borrowed labour which is cheaper rather to hired one.

The proportion of income from cropping activities negatively predicted farmer who belonged to Type 4 (Table 4.4). Farmers who had a low proportion of income from agricultural activities were more likely to belong to this farm typology. The Type 4 farms are predominantly in marginal areas with low agricultural potential where farmers grow drought-tolerant crops (e.g. Millet) Ngetich *et al*. (2014b) which have low economic value hence the low proportion of income from cropping activities. The proportion of income from livestock activities positively influenced farmers who belonged to this typology (Table 4.4). This farm type had the highest total TLU (Table 4.2), and this could be the reason why this farm proportion from livestock positively predicted whether farmer belonged to this farm category. This agrees with Mganga *et al*. (2015), who stated that farmers in arid and semi-arid areas mostly depend on livestock rearing for livelihood.

Household head education level positively predicted whether a farmer belonged to Type 5 (Table 4.4). This indicates that farmers belonging to this farm type had attained higher education. Secondly, the age of the household head positively predicted farmers who belonged to this typology (Table 4.4). This again implied that the older farmers were likely to belong to this farm type. Similarly, the farmers in this typology used hired labour, which positively predicted belonging to Type 5 (Table 4.4). This typology had the oldest farmers across the farm typologies (Table 4.3), and they used hired labour to manage their farms. Aged farmers are less energetic, and they need the support of hired labour to manage their farms. According to Bassey *et al*. (2014), aged farmers use hired labour to enhance farming activities, which require more energy that they might not have. According to Bathon & Maurice (2015), young farmers are more energetic and economically active; therefore, with adequate access to farm inputs, they can boost agricultural productivity. More so, the proportion of income from livestock activities negatively influenced farmers who belonged to farm this typology (Table 4.4). Farmers who had small herds of livestock could belong to farm Type 5 than any other. Farmers in this typology had moderate total TLU, which signifies the small number of livestock kept. This could explain why the proportion of income was negative predictors as low total TLU suggests they kept a small number of ruminants (Chilonda and Otte, 2006). Further, ruminants are essential in agricultural systems and the economy as they raise more profits (Lawal-Adebowale, 2012).

5.4 The DNDC Calibration and Validation

The DNDC model captured both timing and magnitude of the soil N_2O fluxes peaks across treatments except control. As noted in other DNDC simulating studies including Uzoma *et al*. (2015) and Giltrap *et al*. (2010) peak soil N_2O fluxes occurred following soil fertilisation which coincides with the timing of precipitation. The peaks under control treatment coincided with precipitation events which were in agreement with Abdalla *et al*. (2020) who reported peak N_2O fluxes under control treatment following rainfall events in Hebei, China. Additionally, the model did not capture the negative daily soil N_2O fluxes across soil fertility management technologies that could be ascribed to underestimation of soil moisture and N mineralisation. Though after calibration, the observed and simulated seasonal and annual soil N_2O fluxes were close, the model over and underestimated the emissions in some days (Figure 4.2). This can be ascribed to the high spatial and temporal distribution of extractable nitrogen (Rafique *et al*., 2011). The calibrated model captured the magnitude and time of the soil N_2O peaks events. This can be ascribed to lowering C:N ratio, however, lowering the C:N ratio can adjust the simulated soil N_2O closer to measured values (Rafique *et al*., 2011). The lowest simulated soil N_2O was 0 ug N ha^{-1} d^{-1}; thus, the DNDC model did not predict soil N_2O uptake. These results are dissimilar to Syp & Faber, (2017) and might have been as a result of an overestimation of N_2O fluxes.

The wet season had more soil N_2O peaks compared to the dry season, and this similar the findings of Deng *et al*. (2016) and Jiang *et al*. (2019). The differences in N_2O fluxes can be attributed to soil temperature, nitrogen, moisture, texture, pH and precipitation dynamics (Geng *et al*., 2017). The peak soil fluxes were high following fertiliser or manure application. These results are in line with other studies such as Uzoma *et al*. (2015) and Zhang *et al*. (2016). The high daily soil N_2O fluxes recorded during the wet season can be attributed to effective nitrogen uptake by maize plant that is influenced by soil water content. Further, soil moisture increases soluble solutes in the soil that act as substrates for microorganism responsible for N_2O fluxes through nitrification and denitrification process.

