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The impact of climate-smart technology adoption on farmers' welfare in Northern Zambia

By

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Submitted in fulfilment of the requirements for a Master of Science Degree in Agricultural Economics

in the

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DECLARATION OF ORIGINALITY

I, **Sulinkhundla Maseko**, declare that this dissertation, which I hereby submit for the degree of MSc Agric (Agricultural Economics) at the University of Pretoria, is my work, and it has not been previously submitted by me for a degree at this or any other university.

Signature:

Date: July 2021

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DEDICATION

This work is dedicated to my family, especially my loving Mother, Ms Agnes Bonani Simelane.

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ABSTRACT

Smallholder farmers in Zambia face serious challenges caused by climate change and by variability that threaten their livelihoods. To increase their resilience to climate change, farmers need to adopt various climate-smart agricultural technologies. However, their decisions on the types of technology often lack information about the beneficial effects of particular technologies. The overall objective of this study was to examine the effect of CSA technologies on the welfare of farmers in Zambia. The data used was from a household survey by Total Land Care Zambia as part of the Smallholder Productivity Promotion Programme. The dataset consisted of 407 sampled maize farmers from Northern and Luapula provinces in Northern Zambia, who were selected using a stratified random technique. The study used the propensity score matching technique to account for selection bias in technology adoption in estimating the welfare effects of manure and residue retention. The use of t-test confirmed the existence of systematic differences (selection bias) in the adoption of manure and residue retention. Between these technologies, adopters and non-adopters were statistically different in having received agribusiness training, location (province), legume cultivation, access to agricultural inputs, and access to a water source, household having a male head (gender), climate change awareness, extension access, use of a treadle pump and being involved in seed production. Empirical results, showed that manure adoption resulted in positive and significant gap in household maize yield (32% to 39.2% increase) between adopters and non-adopters at 5% level of significance. The maize income gap between the adopters of manure and non-adopters was positive, ranging from 21.8% to 22.3%. Overall, the adopters of manure who were comparable with non-adopters had a higher maize yield and income. On the impact of residue retention,

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the results showed that the adoption of residue retention led to a positive gap in the household maize yield (ranging from 19.5% to 25.3%). The crop income (maize) was not significantly affected by residue retention adoption, with effect ranging from negative 3.95% to positive 5.1%. Overall, residue adoption increased farmers' maize yield while the effect on income was smaller. These technologies were found to have positive effect on farmers welfare. Increase in yield reduces household food insecurity. However, the adoption rate of these technologies was low at 13.60% and 32.8% for manure and residue retention respectively. These findings point to the need for agricultural institutions to continue prioritising and promoting the adoption of manure and residue retention. This can be achieved by developing strategies that promotes and encourages farmer to attend agribusiness trainings, as it encourages farmers to adopt CSA technologies, and also ensures that smallholder farmers progress from practising subsistence farming to participating in markets to earn a better income. Furthermore, improving farmers' market participation should be given a greater focus by distributing market information to all farmers so that they could reach markets and sell their produce, thus raising income. Agricultural institutions should ensure that farmers receive adequate extension contact, as this helps in increasing farmers' chances of adopting technologies that improve production.

Keywords: Zambia, Climate-smart agriculture, Impact evaluation, Propensity score matching, Smallholder farmers.

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ACRONYMS

ATT	Average treatment effect on the treated
CA	Conservation agriculture
CFU	Conservation farming unit
CSA	Climate-smart agriculture
CSO	Central Statistical Office
FAO	Food and Agriculture Organization
GRZ	Government of the Republic Zambia
GHGs	Greenhouse gases
IFAD	International Fund for Agricultural Development
MLNREP	Ministry of Lands, Natural Resources, and Environment Protection
NGOs	Non-governmental Organisations
PSM	Propensity score matching
SADC	Southern Africa Development Community
SB	Standardised Bias
SDGs	Sustainable development goals
S3P	Smallholder Productivity Promotion Programme
TLC	Total land care
UN	United Nations

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CHAPTER 1: INTRODUCTION

1.1 Introduction and background information

Understanding ways to lift individuals out of poverty is an integral element of economic development. Most countries especially developing countries have most of their population living in rural areas, with their livelihoods depending on agricultural activities. Economic development in these countries depends on the performance of their agricultural systems. But those agricultural systems are negatively affected by climate change, which is happening faster than predicted, and with associated effects being felt across the world (UN, 2016). The negative impacts of climate change affect most countries' progress towards achieving sustainable development. Through planning and policymaking, countries embark on climate action (adaptation and mitigation) to address the problem of climate change in adopting the 2030 Agenda for Sustainable Development (UN, 2019). As a result of climate change, the world is not due to end poverty in all its forms by 2030, the goal stated in Sustainable Development Goal One (SDG1)[1]. According to the UN (2019), the world has experienced a steady increase in hunger since 2014 because of conflicts and climate-induced shocks.

Persistent increases in greenhouse gas emissions exacerbate the effects of climate change and variability (FAO, 2019; Oseni and Masarirambi, 2011). According to FAO (2019) forecasts, climate change could push 122 million people globally, including farmers, into extreme poverty by 2030. Agricultural production is vulnerable to the effects of climate change, as climatic conditions are a determining factor of production in agricultural systems (Nhemachena and Hassan, 2007). Negatively affected and vulnerable groups in society include smallholder farmers whose livelihoods depend on agriculture (Deressa et al., 2008; Kunene et al., 2019). To prevent loss of well-being, society needs to adapt. Around the world, the climate-smart agriculture approach is broadly perceived as the best way to increase the resilience of the agriculture sector to the effects of changing climatic conditions (Steenwerth et al., 2014).
The increase in climate variability is driven by increases in global average temperatures. In the years from 1960 to 2003, Zambia experienced a 1.3°C increase in average temperatures

[1] The sustainable development goals (SDGs) were adopted in September 2015 under the 2030 Agenda for Sustainable Development, expanding on the achievements of the millennium development goals (MDGs). There are 17 SDGs; see https://www.un.org/sustainabledevelopment/sustainable-development-goals/.

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(MLNREP, 2016) double the increases in average temperatures recorded by other Southern African countries (South Africa, Eswatini, and Lesotho), which experienced increases of between 0.6 and 1°C over the same period. Consequently, during those years Zambia experienced an increase in climate change-induced events, especially droughts (1986/87, 1991/92, 1994/5, 2004/05, and 2015/16) and floods (1977/78, 1988/89, 1992/93 2006/07, 2009/10) (Libanda et al., 2019). Droughts have the potential to cause heat stress in livestock, land degradation, crop failure, and desertification. These climate hazards affect every economic sector in Zambia, but particularly the agricultural sector. Agriculture plays an important role in fostering economic growth and development in Zambia, contributing an estimated 20% of national gross domestic product (GDP) and source of employment for 67% of the labour force. Additionally, the sector is a source of livelihood for 50% of the Zambian population (MLNREP, 2016). Owing to its high dependence on rainfall, Zambian agriculture is sensitive to changes in climatic conditions (Kuntashula et al., 2014). If they are not addressed, the effects of climate change and variability have the potential to affect agricultural production and economic development negatively.

The impacts of climate change threaten the Government of Zambia's (GRZ) endeavours to eradicate poverty and ensure food security in seeking to achieve the SDGs by 2030. According to Thurlow, Zhu and Diao (2008), Zambia's GDP declined by 0.4 percent points from the 1960s to 2003 because of climate variability. In the 2018/2019 planting season, climate change-induced events (long dry spells) negatively affected the agriculture sector, causing a decline in the growth rate, as farmers – mostly smallholder farmers – reported either reduced harvests (yield) or total crop failures. The performance of the sector declined from a reported 9.8% growth rate in the 2017/18 season to -21.2% in the 2018/2019 season (Chapoto et al., 2019). Rural households, comprising poor smallholder farmers, are vulnerable to these effects because they depend on agricultural production for survival. Empirical studies have shown that the vulnerability emanates from the low adaptive capacity among farmers as a result of their inability to access information on sustainable agricultural technologies, inputs, markets, poor institutional environment, and poverty (Menike and Arachchi, 2016; Shongwe, 2014).

Zambia is a member of the United Nations Framework Convention on Climate Change (UNFCCC), which ratified the Paris Agreement on Climate Change (COP21). As required of UNFCCC members, Zambia has policies - National Agricultural Policy (NAP) and National Policy on Climate Change (NPCC) and programmes in place to increase resilience and to

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mitigate climate change. For example, the NPCC, adopted in 2016 (MLNREP, 2016), was formulated with a mandate to support and facilitate a coordinated response to climate change. The agricultural sector, among other sectors such as forestry and health, is identified as the most vulnerable economic sector in Zambia. The NPCC is a cross-sectorial policy which also compliments the NAP. The NAP supports the development and identification of sustainable ways that ensure food security in all levels of society by improving agriculture productivity and income. The National Adaptation Programme of Action (NAPA), which was formulated in 2007 (MLNREP, 2016). Similar to the NPCC, the NAPA was developed to enhance adaptation capacity against climate change in the agricultural and other sectors. This includes the identification and adoption of sustainable ways to improve the sector's performance under changing climatic conditions. These policies promote adoption of climate-smart agricultural (CSA) technologies by farmers to reduce vulnerability to climate change. Food insecurity remains a challenge in Zambia, and aggravated by climate change which threatens agricultural production. To effectively adapt to climate change, farmers must adopt appropriate (CSA) technologies. Therefore, there is a need to evaluate the effect of different technologies on farmers' welfare to inform future investments and policy development in Zambia.

Climate-smart agriculture (CSA) is an approach that helps to guide the actions that are needed to transform and reorient agricultural systems effectively to support their development and to ensure food security in a changing climate. There are three main objectives of CSA: (i) to increase agricultural productivity and income, (ii) to build resilience against climate change, and (iii) to reduce greenhouse gas (GHG) emissions (FAO, 2013). The government of Zambia promotes the adoption of CSA technologies by farmers. In recent times, the government collaborated with international agencies, including the International Fund for Agricultural Development (IFAD) and the World Bank, in formulating a Climate-Smart Agriculture Investment Plan (CSAIP) to ensure the sustainable development of the agriculture sector (TLC, 2017; World Bank Group, 2019). In addition, the agricultural sector emits 18.9% of all GHGs in Zambia (MLNREP, 2016). Most African countries, except for South Africa and for countries whose economies rely on oil (e.g., Nigeria and Angola), have below world average GHGs emissions. Therefore, the priority is to adapt.

Farmers in Zambia employ different strategies to increase their resilience to the impacts of climate change. These strategies were practised for many years before CSA was conceptualised in 2010 (FAO, 2010). These include technologies under conservation agriculture (CA) (e.g.,

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crop rotation, minimum tillage, and residue retention). Other technologies include the use of improved crop varieties, agroforestry, manure, and liming, as shown in Table 1-1. Collectively they are also referred to as ‘good agricultural practices’ (GAPs) and often promoted as a package (TLC, 2017). Technologies under the CSA approach are diverse, and – when adopted – they have the potential to provide farmers with a greater array of benefits than do conventional practices. The diverse nature of CSA technologies may also confuse farmers about which technology best suits their needs as farmers often adopt specific component(s) from the technology package. An assumption of the new institutional economics is that individuals (farmers in this case) are ‘bounded rational’. According to Gigerenzer and Selten (2002), when humans make decisions under the constraints of limited information, time, and conceptual capacity, which affect their behaviour, they are termed ‘bounded rational’. Thus, when farmers are faced with many choices (such as the package of CSA technologies), they make adoption choices without adequate information about the outcomes of using a particular technology. To remove this uncertainty, this study estimated the impact on farmers’ welfare indicators of adopting particular CSA technologies – i.e., manure or residue retention.

Farmers in general have long been devising and adopting strategies to improve their production. However, the adoption of technologies among developing countries, including Zambia, is slow; as a result, these countries have been experiencing low production and food insecurity (FAO, 2010). Farmers’ technology adoption decisions are private; they adopt technologies if the utility derived from using them is higher than not adopting them (Mendola, 2007). Technologies are promoted as a package (Manda et al., 2016), but smallholder farmers are resource-poor, practising subsistence farming and often adopting specific technologies or complements, leading to partial adoption (Broeck et al., 2013). For example, a farmer may only adopt manure or residue retention among CSA technologies, Therefore, this creates the need to examine the impacts associated with specific CSA technologies on farmers’ welfare outcomes. This study investigated the effect of manure and residue retention use on smallholder farmers’ welfare in northern Zambia. These technologies are perceived to be easily accessible (low capital and skill requirements) for smallholder farmers to adopt, and have the potential to improve soil fertility by adding nutrients therefore increasing productivity (FAO, 2010). In studying the partial adoption of technology by farmers, Grabowski et al. (2014) reported that farmers believe that an improvement in welfare outcomes is realised with the use of technologies that improve soil fertility. Low soil fertility is another problem facing farmers in Zambia amidst changing climatic conditions (Manda et al., 2016). Assessing the impact of

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these technologies on farmers' welfare (household maize yield and income) allows for inferences to be made about the true effect of adopting a specific technology to assist farmers in making adaptation decisions. The outcomes could be used to inform future interventions in promoting CSA technologies that improve farmers' welfare in Zambia. Table 1-1 presents the different types of technology promoted in Zambia in recent years.

