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Subjective preferences for agricultural technology attributes and their influence on technical efficiency of smallholder maize farmers in Nakuru County, Kenya

By

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DECLARATION

I declare that the thesis, which I hereby submit for the degree of Master of Science in Agricultural Economics at the University of Pretoria, is my own work and has not been previously submitted by me either in whole or in part for degree purposes at any other university.

SIGNATURE______________________________________

DATE: August 2021

Name: Zachary Simba Mbaka

DEDICATION

I dedicate this to my parents, Shadrack Simba Miyogo and Martha Kwamboka Oindi and my wife Theresa Nyamoita Onyancha. Their love, patience, selfless support, and motivation, over time, have laid the foundation for the discipline and application necessary to complete this work.

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Finally, I give glory to the almighty God for allowing me good health and showering me with abundant blessings

Zachary Simba Mbaka
Pretoria South Africa
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ABSTRACT

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Degree: MSc. Agric (Agricultural Economics)

Department: Agricultural Economics, Extension and Rural Development

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The study investigates whether the subjective utility of goals driving farmers' technology choices influence technical efficiency, with objectives of improving allocation choices, and providing effective extension services. Main goals of smallholder maize farmers were identified using the best-worst scaling (BWS) approach and efficiency scores generated using stochastic frontier analysis (SFA). A comparison between farming goals and technical efficiency was established using principal component analysis (PCA), cluster analysis, and one-way ANOVA. The study used data collected from 187 randomly selected smallholder maize farmers from Nakuru County, in Kenya. The most crucial goals of farming technology were found to be increasing crop yields, decreasing production costs, and reducing pests and diseases. The least important goals of farming technology were, decreasing on-farm soil erosion, decreasing water requirement through the cropping cycle, and decreasing off-farm pollution. Mean efficiency score was 61% and not statistically significant across the cluster groups, implying that subjective preferences of farming technology do not influence technical efficiency among the group. All coefficients of farming goals were negative when regressed against SFA generated efficiency scores, inferring that current farming technologies lack important farming goals that drive them. The study concluded that subjective utilities of farming goals do not have a significant influence on technical efficiency, contrary to our expectation. we therefore recommend further research to be conducted, to test the robustness of the results and identify reasons for negative and significant relationship between off-farm environmental services and production efficiency. The study is the first one of its kind to relate subjective utility of goals driving farmers’ technology choices and technical efficiency, immensely contribution to the existing literature

Key words: Technical efficiency, Best-Worst scaling, Farming goals, Farming technology, Smallholder farmers, Principal component analysis, Cluster analysis, Cluster groups

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
BIBD	Balanced Incomplete Block Design
BWS	Best-Worst Scaling
CA	Conservation Agriculture
CAN	Calcium Ammonium Nitrate
CBA	Cost Benefit Analysis
CMAD	Corrected Mean Absolute Deviation
COLS	Corrected Ordinary Least Squares
CSA	Climate Smart Agriculture
DAP	Di-Ammonium Phosphate
DEA	Data Envelopment Analysis
ES	Environmental Services
FAO	Food and Agriculture Organization
FDH	Free Disposal Hull
FGDs	Focus Group Discussions
GoK	Government of Kenya
Ha	Hectares
HB	Hierarchical Bayesian
IID	Independently and Identically Distributed
ISFM	Integrated soil fertility management
KG	Kilograms
KNBS	Kenya National Bureau of Statistics
LCA	Latent Class Analysis
MAD	Mean Absolute Deviation
MEA	Millennium Ecosystem Assessment
MLND	Maize Lethal Necrosis Disease
MXL	Maximum Likelihood
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
SDGs	Sustainable Development Goals
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
TFA	Thick Frontier Approach
USD	US Dollars

CHAPTER ONE: INTRODUCTION

1.1 BACKGROUND INFORMATION

Maize is one of about 56 cultivated crops in Kenya, mainly grown by smallholder farmers in most parts of the country for both subsistence and commercial purposes. Majority of the Kenyan population, depend on its production for food security, income and as a means of livelihood (Goldman, 2013). This staple crop is important in meeting food needs and dietary preferences of many Kenyan communities (KNBS, 2017). However, its short supply leaves many households with limited dietary choices (Mama, 2003). According to Ouma and De Groote (2011), The average maize production in Kenya is about 1.6 tons/ha and has been constant in the last two decade. Hence, Kenya will have to rely more on improving yields to feed the growing population since available agricultural land is fixed. Smallholder farmers are therefore important players in that respect because they contribute about 70% of the total agricultural output from an average farming area of between 0.2 and 3 ha (Kamau et al., 2018).

Climate variability, soil fertility and production inefficiencies are some of the main challenges faced by smallholder maize farmers in Kenya. Climate variability interferes with water supplies, impacts ecosystems, affects prices of commodities and hampers timing of planting seasons (Council, 1999, Ochieng et al., 2016). A study that was recently conducted by the Kenyan government concluded that the impact of climate variability will cost Kenyan government between 1 to 3 billion USD annually by the year 2030 (GOK, 2010). Climate Smart Agricultural (CSA) practice is one of the ways of combating the effects of climate variability and change in Kenya and other sub-Saharan countries (Sakuyama et al., 2007). CSA promotes efficiency and sustainability in production thereby raising incomes through adapting and building resilience to climate change. One of the CSA practices is integrated soil fertility management (ISFM) which reduces loss of nutrients to the environment thereby improving production efficiency (Vanlauwe et al., 2010). Improvement in production efficiency can open up opportunities for farmers to scale up production while also diversifying farming through using inputs more efficiently and strengthening farmers' technical capabilities in order to reduce maize yield gaps (Ogundari, 2014).

Analysis of technical efficiency is thus paramount in increasing maize productivity because it can isolate the production risks in inputs which affect technical efficiency estimates (Oppong et al., 2016). Agricultural productivity, especially maize productivity can be enhanced through research and development of new and better technologies while sustaining the environment and the available resources (Bhasin, 2002). There has been an upsurge in research and policy debates centered on the need to be efficient in maize production. However, a production dilemma exist which is on one hand occasioned by cheaper imports from neighboring east African countries such as Uganda and on the other hand high import tariffs imposed by the Kenya government to encourage local production (Kirimi and Swinton, 2004).

According to Kibaara (2005), mechanization of farm operations play a very significant role in enhancing production efficiency. However, as farmers achieve efficiency gains, externalities in the environment are inevitable. The externalities associated with production processes can be positive or negative and increases as the economy grows and therefore the ability of the natural resource to assimilate them is an important natural resource (Ayres and Kneese, 1969).

There are limited studies that has identified and ranked main farming goals based on farmers' subjective utility but none has analyzed the influence of such goals on production efficiency. There have been suggestions that smallholder farmers have not made considerable gains in efficiency because of how they prioritize attributes of their farming technologies. Farmers' knowledge is dependent on their past experience and challenges they face. Therefore, they choose attributes of farming technology based on the subjective utility they attach to the attributes. Attributes with high utility value are prioritized first while those with least utility are prioritized last (Bekele, 2006). Its worthy noting that technology attributes are clear to farmers and their choice of a farming technology depends on utility attached to different farming attributes.

According to Koohafkan et al. (2012), the main attributes of farming technology include; use of improved seed varieties, reducing application of agrochemicals and other substances that harm the environment, reducing farmer dependency on external inputs, use of agro-ecological principals and processes, efficient use of capital, minimizing soil and water pollution , use of farming methods that encourage soil and water conservation, availability of clean water and most importantly encouraging use of practices that can balance between long term adaptability and short term efficiency.

Changes in food industry has led to disruptions in production technologies. Efficiency gains are slowing and most farmers are torn between efficiency and sustainability (Mutoko et al., 2014). To tackle food crisis in Kenya and the world at large, research needs to be carried out to understand important technology attributes based on farmers' production preferences. The impact of these attributes on efficiency is still not clear, forming the background of this research.

Maize is one of the primary staple foods in Kenya. It not only provides food for the masses but also defines the food security situation of the country. Both small and large-scale farmers grow it not only for subsistence but also for commercial purposes. Smallholder farmers contribute to about 70% of the overall production, while the rest is produced by large-scale commercial producers (KNBS, 2017). Maize in Kenya can thrive in any climatic condition and is the only crop that extensively grows in the country. However, the main growing areas include; Trans-Nzoia, Nakuru, Bungoma and Uasin-Gishu counties (KNBS, 2017).

The main challenge farmers face is production inefficiency (Kirimi and Swinton, 2004, Kibaara, 2005, Kibaara and Kavoi, 2012). Mwaniki et al. (2017), attributes the decline in maize grain yields to the loss of soil fertility which is more pronounced when there is heterogeneity of soils in a single farm and lack of soil related extension. The main factors causing an increase in soil degradation include inadequate resources, dependence on subsistence farming and the use of fewer inputs. Additionally, the ever-increasing population, coupled with the Kenyan culture where land is inherited, have led to large subdivisions of land. Besides, the continuous cropping without letting the area lie fallow has led to a decline in yields because of the loss of soil nutrients and environmental degradation. The result is low agricultural productivity and income among farmers, which also contribute to food insecurity both at the household and national level.

Post-harvest losses contribute to a considerable decline in the food reserves that are supposed to cushion the country against seasons of low harvests. According to Zorya et al. (2011), post-harvest losses in Africa contribute to between 20% and 40% of total crop losses. These losses occur mostly during storage, processing and others during other marketing activities Kenyan farmers store corn in sisal sacks, small bags containing cow dung ash, wood and wire cribs, metal bins, open-air or roofed granaries, and roofed iron drums with mud. Maize farmers and other maize handlers, particularly women, have little knowledge of correct harvesting and post-harvesting methods leading to substantial damage by insects and pests during storage and marketing (Muroyiwa et al., 2020).

Smallholder farmers' reliance on rain-fed agriculture has harmed maize production cycles, which has been exacerbated by climate change's effects. During the commencement of long rains, maize is grown in several parts of Kenya (March and April). However, throughout the last ten years, the rainfall pattern has been erratic, with rain arriving sooner than March or later than April. Insufficient precipitation at the tussling stage cause drying up and poor grain development. Because of its reliance on rain-fed agriculture, agriculture is the most vulnerable economic sector, owing to climate change. Climate variability, according to Ray et al. (2015a), accounts for roughly one-third of yield differences. Farmers' capacity to prepare for the farming seasons has been harmed by changes in rainfall patterns and severe droughts, reducing agricultural productivity (Osman-Elasha and Downing, 2007). Kenya has been hit by a number of extreme weather events, including droughts and floods. Droughts, in particular, are widespread in Kenya, where drought shocks follow one another (Oxfam, 2006).

Information asymmetry on pest and disease control makes pests and diseases to be significant constraints to effective production and utilization of cereal crops among smallholder farmers in Kenya (Deichmann et al., 2016, Mahuku et al., 2015). Stem borers are the most damaging maize pest in Kenya and Africa in general. In Eastern Africa, economic losses due to their effect range between 12% and 21% of the total production while in Kenya it is estimated at 11% in the highlands and 21% in the lowlands (De Groote, 2002). The pests destroy all parts of maize plant (leaves, stems, tassels, cobs and kernels). Other pests that invade maize include; aphids, corn earthworm, cutworms, fall armyworm, thrips among others.

Maize lethal necrosis disease (MLND) is one of the primary diseases experienced by smallholder maize farmers in Kenya, especially in the Rift valley region. Even though much research has been conducted to downsize its impact, it still remains a threat to the productivity of the smallholder maize farmers in Kenya. According to Renard and Storr (2014), a more significant percentage of maize varieties were susceptible to the disease in the 2012-13 cropping period. Some of the ways proposed to control MLND include; use of good farming practices, breeding MLND tolerant or resistant varieties, and institutions to monitor and curb the movement of commercial seeds thus reducing contamination (Marenya et al., 2018). Other diseases that affect maize include; grey leaf spot, common rust, charcoal rot, common smut, downy mildew, maize dwarf mosaic virus, among others. Therefore, to enhance food security and safety in developing countries, it is essential for smallholder farmers, especially maize farmers, to adopt simple and effective pest and disease management practices.

1.2 STATEMENT OF THE PROBLEM

In the last decade, Kenya's' population has been increasing, putting pressure on agriculture and natural resources. Therefore, the government has identified smallholders as essential players in breaching food security and dietary shortages of its population. Despite the government's extension campaigns and policies, yields of smallholders have continued to dwindle, leading to an increase in per-unit cost of inputs. The increase in costs can be attributed to the inability of these farmers to acquire modern farming technology, changing climatic conditions, poor resource allocation and ineffective extension services (Salami et al., 2010).

Many efficiency studies conducted are based on ex-post analysis of production inputs and output (Kirimi and Swinton, 2004, Kibaara, 2005, Ahmed et al., 2014). There are very few studies that have identified and ranked main farming goals based on farmers' subjective utility, therefore answering “why farmers engage in farming activities” (Koohafkan et al., 2012, Bekele, 2006). To the best of my knowledge, none has identified main attributes of farming technology and identified the influence of such attributes on production efficiency thus answering “how farmers achieve their goals”. A priori efficiency analysis, based on important farming goals, can spur the formulation of better agricultural policies targeting production efficiency and can lead to an increase in acceptability of most extension interventions.

This study investigated the relationship between technical efficiency of smallholder maize farmers and the main attributes of farming technology with a view of finding out if technology attributes influence efficiency. It identified technology attributes whose priority can enhance production efficiency leading to improved food security. It further pinpointed important environmental attributes, which are key pillars to achieving sustained production growth. The research contributes to sustainable development goals (SDG's) of ending hunger and poverty, improving nutrition and achieving food security as well as promoting sustainable agriculture (Griggs et al., 2013). The research involved an exploratory study among 187 smallholder maize farmers in Nakuru, Kenya.

1.3 OBJECTIVES OF THE STUDY

1.3.1 General objective

The overall objective of this study is to determine whether the subjective preferences for the different attributes characterizing agricultural technologies and practices influence the technical efficiency of small maize producers in Nakuru, Kenya.

1.3.2 Specific objectives

a) To examine smallholder maize farmers' preferences for different attributes characterizing agricultural technologies
b) To estimate the technical efficiency of the smallholder maize farmers
c) To establish the relationship between technical efficiency and smallholder's farming technology attributes

1.4 HYPOTHESES

a) Farmers attach equal importance to all the attributes characterizing agricultural technologies when making production choices

This hypothesis is informed by the fact that all farming goals are important in maize production and when farmers make production choices, they consider different technology attributes in the production process.

b) Smallholder maize farmers are technically efficient in maize production

This hypothesis is informed by the fact that farmers have experience in maize production and over the years they have come up with production technologies that produce maize at least cost. Their allocation of inputs is at the optimal and therefore they are producing maize efficiently.

c) Farmers consider attributes that increase yields and also conserve the environmental.

The choice of farming technology is based on farmer's subjective utility of farming technology goals. The farming goals are informed by challenges farmers face, past farming experience and climatic conditions. Farmers will thus choose a farming technology that can increase their yields and also conserve the environment.

1.5 SCOPE AND LIMITATIONS OF THE STUDY

The study was carried out in Nakuru County, Kenya. The sample comprised of smallholder maize farmers with at most 10 acres of land. Production data collected from farmers was restricted to 2017 cropping year and the best worst scaling experiment data was based on farmers' subjective utilities and past maize farming experience using the recall method. The study did not focus on allocative efficiency and therefore smallholder maize farmers in Nakuru, Kenya, were assumed to be allocatively efficient. The study was solely trying to find the relationship between efficiency scores and farmer preferences of attributes characterizing agricultural technology and not a measure of causality. The study was constrained by the use of recall method, which was a deterrent factor in the data collection process since most smallholder farmers do not keep records, however, exhaustive probing was employed.

CHAPTER TWO: LITERATURE REVIEW

2.1 INTRODUCTION

This chapter focuses on presenting theoretical and empirical literature on attributes of farming technology and efficiency analysis on maize production. It also summarizes literature on suggested methodologies for the study. The purpose of the chapter is to identify knowledge gaps and thus pinpoint contributions of the study.

The chapter is organized as follows; first it discusses the underlying farmers' production goals, attributes and preferences and then empirically summarizes main studies conducted on farmer's production goals, attributes and farmer preferences. Further, the chapter discusses production theory of the firm and main studies conducted on efficiency analysis especially on maize production in Kenya and East Africa in general. Finally, studies that have used Best-Worst scaling approach are summarized

2.2 FARMERS' PRODUCTION GOALS, ATTRIBUTES AND PREFERENCES

2.2.1 Underlying theory: Thurstone's law of comparative judgement and McFadden's random utility theory

The study derives the theoretical framework for best-worst scaling from two main theories: Thurstone's law of comparative judgment and McFadden's random utility theory (Thurstone, 1927, McFadden, 1981). Thurstone recommended a way of comparing two or more items according to the value attached to them, and the item whose value is higher is chosen (Read, 2004). McFadden completed Thurstone's law of comparative judgment for comparisons of more than three items (McFadden, 1976). We can, therefore, infer utilities that individuals make by observing how they make their best and worst choices. The item that is chosen as best will be deemed to have the highest utility, and that which is selected as worst will be assumed to have the least utility (Finn and Louviere, 1992).

Based on McFadden and Thurstone's work, we can draw two theoretical assumptions that can help in further understanding the best-worst scaling method, which are:

1. Individuals' subjective utilities are unobservable and exist on some scalar continuum
2. When individuals make choices, they do so according to this continuum which seeks to maximize the utility associated with the best choice and minimize the utility associated with the worst choice

When you choose the best and worst choices over a set of items, you can be able to rank the utility associated with those items from the lowest to the highest (Finn and Louviere, 1992). McFadden observed random utility to be composed of two items:

A systematic component that can be obtained from choices individuals make (V)

The random error which represents unobserved variability (ε)

Assuming an individual, I, has an observed utility from item j as represented in equation (1)

$$u_{ij} = v_{ij} + \varepsilon_{ij} \ldots\ldots\ldots\ldots \quad (1)$$

We first assume that the random error is independently and identically distributed following Gambell distribution (McFadden, 1973). McFadden multinomial logit model derives its assumption from IID assumption and relates utility and choice behaviour mathematically. As the utility of a particular item increases, the probability of choosing the item from a subset of items goes up leading to the following relationship

The likelihood of selecting item *i* as best from a set of *j* items is as shown in Equation (2) below

$$Pi = e^{u(i)} / \sum e^{u(ij)} \ldots\ldots\ldots\ldots \quad (2)$$

And the probability of choosing item *i'* as worst *(i ≠ i')* from a set of j items is equal to equation (3):

$$Pi' = e^{-u(i)} / \sum e^{-u(ij)} \ldots\ldots\ldots\ldots \quad (3)$$

From the two equations, we can say that when the share of the utility associated with a particular item is high, the probability of choosing the item as best is high and when the share of utility related to a particular item is less, there is a higher probability of selecting the item as worst.

Farmers face difficulties in assembling technologies with ideal farming goals because they face unique challenges each planting season. Such technologies will have to navigate the difficulty balance between goals with short-term efficiency attributes and long-term adaptability features. Most research conducted on farming goals have majored on yield and non-yield farming attributes and preferences.