The model predicted mostly zero emissions during the dry seasons across the treatments which were inconsistent with field observations in the central highlands of Kenya that recorded small N_2O uptakes (Ortiz-Gonzalo *et al.*, 2018; Macharia *et al.*, 2020). The validated DNDC model performed well in simulating both cumulative seasonal and annual soil N_2O fluxes (Table 4.5). The model performance in this study was similar to that of Giltrap *et al*. (2010) and Abdalla *et al*. (2011) who reported that based on the observed performance evaluation matrices; the simulated and observed soil N_2O fluxes were acceptable. Modelling efficiency describes the performance of the model in predicting measured value, where positive value describes that the model is high explained by measured values while negative value ascribing that the simulated value represents the model (Smith *et al*., 1997). The ME_i results depicted that they performed well in describing N_2O fluxes. The cumulative annual findings on zero to intercept linear regression slope and R^2 were within the range of 1.09 and 0.78, respectively reported by (Cui *et al*. 2014).

5.5 The DNDC Model Simulation

Though the DNDC model performance in simulating daily soil N_2O fluxes was fair to poor, the overall simulated cumulative seasonal/ annual fluxes were good (Figure 4.2, Table 4.5). These results were in agreement with various studies that reported that the DNDC model had high discrepancies in simulating daily soil N_2O fluxes but accurately captured the magnitude of cumulative fluxes (e.g. Uzoma *et al*., 2015; He *et al*., 2020). The peak simulated and observed soil N_2O fluxes were recorded following fertiliser application or rainfall event. The first peak occurred immediately after soil fertilisation and rainfall event; this peak can be endorsed to both fertiliser application and rainfall event. Similar results were reported by Horak & Mukhina (2016) who reported peak N_2O fluxes following fertiliser application and rainfall event. The second and third peaks were noted during intense rainfall events hence ascribed to rainfall events. According to Uzoma *et al.* (2015), high N_2O fluxes were recorded following a rainfall event. The rainfall event increases soil moisture and that can trigger denitrification process as described by (Horak & Mukhina, 2016). There were more peaks for simulated compared to observed results, similar results were recorded by Rafique *et al.* (2011) this can be ascribed to the daily DNDC predication mode as opposed to specific dates of measurements on the observed. Despite the model accurately predicting seasonal and annual soil N_2O fluxes, there were discrepancies in recorded daily fluxes. These discrepancies can be ascribed to rainfall events that occur before actual fluxes measurement (Horak & Mukhina, 2016).

The simulated and observed soil N_2O fluxes were lower compared to similar studies with filed data recorded by (Ortiz-Gonzalo *et al*., 2018; Macharia *et al*., 2020) and simulation data (e.g. Rafique *et al*., 2011; Deng *et al*., 2016; Geng *et al*., 2017). The low predicted and observed soil N_2O fluxes documented in this study could be ascribed to differences in precipitation, soil type and other characteristics, environmental factors, soil temperature and soil C:N ratio (Pelster *et al.,* 2017). The DNDC model showed a good prediction of maize production (grain, stems, leaves and roots) similar to the findings of (Liu *et al*., 2018; Jiang *et al*., 2019). Generally, the model performed well in simulating maize (grain, roots, leaves and stems) production.

Fertiliser application had a significant influence on soil N_2O fluxes similar to the observations of Agovino *et al*. (2019), who reported that increased fertiliser application leads to increased yields and GHG emissions. The increased grain yield and soil N_2O emission can be attributed to readily available nitrogen to the soil from the fertiliser (Abdalla *et al*., 2020). Additionally, fertiliser application had the highest emission factors. Though manure application had a low emission factor and high yield scaled emission, maize grain productivity was low. Manure releases available nutrients slowly to the soil Kiboi *et al*. (2019), which could have caused the low maize productivity. Fertiliser and manure combination was effective in mitigating atmospheric GHG emissions while significantly increasing maize production. Generally, the observed and simulated emission factors were lower than the IPCC Tier 1 default EFs of 1%. The emissions were also lower compared to those recorded in East Africa (Ortiz-Gonzalo *et al*., 2018; Macharia *et al*., 2020). This depicted that using default Tier 1 EFs overestimate GHG emissions from the Central Highlands of Kenya smallholder farming systems.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Overview

This chapter presents the conclusions and recommendations drawn from the study. The chapter also highlights areas of further studies.