Table 1-1: Technologies promoted in Zambia

Technology	**Description and benefits**
Crop rotation	It involves rotating legumes with other crops (mostly maize). Increase soil fertility by fixing nitrogen concentration in the soil, which is very important in maize production. Crop-rotation also helps to curb the spread of diseases and pests by introducing new crops, and so breaking their life cycle.
Minimum tillage	Soil disturbance is kept to a minimum, with less use of heavy machinery. This increases soil moisture content, as the soil is not exposed to direct sunlight.
Residue retention	This is a CA practice that prevents soil erosion, as it covers the soil from the direct impact of rainfall. It preserves moisture and improves soil fertility.
Manure	Often used as fertiliser, manure is sourced from livestock. It maintains soil nutrient and moisture balance, and is more beneficial to the environment than chemical fertiliser.
Improved crop varieties	Most smallholder farmers use traditional seed varieties that offer low productivity under changing climatic conditions. Improved varieties offer improved productivity under these circumstances.
Agroforestry	This practice entails mixing crops with trees and sometimes with livestock on the same piece of land. It is commonly practised with citrus and crops. It benefits the soil by controlling soil erosion and preserving nutrients.
Liming	Too much rainfall leaves the soils acidic, and lime is added to neutralise the soil to make it conducive for crop production, which improves growth and bacteria activity in the soil.

Source: Adapted from CFU (2007) and TLC (2017)

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1.2 Crop production in Zambia

Agricultural production in general, and crop production in particular, remains a focal point for the sustainable development of Zambia. Policies and strategies have been put in place to ensure household and national food security. The agricultural sector is the second most important sector in Zambia's economy after mining (copper). More than 50% of Zambians derive their livelihoods from the agricultural sector, and most practise crop production (UN, 2013). The crop production sub-sector includes (but is not limited to) maize, sorghum, sugarcane, groundnuts, dry beans, cassava, rice production, and soybeans. Most households cultivate maize in Zambia, with more than 65% of cultivated land given to maize production. Maize is the staple food of Zambia (Chikowo, 2019). The Northern, Northeastern, Copperbelt, Central, and Luapula provinces produce an estimated 70% of the national production (CSO, 2011). This study focuses on maize farmers. Most of these provinces[2] are found in agroecological region II and region III, which have fertile soils and high rainfall respectively (Hamazakaza et al., 2014).

Crop producers in Zambia are categorised into three groups that are defined by the amount of land under cultivation (Chikowo, 2019). These include: (i) smallholder farmers, who are the vast majority, and who cultivate less than five hectares of land each. They are characterised by the minimal use of inputs (most use hand hoes), the consumption of most of their own products, and the sale of surplus. In addition, smallholder farmers often lack information on the benefits of a particular technology and skills to adopt technologies. This has over the years shaped their adoption behaviour, leading to low adoption rates compared to the other group of farmers. Being resource poor, smallholder farmers often adopt specific technologies that are affordable to them instead of adopting a range of technologies, which are often out of reach. In the event of adoption, smallholder farmers employ technologies in small pieces of land based on their capacity and size of land. (ii) Medium-scale farmers cultivate land of between five to 20 hectares, with a more extensive use of inputs than smallholder farmers. They consistently use improved crop varieties and fertiliser to increase their productivity. (iii) Large-scale farmers cultivate more than 20 hectares of land. They operate highly mechanised farms, with extensive use of inputs. They mainly sell their produce.

[2] The Northern and Luapula Provinces are found in Northern Zambia (in region III), and were used as study areas where CSA technologies were promoted to farmers, thus leading the study to evaluate the effectiveness of two of the promoted technologies.

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In the past two decades Zambia experienced inconsistent rainfall, dry spells, and droughts, which affected crop yield. Consequently rural poverty increased to 80% (FAO, 2015). Most of the rural population are smallholder farmers (75% of the total farming population) who rely on rain-fed agricultural systems. According to (CIAT, 1989; Hamazakaza et al., 2014), poor agronomic practices, changing climatic conditions, and a lack of improved varieties result in low crop productivity in Zambia. Appropriately, the GRZ promotes the adoption of CSA technologies by farmers to improve their welfare. For example, the Smallholder Productivity Promotion Programme (S3P) shows the GRZ's efforts to ensure that smallholder farmers are trained to use CSA technologies, and to access CSA technologies and output markets to increase crop production and income among households (TLC, 2017). Interventions such as the S3P project require a lot of investment in research, training, and ensuring that farmers access these technologies. Therefore, there was a need to evaluate the impact of adopting the promoted technologies.

1.3 Problem statement

Smallholder farmers in Zambia face serious challenges that are caused by climate change and variability, which threaten their livelihoods. To increase resilience to climate change, farmers need to adopt various CSA technologies. To help them, policies are in place in Zambia that promote the adoption of these technologies (TLC, 2017). Despite the need for adaptation and the promotion of CSA, smallholder farmers rarely adopt them. This is why many studies have attempted to identify the factors that influence the adoption of CSA technologies (Deressa et al., 2008; Balew et al., 2014; Ng'ombe et al., 2014; Taruvinga et al., 2016). CSA technologies are promoted as a package (FAO, 2010; Schaller et al., 2017). However, smallholder farmers often only partially adopt the technologies (Leathers and Smale, 1991; Mango et al., 2017), which implies that they rarely adopt the full complement of these technologies because they often lack resources or information. Farmers face problems in making their own decisions about which specific technologies to adopt, as they have little or no information on the impact on their welfare that is associated with adopting a particular technology. This deprives farmers of the opportunity to compare the welfare outcomes of adopting different technologies to inform their adoption decisions. We can therefore hypothesise that a necessary condition for a farmer's adoption of CSA technologies is that the benefits derived from adopting them are perceived to be greater than not adopting them.

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Studies have assessed the impact of CSA technologies on farmers' welfare (Corbeels et al., 2014; Abdulai, 2016; Mango et al., 2017; Nkhoma et al., 2017; Hasan et al., 2018; Makate et al., 2019; Amadu et al., 2020a). However, these studies did not take into account the partial adoption of technologies among farmers (such as specific components – residue retention or manure), as the analyses are based on complements or complete technological package. In addition, studies assume in their analyses that a conservation agriculture (CA) adopter is an individual who adopts at least one principle of CA (Nkhoma et al., 2017). Despite the technology being based on CA principles, the evaluation results provide less accurate estimates (they can underestimate or overestimate the effect) of the actual impact of specific technologies under CA that, as has been noted, farmers partially adopt. Besides, specific technologies have a differential impact on farmers' welfare (Kuntashula et al., 2014; Schaller et al., 2017). Furthermore, Kuntashula et al. (2014) reported that minimum tillage improved household maize gross income significantly, whereas crop rotation had a negative effect on household maize income. Thus, specific CSA technologies cannot be assumed to have a identical impact on farmers (Van den Broeck et al., 2013). Impact evaluation studies of the effect of specific CSA technologies have largely focused on improved crop varieties (Mendola, 2007; Kassie et al., 2011; Shiferaw et al., 2014; Afolami et al., 2015). Furthermore, in Northern Zambia the efficacy of manure and residue retention technologies has caused a debate that has affected the adoption of these technologies (TLC, 2017). Empirical evidence on the effect of manure and residue retention on farmers' welfare remains elusive. Studies of the effect of manure and residue retention are mostly based on field experiments or trials that do not take into account that farmers in the real world face many external factors in production that have the potential to influence the effect of the technologies when adopted (Chivenge et al., 2007; Ibrahim et al., 2008; Jat et al., 2019).

The household survey data used in this study consisted of household information from the 2018/2019 planting season, which had long dry spells, thus creating a good opportunity to assess the impact of technologies against climate change hazards (Chapoto et al., 2019). Therefore, this study highlighted the existing gap in the literature, and sought to fill it by examining observed characteristics that are statistically significant between adopters and non-adopters of the above-mentioned technologies, and by estimating the effect of these technologies in Northern Zambia on farmers' welfare indicators; household maize yield, and income.

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1.4 Study objectives

The overall objective of the study was to examine the effect of CSA technologies on farmers' welfare in Northern Zambia.

1.4.1 Specific objectives

1. To identify observable characteristics that are systematically different among adopters and non-adopters of manure and residue retention.
2. To analyse the household maize yield and income gap between adopters and non-adopters of manure adoption.
3. To analyse the household maize yield and income gap between adopters and non-adopters of residue retention adoption.

1.5 Hypotheses

The study tested the following hypotheses:

1. There is no significant difference in observable characteristics between adopters and non-adopters of manure and residue retention.
2. Manure adoption does not have a positive and significant effect on maize yield.
3. Residue retention adoption does not have positive and significant effect on maize yield.
4. Manure adoption does not have a positive and significant effect on maize income.
5. Residue retention adoption does not have positive and significant effect on income.

1.6 Dissertation outline

This dissertation has five chapters. The first chapter presents background information on Zambia and the impacts of climate change on the country, CSA technology adoption, the problem statement, the study objectives, and the hypotheses. Chapter 2 presents a literature review on climate change and CSA as an intervention strategy to reduce vulnerability, and a review of empirical literature on the impact of CSA technologies and evaluation techniques. Chapter 3 deals with the methods and procedures, and discusses the study area, the data, and the methods used to achieve the objectives of the study. The fourth chapter presents the main findings of the study, with a detailed discussion and interpretation of the results. The fifth chapter presents the conclusion and recommendations of the study.

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CHAPTER 2: REVIEW OF LITERATURE

2.1 Overview

This chapter reviews the relevant literature on CSA technologies and their impact on farmers. Section 2.2 of this chapter discusses climate change in general. Section 2.3 focuses on CSA, defining what it entails, and discussing technologies that are considered to be climate-smart, with a focus on manure and residue retention. Factors influencing the adoption of CSA technologies by smallholder farmers are discussed in section 2.4, with a focus on household characteristics. Section 2.5 presents the impact associated with the adoption of technologies on farmers' welfare. Finally, section 2.6 explains the impact evaluation problem and the different methods used to carry out an impact assessment at the household level, with a focus on quantitative methods.

2.2 Climate change

There is increasing and widespread concern around the world about the potential effects of changing climatic conditions on humans. According to the IPCC (2018), the global average temperature remains high compared with the previous centuries, with an expected increase of 1.5^{o}C before 2100. By 2030, current global emissions need to fall by 45% from the levels of 2010 to keep the average increase below 1.5^{o}C in the 21st century to avoid catastrophic and irreversible changes (UN, 2019). The rise in average global temperatures catalyses the increase in climate change and variability, which causes extreme events, including droughts and floods. Climate change-induced events negatively impact societies, causing socio-economic, physical, and environmental costs. The consequences of environmental change attributed to climate change are far-reaching, and affect agriculture production, food security, energy, water, biodiversity, and human health (Dube et al., 2016; IPCC, 2013). These impacts vary across the world, with developing countries being most vulnerable (Adger et al., 2003; Pricope et al., 2013).

Africa continues to experience an above-average increase in temperature compared with other parts of the world (Mertz et al., 2009). Africa experiences a high number of climate change-induced events (UNFCCC, 2011). Thus, Africa has more people who are affected by climate change than the rest of the world (Dinar et al., 2012). According to Garcia (2008), the

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continent's vulnerability stems from three things: (i) Africa's proximity to the equator, where the atmosphere is the hottest; (ii) the majority of African countries depend on rain-fed agriculture production, and agriculture (especially crop production) is sensitive to climate change; and (iii) a low adaptive capacity in society as a result of poor governance, lack of government financing, poverty, and population growth. Changes in climate conditions have pronounced effects on many African economies because of their high dependence on agriculture (Ayanlade et al., 2018). Rainfall and temperature are important inputs in agriculture, as crops require particular climatic conditions during their production. Therefore the changes in climatic conditions are forecast to reduce agricultural productivity by 16% by the year 2080 (Mahato, 2014). Societies' ability to mitigate their vulnerability depends on preparedness for the impacts of climate change. CSA technologies are seen as the best sustainable approach for farmers to reduce their vulnerability.