2.2.2 Empirical literature on farmers' production goals, attributes and preferences

Bekele (2006) used a stated preference approach to understand the preferences of farmers on different attributes of development interventions. The development interventions involved input and output markets, soil and water erosion, development of irrigation, and resettlement in potential areas. The main attributes considered included; drought, erosion, shortage of farmlands, shortage of grazing lands, and attack by pests and diseases. Soil erosion and lack of enough agricultural land were the two main influential attributes that influenced choice of development interventions. The results further revealed that socio-economic and agricultural challenges were critical in influencing preferences in development interventions. These factors were therefore crucial in acceptability and success of development initiatives.

Another research conducted by Koohafkan et al. (2012) pinpointed goals that are ideal in driving communities towards achieving food security threshold while using environmental and agricultural services assembled locally. Some of the goals identified included; using improved crop varieties, reducing the use of agrochemicals, using resources efficiently, efficient use of human capital such as labour, minimizing greenhouse emissions, minimizing soil and water pollution and enhancing agricultural conservation practices. They concluded that the right mix of the goals could drive communities to produce enough food while maintaining the quality of environmental services.

Ortega et al. (2016) further examined farmers' preferences for intercropping soybean, pigeon peas and groundnuts with maize using a choice experiment. The results showed that maize yield has a positive influence on utility. Also, distance to markets and high labour requirements had a significant but negative influence on utility. Further results showed that farmers preferred intercropping maize as compared with sole maize cropping system. They observed that quantifying preference traits of smallholder farmers is a significant constraint that hinders adoption of new technologies

Ajambo et al. (2017) carried out research to evaluate and identify important non-yield attributes that influenced maize prices in western Uganda using a hedonic pricing model. Some of the attributes identified include early maturing, tolerant to pests, diseases and drought, grain size and grain colour. From the results, most farmers preferred medium and large grain size as they had a higher weight. White maize was preferred to others because its market demand was high. Farmers were, therefore, willing to pay more for grains that met their preferred attributes. However, attributes related to tolerance to pests and diseases and drought did not significantly influence the price farmers were willing to pay for maize grain.

2.3 MEASUREMENT OF PRODUCTION EFFICIENCY AMONG SMALLHOLDER FARMERS

2.3.1 Underlying theory: Production theory of the firm

A firm is a decision-making unit concerned with production. It transforms inputs to outputs by using technology. Its sole purpose is to maximize returns given a set of scarce resources. The theory of the firm uses production function to rationalize optimal agents. Therefore, the backbone of the theory of the firm is a production function. The function describes the nature and type of technology used and the way inputs are converted into outputs (Coelli, 1998). The production function of a maize producing farmer is expressed in equation (4) below;

$$Y = f(x) \qquad (4)$$

Where Y is the total maize output, and x is n x1 vector of variables signifying the factors of production that is land, labour, and capital.

Concavity, non-negativity, monotonicity, and weak essentiality are among the principles behind the maize production function. The premise of non-negativity ensures that the yields from maize production are either zero or positive. Monotonicity suggests that adding more units of input to the production process should result in higher maize yields, hence the extra units of input utilized to produce maize should be positive. Weak essentiality means that at least one positive input should be utilised in the production of maize. Because maize cannot be grown without any planting material, the weak essentiality assumption is valid.

The concavity assumption assures that the output acquired from a large number of inputs is greater than the output obtained from a single input. The producer's goal is to maximize profit by producing maize as efficiently as possible. The production function depicts the various output amounts that can be obtained by combining various inputs.

Farrell (1957) devised a simple depiction to assess productivity and efficiency, which is an outgrowth of Koopmans (1951) and Debreu (1951) as shown in Figure 1 below. They assumed that the only inputs required for production were land and labor. They also thought that when land and labor are used in production, the output level will be (Y). Loci SS' is an isoquant that represents a technology with a uniform output but distinct land and labor combinations. AA' is the highest yield a firm may achieve using various land and labor combinations. As a result, if a firm is located along AA', it is deemed to be technically efficient because it is producing along the efficiency line. DD' denotes an isocost line with several cost ratio combinations that result in the same total cost. The least-cost combination of two inputs is tangential to the isoquant at point Q' for a firm whose goal is to maximize output.

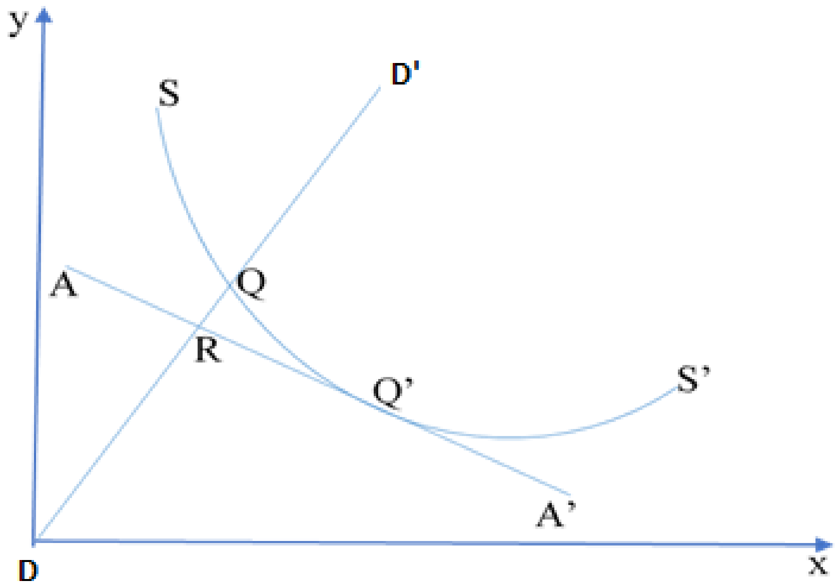

Figure 1: Measurement of production efficiency

Source: Farrell (1957)

2.3.2 Empirical literature on measurement of production efficiency among smallholder farmers

Measurement of production efficiency provides empirical evidence on how farms can be competitive and what potentials can be tapped to enhance productivity, given the available resources and technology use (Otieno et al., 2014). There is an increased demand for improving methodologies that measure production efficiency. Early methodologies never accounted for factors other than inefficiency that made farmers operate below the frontier. However, with recent advancements in efficiency analysis, it is now able to distinguish between those elements that are outside the farmers' control and those that are related to inefficiency. Attempts to evaluate productive efficiency have been made as the production frontier has progressed. In general, determining efficiency entails comparing actual performance to the optimal performance located in the frontier. Due to the fact that the true frontier is unknown, the frontier is an approximation. The frontier that has been approximated is referred to as the ‘Best practice' frontier. To get this best practice frontier, two methods have been applied in literature. Parametric and non-parametric approaches, both of which use constraints to optimize the behaviour of individuals.

Different strategies for triangulating the "best practice" frontier have been identified by Berger and Humphrey (1997). Data envelopment analysis (DEA), free disposal hull (FDH), stochastic frontier approach (SFA), and thick frontier approach are some of these methodologies (TFA). The methodologies serve as a foundation for calculating relative efficiency scores. Although neither method is deemed superior to the other, similarities can only be drawn based on the following assumptions:

i) Nature of the functional form (parametric or non-parametric);

ii) Presence of the random error

iii) The probability distribution of the efficiency scores if a random error is assumed

Several efficiency studies have utilized SFA to measure production efficiency. Use of SFA to estimate production efficiency of farms has broader acceptance in literature due to ease of estimation as well as consistency in theory (Olarinde et al., 2011). Since 2000, a number of efficiency studies have been conducted in Kenya and its neighboring countries.

One of the main efficiency studies conducted was by Kirimi and Swinton (2004). They Measured technical and allocative efficiency using stochastic cost frontier model as suggested by (Aigner *et al*., 1977). They allowed economies of scale to vary by assuming a flexible trans-log cost function. The analysis was done for 581 farmers drawn from both Uganda and Kenya. The results showed that input prices had a positive and significant influence on costs. The mean cost efficiency index was 1.95 and ranged between 1.12 and 6.71. Most households in Ugandan had a better cost efficiency score than the Kenyan households and large-scale producers were less efficient in production than the smallholder farmers. The main sources of inefficiency were late planting of maize and use of recycled maize seeds.

Later, Kibaara (2005) analyzed the level of technical efficiency in Kenyan maize production and identified the main socio-economic factors and management methods that influenced maize production technical efficiency. According to the findings, Kenya's maize production had a mean technical efficiency of 49%, (with variations from 8 percent to 98 percent). Technical efficiency differed between and within maize-growing regions, as well as between cropping methods. Mono-cropped fields, in particular, were found to have a better technical efficiency than intercropped fields.

Kibaara and Kavoi (2012) then applied the Battese and Coelli (1995) technical inefficiency effects model to estimate technical efficiency of Kenya's maize production. They assumed a translog production function because of its flexibility. They disaggregated households into low, medium and high potential maize zones. The results revealed the mean technical efficiency to be 49%. Labour had a positive and significant impact on maize yields. The inputs with high effect in determining inefficiency of maize were use of hybrid seeds, use of tractors in preparing land, access to credit and high potential zone.

Another study conducted by Ahmed et al. (2014) analyzed the technical efficiency of smallholder maize production in Central Rift valley of Ethiopia using the stochastic frontier approach. They defined technical efficiency as "the ability to produce the greatest amount of output possible from fixed inputs" and an efficient firm as "one that given a state of technical know-how, can produce a given quantity of goods by using the least quantity of inputs possible". Ahmed's model identified DAP fertilizer, area, labour, seed and oxen as being significant determinants in maize production. It further identified, family size, frequency of extension contacts, distance to market, access to credit and number of weeding as main factors determining the level of efficiency in maize production.

Using a stochastic frontier approach, Debebe et al. (2015) investigated the allocative, technical, and economic efficiency of smallholder maize producers in Ethiopia. The majority of farmers were found to be inefficient, according to the study's findings. The average efficiency of allocative, technical, and economic allocation was 57, 62, and 39 percent, respectively. Family size, education level of the household head, access to extension services, membership in a farmer's group, use of a mobile phone, and herd size were all important factors that influenced production efficiency.

Kiprop et al. (2015) conducted a study on smallholder farmers' technical efficiency in Kisii County, Kenya, and found that increased land fragmentation, the amount of fertilizer used on the farm, and the use of certified seeds influenced farmers' technical efficiency. More than half of the farmers' technical efficiency was less than 50%. Salau et al. (2012) looked at the levels of farm-specific technical efficiency of maize-based farming systems at various intensification degrees. For both low and high-intensity households, farm size and availability to credit were common variables. The high-intensity homes were 78 percent efficient, while the low-intensity households were only 30% efficient.

Mutoko et al. (2015) did research to estimate technical and allocative efficiency of maize farmers in North-west Kenya. They used self-dual stochastic functions to generate efficiency scores. The result show that on average, farmers were 64% technically efficient. The research identified inorganic fertilizers and maize seeds to be the main limiting inputs in maize production. Farmers who used ISFM practices achieved higher technical efficiency scores and lower allocative efficiency scores. Farming experience, agricultural extension, application of ISFM practices and off-farm income were main variables influencing technical and allocative efficiency of maize farmers.

Salat and Swallow (2018) conducted research in the Nyando region of Kenya to determine the influence of smart agriculture techniques on smallholder farmers' technical efficiency. The truncated normal technical efficiency model of Baatese and Coelli was employed in this investigation. They assumed a Cobb-Douglas production function as their starting point. All output elasticities were found to be positive with maize yield responding more to changes in carbon, maize seeds and labour. The mean technical efficiency was 45% and ranged between 3% and 87% with none being fully efficient. Intercropping, residue management, sub-plot distance and radio negatively influenced technical efficiency of farmers. They concluded that soil conservation practices have the ability to improve production efficiency of farmers. The study concluded that there was room for improving production efficiency using same inputs when employing climate-smart agricultural practices and using practices that increase carbon levels.

While the stochastic frontier approach is commonly utilized in the literature on efficiency, the Data Envelopment Analysis (DEA) approach has also been used in several studies, particularly where scale efficiency is being examined. One of the studies that used DEA to analyze economic efficiency in agricultural production on smallholder maize farmers in western Kenya is (Mulwa et al., 2009). The authors employed a two-step process, first using DEA to estimate farm efficiencies and then using a Tobit model to regress chosen farm and farmer variables against the predicted efficiencies. The findings suggested that maize production in Western Kenya was inefficient and could be more efficient. The quality of seed used and the size of the household were also found to have a substantial impact on overall efficiency. The authors observed a negative coefficient for household size, implying that efficiency levels decrease as homes grow larger.

Another study using DEA was by Ogada et al. (2014). This study investigated the correlation between technical efficiency of smallholder food crop farmers in Kenya and environmental factors. The study concluded that risks in production, environmental factors and individual farmer characteristics were main differences in farmers’ technical efficiencies.

2.4 BEST-WORST SCALING APPROACH

Best-worst scaling approach is a theoretical choice-based method that measures latent and subjective quantities whose properties are known. It provides not only information on most and less attractive choice options but also an individual's utility. It is a method of data collection and a theory of how humans rank the best and worst products based on the random utility framework proposed by Flynn and Marley (2014). Flynn (2010) argued that BWS can be a rating scale because of its known theoretical properties. He further observed that although the scores under BWS are bounded (based on the number of times chosen as either best or worst), it can replace the traditional logistic regression choice models. He concluded by saying that BWS can also be used to assess attribute impact and their respective importance using the weights attached.

BWS can also be used in profile-based designs and to analyze the scores and other statistics. The method is gaining popularity because of its exciting properties that have been found useful and is an extension to the discrete choice experiments (Flynn and Marley, 2014). Several studies have been done using BWS approach. However, there is hardly any study that has focused on farming technology attributes and to the best of our knowledge, none has been carried out in Kenya.

Very few studies have employed BWS in agricultural research in Kenya and the East African region. One of the studies is by Lagerkvist et al. (2012) who compared attribute importance using anchored scale BWS and relative BWS and also compared heterogeneity of attribute importance using Hierarchical Bayesian and latent class analysis (LCA) (Kang et al., 2009). They gathered information on 16 different food attributes of kales grown in Kenya's peri-urban locations from 449 customers. When compared to the relative BWS technique, the results suggest that anchoring improved decision predictions. Moreover, HB fitted data better than LC when identifying heterogeneity of attribute importance. They concluded that anchoring gave relatively less heterogeneity results while improving prediction of the results. They also noted that HB predicted results better and therefore a better tool in analyzing BWS data

Mtimet et al. (2014) used BWS to assess sheep traders' preferences in Kenya using data collected from 108 traders across 3 different sheep markets; Kiserian, Bissili and Mile 46. The study's aim was to identify sheep attributes that traders preferred and which producers had management control over. The attributes were put into cards each containing 4 attributes. Farmers were allowed to first select the most important sheep attribute and then from the remaining attributes the least important sheep attribute. They were later required to select if they could buy a sheep with the combination of attributes presented in the card. The results show that livestock trading is the main income generating activity of the respondents. Attribute of breed and price were identified as the main important attribute across the markets while age and sex were identified as the least attribute choices. Pure black Persian was the most preferred sheep breed.

Mtimet et al. (2015) used BWS to investigate the impact of quality attributes on small ruminants in Somaliland, using data from 200 families across two Agro-Ecological Zones. The best and least important features determining the price of small ruminants was chosen by respondents. Best worst scores were generated and cluster analysis used in grouping the farmers thus providing insight into the composition of the groupings. Health status of the small ruminants was ranked as the most important attribute with relative importance of 100%. Other important attributes included demand season and body conformation. The least important attributes included Knowledge of the trader, goat color and breed. The differences among groups were witnessed on orientation of the groups and gender

There are more studies outside East Africa that have used BWS in eliciting attribute preferences in agricultural sector. One such study is by Hansson and Lagerkvist (2016) who empirically evaluated use and non-use values motivating Swedish dairy farmers in their production work with a view of finding out how they prioritized between use and non-use values. The attributes they used as values included; maximum production, maximum productivity, continuity of business, having time for other activities, own work environment, and complying with government welfare legislation. In total, 27 attributes were considered. They used anchored best worst scaling to come up with sets of 5 attributes each. Anchoring allowed for absolute ranking of attributes along a scale. From the results, it was revealed that dairy farming is influenced by use and non-use values. The most important attribute was “to feel happy knowing that my dairy cows are well kept”, showing that dairy farmers consider attributes other than profitability and yields.

Dumbrell et al. (2016) Also used BWS to identify carbon-sequencing practices preferred by Australian farmers and the factors that influenced farmers’ decisions. They used data collected from 43 individuals managing farm businesses. The results show that the most important benefit of carbon sequestering is improving soil quality. Mixed crop livestock farmers were likely to retaining stubble and rotational cropping practices. However, the cropping only farmers were willing to adopt retaining stubble, no-till cropping and mulching

Some scholars have hypothesized that combining BWS with other choice experiment methodologies leads to a better model. One such study was conducted by Balbontin et al. (2015) who carried out research on residential location to analyze if combining best-worst data and stated choice data could improve the model.

They used a mixed logit model in estimating the parameters for the best worst and binary stated choice responses. The general understanding is that the utility levels associated with the best worst scaling are different from those associated with the stated choice experiments. The study concluded that combining the best worst responses with the stated choice responses improves the model. However, the worst answers behaved differently from the best and stated choice responses, therefore, not possible to be pooled together.

BWS has been widely applied in health economics. One such application is by Mori and Tsuge (2016) who used a web-based best-worst scaling approach to elicit the publics' perception of various adverse consequences of using tobacco. Inhalation of chemicals and disturbance of non-smokers were ranked top while high expenditure and weight loss after cessation were ranked low.

Kiritchenko and Mohammad (2017) on the other hand used annotation technique of best-worst scaling to get real-valued sentimental scores for words and phrases in three different domains; general English, English twitter, and Arabic twitter. The annotators were given four different items and asked to choose the items they felt were best, and those that they felt were worst. They then used the association scores generated to compute a rank of the items as per their association with the property of interest. The results showed that when the procedure was repeated, it produced a consistent ranking of items.

Bridges et al. (2018) sought to quantify the treatment goals of people recently diagnosed with schizophrenia to understand their impact on a treatment plan. The treatment goals were assessed using a validated best-worst scaling instrument using thirteen possible treatment goals evaluated using a balanced incomplete block design (BIBD). The participants then selected the most important and the least essential goals from each task. The research showed that recently diagnosed patients, recognize the importance of the disease symptoms and their impacts on everyday activities.

Another study was done to pilot test best-worst scaling instruments designed to assess trade-offs among caregiver-defined, meaningful health outcomes. Different stakeholders were involved in designing the BWS experiment to elicit caregiver-defined outcomes in different domains. It used a balanced incomplete block design (BIBD) to develop a BWS instrument. Conditional logit was used to estimate the utility scores for each attribute. From the study, it was concluded that best-worst scaling could be an essential tool when identifying preferences for healthcare outcomes (Castillo et al., 2018).

