Preferences for sustainable agriculture attributes and technical efficiency among family maize farmers in Lufwanyama district, Zambia

By

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Thesis submitted in partial fulfilment of the requirements for the degree of

Master of Philosophy in Agricultural Economics

Department Agricultural Economics, Extension and Rural Development

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DECLARATION OF ORIGINALITY

I, Mwamba Kapambwe, declare that the dissertation, **"**Preferences for sustainable agriculture attributes and technical efficiency among family maize farmers in Lufwanyama District, Zambia", hereby submitted in partial fulfilment of the requirements for the degree MPhil Agricultural Economics at the University of Pretoria has not been submitted by me for any other degree at this or any other institution of higher learning. I also declare that this is my own work and ideas borrowed from other sources are fully referenced.

Signature: Student Number: 16360487

Approved by:

Name: Prof. E.D Mungatana

Signature: .

Date: June 10, 2020

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DEDICATION

To Kisa

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Preferences for Sustainable Agriculture Attributes and Technical Efficiency among Family Maize Farmers in Lufwanyama District, Zambia

By

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ABSTRACT

This study investigated the relationship between farmer preferences for attributes of sustainable agricultural practices and their technical efficiency, in order to inform and improve policy targeting and programme packaging with regard to promoting adoption of the said sustainable agricultural practices.

Farmer preferences for the attributes of eleven sustainable agricultural practices were elicited in a best-worst experiment from a random sample of one hundred and sixty-three family farmers. Their responses were analysed to determine preferences using the best-worst scaling approach. An assessment of preference heterogeneity was made using agglomerative hierarchical clustering. Additionally, using the stochastic frontier approach, maize production input and output data were collected and analysed to estimate the farmers' technical efficiency. Finally, the relationship between the technical efficiency scores and cluster group membership was investigated, using t-tests and the analysis-of-variance method.

The best-worst scaling results ranked eleven attributes in order of the most preferred to the least preferred. They ranked as follows: increased crop yield; decrease in pests and diseases; increase in drought resistance; increased soil fertility; decreased production costs; decreased on-farm soil erosion; decrease in external inputs used; decreased water requirements; decreased labour use and decreased off-farm pollution as well as a reduction in extension requirements. Cluster analysis gave rise to five preference clusters: cost minimising; crop yield-maximizing; input-

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minimising, environmental-resilience-maximisers and the environmentally-conscious cluster. The mean technical efficiency of the sample was 50.9%. Efficiency was modelled on farmer contextual variables and cluster membership. The gender of the household head, practice of soil conservation and membership of the yield-maximising cluster were found to be significant in explaining efficiency. Relative to the environmental-resilience-maximizing cluster, the yield-maximizing cluster farmers were 9.8% more efficient. The result was suggestive of a relationship between farmer preferences and technical efficiency. However, an analysis of variance test between technical efficiency scores and cluster membership failed to reject the null hypothesis of equal mean efficiency across the clusters. Therefore, the data demonstrated no substantial relationship between the farmer preferences for sustainable agricultural practices and their technical efficiency.

Keywords

Best-worst scaling, farmer preferences, Lufwanyama district, production function, stochastic frontier analysis, sustainable agricultural practices, technical efficiency, Zambia

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LIST OF ABBREVIATIONS AND ACRONYMS

AHC	Agglomerative Hierarchical Clustering
ANOVA	Analysis of Variance
BWS	Best-worst scaling
CA	Conservation agriculture
CD	Cobb-Douglas
CMAD	Corrected Mean Absolute Deviation
COLS	Corrected Ordinary Least Squares
CSA	Climate smart agriculture
CV	Coefficient of variation
DEA	Data Envelopment Analysis
FAW	Fall armyworms
FGD	Focus group discussion
GDP	Gross Domestic Product
GHG	Greenhouse gases
IO	Input-output
LCM	Latent class model
LR	Likelihood ratio
MLE	Maximum likelihood estimator/estimation
MNL	Multinomial logit
OBWS	Object best-worst scaling
OLS	Ordinary least squares
OO	Output-oriented
PCA	Principal-components analysis
RPL	Random parameter logit
SAP	Sustainable agricultural practices
SFA	Stochastic frontier approach
SSA	Sub-Saharan Africa
ZNFU	Zambia National Farmers Union

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Chapter 1. INTRODUCTION

1.1 Background

Smallholder farmers and family farmers are responsible for producing between 50-80% of the world's food and between 30 and 34% of world food supply (the difference is mostly used up in their own consumption). However, this same category of farmers constitute the larger part of the world's poorest and most food-insecure (Collier and Dercon, 2014; FAO, 2014; Bhatkal, Samman and Stuart, 2015; Samberg *et al.*, 2016; Ricciardi *et al.*, 2018; Dyck and Silvestre, 2019).

Although the terms ‘smallholder’ and ‘family farming’ are often used interchangeably in literature, they are not the same (Wolfenson, 2013; Garner and de la O Campos, 2014; Bongers *et al.*, 2015; Graeub *et al.*, 2016; Lowder, Skoet and Raney, 2016; Samberg, 2016). There is a multiplicity of ways to define smallholder farming, including their assets and productive resources, nature and scale of their activities, land tenure, share of family labour and so on (Bongers *et al.*, 2015; Samberg, 2016). This implies that the definition of smallholder farmer will vary from context to context. However, the most widely used definition is that of farmers with farms less than 2 ha (Wolfenson, 2013; Lowder, Skoet and Raney, 2016). On the other hand, family farming has not so much been defined by land holding, but by family ownership of the farm which is often characterised by the heavy reliance on family labour (Garner and de la O Campos, 2014; Lowder, Skoet and Raney, 2016). It then follows that family farming is a broader concept than smallholder farming is. For instance, Lowder (2016) indicated that in excess of 90% of the world's farms, estimated to be 570 million, may be classified as family farms, whereas 84% of the world's farms are less than two hectares, and are thus termed smallholder farms. While 12% of the world’s agricultural land is classified as smallholder farms, 75% of this is family farms (Graeub *et al.*, 2016). For the purpose of this study, the terms ‘farmers’ or ‘smallholder farmers’ are used interchangeably and refer to family farmers.

Raising the productivity of smallholder agriculture is key in improving food security, rural household incomes and in achieving better environmental sustainability amongst farmers, because the smallholder farmers are the most food insecure and interact the most with threatened landscapes (Robertson and Swinton, 2005; Bhatkal, Samman and Stuart, 2015; Lowder, Skoet and Raney, 2016; Samberg *et al.*, 2016). Farmer livelihood exerts pressure on the use of environmental resources which can compromise on the ability of the environment to meet the needs of future generations if this is done unsustainably. This brings smallholder and broadly, family farmers, into focus in the fight against global poverty as well as the

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attainment of a sustainable environment (Rosset, 1999; IFAD and UNEP, 2013; Jug *et al.*, 2018).

In Sub-Saharan Africa (SSA), although the majority of rural households are engaged in agriculture, the region has a food gap due to low agricultural productivity (Mozumdar, 2012; Tangermann, 2016). Moreover, the number of food insecure households has been growing (van Ittersum *et al.*, 2016; FAO *et al.*, 2018; Azzarri and Signorelli, 2020). The demand for cereals is expected to increase by 300% by 2050, due to a projected population increase of 250%. If food production does not increase, the region will need to intensify food importation to meet this increasing demand (van Ittersum *et al.* 2016). For Zambia, the projected population growth for 2050, relative to 2010, stood at 325%, whereas the projected growth in cereal demand was 519%. Although the utilisation of cropland area was 3.5 Mha representing 14% of total arable land, meeting the 2050 demand will have to go beyond bridging the yield gap (van Ittersum *et al.* 2016). The mismatch in growth rates between population and demand for food inherently exerts pressure on the environment, as raising production will involve expanding the cropland.

Climate change has further constrained the growth in agricultural productivity. A loss of up to 20-30% of global yield trends in cereals has been attributed to climate change. Rain fed maize production is the most vulnerable with an estimated reduction in yield ranging from 18% to 22% across SSA (Lobell and Gourdji, 2012; AGRA, 2014; Zinyengere, Crespo and Hachigonta, 2014).

In Zambia, extreme weather conditions threatened agricultural development; extreme temperatures, droughts and floods have caused huge losses in the agricultural sector. The cost of climate change in Zambia between 2007 and 2016 has been estimated at US $13.8 billion (World Bank, 2018a). These climate change effects have restrained agriculture's contribution to GDP growth. Agriculture, therefore, is affected by climate change and is also key in mitigating climate change by curbing greenhouse gases (GHG) emissions through carbon sequestration, provision of carbon sinks, and production of biofuels to replace fossil fuels (Al-kaisi, 2008; Erias *et al.*, 2016).

Studies on the Green Revolution in Asia and Latin America show that increasing productivity of the smallholder farmers came at the cost of deteriorating environmental performance (IFPRI, 2008; National Research Council, 2010). This led to increased promotion of more environmentally friendly agricultural practices in attempts to raise productivity of smallholder farmers with minimised adverse effects on the environment (IFPRI, 2008; National Research Council, 2010; IFAD and UNEP, 2013; SDSN, 2013; Jayne *et al.*, 2019; Rusere *et al.*, 2019; Thomson *et al.*, 2019). In Zambia, increase of agricultural production was achieved largely by increasing the cropland. This has had a huge impact on the environment as the practice of cut and burn shifting cultivation, known as the Chitemene system, has caused a lot of

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deforestation and has increased contribution to atmospheric carbon content. Deforestation has exacerbated soil erosion, reduced water retention, and soil fertility (World Bank, 2018b). Furthermore, the excessive use of external inputs has contributed to the pollution of water, poisoning of farmworkers, and declining soil quality (National Research Council, 2010).

Many practices have been advised to increase agricultural productivity and improve environmental sustainability. This is motivated by the fact that climate change and agriculture have a two-way relationship; environmental degradation hampers the productivity and growth of agriculture and agricultural activity contributes to climate change (Ncube *et al.*, 2016; Kassam, Friedrich and Derpsch, 2018; Djurfeldt *et al.*, 2019; Singh, Pratap and Vaibhav, 2020). These range from ecological agriculture, climate-smart agriculture (CSA), sustainable intensification (SI) and ecological intensification to conservation agriculture (CA), all of which will henceforth be referred to as sustainable agriculture practices (SAP) (Blignaut *et al.*, 2014; Khatri-Chhetri *et al.*, 2016; Mutyasira, 2017; Pretty, 2017; Pretty *et al.*, 2018; Nyanga *et al.*, 2020). Investigation into the effects of these environmentally friendly agricultural practices on productivity has shown mixed results; Pittelkow *et al.* (2014) after analysing 610 studies comparing CA to conventional practices, found that in most cases CA showed lower productivity, suggesting a trade-off between productivity and environmental performance. Mazvimavi *et al.* (2012) nonetheless found that implementing conservation agriculture raised the productivity of smallholder maize farmers in Zimbabwe by up to 39%, demonstrating the complementarity between productivity and environmental performance. Likewise, Kabamba & Muimba-Kankolongo (2009) found gains in maize yields for conservation farming adopters of over 100% improvement, over conventional agriculture, from a sample of 252 farm households collected in Kapiri-Mposhi. This was consistent with Pretty's (2006) findings from a meta-analysis of 286 studies, which measured the effect of smallholder CA interventions that found over 100% improvement. Nkala *et al.* (2011) also discovered that conservation agriculture raised the productivity of smallholder farmers and indirectly, their incomes, in Mozambique, suggesting a positive relationship between productivity and environmental performance. Mango *et al.* (2017) on the other hand, reported that adoption of conservation agriculture had no impact on yields and food security in Zimbabwe and Malawi. The findings of Thierfelder and Wall (2012) from a long term experiment investigating the effect of CA on soil quality and productivity in contrasting agro-ecological environments in Zimbabwe showed that CA did not affect maize productivity until up to four planting seasons when it was able to raise productivity relative to conventional agriculture.

Torres *et al.*, (2019) in a study in Northwest Mexico, investigated farmers' preference for mitigation and adaptation actions against climate change, to determine whether these preferences affected their technical efficiency. Using a stochastic frontier analysis (SFA), they estimated a mean efficiency of 57% and the farmers were grouped in four clusters, based on

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their preferences. Farmers that showed more preference for strategies for climate change mitigation that prioritised the environment, were found to perform less efficiently than those who prioritised other measures.

1.2 Problem Statement

Several sustainable agricultural practices (SAP) have, for decades, been promoted amongst smallholder and family farmers in Zambia because of their various attributes (Arslan *et al.*, 2015; Mbata, Chapoto and Hachambwa, 2016; World Bank, 2018b; Kidane *et al.*, 2019). These attributes include better water use efficiency, lower cost of production, improved soil fertility, improved yields, decreased pests and diseases, decreased soil erosion, soil micro-biodiversity being maintained, lower use of external inputs, lower use of external fertiliser, and improved on-farm and off-farm environmental sustainability. The constraints farmers are faced with in production have been exacerbated by climate change effects and these have driven farmers to develop preferences over SAP, based on their attributes in an attempt to intensify production in a sustainable manner (Mutyasira, 2017; Torres *et al.*, 2019).

Many studies have been undertaken to investigate aspects of SAP, including adoption, dis-adoption, as well as farmer perceptions and preferences for attributes of SAP (Haggblade and Tembo, 2003; Arslan *et al.*, 2013; Wahida, 2015; Dumbrell, Kragt and Gibson, 2016; Khatri-Chhetri *et al.*, 2016; Mbata, Chapoto and Hachambwa, 2016; Suprehatin, 2016). Many investigations into farmer preferences for the SAP attributes have used best-worst scaling (BWS) and preference heterogeneity employing cluster analysis methods, including agglomerative hierarchical clustering (AHC) (Serrano-Megias and Lopez-Nicolas, 2006; Tarfasa *et al.*, 2018). Nonetheless, there is a dearth of studies investigating the relationship between the farmer preferences for attributes of SAP and their technical efficiency. It is, therefore, the aim of this study to investigate the relationship between farmer preferences for attributes of SAP and technical efficiency with application to the Lufwanyama district of Zambia.

Lufwanyama district is a typical farming district with a low concentration of commercial farming with the majority of the residents depending on smallholder agriculture for livelihood. It made for a good study area as the livelihood of the majority of the residents was typical of the majority of the farming households of Zambia: dependant on small scale household production with little or no excess production to supply to the market. It was also affected by recent adverse events of drought spells and fall armyworms (FAW) infestations the country has experienced in the recent past. Further, the district has the typical agricultural extension program that the government runs in the different districts across the country which are

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instrumental in offering extension advise to the farmers and the distribution of fertiliser and input support (FISP). These factors made Lufwanyama district a good study area in that the finding could be easily generalisable.

1.3 Objectives and Hypotheses

1.3.1 General objective

To investigate the relationship between preferences for attributes of SAP and technical efficiency of maize family farmers in Lufwanyama district of Zambia.

1.3.2 Specific objectives

i. To investigate farmer preferences for SAP attributes
ii. To investigate the heterogeneity in preferences
iii. To estimate the technical efficiency of the farmers
iv. To investigate the relationship between farmer preferences for SAP attributes and relative technical efficiency scores.

1.4 Study Contribution

The contribution made by this study is that it fills a knowledge gap identified through a review of relevant literature. It examines the relationship between farmers' preferences for those attributes that contribute to sustainable agricultural practices and their technical efficiencies. This relationship has not been previously researched and therefore its unique contribution is to offer findings that could improve targeting of related policies and programmes aimed at promoting the adoption of SAP amongst family farmers.

1.5 Scope of the Study

The study was limited to Lufwanyama district and interviews were done just amongst family farmers growing rain-fed maize in the study area. The study was limited to rain-fed maize production, due to the lack of records for irrigated maize harvested in winter and sold mostly as fresh maize.

1.6 The Organisation of the Study

The study is organised in five chapters**.** Chapter 1 provided an introduction, covering the background and context for the study, the problem statement, the objectives and hypotheses

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as well as the contribution and scope of the study, its organisation and an overview of the literature researched. Chapter 2 presents a review of the literature on the theoretical and empirical background of choice modelling using the best-worst scaling approach and heterogeneity analysis using agglomerative hierarchical clustering. Chapter 2 additionally examines the theoretical and empirical reviews of technical efficiency analysis that use the SFA. Chapter 3 deals with the research methods and procedures, including the study area; the study design, including obtaining ethical permission, sampling and the data collection process as well as the data analysis. Chapter 4 provides the results and discussions thereof. Finally, Chapter 5 offers the policy implications and policy recommendations, the study limitations and recommendations for further research.

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Chapter 2. LITERATURE REVIEW

2.1 Introduction

The environmental performance of farms and their technical efficiency is largely affected by the activities they conduct and the technologies they use (OECD, 2008; Samberg *et al.*, 2016). Farmer's perceptions of and preferences for the available practices, and the constraints and risks associated with the attributes of these practices are influenced by a tendency to prioritise practices based on their technical efficiency. Thus, establishing farmers' preferences for attributes of sustainable agricultural practices is important in understanding why these are, or are not, adopted.

Many welfare benefits accrue to raising family farmers' technical efficiency sustainably especially as the effects of climate change increase their livelihood risks (Danso-Abbeam and Baiyegunhi, 2020). Raising technical efficiency has been the target for agricultural development policy in Zambia for the many pathways it can increase the welfare of the farmers including higher output, higher income, improved food security and lower poverty levels. For the government, achieving this objective is a return on its increasing budget expenditure on agriculture and anti-poverty programs (Kodamaya, 2011). The lack of safety nets in SSA has meant that climate change has increased livelihood risks posed on smallholder farmers who depend on harvesting natural resources and rainfed agriculture. Stakeholders have for this reason promoted SAP as one of the adaptation strategies to adapt to these changes. For example, Zambia National Farmers Union (ZNFU) started a project in 1995 to promote the practice of conservation farming which was adopted into national agriculture policy in 2004 (Harvey *et al.*, 2014; Alfani *et al.*, 2019). Adoption of agricultural practices is influenced by the knowledge farmers have, their perception of the risks and returns associated with the technologies and a host of other factors (Aniah, Kaunza-nu-dem and Ayembilla, 2019). Since there are several benefits associated with SAP, understanding the farmer preferences over these and what kind of relationship exist between farmers' technical efficiency and their SAP preferences will not only improve policymaking but also contribute to achieving better livelihood resilience through the pathway of improved adoption of SAP (Lewis, Monem and Impiglia, 2018).

There is a rich body of knowledge on the measurement of various kinds of efficiency, including technical efficiency of farming units. It was of interest to this study to review the knowledge of preference-analysis using the BWS approach, and to similarly review knowledge of technical efficiency using the SFA. The chapter further reviews the literature on heterogeneity analysis using the AHC approach. Therefore, this chapter presents theoretical reviews of the BWS approach; and heterogeneity analysis using hierarchical clustering is presented in Section 2.2.

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Their empirical reviews are presented in Section 2.3. While the theoretical review provides the background of preference analysis using the BWS, the empirical review shows how farmer preferences are analysed using the BWS and cluster analysis. The theoretical and empirical reviews of technical efficiency studies are presented in Section 2.4 and Section 2.5, respectively. The theoretical review examines and discusses the theoretical underpinnings of technical efficiency analysis and its approaches, whereas the empirical review investigates and discusses the determinants and methods of the study, for technical efficiency. The intent is to inform the methods for this study. The chapter concludes in Section 2.6.

2.2 Theoretical Review of Best-Worst Scaling

There are two broad categories of techniques for eliciting respondents' preferences**:** the ones based on ratings and the ones based on choices. However, the rating techniques suffer from several biases (Jaeger and Cardello, 2009; Kiritchenko and Mohammad, 2017; Pinto *et al.*, 2019).

Firstly, when the respondent rates each object independently of other objects, the ratings do not force the respondent to make trade-offs. This may result in positive ratings for all of the objects (acquiescence bias). In that case, it is not possible to identify which object is preferred.

Secondly, the nature of the scale allows the respondents to select the middle scale when not sure (mid-point bias), thereby reducing the discriminatory ability of the ratings (Flynn and Marley, 2014; Louviere, Flynn and Marley, 2015).

Thirdly, the technique assumes equidistance between the levels of a scale of intervals, which may not be so practical. For instance, it is not easy to tell how much more one object is preferred over another if one is rated ‘important’ and another ‘very important’ (Lantz, 2013; Orme, 2018).

Fourthly, the scales are susceptible to cultural biases as people may interpret them in the context of their cultures. Case in point is how certain numbers are perceived as “lucky numbers” in some cultures and others as “unlucky numbers”. This implies that if you are asking respondents to pick objects from a list, you may get objects in the position perceived as lucky numbers selected more often than those on unlucky numbers’ position. For example, 6 and 8 are considered lucky numbers in China, while 4 and 13 are considered unlucky numbers in China and the West, respectively (Huang and Teng, 2010; Shum, Sun and Ye, 2014). This would make results across cultures, such as from different countries difficult to interpret and incomparable (Baumgartner and Steenkamp, 2001).

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Finally, since the ratings are personal, they are quite limited in generalizability to other individuals. These personal biases are reflected in the nay-sayers' tendency to give unfavourable ratings whereas yea-sayers tend to give favourable ratings (Kim *et al.*, 2019).

Shortcomings of the rating scales are overcome in the second of the two techniques above, that is, the choice-based techniques.

The first class of choice-based techniques developed was the pairwise comparisons introduced by Thurstone (1927). This involved presenting pairs of objects in which the respondent had to pick the best from the pair. It was limited in the number of attributes to be taken into consideration in the comparison. The method was then developed to include more objects and asking the respondent to pick the best or the worst from the set (Louviere and Woodworth, 1983). Louviere (1988) presented a way of eliciting preferences from respondents by choosing their best and worst options from a series of choice sets known as the Best-Worst Scaling method. This method forces the respondents to discriminate from amongst the choices; thus it is closest to real-world choice making (Auger *et al.*, 2007). Further, the BWS provides a ratio scale of preferences, thereby revealing the actual preferences (Lusk and Briggeman, 2009; Bazzani *et al.*, 2016).