2.3 Climate-smart agriculture (CSA)

CSA is a concept that the Food and Agriculture Organisation (FAO) conceptualised in 2010, in response to the effect of changing climatic conditions on agriculture (FAO, 2018). CSA consists of diverse practices or technologies that farmers adopt, with some technologies that have been practised since time immemorial. These technologies are seen as the best way to provide for the sustainable development of agricultural systems. Farming technologies that adhere to the climate-smart agriculture approach are defined as any of the technologies that fulfil at least one of the three objectives of CSA (FAO, 2010; Khatri-Chhetri et al., 2017). These are: increased productivity and income, enhanced adaptation, and reduced GHGs under changing climatic conditions; together they are referred to as the 'triple-win approach'. The relative importance of each of the CSA objectives varies across locations and situations. For example, in developing countries such as Zambia, which rely on the agricultural sector and face challenges such as food insecurity and poverty, the priority is to be able to adapt.

Farmers adopt practices under the CSA approach to reduce the impact of climate change and to improve their livelihoods sustainably. The situation of increasing climate change has intensified the need for the adoption of strategies that improve farmers' welfare. CSA technologies are based on creating agricultural systems that are capable of ensuring food and income security under dynamic environmental conditions (Vermeulen et al., 2012). Furthermore, CSA requires site-specific assessments to identify suitable production

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technologies (Schaller et al., 2017). Common examples of CSA technologies include conservation agriculture practices (crop rotation, minimum tillage, and residue retention), water management, improved seed varieties, manure, agroforestry, and fertilisers. These practices have the potential to improve production and nutrient use in crops, thus creating sustainable livelihoods. The different technologies often perform differently across the objectives of CSA, Thus, they are promoted as a package so that they complement each other and maximise their benefits. Farmers rarely adopt complete technological bundles, but rather employ specific technologies, depending on their needs and preferences (Banda, 2017). Farmers might use these technologies individually or as complements. For example, farmers might either retain crop residues or add manure – or employ both. The welfare of farmers depends on the effectiveness of these practices.

2.3.1 Manure

Manure use has been practised since long before the conceptualisation of CSA. It is commonly applied to the soil as a fertiliser to improve the soil's fertility. Farmers use multiple sources of manure. It is often sourced from excreted animal waste. According to Korsaeth et al. (2002), manure is important for crops because it supplies plants with nitrogen. Besides, the good management of manure reduces water, air, and land pollution. According to Ibrahim et al. (2008), manure increased crop yield (wheat) by 100% in an experiment in Pakistan, which confirmed the potential of manure to improve crop yields. However, farmers face different factors (such as socio-economic factors) that are not accounted for in such studies.

Smallholder farmers often lack the resources that are needed to acquire fertilisers. The expectation would be for high adoption levels of manure. However, the bulkiness and labour-intensive nature of applying manure results in low adoption levels. For example, animal manure needs to be transported from shed or kraal to field, requiring a lot of labour, which is not economical for resource-poor farmers (Ibrahim et al., 2008). Moreover, the major source of manure is livestock, implying that households practising mixed farming are expected to have a higher probability of using manure than those that do not practise mixed farming[3]. The term 'manure' can also include compost, a mixture of crop remains and animal waste (FAO, 2013).

[3] Mixed farming entails both growing crops and keeping livestock.

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2.3.2 Residue retention

Residues are the substances that are left after crops have been harvested. Crop residues can include stalks, leaves, etc. These residues are retained for use as a soil cover (mulching). According to the FAO, (2010) crop residue retention is effective in reducing soil erosion. Besides, residue retention has the potential to enhance soil fertility, as it adds organic matter and preserve moisture in the soil. Households rarely retain crop residues; they often burn them to clear fields for the next planting season. The soil is left unprotected, causing serious issues such as soil degradation and environmental pollution (Jat et al., 2019). In addition, soil degradation decreases the land under cultivation, reducing crop production. Crop residues are perceived to harbour pests and diseases from previous planting seasons, which may validate the reason to burn them. Furthermore, households use crop residues as biofuel as an alternative to the much more expensive electricity. Moreover, during dry seasons households feed their livestock crop residues as fodder, thus leading to poor adoption of the residue retention technology (Van den Broeck et al., 2013; Corbeels et al., 2014). Field experiments (Sidhu and Beri, 1989; Chalise et al., 2019) found that residue retention improved soil fertility, which in turn resulted in significantly improved crop yields. In a similar study on the effect of residue retention on rice yields, Huang et al. (2013) reported a positive and significant effect on the quantity of rice produced, and suggested that residue retention was a good substitute for fertiliser. Even so, the effect of crop residue retention is site-specific (Erenstein, 2002; Van den Broeck et al., 2013). Therefore, the adoption of residue retention does not necessarily ensure improved returns for farmers everywhere.

2.4 Smallholder farmers and technology adoption

According to Feder et al. (1985) 'adoption' is defined as the degree to which farmers use new inventive ways, with complete information on their uses and benefits. However, farmers in developing countries often make adoption decisions with incomplete information on the benefits of technologies. Technologies may complement each other, or may be adopted independently, to offer farmers an opportunity to increase production and income (Feder et al., 1985). The importance of agricultural technology in enhancing production and productivity can be realised when production-increasing technologies are widely used and diffused (Hailu et al., 2014). Despite the potential benefits to farmers, there has been only partial success in the adoption of CSA technologies. Farmers in Sub-Saharan Africa use only certain components of

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the CSA approach, leading to partial adoption (Grabowski et al., 2014; Leathers and Smale, 1991). This study followed this definition in understanding CSA technology adoption and its effect on farmers' welfare in northern Zambia.

2.4.1 Determinants of technology adoption

The literature shows what influences the adoption of CSA technologies (Ajayi et al., 2003; Deressa et al., 2008; Kabwe et al., 2009; Lopes, 2010; Akudugu et al., 2012; Ng'ombe et al., 2014; Ntshangase et al., 2018; Lungu, 2019). According to (Mariano et al., 2012), the adoption of technology is influenced by institutional constraints, household characteristics, and economic factors. Institutional constraints include lack of access to credit, markets, membership of agricultural groups, and information. Kudi et al. (2011), reported that access to credit positively influenced smallholder farmers' decision to adopt the technology.

Sub-Saharan African countries rely on agriculture that is dominated by smallholder farmers. These farmers are resource-poor, and have very limited access to credit – the capital required by most agricultural technologies (FAO, 2001). Moreover, smallholder farmers in Sub-Saharan African countries are predominantly found in rural areas under customary land tenure systems (IFAD, 1999). Uncertainty is high under this system of tenure, owing to poorly defined property rights that restrict farmers from accessing financial capital from financial institutions using land as collateral (IFAD, 1999). Ntshangase et al. (2018), found that farmers with higher incomes are more likely to adopt technologies than those with low incomes. Smallholder farmers' low productivity and lack of market access lead to low income. Most farmers are highly dependent on agricultural income. However, for them to improve their income, agriculture productivity and access to markets must be improved. Those receiving off-farm income are often better off, as they can invest in the farms and adopt technologies to their improve performance. Technologies such as irrigation systems, improved seed varieties, herbicides, and fertilisers are often costly for smallholder farmers to adopt (Misaki et al., 2018). Technologies such as manure, minimum tillage, residual retention, and crop rotation are easily accessible to farmers; however, most farmers perceive these practices as providing fewer benefits than other technologies (TLC, 2017; Ntshangase et al., 2018).

After studying farmer groups in Uganda, Adong (2014), found that being part of a farmer group positively influences farmers to adopt improved technologies. Farmer groups provide

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information to members on farming methods and available market opportunities. Information influences how farmers perceive adaptation. Most smallholder farmers access information through extension services that provide critical information on new industry developments including technologies, skills, and early warnings (Ayinde et al., 2010). Extension services are often provided by the government and by farmer-based organisations. According to Ntshangase et al. (2018), farmers with access to extension services often adopt technologies. In Zambia, extension services were found to positively influence the adoption of technologies by farmers (Arslan et al., 2014; Khonje et al., 2018). These findings are similar to those of Akerele, (2014) when examining factors influencing farmers' adoption decisions in Nigeria. Lack of access to extension services denies farmers exposure to information about the use of and benefits associated with technologies. Poor road networks, deficiency of extension officers, and long distances hinder extension services in developing countries (Emmanuel et al., 2016). Extension contact is essential, as it provides reliable information that removes the risk and uncertainty that farmers feel who are not sure about the benefits associated with particular technologies.

Household characteristics that influence technology adoption include education, age, household size and gender (Mariano et al., 2012). Education is an important socio-economic variable that influences technology adoption among farmers, and is thought to build a favourable mental attitude to the acceptance of new practices. For instance, (Ayinde et al., 2010; Manda et al., 2016b) studied the factors influencing technology adoption among small-scale farmers in Nigeria and Zambia respectively. They found that the probability of educated farmers adopting technology is higher than that for uneducated farmers. These findings are similar to those of (Beshir and Wegary, 2014; Kudi et al., 2011), who found that each additional year of formal schooling increased the chances of CSA technology adoption. Another common household characteristic that has been found to explain farmers' adoption behaviour is age. However, findings on the influence of age in the adoption of technology differ. Some studies have shown that age has a positive effect on adopting new technologies (Ng'ombe et al., 2014; Nkhoma et al., 2017; Lungu, 2019); older farmers have enough experience to know the importance of adopting improved technologies. In contrast, other adoption studies have found that age negatively affects adoption (Danso-Abbeam et al., 2017; Green and Ng'ong'ola, 1993). Younger individuals are perceived to be more technology-oriented than older individuals. Household size is mostly used as proxy for available labour. According to Cunguara and Darnhofer (2011), households with fewer members may be discourage to adopt labour intensive technologies. On gender, males are found to have higher probability of

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adopting technologies than females. In Ethiopia, being a male farmer increased probability of adopting technologies (Melisse, 2018). Furthermore, Makate et al., (2019) suggested that technologies that are promoted should be gender sensitive to improve adoption of technologies.

Another factor that tends to influence technology adoption is farm size. The literature also offers conflicting results on the influence of farm size on technology adoption. For example, Idrisa et al. (2010) investigated the factors affecting the likelihood of technology adoption among farmers. They reported interesting results that showed that farm size negatively affected the adoption of improved technologies. This suggests that small-scale farmers are quicker to adopt technologies than are large-scale farmers. The implication is that technologies such as conservation agriculture principles and manure are not commonly practised by large-scale farmers. On the other hand, the results of (Ayinde et al., 2010; Melisse, 2018) showed a positive relationship between farm size and technology adoption. Farm size is perceived as a sign of wealth, and farmers with large farm sizes have the capital to invest in their farms. Additionally, household assets including livestock, cellphone, knapsack sprayer, machinery and boreholes are also seen as sign of wealth. Nkhoma et al., (2017) found that livestock and borehole ownership positively influenced adoption of technology. In the context of this study, livestock ownership is expected to positively influence adoption manure and negatively influence adoption of residue retention. To evaluate effectively the effect of technologies on farmers' welfare outcomes, the determinants of technology adoption are controlled between adopters and non-adopters such that farmers have similar characteristics. This way, it is possible to reveal the real-world impact associated with technologies that are adopted, thus removing the uncertainty that farmers might have about adopting the technology.

2.4.2 Impact of CSA technology adoption

CSA technologies are adopted and promoted with the potential to improve farmers' welfare under changing climatic conditions. Studies have assessed the impact of CSA technologies on farmers' welfare (Hailu et al., 2014; Kuntashula et al., 2014; Afolami et al., 2015; Manda et al., 2016; Khonje et al., 2018; Amadu et al., 2020). After studying the performance of CSA technology on households agricultural production in Madagascar, Minten and Barrett (2008) argued that agricultural technology adoption has the potential to increase food security for all of the poor. CSA technologies are promoted as a package; this makes it difficult to evaluate

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the effect of a specific technology, as they often complement each other. However, there is a need to estimate the impact associated with the adoption of individual technologies because farmers tend to adopt them only partially. As mentioned earlier, technologies are diverse, and thus they tend to impact farmers' welfare differently. The performance of technology depends on a catalogue of factors that include (but are not limited to) farmers' agricultural management practices, their socio-economic status, and their location (agroecological zone) (FAO, 2013; Leathers and Smale, 1991). Furthermore, the literature shows that various welfare indicators are used to measure the impact of technology adoption, such as crop production, yield, income, per capita expenditure, or the incidence of poverty (Mendola, 2007; Kuntashula et al., 2014).