2.5 SUMMARY OF THE LITERATURE REVIEWED

The literature reviewed centered mainly on production goals, attributes and preferences, summarized different measures of production efficiency among smallholder farmers and used BWS approach in eliciting subjective preferences of attributes characterizing farming technologies. From the literature, the most common goals noted that can drive farmers to improve production efficiency while sustaining the environment include; using improved varieties, reducing use of agrochemicals and fertilizer, using resources and human capital efficiently, minimizing greenhouse gas emissions, containing soil and water pollution and enhancing agricultural conservation practices (Koohafkan et al., 2012).

The literature also reviewed both parametric and non-parametric measures in measuring production efficiency. Some of these measures include; data envelopment analysis (DEA), free disposal hull (FDH), Stochastic frontier analysis (SFA) and thick frontier analysis (TFA). The literature pinpointed that none of the summarized methods is superior than the other. However, most studies have utilized SFA to measure production efficiency because of ease of estimation, broader acceptance and consistency in theory. Further, the factors that contributed to inefficiency include: intercropping, residue management, farming experience, agricultural extension, use of ISFM practices and off-farm income among others.

The literature also made note that very few studies have employed the BWS methodology in eliciting farmer’s attribute preferences and none has elicited farmer’s preference of attributes characterizing farming technology and linked the attribute preferences with efficiency to determine if the subjective preferences influence efficiency. This study thus made an important contribution in breaching that knowledge gap

CHAPTER THREE: RESEARCH METHODS AND PROCEDURES

3.0 INTRODUCTION

The chapter presents the research design, data collection, data analysis procedures and analytical framework where different methods used in analysis are discussed.

3.1 STUDY AREA

The research was conducted out in one of the counties in Kenya found in the Great Rift Valley, Nakuru County, Kenya. The County covers an area of 7,495.1 Km2 of which 5,039.40 Km2 is agricultural land. The County borders eight other Counties namely; Nyandarua to the east, Kericho and Bomet to the west, Baringo and Laikipia to the north, Narok to the south-west, and Kajiado and Kiambu to the south. It has eleven sub-counties including Njoro and Molo. In total, Nakuru has 55 wards spread all over the sub-counties. The altitude and physical features strongly influence the climate of Nakuru County. A bimodal rainfall pattern with a high of 1800mm and a low of 500mm allows the County to enjoy two seasons every year. The short rains occur from October to December, whereas the long rains occur from March to May. Temperatures range from 210 to 350 degrees Celsius.

Agriculture is the main economic activity in Nakuru county with largescale crop farming, horticulture and dairy farming being the main agricultural activities. The main food crops grown in the county include maize, beans, carrots, cabbages, peas, tomatoes, irish potatoes, peas, kales, pyrethrum and wheat. The produce is marketed locally, others sold in the neighboring counties and other major cities. Maize is the main food stable in Nakuru county, grown in the entire county under rain-fed systems. Production is mainly small scale mostly done by female headed households. Maize value addition in the county is through threshing, sorting and transporting to the markets. The main challenges faced in maize value chain include; attack by pests and diseases, low farm gate prices, high input prices, poor road network and varying onset and offset seasons. Tourism is another main economic activity in Nakuru county with several notable attraction sites like Menengai crater, Lake Nakuru national park, Hell's gate national park, Lake Naivasha among others. The county is also a major manufacturing hub with major industries and car assemblies located in its industrial area. Figure 2 below shows a map of the study area.

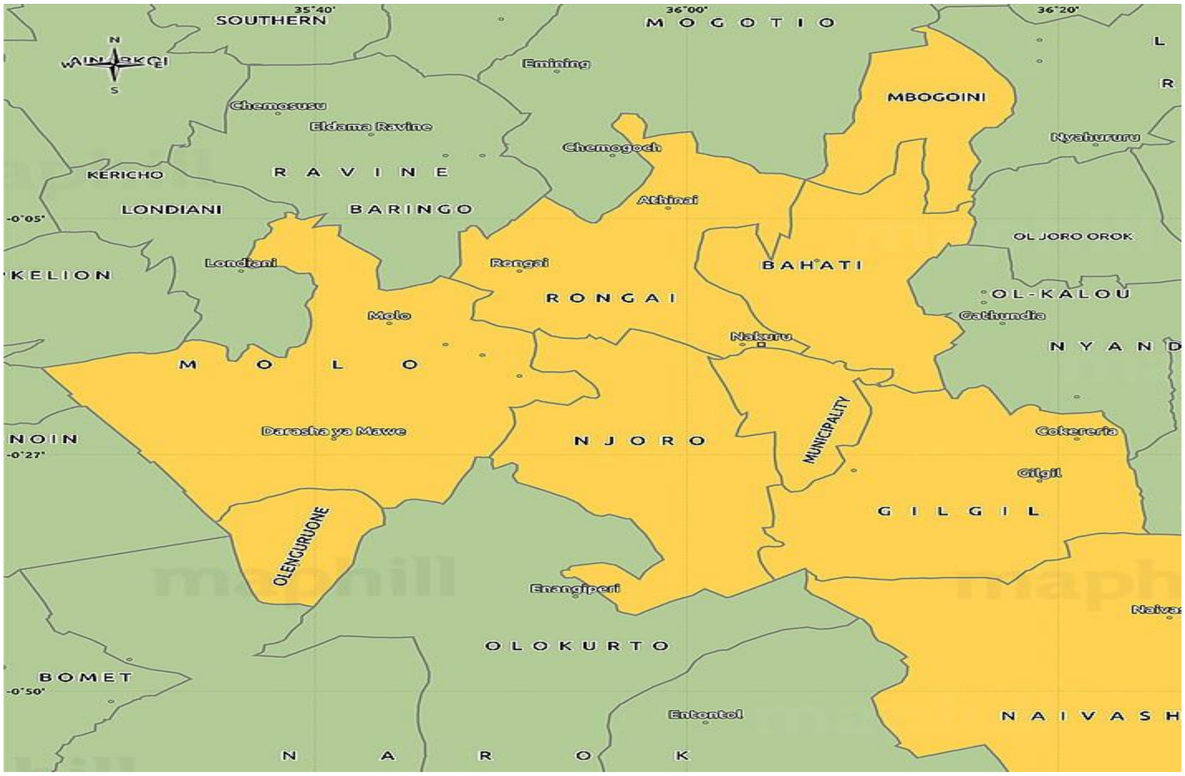

Figure 2: Map of Nakuru County

Source: World Resource Centre (2016)

3.2 SAMPLE SIZE DETERMINATION

To determine the sample size, the study used a proportionate to size sampling methodology as proposed by Kothari (2004) using the following formulae:

$$n = \frac{Z^2 pq}{e^2} \quad \text{.........} \quad (5)$$

Where; n= required sample size

Z= Confidence level at 95% (standard value of 1.96)

p= Estimate of smallholder maize farmers which was estimate at 85% in our study area (0.75) (Salami et al., 2010)

q= This is the weighting variable given by 1- P

e2= Margin of error at 5% (standard value of 0.05)

Therefore;

$$n = \frac{1.96^2 * 0.75 * (1 - 0.75)}{0.05^2} \quad \text{.........} \quad (6)$$

=288 households

This resulted to a sample population of 288 households.

3.3 SAMPLING PROCEDURE

The population comprised of smallholder maize farmers in Nakuru, Kenya and the sampling unit constituted of farming households. A multistage sampling technique was employed to arrive at the sample. First, Nakuru County was purposively sampled because it is one of the counties with high maize production, mostly produced by smallholder farmers (Salami et al., 2010). Njoro sub- county was also purposively selected because of its accessibility and topographical uniformity. Purposeful sampling was used because when measuring the efficiency of farmers, farm, and household characteristics should be similar for it to be possible to compare the respective individual scores.

Although purposeful sampling method does not account for proportionality and is prone to researcher bias, it is useful since it does not require many resources to implement and is vital in studying similarities or differences of subjects (Palinkas et al., 2015). The County has a very high potential in maize production although farmers have not been able to increase their yields significantly. Secondly, Njoro sub-county was purposively selected because it has a higher concentration of smallholder maize farmers who are homogeneous in terms of maize production. Random sampling was then used to select four villages (Kamungei, Kiptenden, Njoro, and Wendani). Finally, random sampling was used to select households in all four selected villages.

Availability of funds constrained the number of households interviewed. The number of households varied depending on the number of smallholder maize farmers in the village, as shown in Table 3. 1 below. The sampling of the villages and households were done with the help of the local administration (chiefs and village elders) and the ministry of agriculture officials in the county government of Nakuru.

Table 3. 1: Number of sampled households in each village

	Number of interviewed farmers	
Village	n	%
Kamungei	78	41.7
Kiptenden	39	20.9
Njoro	35	18.7
Wendani	35	18.7
Total	**187**	**100**

3.4 DATA COLLECTION PROCEDURE AND DATA SOURCES

Primary and secondary data were used in the research. Cross-sectional data on maize production inputs and outputs, farmer characteristics, and a Best-Worst scaling experiment was used to collect primary data for preferences for attributes of farming technology. A semi-structured questionnaire was used to collect data from respondents in the sampled houses, which was presented by trained enumerators. Before the actual data collection, the questionnaires were pretested to confirm their validity.

The primary data included information on the costs of all inputs and outputs used in maize production (land, labor, fertilizers, insecticides, and herbicides). Farmers' age, gender, occupation of the household head, level of education of the household head, household size, access to agricultural extension services, and use of chemical fertilizer on maize production were all collected as farmer characteristics. The information was gathered for the 2017 agricultural season. Secondary data was gathered from a variety of sources, including government publications, journals, published theses, and research organizations.

3.5 ANALYTICAL FRAMEWORK

Objective one: *a) To examine smallholder maize farmers' preferences for the different attributes characterizing agricultural technologies*

3.5.1 The BWS approach

Farmers were required to choose the best and worst farming goals from a list of technology sets. The list of the farming goals was populated using two focus group discussions conducted in the study area. Each group discussion was comprised of 10 smallholder maize farmers from the study area (5 males and 5 females). The selection ensured equal representation of male, female, and youths in the discussions.

The main question discussed in the FGD's was*; "I have a technology that is good for you, but before I give it to you, I need you to tell me the characteristics of the technology that will make you adopt it (what features do you consider when choosing a technology?) "*. Farmers gave different responses whose unedited responses are presented in Table 3. 2 below.

Table 3. 2: Unedited FGD responses

FGD1		**FGD2**
1	High in production (if seed)	High yielding
2	Sustainable; ability to continue being in use for a long time after initial introduction	Drought resistant; requiring less water and ability to retain moisture for a long period.
3	Easily Available	Cheap; affordable
4	Affordable	Disease/pest resistant
5	Have beneficial nutritive value, if seed	Adoptable to bad weather
6	Early Maturing if seed	Marketable
7	Drought resistant	Easy to store
8	Adoptable to the changing climatic conditions such as rain during harvest time.	Have good storage qualities
9	Pest resistant	Not requiring too much pesticides
10	Environmentally friendly e.g. being less prone to soil erosion or less exhaustive on soils	If irrigation, should have a sustainable source of water, e.g. harvesting of run-off water instead of drawing from a river
11	Ability to be used as a by-product (many uses)	If irrigation, should not cause conflict among users of the water resource.
12	Need less water	Technology should be able to conserve the environment, e.g. offering less soil erosion
13	Easy to apply	Should be less labour demanding.
14	Offering less pollution, if irrigation	Should be appropriate for the locality
15		Requiring less pesticides during storage

16	Requiring fewer pesticides during different stages of production and storage.	Fit for human consumption without harmful side-effects (carcinogenic).

The responses from the FGDs were compiled to form 11 different farming technology attributes as presented in Table 3. 3 below.

Table 3. 3: Different attributes of farming technology

List of technology attributes			
1	Decrease pests and diseases	**7**	Decrease on-farm soil erosion
2	Reduce extension requirement throughout the cropping cycle	**8**	Decrease external input used
3	Decrease labor use	**9**	Decrease off-farm pollution
4	Increase on-farm soil fertility	**10**	Increase resistance to drought
5	Increase crop yield	**11**	Decrease cost of production.
6	Decrease water requirement		

3.5.2 Designing the BWS experiment

We set up a BWS experiment with different combinations of technology attributes. The combinations/sets were uniquely put together using a Balanced Incomplete Block Design (BIBD). BIBD is an experimental design that produces fixed set sizes and ensures equal occurrence and co-occurrence of objects across all the comparison sets. BIBD improves the design of the experiment since it ensures that each scenario contains an equal number of attributes, and the attributes appear the same number of times across the sets. The attributes of farming technology were then put together into 11 different sets, each consisting of 5 attributes. Each attribute appeared only five times in all the 11 sets. Table 3. 4 below is an example of the sets that were designed using BIBD.

Table 3. 4: A Technology set with 5 different goals designed using a BIBD

Most Important	**Effects of the cropping system**	**Least Important**
	Decrease pests and diseases	
	Reduce extension requirement	
X	Decrease labour use	
	Increase on-farm soil fertility	
	Increase crop yield	X

For each technology set, farmers were first required to select the most important attribute (Best) of the technology and then from the remaining four, to select the least essential attribute (Worst).

3.5.3 Calculating Average Preference ranking

An average ranking was then evaluated where responses from all farmers interviewed were pooled to form one set, and the following indices computed for each farming attribute:

1. B=The number of times the goal was selected as the most important,
2. W=The number of times the goal was selected as the least important
3. (B-W) = A count of the number of times a farming goal was chosen as worst subtracted from the number of times the same goal was selected as best. A positive B-W score means that the goal was selected as best more frequently than it was selected as worst and vice versa.
4. The standard score $SS = (B - W)/(N * K)$ ………………………………………... (7)
   where N is the number of surveys, and K is the number of times each goal was presented to each farmer,
5. The analytical best worst: $ABW = Log(1 + SS)/Log(1 - SS)$………………………. (8)
6. The ratio scores: $BS = \sqrt{B/W}$…………………………………………………………. (9)

Ratio score transformed the square root of best minus worst scores into a ratio ranging between 0 to 100. This enabled farming goals to be compared using their relative ratios by comparing them to highest ranked goal.

3.5.4 Heterogeneity in the preferences for technology attributes

As a second step, we analysed the heterogeneity of the preferences using variance, standard deviation and coefficient of variation (SD/Mean) based on the individual BWS scores.

3.5.5 Farming technologies

Principal component analysis (PCA) was used to determine related drivers of attribute importance. PCA is frequently used for data reduction and exploratory analysis (Vidal et al., 2016). To capture significant variations, the approach allows for fewer principal components than the variables employed (Alani, 2014). The first principal component is the vector with the greatest variation. The second principal component is an orthogonal vector that captures the second biggest variation, and so on. PCA focuses on variance since it uses a covariance matrix of a set of variables (Scharadin, 2012). The principal components are usually ordered from one with the largest variance all the way to the one with the lowest variance. The total number of principal components will equal the number of variables.

Objective two: *To measure the technical efficiency of smallholder maize farmers in Nakuru, Kenya*

3.5.6 Agricultural production function and Technical Efficiency

Maize production requires the transformation of inputs (seeds, fertilizer, labour, capital) into output. A production function is a mathematical formulation for transforming inputs into outputs. It can also be referred to as a frontier of feasible production set (Ray et al., 2015b). As earlier said, the production function must satisfy all the assumptions of the production technology. Technically inefficient production technology is where a higher output is feasible for the same inputs (Output oriented measure). It can also refer to a technology where the same output can be achieved using fewer inputs (Input oriented measure). This study, therefore, follows the output-oriented technical measure.

The origin of efficiency measures can be traced back to the work of (Farrell, 1957). He pointed out that a firm's efficiency is divided into two categories: technical efficiency and allocative efficiency. Allocative efficiency refers to a firm's ability to make the best use of a given set of inputs, whereas technical efficiency refers to the ability to get the most out of a given set of inputs. Recent developments have let to new efficiency categorization. These categorizations can broadly be referred to as parametric (SFA) as developed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) and non-parametric (DEA) approaches as developed by Charnes et al. (1978). Both approaches have strengths and shortcomings. However, SFA's ability to separate the inefficiency component from stochastic noise makes it more practical. This study therefore uses SFA by assuming a cobb-douglas production function

Coelli et al. (1998) observed that SFA has more application in agriculture, especially in developing countries than DEA. He noted that the developing countries face challenges that only SFA can accommodate in its use. The problems he identified included; measurement errors, erratic rainfall patterns, and ever-changing climatic conditions, among others. The stochastic frontier production with two error components can be described in the following way, according to Aigner et al. (1977) and Meeusen and Van den Broeck (1977);

$Yi = f(Xi; \beta) + \varepsilon_i \; i = 1,2, \dots . n$………………………………………………….. (10)

Where *Yi* is the output, *f (Xi; β)* denotes the suitable function such as the trans-log or the Cobb-Douglas production functions for vector, Xi, of inputs for the i-th farm, where vector β, is the production function's vector. Ɛ is an error term that is made up of two components, namely:

$$\varepsilon = V_i + U_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (11)$$

From equation 8, the two-sided error term is Vi, while the one-sided error term is Uj. Different assumptions regarding the distribution of the two error terms determine the components of the two error terms. Vi is assumed to be identically and independently distributed (IID) as N $(0,\sigma_v^2)$ and is unaffected by Uj. Weather, machine breakdown, fluctuating input quality, measurement errors, and omitted variables from the functional form are all examples of random fluctuations in the economic environment that the production units face (Aigner *et al*., 1977). U_i represents non-negative truncated half-normal random variable associated with technical production inefficiencies and is independently and normally distributed as N $(0,\sigma_u^2)$. The non-negativity property of U_i term ($U_i \geq 0$), allows all observations to fall on or below the frontier. The distribution assumptions are vital to the estimation of the frontier. Following Battese and Coelli (1995), the technical inefficiency effects, U_i can be expressed as:

$$Ui = Zi\delta + Wi \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ...\ldots\ldots\ldots (12)$$

W stands for random variables, which are described by a normal distribution with a mean of zero and a variance of σ2 u. Zi is a vector of farm-specific factors linked to technical inefficiency, and δ is a vector of unknown parameters that must be approximated. The i-th sample farm's technical efficiency, represented as TE, is calculated as follows:

$$TEi = \exp(-Ui) = \frac{Yi}{f(Xi\beta)\exp(Vi)} = \frac{Yi}{Yi^*} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where $Yi^* = f(Xi\beta)\exp(Vi)$ is the stochastic frontier unique to the farm. When Yi equals Yi*, TEi =1 denotes 100 percent efficiency. Ui contains the distinction between Yi and Yi*. The farm achieves its maximum possible output given its level of input if Ui=0, meaning that production is on the stochastic frontier. If Ui <1, production is below the frontier, indicating inefficiency. Assuming a half-normal distribution, we estimate the frontier using maximum likelihood method whose formulae is;

$$Li = -\ln\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\ln(\sigma_v^2 + \sigma_u^2) + \ln\emptyset\left(\frac{ei}{\sqrt{\sigma_v^2+\sigma_u^2}}\right) + \ln\emptyset\left(\frac{\mu_{*i}}{\sigma_*}\right) \ldots\ldots\ldots\ldots\ldots (14)$$

Where $\mu_{*i} = -\frac{\sigma_u^2 \varepsilon i}{\sigma_v^2+\sigma_u^2}$ and $\sigma_*^2 = \frac{\sigma_v^2\sigma_u^2}{(\sigma_v^2+\sigma_u^2)}$.. (15)

3.5.7 Model specification

a) Choice of variables

Maize output, just like any other agricultural technology is produced by inputs. The stochastic frontier production function variables and hypothesized relationships are shown in Table 3. 5 below.