6.2 Conclusion

Smallholder farming systems can be essential entry points in greenhouse gas emissions mitigation and adaptation. However, smallholder farming systems are both socially and spatially heterogeneous, which can hinder GHG emissions quantification; reporting and mitigation as each farm demand a specific approach. Individual farm-based GHG emissions quantification and mitigations intervention are quite impractical at a national or regional level, thus the need for developing farm typologies that can address their heterogeneity and use biogeochemical models. This study demonstrated the use of farming systems typology in identifying GHG emissions hotspots, designing quantification experiments, assessing the adoption of mitigation measures, and proposing climate action policy. The study also evaluated the performance of the DNDC model in simulating soil N_2O fluxes, maize yields, yield scaled N_2O emissions and emissions factors in Tharaka-Nithi County.

Land size owned, total tropical livestock unit, nitrogen applied and land size under different cropping systems were important variables in typifying smallholder farming systems. Based on these variables, GHG quantification priorities can be set in the study area and similarly agro-ecological zones in Sub-Saharan Africa. Further, socio-economic variables household head education, hired labour, group membership, credit access and proportion of income from cropping activities played a significant role in defining farm belonging to a farm typology. Since it is not economically possible to quantify greenhouse gas at each farm for national GHG inventories, these typologies provide plausible entry points in GHG emissions quantification experiments.

Given that direct quantification of soil greenhouse gas emissions is expensive and impractical in accurately reporting soil GHG emissions, especially in developing countries including Kenya, the use of the DNDC model could be a plausible alternative. Though the DNDC model performed poorly in simulating daily soil N_2O fluxes, it accurately captured the cumulative seasonal/ annual fluxes. The observed emission factors we on the low end compared with IPCC Tier 1 default factor of 1%. Therefore, using the IPPC Tier 1 EFs overestimate soil GHG emissions in the Central Highlands of Kenya. Finally, the fertiliser and manure combination is capable of increasing agricultural production with minimal increase in agricultural GHG emissions significantly.

6.3 Recommendations

The following recommendations were drawn from the study:

1. Smallholder farming systems typologies should be used in GHG emissions hotspots identification, quantification, simulation, and mitigation.
2. Policies and intervention measures directed towards increasing agricultural productivity while reducing GHG emissions should consider not only soil fertility management and tropical livestock unit but also other socio-economic factors influencing farmers belonging to different farm typologies.
3. The DNDC model needs to be improved and developed to accurately predict daily emission and occasional uptakes in the central highlands of Kenya.
4. Use of fertiliser and manure combination should be promoted to farmers to enhance agricultural productivity while lowering agricultural tracer gas emissions.

6.4 Areas of Further Study

Further studies need to be conducted to simulate agricultural soil GHG emissions from various integrated soil fertility in varying agricultural ecological zones and water management technologies that are instrumental in crop performance. A meta-analysis on agricultural soil N_2O emission factors needs to be conducted to delineate specific emission factors to be used in different agro-ecological settings. Finally, there is a need to carry out scientific research to determine why the DNDC model did not capture negative N_2O fluxes. Studies should be implemented to investigate the implication split fertiliser application on soil N_2O fluxes in Kenya.

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APPENDIX

APPENDIX I: INTERVIEW SCHEDULE

Farming systems characterization and socio economic factors influencing diversity of farm typologies

Date of interview: ________________ Interviewed by: __________________

Start time:_______________________ End time:____________________________

Ward ______ Location:_______ Sub-location: _____________ Village:_________

GPS:Long:___________Lat: _______________Altitude (m) _______Way Point Number:_______

1.0 Household head identity

1.1 Name __________________________**1.2** Gender **(1=**male, **0=**female**)**____________________

1.3 Education level [*Refers to completed levels*] (1=Non formal education, 2= Primary, 3=Secondary, 4= Tertiary): ___________

1.4. Mobile Number__________________**1.5** Age _______________________

1.6. Do you keep farm records. 1=Yes, 0=No

2.0 Social networking

2.1: Are you a member of a farmers' group? (1=Yes, 0=No)

2.2: Name of farmer group____

2.3: Purpose of farmer group:____

2.4: Have you accessed credit for farming activity in the last 1 year? (1=Yes, 0=No);

2.5: Purpose of credit____

2.6: Have you ever attended training on agriculture enterprises? (1=Yes, 0=No)

2.7: Nature /purpose of training____

2.8: Have you been visited by the Extension service? (1=Yes, 0=No)