The effects of CSA technology on society can be categorised as either direct or indirect. Shiferaw et al. (2014) expanded on this, describing direct effects such as increased crop production and decreased input costs for those who adopted, thus increasing farm income. The increased agricultural production and farm income has multiplier (indirect) effects. For example, the increased supply of agricultural produce reduces food prices, depending on the elasticity of demand (Minten and Barrett, 2008). Labour demand tends to increase with production, creating opportunities for the rural population who rely on on-farm labour income. This is one way in which the problem of poverty in Africa can be sustainably eradicated. However, in large-scale farming certain CSA technologies are rarely adopted (especially the application of CA principles and manure), as conventional ways are predominantly used. For example, the use of heavy machinery in many farm activities (e.g., soil tilling) limits labour opportunities for the unskilled rural population.

To evaluate the impact of CSA technology on household food security, Shiferaw et al. (2014) used the propensity score matching method. Findings from the study showed an increase in food security among households adopting a technology. Specifically, there was a significant increase in per capita food consumption expenditure and food surplus among households, which was attributed to the adoption of CSA technology (e.g., improved varieties). These findings are similar to those of Becerril and Abdulai (2010), who showed that households in Mexico that adopt improved maize varieties had increased household per capita expenditure. Previous studies in Malawi, Zambia, and Zimbabwe, found that CSA technologies improve household income (Manda et al., 2016; Nkhoma et al., 2017; Khonje et al., 2018; Makate et al., 2019). In their study, Makate et al. (2019), concluded that the impact of CSA technologies was not uniform across different geographical areas, and that it requires adherence to local

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specific contexts. Technologies' potential to increase yield means that farmers record surplus which they can sell to gain income. For, instance, Abdulai (2016), reported that CA technology adoption improved farm output and reduced household poverty in Zambia. The positive impact in farm output shows that technologies have the potential to reduce poverty by increasing yield and income. Following the latest drought to hit Malawi in 2015/16, Amadu, McNamara and Miller (2020) conducted a study and found that adopters of CSA technologies realised higher yields than non-adopters. Their findings show that during hazardous climatic conditions technologies are able to reduce impact on farmers. CSA technologies such as manure, residue retention, and minimum tillage are more easily accessible by smallholder farmers than other CSA technologies, including improved varieties of fertiliser and irrigation systems. After conducting an experiment on the effect of manure on maize yield in Ghana, Boateng et al. (2006) found that the adoption of manure led to a significant increase in yield. The results showcased the potential of manure as a sustainable and suitable alternative to costly chemical fertilisers. See (Ibrahim et al., 2008; Paul et al., 2013; Turmel et al., 2015) on the impact of manure and residue retention based on randomised studies. These studies focused on the technical impact (environmental) of these technologies, including their effect on soil properties. These studies do not take into account that farmers' production is influenced by other factors.

In Zambia, Kuntashula et al. (2014), assessed specific technologies, and found that CSA technology (minimum tillage) resulted in an increase in household crop yield. Interestingly, other technologies (e.g., crop rotation) had an insignificant effect on yield. Increased crop yields are important in achieving a food-secure society; technologies enable farmer to increase their output on the limited land area they own. Studies by (Mendola, 2007; Kuntashula et al., 2014) used the propensity score matching method, and the results showed that technologies have contrasting impacts on farmers' welfare. For example, Mendola (2007) found that technology adoption had a significant and positive effect on income. In contrast, Kuntashula et al. (2014) found that other technologies adoption (in this case, crop rotation) had a negative effect on income; and that was attributed to the fact that smallholder farmers' priority is to feed their household rather than to sell produce, and also to their lack of access to market information and channels. These contrasting findings validate the need to investigate the adoption effect of specific technologies. Interestingly, (Hazell, 1992; Nyangena and Köhlin, 2009) showed that adopters of technologies can face a lower production than non-adopters. The findings of Wu et al. (2010) showed that the effect of technology on welfare outcomes

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decreases with time. This can be expected, as rapidly changing climatic conditions require farmers to be innovative in using CSA technologies.

Findings from the literature on the impact of technologies substantiate the need to examine the impact of specific technologies on farmers, as specific CSA technologies cannot be perceived to have uniform impact on different groups of farmers.

2.5 Impact evaluation problem and strategies

2.5.1 Overview

There is a growing need for impact evaluation studies that focus on agricultural systems to understand ways in which people can be lifted out of poverty and sustainable livelihoods be ensured for societies (Mendola, 2007). Most countries – especially developing countries – have economies that rely on agriculture; and CSA technologies in these countries (e.g., through intervention programmes) are promoted by institutions and adopted by farmers. These technologies are aimed at improving the agricultural systems, improving farmers' productivity, income, and adaptation, and reducing GHGs. However, making inferences about the true effect of CSA technologies on farmers requires an impact evaluation. Moreover, the literature shows that the effects of specific technologies on farmers are not the same, and tend to differ according to the agroecological zone and household characteristics (Leathers and Smale, 1991; Van den Broeck et al., 2013).

In impact evaluation, the task is to capture the difference in welfare between adopters and non-adopters as a result of their adopting those technologies (Khandker et al., 2009). Technologies are promoted as a package and often studied as one, which makes it difficult truly to understand the effects of specific technologies. Moreover, observational studies, including this one, have the potential to suffer from the non-randomisation of technology adoption from promotion and self-selection bias. In particular, the two groups of farmers might not have similar characteristics, even before adoption; thus, the differences in their outcomes could not be attributed to technology. As reported by Becerril and Abdulai (2010), when investigating the impact of adopting improved maize varieties in Mexico, they found that farmers who tend to adopt agriculture technologies are wealthier than non-adopters before adopting as they have the higher disposable income to invest in on-farm activities. In Zambia, Kuntashula et al. (2014) found that access to extension services and having a male-headed household being

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associated with the adoption of CSA technology. This is a major challenge in impact evaluation studies, (Rubin, 1974; Heckman et al., 1998; Smith and Todd, 2005; Khandker et al., 2009), as farmers self-select to adopt or not to adopt, which can be as a result of either their observed or their unobserved characteristics, or both. The differences between adopters and non-adopters prior to adoption is called selection bias. Selection bias leads to biased estimates. The approaches used in impact evaluation have to account for potential selection bias by mimicking a randomised study. These methods must also isolate the effect of technology adoption on farmers' welfare from other factors by imposing certain assumptions. Another challenge for observational studies when conducting an impact evaluation is the issue of missing data, because it is impossible to find a farmer in two states; a farmer can only be observed as either adopting or not adopting (Rubin, 1974; Heckman et al., 1997; Winship and Morgan, 1999; Khandker et al., 2009), and so the other state cannot be observed. It is for this reason that impact evaluation is about determining what might have happened if the adopters of technologies did not adopt (Heckman et al., 1998). The possible outcome had the farmer not adopted is called 'the counterfactual'. A good impact evaluation study estimates the counterfactual by finding a good comparison group (Caliendo and Kopeinig, 2008). These challenges have resulted in an extensive debate in studies of impact evaluation about which approach is more efficient to use.

For example, in surveys where data was collected before and after the intervention (adoption), the before-and-after evaluation method has been used. In cases where surveys were done before and after the intervention, the ex-ante outcomes of adopters can be compared with the ex-post outcomes. The effect is achieved by identifying the differences in the outcomes before and after a farmer has adopted. This way of evaluating the technology's impact is referred to as 'the reflexive method' (Khandker et al., 2009). However, the method has been criticised in the impact evaluation literature because it appears only to determine a counterfeit counterfactual, so that the difference between adopters and non-adopters' outcomes cannot be credited to a certain factor (Kuntashula et al., 2014). In essence, this approach cannot separate technology impact from other confounders that may compromise the reliability of the results. However, this method suffers from reduced selection bias problem, which is possible when the available data is collected from the same individuals before and after adoption.

To address the problem of counterfeit counterfactuals that arise in before-and-after evaluation studies, several different other methods are found in the literature. These approaches make assumptions about the nature of selection bias in technology adoption and in estimating the

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impacts associated with the technology. These approaches include randomised valuations, matching methods (especially propensity score matching (PSM)), the 'difference in difference' method, the instrumental variable method, regression discontinuity design, distributional impacts, and structural approaches (Khandker et al., 2009). In the agricultural technology adoption literature, matching methods (especially PSM) and instrumental variable methods are most widely used. These are quantitative rather than qualitative approaches. This is because qualitative approaches are unable to show what would happen without the intervention (Khandker et al., 2009) – that is, the counterfactual. Consequently, these approaches cannot assess the outcome of adopting new technology against that for not adopting.

2.5.2 Instrumental variable method

The instrumental variable (IV) approach involves finding a variable (or instrument) that is highly correlated with participation but that is not correlated with any unobserved characteristics affecting outcomes (Abadie, 2003). In this way the IV method controls for selection bias that might result from endogeneity. CSA technology interventions may be found in deliberately selected areas with specific human characteristics, including social norms, that might have a relationship with the outcomes. Second, unobserved individual heterogeneity might cause selection bias because participants self-select to adopt or not to adopt. This method addresses the selection bias problem by accounting for both the observable and the unobservable factors influencing adoption and outcomes by imposing distributional and functional form assumptions. However, (Abadie, 2003) suggested that avoiding imposing model specifications is an efficient way to remove selection bias.

A limitation of the method is the difficulty in finding and identifying instruments in the estimation. Another problem is with weak IVs, which can bias estimates further. A weak IV is a variable that has a weak correlation with endogenous independent variables (Staiger and Stock, 1997). The use of such variables leads to misleading estimates. The IV approach also imposes a linear specification structure, suggesting that the coefficients on the control factors are comparable for both adopters and non-adopters; however, this might not hold because coefficients can differ (Ravallion and Jalan, 2003). Chibwana et al. (2014) used the IV approach in measuring the impact of an input subsidy programme in Malawi. The approach was used to control for selection bias caused by endogeneity. Other methods similar to controlling for selection bias using observed and unobservable characteristics include

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endogenous switching regression and the Heckman estimator's technique. These methods have similar limitations to those of the IV technique. Another method that can control for selection bias based on observable and non-observables characteristics is the 'difference in difference' method, which is mainly suitable for panel data.

2.5.3 Propensity score matching method

Propensity score matching (PSM) is a semi-parametric statistical approach that is used to measure the effect (average difference) on outcomes between adopters and non-adopters. It does so by matching participants with non-participants based on their probability to adopt technology. The assumption is that adopters might be different from those who did not adopt; thus the two groups need to be matched (Rosenbaum and Rubin, 1983). Matching adopters with non-adopters based on their probability of adopting that technology using observable characteristics (Heckman and Navarro-Lozano, 2004). Propensity scores are the probability of farmers adopting the technology. The treatment or adoption effect is estimated as the mean difference in outcomes between the two groups. Most empirical work uses observational data. The distribution of technology adoption cannot be assumed to be random. Individuals often make private decisions to participate (adopt) or not to participate (not adopt); they self-select. If it is believed that only observed characteristics affect technology adoption, this method is appropriate to control for selection bias.

The PSM method has been used in estimating the impact of adopting CSA technologies (Becerril and Abdulai, 2010; Bezu et al., 2014; Mendola, 2007). This method creates the conditions of a randomised experiment (Rosenbaum and Rubin, 1983). First, it establishes an adequate counterfactual, and is thus able to estimate the true causality of change. An impact evaluation study assesses what the situation of households would have been if they had not adopted. Second, this method accounts for potential selection bias that might arise in CSA technology adoption (observational studies). In addition, this technique does not make assumptions about the structure of the model, unlike OLS and instrumental variable methods (Becerril and Abdulai, 2010), which assume a linear functional form. However, if unobservable characteristics were thought to impact farmers' adoption decisions, PSM estimates would be biased (Heckman and Navarro-Lozano, 2004). Thus, the major limitation of PSM is that it works only with observable characteristics. However, Ravallion and Jalan (2003) view the drawback that comes with the assumption of observables in PSM as equivalent to the challenge

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of weak instruments when the instrumental variable or Heckman technique methods are used in cross-sectional studies.

The adaptation of agricultural systems in most sub-Saharan countries depends on the widespread adoption of agricultural technologies by small-scale farmers. To assist farmers' adoption decisions, there is a need to understand the true effect on farmers' welfare that is associated with adopting a particular technology. The approaches discussed above provide the best scientific evidence to estimate the impact of technology adoption on farmers.

2.6 Summary of literature review

The chapter began by providing insight into changing climatic conditions. This paved the way to discuss the climate-smart agriculture (CSA) approach, showing why it is seen as the best approach to increase farmers' resilience amid climate change. This chapter also reviewed the literature on the determinants of CSA technology adoption that influence farmers' adoption decisions. Age and farm size were found to give conflicting results for CSA technology adoption. The literature also shows that CSA technology adoption is low among households, which can be attributed to many factors, including lack of information. Additionally, the literature shows that the impact of technologies cannot be assumed to be similar for different farmers, which validates the estimation of the impact of specific CSA technology on farmers' welfare.