The second class of choice-based techniques, discrete choice experiments (DCEs), have their roots in the Random Utility Theory (RUT) proposed by Thurstone (1927) and developed in McFadden, (1974). The theory posits that individuals make choices driven by the desire to maximize their utility. In the BWS approach, the objects that give the respondent the highest utility tend to be chosen 'best' more often than they are chosen 'worst'.

The BWS assumes that there is some underlying subjective dimension such as degree of preference. We wish to measure the position of a set of objects, or in our case, goals, by assigning scale values to them on that subjective dimension (Auger *et al.*, 2007; Amadou, 2014; Mansaray *et al.*, 2018; Kim *et al.*, 2019).

If we start with a complete set of K items, and we form subsets c, of size P, then there are $M = K\,(c-1)$ pairs of subsets an individual chooses from each time they choose the best, and worst. The RUT model is represented by equation [2.1]

$$D_{ij} = \delta_{ij} + \varepsilon_{ij} \qquad \textbf{[2.1]}$$

where

D_{ij} is the unobservable true difference in items *i* and *j* on the underlying dimension

δ_{ij} is an observable component of the unobservable difference that is measured, and

$\varepsilon_{ij}$is an error component associated with each ij pair.

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The ε_{ij} captures the fact that the choice process is stochastic as observed by the researcher since they cannot know what that respondent is thinking with certainty, and the respondent may not state their choice with certainty. It is assumed to be independently and identically distributed as a Gumbel, Weibull or double exponential. These assumptions lead to a multinomial logit (MNL) model;

$$\mathrm{P}(ij|C)=\frac{\exp(\delta_{ij})}{\sum_{ik} exp(\delta_{ik})} \quad \text{for all } M\delta_{ik} \text{ in } i_C \qquad \textbf{[2.2]}$$

The observable component, δ_{ij} can be expressed as the difference between two scale values, best, s_i and worst, s_j the model can thus be rewritten to express the utility between the best and worst items of the respondent's choice probability,

$$\mathrm{P}(ij|C)=\frac{\exp(s_i - s_j)}{\sum_{ik} exp(s_i - s_j)} \quad \text{for all } M\{s_i, s_k\} \text{ pairs in } i_C \qquad \textbf{[2.3]}$$

The unknown difference $s_i - s_j$ for each individual is estimated by the score (total best i - total worst i).

2.2.1 Typologies of best-worst scaling

There are three variations of the BWS approach.

Case 1 variant is the Object BWS (OBWS). This technique is used when the items or attributes that have been ranked are not described by their various profiles and the researcher is interested in the relative importance associated with each attribute in a comparable set (Flynn and Marley, 2014; Louviere, Flynn and Marley, 2015; Pinto *et al.*, 2019). OBWS has wide applications, *inter alia*, in agricultural studies, such as adoption of farming practices (Lai, 2017; Tong, Zhang and Zhang, 2017; Mansaray *et al*., 2018; Shittu and Kehinde, 2018; Thompson *et al*., 2019).

Case 2 variant of BWS is the profile case, which presents the attributes with some of their profiles from which the respondent chooses the best and worst choice based on the profiles. This is commonly used in health care goods or services in which each option will have a profile of some of its features.

Case 3 is the multi-profile case ,which requires a respondent to pick the best profile and the worst profile from a given choice set based on the features of each profile (Louviere, Flynn and Marley, 2015).

OBWS is easy to apply: it gives more information, and inflicts less cognitive burden on respondents than rating-based approaches do. It has more discriminating power in measuring attribute importance than both rating scales and paired comparisons since it forces the

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respondent to pick the extremes of their latent subjective scale (Hansson, Lagerkvist and Vesala, 2018). Further, it eliminates bias; rating and middle point rating biases because the respondent does not have to rate each object and is forced to pick the extremes of the scale respectively (Flynn and Marley, 2014). It is also better suited for international comparisons because it overcomes the limitations associated with numbers and their cultural interpretations (Casini, Corsi and Goodman, 2009; Burge *et al.*, 2011).

This study adopted the OBWS since the attributes were presented in the choice sets as objects, that is, without profiles as in Case 2 or multiple profiles as in Case 3.

2.2.2 Object best-worst scaling experimental design

Earlier designs of OBWS used the 2^j designs, where j was equal to the total size of the attributes set. The 2^j designs, however, formed weak comparisons due to their inherent design weaknesses (Flynn and Marley, 2014; Louviere, Flynn and Marley, 2015; Teffo, Earl and Zuidgeest, 2019)~~.~~ Some of these weaknesses were the unequal appearances and co-appearances of attributes as well as unequal choice set sizes; these features were prone to psychologically signal unintended importance of the attributes in the experiment. For instance, the respondents may perceive the attributes that appear more often and those that appear in smaller comparison sets as being more important (Louviere *et al.*, 2013).These problems have been addressed in recent experiments by use of the balanced incomplete block design (BIBD).

In the field of agricultural experimentation, experimental designs have their foundation in the work of Fisher (1934). He proposed three principles of experimentation**:** randomisation, replication and blocking.

Of the three principles, blocking is the most difficult as it places constraints on the experimental design. However, proper blocking reduces experimental error, and that makes an experiment more capable of detecting the significance of effects (Rashmi and Shakti, 2013). When an experiment has a large number of treatments, and blocking is essential, it is not possible to include all treatments in each block. In that case an incomplete block design is employed (Rashmi and Shakti, 2013). For instance, blocks which will be referred to as choice sets, henceforth will each contain less attributes than the full size of all attributes.

BIBD ensures that the occurrences and co-occurrences of the attributes within each choice set are the same, hence the incomplete block design is balanced (Okpiaifo, 2019). For instance, each attribute appears as frequently as any other attribute in the choice sets, and each attribute appears as many times with another attribute as any other attribute. Further, the experimental design ensures the attributes appear in different positions. All this ensures

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that respondents do not rank the attributes in ways deduced from the order or frequency of appearance of attributes in choice sets.

There are several advantages to the BIBD (Uy *et al.*, 2018; Teffo, Earl and Zuidgeest, 2019; Peitz and Mcewan, 2016). Firstly, it has frequency balance with each item occurring an equal number of times. Secondly, it has orthogonality with each attribute occurring equally often with every other attribute. Thirdly, it has positional balance since each attribute appears an equal number of times in each of the positions of the choice set. Fourthly, it achieves connectivity among the attributes since each choice set has the same number of elements and because each attribute is compared directly and indirectly with every other attribute. This feature of the design makes it possible for the attributes to be compared on a common scale.

2.2.3 Cluster analysis: agglomerative hierarchical clustering

Cluster analysis falls in the class of methods for extracting the structure of data sets referred to as unsupervised classification methods. These methods have no observed output variable and they are used to seek natural segments in the data (Chavent, Genuer and Saracco, 2019). The aim is to find segments in the dataset such that data sub-samples within the cluster are more closely related to those within the same cluster than those in other clusters (Hastie, Tibshirani and Friedman, 2017). It therefore, serves as a first step in organising samples based on some object for further analysis.

All methods of clustering attempt to maximise homogeneity within clusters and maximise heterogeneity between clusters. Each method of clustering specifies the distance function, similarity/dissimilarity rule, and determination of number of clusters (Kriminger, 2015). There are three dissimilarity measures: squared Euclidean, Manhattan and Maximum. The Euclidean measure is the most widely used (Yang, 2012; Kamalha *et al.*, 2017).

The distance between two cases i and j on the kth pattern is given by:

$$d_{ij} = \sum_{k=1}^{M} (x_{ik} - x_{jk})^2 \qquad \textbf{[2.4]}$$

Similarity/dissimilarity is has a notion of distance, a measure of how close or how far away two observations are from each other (Zhang, 2015; Hastie, Tibshirani and Friedman, 2017). For each pair of samples in the data, $x_i, x_j \epsilon$ **X,** a similarity representation is given as s_{ij}. A dissimilarity measure can be gotten from the similarity measure through the transformation $s_{ij} = e^{-\beta d(x_i, x_j)2}$ where $s_{ij} = (0,1]$ and β follows kernel bandwidth (Kriminger, 2015). The merging process involves two measures of distance, namely dissimilarity and linkage. Whereas dissimilarity is for measuring the distance between two observations, the linkage criterion is a function of the distance measure. The methods used to minimize distances is

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either by the complete linkage, the Ward's linkage or Zhang function. This study favoured the widely used Ward linkage specification given below:

$$Ward\ linkage\ distance = \sqrt{\frac{2n_1 n_2}{n_1+n_2}||x_1 - x_2||^2} \qquad \textbf{[2.5]}$$

where ||.|| is the squared Euclidean distance of the vector and n_i is the number of cases in cluster i.

Clustering analysis has two broad approaches; hierarchical and non-hierarchical. The non-hierarchical methods search for clusters in the data with a preconfigured number of clusters and partition the data set into a single partition whereas the hierarchical method is used when the number of clusters is not predefined and produce partitions at multiple levels (Kriminger, 2015; Dutta and Das, 2019).

Hierarchical clustering is either divisive (top-down) or agglomerative (bottom-up). Divisive hierarchical clustering starts with the dataset as a single cluster and incrementally splits it until all samples are split into singleton clusters. Agglomerative hierarchical clustering (AHC) on the other hand starts with initial partition consisting of each sample as a singleton cluster on which cluster structures are built incrementally until all samples in the dataset amalgamate into a single cluster (Kriminger, 2015).

For ease of application, AHC is a more commonly used method of clustering than the divisive method. Because divisive methods are generally more involved and, due to the difficulty of applying them, they are less frequently employed than AHC. The latter starts with each element as a sample in its own cluster (singleton). Hierarchical clustering has the advantage of providing a visual representation of the result in a dendrogram, as illustrated in Figure 2.1, below.

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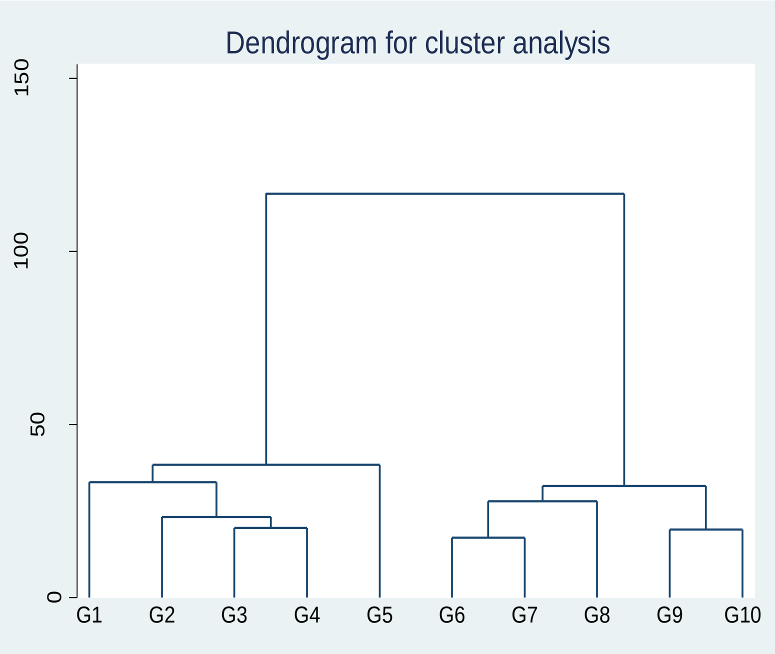

Figure 2.1. Sample Dendrogram

The interpretation of the dendrogram depends on the criterion used for reading the number of clusters, these are also known as the cutting criterion. The commonly used criterion is to cut at a distance where the dendrogram yields a given number of partitions, which becomes the resulting number of clusters. Clustering methods are either formulated with the foreknown number of clusters by some meaningful criterion or determined explicitly in the clustering process. The data reduction method, known as the principal component analysis (PCA) is often employed to determine the number of clusters.

PCA serves as a data reduction and pattern recognition tool that replaces highly correlated variables with a small number of correlated variables (Pacini *et al.*, 2014). It is used to accentuate structures in the dataset thus making it easy to detect patterns and interpret them (Jolliffe and Cadima, 2016; Fotiadis and Anastsiadou, 2019). This often serves as the first step to start examining relationships amongst variables for correlations and/or causation.

PCA groups' highly correlated variables together to form components which are not correlated with other components (Erdem, Rigby and Block, 2013). This eliminates data redundancy and is a useful way of dealing with information that is difficult to measure (Chavent, Genuer and Saracco, 2019; Ferrara *et al.*, 2019).

Principal components are given as $PC_i = \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_m$. The sum of each PC_i is called its Eigen value. The number of optimal components is often based on the Eigen values. The commonly used rule is to take Eigen values of at least equal to one, or at least 0.7. Another criterion, usually used jointly with the Eigen values is the scree plot (Kamalha *et al.*,

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2017; Fotiadis and Anastsiadou, 2019). Ease of implementation, interpretation and usability of the results are also used as criterion for determining number of components (Tsiptsis and Chorianopoulos, 2009).

2.3 Best-Worst Scaling Empirical Review

Similar studies to this study in the literature have adopted OBWS including Loureiro and Arcos (2012) in the study of preferences of forest management programmes. Kragt, Dumbrell and Gibson (2014) used OBWS to model preferences in climate change abatement practices by farmers in Australia (Dumbrell, Kragt and Gibson, 2016). The study was an investigation of what carbon-reduction farming activities farmers in Western Australia are likely to adopt. Morgan (2016) used OBWS in a study of perceptions of agriculture and food corporate social responsibility in the United States, while Mansaray *et al.*(2018) used the technique in the elicitation of preferences for, *inter alia*, attributes of seed rice in Sierra Leone. Additionally, several other studies have used cluster analysis to investigate the preferences uncovered by BWS (Tong, Zhang and Zhang, 2017; Lai, Widmar and Wolf, 2019; Pérez y Pérez, Egea and de-Magistris, 2019).

Lai, Widmar and Wolf, (2019) collected data from a sample of 257 dairy farmers drawn proportionally from the highest milk producing states in the U.S. They investigated the dairy farm management priorities and implications for growth using the BWS approach. The focus was on seven task areas: employee and labour management, calf and heifer management, feed and crop management, risk management, production and milking management, milk marketing, and financial management. There were four focal areas in which the farmer was asked to state the most important and least important area. A multinomial logit (MNL) was estimated in order to analyse the most-least important responses for the preferences as a base model from which a random parameter logit (RPL) and a latent class model (LCM) were estimated to model heterogeneity of preferences. It was found that managers allocated 52% of their efforts towards production and milking management. Risk, milk and employee and labour management were least prioritised. Heterogeneity analysis revealed that farmers could be clustered into four classes, based on their preferences:

Pérez y Pérez, Egea and de-Magistris, (2019) attempted to identify heterogeneity in societal preferences for externalities generated by marginal olive groves in Aragon Spain using a BWS approach. A sample of 549 Spaniards were asked to rank sets of three identified externalities into best and worst. The B-W responses' utilities were modelled with an MNL. An RPL and LCM were used to investigate heterogeneity in the preferences. The results showed that environmental externalities such as biodiversity and erosion were most preferred, while socio-

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cultural externalities such as governance were least preferred. The cluster analysis found that the citizens could be clustered in four classes based on their preferences: socio-cultural preferences, environmentalists, socio-ecologists and productives.

Tong, Zhang and Zhang, (2017) in a study to evaluate GHG mitigation measures in rice cropping and effects of farmers' characteristics in Hubei China employed a BWS and LCM. Two aspects of the mitigation measures were investigated: effectiveness and applicability. A total of 11 measures were identified and the105 farmers were presented with scenarios of 4-6 measures from which they ranked the best and worst from each set. BWS scores were calculated and the measure "applying soil testing and formulated fertilization" was ranked most applicable and "reducing the use of chemical fertilizers" was ranked the most effective. Four clusters of farmers from the latent cluster analysis were found in the sample.

2.4 Theoretical Review of Productivity and Efficiency

Productivity is the ratio of a firm's output to its input (Coelli et al., 2005; Fried, Lovell and Schmidt, 2008; Harold *et al*., 2008; Yeboah *et al.*, 2011; Mechri *et al.*, 2017). In practice, many firms have multiple inputs and outputs and their productivity is measured by the ratio of their outputs to inputs aggregated in some economically sensible manner. The ratio of output to all inputs is referred to as total factor productivity, whereas the ratio of output to one input is referred to as partial factor productivity (Coelli, Rao and O'Donnel, 2005). Growth in productivity then will be calculated by the difference between output growth and input growth. Variations in productivity is a residual implying that uncovering what is in the residual is what gives insights into the sources of inefficiency. Measurement errors in inputs and outputs contribute to the residuals but these errors are the component of the residuals that are not useful in explaining the variations in productivity. Therefore, the developments in the measurement of productivity have been about minimizing measurement errors (Fried, Lovell and Schmidt, 2008).

Production efficiency is a comparative measure between observed versus optimal production (Farrell, 1957; Fried, Lovell and Schmidt, 1993; Coelli, Rao and O'Donnel, 2005). Economic efficiency has been divided into two groups: technical efficiency and allocative efficiency. Optimal production is informed by a well-behaved production function. An input-based efficiency measure compares the observed input to the minimum possible, whereas an output-based measure compares observed output to maximum possible. Sometimes, an efficiency measure is a blend of input and output components. These measures are referred to as measures of technical efficiency since they are defined relative to production possibilities. Technical efficiency is a ratio of output-to-inputs; that is to say, by how much inputs can be

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reduced equi-proportionally and maintain the same output. A farm is considered efficient the smaller the maximum equi-proportional reduction possible. For example in Figure 2.2 below the minimum combination of x and y that can produce the output level represented by the isoquant ss' is Q. If the firm is using a combination of x and y at P, then efficiency can be calculated from the size of an equi-proportional reduction in x and y that will drop inputs to Q, the minimum possible to maintain the same level of output.

The overall measure of technical efficiency is disaggregated into three components: first, pure technical efficiency due to producing within an isoquant frontier. Second is congestion due to over-utilization of inputs and thirdly, scale efficiency measured by deviations from the constant returns to scale case (Lau and Yotopoulos, 1971; Battese and Coelli, 1995; Mendes, Silva and Santos, 2013).

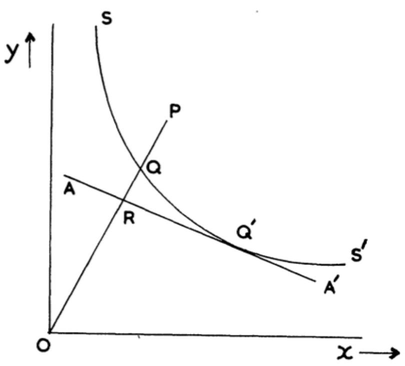

Figure 2.2 Input-oriented efficiency measure

Source: Farrell (1957)

Other measures of efficiency can be worked, which are defined relative to economic behavioural goals of the firm such as revenue maximization, cost minimization or profit maximization (Coelli, Rao and O'Donnel, 2005; Fried, Lovell and Schmidt, 2008; Mendes, Silva and Santos, 2013). These economic efficiency measures are comparisons between the observed and optimal possible measures. The deviation of the observed from the maximal (minimal) possible is herein conceptualized as the residual. The residual is attributed to differences in factors that affect the firm's output that can be classified as either under the control of management or not. Under the control of the management are the factors of production technology used, the scale of production and operating efficiency, while out of the control of management is the operating environment of the firm (Grifell-tatjé, Lovell and Sickles, 2018). The allocative efficiency assesses how well the farm combines inputs in

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production with due consideration to input costs. A farm achieves allocative efficiency if it combines inputs in the least costly way for its output. In Figure 2.2 a firm producing at Q achieves technical efficiency but is allocatively inefficient since the output at Q, ss' can be attained at a lower cost at Q', the allocatively efficient point. An additional measure of efficiency is the industry efficiency measure calculated for an entire industry, a concept Farrell (1957) called structural efficiency.

2.4.1 Importance of productivity and efficiency studies

Productivity and efficiency analysis is important in informing agricultural development policies (Mendes, Silva and Santos, 2013; Grifell-tatjé, Lovell and Sickles, 2018; Dakpo *et al*., 2019). Output growth is driven either by factor accumulation or productivity growth. Productivity growth, in turn, is composed of technological change and efficiency gain. Technological improvement is more costly and tends to be a long term phenomenon. Factor growth is more bounded and with growing pressure on the environment and the demand for productivity growth from economies is higher. Thus, growth in output could be achieved more rapidly by means of raising productivity (Grifell-tatjé, Lovell and Sickles, 2018; Tesema, Kebede and Shumeta, 2019). The starting point for crafting policy solutions to the productivity and efficiency problems of the farmer is, therefore, building a production function that sufficiently characterizes the farm (Mendes, Silva and Santos, 2013). The production function can then be extended to uncover organisational and institutional drivers and or impediments to productivity growth. Changes in farm management can be proposed to address farm-level constraints and institutional constraints can be addressed by policy interventions (Grifell-tatjé, Lovell and Sickles, 2018).

Raising the productivity of the farm spurs growth and the aggregated microeconomic growth leads to growth in the aggregate economy (Fried, Lovell and Schmidt, 2008; Hossain *et al.*, 2012; Mozumdar, 2012; Mendes, Silva and Santos, 2013)**.** Since productivity growth implies increased output per unit input or reduced input use per unit output, it can increase the profitability of the economic agents. This has several benefits; Firstly, it enhances the sustainability of the farm as a business entity in the long run through increased income generation (Grifell-tatjé, Lovell and Sickles, 2018; Khataza *et al*., 2019). Secondly, the productivity effect and price effect working in opposite directions implies that increasing productivity can result in increased consumption, and consequently the improved welfare of consumers. Thus, raising productivity is a way of improving the wellbeing of the people in a country (Mango, Siziba and Makate, 2017; Grifell-tatjé, Lovell and Sickles, 2018). Thirdly, raising the productivity of smallholder farmers is important because it closes the food gap, especially in Sub-Saharan Africa (SSA) and improves resource utilisation, thus slowing down

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resource depletion (Nandy, Sigh and Sigh, 2018). Fourthly, productivity gains in agriculture have spill-over benefits to other industrial sectors such as the manufacturing and service sector through freeing up more labour to other sectors and increasing inputs into the manufacturing sector (Hossain *et al.*, 2012). Therefore, raising smallholder farmer productivity is the pathway out of poverty, unemployment and food insecurity, and towards human development and a sustainable environment.