Table 3. 5: Variables used in estimating production function

Variable	Description	Hypothesized sign
Output (Y)	Quantity of maize output produced in 2017/18 cropping season (Kg)	+
Seed	Quantity of maize seed used measured in Kilogrammes (Kg)	+/-
Area	Size of land planted with maize in hectares (Ha) during 2017/2018 cropping season	+
Harvesting Labour	The amount of hired and family labour used by the farmer during harvesting maize, measured in man-days	+/-
Fertilizer	Kilograms of chemical fertilizer used (Kgs)	+/-
Weeding labour	The amount of hired and family labour used by the farmer during weeding, measured in man-days	+/-

Notes*: A positive sign (+) indicates that an increase in the variable increases technical efficiency, whereas a negative sign (-) indicates that an increase in the variable decreases technical efficiency.*

The model will use a linearized Cobb-Douglas functional form that can be written as:

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 \ln X_{4i} + \beta_5 \ln X_{5i} + V_i + U_i \ldots\ldots\ldots\ldots\ldots (16)$$

Where,

Y=Maize output produced (Kg) $\mathbf{X_1}$=Seed (Kg) $\mathbf{X_2}$=Land (Ha)

$\mathbf{X_3}$=Harvesting Labour (Man days) $\mathbf{X_4}$=Fertilizer (Kg)

$\mathbf{X_5}$=Weeding labour (man days)

β =Vector of unknown parameters to be estimated

V=Statistical disturbance term

U= Farm specific character related to efficiency

b) Expected determinants of inefficiency

Literature suggests several factors to influence inefficiency as shown in Table 3. 6 below

Table 3. 6: Determinants of inefficiency

Variable	Description	Hypothesized sign	References supporting priori expectation
Post-primary education	Acquired post-primary education= 1, Yes	+/-	(Alene and Hassan, 2003, Debebe et al., 2015)
Gender	Household head's gender (=1, Male)	-	(Marinda et al., 2006, Koirala et al., 2015)
Decision making	Who makes decisions on the farm? = 1, Head	-	(Kibaara and Kavoi, 2012)
Total asset value	Total asset value of selected agricultural assets (Kenya shillings)	+	(Mango et al., 2015)
Challenges in soil management	If farmers incurred any challenges in soil management = 1, Yes	-	(Mutoko et al., 2015)
Intercropping	If the practiced intercropping in their maize farms = 1, Yes	+	(Salat and Swallow, 2018)
Total land size	Total land owned by the household (Acres)	+	(Alene and Hassan, 2003, Kiprop et al., 2015)

The inefficiency effect will contain the social economic factors that provide explanations for differences in the farmers' technical efficiency levels and are expressed as;

$$U_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + \delta_6 Z_{6i} + \delta_7 Z_{7i} \ldots\ldots\ldots\ldots\ldots\ldots \text{(17)}$$

The equation shows the inefficiency model, where;

δ= Unknown parameter vector to be evaluated

Z_1= Acquired post-primary education= 1, Yes

Z_2= Household head's gender (=1 if male)

Z_3= Who makes decisions on the farm? = 2, Spouse

Z_4= Total asset value of selected agricultural assets

Z_5= If farmers incurred any challenges in soil management = 1, Yes

Z_6= If the practiced intercropping in their maize farms = 1, Yes

Z_7= Households' total land ownership (acres)

Objective three: *To establish the relationship between technical efficiency and smallholder's farming* goals

3.5.8 Relation between farmers' technology preferences and efficiency scores

Farmers' technology goals are expected to have an influence on production efficiency. This is because farmers' cognitive utility is influenced by challenges farmers are facing in their production. It is not clear on the nature of influence of these farming technology goals on efficiency. We thus hypothesize that they will have a positive or negative influence.

a) Farmer groups

Cluster analysis was used to create groups of farmers with similar attribute choices for farming technology (Hand et al., 2001). Cluster analysis partitions observations in a data set in such a way that observations with similar characteristics or attributes form a group. The uniqueness of the observations is measured by the distances of the vectors representing the observations, therefore placing objects with less vector distance together. The main clustering methods used include; Partitioning methods, hierarchical method and model-based method (Hand et al., 2001). In this research, we employ a k-means hierarchical clustering methodology to group farmers with similar farming technology attributes. Hierarchical clustering generates a systematic matrix consisting of pairwise distances between the observations. It follows the following steps

i) Observations are assigned unique clusters thereby obtaining n clusters

ii) Closest clusters are combined to form one cluster

iii) Distances of the new cluster formed in (ii) above are computed for all the other clusters

iv) An iteration of steps (ii) and (iii) above is done so as to merge all the households into a single cluster

The hierarchical clustering puts together observations used in clustering into sub-trees and finally into one tree and the clusters formed can be represented graphically using a dendrograms.

b) Differences in efficiency scores across cluster groups

Differences of efficiency scores across cluster groups were computed using Analysis of Variance (ANOVA). Clustering is done based on the retained principal components. ANOVA is a statistical technique that tests for differences in means of different populations. In our study, it was used to test the differences in mean efficiency scores across different cluster groups. One-way ANOVA was ideal since there were more than two homogeneous cluster groups. The null hypothesis states that the mean of the independent variable does not differ significantly between groups. A p-value of less than 0.01 indicates that the null hypothesis is rejected, indicating that there is a significant difference in the mean of the independent variables across groups. Posthoc test using Tukey's method was then applied to justify the ANOVA results and to identify the cluster groups whose means were significantly different from other means. This was achieved through comparing all possible pairs of means.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 INTRODUCTION

The chapter discusses results of the study. Both T-test and chi-square tests are computed and presented as descriptive statistics in the analysis. The best-worst scaling approach is employed in studying important attributes of farming technology. Efficiency scores are computed and compared under different parametric methods. Finally, the relationship between efficiency and environmental services is identified.

4.2 DEMOGRAPHIC AND SOCIO-ECONOMIC CHARACTERISTICS

Table 4.1below summarizes selected household demographic and socio-economic characteristics disaggregated by villages. The inferential statistics on the right-hand side column tests whether the differences across the sampled villages are statistically significant.

Table 4. 1: Household Demographics and socio-economic characteristics

Variables	Kamungei	Kiptenden	Njoro	Wendani	Mean	t-test
Household size (number)	5.6	7.1	5.2	4.6	5.7	6.735***
Age	49.6	48.3	46.2	51.2	49.0	0.986
Total land size (Ha)	0.97	0.97	0.86	0.53	0.87	0.9591**
						***Chi^2* value**
(%) of Male household head	66.67	66.67	77.14	65.71	68.45	1.518
Education level of the household head (%)						***Chi^2* value**
Primary	42.31	58.97	31.43	48.57	44.92	6.0921
Secondary	26.92	17.95	40.00	40.00	29.95	6.3884*
College/University	20.51	7.69	22.86	11.43	16.58	4.7688
None	10.26	15.38	5.71	0.00	8.56	6.2486
Household decision-making (%)						***Chi^2* value**
Head of household	92.3	92.3	80.0	80.0	87.7	6.1505

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

The average household size across the four villages was six persons, which is smidgeon over the national average of 4.4 (ArcGIS, Dec. 2016.). The average household size was significantly different across villages (t=6.735, p=0.0002), with Kiptenden having the highest and Wendani the lowest. Mean age of farmers was

49 years and was not statistically different across the villages (t=0.9862, p=0.4664), signifying a relatively young farming population. The average farm size was 0.87 hectares and was statistically different across all sampled villages (t=3.27, p=0.0224), with Wendani having farmers with smallest farm sizes which on average was 0.533 hectares. The farm size is, however, lower than the national average of 1.54 hectares for smallholder households in Kenya (Kamau et al., 2017).

About 68% of households were male-headed, consistent with KNBS (2012), which reports that on average, 68% of Kenyan households are male-headed. Over 90% of household heads had attained either primary, secondary or tertiary levels of education, suggesting that the sample had a basic literacy level to understand the objectives of the study. The household head's secondary level of education was statistically different across villages ($\chi 2=6.3884$ p=0.050). Besides, 88% of household decision-makers were household-heads.

4.3 MAIZE PRODUCTION

4.3.1 Production Systems Employed

Table 4. 2 below presents land size, land tenure systems (defined as either titled or other) and main production systems practiced on maize fields by smallholder maize farmers disaggregated by villages. The statistics in the column at the far right of the table is used to test significant differences across the villages.

Table 4. 2: Production system employed by farmers

Variables	**Kamungei**	**Kiptenden**	**Njoro**	**Wendani**	**Mean**	**t-test**
Land under maize (acres)	0.54	0.57	0.51	0.49	0.53	0.44
Tenure status (%)						***Chi*^{2} value**
Titled	88.0	80.9	91.7	67.5	83.01	10.32**
Cropping system practiced (%)						***Chi*^{2} value**
Mixed intercropping	60.2	80.9	63.9	35.0	60.7	19.23***
Mono-cropping	30.12	17.0	19.4	10.0	21.4	7.47*
Row intercropping	8.43	2.1	16.7	50.0	16.5	43.54***
Strip cropping	1.20	0.0	0.0	5.0	1.5	4.76
Tillage method practiced (%)						***Chi*^{2} value**
Conventional tillage	100.0	100.0	88.9	100.0	98.1	19.26***
Zero tillage	0.0	0.0	5.6	0.0	1.0	9.54**
Minimum tillage	0.0	0.0	5.6	0.0	1.0	9.54**

Practiced crop rotation (%)	59.0	68.1	72.2	62.5	64.1	2.33

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

The average size of land under maize was 0.53 hectares, 83% of which was titled, signifying land security because of well-defined property rights. Tenure status was however significantly different across villages ($\chi2$=10.32, p=0.016), which can be attributed to the fact that some villages like Wendani and Kiptenden were close to shopping centers and therefore, farmers rented-in most of their farming land. Over 75% of the farmers intercropped maize with other crops. However, mixed intercropping was the most preferred cropping system and was statistically significant across sampled villages ($\chi2$=19.23, p=0.000). Table 4.2 further shows that conventional tillage (as contrasted from zero tillage), was practiced by almost all farmers in the sample and about 64% of maize farmers practiced crop rotation.

4.3.2 Inputs in maize production

Table 4. 3 below summarizes main inputs used in maize production with inferences column testing for variations across the sampled villages.

Table 4. 3: Inputs used in maize production

Variable	Kamungei	Kiptenden	Njoro	Wendani	Mean	Statistic
Total quantity of seed (KGS)	14.4	16.7	12.3	12.3	13.9	1.3
Chemical fertilizers						
% of farmers using	100.0	97.4	82.9	100.0	96.3	21.99***
Quantity applied (KGS)	66.5	68.5	73.9	75.4	69.8	0.33
Dose rate (KGS/acre)	129.7	131.0	134.9	136.5	132.1	5.97***
Manure						
% of farmers using	2.6	0.0	14.3	11.4	5.9	10.40***
Quantity applied (KGS)	265.0	0.0	1140.0	1887.5	1252.7	1.51
Dose rate (KGS/acre)	1696.7	0.0	1428.2	3613.8	2271.8	2.86
Pesticides (herbicides, fungicides, insecticides)						
% of farmers using	9.0	23.1	45.7	34.3	24.6	17.41***
Quantity applied (KGS)	1.2	1.7	2.2	1.6	1.8	0.67
Labour applied to activity (man-hours)						
Land preparation	71.0	95.3	33.1	99.9	64.4	3.44**
Planting	60.1	73.2	66.7	56.4	63.3	0.95
Basal fertilizer application	18.9	29.3	17.8	20.3	20.2	2.81**
First weeding	122.1	118.7	114.9	126.3	121.2	0.12
Top dressing	22.3	42.0	20.7	21.2	22.3	0.76
Second weeding	106.1	108.6	111.7	95.5	105.4	0.39
Spraying	12.2	22.2	9.1	14.9	13.3	1.93
Harvesting	99.0	95.3	103.0	75.0	94.5	1.37

Note: **, ***=significant at 5% and 1% level, respectively

The overall mean quantity of maize seed planted was 13.9 Kgs. Over 96% of all maize farmers applied fertilizers. However, the application rates were lower than the recommended rate of between 150-200kgs/ha for DAP and 250kgs/ha for CAN (Oseko and Dienya, 2015). The application rates also differed significantly across the villages (t=5.97, p=0.0007). Only 6% of the farmers applied manure and were statistically different across villages ($\chi2$=10.40, p= 0.015), which is an indication of low organic fertilizer use. Moreover, less than 25% of farmers applied pesticides and the proportion was statistically different across the villages ($\chi2$=17.41, p= 0.001), with Njoro having the largest proportion (46%). The quantities of pesticides used were deficient, as shown in Table 4.3 above.

Farmers used a lot of labour hours in their farms with the most labour-intensive activities being first weeding, second weeding and harvesting. Labour hours for land preparation (t=3.44, p=0.0205) and basal fertilizer application (t=2.81, p=0.0433) were however significantly different across villages. Majority of the labour was provided by family as shown in Appendix 1. **1** thus emphasizing the role of family labour in social capital. Overall, farmers used labour-intensive technology and thus substituted resources meant to acquire inputs for labour. Respondents were asked to select some of the productive asets they owned and to value the assets in their current condition. Table 4. 4 below shows the number and value of selected household assets important in maize production.

Table 4. 4: Number and value of selected productive assets

Assets	Variable	Kamungei	Kiptenden	Njoro	Wendani	Mean	t-test
Hand hoe	Number owned	3.51	3.21	3.31	3.47	3.4	0.23
	Value (USD)	*(1.33)*	*(1.61)*	*(2.02)*	*(1.19)*	*(1.49)*	*5.16***
Machete	Number owned	1.67	1.74	1.91	1.74	1.74	0.37
	Value (USD)	*(1.35)*	*(1.56)*	*(1.88)*	*(1.08)*	*(1.44)*	*3.02***
Knapsack sprayer	Number owned	1.03	1.26	1.5	1	1.15	3.16**
	Value (USD)	*(10.74)*	*(12.49)*	*(20.92)*	*(10.59)*	*(12.62)*	*2.76***
Animal traction Plough	Number owned	1.35	1	0	0	1.2	2.56**
	Value (USD)	*(45.17)*	*(35.27)*			*(41.28)*	*0.83*
Stores	Number owned	1.11	1.18	1.25	1	1.13	0.99
	Value (USD)	*(141.66)*	*(124.93)*	*(90.70)*	*(74.55)*	*(120.27)*	*2.63**
Borehole	Number owned	1	0	1	1.25	1.15	0.27
	Value (USD)	*(198.04)*		*(19.00)*	*(131.06)*	*(143.05)*	*0.86*
Wheelbarrow	Number owned	1.06	1.16	1.38	1	1.14	1.8
	Value (Ksh)	*(13.22)*	*(10.76)*	*(7.51)*	*(9.74)*	*(10.44)*	*0.99*
Total Assets	**Value (Ksh)**	***(109.47)***	***(91.10)***	***(56.23)***	***(65.91)***	***(87.52)***	***2.38****

Note: No. owned stands for number owned. *, **, ***: significant at 10%, 5% and 1% level respectively

To elicit the value or close approximation of the true value of the main farm implements owned, farmers were asked, " if you were to purchase an asset whose condition is similar to the one you own at the moment, how much will you be willing to pay for it?". From the data, the main farm implements farmers used were hand hoes, machetes, animal traction ploughs and wheelbarrows, depicting a low and primitive farming technology. Mean number of these assets was less than two and was statistically significant across villages for knapsack sprayer (t=3.16, p=0.0302) and animal traction plough (t=2.74, p=0.0212). The total average asset value of the selected assets in all villages was USD 87.52, showing that the farmers were relatively poor with low asset value. Values of hand hoe (t=5.16, p=0.0019), Knapsack sprayer (t=2.76, p=0.0487) and stores (t=2.63, p=0.0547) were statistically different across villages, probably due to asset depreciation and poor maintenance.

4.4 EXTENSION INFORMATION

Information on agricultural extension is presented in Table 4. 5 below. Agricultural extension refers to dissemination of agricultural information and research to farmers.

Table 4. 5: Extension information

Variable	Kamungei	Kiptenden	Njoro	Wendani	Total	Test
% Receiving extension advice	11.5	5.1	22.9	5.7	**11.2**	7.279*
Number of visits	1.7	1.5	3.0	5.0	**2.5**	5.09**
% Who did not pay for advice	100.0	100.0	100.0	100.0	**100.0**	
% Satisfied with extension source	100.0	100.0	100.0	100.0	**100.0**	

Note: *, **: significant at 10% and % level respectively

Results record low uptake of extension services with only 11% receiving it. The proportion of farmers receiving extension services was statistically significant across villages ($\chi 2$=7.279, p=0.064). Njoro, (22.9%), had the highest percentage of farmers receiving extension advice on maize farming followed by Kamungei (11.5%). Njoro and Wendani were the villages with the highest number of visits (3.3 and 5) respectively. Extension advice received was free because government agents mainly offered it and the farmers who received it were satisfied with its quality.

4.5 CHALLENGES IN MAIZE PRODUCTION

Challenges farmers were facing are presented in Appendix 1. 2. The results show that attack by pests and diseases, especially fall armyworms, drought, and low maize yields were the main challenges faced by farmers in general production. Further, high input prices, late delivery of subsidized fertilizers and poor-quality seeds were the main challenges in acquiring inputs. Challenges in soil management included; soil erosion, declining soil fertility and inadequate training, especially on better soil management practices. Finally, Poor maize prices and exploitation by intermediaries were the main challenges in maize marketing.

4.6 FARMERS PREFERENCE FOR ATTRIBUTES OF AGRICULTURAL TECHNOLOGIES

The attribute preferences are analyzed in different ways. First, attribute importance is analyzed using aggregate level indicators while heterogeneity of attribute importance is analyzed using Variance, standard deviation and coefficient of variation.

4.6.1 Average preferences

B-W method was used to analyse importance of farmers' technology attributes as first used by (Finn and Louviere, 1992), as presented in Table 4. 6 below.