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CHAPTER 3: METHODS AND PROCEDURES

3.1 Overview

This chapter provides a comprehensive explanation of the data and methods that were employed to achieve the study's objectives. Section 3.2 covers the study area, with a focus on the Northern and Luapula provinces. The data used in the study is explained in detail, including the sampling method and sample size in section 3.3. Sections 3.4 and 3.5 explain the analytical framework and the PSM procedure. Section 3.6 discusses the variables used in the study.

3.2 Study area

Zambia is a landlocked country covering 743,390 square kilometres, with an estimated population of around 16.5 million people in 2016 (World Bank, 2019). It is located in southern central Africa, bordering eight countries: The Democratic Republic of Congo, Malawi, Tanzania, Zimbabwe, Botswana, Mozambique, Namibia, and Angola. Administratively, the country is divided into 10 provinces, of which two were used as study areas. The northern part of Zambia, consisting of the Northern and Luapula provinces, was the focus of the study. Furthermore, the country is divided into three agro-ecological regions: Regions I, II, and III, as shown in Figure 3-1. According to (Arslan et al., 2014), Region I covers the southern, eastern, and western areas of Zambia, and predominantly has smallholder farmers. It is a semi-arid region that is prone to drought. On average this region receives 600mm to 800mm of rainfall annually, with a short growing season of between 80 and 120 days. Most crops grown in this region are starchy food crops, including finger millet, maize, and sorghum (Chikowo, 2019).

Region II covers much of central Zambia, including the Central, Lusaka, Eastern, and Southern provinces. It has the most fertile soils in Zambia, which has made it the commercial hub for large-scale farming. This region records annual rainfall ranging from 800mm to 1000mm. Region II is further divided into Region IIa and Region IIb; the latter experiences dry spells that negatively affect crop yields, and is characterised by loam and sandy soils (Chikowo, 2019). The growing season lasts up to 140 days; major crops grown in this region include maize, soybeans, wheat, cotton, tobacco, and coffee. Region III receives a high annual rainfall of at least 1000mm. It covers northern Zambia, including the Copperbelt, Luapula, Northern,

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and North-western provinces. The soils in this region are highly acidic because of the high rainfall. Farmers in this region have a long growing season of around 150 days. The study area Northern Zambia consisting of Northern and Luapula provinces, found in Region III.

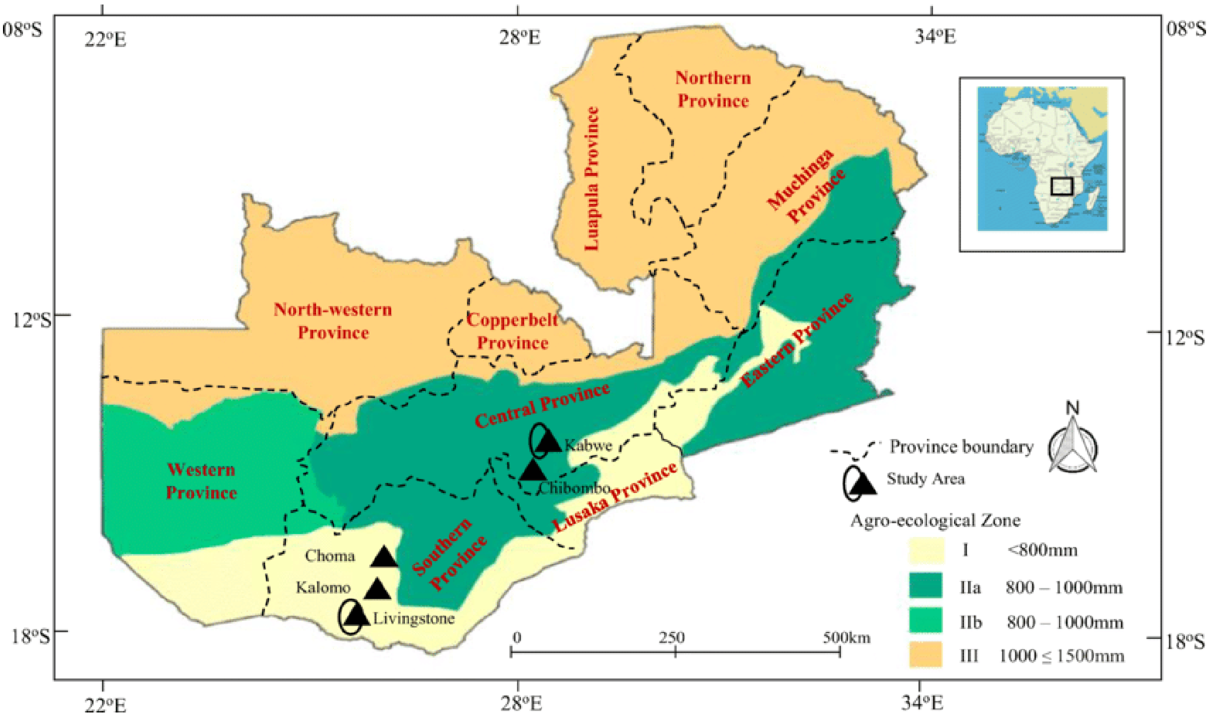

Figure 3-1: Agro-ecological regions and Provinces in Zambia
Source: Makondo and Thomas (2020)

3.3 Data

The study used cross-sectional secondary data collected by TLC Zambia in 2019. The data was collected as part of a farm household survey in Northern Zambia, covering the Northern Province (which includes Kasama, Mungwi, Mbala, and Luwingu districts) and Luapula Provinces (which includes Mansa, Samfya, and Kawambwa districts). The survey was carried by TLC Zambia as part of the Smallholder Productivity Promotion Programme (S3P). The S3P project was designed to address low yield and improve output market access in the agricultural sector (TLC, 2017). A stratified random sampling technique was employed to select respondents in the study areas. Data collection began with a meeting with various stakeholders, and key informant interviews and focus group discussions were held with extension officers and farmers in agricultural camps in the districts. Farmers were randomly sampled from the two agricultural camps found in each district, targeting 30 farmers per camp. The survey consisted of 407 respondents. Owing to missing values from the variables (i.e., the explanatory,

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outcome, and treatment variables) in the dataset, 375 and 306 observations were used for the manure and residue retention models respectively.

3.4 Analytical framework

In specifying the models used in this study, a farmer was categorised as 'adopting' (coded as 1) if the farmer used specific CSA technology in the 2018/2019 farming season – i.e., manure or residue retention – and as 'non-adopting' (coded as 0) if the farmer did not adopt CSA technology in the same farming season. The study strived to make causal inferences on the effect of technology adoption, and adopted the potential outcomes framework approach (Rubin, 1974). This approach was suitable for making causal inferences in this study, since it is impossible to observe both household potential outcomes at once (missing data[4]). Furthermore, observational studies such as this study have a selection bias problem. Technology adoption being non random. Various methods in the impact evaluation literature (discussed in Chapter 2) follow this approach and account for potential selection bias (Khandker et al., 2009). These methods assume that the individuals selected for the treatment (adopters) and control (non-adopters) groups have potential outcomes in both states – that is, the one in which they are observed and the one in which they are not observed (Winship and Morgan, 1999). Therefore, they can make inferences about what would have happened to the adopters had they not adopted CSA technology.

The study used the propensity score matching (PSM) method to estimate the treatment effect of technology adoption on farmers' welfare (Afolami et al., 2015; Ajayi et al., 2003; Becerril and Abdulai, 2010; Mendola, 2007; Wu et al., 2010). The PSM method was suited to achieving the objectives of the study, as it accounts for potential challenges in impact evaluation. By using observed characteristics, PSM controls for systematic differences that might exist between adopters and non-adopters by creating a statistical group that would allow for the determination of the counterfactual (Rosenbaum and Rubin, 1983; Winship and Morgan, 1999). For example, households might choose to adopt a particular technology based on its observed characteristics. Further, (Heckman et al., 1998; Heckman et al., 1997) reported that the PSM approach is efficient when a study design meets three conditions: first, the same

[4] *Missing data* in impact evaluation refers to the fact that we cannot observe the outcomes of adopters if they have not adopted, or vice versa (Khandker et al., 2009).

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survey instrument must be used for adopters and non-adopters – which is how the data used from the study was sourced; second, the survey data must have a good representative sample of non-adopters and adopters; and third, adopters and non-adopters faced the same incentives to be in treatment or not. The way the survey was carried out met the above-mentioned conditions to adopt a PSM approach for an impact evaluation study (TLC, 2019). The study followed the PSM procedure for each technology by identifying the observable characteristics between adopters' and non-adopters' technologies, and estimated the gap in outcomes between the adopters and non-adopters and the identifying factors influencing CSA technology adoption. To test the hypotheses driving the study, the t-test was employed to test if any significant systematic differences existed between adopters and non-adopters and the PSM method (causal effect).

3.5 Propensity score matching procedure

This study strived to estimate the impact on farmers of adopting either manure or residue retention, using the PSM method used by Mendola (2007). Using Stata version 15.1, the effect of manure and residue retention on household maize production, yield, and income in northern Zambia was estimated. To address the evaluation problem (i.e., missing data and potential selection bias), propensity score matching, a semi-parametric approach, was used to make causal inferences about the adoption of the abovementioned technologies on farmers' welfare. The data presented in section 3.3 was analysed, presented, and discussed in the steps illustrated in Figure 4-1 (Caliendo and Kopeinig, 2008):

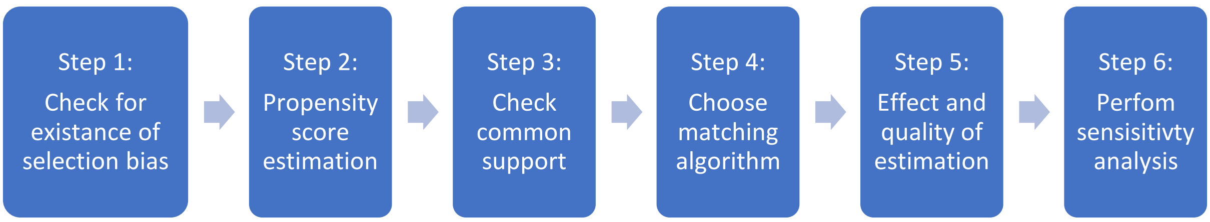

Figure 3-2 Steps in propensity score matching
Source: Caliendo and Kopeinig (2008)

Following (Rubin, 1974), the outcomes for non-adopting and adopting households were defined as shown in equations 1 and 2 respectively, with Y_0 representing the outcomes for non-adopters and Y_1 for adopters. The X represents the observable household characteristics that

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simultaneously influence technology adoption and the outcome variables (maize yield and income). The assumption is that unobserved random errors are different: $\mu \neq \varepsilon$. Because of potential selection bias, the effect of technology adoption was not estimated as the difference in the outcomes of adopters and of non-adopters ($Y_1 - Y_0$), known as the average treatment effect (ATE).

$$\boldsymbol{Y_0 = B_0 X + \mu} \qquad \textbf{(1)}$$

$$\boldsymbol{Y_1 = B_1 X + \varepsilon} \qquad \textbf{(2)}$$

The existence of selection bias owing to observable characteristics was tested using the t-test. The PSM method control for selection bias by matching adopters and non-adopters with similar observed characteristics using propensity scores, and estimated the more robust average treatment effect on the treated (ATT). The ATT being the average difference in welfare outcomes between adopters and non-adopters with similar observable characteristics. The method relies on two main assumptions: (i) the conditional independence assumption (CIA), and (ii) the common support or overlap assumption, which need to hold to estimate the treatment effect (technology adoption). The CIA assumption requires that technology adoption to be random and not correlated with welfare outcomes when the observed characteristics of farmers are controlled (Mendola, 2007). The common support assumption ensures that farmers with similar characteristics have positive probability to adopt or not to adopt. (Khandker et al., 2009). In addition, the common support assumption ensures that adopters and non-adopters have adequate matches. This study assumed that only observable household characteristics affect technology adoption (i.e., CIA assumption) (Rosenbaum and Rubin, 1983), as shown in equation 3.

$$\boldsymbol{Y_i \perp D | X} \qquad \textbf{(3)}$$

Where D is a dichotomous dependent (treatment) variable, equal to 1 when farmers adopted (and zero otherwise). The '⊥' denotes independence, and the variables to the right of '|' are the conditioning variables. Conditioning on variables is similar to conditioning on propensity scores (Rosenbaum and Rubin, 1983). To be precise, the potential outcomes (Y_i) are independent of the treatment assignment, given the set of variables unaffected by treatment. This assumption was ensured, and the study proceeded to estimate the propensity scores. The