2.4.2 Theoretical background of efficiency measurement

Efficiency measurement has its roots in the microeconomic theory of production (Battese, 1992; Greene, 2008). Working out measures of productivity requires the construction of a production function. This is the technical relationship between inputs and outputs, which shows the maximum possible output from a given set of inputs for a given technology. A well-behaved production function satisfies the regularity conditions which makes analysis of production with calculus possible. This should imply that increasing inputs cannot lead to lesser output, and thus marginal products are all non-negative, inputs sets will be convex and output sets quasi-concave. This entails that marginal rate of technical substitution is diminishing (Coelli, Rao and O'Donnel, 2005; Kumbhakar, Wang and Horncastle, 2015). Neoclassical economics made a simplifying assumption that all firms are fully efficient but in practice, output deviates from the level predicted by the production function for a number of reasons. The reasons include those within the firm's control and which the firm can adjust to change its level of efficiency, and those which are random exogenous shocks which the firm has no control over (Battese and Coelli, 1995; Kumbhakar and Tsionas, 2006; Kumbhakar, Wang and Horncastle, 2015; Kumbhakar, Parmeter and Zelenyuk, 2017). This possibility gave rise to the interest in the concept of efficiency of a farm (Sarafoglou and Forsund, 2002; Namonje, 2015).

The earlier works on production efficiency analysis used Ordinary Least Square (OLS) methods to model the production function, upon which indices of efficiency were worked out (Farrell, 1957). The OLS based methods were limited in their ability to capture the essence of what a production function is, since OLS gives a construction of the mean output for the given inputs and not the maximum possible output for a given set of inputs. This limitation was overcome by the development of the frontier models.

A frontier model is a better conception of a bounded function and is better suited for the measurement of efficiency (Farrell, 1957; Battese, 1992; Battese and Coelli, 1995; Greene, 2008). It has several advantages over the production function. Firstly, since the frontier represents the best technology in the industry, it forms a benchmark for the industry against

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which every firm's efficiency will be measured. Secondly, the frontier estimate will be able to reflect the technology set employed by the best firm since the maximum output is what forms the frontier. The production function is unable to do that since it is the mean expected output from a given input set implying that it can only reflect the technology set employed by the average firm. Thirdly, whereas the non-frontier functions can only provide aggregate measures of efficiency for the industry, frontier models can be used to get measures of efficiency for each firm in the industry (Aye, 2011). The study of efficiency uses a frontier model as opposed to a normal regression model because it has a component of finding out to what extent a firm falls short of the maximum possible**,** whereas Ordinary Least Square regression only explains variation in the output predicated on the input variable set (Mendes, Silva and Santos, 2013).

Frontier models are either classified as stochastic or non-stochastic based on their functional specification (Charnes and Cooper, 1989, 1996; Lovell, 1995; Cooper *et al.*, 2007). Non-stochastic models are constructed by non-parametric approaches like mathematical programming. These production frontiers are deterministic with all observations on one side of the frontier while deviations from the frontier are all accounted for as inefficiency. Stochastic models, on the other hand, are constructed by parametric approaches with all observations on both sides and the deviations form a composite error term that can be broken into random error and inefficiency (Mendes, Silva and Santos, 2013). The Data Envelopment Analysis (DEA) technique is the most popular of the most widely used of the non-parametric methods and the Stochastic Frontier Analysis (SFA) is the most widely used parametric approach (Mendes, Silva and Santos, 2013).

2.4.3 Stochastic frontier analysis

The SFA has developed as an alternative to the DEA and sufficiently overcomes some limitations of the DEA; key among these is the inability to separate random error from inefficiency (Aigner, Lovell and Schmidt, 1977). Early works in the efficiency analysis was done by Koopman (1951) and Debreu (1951), but it was not until Farrell's (1957) seminal work came that the approach gained traction. Farrell (1957) extended the analysis from using a production function to estimating a production frontier. It is on this foundation that Aigner and Chu (1968) built to give us the SFA.

2.4.4 Deterministic parametric frontier

The deterministic frontier as first presented by Battese (1992);

$$Y_i = f(\boldsymbol{X}_i; \beta)\exp\ (-u_i) \text{ where } i = 1, 2, \dots, N \qquad [\,\mathbf{2.6}]$$

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where Y_i represents the possible production level for the i^{th} sample firm;

$f(x_i; \beta)$ is a suitable function such as Cobb-Douglas or Translog, of the vector, $\boldsymbol{X}_i$, of inputs for the i^{th} firm and a vector, β , of unknown parameters

u_i is a non-negative random variable associated with firm-specific factors which contribute to the i^{th} firm not attaining maximum efficiency of production;

N is the number of firms involved in a cross-sectional survey of the industry.

The presence of non-negative u_i values represent technical inefficiency of the firm and $\exp\ (-u_i)$ lies between zero and one, inclusive. Although allowing the $Y_i > f(\boldsymbol{X}_i; \beta)$ is plausible as in the case of outliers, it lacks sound statistical and economic rationale. Therefore, the inequality below is assumed to hold

$$Y_i \leq f(\boldsymbol{X}_i; \beta) \quad \text{where} \quad i = 1, 2, \dots, N \qquad [\,\mathbf{2.7}]$$

Thus possible production, Y_i, is bounded above by the non-stochastic (i.e., deterministic) quantity, $f(\boldsymbol{X}_i; \beta)$. Hence, the model [2.6] is referred to as the deterministic frontier production function

2.4.5 Stochastic model

$$Y_i = f(\boldsymbol{X}_i; \beta).\exp\ (v_i - u_i) \quad \text{where} \quad i = 1, 2, \dots, N \qquad [\,\mathbf{2.8}]$$

where v_i is a random error, independently and identically distributed (iid) as $N\ (0, \sigma_v^2)$ and associated with random factors outside the control of the farm such as weather, and measurement errors;

Y is bounded above by the stochastic quantity, $Y_i = f(\boldsymbol{X}_i; \beta).\exp\ (v_i)$; hence the term stochastic frontier.

The random errors, v_i are assumed to be independent of the u_i's, the inefficiency term which is assumed to be a non-negative normal distribution, $N^+\ (0, \sigma^2)$, that is a half-normal distribution or have an exponential distribution.

Depending on the size of the random error, v_i, the frontier output can exceed or be less than the deterministic production function as shown in Figure 2.3. As in the deterministic frontier case, the technical efficiency will be gotten as a ratio of the observed to the frontier output;

$$TE_i = \frac{Y_i}{Y^*} = \frac{f(\boldsymbol{X}_i;\beta).\exp\ (v_i - u_i)}{f(\boldsymbol{X}_i;\beta).\exp\ (-u_i)} = exp\ (-u_i) \qquad [\,\mathbf{2.9}]$$

Efficiency scores are obtained from the SFA for a production function modelled as a Cobb-Douglas (CD) production function or a translog production function thus:

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Translog production function

$$lnY_i = \beta_0 + \sum_{i=1}^{n} \beta_i lnX_i + \frac{1}{2}\sum_{i=1}^{n} \beta_{ii} lnX_i^2 + \sum_{i=1}^{n}\sum_{j \neq i=1}^{n} \beta_{ij} lnX_i lnX_j + v_i - u_i \qquad [\mathbf{2.10}]$$

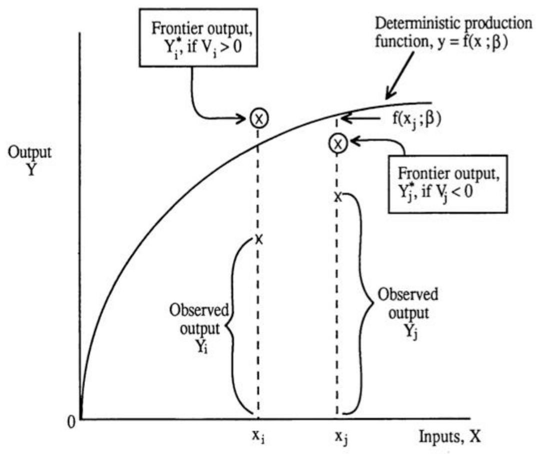

Figure 2.3 Stochastic frontier

Source: Battesse 1992

Cobb-Douglas production function

$$lnY_i = \beta_0 + \sum_{i=1}^{n} \beta_i lnX_i + v_i - u_i \qquad [\mathbf{2.11}]$$

where Y_i is the output of the i th farm

X_i are input variables

β_0, β_i, β_{ii} and β_{ij} are unknown parameters to be estimated

v_i is the systematic error component, assumed to be independently and identically distributed (IID); $v_i \sim N\ (0, \sigma_v^2)$.

The term u_i represents inefficiency and is a ratio of the observed output to the frontier output and so ranges between 0 and 1. It is a nonnegative iid random variable following a half-normal distribution truncated at zero (Lovell, 1995).

After estimation, the parameters from *equation* [**2.11**] inefficiency is modelled as in *equation* [**2.12**] (Kumbhakar, Ghosh and McGuckin, 1991; Battese and Coelli, 1995)

$$u_i = \delta \boldsymbol{Z}_i + W_i \qquad [\mathbf{2.12}]$$

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where $\boldsymbol{Z}_i$ is a vector of observable exogenous factors used to explain differences between firms, δ are the corresponding parameters to be estimated. W_{i} is an unobservable random variable, defined as a nonnegative truncation of the normal distribution with mean zero and variance σ^2 such that $u_i \sim N^+ \, (\delta Z_i, \sigma^2)$. The functional specification of the inefficiency term has to do with the data generating process of the inefficiency term is following. It can either be normally distributed or some variations of the normal distribution such as half-normal or truncated normal or the exponential (Greene, 2008; Sampiao, 2013). Half-normal is the commonest assumption used.

Developments in the SFA have been directed in the direction of modelling firm heterogeneity and more recently in developing its use in the field of economic sustainability development which involves modelling how economic bads resulting from the process of production can be minimized (Sampiao 2013).

SFA, however, assumes parametric specification for the production function and this tends to produce biased results particularly when the causes of inefficiency are non-stochastic, in which case a DEA produces better efficiency scores. The imposed production function structure on the SFA may violate some theoretical conditions. For example, the translog violates the condition of input convexity. Further, misspecification of functional form or multi-collinearity may be confused for inefficiency (Mendes, Silva and Santos, 2013).

Estimating the inefficiency scores from a parametric model is a two-step process which first estimates parameters of the frontier function $f(\boldsymbol{X}_i; \beta)$. before the inefficiency. The method of estimating $f(\boldsymbol{X}_i; \beta)$. parameters depend on whether or not distributional assumptions are imposed on the error components. When no distributional assumptions are made on the error components distributional-free approaches are used. These include Corrected Ordinary Least Squares (COLS), Corrected Mean Absolute Deviation (CMAD) and Thick Frontier Approach (TFA). This study will adopt COLS, the most widely used because it is more suited to production and lends itself to econometric rigour (Greene, 2008; Kumbhakar, Wang and Horncastle, 2015; Sampiao, 2013)

Although the distribution-free approaches have an advantage of estimating the frontier parameters without imposing distributional assumptions on the error components, they are unable to separate inefficiency from statistical error in cross-section data. To do that, we have to identify the two error terms u_i and v_i by imposing parametric distributions and obtain the log-likelihood function of the model. Then the maximum likelihood (ML) method of maximisation can be used to estimate the model parameters (Kumbhakar, Wang and Horncastle, 2015)

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Central to the ML approach is the choice of distributional assumptions imposed particularly on u_i since in the SFA context zero-mean normal distribution is accepted (Kumbhakar, Parmeter and Zelenyuk, 2017). The distribution of u_i will have to satisfy the conditions of been non-negative and having a closed-form joint distribution with v_i. The independence between u_i and v_i is easily satisfied since v_i represents shocks outside the control of a firm and thus unlikely to be correlated to u_i, the inefficiency (Belotti *et al.*, 2012; Kumbhakar, Wang and Horncastle, 2015; Kumbhakar, Parmeter and Zelenyuk, 2017).

Various parametric distributional assumptions can be made, but due to the difficulties associated with ML estimators, it is imperative to have a simple test of the validity of the stochastic frontier specification before doing the ML estimation. Two tests have been developed based on skewness which checks for the presence of left (negative) skewness in production type stochastic frontier or right (positive) skewness in cost type stochastic frontiers to use MLE. If these tests are not used, then it is better to use OLS (Kumbhakar, Wang and Horncastle, 2015)

2.5 Empirical Review of Technical Efficiency

Tesema, Kebede and Shumeta (2019) analysed the levels of technical, allocative and economic efficiency of smallholder farmers in Gudeya Bila district of Ethiopia estimating a CD stochastic production model and Tobit model to analyse factors affecting efficiency. The study used the input variables of seed, land, NPS, urea, oxen power and labour. The efficiency explanatory variables that were found to have a positive impact were: education level, family size, frequency of extension visits, access to credit and involvement in off-farm economic activities. The mean technical efficiency was found to be 71.65% showing significant room for improvement.

Abdulai, Nkegbe and Donkoh (2018) assessed the technical efficiency of smallholder maize farmers in northern Ghana by employing a DEA. The mean technical efficiency was found to be 77% with the factors of agricultural mechanisation and education negatively impacted efficiency while extension had a positive effect.

Abdulaleem, Oluwatusin and Ojo (2019) investigated the technical efficiency of maize production among smallholder farmers in Southwest Nigeria using a multistage sampling method to sample 270 farmers to whom questionnaires were administered. Specifying a stochastic frontier Cobb-Douglas production function and employing maximum likelihood estimation, they estimated the input elasticities and found farm size, the quantity of fertilizer and capital input positive and significant. The inefficiency model was modelled on socio-economic characteristics of the farmer: inefficiency was found to be positively related to

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household size at the 1% level of significance, was found to be higher in unmarried farmers at 1% significance level, and significantly higher in men than women at the 10% level of significance.

Etienne, Ferrara and Mugabe (2018) assessed the technical efficiency of maize production among smallholder farmers in Zimbabwe with an interest in understanding how the Fast Track Land Reform Program (FTLRP) could have impacted their efficiency. They made a comparison of the results from a fully parametric stochastic CD production frontier and the semi-parametric one by Ferrara and Vidoli (2016). Employing a two split sampling technique, the parameters of the frontier were estimated and the inefficiency modelled on contextual variables. In the pooled results, output was found to be positively related to land and labour only, at 1% level of significance under the parametric model and related positively to just land, labour and capital under the semi-parametric model. The extension variable was the only significant explanatory variable and had an inverse relationship with output under both the parametric and semi-parametric. Age and sex of household head were insignificant. This study found the efficiency of the entire sample ranged between 0.595 and 0.772, which was .685 on average representing a very slight improvement in the score of 0.65 Mango *et al.*, (2015) found for the same class of farmers in the post-FTLRP era in Zimbabwe.

Ngombe *et al.* (2014) analysed the technical efficiency of maize production under minimum tillage in Zambia using a Cobb-Douglas stochastic frontier. The efficiency term was modelled on the half-normal and exponential distributions, which gave average efficiency scores of 60 and 71.7%, respectively. The results of regressing the inefficiency term on the household characteristics showed that marital status, household head's level of education, the household size, off-farm income, agro-ecological zone, distance to main road and access to credit determined technical efficiency of the smallholders who practised minimum tillage.

Ayinde, Aminu and Ibrahim (2015) examined the technical efficiency of smallholder maize farmers in Ogun State in Nigeria using a multi-stage sample of 100 farmers from the area. A CD production frontier was estimated and it was found that the variables seed, herbicide, labour and farm size were significant in affecting output, and the factors affecting inefficiency were the household size and educational attainment of the household head.

Cui *et al.* (2018) reported the outcomes of efforts of a network of 1,152 researchers, extension agents and agribusiness specialists to about 20.9 million smallholder farmers in China offering them comprehensive decision support in the period 2005 - 2015 aimed at simultaneously raising productivity and environmental performance. An average increase of 10.8 - 11.5% in yields of maize, rice and wheat was reported and simultaneous reduction of nitrogen application by 14.7 - 18.1%. Further, the interventions reduced the loss of active nitrogen by

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approximately 25.8% compared to farming without the interventions. Greenhouse gas (GHG) emissions such as the CO_2 equivalent per Mg of maize, rice and wheat produced reduced by 22.3, 13.7 and 20.9% compared to emissions without the intervention, respectively. This study gives evidence that sustainable productivity gains are possible.

Abdulai and Abdulai (2016b) explored the impact of CA on environmental efficiency of smallholder maize farmers in Zambia employing the Nitrogen Index Tier Zero tool to obtain farm level balance sheet and stochastic frontier analysis to obtain efficiency scores. Correcting for selection bias and technology heterogeneity, they found that the farmers that adopted CA were found to be more technically and environmentally efficient than those practising conventional agriculture. This finding is useful in policy as it reveals that CA has the potential to reduce social cost, create economic benefits and reduce negative environmental externalities of agricultural production.

The literature reviewed on efficiency analysis revealed that technical efficiency can be approached from the inputs side of the production process, input-oriented (IO) approach, or from the output side, the output-oriented (OO) approach (Fried, Lovell and Schmidt, 1993, 2008; Fare, Grosskopf and Lovell, 1994; Kumbhakar and Tsionas, 2011; Ancev, Azad and Akter, 2017). The results of efficiency measurement change based on whether one uses an input-oriented or output-oriented approach. The results in terms of elasticities and returns to scale are only identical from the two approaches if the production function is homogenous (Kumbhakar and Tsionas, 2006). This is due in part to the complication the input-orientation brings to the maximum likelihood estimation (Kumbhakar and Tsionas, 2006; Fried, Lovell and Schmidt, 2008). This study, therefore, adopted the OO approach in the calculation of efficiency scores due to its additional desirable attribute of being neutral; the impact of inefficiency on output does not depend on the level of input and output quantities. It is widely used in literature for this reason (Coelli, Rao and O'Donnel, 2005; Kumbhakar, Wang and Horncastle, 2015).

Empirical literature also revealed that many efficiency studies in agriculture have adopted SFA over DEA (Battese, 1992; Vishwakarma *et al.*, 2010; Gebregziabher, Namara and Holden, 2012; Oyakhilomen and Daniel, 2015; Memon *et al.*, 2016; Raphael and Rejoice, 2017; Osundare, 2017; Abdul-Rahaman and Abdulai, 2018; Ma *et al.*, 2018; Yan, Chen and Hu, 2019; Hong *et al.*, 2019; Mwalupaso *et al.*, 2019)**.** This is in part because the DEA assumes no noise in the data, which is unlikely to be the case. Further, SFA produces more consistent estimators than DEA (Asante and Villano, 2019). This study thus adopted the SFA over DEA.

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2.6 Conclusion

This chapter has laid out a review of BWS as a useful choice-modelling technique in preference studies and AHC as a heterogeneity analysis technique. The empirical literature revealed the widespread application of these techniques in studies similar to this study. The BWS and AHC are, therefore, suitable in the preference analysis of this study. The chapter brought out the interaction between the farmer characteristics and their response to the effects of climate change in preferences on adopting SAP. Farmers develop preferences for SAP that best meet their objectives subject to their characteristics such as farm size, their risk appetite and subjective expected returns to the different SAP. Farmers often have to make mental subjective valuations of expected returns to the different SAP because these practices come at a cost in the present with potential benefits in the future. This separation between the time of incurring the cost and when to start reaping the benefits to the practices increase the dis-adoption rate; the greater the separation, the higher the dis-adoption rate. Given the unique constraints that the individual farmers face in production or in responding to climate change effects on production, farmers develop preferences over the SAP.

Technical efficiency studies in agriculture reviewed in this chapter revealed the suitability of adopting the output-oriented SFA approach, and the half-normal distributional specification of the error term in the second order equation. The use of input variables labour, area planted, inorganic fertilizer, capital, insecticide and herbicide use were used in modelling the output and were expected to be positively correlated with output. Several contextual variables were used to explain inefficiency in empirical studies, including household size, educational level of household head, farming experience, access to extension, access to credit, off-farm income and usage of improved seed, all of which were expected to have a negative effect on inefficiency. In addition, males were assumed to be more efficient than females, the married were expected to be more efficient than the unmarried, farmers closer to main tarred roads and /or the markets, were expected to be more efficient.

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Chapter 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology used in accomplishing the purpose of this study, which is to investigate the relationship between farmer preferences for sustainable agriculture attributes and their technical efficiency. Section 3.2 presents the study area, and Section 3.3 presents the sampling and data collection methods, while Section 3.4 presents the research design and Section 3.5 presents the analytical framework. Finally, Section 3.6 concludes the chapter.