3.0 CROP FARMING

3.1: What is your main farming objective?_______________________________________

3.2: What is your total farm size area (acres) ______________________________________

3.3: What is your total cultivated farm size? (acres)____________________________

3.4: Major four crop enterprises____

3.5: For how long have you cultivated your farm since you started farming (**Years**)? ___________________________

3.6: Farm Density

Parcel ID	**Main Crop/ Animal/ tree enterprise**	**Size in Acres**	**Who is the main manager of the plot (See Codes)**	**Land tenure (See Codes)**	**Cropping system (See Codes)**
Plot1:					
Plot2:					
Plot3:					
Plot4:					
Plot5:					
Plot6:					

Cropping system: 1=Monoculture, 2=Rotation, 3=Intercropping, 4 = Mixed Cropping

3.7. Previous long rain cropping activities and harvest data

PlotNo	Crop /Name	Crop Code	**Area under this crop** in acres	**Propagation materials (Seed use)**				**Mineral Fertilizer Use**						**Organic Fertilizer Use**			Use hired labour (1=Yes, 0=No)	Harvest		Sales		Price (unit)	Market sold	Distance to market
				Seed type? **1=Local 2=Improved 3=Mixed**	Qty	Unit	Price per unit	1st PLANTING			2nd Top dressing													
								Type **Code below**	Qty	Unit	Type **Code below**	Qty	Unit	Type **Code below**	Qty	Unit		Qty	unit	Qty	Unit			
1																								
2																								
3																								
4																								

3.8. Previous short season cropping activities and harvest

PlotNo	Crop /Name	Crop Code	**Area under this crop** in acres	**Propagation materials**				**Mineral Fertilizer Use**						**Organic Fertilizer Use**			Use hired labour (1=Yes, 0= No)	Harvest		Sales		Price (unit)	Market sold	Distance to market
				Seed type **Local=1 Improved =2 Mixed=3**	Qty	Unit	Price per unit	1st PLANTING			2nd Top dressing													
								Type **Code below**	Qty	Unit	Type **Code below**	Qty	Unit	Type **Code below**	Qty	Unit		Qty	unit	Qty	Unit			
1																								
2																								
3																								
4																								

4.0 SOIL MANAGEMENT AND LAND CONVERSION

4.1 Soil Management in the last 12 months

Soil Fertility Management	Household implemented any of the practices for the **last 12 months? [1= Yes, 0= No]**	**Land area (acres) under practice**	**Crop Enterprise (s)**	**Plot Number (s)**
Planting of strip grass				
Bunding and tied ridging				
Contour ploughing				
Building Contour Barrier				
Mulching- Livestock feeds				
Building terraces				
Agroforestry trees				
Conservation Agriculture?				
Other (Specify)				

5.0 MANAGEMENT OF ORGANIC RESOURCES

5.1: Do you use organic manures (livestock or plant based) in cultivating crops? (1=Yes, 0=No)

5.2: Please indicate your organic resources management practices in the field. Please fill in the organic resources which you use?

Organic fertilizer	**Period of planting when farmer uses it (tick as applicable)***			**Amount applied**	**For how long have you used organic residues? (Years)**	**Sources of organic resources**	**Plots ID/ Crops**	**Area applied (Acres)**	**Constraints of organic manures**
	Before	**At**	**After**						
Animal manure									
Crop residues (Mulching and incoorporation into the soil)									
Green manure (specify)									
Compost									
Other (specify)									

Sources of organic resources: **1=Farm, 2=Neighbours, 3= Bought**

6.0 LIVESTOCK SYSTEM

Livestock Inventory

6.1. Does this Household keep Livestock? **[1=Yes, 2=No]** ________________If **Yes,** fill the table below. If completely **No** Livestock is kept, skip to **next section**

Type of Livestock		Owned in the last 12 months **1= Yes, 2= No]**	Sales in the last 12 months		Purchases in the last 12 months		No. Currently Owned	Average Value per Head **[if no sales or purchases] (KShs)**	Feeding regime **Code below**	Feed stock **(See code)**	Main livestock product **Code below**	**Quantity**
Livestock ID	Name		No. sold	Total amount received **(Kshs)**	No. Purchased	Total amount paid **(KShs)**						
1	Cow –female cattle											
2	Heifer –young female cattle >12 months											
3	Bull – mature male cattle											
4	Young Bull- young male cattle >12 months											
5	Calf- young male/female cattle < 12 months											
6	Ram – male sheep											
7	Ewe - female											

	sheep											
8	Lamb- young one of sheep											
9	Buck – male goat											
10	Doe – female goat											
11	Kid - young one of goat											
12	Poultry- chicken, goose,											
13	Pigs											
14	Other (specify)											