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study adopted the probit model to estimate the propensity or probability scores, as shown in equation 4 – the probability that a farmer adopts a particular CSA technology.

$$\boldsymbol{P}(\boldsymbol{X}) = \mathbf{Pr}(\boldsymbol{D} = \mathbf{1}|\boldsymbol{X}) = \boldsymbol{E}(\boldsymbol{D}|\boldsymbol{X}) \qquad \textbf{(4)}$$

Where P(X) represents the estimated propensity scores. Each farmer has an estimated propensity score, the farmer's probability to adopt CSA technology. Rigorous testing and checking ensured that all covariates that determined participation were included in the propensity score equation. Covariates that influenced adoption are likely to be data-driven, taken from literature- and context-specific. Using the propensity scores, the region of common support was defined; this is where distributions of the propensity score for adopters and non-adopters overlapped. Adopters or non-adopters that fell outside the common support region were dropped. The estimation of the treatment effect (adoption) take place in the region of common support. Satisfying the common support assumption ensures that households with similarly observed variables had a positive probability to adopt or not to adopt (Heckman et al., 1999; Caliendo and Kopeinig, 2008). In essence, it ruled out the perfect predictability of the adoption state, given the observed variables as shown below (in equation 5):

$$\mathbf{0} < P(\boldsymbol{D} = \mathbf{1}|\boldsymbol{X}) < 1 \qquad \textbf{(5)}$$

With the common support assumption satisfied, non-adopters were matched with adopters, based on the distribution of covariates such that farmers from the two groups shared similar observable characteristics (Rosenbaum and Rubin, 1983). Propensity scores (probability) were used to match adopters and non-adopters. Under CIA and common support assumptions, matching on P(X) is similar to matching on observed characteristics. The study applied common matching methods: nearest neighbour, radius matching, and kernel (Rosenbaum and Rubin, 1985). The weights assigned in each matching method affected the estimation of the treatment effect. Balancing property tests were conducted to ensure that the distribution of propensity scores was based on similar observed X (Rosenbaum and Rubin, 1983). The standardised bias, t-test, and pseudo-R^2 tests were used to assess the matching quality (i.e., the balancing property). Matching with a good comparison group ensures that a true hypothetical mean outcome is estimated, as shown in equation 6. For instance, the observed mean outcome

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for adopters is given as $E(Y_1|D = 1)$ and their hypothetical mean outcome as $E(Y_0|D = 1)$[5]. The ATT was estimated as shown in equation 7 (Rosenbaum and Rubin, 1985), such that:

$$\boldsymbol{E(Y_0|D = 1) - E(Y_0|D = 0) = 0} \quad \textbf{(6)}$$

$$\boldsymbol{ATT = E(\Delta|D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1)} \quad \textbf{(7)}$$

The treatment effect includes the variance attributed from the derivation of the propensity scores, common support region, and matching. Failure to account for this variation can result in wrongly estimated standard errors (Caliendo and Kopeinig, 2008). One widely used method to deal with this problem is bootstrapping (Johnson et al., 1989; Lechner, 2002; Horowitz, 2003). In bootstrapping, results are re-estimated, including the initial stages in the estimation – i.e., propensity score and common support. The PSM method hinged on the CIA assumption, thus requiring a sensitivity analysis to be carried out to establish how the potential existence of unobserved characteristics (hidden bias) might affect adoption. A Rosenbaum bounds sensitivity analysis was employed to check how hidden bias (unobserved influences) may affect results of the study (i.e., the degree to which unobserved influence would require for the results of the study to be questioned).

3.6 Description of variables used in the study

Table 3-1 shows the variables used in the study, including the variables used to estimate the propensity scores that were selected based on the literature and their association with the adoption and outcome variables. The literature shows that age, gender, market information, livestock ownership, extension services, input access, perception of climate change (CC), and farm size might influence technology adoption (Deressa et al., 2008; Ng'ombe et al., 2014).

[5] E is the expectation operator.

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Table 3-1: Definitions of variables used in the study

Variable	Definition/Codes	Adoption
Age[6]	Age of farmer in years 1 if the age of farmer is 18-35 (youth); otherwise 0	+/-
Gender	1 if household (HH) head (farmer) is male; otherwise 0	+
Marital status	1 if HH head was married; otherwise 0	+
Education	Level of education of farmer (0 never, 1 primary, 2 secondary, 3 tertiary)	+
Household size	Number of household members	+
Maize area	Size of the maize farm cultivated, in hectares	+/-
Agribusiness	1 if farmer received training to run a farm as a business; otherwise 0	+
Aware of GAPs	1 if the farmer was aware of good agricultural practices; otherwise 0	+
Extension access	1 if the farmer had extension services; otherwise 0	+
Market access	1 if the farmer had access to market information	+
Climate change	1 if farmer perceived climate change; otherwise 0	+
Input access	1 if the farmer had access to agricultural inputs (seed and fertiliser); otherwise 0	+
Legumes	1 if a farmer planted legumes; otherwise 0	+
Province	1 if a farmer from Northern Province; otherwise 0	+
Livestock	1 if HH had livestock; otherwise 0	+/-
Manure / residue	1 if HH adopted manure or retention; otherwise 0	
Tillage	1 if HH had practised minimum tillage in the past; otherwise 0	+
Treadle pump	1 if HH used treadle pump in farming; otherwise 0	+
Knapsack sprayer	1 if a farmer used sprayer in farming; otherwise 0	-
Seed multiplication	1 if HH involved in seed multiplication in farming; otherwise 0	+
Maize yield	Quantity of maize produced per hectare by HH	+
Crop income	Income from maize produce sold, per hectare (ZK/Ha)	+

Source: Author's analysis

[6] The official range for young people's (youth) age in Zambia ranges from 18 to 35 years (GRZ, 2017).

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CHAPTER 4: RESULTS AND DISCUSSION

4.1 Overview

This chapter presents the study's results and a detailed discussion. To begin this chapter, the farmers' descriptive statistics are discussed. The third section (4.3) discusses the farmers' perceptions of climate change and the observed climate change impacts respectively. The fourth section presents the test results on the potential existence of selection bias. Section 4.5 explains the outcome variables used in the study. Sections 4.6 and 4.7 present the empirical results from estimating the effect of CSA technologies (manure and residue retention adoption respectively) on household maize production quantity, yield, and income in 2018/19 season, using the PSM method. The last section summarises the hypotheses tested.

4.2 Descriptive statistics of households' characteristics

Owing to missing values in the dataset, the presentation and discussion of the descriptive statistics were carried out separately. The descriptive statistics provide a summary of information about the characteristics of the sampled population. Frequencies distributions, means, and percentages were used.

4.2.1 Descriptive statistics of households in manure models

Table 4-1 shows the summary statistics of the sampled farmers in the manure adoption group. The average age of the farmers was found to be 48 years, which shows that most smallholder farmers in the northern region of Zambia are in their most productive years and have the potential to adopt new farming practices (Afolami et al., 2015). Majority of respondents were male (56.8%) and 43.2% female farmers. This could be that males have greater access to farmland than females (Nkhoma et al., 2017). There were 363 (96.8%) respondents who indicated that they had received formal education. Education is said to enable farmers to acquire, understand, and interpret information that helps in decision-making (Mariano et al., 2012; Makate et al., 2019). As a result of the higher percentage of farmers who have received a formal education, the assumption is that most respondents have the knowledge and skill to understand the potential benefits of CSA technologies. A farmer with formal education or many years at school is expected to have more knowledge and to be highly skilled, and thus more

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likely to adopt technology than a farmer with an informal education or fewer years at school. Luapula Province accounted for 38.13% of the respondents, while the Northern Province accounted for 61.87%. The sampled group consisted of a large number of married individuals (84%). For the binary variables – for example, whether married or not (those coded 1 or 0) – the mean was similar to the percentage of the number of individuals who were married. The household size was relatively high, with mean number of 7 respondents per household. Agriculture production requires labour, and household size is perceived as an indicator of the availability of labour for the households to execute their agricultural activities. Certain CSA technologies are labour intensive which may deter households with fewer members from adopting them (Cunguara and Darnhofer, 2011). Among the 375 sampled respondents, 68.27% had received with extension services. Extension services provide farmers with knowledge and skill to be innovative in farming (Akerele, 2014). The sources of the extension services were the GRZ and non-governmental organisations such as TLC Zambia. Most individuals receiving extension services from the GRZ. On average, households cultivated maize on 1.01 hectares of land.

Table 4-1: Descriptive statistics of sampled households for manure (N=375)

Variables	Mean	Standard deviation	Percentage
Age	48.96	12.913	-
Gender of farmer			
Female	-	-	43.20
Male	-	-	56.80
Education			
Never	-	-	3.20
Primary	-	-	49.07
Secondary	-	-	47.20
Tertiary	-	-	0.53
Province			
Luapula	-	-	38.13
Northern	-	-	61.87
Married	0.84	0.367	-
Household size	7.20	3.000	-
Extension access	0.68	0.466	-
Maize area	1.01	0.991	-

Source: TLC household survey 2019

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4.2.2 Descriptive statistics of households used in residue retention models

Table 4-2 presents a summary of the characteristics of the sampled population used in the residue retention model. As the table shows, the mean age of the respondents was 49 years. The female respondents (43.14%) were fewer than the males (56.86%). Female have limited access to land compared to males. When it comes to location, most of the respondents (54.58%) were from the Northern Province. The educational background of the respondents showed that 3.59% had never received a formal education, 50% had a primary school education, 45.75% had attempted a secondary education and only 0.65% of the respondents completed their tertiary education. On average, the respondents cultivated maize on 1.24 hectares of land. Size of land is seen as an indicator of wealth among farmers (Nkhoma et al., 2017). Most respondents, 69%, had contact with extension officers suggesting that most have knowledge about production improving technologies (IFAD, 2016).

Table 4-2: Descriptive statistics of sampled households for residue retention (n=306)

Variables	Mean	Standard deviation	Percentage
Age	49.2	13.136	-
Gender of farmer			
Female	-	-	43.14
Male	-	-	56.86
Education			
Never	-	-	3.59
Primary	-	-	50.00
Secondary	-	-	45.75
Tertiary	-	-	0.65
Province			
Luapula	-	-	45.42
Northern	-	-	54.58
Married	0.83	0.376	-
Household size	7	2.910	-
Extension access	0.69	0.462	-
Maize area	1.24	4.339	-

Source: TLC household survey 2019

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4.3 Farmers' perception of climate change consequences

Tables 4-3 and 4-4 show that most households in the studied areas were aware of climate change and of the impacts associated with it respectively. On awareness, table 4-3 show that 86.40% of the respondents in the manure sample and 83.33% of those in the residue retention sample were aware of climate change. This is in line with the results of Fosu-Mensah et al. (2012), who showed that climate change awareness was high among smallholder farmers in Ghana. According to Nzeadibe et al. (2011), no or only limited awareness of climate change hinders farmers' adaptation ability. For an in-depth discussion on what influences farmers' perception or awareness of climate change, see (Deressa et al., 2011; Foguesatto and Machado, 2020). Climate change awareness is important in farmers' adaptation process because it encourages them to change their behaviour and helps them to adapt appropriately.

Table 4-3: Climate change awareness in manure and residue retention samples

Climate change awareness	**Aware of climate change (yes)**	**Aware of climate change (no)**
Manure	325 (86.40%)	50 (13.33%)
Residue retention	255 (83.33%)	51 (16.12%)

Source: TLC household survey 2019

To adapt effectively to climate change, farmers must correctly perceive current and future climate trends. As shown in Table 4-4, households reported varying effects of climate change. About 78.13% of the households in the manure sample and 72.88% of those in the residue retention sample population (cumulative percentages) experienced at least one impact attributed to climate change. Additionally, the cumulative percentage of farmers reported that climate variability led to a decline in crop yield: 50.13% in the manure sample, and 47.38% in the residue retention sample. This confirmed the findings reported by Gbetibouo and Hassan (2005), that reduced rainfall negatively affected net revenue owing to a decrease in crop yield. Most farmers reported that climate change affected crop production more than it did other agricultural activities. This shows the need to find sustainable ways to improve crop farmers' resilience amid climate change. Climate change results in a shortage of rainfall and drought, which affects most households in Zambia, as they rely on rainfall for irrigation. Thus, a shortage of rain negatively affects households. Interestingly, on average, only 2.93% of the respondents in both samples experienced a decline in livestock production because of climate

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change. Livestock is reported to be less affected by climate change and variability than crops. In South Africa, Thomas et al. (2007) found that smallholder farmers cease investment in crops and focus on livestock production during drought seasons. Most households in Africa practise mixed farming; and Zambian farmers are no different. This has the potential of playing a role in sustainable development; and in this way farmers can diversify their income (Howden et al., 2007).