3.2 Study Area

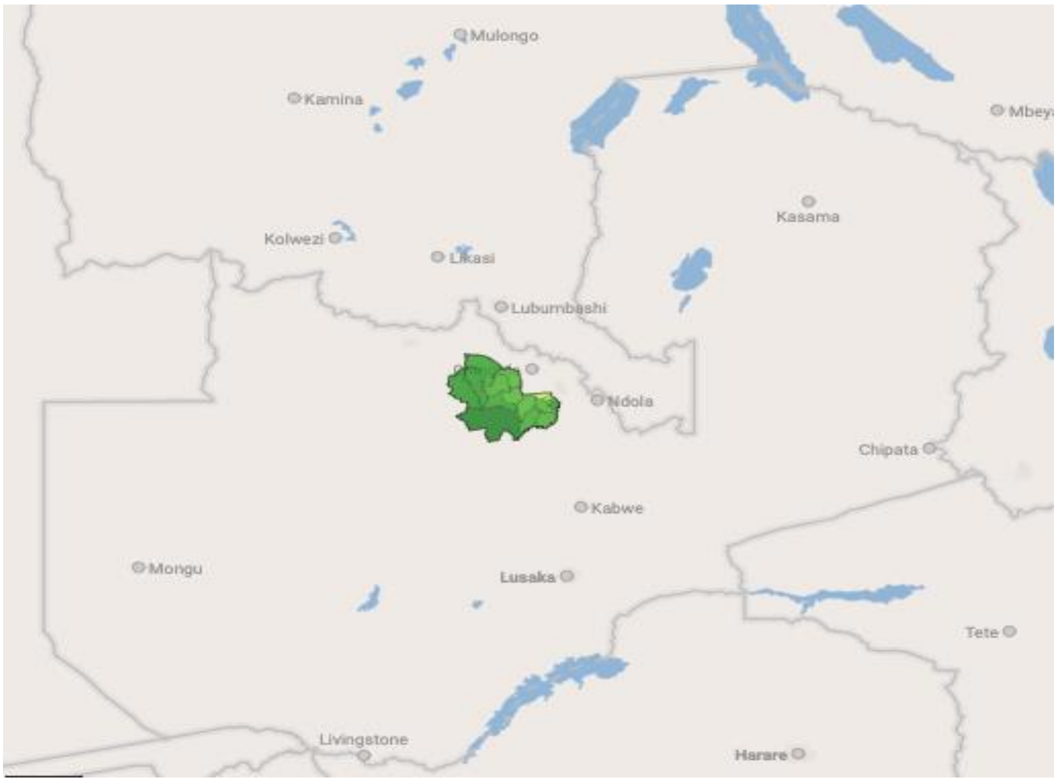

Figure 3.1: The map of Lufwanyama district

Source: www.citypopulation.de

With an area of 11,900 square kilometres, Lufwanyama is the largest district by area in the Copperbelt Province of Zambia. It has an estimated population of 100, 401 and a population density of 8.8 people per square kilometre, the lowest in Zambia, with a national average of 23 people per square kilometre. Economic activities include Copper and Emerald mining, agriculture and forestry and an underdeveloped tourism sector. There are over 400 small scale emerald mining license holders in the district. The mines have not managed to create enough employment for the local population who largely depend on smallholder agriculture,

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predominantly maize production. In this regard, Lufwanyama district represents a typical rural district in Zambia in that household agriculture is the major economic activity (CSO 2012). The climatic conditions in the area are moderate temperatures and an average rainfall of over 1000 millimetres per year (FAO, 2005; UNDP and GRZ, 2010; CSO, 2012).

Lufwanyama district was purposively chosen for the study because it is affected by low levels of maize productivity (CSO, 2018), has been affected by climate change in the recent past and has a low concentration of large scale farms (Alfani *et al.*, 2019). The findings in the district could, therefore, be generalizable to other family maize farmers in the country without having to reckon with spill-over effects from a high concentration of commercial farmers in an area (Ali, Deininger and Harris, 2015; Lay, Nolte and Sipangule, 2018).

3.3 Sampling and Data Collection

Family farmers in Lufwanyama district were the target population. Sampling was done at two stages; firstly, at the district level where the villages were purposively sampled and secondly, at the village level where households were randomly sampled (Lavrakas, 2008; Aneshensel, 2013). Three of the largest villages in the district, namely Lukanga, Mangwende and Nkana, were sampled because they had the highest concentration of farmers. Using the sampling frame available for the three villages, random numbers were generated to select a random sample. Although the calculated sample size at the 95% confidence interval was 398 (Israel, 1992) this study aimed at collecting a sample size of 150, which was sufficient for the study's analysis based on the reviewed studies of efficiency, BWS experiments and the cost considerations. A sample size of 164 participants drew 56, 50 and 58 respondents from Lukanga, Mangwende and Nkana villages, respectively. The sample was fairly homogenous since the respondents were engaged in the same occupation and grew the same crop (Saasa, 2003; Bryman, 2012).

Primary data was collected by means of a pre-tested questionnaire in a one-on-one interview in the field (Mohajan, 2017). The initial questionnaire was constructed using variables identified from literature on production data as well as sustainable agriculture attributes. Local experts were consulted to understand local conditions and practices from their perspective in addition to focus group discussions (FGD) with farmers to understand local conditions and practices from their perspective too. The abovementioned pre-test of the questionnaire was undertaken with 30 farmers randomly drawn from the target area. Responses from the pre-test questionnaires and FGD were analysed and appropriate adjustments were made to construct the final questionnaire (Singh, 2007). The final questionnaire, attached in Appendix 1, was used to collect maize input and output data, and BWS experimental data.

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Using a mobile phone, the data were collected and directly entered onto a SurveyCTO™ server by the interviewer. The interview started with a brief introduction to the study in which consent was sought to continue the interview. The respondent was then oriented on each section of the questionnaire, followed by the interview (Ruane, 2005; Leedy and Ormrod, 2015).

3.4 Attributes of Sustainable Agriculture Practices to be Ranked

A set of twenty desirable SAP attributes, relative to conventional agriculture, were identified from the literature (Pretty, Toulmin and Williams, 2011; Umar, 2012, 2014; Arslan *et al.*, 2015; Branca *et al.*, 2016; Bryan *et al.*, 2016; Zilberman, Goetz and Garrido, 2018; Dyck and Silvestre, 2019; Komarek *et al.*, 2019; Michler *et al.*, 2019; Adegbeye *et al.*, 2020; Amadu, Miller and McNamara, 2020; Dubey, Singh and Abhilash, 2020; Nyanga *et al.*, 2020). The SAP attributes that pertain to the farming household and on-farm environment include improved crop yields, reduced cost of production, reduced soil erosion, better water-use efficiency, improved soil biodiversity, decreased labour input, improved dietary nutrition among farmers, improved household incomes, decreased variability in crop yields, improved nutrient use, improved soil fertility, reduced extension requirement, decreased use of external inputs, decreased requirement for fertiliser input, improved health of farmers and societal wellbeing, and improved capacity to cope with events such as droughts, floods, pest diseases or salinity stress in crop plants. The attributes of SAP that pertain to the environment include**:** a decrease in adverse effects on the ecosystem, improved provision of ecosystem services, reduced off-farm pollution, reduced GHG emissions and enhanced carbon sequestration.

The identified SAP attributes from the literature were confirmed through consultations with agricultural extension officers and a FGD with farmers in order to identify the most relevant to the local context of Lufwanyama district. The FGD participants were drawn from a regular agricultural camp meeting, which attracted farmers from the different villages. Consultations with agricultural extension officers and the FGD were informed by the SAP attributes identified in literature and the objective was to streamline the list of questions to those most relevant for the local context. Eleven of the most frequently recurring attributes from the FGD and consultations were adopted in the final questionnaire to form the BWS experiment as recorded in Table 3.1. This number of attributes was within the recommended range to give sufficient information without imposing a huge cognitive burden on the respondents (Casini, Corsi and Goodman, 2009; Pinto *et al.*, 2019).

Eleven (11) choice scenarios with five (5) choice options each were presented to the respondents They were asked to select which of the attributes was the most important (or best) and, from the remaining ones, choose which was the least important (or worst). The scenarios were presented on separate cards in succession and the data as mentioned, were

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entered to SurveyCTO™ using a mobile phone. Table 3.1 below presents an example of a choice scenario.

Table 3.1 Sustainable agriculture attributes

The attributes of sustainable agriculture used in the best-worst experiment with brief descriptions

	Attribute	Attribute description
PD	Decrease pests and diseases	Reduce the incidence of pests and diseases on the farm
ER	Reduce extension requirement	Select practices that are easy to implement without constantly needing the guidance of an extension officer
LU	Decrease labour use	Reduce the amount of labour required to work on the farm
SF	Increase soil fertility	Select practice that increases soil fertility
CY	Increase crop yield	Carry out activities that increase crop yield
WR	Reduce water requirement	Use technologies that require less water
SE	Decrease on-farm soil erosion	Minimise soil erosion on the farm
EI	Reduce external input use	Adopt technology that requires less external inputs such as fertiliser
OP	Decrease off-farm pollution	Adopt technology that reduces off-farm pollution due to farm activity
DR	Increase drought resistance	Adopt practices that withstand droughts better
CP	Decrease cost of production	Adopt production techniques that reduce the cost of production

Source: Author

3.4.1 Best-worst scaling experiment design

The BWS study used a Balanced Incomplete Block Design (BIBD) in the format of (j, b, r, k, l) where j is the total number of objects (goals), b is the number of blocks which are the designated subsets of fixed size, r is the number of blocks where each goal appears, k is the number of goals in each block, and l is the number of times each goal appears with any other goal (Auger *et al.*, 2007; Louviere, Flynn and Marley, 2015; Pinto *et al.*, 2019). The design was developed to control for context effects by making each goal appear equally as frequently as other goals and co-appear equally as often with each of the other goals in the choice sets. Each goal appeared in each of the r positions to control for order effects, which reduced the

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chances of respondents (mis)perceiving the importance of a goal based on the order in which it is presented (Lee, Soutar and Louviere, 2007; Campbell and Erdem, 2015).

These goals were used to construct the a BIBD BWS experiment using subsets of 5 of these 11 goals, each goal co-appearing with every other goal equally in 11 choice scenarios as presented Table 3.2

Table 3.2 Best-worst experiment choice sets

Ranking sets	Attribute 1	Attribute 2	Attribute 3	Attribute 4	Attribute 5
Ranking 1	PD	ER	LU	SF	CY
Ranking 2	WR	SE	SF	EI	ER
Ranking 3	OP	SE	DR	CY	SF
Ranking 4	CP	ER	PD	OP	SE
Ranking 5	LU	CP	SF	OP	WR
Ranking 6	CP	CY	EI	SE	LU
Ranking 7	DR	ER	CP	CY	WR
Ranking 8	SE	WR	PD	LU	DR
Ranking 9	CY	WR	PD	EI	OP
Ranking 10	ER	OP	EI	DR	LU
Ranking 11	DR	EI	PD	SF	CP

Source: Author

A sample ranking scenario is provided below;

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 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.

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

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

3.5 Analytical Framework

3.5.1 Best-worst scaling aggregate analysis

The rankings were analysed by aggregating the responses for the whole sample (Goodman *et al.*, 2005; Ochieng' and Hobbs, 2016). To obtain BWS scores for each attribute (j) the number of times farmers chose it as most important (B_j) and the number of times they chose it as least important (W_j) were counted respectively. The BW score for the attribute j is equal to B_j - W_j. To make these BW scores interpretable in terms of relative importance, a ratio-based scale defined as $\sqrt{\frac{B}{W}}$ was obtained. Finally, this ratio-based scale was transformed to a scale of 0 to 100 for all attributes by dividing by the highest score, $(\sqrt{\frac{B}{W}})$ *, and multiplying by 100; [$(\sqrt{\frac{B}{W}}$x100)/ $(\sqrt{\frac{B}{W}})$*]. This assigns 100 to the attribute with the highest score and the other attributes are thus scaled relative to this attribute (Loureiro and Arcos, 2012; Kubo *et al.*, 2019).

3.5.2 Heterogeneity analysis

The indicators described in the previous section were also calculated for each individual farmer, and used to evaluate the heterogeneity of rankings for each goal (univariate analysis) and the presence of homogenous groups of rankings in the population. The standard deviation of the individual BWS scores provide an indication of the extent to which choices made by farmers during the BWS experiment were consistent (homogenous) or whether those choices exhibited heterogeneity. To establish the extent of heterogeneity, the individual coefficient of

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variation (CV) of the B-W score, calculated as $\frac{SD}{mean}$, was used. High absolute values of CV are indicative of high levels of disagreement among respondents about the relative importance of a given attribute hence greater heterogeneity. Absolute values of CV that are close to zero indicate high levels of agreement among respondents about the relative importance of a given attribute hence greater homogeneity in preference (Uy *et al.*, 2018).

The CV of attributes only goes as far as indicating the presence and extent of heterogeneity in preference for an attribute and cannot distinguish farmer preference clusters based on the preference attributes (Louviere *et al.*, 2013; Louviere, Flynn and Marley, 2015; Cheung *et al.*, 2018). For this reason, an agglomerative hierarchical cluster analysis was carried out to identify unique preference clusters in the data as detailed below.

3.5.3 Agglomerative hierarchical analysis

The preference results from BWS were investigated for heterogeneity using AHC. The BW scores were standardised to deal with issues of outliers and they were inspected for missing values before proceeding to principal component analysis (PCA).
The number of clusters were determined by doing a PCA on standardised BW scores of the SAP goals using the eigen values approach. Using the number of clusters obtained, the AHC performed with the Euclidean distance and the Ward linkage function specification.

3.5.4 Technical efficiency

The technical efficiencies of the smallholder farmers were estimated from the input and output data using the software Stata™ version 15.0 by the stochastic frontier approach. The top and bottom 5% of the estimates of efficiency scores were dropped to eliminate outliers (Gong, 2016). The efficiency scores were then regressed on the contextual variables of the farmers to explain the sources of inefficiency for the farmer.

3.5.5 Production frontier model

Using the input and output data, production functions were estimated with two of the most widely used specifications of the translog and the Cobb-Douglas function.

$$
\begin{aligned}
lnY_i = {} & \beta_0 + \beta_1 ln\ (Area_i) + \beta_2\ ln\ \ (Seed_i)\ + \beta_3 ln\ (Labor_i) + \beta_4 ln\ (Fertilizer_i) + \tfrac{1}{2}[\beta_{11} l\,n(Area_i^2) + \beta_{22} \\
& ln\ (Seed_i^2) + \ \beta_{33} ln(Labor_i^2) + \beta_{44} ln(Fertilizer_i^2) + \beta_{12} ln\ (Area_i) * ln\ (Seed_i)\ + \beta_{13} ln\ (Area_i) * \\
& ln\ (Labor_i)\ + \beta_{14} ln\ (Area_i) * ln\ (Fertilizer_i) + \beta_{23} ln\ (Seed_i) * ln\ (Labor_i) + \ \beta_{24}\ ln\ (Seed_i) * \\
& ln\ (Fertilizer_i) + \beta_{34} ln\ (Labor_i) * \ ln\ (Fertilizer_i)] + v_i - u_i
\end{aligned}
\qquad \textbf{[3.1]}
$$

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Empirically, the translog stochastic frontier production model took the form of [3.1] above. The empirical Cobb-Douglas stochastic frontier production model took the form of [3.2] below:

$$lnY_i = \beta_0 + \beta_1 ln\ (Area_i) + \beta_2\ ln\ ln\ (Seed_i)\ + \beta_3 ln\ (Labor_i) + \beta_4 ln\ (Fertilizer_i) + \beta_5 ln\ (Capital_i) + v_i - u_i \quad \textbf{[3.2]}$$

where

$i = i$ th farm, i = 1, 2 … n

Y_i = output of the i th farm

$Area_i$ = area harvested from the i th farm

$Labor_i$ = total labour input of the i th farmer

$Fertilizer_i$ = fertilizer input in the i th farm

$Capital_i$= capital input in the i th farm

In each specification the best fitting model was selected based on the t-statistics of the coefficients and the adjusted R squared.

3.5.6 Model selection

The likelihood ratio (LR) test was used to choose the specification of the production function to adopt for the analysis. The test was on the hypothesis that the C-D function is nested in the translog model.

$$LR = -2[ln\ (LLF_{TL}) - ln\ (LLF_{CD})] \sim X^2_{df} \quad \textbf{[3.3]}$$

The results of the test were in favour of a translog specification and so the production frontier was estimated based on the translog specification. Half-normal distributional assumptions presented in Aigner, Lovell and Schmidt (1977) were adopted for ease of implementation. Additionally, the half-normal assumptions were appropriate because smallholder maize farmers were akin to perfect competition, which is the condition consistent with this distributional assumption (Kumbhakar, Wang and Horncastle, 2015).

3.4.7 Inefficiency model

The inefficiency model was be modelled thus:

$$u_i = \delta_0 + \sum_i \delta_i Z_i + w_i \quad \textbf{[3.4]}$$

where:

Z_1 – Gender of the household head

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Z_2 – Highest level of education for the household head (years)

Z_3 – Household size

Z_i- Primary occupation of the household head

Z_i – Crop rotation dummy

Z_i- Cropping system

Z_i- Extension service

Z_4 – Land tenure status

Z_5 –Soil conservation dummy

Z_5 - Conservation tillage dummy

Z_6– Preference cluster membership dummies

w_i - Unobservable random variable, N$^+$ $(0, \sigma^2)$ such that $e_i \sim N^+ \ (\delta Z_i, \sigma^2)$

3.5.8 Relationship between preferences for attributes of SAP and technical efficiency

The relationship between farmer preferences for SAP attributes and their technical efficiency were assessed through the t-test on the cluster membership variables in equation [3.4]. The relationship was further investigated with a one-way analysis of variance (ANOVA) between preference cluster groups and efficiency scores.

3.6 Conclusion

This study calculated technical efficiency scores for the farmers from an estimated stochastic production frontier. The efficiency scores were regressed on the socioeconomic characteristics of the farmers to determine the drivers of inefficiency. To establish preferences of farmers for sustainable agriculture attributes, BWS methods were used on a set of attributes. A PCA was carried out on the BW scores for the attributes in readiness for analysis of data for preference heterogeneity. The agglomerative hierarchical analysis was used to group the farmers according to their SAP preferences. The relationship between efficiency and preferences was investigated by t-tests and ANOVA.

This chapter explored the appropriate study methodology to achieve the study objectives. Several methods were drawn upon to achieve the study objectives as outlined in this chapter. This was because each method had its limitations that another method could complement, and when used together the study objectives could be achieved. For example, in eliciting SAP

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preferences from the farmers the BWS approach could give us the ranking of the SAP attributes for each farmer but could not reveal whether the preferences were heterogeneous or homogenous among the farmers. So heterogeneity analysis was necessary and that was accomplished by doing AHC with the BW scores for each of the farmers.

The approach taken in the investigation of technical efficiency in the study was similar to that taken by many of the technical efficiency studies referred to in the empirical review (Section 2.5). However, in modelling technical inefficiency, this study took a novel approach of including preference cluster dummies in the inefficiency model. And this is the model that was used to reveal the relationship between technical efficiency and SAP preference.

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Chapter 4 RESULTS AND DISCUSSIONS

4.1 Introduction

The results from the sample data analysis from the household, farm and farming system characteristics are presented in Section 4.2 and preference analysis results are provided in Section 4.3, while the technical efficiency results are addressed in Section 4.4 and the chapter concludes in Section 4.54. The presentation indicates how these results compare with those from other studies as well as their implications.

4.2 Household Characteristics

A summary of the socio-demographic characteristics of the households is presented in Table 4.1 below:

Table 4.1: Household, demographic and socio-economic characteristics

Village	Lukanga	Mangwende	Nkana	Total	Prob > F
Sample	56	50	58	164	
Average total landholding (ha)	4.92	3.82	8.93	6.01	0.30
Percentage of full-time farmers	96.43	92.00	96.55	95.12	0.48
Male-headed households (%)	54.57	50.00	56.90	53.66	0.78
Average number of years of schooling (years)	6.89	5.32	7.03	6.46	0.04
Average household size (persons)	7.64	7.38	6.93	7.31	0.42
Decision making by household heads (%)	82.14	82.00	96.55	87.20	0.03

Source: Author

The average household landholding was 6.01 hectares, which was higher than the national average of 5.1 ha (CSO, 2012). Differences in average total land holding among the three villages were not statistically significant at 5% level of significance. The observed household landholding was higher than what was found in larger nationally representative samples; 1.78 ha from a sample of 3,973 farms (Kimhi, 2006) and 1.8 ha from a sample of 1,097 farms (Amondo *et al.*, 2019). The two studies 13 years apart showed a similar average size of landholding. This could be indicative of the abundance of land in Lufwanyama and or the low demand for land in the area, consistent with the low population density there, which is also the lowest in Zambia. Other studies such as those by Saenz and Thompson (2016), Chiona, Kalinda and Tembo (2014), and Abdulai and Abdulai (2016) found higher average

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landholdings of 2.41 ha, 2.18 ha and 3.13 ha respectively, but they were nonetheless lower than the findings of this study. The studies above also had bigger samples than this study: Saenz and Thompson had a nationally representative sample of 8 310, Chiona, Kalinda and Tembo had 400 drawn from Mkushi district, one of the most agriculturally engaged districts in the country, while Abdulai and Abdulai had a nationally representative sample of 779. However, the average household landholding found in this study was comparable to the 6.56 ha that Musaba and Bwacha (2014) found from a sample of 100 smallholder maize farmers in Masaiti district of Zambia, neighbouring district to Lufwanyama district.

The primary occupation of the respondents was farming; this stood at 95.12% on average across the villages without significant differences between them (at the 5 % level of significance). This result was comparable with Kabwe's (2012) finding of 98.3%, indicating that farming was the predominant occupation. Although there are several mines in the district, very few of the people from the area were employed in them: these were mostly in low-skilled (mining) jobs, leaving the majority of the residents dependent on agriculture for their livelihood.

The percentage of male-headed households stood at 53.66% which was much lower than the 73% national average, and the differences across the villages were insignificant at the 5 % level of significance (CSO, 2012). This result was lower than those which Musaba and Bwacha (2014), Abdulai and Abdulai (2016), Saenz and Thompson (2016) and Mwalupaso *et al.* (2019) found in samples of farmers from Zambia, at 60%, 63.75%, 77.4%, and 83% respectively. It was deduced that the study area had more female-headed households than have been observed in other studies.

The average number of years of schooling for the household head was estimated as 6.46 years and the differences across the three villages were significant at the 5% level of significance. The estimated average level of schooling was above the 4.1 years observed among smallholder farmers in Sub-Saharan Africa (Garner and de la O Campos, 2014; de la Fuente, 2015) and reported in other Zambian studies. It was also above the 5.14 years from the study by Saenz and Thompson (2016), above the 5.88 years in the study by Abdulai and Abdulai (2016b), and also higher than the 5 years that Memon *et al.* (2016) found for smallholder maize farmers in India. However, 12.8% of the farmers in the sample had zero years of schooling, which was lower than 22.3% found in Nkomoki, Bavorov and Banout (2019) for a sample drawn from the Southern province of Zambia. Overall, findings revealed that on average, the farmers in the sample had more years of schooling than reported by other studies.