Table 4. 6: Importance of farming goals on aggregated level

Goals	Best	Worst	B-W	SS	ABW	RS	RS(Index)
Increase crop yield	594	12	582	0.62	-0.5	7.04	100
Decrease cost of production	301	41	260	0.28	-0.75	2.71	38.51
Decrease pests and diseases	236	71	165	0.18	-0.84	1.82	25.91
Increase on-farm soil fertility	194	119	75	0.08	-0.92	1.28	18.15
Decrease external input used	158	101	57	0.06	-0.94	1.25	17.78
Increase resistance to drought	233	156	77	0.08	-0.92	1.22	17.37
Decrease labour use	151	162	-11	-0.01	-1.01	0.97	13.72
Decrease on-farm soil erosion	60	319	-259	-0.28	-1.33	0.43	6.16
Decrease water requirement	53	337	-284	-0.3	-1.36	0.4	5.64
Decrease off-farm pollution	46	355	-309	-0.33	-1.41	0.36	5.12
Reduce extension requirement	31	384	-353	-0.38	-1.48	0.28	4.04

From the results, increasing crop yields was selected as the most important farming technology attribute, showing that increasing yields is the most important attribute to almost all the farmers. The high importance of increasing crop yields can be attributed to farmers' low production efficiency (61%) which has significantly affected maize yields. Ahmed et al. (2014) noted that improvements in production efficiency can increase yields through exploiting the sources of inefficiency while maintaining the same technology and inputs.

The second most important farming goal was decreasing the cost of production. Maize production is input-intensive, and it's cost of production is very high. Therefore, farmers attach high utility to reducing the cost of production in order to increase net farm income. A study by Nyoro et al. (2004) singled out cost of production as the single most important production attribute that defines farmers competitiveness, defines food security situation and determines the value of farmers' net farm income. They argued that the cost of production of farmers greatly varies depending on region, farming knowledge, farmers management practices and weather. Therefore, a technology that reduces cost of production will improve efficiency of smallholder farmers and make their produce more competitive.

Decreasing pests and diseases was also an important technology attribute for smallholder maize farmers. By reducing pests and diseases, smallholders not only scale down the cost of inputs but also reduce pollution to the environment by applying less quantities of chemicals such as pesticides, insecticides and herbicides. Oerke (2006) estimated losses of maize yield due to pests and diseases in most parts of Africa to be equal to about one thirds of attainable production and argued that these losses are higher than combined losses due to other causes. However, our data shows only a small proportion of interviewed farmers used pesticides in the reference period. Therefore, we assume that pests and diseases have been a challenge for smallholder farmers in the study area in the past cropping seasons.

Improved soil fertility was another important farming goal identified by most smallholder farmers. Fertile soils are associated with high crop yields and thus farmers attach high importance to it. A study conducted both in Ghana and Kenya to ascertain the impact of integrated soil fertility management practices (ISFM) on maize yields observed that use of ISFM practices increases maize output and reduces encroachment into forests thus conserving the environment (Adolwa et al., 2019).

Decreasing external input used such as chemical fertilizers and diesel was another important farming attribute selected by most smallholder maize farmers. However, it was not as important as compared to other farming attributes, which can be attributed to the observed less use of external inputs by farmers as evidenced by the results on inputs use. This result agrees with findings of De Jager et al. (2001) who argued that external inputs are constrained by low economic returns from agriculture, and to cope with the low returns, farmers are forced to use low-external-input-agriculture (LEIA) thereby managing agricultural resources and conserving the environment.

The next important farming attribute is increasing resistance to drought. Its importance to farmers was lower probably because of the impacts of climate change. Climate change can have both positive and negative impact on maize production (Kabubo-Mariara and Karanja, 2007, Ochieng et al., 2016). A study that was conducted by Ochieng et al. (2016) on the impact of climate variability and change over time on maize yields in Kenya concluded that changes in temperature and precipitation caused by climate change can have either positive or negative impact on maize yields. They observed temperature to have a positive effect on maize yields. They attributed the nature of the impact on regional variations on climatic and economic conditions. Further, the study area receives steady rainfall for most months of the year, only onset and offset of rainfall have been farmers' challenge. The unreliability of the rainfall during planting and harvesting periods has made farmers not to plan their planting seasons adequately.

Decreasing labor use was another less important attribute for farming technology. Labour in an important factor of production. however, for smallholders, it is mostly provided by family and thus not a major challenge. This result agree with the findings of Jayne et al. (2010) who argued that although labour was a challenge in sub-Saharan Africa in 1980’s and 1990’s, recent increases in land subdivisions and increase in population has resulted in a decrease in the land-to-labor ratio, thus reducing challenges related to inadequate labor supply.

On-farm soil erosion was a less important farming goal to smallholder farmers. This is the result of the fact that the land where farmers planted maize was flat and not susceptible to soil erosion. Further, farmers intercropped maize, which not only improved soil structure but also provided cover for soil erosion. This is supported by a research carried out by Sharma et al. (2017) on the effect of intercropping on soil erosion. They concluded that intercropping maize with leguminous crops reduced soil runoff by 26% and top soil loss by 43%.

Similarly, decreasing water requirement was identified as another less important farming attribute. One important factor that might be influencing farmers to attach low utility to the goal of decreasing water requirement is the proximity of the study area to the Mau Forest, which is the most crucial water catchment area in the region. These farmers, therefore, experience steady rainfall pattern throughout the year hence making water requirement not to be an essential attribute to most of them. This is supported by Cairns et al. (2013) who predicted climate changes for Kenya and other sub-Saharan countries over the next 50 years. They projected Kenya’s rainfall to generally increase in the next 50 years with high potential maize zones being the main areas affected with the increase. They also predicted variations in onset and offset of rainfall during the planting seasons in the same periods.

Farmers attached less utility to decreasing off-farm pollution as a farming technology attribute. This is surprising since pollution is a significant challenge in most rural societies in Kenya. However, it's reduced importance to farmers can be linked to the fact that individual farmers bear the cost of pollution reduction while society as a whole reaps the benefits. Therefore, most farmers are not willing to include it as a major technology attribute since the benefits accruing from their efforts is spread to all.

Another least important goal was reducing extension requirement throughout the cropping cycle. Government extension in Kenya is demand driven and not common to smallholder farmers who can get advice from their peers. Private extension services are mainly offered at a cost and thus making them suitable for largescale farmers and farmers with multiple sources of income. Actually, despite government extension services being free, only about 6% of all the farmers sourced it from government agents in the whole sample. Most of the extension services being provided by the government has not been successful in improving efficiency of the farmers.

4.6.2 Heterogeneity in the preferences for technology attributes

The variance, standard deviation and coefficient of variation (SD/Mean) of farming goals are presented in Table 4. 7 below.

Table 4. 7: Variance and standard deviation of important farming technology goals

Technology goals	Mean	Variance	Std. Deviation	Ratio of SD/Mean
Increase crop yield	3.11	2.79	1.67	0.54
Decrease cost of production	1.39	1.79	1.34	0.96
Decrease pests and diseases	0.88	2.50	1.58	1.80
Increase resistance to drought	0.41	3.71	1.93	4.71
Increase on-farm soil fertility	0.40	2.30	1.52	3.80
Decrease external input used	0.30	1.75	1.32	4.40
Decrease labour use	-0.06	2.70	1.64	-27.33
Decrease on-farm soil erosion	-1.39	2.63	1.62	-1.17
Decrease water requirement	-1.52	2.71	1.65	-1.09
Decrease off-farm pollution	-1.65	2.96	1.72	-1.04
Reduce extension requirement	-1.89	2.11	1.45	-0.77

The results show that increase crop yields, decrease cost of production and decrease pests and diseases are technology attributes selected as most important by most smallholder maize farmers. The preferences had low standard deviation to mean ratios (CV) showing that most farmers were in agreement that these technology attributes were important in maize farming. Similarly, reduced extension requirements, decrease off-farm pollution and decrease water requirement are the technology attributes considered as least important. These attributes had a low coefficient of variation (CV) showing a relatively high agreement of their importance to farmers in making production decisions. Smallholder farmers are technically inefficient in maize production therefore will benefit from farming technology that can increase their yields using same level of inputs or decrease farm inputs while maintaining same level of output. In this regard, increasing yields, reducing cost of production and decreasing pests and diseases are the main technology attributes that can improve efficiency levels of these farmers.

Technology attributes with high SD to mean ratio (CV) were; decrease labour use, decrease external input use, increase resistant to drought and increase on-farm soil erosion. The high CV signifies high variability of importance of technology attributes to farmers when making their production decisions. These groupings can be identified using principal component analysis and cluster analysis. Importance of decreasing labour use to farmers varies because the quality of family labour which is mostly available for some smallholder households is low since it is provided by children and in some cases elderly members of the family.

The importance of decreasing external inputs as an important technology attribute is highly variable because of differences in on-farm soil fertility, which is also dependent on farming practices. If farmers use practices that reduce the fertility of the soil, they will be forced to use a technology that uses more external inputs so as to replenish the lost nutrients. Consequently, where the practices are such that they improve on-farm soil fertility, a technology that uses less quantities of external inputs will be sufficient.

Importance of increasing resistance to drought as a farming technology attribute is highly variable because of variations of farmers in adapting to changes in weather patterns. Weather patterns have been highly variable and farmers need to adapt so as to maintain or improve their yields. Where farmers are resistant to changes in weather patterns, their yields will be affected by weather shocks and therefore attaching more utility to this attribute. However, where farmers' practices change with the variability in the weather, their yields will not be highly affected and therefore will not attach much utility to this attribute when selecting appropriate technology choice. This means that there is a possibility of different farmer groupings given their inherent characteristics.

4.6.3 Farming technology dimensions based on homogeneity of farming attributes

A Principal Component Analysis (PCA) was carried out to determine different possible combinations of farming technology attributes based on the utility dimensions. The attributes that loaded high in each principal component mirrors unique combination of attributes forming a unique farming technology. The number of principal components were determined based on Guttman-Kaiser criterion (Guttman, 1954, Kaiser, 1960, Jolliffe, 2002). Their criterion assumes that only components greater than 1 are considered because they account for at least as much variation as a single original variable Table 4.8 below shows eigen values and sample variances

Table 4. 8: Eigen values and sample variance

Components	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.4102	0.9158	0.2191	0.2191
Comp2	1.4945	0.0583	0.1359	0.3550
Comp3	1.43615	0.3426	0.1306	0.4855
Comp4	1.0935	0.1498	0.0994	0.5849
Comp5	0.94375	0.0487	0.0858	0.6707
Comp6	0.8950	0.0256	0.0814	0.7521
Comp7	0.8694	0.1098	0.0790	0.8311
Comp8	0.7596	0.1857	0.0691	0.9002
Comp9	0.57386	0.0497	0.0522	0.9523
Comp10	0.5242	0.5242	0.0477	1
Comp11	0	.	0	1

Four components were retained since they had high eigenvalues that accounted for more than 58% of total variation of attributes representing farming technology. This was above the 50% mark which is a presumed cut-off point for data reduction. Information conveyed by farming technology attributes were condensed by only reporting the latent factors influencing decision making by farmers in their farms. The latent factors were used to create different technology segments based on farmer's inherent choices.

The technology segments were not interpreted as farmer groups since they represent cognitive utility dimensions (Luce, 2012). Table 4.9 below shows rotated factor loadings of the 4 retained principal components for all 11 attributes of farming technology. The components can be interpreted as different combinations of farming technologies with unique farming attributes.

Table 4. 9: Rotated patterns of farming goals (eigenvectors)

Farming technology goals	Principal components			
	Tech1	Tech2	Tech3	Tech4
Decrease pests and diseases	-0.0538	0.1084	**0.6242**	-0.0352
Reduce extension requirement	-0.0217	-0.4176	-0.0053	0.1559
Decrease labour use	0.3097	**0.5498**	-0.0967	0.0521
Increase on-farm soil fertility	-0.0659	0.1514	-0.0909	**-0.7492**
Increase crop yield	-0.0501	0.1203	**-0.6561**	-0.0514
Decrease water requirement	0.3467	-0.3508	-0.0135	0.022
Decrease on-farm soil erosion	-0.4378	-0.0054	0.2117	0.0287
Decrease external input used	**0.5039**	0.1767	0.2969	0.0061
Decrease off-farm pollution	**-0.5369**	0.0275	0.0425	-0.0005
Increase resistance to drought	0.1697	**-0.4959**	-0.1068	0.0116
Decrease cost of production	-0.1051	0.2705	-0.1261	**0.6374**

Components with high loadings are in bold

From the results, Attributes that load high in first technology dimension are; decreasing external inputs used and decreasing off-farm pollution. Decreasing external inputs used has a positive sign, implying that farmers are concerned with attributes that involve better utilization of resources. Moreover, the attribute with a negative sign is decreasing off-farm pollution, which is associated with provision of environmental services. We therefore note that the first technology dimension is for farmers who are concerned about reducing use of inputs (better utilization of resources) but are not conscious about the quality of environmental services.

Attributes that load high in second technology dimension include; decreasing labour use and increase resistance to drought. Reducing labour use has a positive sign meaning that the second technology dimension involves reducing labour hours used in production process. The negative signs on the attribute of increasing resistance to drought signifies least possible attribute choices for such a technology. This technology dimension can be important for farmers who incur high expenditure on labour but are not faced with challenges related with drought.

The third technology dimension involves attributes related with decreasing pests and diseases and increasing crop yield. The positive sign on decreasing pests and diseases shows that this technology dimension attaches high utility to reducing pests and diseases in the farms. Consequently, the negative sign on the attribute related with increasing crop yields signifies that the technology attaches very little utility on the attribute of increasing crop yields. The third technology dimension will thus be ideal for farmers that are using more chemicals in controlling pests and diseases and don't face a challenge of low maize yields.

Choice of main attributes for the last technology dimension include; increasing on-farm soil fertility and decreasing cost of production. Cost of production has a positive sign while increasing on-farm soil fertility has a negative sign. This can be interpreted to mean that this technology dimension attaches high utility on attribute that reduces cost of production and low utility on attribute that increases on-farm soil fertility. Such a technology will be ideal for inefficient farmers who incur high input costs but don't have a challenge with the fertility of their farms.

4.6.4 Importance of farming technology attributes by cluster groups

Further analysis was carried out to determine important farming goals in each of the cluster groups as shown in Table 4. 10 below. First, cluster analysis was used to cluster farmers into four different groups with similar attribute preferences. Clustering was based on the four retained principal components that explained high variation of farmers' technology choices

Table 4. 10: Farming technology goals by cluster groups

Farming technology goals	**Cluster Group**							
	1		**2**		**3**		**4**	
	B-W	**SS**	**B-W**	**SS**	**B-W**	**SS**	**B-W**	**SS**
Increasing yields	186	0.20	139	0.15	99	0.11	158	0.17
Reducing cost of production	127	0.14	26	0.03	59	0.06	48	0.05
Decreasing pests and diseases	102	0.11	86	0.09	12	0.01	-35	-0.04
decreasing external inputs used	69	0.07	-15	-0.02	-2	0.00	5	0.01
Decreasing labour requirements	29	0.03	-59	-0.06	27	0.03	-8	-0.01
Increasing resistance to drought	15	0.02	22	0.02	-44	-0.05	84	0.09
Increasing on-farm soil fertility	-10	-0.01	67	0.07	15	0.02	3	0.00
Decreasing water requirements	-84	-0.09	-112	-0.12	-79	-0.08	-9	-0.01
Decreasing on-farm soil erosion	-116	-0.12	-27	-0.03	-14	-0.01	-102	-0.11
Decreasing extension requirements	-147	-0.16	-105	-0.11	-63	-0.07	-38	-0.04
Decreasing off-farm pollution	-171	-0.18	-22	-0.02	-10	-0.01	-106	-0.11

Group1 farmers

The results show that the first group of farmers preferred technology whose main attributes are increasing yields, reducing the cost of production, and decreasing pests and diseases. High cost of production is associated with an inefficient farming technology. Nyoro et al. (2004) and Oerke (2006) supports our findings on important attributes of farming technology. Nyoro et al. (2004) argued that average cost of production is dependent on nature of farming technology used, region and scale of production. He concluded that reducing cost of production could potentially lead to efficiency gains in maize production. Oerke (2006) on the other hand quantified maize yield losses as a result of pests and diseases to approximately be equal to one third of total maize yield losses, making it the highest source of maize yield losses. Increased pests and diseases on the other hand is the main sources of pre and post-harvest losses.

The least preferred farming goals of technology for farmers in group 1 are; reducing off-farm pollution, decreasing extension requirements, and decreasing on-farm soil erosion. Although use of chemicals increase pollution, they also lead to better yields. Tai et al. (2014) argued that use of chemicals and water were main source of farm pollution. They however highlighted that decreasing use of these inputs could reduce maize yields significantly. Intercropping maize with other crops has been suggested as possible solution to soil erosion in maize farms (Sharma et al., 2017). The utility of reducing on-farm soil erosion is very low amongst the first group of farmers because it does not affect them as most of them intercrop maize with other crops thereby controlling its effect. Therefore, Farmers in group 1 prefer a technology whose main attributes are to increase their net farm income but are less interested in a technology whose primary purpose is conserving the environment.

Group2 farmers

Second group of farmers are concerned with a technology whose main farming attributes are; increasing yields, decreasing pests and diseases and increasing on-farm soil fertility. Decreasing pests and diseases has two main advantages to farmers; it leads to increases yields and also reduces on-farm pollution. This is supported by (HE et al., 2019) who argues that past production technologies have focused on increasing yields leading to increased farm pollution. They further pinpoint that sustainable agricultural production should involve technologies that reduces attack by pests and lowers the impact and occurrences of diseases without using chemicals.

Decreasing water requirements, reducing extension requirements, and decreasing labour requirements are the attributes farmers identified as least important to farmers in group 2. These least important farming attributes included attributes related with production efficiency (reducing extension requirements and decreasing labour use) and conservation of the environment (reducing water requirements). Reduced water requirement was selected among the least important attribute probably because the intensity of rainfall has been increasing in the study area and therefore water is not a major problem to the farmers. This argument can be supported by (Kang et al., 2009) who points out that rainfall is generally projected to increase in most parts of the world which may lead to increase in maize yields. Therefore, the technology of these farmers blended goals that increase input use efficiency and sustainability of environmental services.

Group3 farmers

Increasing yields and reducing the cost of production are the main technology attributes for farmers in group 3, while decreasing water requirements, decreasing extension requirements and increasing resistance to drought were the least important technology attributes. Just as the farmers in group 1, these farmers were interested in a technology that will lead to an increase in net farm income (increasing yields and reducing cost of production). However, their technology had a very low preference for technologies that improve environmental services (decreasing water requirements and increasing resistance to drought). Group 3's utility for technology preferences are consistent with the findings of (Droppelmann et al., 2017) who studied sustainable intensification options for smallholder maize producers and noted a tradeoff between yields and environmental services. Increased output from maize production led to decline several ecosystem services.

Group4 farmers

Farmers in group 4 were interested in a technology whose main preferred technology attributes were; increasing yields and increasing resistance to drought. Consequently, the least preferred attributes of the technology were; decreasing off-farm pollution and decreasing on-farm soil erosion These farmers were therefore, interested in a technology whose farming attributes were to increase yields and were less interested in a technology that conserved environmental services.

4.6.5 Farmer groups in different villages

The distribution of the unique groups across different villages is presented in Table 4. 11 below.