About 11% of the households in the manure and residue retention samples reported that climate change led to diseases. Harvey et al. (2018) reported similar findings for smallholder farmers in Central America, where changing climatic conditions led to the incidence of pests and diseases that affected crops. This in turn led to increased farm production costs and decreased crop production. Another effect noted by households was reduced water availability, as climate change led to dry spells (Oseni and Masarirambi, 2011). Climate change also led to fluctuations in the rainfall seasons (relating to the planting seasons), making it harder for farmers to be certain about the most appropriate time of the year to plant. In the manure and residue retention samples, 8.53% and 7.84% of the respondents respectively confirmed having difficulties or uncertainty with timing the planting seasons (Kuntashula et al., 2014). Only 23% and 27% of the respondents from the respective samples reported having not experienced the effects of climate change. This might have been unique to those farmers, and might be attributed to farmers experiencing different socio-economic factors that affected their awareness and adaptation. Nevertheless, the results showed that the effects of climate change vary among farmers, and that agricultural technologies are required to improve farmers' resilience to the impacts of climate change.

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Table 4-4: Reported effects of climate change

Climate change effects	Manure		Residue retention	
	Frequency	Percentage	Frequency	Percentage
Decline in crop yield	131	34.93	111	36.27
Decline in livestock	13	3.47	7	2.29
Difficulty in timing seasons	32	8.53	24	7.84
Increased yields	5	1.33	4	1.31
Increased diseases	40	10.67	35	11.44
Decreased water availability	15	4	8	2.61
Declining crop yield and livestock	57	15.20	34	11.11
No consequences	82	21.87	83	27.12

Source: TLC household survey 2019

4.4 Presentation and analysis of the selection bias

Using the observable characteristics of the farmers, systematic differences were checked between the adopters and the non-adopters of the technologies under investigation. Checking for systematic differences between adopters and non-adopters is the first and most important step in impact evaluation, and might direct the researcher to which valuation method to use. Observational studies on technology adoption often suffer from the existence of selection bias, causing the sample population between the two groups to be non-random or not a true representation of the whole population (Becerril and Abdulai, 2010; Kassie et al., 2011; Mendola, 2007). In contrast, randomised studies in which individuals from both groups share similar characteristics ensure that the mean difference in outcomes between two groups provides true estimates of the treatment.

To check for the existence of selection bias, the observable farmers' characteristics[7] were chosen for each technology, and carried out separately, as the factors that influence the adoption of different technologies often differ, depending on the nature and setting of the data used, the economic theory, and the degree of association between the covariates and the technology. The study employed the statistical significance method when choosing the

[7] The covariates were chosen based on the literature and their association with technology adoption and outcome variables (Rosenbaum and Rubin, 1983).

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variables, using the t-test (equality of means test). The Pearson correlation was also employed to avoid collinearity in the modelling. Covariates were also chosen based on the literature (theory). See Caliendo and Kopeinig (2008) for a detailed discussion on recommended methods to use to select covariates when using PSM. The same covariates were used later in the propensity score estimation. As shown in Tables 4-5 and 4-6, the t-test was used in checking for systematic differences in the observable characteristics between the adopters and the non-adopters of manure and residue retention.

The study found that selection bias existed in the adoption of manure, as shown in Table 4-5. For example, farmers who received training on the running of a farm as a business were associated with adopting manure, and there was a significant difference in the farmers who trained in farm business among the adopters and the non-adopters of manure ($p>0.031$). These farmers may have a better understanding on the potential benefits of manure. Manure adoption is associated with farmers who have access to agricultural inputs (seeds), and a significant difference exists between adopters' and non-adopters' access to inputs ($p>0.002$). There were other significant differences in the characteristics between the adopters and the non-adopters of manure: farmers differed in location (province, $p>0.003$); and the distribution of the farmers in the two provinces was significantly different between the two groups. It could be that more farmers with livestock ownership were from the Northern Province. The implication of this is that farmers with livestock are likely to adopt manure. Manure adopters were also significantly different from non-adopters in the cultivation of legumes ($p>0.001$), having practiced minimum tillage in the past ($p>0.000$) and in access to a water source ($p>0.029$).

In manure adoption, respondents (adopters and non-adopters) had similar characteristics in terms of access to extension services, gender, age, awareness of technologies, access to market information and livestock ownership.

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Table 4-5: Variables used in manure propensity score matching estimation

Variable	Manure (yes)	Manure (no)	$P > T(X^2)$
Gender	0.51	0.58	0.368
Age	46.53	49.34	0.148
Agribusiness	0.88	0.74	0.031**
Extension access	0.75	0.67	0.304
Input access	0.804	0.574	0.002***
Market information	0.90	0.90	0.987
Livestock[8]	0.88	0.85	0.530
Aware of GAPs	0.80	0.79	0.861
Province	0.80	0.59	0.003***
Legumes	0.88	0.66	0.001***
Water source	0.27	0.15	0.029**
Tillage	0.45	0.18	0.000***

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

Table 4-6 shows the existence of selection bias in residue retention adoption. The results showed that farmers were distributed differently between the adopters and the non-adopters of residue retention with regards to gender (p>0.074). Secondly, a significant difference existed between residue retention adopters and non-adopters on climate change awareness (p>0.004). The adopters and non-adopters of residue retention were significantly different with regard to extension contact (p>0.000). Farmers with access to extension services were likely to adopt agricultural technologies. Extension services expose farmers to diverse technologies, and they can acquire skills to implement them (Emmanuel et al., 2016). Other observable characteristics that were systematically different between the two groups included access to agricultural inputs (p>0.011), agribusiness training (p>0.031), legume planting (p>0.002), and involvement in seed multiplication (p>0.000). Access to agricultural inputs – i.e., fertiliser and seeds – was also significantly different between the two groups. Respondents were similar in terms of awareness of technologies, ownership of livestock and knapsack sprayer and the amount of land cultivated.

[8] The livestock variable in manure models was coded as '1' for any household owning cattle, goats, or chickens. Livestock is a major source of manure among smallholder farmers.

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Table 4-6: Variables used in residue retention propensity score matching estimation

Variable	Residue retention (yes)	Residue retention (no)	$P > T(X^2)$
Gender	0.83	0.74	0.074*
Climate change[9]	0.92	0.79	0.004***
Aware of GAPs	0.80	0.72	0.148
Maize area	1.09	1.31	0.681
Extension access	0.83	0.63	0.000***
Input access	0.65	0.50	0.011**
Market access	0.94	0.87	0.076*
Livestock[10]	0.39	0.35	0.545
Treadle pump[11]	0.07	0.03	0.097*
Legumes	0.78	0.60	0.002***
Seed multiplication	0.51	0.30	0.000***
Knapsack sprayer	0.19	0.17	0.590
Agribusiness	0.86	0.75	0.031**

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

The existence of selection bias, based on the observable characteristics in the adoption of these technologies, drove this study to use the propensity score matching method. In the event that adopters and non-adopters had similar observable characteristics, the difference in the outcome variable means between the two groups would have been sufficient to estimate the effect.

[9] Climate change awareness.
[10] The livestock variable in the residue retention models was coded '1' if a household had cattle or goats, and '0' otherwise. Smallholder farmers practising mixed farming might feed fodder (crop residues) to livestock during dry seasons.
[11] Treadle pumps are used for irrigating.

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4.5 Outcome variables

The study used household maize production quantity, yield[12], and crop income (i.e., for maize) in the 2018/2019 season as outcome variables (Amadu et al., 2020b; Kuntashula et al., 2014; Mendola, 2007; Rimal et al., 2015). Crop income[13] refers to income from maize sold per hectare (gross income). CSA technologies are aimed at improving farmers' welfare by improving productivity and income (FAO, 2013). The intervention project from which the data was sourced aimed to improve crop production in promoting these technologies, among others (TLC, 2019). From Table 4-7 below, the significant difference in maize quantity between the two groups in both technologies is noticeable. Although the differences between maize yield and income were insignificant, the adopters had better return.

Table 4-7: Outcome variables

Outcome variables	**Adopted manure (yes)**	**Adopted manure (no)**	$P > T(X^2)$
Maize production quantity 2018/2019	5118.63 (7.82)	2544.55 (7.43)	0.008***
Maize yield in 2018/2019	2708.77 (1.01)	2555.39 (0.83)	0.146
Crop income in 2018/2019	8490.80 (8.26)	5435.73 (8.15)	0.482
	Residue retention (Yes)	**Residue retention (No)**	$P > T(X^2)$
Maize production quantity 2018/2019	3741.98 (7.64)	2595.51 (7.36)	0.027**
Maize yield in 2018/2019	2609.67 (0.93)	2634.82 (0.79)	0.257
Crop income in 2018/2019	5515.93 (8.17)	6652.41 (8.18)	0.973

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.
Notes: Values in brackets are the logged values of the outcome variables.

[12] 'Household (HH) maize yield' refers to the maize produced by HH in the 2018/2019 planting season, expressed in kilograms per hectare. The outcome variables were logged transformed in modelling to ensure normality, as they were very right skewed (Mendola, 2007; Kuntashula et al., 2014; Makate et al., 2019).
[13] Income is in Zambian Kwacha (ZK 11.97 = US$ 1, exchange rate in January 2019).

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The study strived to ascertain whether the differences in the outcome variables should be attributed to the adopted technology. Comparing the means of the two groups with standard statistical techniques might not provide a good indication; and the differences in the outcome variables in both cases cannot be assumed as a result of either technology. Other factors (confounders) might have led to the gap in maize production, yield, and income between the two groups. The study proceeded to estimate the impact on production, yield, and income associated with adopting either technology.

4.6 Impact evaluation of manure adoption

This section discusses the empirical results on the effect of manure adoption on farmers in Northern Zambia.

4.6.1 Manure adoption

A manure adopter in this study is described as any farmer who applied manure from either animals or plants as composts. The results in Table 4-8 show that the adoption of manure is low at 13.60%. Manure is promoted as a sustainable practice that smallholder farmers should adopt to improve soil structure and fertility, thus improving crop yield and income. Manure use and management are perceived to complete the three pillars of CSA technologies by improving productivity and adaptation and reducing emissions. The proper management of manure helps to reduce emissions, as animal manure is the largest emitter in agriculture (FAO, 2013).

Table 4-8: Manure adoption

Household adopted manure in 2018/2019	**Yes**	**No**
	51 (13.60%)	324 (86.40%)

Source: TLC household survey 2019

Smallholder farmers often lack access to the inputs that are required by most CSA technologies, such as fertiliser, improved seed varieties, and other industrial inputs. Manure provides an alternative for farmers to realise improved crop production at lower costs (Thangata et al., 2007). Even with all the potential benefits, the adoption of CSA technologies, including manure, is low (FAO, 2013). Also, farmers often adopt CSA technologies in small parts of their farms (Grabowski et al., 2014). The literature shows that socio-economic and institutional

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factors such as age, gender, access to extension services, and location influence the adoption of manure use (Franzel, 1999; Nyengere, 2015).

4.6.2 Manure propensity score estimation

Table 4-9 presents the results of the probit model that was used to estimate the propensity scores. A probit regression being a binary dependent model, manure adoption was used as a dependent variable and coded manure = 1 if a household adopted manure and 0 if the household did not adopt manure. In estimating propensity scores, determinants of manure adoption were also estimated. The propensity score is the probability that an individual will adopt manure. Using PSM requires that the CIA assumption hold – that is, that the observable characteristics between individuals are not affected by the treatment. Observations should not differ in their characteristics because of the treatment. As suggested by Rosenbaum and Rubin (1985), the propensity or probability scores were estimated. As balancing scores, the propensity scores ensured that potential outcomes were independent of the treatment, conditional on the observable characteristics. See also Caliendo and Kopeinig, (2008)

Manure adoption among farmers in northern Zambia is significantly and positively influenced by farm business training; farmers trained to run a farm as a business had a high probability of adopting manure ($p>0.030$). This group of farmers might have a better understanding of the potential impact of technologies, including manure use, on the quality and quantity of the production earmarked for the market. Moreover, Hagos and Geta, (2016) found a positive relation being adoption of technology and farmer running farm as a business. Secondly, location influenced the adoption of manure; e.g., households from Northern Province had a higher probability of adopting manure ($p>0.033$). Also, farmers who cultivated legumes had a high probability of adopting manure. This could be that households often intercrop beans with maize, and might need to supplement the soil with the additional nutrients from manure ($p>0.092$). Like legumes, manure adds nitrogen – a major nutrient for most crops – to the soil. Moreover, access to a water source influenced farmers' adoption of manure ($p>0.076$). Interestingly, farmers who had practised minimum tillage practices in the past have a higher probability of adopting manure ($p>0.002$). The implication is that farmers tend to adopt technologies sequentially. For instance, a farmer may adopt a specific technology to learn more about the innovation only to stop adopting it later and adopt another technology (Leathers and Smale, 1991). Female farmers had a higher probability of adopting manure than did males.