The average household size was found to be 7.31 persons per household and the differences across the villages were insignificant (p-value = 0.421). This was higher than the 2016

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Zambian national average of 5.8 (CSO, 2012; ArcGis. Accessed 22/01/2019). This could be attributed to the sampled area being a rural area where the average household size tends to be larger than the urban average. The household size found in this study was close to the 7.48 persons that Musaba and Bwacha (2014) found for the same class of farmers in the Masaiti district of Zambia and was within the range of 5-8 persons per household that other Zambian studies found for rural farming households (Ng'ombe and Kalinda, 2015; Mwalupaso *et al.*, 2019; Nkomoki, Bavorov and Banout, 2019). Studies in similar setups in other countries have found even higher household sizes, for instance, Abdulai, Nkegbe and Donkoh, (2018) found 8.66 persons per household in a study of a sample from northern Ghana.

On average, in 87.2 % of the households the household heads made the farming decisions. The highest recorded was 96.55 % in Nkana village and the lowest was 82% in Mangwende village.

This study found an average maize plot of 1.10 ha representing 95.61% of the household total landholding. Amondo and Simtowe (2019) and Saenz and Thompson (2016) found average maize plot sizes of 0.77 ha and 0.95 ha respectively, which were lower than the findings in this study. Our finding is comparable to the 1.20 ha that Musaba and Bwacha (2014) found for Masaiti district as well as to the 1.16 Kimhi (2006) estimated from a nationally representative sample. However, some studies found slightly larger maize plots; for instance from a nationally representative sample Ng'ombe and Kalinda (2015) estimated a mean maize plot of 1.61 ha, while Mwalupaso *et al.*, (2019) found 1.75ha for Mkushi district, Zambia.

4.2.1 Farm characteristics

Table 4.2 presents the farm characteristics and farming practices:

Table 4.2: Farm characteristics

Village	**Lukanga**	**Mangwende**	**Nkana**	**Total**	**p-value**
Land tenure					
Owned with the title (%)	10.71	6.00	20.69	12.80	0.06
Cropping system					
Intercropping (%)	60.71	44.00	63.79	56.71	0.09
Tillage Method					
Conservation tillage (%)	10.71	6.00	3.45	6.71	0.30
Soil Conservation					
Crop rotation (%)	69.09	38.00	74.14	61.59	0.00

Source: Author's computation

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The majority of the farmers owned their farmland without titles because most smallholder and family farmers use customary land in Zambia, which makes up about 93% of all farmland (UNECA, 2019). The differences in land tenure status across the three villages were not significant at 5%. That only 12.8% of the farmers own land, and have title to it, is in keeping with my expectations since over 60% of the land is under customary holding (Nkomoki, Bavorov and Banout, 2019). The farmers who owned titles to their land had an average land size of 26.19 ha compared to the sample average of 6.01 ha. It was thus observed that the farmers with larger parcels of land were more likely to hold titles to their farmland.

Mixed intercropping was the predominant cropping system across all the three villages with an overall 56.71% of all farmers practising it. Mangwende village had the lowest level of farmers practising it, with less than half of them (44%) using this system. The comparable figures are 60.71% and 63.9% for Lukanga and Nkana village respectively. This difference across villages is insignificant at 5% level of significance. In spite of many efforts to encourage mixed cropping among the farmers consistent with conservation agriculture, the levels of practice were still low. In part, the low level of mixed intercropping has been encouraged by the Farmer Input Support Programme (FISP), since this support programme offers maize production inputs alone (Saenz and Thompson, 2016).

The vast majority of the farmers (93.29%) practiced conventional tillage. A mere 6.71% practice conservational tillage, with 4.27% practising zero (0) and 2.44% practicing minimum tillage. This low level of conservational tillage is indicative of the low adoption of CA practices in Zambia. The difference between villages was not significant (p= 0.30). The most-practised soil conservation measure was crop rotation owing to the ease of implementation, with 61.59% of farmers practising it across the three villages, followed by minimum tillage at 37.20% and the rest of the measures with less than 5% of the farmers practising them. Terracing was the least practised of all the measures with just 2.44% of the farmers using it as a soil conservation measure. The differences among villages in the practice of mulching, zero cropping and afforestation were significant at 5% level of significance and not significant in the rest of the practices.

4.2.2 Maize inputs

This section presents the inputs in the production of maize including external inputs and labour input (in manhours) and are summarised in Table 4.3 below. The overall average amount of certified maize seed input used was 45.26 kg/ha with Lukanga village using more, 59.59 kg/ha, than Mangwende and Nkana (27.49 kg/ha and 47.01 kg/ha respectively). These differences across villages was not significant at 5% level of significance. The high standard deviation in each village and in the total are indicative of heterogeneity in the seeding rate among farmers

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in the sample. The estimated rate of maize seed usage of 45.26 kg/ha was much higher than what both Musaba and Bwacha, (2014) and Mwalupaso *et al.*, (2019) estimated (20.67 kg/ha and 15.18 kg/ha respectively) in other Zambian studies and the 17.35 kg/ha Abdulai, Nkegbe and Donkoh, (2018) estimated in a Ghanaian study. It was comparable to the 41.16 kg/ha observed in Abdulai and Abdulai (2016a) and lower than 67.07 kg/ha estimated in Ng'ombe and Kalinda (2015).

Table 4.3 Maize inputs

Variable	Lukanga	Mangwende	Nkana	Total	P value
Certified seed (kg/ha)	59.58	27.49	47.01	45.26	0.14
Standard deviation	121.12	21.92	69.80	83.17	
Fertiliser (kg/ha)	282.05	294.41	623.90	407.48	0.05
Standard deviation	205.85	249.81	1377.05	852.21	
Land prep (manhours)	555.07	319.88	1144.43	1144.43	0.01
Standard deviation	1073.96	507.30	1913.82	1913.82	
Planting (manhours)	82.17	77.93	572.58	255.37	0.00
Standard deviation	187.86	139.33	1541.27	953.62	
First weeding (manhours)	99.23	258.44	645.93	342.60	0.01
Standard deviation	194.45	482.05	1601.03	1019.82	
Second weeding (manhours)	60.08	124.9	279.91	158.19	
Standard deviation	103.94	220.66	760.50	480.36	0.04
Basal fertiliser app (manhours)	37.64	45.43	259.9	119.12	
Standard deviation	90.51	73.43	683.53	424.00	0.01
Top dressing fertiliser (manhours)	53.09	53.03	324.30	149.58	
Standard deviation	178.14	86.67	677.01	437.14	0.00
Spraying (manhours)	4.53	7.61	52.05	22.38	
Standard deviation	23.86	29.98	154.07	96.46	0.01
Harvesting (manhours)	445.99	590.87	1378.12	822.11	
Standard deviation	523.82	791.47	2093.53	1413.60	0.00
Total labour (manhours)	556.18	249.6	721.64	521.01	
Standard deviation	1142.92	430.28	1067.20	964.22	0.04

Sources: Author's computation

The average usage of fertilisers was 407.48 kg/ha, with Nkana using the greatest amount and Lukanga least at 623.90 kg/ha and 282.05 kg/ha respectively. These variations in amounts of usage per village were not significant at 5% level of significance. The estimated fertiliser usage rate was more than fourfold compared to the 96.38 kg/ha that Kimhi (2006) estimated in a 2006 study with a nationally representative sample. This result would suggest an upward trend in the usage of fertilizers among household maize farmers in Zambia. It was also higher than

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the 124.71, 177.78, 253.97 and 331.69 kg/ha found in Chiona, Kalinda and Tembo (2014), Amondo and Simtowe (2019), Abdulai, Nkegbe and Donkoh (2018) and Mwalupaso *et al.*, (2019) respectively.

Nkana village also had the greatest average usage amount of pesticides and herbicides of 1.16 l/ha, Mangwende the least amount of 0.49 l/ha while the overall average usage was 0.86 l/ha. The differences are statistically significant at 5% level of significance. Despite the benefit of saving the farmer up to 80% of labour hours on weeding and reducing the incidence of fall armyworms (FAW) in the area, just 41.46% of the farmers used pesticides and herbicides (Parker and Vernon, 1982; Banson, Asare and Dery, 2019; FAO, 2019), compared to 50% Mutambara (2013) found among smallholder farmers in the Federal Capital Territory of Nigeria in the absence of an outbreak of army worms. Access to these inputs was a challenge for the farmers (see Table 4.6) similar to the challenges with use of herbicides Lee and Thierfelder (2017) found among smallholder farmers in Zimbabwe. The average amount of herbicides and pesticides 0.86 litres/ha estimated for the sample was much lower than the 3.64 litres/ha Abdulai, Nkegbe and Donkoh, (2018) found for a similar group of maize farmers in Ghana. Since Lufwanyama district was infested with armyworms, it was a seemingly low amount of usage.

Land preparation used the greatest number of man-hours (518.93 hours) followed by first weeding (190.91 hours) and planting (148.22 hours). The variations in these results across villages were not statistically significant at 5% except for the second weeding and harvesting. The three activities are the most labour intensive. Across the farming activities in every village, the most used labour type is the family-supplied labour (Table 4.4).

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Table 4.4: Labour type by activity

Activity	**Lukanga**	**Mangwende**	**Nkana**	**Total**	**Chi^2 value**
Land preparation					0.95
Family	36.84	33.33	39.66	37.40	
Hired	31.58	7.41	34.48	27.64	
Both	31.58	59.26	25.86	34.96	
Planting					1.67
Family	85.71	88.46	81.82	84.62	
Hired	0.00	3.85	11.36	6.59	
Both	14.29	7.69	6.82	8.79	
First weeding					6.32
Family	55.00	70.37	83.78	72.62	
Hired	25.00	11.11	10.81	14.29	
Both	20.00	18.52	5.41	13.10	
Basal fertiliser application					0.67
Family	94.12	92.00	94.12	93.42	
Both	5.88	8.00	5.88	6.58	
Second weeding					2.81
Family	47.06	66.67	83.33	64.29	
Hired	47.06	33.33	16.67	33.93	
Both	5.88	0.00	0.00	1.79	
Top dressing fertiliser application					14.32
Family	94.44	92.00	91.89	92.50	
Hired	0.00	0.00	8.11	3.75	
Both	5.56	8.00	0.00	3.75	
Spraying					0.58
Family	100.00	100.00	92.31	96.43	
Hired	0.00	0.00	7.69	3.57	
Harvesting					11.18
Family	77.78	76.00	83.33	80.00	
Hired	11.11	4.00	14.29	10.59	
Both	11.11	20.00	2.38	9.41	

** (**)[***] Statistically significant at a 10 (5)[1] % level*

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4.2.3 Extension information

The information about extension service in the sample is summarised in Table 5.5 below;

Table 4.5: Extension information

Variables	**Lukanga**	**Mangwende**	**Nkana**	**Total**	**Prob > F**
Extension received	18.18	28.00	20.34	21.95	0.44
Average number of visits per farming season	3.50	3.57	3.42	3.50	0.98
Paid for extension (%)	70.00	78.57	16.67	55.56	0.00
Amount paid (ZMW)	421.43	262.27	30.00	294.75	0.02
Satisfaction (%)					
Paid	57.14	18.18	0	5	
Didn't pay	0	33.33	10	12.5	

** (**)[***] Statistically significant at a 10 (5)[1] % level*

The average number of farmers who received a visit from an agriculture extension officer was 21.95%, with Mangwende leading with 28% followed by Nkana (20.34%) and lastly Lukanga at (18.18%). Nkana and Lukanga villages fall in the catchment of one extension officer, whereas Mangwende in the catchment area of another extension officer. This may explain the difference in the incidence of visits across villages. These variations are nonetheless insignificant at 5% level of significance. The average number of visits per cropping year was 3.5 visits with minor and insignificant variations among villages. Farmers who indicated that they never received any extension visit also did not belong to cooperatives. Zambia has a very high ratio of extension officer to farmer, at 1:1 200 for crop production, which falls short of the 1:400 recommended level for crop production (GRZ, 2016). This study revealed that 21.95% of the farmers had access to extension services in the 2018 farming season. This proportion was consistent with 20% estimated in Ng'ombe and Kalinda (2015) but lower than the 27.2% Mussa (2015) found in a Malawian study. Other studies in different areas in Zambia found more than 50%of the farmers accessed extension services (Kimhi, 2006; Abdulai and Abdulai, 2016b, 2016a). Higher rates of access to extension (73.45%) were found among Zimbabwean farmers in Etienne, Ferrara and Mugabe (2019).

On average, more than half (55%) of those who received extension services paid for it. The average amount paid for the service for those who benefited was ZMW 294.75; Lukanga village farmers paid significantly higher (ZMW 421.43) than Nkana (ZMW 30.00). This could be because Lukanga is further not just from the urban area, but is also less populated than Nkana and so had to contribute more per farmer for the extension officer's transport. Recipients of extension services were on average not satisfied. It was observed that the level

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of satisfaction was zero (0) among those that did not pay for extension in Lukanga village while 57.14% were satisfied with the paid-for extension service they received in the same village. In Mangwende village, the farmers who did not pay anything towards extension service were more satisfied with the service than those who paid, 33.33% versus 18.18%, respectively. A similar result was obtained in Nkana village where 10% of the farmers who received extension advice without paying were satisfied, whereas none of those that paid for the service they received were satisfied. Overall, the farmers who received extension advice without paying showed more satisfaction with the service. This could be explained by considering their expectations, in that those who paid for the service had higher expectations about the service than those who did not pay and thus had lower expectations of the value they would receive. Table 4.6 reports on the challenges faced in maize production.

Table 4.6: Challenges in maize production

Variables	**Lukanga**	**Mangwende**	**Nkana**	**Total**	**Chi^2 Stat**
Production					
Droughts	21.82	26.00	13.56	20.12	3.54***
Pests	16.36	18.00	1.69	11.59	62.32***
Increased labour cost	7.27	2.00	8.47	6.10	23.73
Input market					
Expensive inputs	10.91	12.00	1.69	7.93	46.79
Late delivery of inputs	7.27	6.00	1.69	4.88	27.34***
Poor seed quality	1.82	4.00	5.08	3.66	13.33***
Soil management					
Infertile soil	7.27	0.00	22.03	10.37	11.55***
Maize marketing					
Delayed FRA payment	0.00	0.00	3.39	1.22	0.17
Lack of market access	1.82	0.00	0.00	0.61	0.37
Low maize price	3.64	4.00	18.64	9.15	39.09
Fertiliser/manure					
Delayed fertilizer	45.45	40.00	42.37	42.68	0.01
Lack of fertilizer	27.27	28.00	22.03	25.61	0.43
Lack of manure	5.45	0.00	0.00	1.85	0.05

** (**)[***] Statistically significant at a 10 (5)[1] % level*

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4.2.4 Challenges in maize production

Farmers cited many challenges concerning the production of maize; these have been grouped and are summarised in Table 4.6, above.

Most of the farmers depended on fertiliser and input support from the government subsidy programme and the delayed delivery of fertiliser was a challenge that 42.68% of the farmers alluded to. This was the greatest challenge in maize production, followed by the lack of fertiliser (25.61%), droughts (20.12%), pests and disease (11.59%), and infertile soils (10.37%). This varied across villages, a variation that was significant at 1% level of significance, with none from Mangwende, 7.27% from Lukanga and 22.03% from Nkana alluding to it as a challenge. This implies that the farmers in Nkana village most likely have farmlands of poorer soil quality than the other two villages. Late delivery of fertilisers hampers the technical efficiency of the farmers. Namonje (2015) estimated a 4.2% loss in output due to this factor. The two greatest challenges in production both have to do with fertiliser. It is a limiting input in the production of maize as the farmers reported that both the delayed delivery and its lack negatively affected their production. The lack was mostly reflected not in zero access to fertiliser, but in the limited access to the input. The subsidised fertiliser provision remains insufficient for the vast majority of the farmers. This challenge in maize production has been alluded to in other studies on household famers in Zambia (Xu *et al.*, 2009; Burke *et al.*, 2019).

Climate change has affected maize production in SSA. This region has been through extreme weather conditions such as droughts and floods, and in slow-onset changes in weather (Alfani *et al.*, 2019). The occurrence of the El Nino drought affected the area in the 2018 growing season and 20.12% of the farmers alluded to it as a challenge. Alfani *et al.* (2019) estimated that the effect of El Niño drought in the 2015/16 farming season was a 20% loss in potential output and 37% income loss. The slow-onset in the rainy season creates conditions optimal for the survival and thriving and distribution of pests and diseases, such as the fall armyworms (FAW) which were reported in all the provinces in Zambia in 2018 (FAO, 2019). Lufwanyama district was no exception, at least 11% of the farmers reported FAW as a challenge in the production of maize. Maes in Banson, Asare and Dery, (2019) estimated that FAW cost between 21% to 53% of crop yield in the infested areas. Furthermore, FAW raised the cost of production for the farmers as well as to government due to the additional costs of buying pesticides. For instance, the government of the Republic of Zambia (GRZ) spent USD 3 million in the fight against FAW in 2018 (Banson, Asare and Dery, 2019).

Poor seed quality was considered a challenge in production by 3.66% of the farmers. There has been an increasing mismatch between the seed variety and the agro-ecological zone due

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to climate variability, which has become a more common factor in recent years. Moreover, some seed varieties that were previously suited for the area could not perform as well due to the El Niño shock that disturbed the precipitation patterns. For example, some farmers in Lufwanyama district that planted on time had to replant their seed after the spell of drought that dried their initial seedlings. In a study in Zimbabwe, Katengeza, Holden and Lunduka, (2019) found that households that adopted drought-tolerant maize variety under mild drought conditions harvested 617kg/ha more than non-adopting households.

Late delivery of inputs such as seed, pesticides and herbicides was alluded to by at least 5% of the farmers as a challenge to maize production, because, in the case of seed, timely planting is critical in the successful production of maize. This has become especially relevant now that farmers have to use climate change adaptation strategies, such as matching planting with the onset of the rains (Twagiramaria, Tolo and Zinyengere, 2017). Late planting of maize was found to reduce yield to about half the yield early planting produced, 1.2MT/ha compared to 2.1 MT/ha (Tittonell and Giller, 2013). In Zambia, late delivery of inputs is delivery after 15th December (World Bank, 2018b) and about 15% of all farmers in Zambia on the FISP receive their inputs late (Namonje, 2015). While only 5% of the farmers perceived late delivery of inputs as a challenge, 39.26% considered delayed fertilisers as a challenge. Therefore, the farmers regarded themselves as more constrained by fertiliser, than by seed in production.

Although the maize marketing rigidities arising from delayed payments for maize sales were expected to affect the farmer's maize production, only 1.22% of the farmers reported it as a challenge. This was a small proportion of the sample. It can thus be concluded that delayed payments for maize sales have a negligible impact on maize production in Lufwanyama district. Furthermore, it is indicative that the vast majority of the farmers do not produce enough to have surplus for sale.

4.2.5 Selected Productive Assets

Table 4.7 below presents a summary of selected productive assets of farming households.

Hoes were the predominant productive asset used in the production of maize. On average, each household comprised 7 people and owned 5.48 hoes. The high people-to-hoe ratio is reflective of labour intensive production system. The hoes are used in both land preparation and weeding, making them a key productive asset. An average farming household also has at least a machete, sprayer, stores, an axe and a wheelbarrow (1.5, 1.44, 1.32, 1.81 and 1.21 respectively).

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Table 4.7 Productive assets per household

Asset	Variables	Lukanga	Mangwende	Nkana	Total	Chi^2 value
Hoe	Quantity	5.11	6.64	4.78	5.48	103.36***
	Unit price	49.39	86.02	44.40	59.18	412.01***
Machete	Quantity	1.39	1.57	1.67	1.50	0.42
	Unit price	89.72	28.91	32.78	56.71	237.41***
Sprayer	Quantity	1.33	1.37	1.88	1.44	11.63***
	Unit price	241.43	152.16	265.00	210.02	1.51
Storage	Quantity	1.00	1.00	1.63	1.32	0.17
	Unit price	173.33	118.33	144.67	142.50	5.05***
Bicycle	Quantity	1.28	1.38	1.26	1.30	1.28
	Unit price	997.78	764.38	772.11	846.96	42.16***
Axe	Quantity	2.33	1.90	1.00	1.81	1.53
	Unit price	31.67	26.70	26.67	27.63	3.95
Wheelbarrow	Quantity	1.00	0.00	1.27	1.21	0.35
	Unit price	350.00	-	354.55	353.57	1.18

** (**)[***] Statistically significant at a 10 (5)[1] % level*

On average, each household owned a bicycle (1.30 per household). Bicycles are the key mode of transport. In some cases, these households hired vans to transport either their fertiliser or their maize.

4.3 Preference Analysis

This section presents the results of preference and preference heterogeneity analysis of this study. BWS preference results are presented in this section, thereby addressing the first objective of this study. Aggregate heterogeneity analysis results, PCA and AHC results and discussions are likewise presented here, thus meeting the second objective of the study.

4.3.1. Aggregate best-worst results

The aggregate BW results are presented in Table 4.8 showing aggregate Best (B), Worst (W), Best – Worst (B-W), standard ratio scale and rank for each SAP attribute in the experiment. Density plots for all the attributes are provided in Appendix 2.