Table 4. 11: Distribution of farmers by cluster and villages

Cluster group	Kamungei		Kiptenden		Njoro		Wendani		Overall	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
1	32	41.03	14	35.9	16	45.71	11	31.43	73	39.04
2	21	26.92	13	33.33	10	28.57	11	31.43	55	29.41
3	5	6.41	12	30.77	0	0	5	14.29	22	11.76
4	20	25.64	0	0	9	25.71	8	22.86	37	19.79
Total	**78**	**41.7**	**39**	**20.9**	**35**	**18.7**	**35**	**18.7**	**187**	**100**

Most farmers were clustered in group 1 and group 2. Kiptenden and Njoro did not have any farmers in cluster group 4 and 3 respectively. The grouping was based on farmers' preferred technology goals as collected in the BWS.

4.6.6 Association of farmer groups with socio-economic characteristics and current practices

ANOVA and Chi-square tests were conducted to identify if there were differences across the cluster groups for various farmer characteristics. The null hypothesis (H0) of the analysis was that there are no differences across the cluster groups for the identified variables. The alternative hypothesis (H1) was that there are differences in variances across the cluster groups. The null hypothesis (H0) is rejected when significance level $p \leq .050$. Tukey's test was then used as a posthoc test for variables to validate the ANOVA results.

4.6.7 Socio-economic characteristics of different farmer groups

Table 4. 12 below shows the socio-economic characteristics of households across different farmer groups.

Table 4. 12: Socio-economic characteristics by farmer groups

Variable	Cluster				Total	p-value
	1	**2**	**3**	**4**		
Age of the Household head	48.233	48.218	56.364	47.378	49.016	0.0655
Education level of household heads	8.425	8.818	7.545	11.676	9.08	0.0004
Household size (#)	5.904	5.545	6.545	4.811	5.658	0.0619
total farm size (Ha)	0.97	0.93	0.84	0.60	0.87	0.804
% Of male headed households	65.75	69.09	86.36	62.16	68.45	0.24
% Of male decision makers	80.82	87.27	90.91	100	87.7	0.035

Age, education level of the household head and household size produced significant ANOVA results ($p < 0.10$). We, therefore, rejected the null hypothesis that there were no significant differences in the mean of these variables across the cluster groups. In education level of the household head, Tukey's test identified significant differences between group 2 and 1, group 3and 2, and group 4 and 2 Appendix 1. 3. For age, the differences were noted between group 3 and 1, and also in group 4 and 2. The differences in household size were between group 4 and 3. Results of Chi^2 on farm decision makers showed significant differences in the proportion of male decision makers. This show that there were notable differences on the socio-economic characteristics of farmers in different farmer groups with unique choices of farming technology attributes.

4.6.8 Association with efficiency and current practices

Current agricultural practices and efficiency scores of the different cluster groups are shown in Table 4. 13 below.

Table 4. 13: Agricultural Practices and Efficiency by farmer groups

Variable	Cluster				Total	p-value
	1	2	3	4		
Efficiency scores	0.606	0.592	0.679	0.617	0.613	0.3264
Total Maize harvested	1484.4	1344.3	1542.3	1143.2	1382.5	0.333
Land preparation cost	2615.1	2349.1	1947.7	2055.4	2347.6	0.5042
Basal fertilizer	71.585	60.991	57.114	51.956	62.693	0.184
Land size	2.39	2.305	2.074	1.474	2.147	0.5042
Total seed quantity	15.747	13.945	12	11.284	13.893	0.0708
Chemical fertilizer	75.406	71.435	65.068	59.329	69.825	0.4476
Total assets (USD)	86.7	74.07	102.17	66.36	80.78	0.4515

The ANOVA results of total seed quantity showed significant differences across the farmer groups ($p<0.10$), thus rejecting the null hypothesis of homogeneity of variance. A Tukey’s test conducted to identify the contrasted groups with significant differences noted the differences to be between group 4 and 1 (Appendix 1. 3). The results from ANOVA further showed that the variance of efficiency scores was not significantly different across clusters ($p>0.10$), therefore failing to reject the null hypothesis of homogeneity of variance. Tukey's test conducted on the efficiency scores did not find any significant values in all the contrasted cluster groups Appendix 1. 3. Other selected variables (Total Maize harvested, land preparation cost, basal fertilizer, quantity of chemical fertilizer and overall value of selected assets), did not have any significant p-value for ANOVA tests. These variables were also tested using Tukey's test and none of the contrasted groups had significant p-values Appendix 1. 3.

4.7 TECHNICAL EFFICIENCY ANALYSIS

In this section, technical efficiency was estimated using output-oriented production frontier model. To begin, the frontier parameters and inefficiency were calculated using a parametric functional form of the production frontier f. (x). Maize as a production technology was assumed to satisfy all regularity conditions such as; monotonicity, convexity/quasi concavity, closed and non-empty set and continuous and twice differentiable everywhere. The following is a stochastic production frontier model that assumes output-oriented technical inefficiency:

$$Ln\,Yi = f(Xi\,;\,\beta) + \varepsilon i \quad (17)$$

$$\varepsilon i = vi + ui \quad (18)$$

Where, $\boldsymbol{\varepsilon_i}$ is the composed error, $\mathbf{u_i}$ is the output-oriented technical inefficiency index and v_i is zero mean random error. Both distribution free approach and stochastic frontier approach were used in estimating the model.

4.7.1 Distribution Free Approach

This approach does not make any distributional assumptions on the error components. It includes corrected ordinary least squares (COLS) and corrected mean absolute deviations (CMAD) (Ray et al., 2015b).

4.7.1.1 Estimation results for OLS and MAD

Independent variable inputs were regressed against quantity of maize yield (Kgs) using ordinary least squares and mean absolute deviations (MAD) methods for 187 maize farmers and the estimated results presented in Table 4. 14. The difference in the two methods is that, OLS regression passes through the mean of the data while MAD regression passes through the median (Ray et al., 2015b).

Table 4. 14: OLS and MAD estimation results

Variables	COLS		MAD	
	Coeffs	Standard error	Coeffs	Standard error
Maize output (Y)				
Constant	5.059***	(0.497)	4.748***	(0.608)
Maize seed (lseed)	0.0583	(0.154)	0.0701	(0.130)
Chemical fertilizers (lfert)	0.236***	(0.0596)	0.278***	(0.0598)
Harvesting labour in man-hours (lharv)	0.387***	(0.0931)	0.258***	(0.0776)
Land under maize in acres (llsize)	0.307**	(0.151)	0.407**	(0.165)
Weeding labour in man-hours(lweed)	-0.160**	(0.0782)	-0.0288	(0.102)
Observations	187		187	
R-squared	0.592			

Note: *, **, ***=significant at 10%, 5% and 1% level, respectively. Robust standard errors in parentheses, Std errors stands for standard errors

All coefficients under COLS were statistically significant at different levels except for the quantity of maize seed planted whose coefficient was not statistically significant. Harvesting labour and land under maize were the variables with the most substantial influence on maize production under COLS. Weeding Labour had a negative and significant coefficient, meaning that it negatively influenced the quantity of maize harvested. The analysis thus shows that labour hours used during harvesting was still low, and farmers could realize increased yields from allocating more working hours in harvesting. The coefficient of the quantity of maize seed planted was not significant and thus did not influence maize yield.

Under CMAD, use of chemical fertilizers, size of land under maize and labour used during harvesting had positive and significant coefficients, signifying a positive influence on maize yield. Therefore, farmers could significantly increase yields by using more of these inputs. The coefficients of the quantity of maize seed planted and labour hours used for weeding were not statistically significant and thus did not influence the amount of maize harvested. OLS coefficients for all variables are consistent for the production frontier model, but the intercept (constant) is not. The intercept (β0) is not consistent because the error term (ui) is not equal to zero and therefore biasing it.

4.7.1.2 COLS and CMAD efficiency score estimation

Efficiency scores were further estimated using residuals from OLS, and MAD regressions and a t-test computed to test the differences in their mean efficiency as presented in Table 4. 15.

Table 4. 15: COLS and CMAD efficiency scores

Variable	Obs	Mean	Std. Dev.	Min	Max	t-test
Efficiency scores (COLS)	172	0.3789	0.1753	0.0659	1	5.01 ***
Efficiency scores (CMAD)	172	0.3608	0.1659	0.0469	1	

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

Efficiency scores estimates under COLS were 38% while the score estimates under CMAD were slightly less (36%). The least efficient farmers in COLS had a maximum potential of about 7% while in CMAD, the least efficient farmer had a maximum potential of about 5%. Both COLS and CMAD registered a maximum efficiency potential of farmers to be 100%. T-test results conducted on efficiency scores generated under COLS and CMAD showed significant differences at 1% level. The difference proves that there were substantial differences in the distribution of the mean efficiency scores under the two approaches. The distribution of farmers' efficiency scores for both COLS and CMAD were plotted in histograms and presented in Figure 3 below.

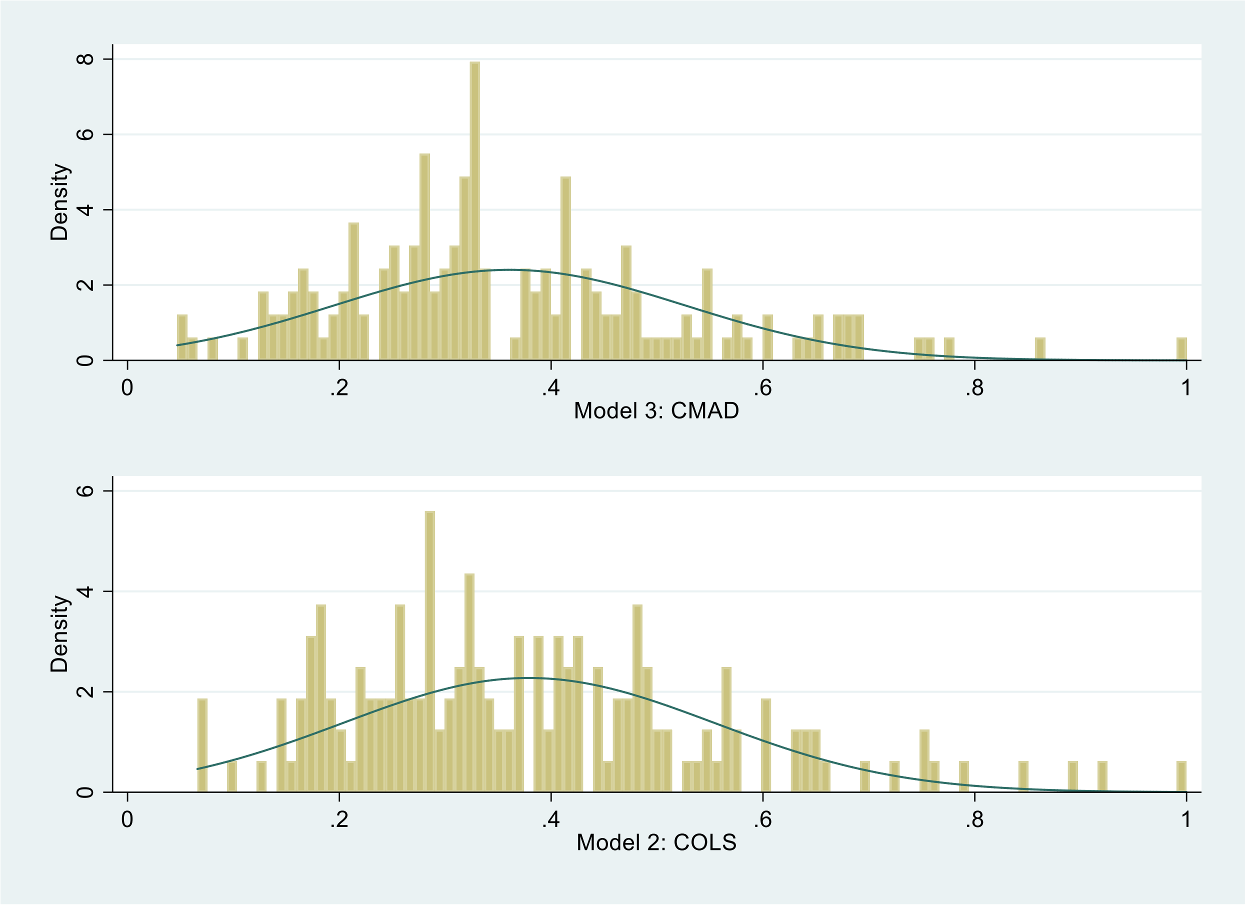

Figure 3: Histogram of efficiency scores under COLS and CMAD models juxtaposed

The vertical axis (density) represents the number of farmers, while the horizontal axis represents efficiency scores. Under COLS, efficiency scores of most farmers were spread out, contrasting CMAD whose scores were clustered around the mean. Further, COLS scores between 0.4 and 0.8 had large density spikes, signifying high heterogeneity in efficiency scores. CMAD had some uniformity in efficiency scores signifying score homogeneity.

4.7.2 Stochastic frontier approach

This model uses maximum likelihood estimation and distinguishes between inefficiency effect of the model and the statistical errors. It identifies random variables by imposing parametric distribution assumptions. The log-likelihood function of the model is mostly nonlinear and its estimation difficulty. It is therefore necessary to test the validity of stochastic frontier specification before proceeding with estimating the model.

4.7.2.1 Validity of stochastic frontier specification

The validity of the model specification was tested using an OLS residual test, as suggested by (Schmidt and Lin, 1984). The test served as a pre-test of the model. The test was carried out with the assumption that the composed error vi-ui, ui≥0 and vi were symmetrically distributed around zero and the OLS residuals were skewed to the left. OLS residual test is done to test if the residuals of a production type stochastic model specification are skewed to the left. A null hypothesis of no skewness was therefore tested using the sample-moments method. A skewness statistic of -3.112 was observed, thereby rejecting the null hypothesis of no skewness. The negative sign proves that the distribution of the residual is skewed to the left, which is consistent with our priori expectation of a production stochastic model specification. An sktest command was used to test the null hypothesis of no skewness by assessing the statistical significance of the specification. A p-value of 0.0024 was observed, thus rejecting the null hypothesis of no skewness.

4.7.2.2 Model estimation (SFA)

Results for maximum likelihood estimates of the cobb-douglas production function, (calculated using STATA 15 program), are presented in Table 4. 16 below

Table 4. 16: Maximum likelihood estimates of the production frontier function

Variables	Coeffs	Standard error
Production function		
Dependent variable: Log (Maize output (Kgs))		
Constant	5.780***	(0.490)
Maize seed (lseed)	0.180	(0.120)
Land under maize in acres (llsize)	0.284**	(0.131)
Chemical fertilizers (lfert)	0.298***	(0.0682)
Harvesting labour in man-hours (lharv)	0.269***	(0.0740)
Weeding labour in man-hours(lweed)	-0.196**	(0.0861)
Usigmas	-0.6613***	(0.226)
Vsigmas	-2.8196***	(0.430)
Sigma_u_sqr	0.5162***	(0.1156)
Sigma_v_sqr	0.0596**	(0.0256)
Efficiency scores	61.34	
Observations	187	

Note: *, **, ***=significant at 10%, 5% and 1% level, respectively. Robust standard errors in parentheses, Std errors stands for standard errors

The coefficient of the quantity of maize seed used was positive but not statistically significant and therefore, did not influence the quantity of maize harvested. Land under maize had a positive and significant coefficient at 5% level showing that maize output is elastic to variations in land size. This can be attributed to the fact that land is a crucial factor in maize production and its changes usually affect maize output. The result is conflicts with the findings by Mburu et al. (2014) and (Kirimi and Swinton, 2004) who compared efficiency between large and small farm sizes of rice production and concluded that, although small farms are more efficient in allocating resources, increasing farm size can lead to increased output. However, Ugwumba (2010) observed land underutilization as being caused by land tenure problems stemming from increased land fragmentation. It is therefore worth noting that, it is challenging to increase productivity and efficiency through increasing land sizes given the challenges associated with land fragmentation.

Fertilizer use had a positive and statistically significant coefficient meaning that maize output is elastic to changes in fertilizer application. The result is in agreement with a study conducted by Endale (2010), who found a positive influence of fertilizer use on productivity. He, however, noted that the influence of fertilizer was still low because of low application rates arising from high cost of fertilizer and low fertilizer extension information. Optimum use of fertilizer is therefore crucial in increasing efficiency of production.

Overall, labour components had a significant influence on maize yields. This is expected since maize production is labour intensive. The coefficient of harvesting labour was significant at 1% level, showing that harvesting labour had a significant influence on yields. The increase in output can be attributed to increased efficiency in harvesting, given increased harvesting labour force. Weeding labour, on the other hand, has a negative and significant coefficient at 5% level. The negative sign can be interpreted to mean that farmers are using more labour in weeding than the optimum levels and can increase output by reducing the labour used on weeding. Weeding was the component that consumed many labour hours when compared to the other labour components. Generally, maize production is labour intensive and highly sensitive to changes in allocations in labour use.