FEEDING REGIMES:1=Full-time Zero-grazing, 2=Partly Zero-grazing, 3= Grazing, 4=Tethering, 5=Other specify ________________

FEED STOCK: 1=Pasture, 2=Crop residues, 3=Livestock feeds, 4=Fodder crops, 5= Household wastes, 6= Others

PRODUCTS:1=Manure, 2=Milk,3=Eggs, 4=Hides/ Skin,5= Wool, 6=Meat,7=Other

7.0 HOUSEHOLD DEMOGRAPHIC AND WEALTH INFORMATION

7.1: Family Labour

Family Labor Use in the Last 12 months	**Males**			**Females**		
Household Members	Total No. in the household	No. available for full-time farming	No. available for part-time farming	Total No. in the household	No. available for full-time farming	No. available for part-time farming
No. of persons aged below 16 years						

No. of persons aged 16-65 years						
No. of persons aged above 65 years						

7.2 HOUSEHOLD SALE OF LABOR (IN THE LAST 12 MONTHS)

Exclude those aged below 15 years

Off-farm activity		**Number of household members involved**	**Months involved in the last 1 year**	**Total amount earned per month**
1	**Farm laborer**			
2	Casual wage earner			
3	Salary earner **(e.g., teacher, police man)**			
4	**Petty business/ Trading** (e.g. Butcher, Charcoal burning, Trading farm produce, kiosk)			
5	**Artisanal** (e.g. Bicycle repair/mechanics, Brick making, Carpentry, Construction, Tailor)			
6	**Other (specify)**			

***The average monthly earnings, excluding operational costs (fuel, goods, hiring labors, etc) and fixed costs or capital**

7.3 REMITTANCE

7.4: Did any of the members of the household receive any earnings in form of **Remittance** (Both in cash & in kind)**? [1=Yes, 2=No**] ___________________

If **Yes,** fill the table below. If no move to section 9.5

Remittance in Cash				Remittance in Kind			
Was the remittance in the last 12 months **constant**? **[1=Yes, 2=No**]	If **Yes**, indicate the average earnings per month **(KShs)**	If **NO**		Was the remittance in the last 12 months **constant**? **[1=Yes, 2=No**]	If **Yes**, what was the average value of the remittance per month **(KShs)**	If **NO**	
		on average, how many months in the last 12 months did you receive remittance in cash?	Average earnings per month **(KShs)**			on average, how many months in the last 12 months did you receive remittance in kind?	what was the average value of the remittance per month **(KShs)**

7.5: HOUSEHOLD WEALTH AND ASSETS

Asset		No. of items **currently** owned	No. of items **purchased** in the **last 12 months**	Total (current) value **(KSh) Owned+purchased**	Asset		No. of items **currently** owned	No. of items **purchased** in the **last 12 months**	Total (current) value **(KSh) Owned+purchased**
Farm Assets	**ID**				***Other assets***	**ID**			
Automobile (Tractors, Trailers, Vehicles, Motorcycle)	**1**				Grinders	**15**			
Carts	**2**				Bicycle	**16**			
Donkeys	**3**				Radio/ Tape-recorder	**17**			
Wheelbarrows	**4**				Car Batteries	**18**			
Ploughs	**5**				Television	**19**			
Borehole	**6**				Mobile Phones	**20**			
Well	**7**				Axe	**21**			
Sickle	**8**				Fork Jembe	**22**			
Hand hoe	**9**				Utensils	**23**			
Chaff cutter for fodder	**10**				Saw	**24**			
Spraypumps	**11**				Tool box	**26**			
Diesel pumps	**12**				Lanterns	**27**			
Water tanks	**13**				Generators	**28**			
Pangas	**14**				Others				

7.6: What is your occupation (formal) other than farming? ______________________________

7.7: Estimated monthly salary from occupation (Ksh) __________________________

7.8: What are the main farm products that you sell?

Product	**Estimated annual income (Kshs)**
1:	
2:	
3:	
4:	

End Thank you