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Table 4.8: Ranking of attributes

Attributes	Best (B)	Worst (W)	B-W	Sqrt (B/W)	Standard ratio scale	Rank
Increased crop yields	351	77	274	2.14	1.00	1
Reduced pests	279	111	168	1.59	0.74	2
Increased soil fertility	191	94	97	1.43	0.67	3
Reduced droughts	223	119	104	1.37	0.64	4
Decreased soil erosion	123	105	18	1.08	0.51	5
Decreased cost of production	161	141	20	1.07	0.50	6
Decreased external inputs	139	179	-40	0.88	0.41	7
Decreased water use	102	177	-75	0.76	0.36	8
Decreased labour use	100	219	-119	0.68	0.32	9
Decreased off-farm pollution	77	315	-238	0.49	0.23	10
Decreased extension requirement	58	267	-209	0.47	0.22	11

Source: Author's computation

The results showed the highest preference for increasing crop yield. This is generally expected since the smallholder and family farmers are known to have low yields, and low efficiency in the production of maize (Chiona, Kalinda and Tembo, 2014). The *decrease pests and diseases* attribute, was ranked as the second most important attribute, a preference that could have been influenced by the FAW outbreak in the area. The third most important was the *increased soil fertility* attribute. The importance placed on this attribute was likely driven by the challenge of low fertility soils, while the increasing *resistance to drought* attribute was ranked fourth most important attribute. This could have been motivated by the impact of drought spells in the area over the previous two farming seasons.

The three lowest ranked attributes were the *reduction of extension requirement*, *decreased off-farm pollution* and the *decreased labour use*. There was little wonder that the *reduction of extension requirement* attribute ranked as least important, since most farmers have been growing maize for several years. Maize being the most widely grown crop in Zambia has led to maize farming knowledge being widely spread; hence, farmers did not perceive reducing *the need for extension requirement* as important. The second lowest-ranked attribute was *decreased off-farm pollution*; this would seem to suggest that the farmers showed less concern about the quality of the environment outside their farm. The third least important attribute was *decreased labour use*. This would appear to indicate that labour is not the binding constraint in their maize production.

The sample mean B-W score of the attributes show the importance farmers placed on each SAP attribute. The CV of B-W score which is calculated as ratio of standard deviation to mean for each SAP attribute (B-W) score is a measure of relative variability and was used to proxy the heterogeneity of farmer preferences for the SAP attributes presented in Table 4.9 below.

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The importance of an attribute is positively related to the mean of the attribute, i.e. the attribute with the highest mean (B-W) is most preferred. The higher the heterogeneity in absolute terms the higher the level of disagreement about the importance of a given SAP attribute and the converse is true.

Table 4.9: Attribute variability

Attribute	Importance	Standard Deviation	Heterogeneity
Increased crop yield	1.67	1.61	0.96
Decreased pests and diseases	1.02	1.59	1.55
Increased on-farm soil fertility	0.59	1.41	2.38
Increased resistance to drought	0.63	1.48	2.34
Decreased on-farm soil erosion	0.11	1.29	11.73
Decreased cost of production	0.12	1.46	11.94
Decreased external input used	-0.24	1.54	-6.33
Decreased water requirement	-0.46	1.45	-3.17
Decreased labour use	-0.73	1.54	-2.12
Decreased off-farm pollution	-1.45	1.71	-1.18
Reduced extension requirement	-1.27	1.72	-1.35

Source: Author's computation

There was high agreement among farmers that *Increased crop yield* was the most preferred attribute. Similarly, there was high agreement among farmers that *Decreased off-farm pollution* and *Reduced extension requirement* attributes were the least and second least preferred, respectively. These results confirm the primacy of increasing crop yields in among farmers but also reveals how there is little concern about off-farm pollution and their perception of extension in their current farming system. On the contrary, there was high disagreement about the preferences for *Decreased cost of production, Decreased soil erosion* and *Decreased external inputs*. This observed heterogeneity in preferences was indicative of distinctive preferences among the farmers on the rest of the SAP attributes and this is what was further investigated in cluster analysis.

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4.3.2. Preference heterogeneity analysis

The heterogeneity observed in preferences was investigated in agglomerative hierarchical analysis. It was preceded by a principal component analysis (PCA).

A PCA was done on the SAP attributes BW scores and the results are depicted by the Scree plot given in Figure 4.2. Using the rule of "eigenvalue greater than or equal to one" for selecting the number of principal components/clusters, five principal components were found to be optimal from the graph.

Agglomerative hierarchical clustering (AHC) was carried out on individual BWS scores using a euclidean distance and Ward linkage function with a cut number of 5 clusters. The cut number was obtained from the scree plot result in Figure 4.1 below. The clustering result is depicted in Figure 4.2 in a dendrogram below. The horizontal axis has the euclidean distance between any two farmers on the same node are most similar to each other than any other farmer in the dataset. This is iterated until the whole dataset has only one node. Each of the red rectangles on the dendrogram is a preference cluster.

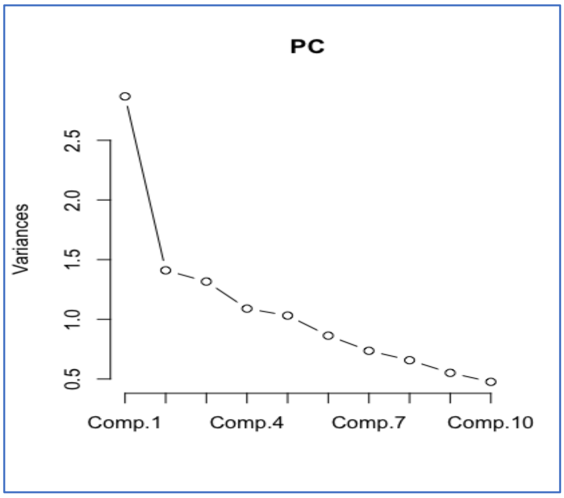

Figure 4.1 Scree plot

Source: Author's computations

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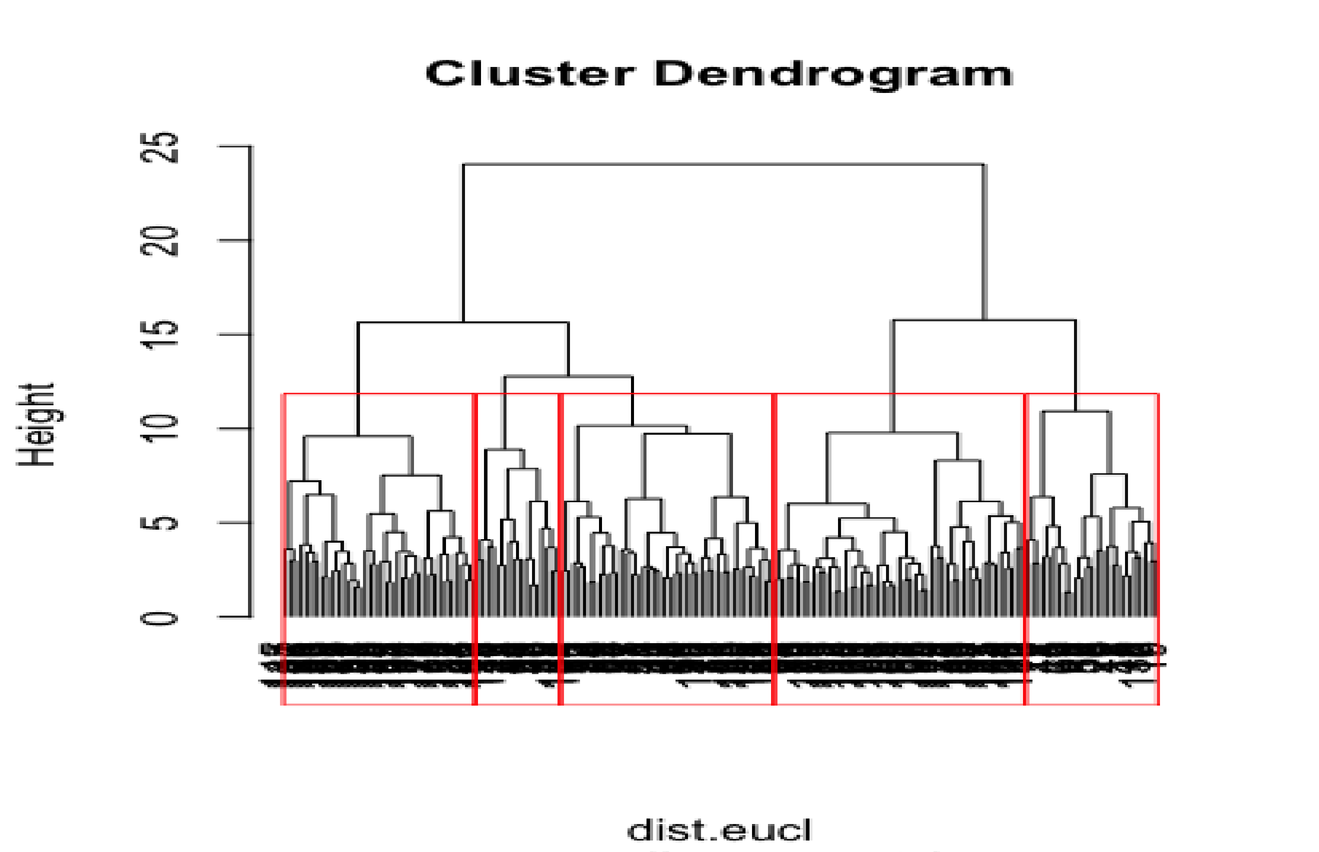

Figure 4.2 Cluster dendrogram

Source: Author's manipulations

4.3.3. Cluster description

In Table 4.10 it was observed that the differences across clusters are significant for all attributes except for the *Decreased labour use* attribute at the 10% level of significance and the *Decreased on-farm soil erosion* attribute at 5% level of significance.

The farmers from Cluster 1, which represented 15.24% of the sample, rated the attributes *increased crop yield* and *increasing soil fertility* higher than any other cluster (Table 4.10). This cluster was therefore called the *crop yield maximising cluster*. The members of this cluster also showed a preference for *decreasing pests and diseases* but showed the least concern for *decreasing labour use*.

Cluster 2, which made up 28.66% of the sample, rated *decreasing pests and diseases, increasing drought resistance* and *decreasing soil erosion* higher than any other cluster (Table 4.10). The farmers in this cluster showed the least concern for off-farm pollution of all the other clusters. Due to the orientation of their preferences towards increasing resilience of their farming system to environmental stressors, their cluster was known as the *resilience cluster*.

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Table 4.10: Cluster-attributes ANOVA results

Cluster	1	2	3	4	5
Percentage	15.24	28.66	9.76	24.39	21.95
Descriptor	Yield maximising	Resilience	Input minimising	Environmentally conscious	Cost minimising
Crop yield	2.92	2.60	1.13	0.23	1.44
Decreased pests	1.04	1.68	0.44	0.35	1.17
Increased soil fertility	2.20	0.91	0.38	-0.30	0.14
Drought resilience	0.52	1.53	0.00	0.93	-0.50
Reduced erosion	-0.32	0.70	-0.63	0.50	-0.47
Decreased production cost	-0.72	-0.15	-0.63	0.30	1.19
Reduced external input use	0.12	0.43	1.00	-1.73	-0.28
Decreased water use	-1.24	-1.26	1.44	0.45	-0.72
Reduced labour use	-2.16	-0.57	-0.13	-0.35	-0.61
Decreased off-farm pollution	-1.40	-3.04	-1.38	-0.45	-0.56
Reduced extension required	-0.96	-2.83	-1.63	0.08	-0.81

Source: Author's computation

The smallest cluster was cluster 3, which comprised 9.76% of the sample and was labelled the *input minimising cluster*. Farmers in this cluster rated *decrease external inputs* attribute higher than any other cluster (Table 4.10). They also rated *decreased water requirement* higher than any other cluster and showed a high preference for increasing crop yields.

Cluster 4 contributed 24.39% to the sample and rated *decreasing off-farm pollution* and *decreasing extension requirement* higher than any other cluster (Table 4.10). Within the cluster, the attribute *increased drought resistance* had the highest preference score. Due to its preference for attributes that have to do with increasing environmental sustainability, the cluster was called the *environmentally-conscious cluster.*

The final cluster, cluster 5, which made up the last 21.95% of the sample was named the *cost-minimising cluster*. This followed the observation that the cluster had a higher preference for the attribute of *decreasing the cost of production* than any other cluster (Table 4.10). Farmers within this cluster rated *increasing crop yield* as most important and *reducing extension requirement* as least important.

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In summary, the observed heterogeneity in the farmer preferences for attributes other than *increase crop yield* has been investigated in this section. The results show that farmers have heterogenous preferences over the rest of the attributes and based on their preferences, the farmers could be grouped into five clustered: the crop-yield-maximising, the resilience maximising, the input-minimising, the environmentally-conscious, and the cost-minimising clusters. These clusters were named based on the combination of their relative strength of preference towards the SAP attributes or combination of attributes. The clusters identified clusters were further examined to see if and how they differed based on farmer and farm characteristics.

4.3.4 Cluster analysis

The five preference clusters were investigated for their relationships with the farmer, household, farm and production system characteristics. This was an attempt to gain insight into how farm and farmer characteristics could have driven the observed preferences. Table 4.11 presents ANOVA results of the relationships.

It was observed that clusters with a higher concentration of male-headed households were less inclined to prioritise attributes of SAP that concern environmental sustainability and adaptation to climate change. Rather, they placed more premium on maximising their yields, and minimising costs and inputs. The farmer's level of education was estimated to affect the farmer's preferences for SAP attributes with the most educated farmers being more environmentally conscious. These observations seemed to indicate that the farmers' preferences are affected by the gender of the farmer as well as the level of education of the farmer.

Smaller farmer households had a higher preference for attributes of SAP that had the benefit of minimising the inputs in the production of maize. Farmers with agriculture as their primary occupation preferred attributes of SAP that reduce the inputs to the production process, as reflected in their concentration in the cost-minimising and input-minimising clusters. These farmers did not have alternative sources of income, in contrast to farmers who had other off-farm economic activity that could cover some costs of farm inputs and who were thus less concerned with minimising input costs.

The farmers who engaged in some combination of soil conservation practices were found to be more environmentally conscious in their preferences. This was deduced from the observation that the environmentally-conscious cluster had a higher concentration of farmers who practised soil conservation.

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It can thus be posited that the current practices the farmer engaged in on the farm influenced their preferences

Table 4.11 Cluster-farmer characteristics

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	F-stat
	Yield maximizing	Resilience	Input minimizing	Environmentally conscious	Cost minimizing	
Gender(% males)	0.68	0.35	0.56	0.45	0.75	4.44***
Education(years)	6.20	5.24	6.50	7.38	7.08	2.04*
HH size(persons)	7.12	8.39	5.63	6.88	7.31	3.34**
Hhh farming primary occupation(%)	0.84	0.93	1.00	0.98	1.00	2.59**
Soil conservation(%)	0.16	0.24	0.25	0.45	0.19	2.42**
Crop rotation(%)	0.60	0.30	0.75	0.63	0.94	11.38***
Access to extension(%)	0.16	0.39	0.13	0.23	0.08	3.46***
Crop inputs (l)	1.80	1.17	5.88	5.33	2.76	2.03*
Labour cost(manhours)	385.20	749.13	328.13	641.00	929.17	2.17*
Seed productivity(kg/ha)	55.44	30.03	54.73	63.43	34.40	4.98***
Yield(kg/ha)	1105.46	772.46	937.92	1923.15	1272.97	2.05*

Source: Author

Farmers who had higher access to extension were more inclined to prioritize aspects of SAP that maximize resilience to environmental stressors such as droughts, pest and diseases. It can be argued, therefore, that extension raised farmers' awareness of climate change and adaptation strategies.

Farmers who favoured attributes of SAP that enhance the resilience of the farming system also, on average, had the lowest productivity of seed and lowest maize yield. This raises the question of cause and effect: does a preference for resilience result in lower productivity?

In the focus-group discussions farmers mentioned that due to spells of droughts and fall armyworms they had to replant their fields in some cases. This meant using more seed in the process. Some expressed doubts about their current seed variety's suitability for the precipitation patterns they experienced in the recent past years. The findings appeared to suggest that reduced seed productivity and yields due to environmental stressors caused farmers to have higher preference for attributes that raised resilience.

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Input-minimising farmers on average used more crop inputs than any other group of farmers. It then explains why they would have a higher preference for attributes that entail cutting back on the amount of input used in production.

Cost-minimizing farmers had the highest cost incurred in land preparation. This could be the motivation for them to favour attributes of SAP that would cut the cost of production.

To sum up the findings of the preference analysis, the farmers had preferences for SAP attributes which were also heterogeneous. These preferences were influenced by the farmer and farm characteristics, and the challenges the farmer faced in their production. The farmers generally preferred those attributes that directly benefited them to those that had off-farm environmental benefits, for instance, increased crop yield was the most preferred attribute whereas decreased off-farm pollution was least preferred. The results also showed that farmers who had more access to extension rated attributes oriented towards the environment higher than those who did not which is telling of the effect of extension in raising awareness about and affecting farmers' preferences for SAP. It further observed that farmers tend to prefer SAP attributes that were a solution to their most pressing challenge in maize production.

4.4 Efficiency Analysis

Having achieved the first two study objectives in the previous section (farmer preference and preference heterogeneity analyses), this section presents the technical efficiency analysis results and is an attempt at achieving the third and fourth research objectives of this study which were set out in Section 1.3.2. The results will be presented sequentially from the OLS production function to the efficiency index thus achieving the third research objective of this study. The results will also present the efficiency model, which takes clusters from the Section 4.2.3 as regressors in an attempt at meeting the fourth research objective of this study.

4.4.1 Tests on data

To ensure the data was sound enough to give reliable estimates, some checks were done on the data. The first was a test for scale reliability to ensure the instrument captured the data correctly. The data were also checked for multi-collinearity and heteroscedasticity, which are the two problems most associated with cross-sectional data.

Scale reliability

The Cronbach alpha for the variables in the production function of 0.68 is presented in Table 4.12. Since general rule of thumb says that alpha, α, of 0.6-0.7 is acceptable there was good

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scale reliability in the data. It was, therefore, deduced that the data had good internal consistency.

Table 4.12 Cronbach alpha results

Test scale = mean (unstandardized items)	
Average inter-item covariance:	0.28
Number of items in the scale:	5
Scale reliability coefficient:	0.68

Source: Author's computations

Multi-collinearity

The correlation matrix of the production variables in Table 4.13 shows a low degree of pairwise correlations with the highest being the fertilizer-land correlation at 0.472 and the lowest being the labour-seed correlation at 0.01. All the pairwise correlations were below the threshold of 0.70. Based on these results multi-collinearity was not considered to be a problem with this data set.

Table 4.13 Correlation matrix of production variables

	OUTPUT	SEED	LAND	LABOUR	FERTILIZER
OUTPUT	1				
SEED	0.42	1			
LAND	0.36	0.40	1		
LABOUR	0.18	0.01	0.16	1	
FERTILIZER	0.33	0.20	0.47	0.13	1

Source: Author's computations

Heteroscedasticity

The null hypothesis of constant variance could not be rejected at a 5% level of significance in the Breush-Pagan test (Table 4.14). Therefore, heteroscedasticity was not a problem with the data in this study.

Table 4.14 Heteroscedasticity test results

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity
H_o: Constant variance
Variables: fitted values of Q
chi^2 (1) = 0.46
Prob > chi^2 = 0.50

Source: Author

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4.4.1 Model 1: OLS

The ordinary least square (OLS) estimation results for the Cobb-Douglas and translog production functions are presented in Table 4.15. The output is positively related to all the inputs, implying that the estimates satisfy *a priori* expectations of non-decreasing inputs, non-increasing outputs structural properties of the Cobb-Douglas production function (Coelli, Rao and O'Donnel, 2005; Kumbhakar, Wang and Horncastle, 2015). Similarly, the translog model satisfied the regularity conditions: positive slopes for the single terms satisfying the non-decreasing inputs *a priori* expectation condition, and the negative slope on the square term satisfying the diminishing marginal product condition. The negative coefficient on the squared seed variable also indicates there is an optimal seeding rate.

Table 4.15 OLS estimates

	Cobb-Douglas		Translog	
Variables	Estimates	Standard errors	Estimates	Standard errors
FERTILIZER	0.231**	0.100	0.210**	0.099
LAND	0.157	0.105	0.120	0.105
LABOUR	0.046	0.07	0.061	0.058
SEED	0.365***	0.10	1.206***	0.371
SEED*SEED			-0.249**	0.107
Constant	3.852***	0.84	2.565***	0.891

** (**)[***] Statistically significant at a 10 (5)[1] % level*

No attempts were made at interpreting the individual coefficients of the translog model since their interpretation is not straightforward and their use was peripheral to this study. However, the Cobb-Douglas estimates are interpreted in what follows. The coefficients of the inputs represent the output elasticities of each input since the input variables are in logarithms. Output elasticity is the percentage change in output as a result of a 1% change in the respective input. The seed output elasticity of 0.37 means a 10% increase in the amount of seed input raises the maize output by 3.7% on average, holding all else constant. The seed input has the highest elasticity, followed by fertilizer (0.23) then land (0.16) while labour has the least elasticity (0.05). However, land and labour elasticities are insignificant at the 10% level of significance.

The seed quantity elasticity of output of 0.37 compares to 0.38 that Memon *et al.*, (2016) found for smallholder farmers in District Mirpurkhas in India, and 0.46 Kabwe, (2012) found for farmers in Chongwe district of Zambia using a Cobb-Douglas specification of the production frontier. The quantity of improved seed used in production is crucial in the

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production process. It sets the pace for the harvest and is time-sensitive. For example, if a poor quality seed was used, the increasing amount of fertilizers, *ceteris paribus*, will not have a significant impact on output. It has been observed that late planting, *ceteris paribus*, hurts outputs significantly (Liu and Myers, 2009). That seed had the highest contribution to output suggested that the farmers are seed constrained, for instance, improved seed is the most scarce input. This is supported by the proportion of farmers that cited expensive seed inputs as a challenge to their productivity compared to those that cited labour cost of 7.9% compared to 6.1% (Table 4.6) respectively.

The area planted had a lower contribution because this sample of farmers was generally not land constrained, as previously mentioned and as may be seen in the average landholding of 6 ha which is higher than the Zambian national average for smallholder farmers of 5.1 ha and the widely used categorisation for smallholder farmer category of 2 ha (CSO, 2012; Wolfenson, 2013; Lowder, Skoet and Raney, 2016). Therefore, the area planted was more determined by the available input amounts of seed and fertiliser and not the amount of land available.