The mean technical efficiency for farmers in our sample was 61% with a standard deviation of 0.188. The score shows that on average, farmers were able to achieve 61% of the maximum potential output from the set of inputs they used. The technical efficiency scores ranged between 0.126 and 0.92. This means that farmers with the worst practice achieved 12.6% of the maximum potential output and the farmer with the best practice attained an output of 92% of the maximum attainable output. A histogram showing mean technical efficiency under SFA, assuming a half-normal distribution is presented in Figure 4

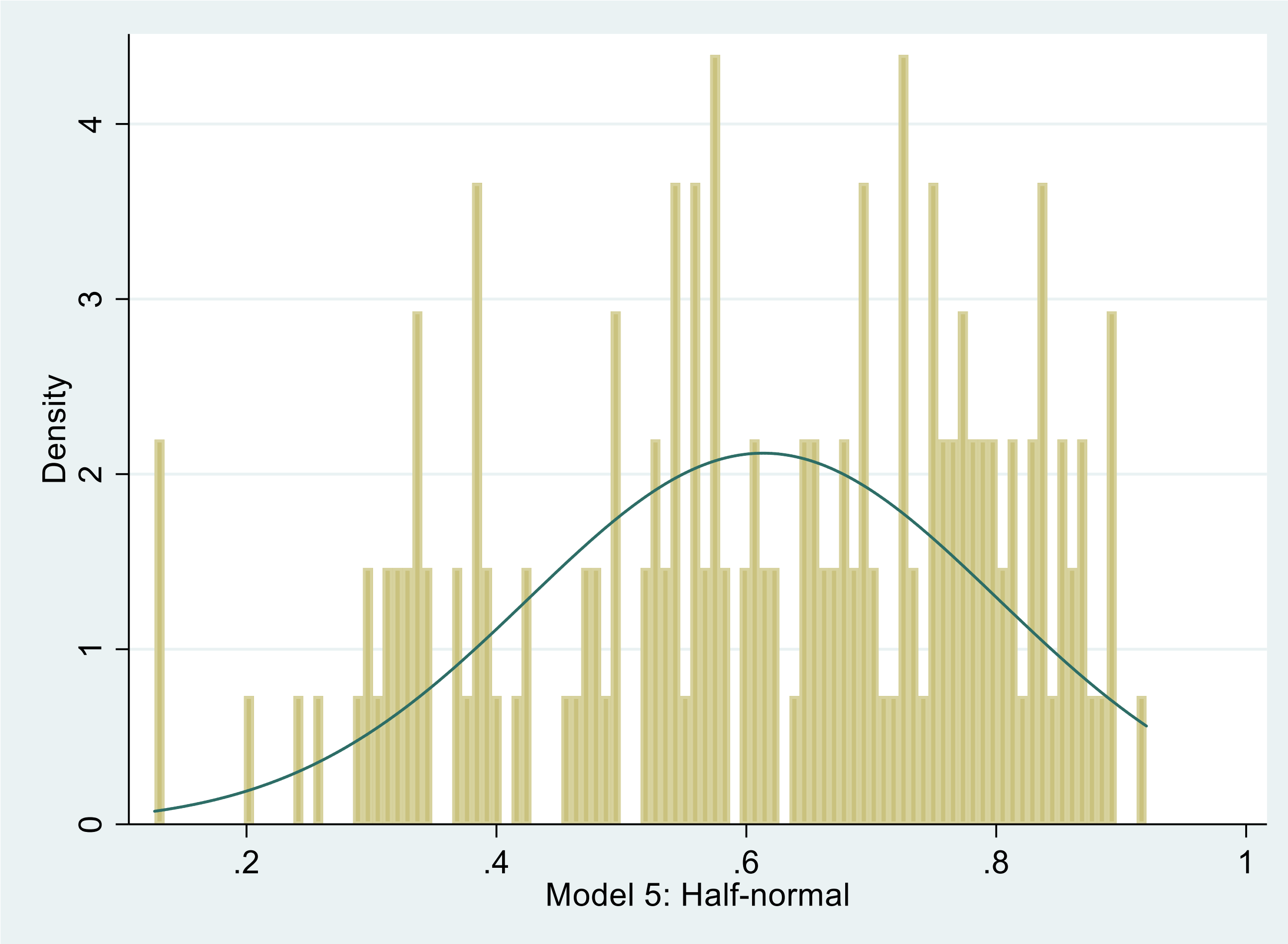

Figure 4: Histogram of efficiency scores under SFA (Half-Normal)

4.7.2.3 Determinants of technical inefficiency

Determinants of technical inefficiency are shown in Table 4. 17 below. The variables identified include; gender of the household head, if households experienced challenges in soil management, total asset value, person making decisions on the farm, practicing intercropping, land size and if the household heads acquired post-primary education.

Table 4. 17: Determinants of technical inefficiency

Variables	**Coeffs**	**Standard error**
Constant	0.3981***	(0.0347)
Gender of Household head =1, Male	0.06213**	(0.0389)
Challenges in soil management = 1, Yes	-0.0903*	(0.0444)
Total asset value	0.000004***	(1.49e-06)

Person making decision on the farm = 1, Head	0.1019**	(0.0411)
Practicing intercropping = 1, Yes	0.08359***	(0.0276)
Land size in acres	-0.02802	(0.00816)
Acquired post-primary education= 1, Yes	0.03943	(0.0375)
Observations	172	
R-squared	0.1861	

Note: *, **, ***=significant at 10%, 5% and 1% level, respectively. Robust standard errors in parentheses, Std errors stands for standard errors

Having post-primary education did not significantly influence the efficiency of smallholder maize farmers since its coefficient was not statistically significant. The coefficient of the gender of the household head was poasitive and statistically significant at 5%. The positive sign implies that male-headed households were likely to be more efficient when compared with female-headed households. This is consistent with our priori expectation since male farmers provide more and efficient labour while also accessing more productive resources. A research carried out by Ogato et al. (2009) supports our findings since it identified limited access to productive resources by women as being a major impediment in achieving increased farm productivity in Ethiopia.

The coefficient associated with challenges in soil management was negative and significant at 10% level, which means that farmers who incurred challenges in soil management were likely to be less efficient in production when compared to those that did not incur soil management related challenges. These soil management challenges range from soil erosion, declining soil fertility and lack of proper training on effective soil management practices. Sustainable soil management is an essential aspect of production systems. Poor soil management leads to soil compaction, erosion, and loss of soil carbon and biodiversity. The net effect is reduced yields which in turn affects food sufficiency and security due to increased food prices.

Total asset value was another factor identified. Its coefficient was positive and significant at 1% level, meaning that households with high asset values were likely to be more efficient in maize production than those with less total asset values. Asset values are synonymous with production technology, and thus we can argue that households with high asset values were employing better production technology. On the other hand, households that had less total asset values are assumed to be using poor and primitive production technology and therefore realize low maize yields.

Gender of the person making decisions in maize production was another important factor considered. The results show that the coefficient of gender of the person making production decisions was positive and significant at 5% level. This means that households, where males made production decisions, were likely to be more efficient than those where female made the decisions. This might be because households with male decision-makers can access more extension information and can get help from their female household members. Households with female decision-makers, on the other hand, get little help from their male household members making them less efficient in production. Oseni et al. (2014) attributes the differences to resource endowments (labour, land and education), and returns to factor productivity which he says are lower in women. These returns are lower because female decision-makers are usually old and widowed, unlike male decision-makers.

Intercropping is another vital aspect that influences production efficiency. The coefficient associated with intercropping was positive and significant at 1% level. It, therefore, means that households practicing maize intercropping are more efficient compared with households practicing mono-cropping. Intercropping allows for better resource utilization. For instance, maize can be intercropped with leguminous crops, thus helping fix nitrogen symbiotically. The rhizobium present in the soil helps improve soil fertility and thus, better nutrient utilization. The finding is supported by Chandra et al. (2013) who analyzed data from an experiment conducted between 2004 and 2005 to compare the productivity of finger millet as an intercrop with finger millet as a mono-crop. They concluded that intercropping resulted in more grain yield-equivalent for finger millet compared with the yield of finger millet as a sole crop.

Total land size had a negative and significant coefficient at 10% level. The result can be translated to mean that farmers that own large pieces of land are likely to be less efficient in production compared to those with small land sizes. The outcome is contrary to our priori expectation because less land size is synonymous with a high degree of land fragmentation and thus making farmers less efficient in production. This agrees with the findings of Paul and wa Gĩthĩnji (2018) who found out an inverse relationship between farm size and yields using Ethiopian national survey data. Muyanga and Jayne (2019) however disagrees with our findings in a research conducted in Kenya that revisited the inverse relationship between productivity and farm sizes using different measures of productivity (profits per hectare, total factor productivity and yield per hectare). They found a strong relationship between productivity and farm sizes with large farm sizes being more productive than smaller farm sizes.

4.7.2.4 Influence of farmer attributes on technical inefficiency

Table 4. 18 below is an extension of determinants of technical inefficiency and it includes influence of goals of farming technology on efficiency.

Table 4. 18: Influence of Farmer attributes on technical inefficiency

Variables	**Coeffs**	**Standard error**
Y= Efficiency scores		
Gender of Household head = 1, Male	0.0624**	0.0031
Challenges in soil management = 1, Yes	-0.1464***	-0.24604
Total asset value	4.36e-06***	1.18E-06
Practicing intercropping = 1, Yes	0.0265***	0.019285
Land size in acres	-0.0133	0.00824
Decrease pests and diseases	-0.148***	-0.0536
Decrease water requirement	-0.188***	-0.0563
Decrease off-farm pollution	-0.123**	-0.0501
Increase on-farm soil fertility	-0.0419	-0.0476
Decrease on-farm soil erosion	-0.0795	-0.0549
Decrease external input used	-0.133**	-0.0621
Increase resistance to drought	-0.0874*	-0.0457
Decrease labor use	-0.0677	-0.0506
Increase crop yield	-0.0538	-0.0555
Constant	0.558***	-0.0472
Observations	187	
R-squared	0.24	

Note: *, **, ***=significant at 10%, 5% and 1% level, respectively. Robust standard errors in parentheses

The socioeconomic characteristics included in the model were gender of the household head, challenges in soil management, total asset value, practicing intercropping and total land size. The coefficients of farm and socioeconomic characteristics were significant at 5% level except for land size, which was not significant. The coefficients associated with increasing on-farm soil fertility, decreasing on-farm soil erosion, decreasing labour use and increasing crop yield were not statistically significant and thus did not have any influence on efficiency.

The attribute of decreasing pests and diseases had a negative and significant coefficient at 1% level, which can be interpreted as; if farmers were to employ a technology that reduces pests and diseases, efficiency would decline. The coefficient is negative because decreasing pests and diseases requires resources and thus would negatively impact the available resources to produce efficiently. This observation is consistent with findings of (Zhang et al., 2018) who studied farmers' incentives to promote natural remedies for pests and disease control in farms. They noted that integrated pest-management practices (IPM) generally improve ecosystem services for crop production. However, in cases where there are high pests damage levels, use of chemicals like pesticides are more likely to increase crop yields. Therefore, given the low use of pesticides by sampled households is an indication of low damage of crops by pests and diseases. We can argue that reducing pests and diseases by applying chemicals might lead to a reduction in crop yields. Secondly, using chemicals to control pests and diseases interferes with soil fertility and therefore eventually leading to low yields.

Decrease water requirement was another attribute whose coefficient was negative and significant at 1% level, meaning that when farmers reduce the water requirements through better technologies, efficiency declines. Water requirements can be reduced through developing seed varieties that can perform well even with less water. However, water is very important in maize production and technologies can only reduce water requirements at certain growth stages of maize plant, otherwise, the yields will decline. Certain physiological growth stages of maize require adequate water. Huang et al. (2006) noted that maize plant responds differently to water shortage depending on the stage of development. They pointed out that during planting, stem development and flowering stages, water is very important as it aids organ development. Therefore, reducing water requirement throughout the cropping cycle is likely to cause a decline it maize yields

The coefficient for decreasing on-farm pollution was negative and significant at 5% level. This can be interpreted as; if farmers prefer a technology that reduces off-farm pollution when making farming decisions, efficiency will decline. Farmers cause pollution through high fertilizer, pesticides and water use (Tai et al., 2014). When farmers apply fertilizers and pesticides in their farms, fertilizers are washed away into rivers and pesticides blown away by wind causing water and air pollution respectively. Use of fertilizers and chemicals is meant to improve yields. Therefore, reducing use of external inputs will be a sustainable practice but will lead to reduced yields. Tai et al. (2014) pinpointed that high fertilizer use especially in countries where there are fertilizer subsidy programs, contribute to farm pollution. They further argued that current farming practices like continuous fertilizer application and ground water pollution are unsustainable agricultural practices in maize production.

The attribute of decreasing external inputs used had a negative and significant coefficient at 5% level, meaning that if farmers prefer a technology that reduces external inputs used (diesel and chemical fertilizers and others), efficiency declines. Despite external inputs increasing maize yields, they are a source of both air and water pollution. Therefore, a technology that reduces external inputs will lead to improvement in the quality of environmental services but also will lead to decline in the yields. This is supported by Dudal and Byrnes (1993) who argued that the continued low use of chemical fertilizers in future will have a more negative effect than anticipated effects of increased use of inorganic fertilizer. Meaning that increased use of fertilizer will have a greater positive impact on yields than the negative impacts it will have on environmental services.

Finally, the attribute of increasing resistance to drought had a negative and significant coefficient at 10% level, interpreted as; if farmers prefer a technology that increases resistance to drought, efficiency declines. To increase resistance to drought, governments and stakeholders have released many drought tolerant (DT) maize varieties for use by farmers (Fisher et al., 2015). However, the uptake of these varieties is low because of high cost of DT maize varieties, lack of information, lack of resources and perceived attributes of other maize varieties (Fisher et al., 2015). The results are coherent with the results of Kamara et al. (2003) who studied the influence of drought on yields and yield components. The results of their research showed that drought affects yields and yield components of all crops including drought tolerant varieties. However, they noted that yields from DT varieties were higher than yields from other maize varieties

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

This study discussed key findings related with technical efficiency and choice of farming technology attributes. It sought to find out if subjective preferences for different attributes characterizing agricultural technologies and practices influence technical efficiency of small maize producers. The study employed t-test and chi-square tests to understand the nature and characteristics of farming systems used. Some of the attributes that were analysed included; household size, farm size, education level of the household head and household decision making. The study concludes that, the farmers were generally young and had obtained basic education. They also had small farm sizes mainly occasioned by land fragmentation.

The study characterized the nature of farming technology used by smallholder maize farmers by analysing main farming inputs, nature of their productive assets, main cropping system and access to extension information. Most of the farming land was owned and titled although the sizes are getting smaller due to subdivisions and land fragmentation. Mixed intercropping stood out as the main cropping system practiced although most farmers were still using conventional tillage practices. On the input economy, almost all the farmers were using chemical fertilizers with only a small proportion applying manure. The application rates of the chemical fertilizers were still very low and farmers could benefit from optimal application. Land preparation, weeding and harvesting were the main labour consuming activities, mainly provided by family members. Generally, smallholder farmers are using traditional farming technologies. Only 10% of farmers received extension services despite many challenges they were facing in producing maize, mainly because its demand driven.

Best worst scaling information revealed that farmers prefer farming technology whose main attributes are increasing yields and decreasing cost of production. Environmental attributes that farmers preferred in their technology were; decrease pests and diseases, increase resistance to drought, increase on-farm soil fertility and decrease water requirements within the cropping cycle. Most farmers were however of the opinion that decreasing water requirements was a less important technology goal probably because they receive enough rainfall throughout the year.

5.1.1 Smallholders' choice of farming goals

Two focus group discussions were conducted in the study area which identified main attributes of farming technology. The attributes were uniquely combined to form different farming technology sets using BWS method. BIBD was employed to ensure equal occurrence and co-occurrence of the goals in the technology sets. The results from best worst scaling showed that the most important farming goals are increasing crop yields, decreasing cost of production, decreasing pests and diseases and increasing on-farm soil fertility. Conversely, the goals farmers identified as least important in farming technology include; decreasing on-farm soil erosion, decreasing water requirement throughout the cropping cycle and decreasing off-farm pollution.

Different dimensions with unique farming technology attributes were identified using principal component analysis. The first technology dimension recorded high utility for attributes that reduced labour and external inputs used. Further, reducing labour requirements, reducing pests and diseases and reducing cost of production were technology attributes preferred in dimension 2, 3 and 4 respectively. The study thus concludes that the attributes that were preferred in all the technology dimensions were those that improves farmers production efficiency and excluded those that maintained environmental services, consistent with the findings of Droppelmann et al. (2017).

The technology dimensions were finally used to categorize farmers into groups with homogeneous preferences for technology attributes. The first group of farmers preferred a technology that increased crop yields, reduced cost of production and reduced attack by pests and diseases. The second group preferred a technology that increased yields, decreased pests and diseases and increased on-farm soil fertility. The third group of farmers preferred a technology that increased yields and reduced cost of production. Finally, the last group preferred a technology that increased yields and increased resistance to drought. We therefore note that increasing crop yields is the most important attribute preferred by all groups of farmers. Moreover, farmers can rank attributes of farming technology subjectively based on the utility they attach to each attribute. The attribute that farmers attach highest utility is selected as the most important while the one where they attach lowest utility is selected as least important. We reject the null hypothesis that “Farmers attach equal importance to all the attributes characterizing agricultural technologies when making production choices”. We conclude that farmers attach high utility to technology attributes that improves their yields and reduces the cost of production and they attach low utility to technology attributes that ensure environmental services are well maintained.

5.1.2 Technical efficiency of smallholder maize farmers in Nakuru, Kenya

There were significant differences in efficiency scores generated under COLS and CMAD. Land under maize and harvesting labour had the greatest influence of efficiency scores in the two approaches. The validity of stochastic frontier analysis method was justified by the negatively skewed residuals, consistent with production function specification. Mean efficiency score under SFA was higher than both COLS and CMAD.

The coefficient of weeding labour was negative and significant showing that farmers were using more labour and could reduce weeding labour hours without affecting the output. Sources of technical inefficiency among smallholder maize farmers included gender of the household head, challenges in soil management, value of total household assets, household decision making, practicing intercropping and total land size. The coefficient of total land size was negative and significant contrary to our priori expectation. This means that households that owned smaller land sizes were more efficient in production while those that owned large pieces of land were less efficient. We therefore reject the null hypothesis that "Smallholder maize farmers are technically efficient in maize production" because farmers had different efficiency scores and thus were not similarly efficient.

5.1.3 Relationship between efficiency and farming technology attributes

Results from ANOVA and chi-square tests identified notable differences on socio-economic characteristics of farmers across the cluster groups showing that socio-economic characteristics of farmers influence choice of farming technology attributes. Efficiency scores were not significantly different across the cluster groups showing that the choice of farming technology attributes did not influence efficiency of smallholder maize farmers.

The coefficients of all farming technology attributes were negative when regressed against SFA generated efficiency scores. Significant farming technology attributes with environmental characteristics include; decrease pests and diseases, decrease water requirements and decrease off-farm pollution. The negative relationship with efficiency signifies presence of trade-offs in the technology attributes. We therefore reject the null hypothesis that "Farmers consider both the attributes that increase yields and those that conserve the provision of environmental services. For instance, reducing pests and diseases require use of chemicals or use of IPM practices. Use of chemicals can only result in increased yields if the impact caused by pests is high. When the impact is low, use of chemicals is unsustainable and therefore farmers should resort to IPM. Also, reducing external inputs used will lead to reduced crop yields but will lead to improved environmental services.

5.2 RECOMMENDATIONS

The results show that productivity of smallholders is still low and environmental externalities ever increasing. Thus, there is need for enhanced research and development on conservation agriculture and climate smart agricultural practices. This will help farmers produce efficiently while conserving the environment.

There was less use of manure, therefore we recommend increased use organic manure as it increases soil carbon, reduces nitrate leaching and also guards against water runoff which causes soil erosion. Excessive use of chemical fertilizers cause acidification of the soils, pollutes water and depletes minerals.

The results also show that smallholder farmers use traditional farming technology that encourage high use of labour, mostly from family members. Mechanization, together with minimum tillage and zero tillage practices should be encouraged in this regard since they not only reduce labour requirements, but are also friendly to the environment since they mitigate against soil erosion and builds soil structure.

Uptake of extension services was very low which calls for increased investment in extension services to farmers by customizing it to fit the challenges they are facing. Extension services and agricultural policies should be customized for each independent farmer group based on homogeneous attribute technology choices. This can be achieved through clustering farmers based on their farming attribute preferences, thus improving production efficiency and environmental sustainability.