The labour input contributes least to the output: increasing the area planted by 100% has the least marginal increase in output of just 5%. This is indicative of surplus labour supply in the sector. Thus, increasing the amount of labour input has no significant contribution to maize output because the farms are not labour constrained.

The fertiliser elasticity of 0.23 was less than half of 0.54 Musaba and Bwacha, (2014) found for fertiliser in a sample collected from the neighbouring district Masaiti (Figure 3.1) but was similar to the 0.28 estimated for smallholders of Chongwe district in Zambia (Kabwe, 2012).

4.4.2 Model selection

Specification tests were performed to see which model fitted the data best between the Cobb-Douglas and the translog model. The results for the likelihood ratio (LR) and Wald test are presented in Table 4.16.

Table 4.16 Model specification test

Test name	Hypothesis	Statistic	p value	Decision
Wald test	H_0: Cobb-Douglas model is nested in the Translog model	Chi^2 (1) = 5.53	0.0187	Fail to reject Ho
Likelihood ratio	H_0: SEED_sq=0	F (1, 145) = 5.40	0.0215	Reject Ho

Source: Author's computations

The null hypothesis that the Cobb-Douglas model is nested in the translog could not be rejected in the Wald test. Also, the LR test showed that the square term of the seed variable

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was significant. Therefore, the translog model was a better fit for the data. Subsequent analysis was based on the estimation of a translog production function. This finding was similar to Mussa, (2015).

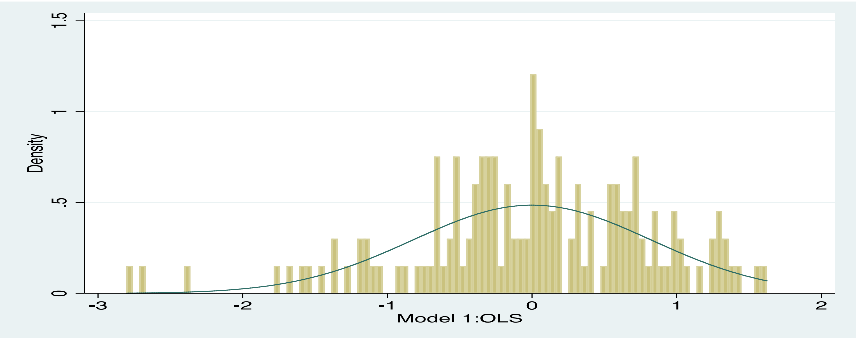

Figure 4.3 Histogram of OLS residuals

Source: Author's computations

4.4.3 Model 2: COLS

The estimations of the corrected ordinary least squares (COLS) model are presented in Table 4.17. COLS compares each farmer's actual output to their possible maximum. The mean efficiency index of the sample is 26%. This level of efficiency is very low and presents a lot of room for improvement for the farmers. The least efficient farmer was achieving only 1.2% of their potential output in the sample.

Table 4.17 COLS efficiency

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
eff_cols	150	0.264	0.2	0.012	1

Source: Author's computation

The histogram, Figure 4.5, below depicts the distribution of the efficiency index score for the sample. The very low mean relative efficiency can then be explained in part by the presence of outliers (super-efficient farmers) in the sample.

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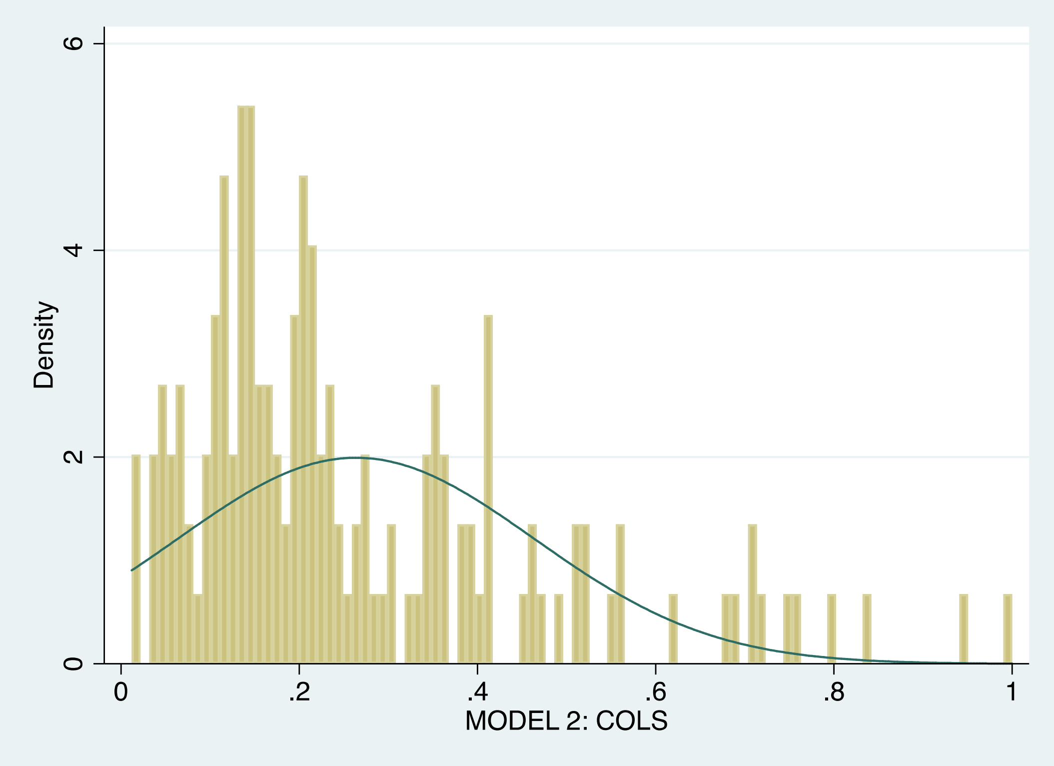

Figure 4.4: Histogram of COLS efficiency

Source: Author's computation

4.4.4 Model 3: CMAD

COLS is based on the OLS residuals and it attributes all deviations from the frontier to inefficiency. This makes the estimates very sensitive to outliers and measurement errors in the data set. To circumvent the influence of outliers on the measure of efficiency the corrected median absolute deviation (CMAD) method was used. We have a reason to suspect outliers are influencing our estimate if the results from the two methods differ substantially. The estimates from CMAD all have the expected signs and with all the inputs significant at 5% level of significance except for the land variable (Table 4.18).

Table 4.18: CMAD estimate

Variable	Coefficient	Standard error
FERTILIZER	0.185*	0.103
LAND	0.163	0.108
LABOUR	0.137**	0.06
SEED	1.062***	0.382
SEED^2	-0.240**	0.111
Constant	2.630***	0.918

** (**)[***] Statistically significant at a 10 (5)[1] % level*

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Most of the estimates for CMAD are very similar to the OLS model estimates. It was noted that labour was significant in the CMAD model. The efficiency index from the CMAD model is compared to the COLS model efficiency in Table 4.19 below:

Table 4.19 COLS and CMAD efficiency

Variable	Observation	Mean	Standard Deviation	Min	Max
eff_cols	150	0.264	0.200	0.012	1
eff_cmad	150	0.277	0.214	0.010	1

Source: Author

Both the COLS and CMAD score estimates reveal significant dispersion and the two results are quite similar, indicative of the robustness of the COLS result. The distribution of COLS and CMAD are compared in Figure 4.5.

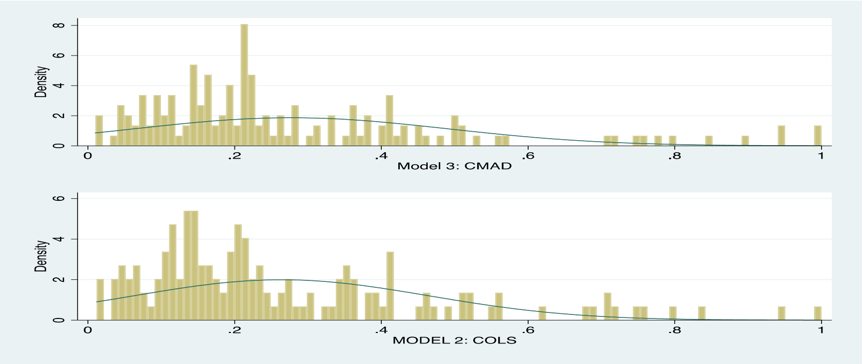

Figure 4.5. Histogram of CMAD and COLS efficiencies compared

Source: Author

4.4.5 Maximum likelihood estimations (MLE)

In the ensuing subsection, the MLE results are given. However, the method is only justified if the OLS residuals are not symmetrically distributed. Figure 4.3 above presented the histogram of the OLS residuals.

Some negative skewness in the distribution was observed from the histogram. This implies there are disproportionately fewer more efficient farms in the sample. The distribution of the residual in Table 4.20 show a skewness of -0.62. Thus, a test of normality was carried out to measure the significance of the skewness, and the results are presented Table 4.21 below.

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Table 4.20 Distribution of OLS residuals

Percentiles	Smallest				
1%	-2.714994	-2.804064			
5%	-1.452956	-2.714994			
10%	-1.103114	-2.364118	Obs		150
25%	-0.4251856	-1.765233	Sum of Wgt		150
50%	0.0270427	Mean		3.46E-09	
Largest	Std.	Dev.		0.821794	
75%	0.5949466	1.398792			
90%	1.003128	1.443852	Variance		0.6753453
95%	1.283053	1.572091	**Skewness**		**-0.6204405**
99%	1.572091	1.624165	Kurtosis		3.866412

Source: Author

Table 4.21 Skewness/ Kurtosis joint test

				joint	
Variable	Obs	Pr (Skewness)	Pr (Kurtosis)	chi^2 (2)	Prob>chi^2
residuals	150	0.0025	0.0502	12.95	0.0015

Source: Author

The distribution of the error term from the OLS model shows a negative skewness, in Table 4.20. The null hypothesis of no skewness is rejected at 1% level of significance based on the p-value of 0.0015 in Table 4.16. Further, the M3T Test for this distribution of -3.102 also supported the rejection of the null hypothesis of no skewness. These test results substantiated the use of the maximum likelihood estimation and the stochastic frontier model with parametric specifications (Kumbhakar, 2015).

4.4.6 MODEL 4: Half-normal distribution with homoscedasticity

The results of the stochastic frontier model are presented in Table 4.22. The model converged after five iterations**.**

The frontier fertiliser coefficient of 0.176 was lower than the coefficient of 0.526 found in a Zambian study of farmers from Central Province (Chiona, Kalinda and Tembo, 2014). The land coefficient of 0.131 is also lower than their estimated 1.040 but the 1.348 seed coefficient was higher than their estimated 0.122. The coefficient associated with the square of seed of -0.301 had a different sign from their estimated 0.044. Compared to the frontier coefficients in Mussa, (2015), the 0.176 fertiliser coefficient was lower than their estimated 0.354 and the

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0.131 coefficient for land was lower than their estimated 0.215. Seed coefficient of 1.348 was higher than Mussa's estimate of 0.068. The -0.301 coefficient of the square of seed had the same sign as Mussa's estimate (-0.022).

Table 4.22. Half-normal (homoscedastic distribution)

	Coefficient	Standard error
frontier		
FERTILISER	0.176*	0.097
LAND	0.131	0.093
LABOUR	0.088*	0.053
SEED	1.348***	0.359
$SEED^2$	-0.301***	0.103
Constant	3.234***	0.813
usigmas		
constant	0.114*	0.297
vsigmas		
constant	-1.356***	0.354

** (**)[***] Statistically significant at a 10 (5)[1] % level*

The variance parameters in the table above are parameterised and Table 4.23 below presents the recovered variances:

Table 4.23 Natural metrics of variances

Variable	Coefficient	Std. Err.	t	P>t	[95% Conf.	Interval]
sigma_u_sqr	1.074	0.375	2.860	0.004	0.541	2.130
sigma_v_sqr	0.332	0.112	2.960	0.003	0.171	0.644

Source: Author

The estimates of the variances are significant at 1% level of significance.

4.4.7 Technical efficiency

Based on the maximum likelihood estimates, an efficiency index was obtained as presented in Table 4.24 and its distribution in Figure 4.7. The mean efficiency score equal to 0.509 implies that the farmers sampled were producing at 50.9% of their maximum possible output. This implies that the farmers were on average losing 49.1% of their potential output to technical inefficiency. Farmers could, therefore, gain up to 49.1% in output by raising efficiency.

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Table 4.24 Efficiency index

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
bc_hh	150	0.509	0.186	0.058	0.823
jlms_hh	150	0.841	0.520	0.210	2.957

Source: Author

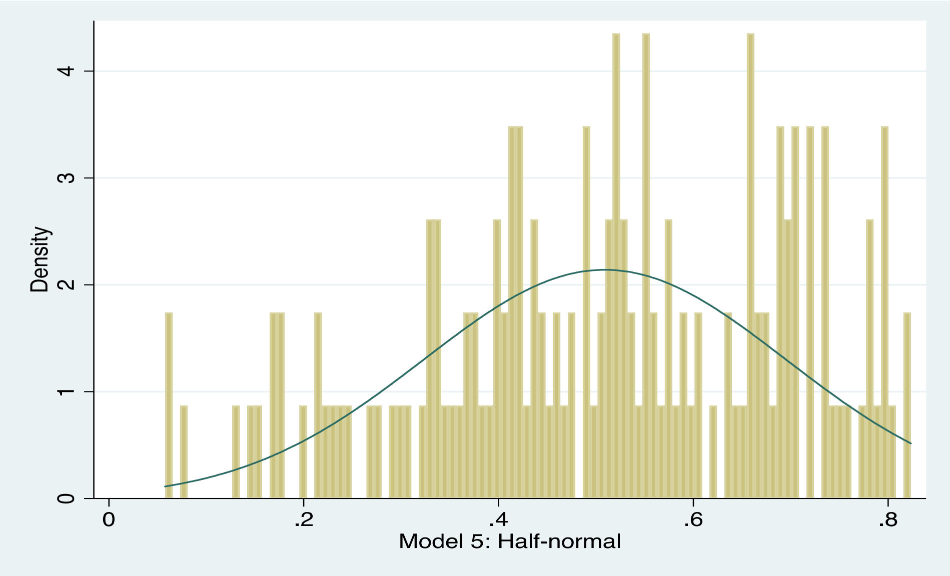

Figure 4.6 Half-normal distribution

Source: Author

4.4.8 Model 5: Half-normal with heteroscedasticity

The homoscedasticity assumption imposed on the error term distribution is relaxed and the model estimated on the assumption that the error term distribution is correlated with the exogenous variable labour cost. The results are shown in Table 4.25.

The coefficient for the labour cost variable is zero and statistically significant, implying the absence of heterogeneity in the distribution of the error term. Thus, the homogenous assumption is valid for the half-normal distribution of the error term. Therefore, the marginal effects of the expenditure on the labour input cannot be considered valid. The estimate for efficiency with homoscedastic assumption was thus maintained.

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Table 4.25 Half-normal with heterogeneity

	Coefficient estimate	Standard error
frontier		
FERTILISER	0.173*	0.098
LAND	0.119	0.095
LABOUR	0.0882*	0.053
SEED	1.324***	0.364
$SEED^2$	-0.297***	0.103
constant	3.292***	0.823
usigmas		
labour expenditure	-0.0001***	0
constant	0.191	0.309
vsigmas		
constant	-1.341***	0.352

** (**)[***] Statistically significant at a 10 (5)[1] % level*

4.4.9 The efficiency model

Efficiency was modelled on the contextual variables of the farming households and their farm characteristics. Table 4.26 below shows the output of the model estimation**.** The efficiency of the farm was affected by the gender of the household head. Female-headed households were on average 11% less efficient than male-headed household, all else being held constant. Djurfeldt, Dzanku and Isinika, (2018) argued that male farmers have more access to fertiliser and other inputs than female farmers, which makes the men more productive. However, in this sample, there was no significant difference in the average amount of fertiliser used by male-headed households and female-headed households (p-value= 0.71), in landholdings (p-value=0.98) and access to extension (p-value=0.10).

The level of education of the household head, the household size, land tenure status, the practice of mixed cropping, the practice of conservation tillage and the practice of crop rotation had no substantial effect on the efficiency of the farmer at the 5% level of significance. Moreover, whether decisions on the farm were made by the household head or someone else, the primary occupation of the household head was farming and access to extension services had no significant effect on the efficiency of the farmer.

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The practice of soil conservation added to the efficiency of the farmers in the sample. It was found that farmers who practised any combination of soil conservation were on average 8.7% more efficient, *ceteris paribus*. The implication of this finding was that the farmers practicing

Table 4.26 Efficiency model

VARIABLE	ESTIMATE	SE
GENDER	-0.107***	0.032
EDUCATION	0.002	0.004
HH SIZE	0.007	0.005
HH LAND HOLDING	-0.001	0.001
CHALLENGES	-0.012	0.067
Tenure	0.07	0.049
Extension	0.022	0.037
Soil Conservation	0.087**	0.036
Cluster 1	0.098**	0.049
Cluster 3	0.037	0.056
Cluster 4	0.065	0.043
Cluster 5	0.06	0.046
constant	0.529***	0.103

** (**)[***] Statistically significant at a 10 (5)[1] % level*

soil conservation were reaping the efficiency benefits from the practices. This result was similar to that of Kabamba and Muimba-Kankolongo (2009) for farmers in Kapiri-Mposhi Zambia.

Preference clusters of the farmers for SAP attributes were included in the model to explain the influence of cluster membership on efficiency. Cluster 2, the resilience cluster, was set as a reference cluster. The results showed that *crop yield maximising cluster* farmers were 8.9% more efficient than the *resilience cluster* farmers, all else being constant. The estimated differences in efficiency between clusters 3-5 and cluster 2 were not statistically different.

The efficiency model results thus suggested that farmers who have a preference for attributes of SAP that tends to raise their crop yield have a higher technical efficiency than those that have other preferences. This result is based on the p-values of the cluster variables in the efficiency model in Table 4.26. This relationship was further assessed in ANOVA and the results are presented in Table 4.27

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Table 4.27 Cluster-efficiency ANOVA

Cluster	Yield maximising	Resilience	Input minimising	Environmentally conscious	Cost minimising	F-stat
Efficiency	0.558	0.447	0.485	0.536	0.529	1.9

Source: Author's computation

Members of the yield maximising cluster had a higher estimated efficiency index than farmers in the rest of the clusters. However, the observed variations in efficiency across the clusters were not statistically significant at 5% level of significance (p-value = 0.11). It was therefore, concluded that there was no significant relationship between the farmers' preferences for SAP attributes and their technical efficiency.

4.5 Conclusion

As the farming household characteristics influence farming activities, this chapter started with looking at household and farm characteristics. With over 95% of the farmers depending on agriculture as their primary occupation, agriculture was the livelihood of most of the farmers and so agricultural outcomes had a huge bearing on these households. There were slightly more male-headed households (53.66%) which meant that if there are gender-specific effects in the practices of agriculture then the effects would easily show due to the high representation of female-headed households in this study than in comparable studies. The average schooling in the sample (6.46 years) was higher than in comparative studies and also had a lower percentage of household heads with zero years of schooling (12.8%) implying these farmers stood to benefit from educational returns to productivity on the farm. With an average farm household of 7 persons, these farmers were mostly relying on own family labour supply and supplementing as the need arose. This meant the family composition in terms of gender mix and ages necessarily affected the labour productivity of the farm, in addition to the nutrition and health status of the family members.

The family farm activities and livelihood were influenced by farm characteristics. Households in this study had an average landholding of 6.01 ha which was greater than the national average landholding of 5.1 ha (CSO, 2012). Since the study area district also has the lowest population density in the country, this could imply that the area has poor quality soils or farming activities are competing with the mining activities in the district. Poor quality soil necessitated the heavy dependency on the use of large doses of fertilizer in maize production: an average fertilizer usage of 400kg/ha per farmer which was higher than in all the comparative studies. The farmers rely on FISP to meet their fertilizer needs and this dependency expose the farmers to productivity loss due to delayed delivery of subsidized fertilizer which was the most

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alluded to challenge in maize production. Other frequently cited challenges were lack of fertilizer and droughts. Climate change has led to the increased occurrence of droughts which further compounds the challenges of agricultural production for these rural households and thus raising their livelihood risks.

Only 12.8% of the farmers had land tenure security and these had an average landholding of 26.19 ha compared to 6.01 ha for the sample. This implied that the few farmers with larger landholdings are the ones who had secure land tenures. More than half of the farmers (56.71%) practised mixed intercropping and this was expected since the average maize plot size in the sample was 1.1 ha which was 95.61% of the average landholding. It meant the farmers were not growing their maize crop in monocultures. The level of adoption of conservation agriculture practices was very low since 93.29% of the farmers were practising conventional agriculture. This implied that, given the efforts of the government in promoting CA in the country and in this area, these farmers could be having challenges in adopting CA. For example, zero tillage require the use of herbicides otherwise the labour input increases exponentially at the weeding stages of production. It was observed that the cost of these inputs was a barrier to the adoption of CA practices.

In sum, this chapter revealed that farmers in Lufwanyama district have preferences for SAP attributes and that there was heterogeneity in the preferences among the farmers. Based on their preferences, the farmers were grouped into five clusters. A translog production function best fitted the maize production data in Lufwanyama. The estimated technical efficiency indicated that family maize farmers in Lufwanyama were on average producing at about half of their potential productive capacity (50.91%). Technical efficiency was significantly affected by the gender of the household head and the practice of soil conservation. Male-headed household had an 11% efficiency advantage over the female-headed ones, although there was no significant corresponding advantage in access to inputs or extension. Furthermore, cluster membership was found to affect the level of efficiency of the farm. Relative to the resilience-maximizing cluster, the crop-yield-maximizing cluster was 8.9% more efficient. The relationship between cluster membership and technical efficiency was nonetheless not substantial in the ANOVA test. There was, therefore, no significant relationship found between farmers' preferences for SAP attributes and their technical efficiency in this sample.

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Chapter 5 POLICY IMPLICATIONS AND RECOMMENDATIONS

5.1 Introduction

This study set out to assess the relationship between the farmer's preferences for sustainable agriculture attributes and the farmer's technical efficiency. The data showed that there was no substantial relationship. There were, nonetheless, some useful insights gleaned from the data about the farmer's preferences and technical efficiency. These insights and their policy relevance are highlighted in Section 5.2. The study limitations are presented in Section 5.3 while propositions for further study are presented in Section 5.4.

5.2 Policy Implications and Recommendations

5.2.1 Preferences for SAP

Farmers were found to have preferences in regard to SAP attributes and the data from the study confirmed there was preference heterogeneity among farmers in Lufwanyama. On average, farmers were observed to favour SAP attributes with immediate benefits to the farmer as opposed to the wider environment. Farmers preferred raising their crop yields the most and reducing extension requirements the least followed by decreasing off-farm pollution. There was more concern for their productivity than the sustainability of the environment. Further, the preference clusters of farmers showed relationships with some farmer characteristics. The data showed that some farmers preferred attributes that would best address the challenges they faced in their maize production, other farmers prioritized SAP attributes they were already engaged in. For example, the resilience-maximising cluster had the highest proportion of farmers who were affected by environmental stressors such as pests and diseases and droughts. Also, it was observed that the environmentally-conscious cluster had the highest proportion of farmers who practiced soil conservation. It can be argued that farmer preferences were driven by the farmers' characteristics, including gender, education, and the challenges they face in maize production. Further, that farmers in the crop yield-maximising cluster had on average the highest yields is suggestive that the preferences of the farmers were correlated with their practices. The observed preference heterogeneity and low preference for extension requirement is indicative of the need for extension to be more accurately tailored to individual farmer preferences to improve the adoption of the promoted sustainable agricultural practices. Extension services to maize farmers must be shifted from a generic approach to a more individualized approach to increase its effectiveness owing to the heterogeneity of preferences among farmers.

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The observations above imply that a policy that does not deliberately tailor extension advise to the farmers' preferred objective on the farm will not be very successful. Furthermore, the challenges of the farmers tend to differ although they are in the same district and this has been seen to affect their preferences for the objectives of SAP they choose to pursue. This then implies that the effectiveness of any policy aimed at promoting SAP will be determined by how well it addresses the unique needs of the farmers. Therefore, it is the recommendation of this study to policymakers to shift to a more individualised approach to extension advice that matches the farmers' unique SAP preferences and constraints they face. This is expected to raise the adoption rate of SAP.

5.2.2 Technical efficiency

It was estimated that the family farmers in Lufwanyama district operated at half their potential output (50.91% efficiency). The seed input had the highest contribution to output followed by fertilizer. Labour had a marginal contribution and land was not significant in explaining the level of output and the technical efficiency of the farmer. Most farmers depend on the fertilizer and input support from the government. Since production is time sensitive as regards the use of these two inputs, delay in the delivery of the two inputs affects the farmers' productivity adversely. The data showed that the farmers in Lufwanyama are neither labour constrained nor land constrained. No evidence of shortage of land was found in the data although the farm soil quality was a challenge in the production of maize as the farmers alluded to.

There are some policy implications for the technical efficiency results in this study. The inputs fertilizer and seed which most farmers sourced with the help of government subsidies constrained efficient production of maize in the area. A direct policy implication of this is that increasing the allocation per farmer of the two inputs would increase the farmers' production of maize and thus contribute more to improve the food security, rural incomes and lower the rural poverty levels in the country. Returns to the two inputs individually and jointly are time-sensitive in production because the time of planting and application of seed and fertilizer, respectively, affects the yields. This implies that the government of Zambia (GRZ) can help the farmers improve their efficiency by improving the implementation of the already instituted policy of input support regarding the timeliness of delivering the inputs to the farmers. It is, therefore, recommended that policy measures to both increase the FISP allocation of inputs and improve the timeliness of delivery of the inputs to the farmers be taken.

The efficiency of the farmers in Lufwanyama district was affected by the gender of the household head and the practice of soil conservation. This result indicated a differential advantage of male-headed households over female-headed households in maize production.

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This held true in land ownership and access to extension also. The policy implications of this observed gender differential are that there are potential gains in technical efficiency to the female-headed households if gender mainstreaming is applied to the distribution of land, inputs support, and dissemination of extension information. However, this must be done in such a way that the policy efforts are targeted at the real drivers of the gender gap in technical efficiency as seemingly gendered differentials tend to be affected by many factors which if not carefully considered may render the policy efforts ineffective. For example, if the differences are really rooted in the culture of the society then policy effort that cannot affect the cultural influence on the production process will not be effective. It is, therefore, the recommendation of this study that agricultural policy to do with farmer input support and extension be gender-mainstreamed to bridge the gap in access to these productive assets and services.

Promotion of soil conservation practices is highly recommended for long term gains in productive efficiency in maize production in the area as this showed a significant impact in raising the technical efficiency of the farmers. Since the nature of most soil conservation practices is such that the costs are incurred today while the benefits come in the future, policies that incentivise farmers to undertake these practices, in addition to the extension, are recommended.

5.3 Study Limitations

This study could not factor in all characteristics of the farmer and the farm. The data showed that these farming households relied heavily on their own household supplied labour. This implies that the health status of the family members affect their productivity and this study did not factor it in. Further, as important as soil quality is in production, this study could not factor in the quality of the soil for lack of capacity to get accurate information from the farmer about it. The assumption that the soil quality of the farmers was homogenous may not be very plausible.

5.4 Recommendations for Further Research

The results in this study did not show a significant relationship between the farmer preferences for SAP attributes and their technical efficiency in the production of maize among family farmers of Lufwanyama District. There are likely to be many intricate interactions between the constraints that farmers are faced with, their SAP attributes preferences, their current agricultural practices and their technical efficiency. This study has attempted to explain the preference-technical efficiency relation. Further research into the other remaining relations would improve our understanding of the relationship between the farmer preferences for SAP

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attributes and their technical efficiency. Furthermore, future research could investigate the drivers of the technical efficiency gap between male-headed and female-headed households in maize production. Inclusion of more crops in the analysis would also enrich our understanding of the relationship between farmer technical efficiency and their preferences for SAPs, and so we recommend it for further research.

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APPENDIX 1: Questionnaire

LETTER OF CONSENT

Informed consent for the participation in an academic research study.

Preferences for Sustainable Agriculture Attributes and Technical Efficiency among Family Maize Farmers in Lufwanyama, Zambia.

Dear respondent,

You are invited to participate in a research study conducted by Mwamba Kapambwe, 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 on-farm environmental performance among small holder maize farmers. The study will further investigate preferences of farmers for sustainable agricultural practices.

Participation in this survey involves responding the questions that will be asked and this should take less than an hour. The questions requires you to provide information on your household characteristics, assets, agricultural practices, maize inputs and outputs, access to agricultural markets as well as any other information that relate to agriculture production. Please note the following when responding;

- This study involves an **anonymous** survey. Although your name will appear on the questionnaire, the information you provide will be treated as strictly **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 at 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…………………………………

SECTION A: Identification Details

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Respondent Name: ______________ Village: ___________________________

Section A1: Demographic Characteristics & Land Section

1.0 What is your total household land holding size________ Unit_______

*(**1**=Hectares **2**=Acres **3**=Meters squared)*

1.1 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**.Farm labourer; **3**. Permanent employment **4**. Casual labourer 5. Other specify	**Tillage method** 1=Conventional 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** Terracing **2** Mulching/ cover cropping **3** Zero tillage **4** Minimum tillage **5** Crop rotation **6** Afforestation **7** Agri-forestry **8** Use of farm yard manure **9** Fallow **10** Composting manure 11 Other specify 12 None

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Section A2: Maize Production

2.1 Cropping activities for maize for 2018/2019 CROPPING SEASON

<table>
<tr><td colspan="2">Land size (please include all the land used in growing maize)

1=Hectares
2=Acres
3=Meters squared</td><td rowspan="2">Main system of watering used

1=Rain fed
2=Irrigated (pumped)
3=Irrigated (gravity)
4=Other specify_</td><td rowspan="2">Hired land prep cost (ZMW)</td><td colspan="2">Quantity of seed used if purchased</td><td colspan="3">Fertilizer used</td><td colspan="2">Harvest</td></tr>
<tr><td>Qty</td><td>Unit</td><td>Qty</td><td>Unit</td><td>Type</td><td>Qty</td><td>Unit</td><td>Qty</td><td>Unit</td></tr>
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</table>

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

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2.2 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	Plough/planter/harvester						
7	Technical support						
8	Transportation						
9	Other, specify_____						

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

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2.3 Labour 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**	**Labour type** 1= Family labour 2= hired labour 3=Both family & hired	***(If labour=3),*** which labour type was most important?	On a scale of 1-5, rank the contribution of the labour 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________						

<u>Section A3: Extension</u>

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

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 Q6e, proceed to Q6g

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)*______

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Section A4: Challenges in Maize Production

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

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

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

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 Biomass	1	
	2	
Fertilizer/ Manure	1	
	2	
Energy Management	1	
	2	

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<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 plough					
11	Tractor				
12	Ploughs for tractor				
13	Plough				
14	Planter				
Other transport					
15	Bicycle				
16	Car				
17	Truck				
Other assets					
18	Water pan				
19	Irrigation equipment				
20	Borehole				
21	Generator/diesel				
22	Other specify				

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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 ways 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 in pests and diseases	
	Reduces extension requirement	
	Decrease in labour use	
	Increase on-farm soil fertility	
	Increase in crop yield	

B2) Ranking 2

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

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

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B3) Ranking 3

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

Most Important	Effects of the cropping system	Least Important
	Decrease in off-farm pollution	
	Decrease in on-farm soil erosion	
	Increase in resistance to drought	
	Increase in 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 impacts. (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 in the cost of production	
	Reduction in extension requirements throughout the cropping cycle	
	Decrease in pests and diseases	
	Decrease in off-farm pollution	
	Decrease in on-farm soil erosion	

B5) Ranking 5

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

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

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B6) Ranking 6

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

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

B7) Ranking 7

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

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

B8) Ranking 8

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

Most Important	Effects of the cropping system	Least Important
	Decrease in on-farm soil erosion	
	Decrease in water requirements	
	Decrease in pests and diseases	
	Decrease in labour use	
	Increased resistance to drought	

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B9) Ranking 9

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

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

B10) Ranking 10

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

Most Important	Effects of the cropping system	Least Important
	Reduction in extension requirements throughout the cropping cycle	
	Decrease in off-farm pollution	
	Decrease in external input used e.g. fertiliser diesel	
	Increased resistance to drought	
	Decrease in labour use	

B11) Ranking 11

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

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

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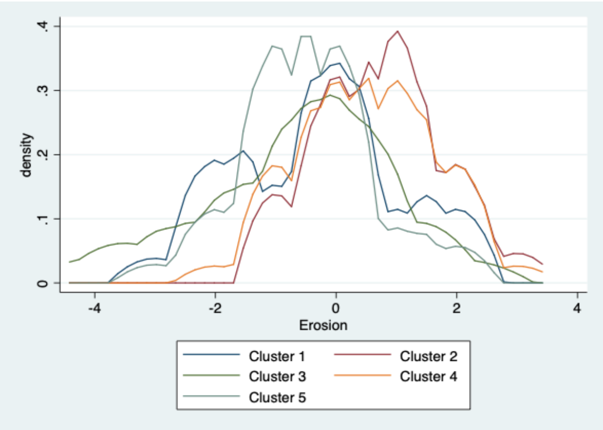
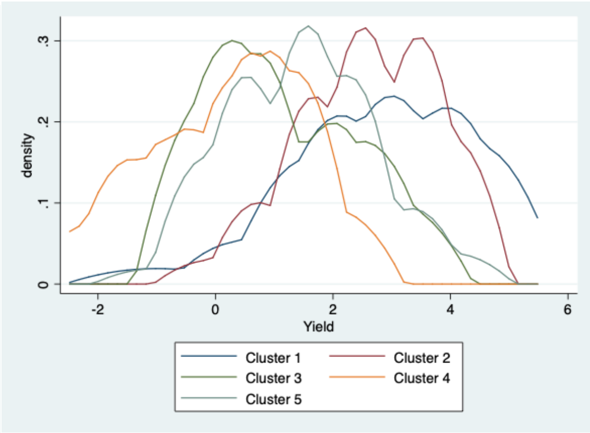
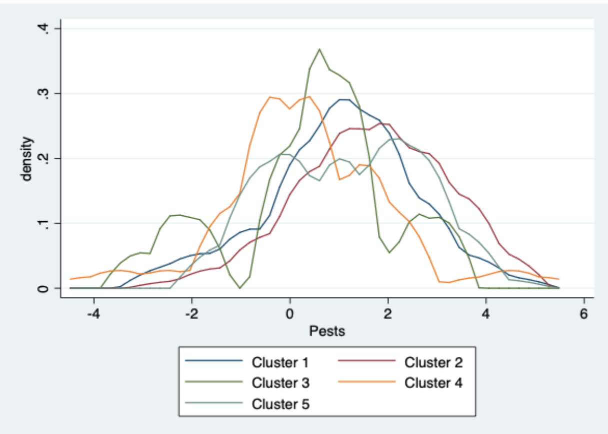
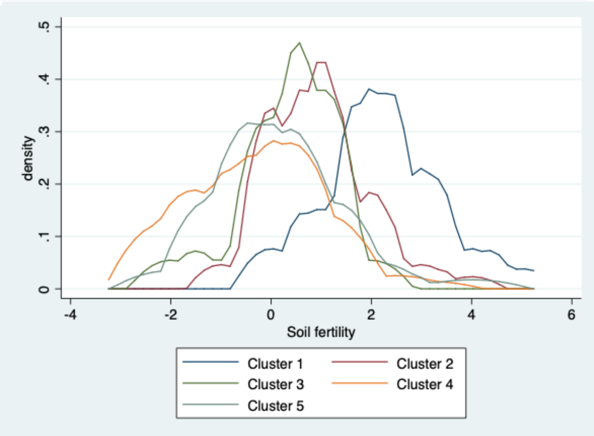
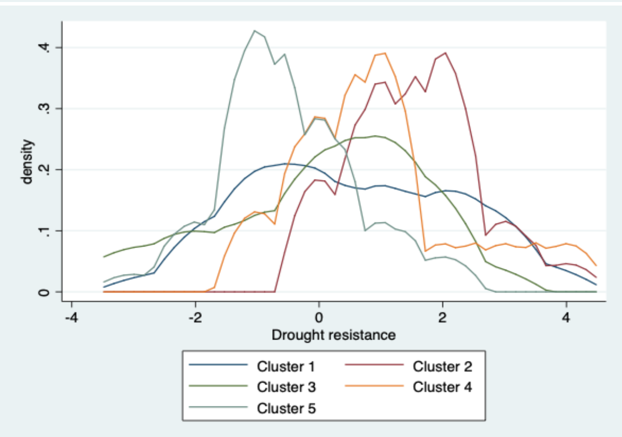
APPENDIX 2: Density Plots

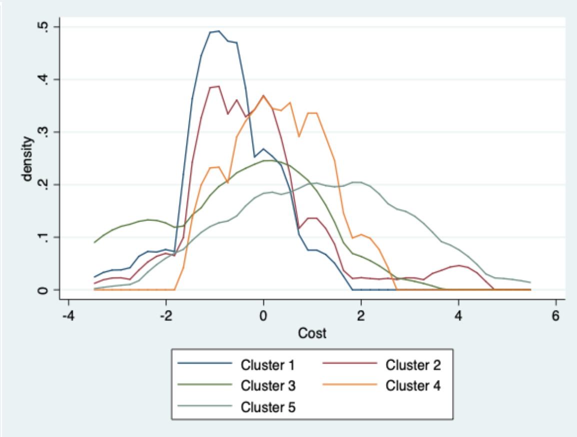












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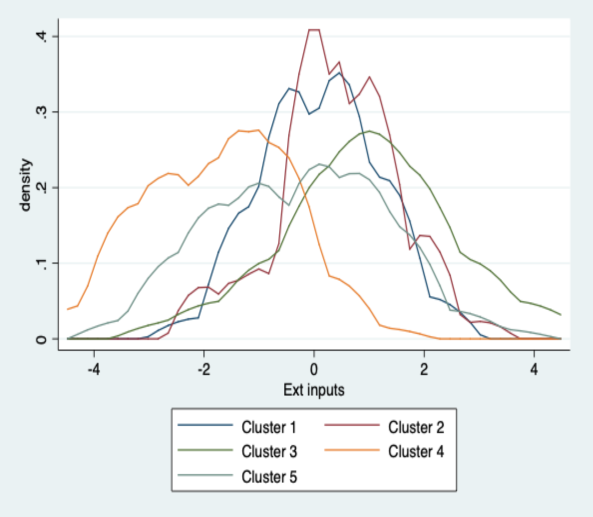

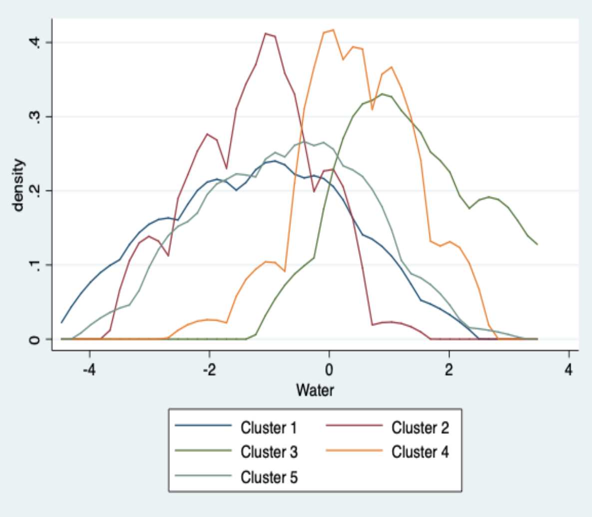

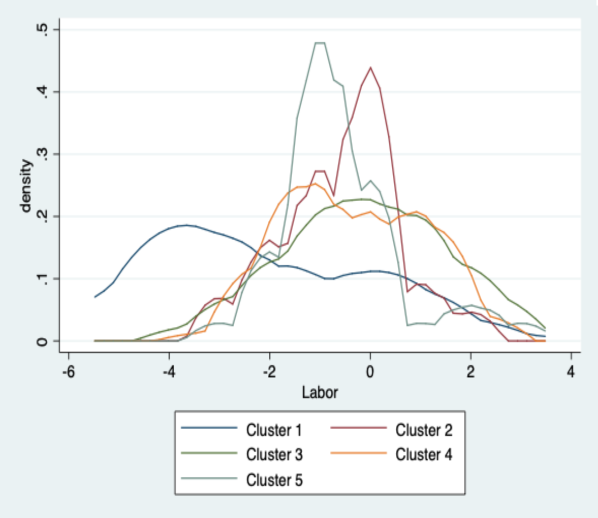

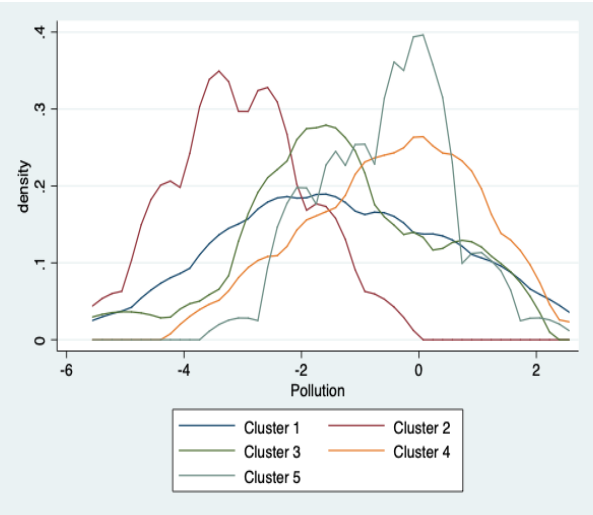

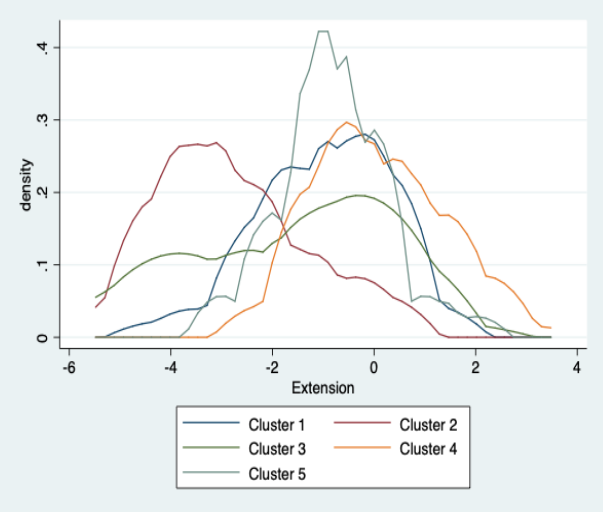

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APPENDIX 3: Correlation Matrix of Attributes

	Yield	Pests	Soil fertility	Drought	Erosion	Cost	External inputs	Water	Labour	Pollution	Extension
Yield	1										
Pests	-0.38	1									
Soil fertility	-0.08	-0.06	1								
Drought	-0.11	-0.22	-0.28	1							
Erosion	0.23	-0.44	-0.15	0.35	1						
Cost	-0.34	0.18	-0.06	-0.26	-0.4	1					
External inputs	0.15	-0.18	-0.07	-0.11	0.04	-0.15	1				
Water	0.1	-0.35	-0.06	0.16	0.2	-0.24	-0.22	1			
Labour	-0.31	0.41	-0.11	-0.27	-0.56	0.24	-0.19	-0.23	1		
Pollution	-0.04	-0.26	-0.19	0.07	0.01	-0.01	0.04	-0.08	-0.2	1	
Extension	-0.21	0.12	0.04	-0.22	-0.2	0.03	-0.14	-0.29	0.08	-0.22	1

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