Farmer attributes depicted trade-offs between production efficiency and environmental services. We thus recommend that farmers should select a technology that incorporates attributes that not only improves their efficiency levels but also conserves the environment

Farmers were able to be grouped into different clusters based on their choice of main farming goals. This can be an important pathway for the government in offering extension services to farmers. It can also help in formulating better policies which are customized for different groups

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APPENDICES

Appendix 1. 1: Table 4. 19: Proportion households using labour types for different activities

Variable		Kamungei	Kiptenden	Njoro	Wendani	Total	*Chi*^{2} value
Land preparation							
	Family labor	61	73.3	31.3	33.3	52.9	8.9010**
	Hired labor	22	6.7	68.8	40	31	16.9390***
	Both family & hired	17.1	20		26.7	16.1	4.5097
Planting							
	Family labor	59	63.2	35.3	34.3	50.8	11.4971***
	Hired labor	14.1	10.5	14.7	11.4	13	0.4540
	Both family & hired	26.9	26.3	50	54.3	36.2	12.2720***
1st weeding							
	Family labor	45.5	51.4	45.2	34.3	44.4	2.2160
	Hired labor	36.4	21.6	41.9	25.7	32.2	4.5265
	Both family & hired	18.2	27	12.9	40	23.3	8.7445**
2nd weeding							
	Family labor	46.1	59.5	48.1	38.2	47.7	3.3567
	Hired labor	31.6	18.9	37	23.5	28.2	3.4130
	Both family & hired	22.4	21.6	14.8	38.2	24.1	5.2296
Basal fertilizer application							
	Family labor	80	50	65.4	58.3	67.6	5.5085
	Hired labor	15	16.7	26.9	4.2	15.7	4.9133
	Both family & hired	5	33.3	7.7	37.5	16.7	15.3277***
Top dressing							
	Family labor	33.3	100	60	58.8	58.1	1.4952
	Hired labor	66.7		30		16.1	10.5479**
	Both family & hired			10	41.2	25.8	4.7937
Spraying							
	Family labor	40	40	58.3	42.9	48.3	0.8427
	Hired labor	60	20	41.7	57.1	44.8	2.1893
	Both family & hired		40			6.9	103111**
Harvesting							
	Family labor	50.6	66.7	40	25.7	47.3	13.5049***
	Hired labor	16.9	10.3	14.3	14.3	14.5	0.9209
	Both family & hired	32.5	23.1	45.7	60	38.2	12.7365***

Appendix 1. 2: Table 4. 20: Proportion of households facing different challenges in maize production

Variable	Kamungei	Kiptenden	Njoro	Wendani	Total
Production					
Attack by pests and diseases	47	62.5	57.4	32.1	48.6
Drought	12	17.5	11.1	18.9	14.2
Low maize yields	11	5	3.7	18.9	10.1
Unpredictable climatic conditions	7		22.2	9.4	9.7
Too much rainfall	8	5	1.9	7.5	6.1
High production costs	7		1.9	13.2	6.1
Financial constraints	5	2.5	1.9		2.8
Lack of training/extension information	1	7.5			1.6
Poor quality seeds	2				0.8
Input market					
High input prices	70.3	50	87.5	55.6	67.6
Late delivery of subsidized fertilizers	21.6	21.4	4.2	18.5	16.7
Poor quality seeds	5.4	28.6	4.2	18.5	11.8
Lack of enough fertilizer/manure	2.7		4.2	3.7	2.9
Lack of training/extension information				3.7	1
Soil management					
Soil erosion		50		70.6	65
Declining soil fertility	100	50		23.5	30
Lack of training/extension information				5.9	5
Maize Marketing					
Poor maize prices	52.6	68.4	66.7	66.7	60.9
Exploitation by middlemen	24.6	10.5	23.3	22.2	21.8
Lack of ready maize markets	12.3	21.1	6.7		9.8
Poor road network	5.3		3.3	7.4	4.5
High transport cost	5.3			3.7	3
Fertilizer/ Manure					
Lack of enough fertilizer/manure	42.9	100	16.7	40	42.3
High Fertilizer prices	42.9		16.7	50	34.6
Late delivery of subsidized fertilizers	14.3		66.7	10	23.1

Appendix 1. 3: Table 4. 21: Tukey's test for household's socio-economic characteristics

Variable	Type	2 vs 1	3 vs 1	4 vs 1	3 vs 2	4 vs 2	4 vs 3
Efficiency scores	**Contrast**	-0.015	0.073	0.011	0.087	0.025	-0.062
	p-value	0.976	0.399	0.994	0.264	0.932	0.625
Total Maize harvested	**Contrast**	-140.11	57.89	-341.14	198.00	-201.03	-399.03
	p-value	0.866	0.995	0.343	0.866	0.787	0.462
Age of the Household head	**Contrast**	-0.015	8.131	-0.854	8.145	-0.840	-8.985
	p-value	1	0.072	0.99	0.088	0.992	0.072
Education level of household head	**Contrast**	0.394	-0.879	3.251	-1.273	2.857	4.130
	p-value	0.953	0.825	0.001	0.627	0.009	0.002
Household size	**Contrast**	-0.359	0.641	-1.093	1.000	-0.735	-1.735
	p-value	0.862	0.732	0.152	0.412	0.533	0.061
Land preparation cost	**Contrast**	-508.3	84.3	320.2	592.6	828.6	236
	p-value	*-0.97*	*0.2*	*0.64*	*1.24*	*1.55*	*0.53*
Basal fertilizer	**Contrast**	-10.59	-14.47	-19.63	-3.88	-9.03	-5.16
	p-value	0.582	0.561	0.17	0.986	0.797	0.975
Land size under maize	**Contrast**	-0.088	-0.241	-0.363	-0.153	-0.275	-0.122
	p-value	0.933	0.625	0.132	0.882	0.399	0.947
Total Land size	**Contrast**	-0.035	-0.128	-0.371	-0.093	-0.336	-0.243
	p-value	0.993	0.888	0.061	0.957	0.137	0.606
Total seed quantity	**Contrast**	-1.801	-3.747	-4.463	-1.945	-2.662	-0.716
	p-value	0.679	0.322	0.071	0.828	0.508	0.991
Chemical fertilizer	**Contrast**	-16.974	-0.4369	0.6044	16.537	17.5782	1.0413
	p-value	*0.486*	*1*	*1*	*0.43*	*0.469*	*1*
Total assets	**Contrast**	-1263.3	1545.9	-2034.8	2809.2	-771.5	-3580.7
	p-value	0.871	0.903	0.698	0.628	0.98	0.48

Appendix 1. 4: Table 4. 22: Tukey's test for farming technology goals

Technology goals	Variable	Cluster group					
		2 vs 1	3 vs 1	4 vs 1	3 vs 2	4 vs 2	4 vs 3
Decreasing pests and diseases	**Contrast**	0.0333	-0.1704	-0.4686	-0.2036	-0.5019	-0.2983
	P-Value	*0.883*	*0.032*	*0.000*	*0.009*	*0.000*	*0.000*
Decreasing water requirements	**Contrast**	-0.1771	-0.4880	0.1815	-0.3109	0.3586	0.6695
	P-Value	*0.001*	*0.000*	*0.005*	*0.000*	*0.000*	*0.000*
Decreasing off-farm pollution	**Contrast**	0.3885	0.3776	-0.1045	-0.0109	-0.4930	-0.4821
	P-Value	*0.000*	*0.000*	*0.236*	*0.999*	*0.000*	*0.000*
Increasing on-farm soil fertility	**Contrast**	0.2710	0.1638	0.0436	-0.1073	-0.2274	-0.1201
	P-Value	*0.000*	*0.083*	*0.869*	*0.434*	*0.000*	*0.391*
Decreasing on-farm soil erosion	**Contrast**	0.2196	0.1905	-0.2335	-0.0291	-0.4532	-0.4241
	P-Value	*0.000*	*0.029*	*0.000*	*0.976*	*0.000*	*0.000*
decreasing external inputs used	**Contrast**	-0.2436	-0.2072	-0.1620	0.0364	0.0816	0.0452
	P-Value	*0.000*	*0.003*	*0.007*	*0.935*	*0.398*	*0.902*
Increasing resistance to drought	**Contrast**	0.0389	-0.4411	0.4130	-0.4800	0.3741	0.8541
	P-Value	*0.893*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Decreasing labour requirements	**Contrast**	-0.2940	0.1660	-0.1227	0.4600	0.1713	-0.2887
	P-Value	*0.000*	*0.096*	*0.166*	*0.000*	*0.033*	*0.002*
Increasing yields	**Contrast**	-0.0041	0.3904	0.3445	0.3945	0.3486	-0.0459
	P-Value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.935*
Reducing cost of production	**Contrast**	-0.2534	0.1884	-0.0885	0.4418	0.1649	-0.2769
	P-Value	*0.000*	*0.005*	*0.226*	*0.000*	*0.005*	*0.000*
Decreasing extension requirements	**Contrast**	0.0209	-0.1700	0.1973	-0.1909	0.1764	0.3673
	P-Value	*0.974*	*0.055*	*0.003*	*0.032*	*0.015*	*0.000*

Appendix 1. 5: Table 23: Sampling adequacy (KMO) and Bartlett's test of sphericity

Determinant of the correlation matrix	0.018
Bartlett test of sphericity	681.407***
H0: variables are not intercorrelated	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)	0.863

Appendix 2. 1: Letter of Consent

Informed consent for the participation in an academic research study

Department of Agricultural Economics, Extension and Rural development

Subjective preferences for agricultural technology attributes and their influence on technical efficiency of smallholder maize farmers in Nakuru County, Kenya

Research conducted by Zachary Simba Mbaka

Cell: +254728060720 / +27817337200

Email: mbakazachary@gmail.com

Dear respondent,

You are invited to participate in a research study conducted by Zachary Simba, a Masters student from the Department of Agricultural Economics, Extension and Rural Development at the University of Pretoria. The purpose of the study is to investigate the relationship between the gains in technical efficiency and environmental services provision among smallholder maize farmers.

Participation in this survey involves responding the questions that will be asked and this should take less than an hour. This study involves an **anonymous** survey. Although your name will appear on the questionnaire, the information you provide will be treated strictly as **confidential.**

- Your participation in this survey is very important to us and the study. However, this is a **voluntary** exercise and you may choose not to participate and you may stop participating at any time without negative consequences.
- Please respond to the questions as honestly as possible.
- The results of this study are solely for academic purposes as well as influencing policies that impact on agriculture and may be published in academic journals. If interested, we will provide you with a summary of the results of this study.
- Please contact my supervisor, Professor Eric D. Mungatana on Tel: +27124203253 (email) eric.mungatana@up.ac.za if you have any queries or comments about the study

Please sign this form to indicate that you understand the information provided above and that you are willing to participate in this study on a voluntary basis.

Respondent signature…………………………………

Appendix 3. 1: Questionnaire

Subjective preferences for agricultural technology attributes and their influence on technical efficiency of smallholder maize farmers in Nakuru County, Kenya

SECTION A: Identification Details

Respondent____

Village : ____

Section A1 : Demographic characteristics & Land section

1.0 What is your total land holding lsize________ Unit_______ *(**1**=Hectares **2**=Acres **3**=Meters squared)*

1.2 Kindly fill in the following information in the table below

Relationship of respondent to **HH**	**Primary** occupation of **HH**	Gender of HH	Highest level of education of **HH**	**HH** size	Who makes decisions on the farm?	**Information on land**					
						Tenure status of land on which you planted maize in last cropping season	(If **rented-in** tenure) total rent paid last year	**Tillage method** practiced in the last cropping season	**Cropping system** practiced	Do you practice crop rotation? ***1**= Yes **2**= No*	Soil conservation measure practiced in your field in the last one season

Relationship to the head/ Farm decisions **1**. Head of household **2**. Spouse **3**. Children 4. Others	**Main occupation** **1**. Farmer; **2**. Agriculture(farm) laborer; **3**. Permanent employment **4**. Casual laborer 5. Other specify	**Tillage method** 1=conventional method 2=Zero tillage 3= Minimum Tillage	**Cropping system** **1**. Mono-cropping; **2**. Mixed intercropping; **3**. Row intercropping **4**. Strip cropping; **5**. Relay cropping	**Conservation measures** 1. Terracin 2. Mulching/ cover cropping	**3** Zero tillage **4**.Minimum tillage **5** Crop rotation **6** Afforestation **7** Agro forestry	**8** Use of farm yard manure **9** Fallow **10** Composting manure 11 Other specify 12 None

Section A2: Maize production

2.1 Cropping activities for maize for 2017/2018 CROPPING SEASON

Season	**Land size** *(please include all the land used in growing maize)* **1**=Hectares **2**=Acres **3**=Meters squared		**Main system of watering used** 1=Rain fed 2=Irrigated(pumped) 3=Irrigated (gravity) 4=Other specify_	Hired land prep cost (Ksh)	Quantity of seed used		Fertilizer used			Harvest	
	Qty	Unit			Qty	Unit	Type	Qty	Unit	Qty	Unit

Unit codes:	6=Gallons	**Fertilizer codes:**	4=SSP
1=50 kg bag	7=Grams	0=None	5=NPK
2=KGS	8=Wheelbarrow	1=DAP	6=Manure
3=Litre	9=Cart	2=MAP	7=Foliar feeds
4=25kg bag	10=Canter	3=TSP	8=Other specify____________
5=10kg Bag			

Maize inputs

What **CROP INPUTS** did you purchase/hire specifically for maize production in the last season? *(Select the inputs and answer the questions that follow)*

Input type		Quantity of input bought/used	Unit	Did you receive any subsidy for the input	Quantity of subsidy received	Unit (codes)	Source of subsidy
1	Pesticide						
2	Insecticide						
3	Herbicide						
4	Fungicide						
5	Sprayer						
6	Transport						
7	Fertilizer						
8	Seed						

Unit codes: 1=50 kg bag 2=KGS	3=Litre 4=25kg bag 5=10kg Bag	6=Gallons 7=Grams	8=Wheelbarrow 9=Cart 10=Canter	**Subsidy Sources** 1=Government 2=NGO's	3=Other Specify

2.3 Labor costs for maize production

Please indicate the **activities** performed during the last year on **maize**

Activity		Number of people worked (**both family & Hired**)	**Total** number of **days worked**	Average working hours **per day**	**Labor type** 1= Family labor 2= hired labor 3=Both family & hired	***(If labor=3),*** which labor type was most important?	***(If labor=3)*** On a scale of 1-5, rank the contribution of the labor that was most important 1=least 5=all
1	Land preparation						
2	Planting						
3	1st weeding						
4	2nd weeding						
5	Basal fertilizer application						
6	Top dressing						
7	Spraying						
8	Harvesting						
9	Other specify__________						

Section A3: Extension

Q3.1 Did you **receive** any extension advice on maize? *(1=Yes 0=No)* ____________________

If no to Q3.1, proceed to Q4.1

Q3.2. How many times do they visit you per year?

Q3.3. Did you pay for the extension advice? *(1=Yes 0=No)* ____________________

If no to Q3.3, proceed to Q3.5

Q3.4. How much did you pay in the last cropping season? ___________________

Q3.5. What is your level of satisfaction with the performance of this extension source? ____________________

1= Satisfied 2=Neutral 3=Dissatisfied

<u>Section A4: Challenges in Maize production</u>

4.1 Do you face any challenges regarding Maize production? *(**1**=Yes, **2**=No)* ___________

(If yes to question Q4.1), proceed to question Q4.2

4.2. What challenges do you face in Maize production? (***Write down the challenges in the table***)

Challenges

Challenge Category		**Challenges**
Production	1	
	2	
Input market	1	
	2	
Soil management	1	
	2	
Maize Marketing	1	
	2	
Own farm pasture	1	
	2	
Own farm Biomas	1	
	2	
Fertilizer/ Manure	1	
	2	
Energy Management	1	
	2	

<u>Section A5: Household assets</u> (**PROMPT** for each item as listed below)

At present, how much/many of the following does this household own that are **usable/repairable**?

Agricultural asset		Quantity Owned now	Purchase price/ unit	usable lifetime of the asset in years	When did you buy the asset
Agricultural equipment					
1	Hoe				
2	Machete				
3	Weeder				
4	Harrow or tiller				
5	Spray pump				
6	Sprayer				
7	Sheller				
8	Animal traction				
9	Harvester machine				
10	Stores				
Tractor and tractor equipment					
11	Tractor				
12	Ploughs for tractor				
13	Plough				
14	Planter				
Other transport equipment					
15	Bicycle				
16	Car				
17	Truck				
Other assets					
18	Water pan				
19	Irrigation equipment				
20	Borehole				
21	Generator/diesel pumps				
22	Other specify				

SECTION B: BEST WORST SCALING EXPERIMENT

Before starting the ranking exercise, we will discuss with you the different possible impacts that a change in the way you grow your maize may have on your farm and your farm organization.

Enumerator: *Take some time to describe all the attributes, and make sure you present these attributes the same way to all farmers, you are interviewing.*

b1) Ranking 1

If you agree, I will now ask you to think about new ways of growing maize (think of a new technique, a new practice, or a new machinery). For each of these (un-named) new way of growing maize, I will give you a list of the impacts on your maize crop if you adopt it.

Please tell me which impact you would consider as the most important to help you decide to adopt this new practice/technique.

Then tell me, which impact you would consider as the least important to help you decided to change in favour of that technique

Most Important	Effects of the cropping system	Least Important
	Decrease pests and diseases	
	Reduce extension requirement	
	Decrease labor use	
	Increase on-farm soil fertility	
	Increase crop yield	

b2) Ranking 2

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease water requirement	
	Decrease on-farm soil erosion	
	Increase on-farm soil fertility	
	Decrease external input used e.g Fertilizer or diesel	
	Reduce extension requirement throughout the cropping cycle	

B3) Ranking 3

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease off-farm pollution	
	Decrease on-farm soil erosion	
	Increase resistance to drought	
	Increase crop yield	
	Increase on-farm soil fertility	

B4) Ranking 4

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease cost of production	
	Reduce extension requirement throughout the cropping cycle	
	Decrease pests and diseases	
	Decrease off-farm pollution	
	Decrease on-farm soil erosion	

B5) Ranking 5

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease labor use	
	Decrease cost of production	
	Increase on-farm soil fertility	
	Decrease off-farm pollution	
	Decrease water requirement	

B6) Ranking 6

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease cost of production	
	Increase crop yield	
	Decrease external input used e.g Fertilizer or diesel	
	Decrease on-farm soil erosion	
	Decrease labor use	

B7) Ranking 7

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Increase resistance to drought	
	Reduce extension requirement throughout the cropping cycle	
	Decrease cost of production	
	Increase crop yield	
	Decrease water requirement	

B8) Ranking 8

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Decrease on-farm soil erosion	
	Decrease water requirement	
	Decrease pests and diseases	
	Decrease labor use	
	Increase resistance to drought	

B9) Ranking 9

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Increase crop yield	
	Decrease water requirement	
	Decrease pests and diseases	
	Decrease external input used e.g Fertilizer or diesel	
	Decrease off-farm pollution	

B10) Ranking 10

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Reduce extension requirement throughout the cropping cycle	
	Decrease off-farm pollution	
	Decrease external input used e.g Fertilizer or diesel	
	Increase resistance to drought	
	Decrease labor use	

b11) Ranking 11

We will now repeat the same exercise with another technique that would have another combination of impact. (Some impact may be the same, but the combination of impacts is not the same)

Most Important	Effects of the cropping system	Least Important
	Increase resistance to drought	
	Decrease external input used e.g Fertilizer or diesel	
	Decrease pests and diseases	
	Increase on-farm soil fertility	
	Decrease cost of production	