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This proved to be a contradiction from Akudugu et al. (2012) findings, they reported that male farmers have greater probability of adopting technologies compare to females. Additionally, younger farmers were found to have a higher probability of adopting manure (Danso-Abbeam et al., 2017). However, Ng'ombe et al., (2014) found age to positively influence technology adoption. Livestock ownership positively influenced the adoption of manure. Livestock is the major source of manure (FAO, 2013).

Table 4-9: Manure probit estimates

Variable	**Coefficient**	**Z**	**P > | z |**
Gender, 1 – Male	-0.264	-1.43	0.152
Age	-0.159	-0.64	0.522
Agribusiness, 1 – Yes	0.607	2.18	0.030**
Extension access, 1 – Yes	0.134	0.62	0.533
Input access, 1 – Yes	0.310	1.41	0.159
Market access, 1 – Yes	0.003	0.01	0.992
Livestock, 1 – Yes	0.134	0.46	0.649
Aware of GAPs, 1 – Yes	-0.331	-1.29	0.198
Province	0.465	2.13	0.033***
Legumes	0.411	1.68	0.092*
Water source[14]	0.391	1.78	0.076*
Tillage	0.665	3.13	0.002***
Constant	-2.385	-4.48	0.000
Summary			
Number of observations	375		
Pseudo R^2	0.153		

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.
Notes: Province coded as '1' if HH is in Northern Province and '0' if it's in Luapula Province.

The estimated propensity scores for the whole sample ranged between 0.0020228 and 0.6545933. For adopters of manure, the propensity scores ranged from 0.0356854 to 0.6545933, with a mean of 0.2467935. Non-adopters' propensity scores ranged from 0.0020228 to 0.594351, with a mean of 0.1186753. Respondents outside the common support[15] region were discarded. The propensity score for the region where the two groups overlapped in the distribution varied from 0.0020228 to 0.594351 (Leuven and Sianesi, 2003). It is in this region that adopters and non-adopters are able to find adequate matches. Figure 4-1 shows how propensity scores were distributed and the region where adopters and non-adopters of manure overlapped each other (common support region).

[14] Water source coded as '1' if a household had access to nearby water source, otherwise '0'.
[15] Treatment (adoption) effect is estimated within the common support or overlap region.

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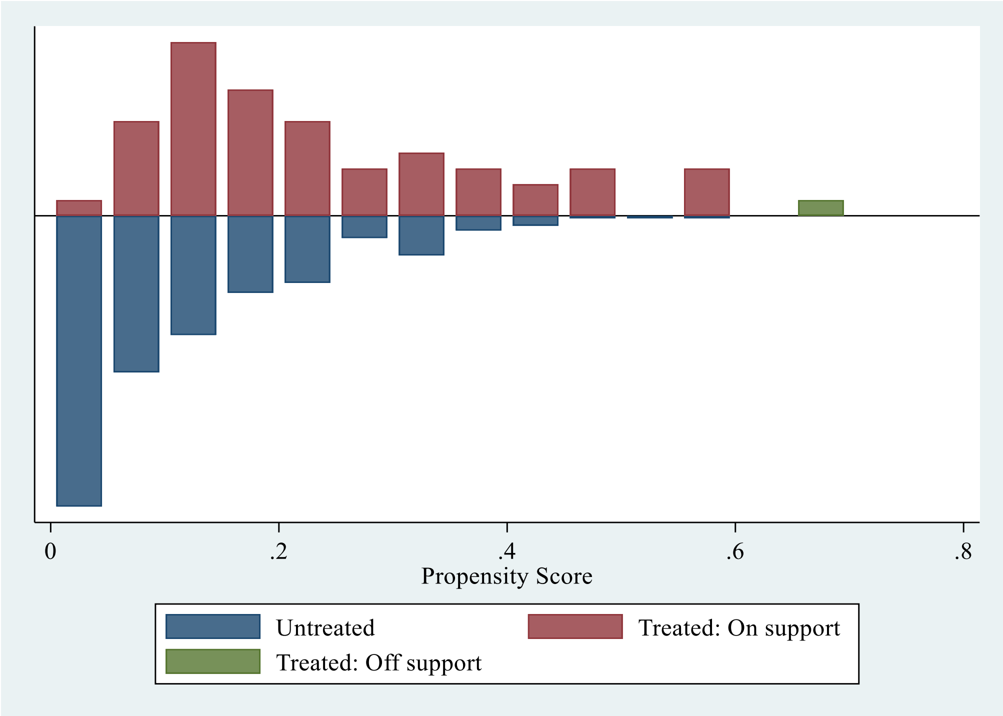

Figure 4-1: Manure propensity score distribution
Source: Own calculations. Stata version 15.1 output

4.6.3 Average treatment effect of manure adoption

The parameter of interest in propensity score matching is the average treatment effect of the treated (ATT). Rosenbaum and Rubin (1983) defined the ATT as the average difference in outcome (household maize production, yield, and income) between adopters and non-adopters over the common support, conditioned on the propensity scores of the observations. Using the Stata 15 psmatch2, the impact of manure on household maize production, yield, and income was estimated (Leuven and Sianesi, 2003). The estimated impact of manure on household is shown in Table 4-10. To ensure consistency and robustness, the study adopted alternative matching algorithms, including nearest neighbour matching (NNM) with replacement (with five neighbours), radius, and kernel-based matching methods (bandwidth 0.06). An efficient estimation of the adoption effect relies on finding a good matching group – a sample from the control group with similar observed characteristics to those of adopters. The standard errors were bootstrapped (100 replications).

All the matching estimators revealed consistent results, confirming that manure adoption had a positive and statistically significant effect on the quantity of maize produced. To be precise, manure adoption resulted in an increased quantity of household maize produced in 2018/2019

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that ranged from 34.0% to 37.1%. This was a greater improvement in quantity produced than they would have had if they had not adopted manure. These findings are consistent with the literature that CSA technologies have a positive effect on farmers' production (Kuntashula et al., 2014). Furthermore, adopting households had a significantly improved maize yield (productivity) than non-adopters, ranging from 32.0% to 39.2% (Khonje et al., 2018). Thus, farmers were able to achieve increased maize yield attributed to manure adoption. The increase in maize yield reduces food insecurity among households and household with surplus may sell their produce. In Zambia, Nkhoma et al. (2017) reported similar findings of agricultural innovations having positive impact on crop yield. Boateng et al. (2006) reported that manure improved crop yield and recommended its use as a valuable alternative to chemical fertilizer. These results suggested that farmers with similar characteristics and who only differ in the adoption of manure differ significantly in the amount of maize produced and yield. Manure adoption had an insignificant effect on crop income, but it remained positive. Studies by (Mendola, 2007; Khonje et al., 2018; Fentie and Beyene, 2019) reported that CSA technology adoption had a positive and significant effect on crop income; however, Kuntashula et al. (2014), reported CSA technologies had contrasting effect on income. Certain technologies had positive effect while others had negative effect on crop income. Technologies may increase crop yield; but if farmers lack access to marketing channels and information, they often have no market in which to sell their produce to increase their income. Additionally, smallholder farmers' main priority is to feed their households rather than to sell their produce.

Table 4-10: Effect of manure on welfare indicators

Matching algorithm*	Adopters	Non-adopters	ATT	Bootstrapped standard errors	t-stat
NNM^P	50	129	0.340	0.179	1.89*
$Radius^P$	50	324	0.371	0.169	2.20**
$Kernel^P$	50	324	0.361	0.172	2.10**
NNM^Y	50	130	0.392	0.159	2.47**
$Radius^Y$	50	322	0.320	0.150	2.14**
$Kernel^Y$	50	322	0.345	0.154	2.23**
NNM^I	45	125	0.309	0.223	1.39
$Radius^I$	45	281	0.252	0.218	1.16
$Kernel^I$	45	281	0.246	0.220	1.12

Source: Own calculations. *Significant at 10%, **significant at 5% and ***significant at 1%.
Notes: Matching algorithms with P, Y, and I denote adoption effect on household maize production, yield and income respectively in manure and residue retention models.

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4.6.4 Matching quality estimation

Estimating the true adoption effect depends on the quality of the matching and satisfaction balancing property condition. After estimating the treatment effect, the next step was to check for matching quality. The idea in PSM is to match adopters and non-adopters with similar observable characteristics, based on their propensity scores. The similarity in characteristics between adopters and non adopters was assessed after matching to confirm whether matched adopters and non-adopters shared similar characteristics, and whether no significant differences existed in the observable characteristics between the two groups. The results of the quality matching checks are presented in Tables 4-11 and 4-12, and show the observable characteristics of the matched adopters and non-adopters. Rosenbaum and Rubin (1985) suggested the use of a two-sample t-test to check for significant differences in the observable characteristics means between adopters and non-adopters.

Before matching, as illustrated in Table 4-5, there were systematic differences in the adopters' and non-adopters' characteristics. The expectation after matching is to have similar observable characteristics between the two groups, which is why it is called 'balancing property'. The matching quality was assessed using standardised bias, Pseudo-R^2, and significance (t-test) tests. Using the t-test, we found that all the covariates in the matched sample were insignificant between the two groups, thus validating good matching. The study also used a standardised bias (SB) indicator (in percentages) for each covariate. Rosenbaum and Rubin (1985) defined standardised bias as the difference between sample means in the treatment and matched controls' sub-samples as a percentage of the square root of the average of sample variances in both groups. The standardised bias for covariate in table 4-11 ranges from 0.2% to 7.2%. These are very low numbers, suggesting good quality matching, as the allowable SB is less than 20% for most covariates (Kassie et al., 2011).

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Table 4-11: Manure matching quality indicators

Variable	Mean		Bias		Pr(|T| > |t|
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.520	0.499	4.1	69.4	0.839
Age	0.820	0.847	7.2	55.2	0.720
Agribusiness	0.880	0.877	0.7	98.1	0.968
Extension access	0.740	0.741	0.2	98.8	0.992
Input access	0.800	0.785	3.4	93.4	0.853
Market access	0.900	0.903	1.1	36.9	0.955
Livestock	0.880	0.901	6.3	36.2	0.735
Aware of GAPs	0.800	0.821	5.2	97.2	0.790
Province	0.803	0.794	1.3	97.4	0.945
Legumes	0.882	0.874	1.4	97.5	0.934
Water source	0.260	0.247	3.2	89	0.590
Tillage	0.440	0.416	5.5	91.1	0.807

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.
%Bias = standardised bias after matching; |**Bias**| = bias reduction percentage.

The mean standardised bias shown in Table 4-12 is low at 3.3%, confirming good matching quality. The use of multiple matching quality tests ensured vigorous testing of the estimated results. The next step was to check pseudo R^2 before and after matching. Table 4-12 shows the results of the quality matching output, with pseudo R^2 of 0.154 before matching and 0.005 after matching. When comparing the pseudo R^2 before and after matching, the pseudo R^2 after matching should be moderately lower than before matching, as differences between adopters and non-adopters are assumed to have been wiped out (Sianesi, 2004).

Table 4-12: Manure summary of matching indicators[16]

Sample	Pseudo R^2	p>chi2	Mean bias	Median bias
Before matching	0.154	0.000	28.3	23.2
Matched	0.005	1.000	3.3	3.3

Source: Own calculations

[16] Tables 4-11 and 4-12 are based on the kernel matching method. See the Appendix, pages 73 to 74, for the quality indicators for other matching algorithms.

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4.6.5 Sensitivity analysis for manure models

The PSM method controls for selection bias using farmers' observable characteristics, which means that we assume that there is no unobserved heterogeneity between adopters and non-adopters. To ensure that the PSM was well-specified, a Rosenbaum bounds sensitivity analysis on hidden bias was run to check at what point the positive effect of manure on welfare outcomes would be questioned if farmers with similar observable characteristics differed in their odds of adopting manure. The sensitivity analysis showed that the strength of the unmeasured influences (unobservable characteristics) would require a change to the effect of manure. The level required by unobservable influences is denoted by the level of gamma, Γ, as shown in Table 4-13. The level of gamma ranged from 30% to 45%; these numbers are normal, given the fact that the covariates used in the study were checked to be highly associated with the adoption and welfare outcomes, thus providing a true adoption effect (Asfaw et al., 2012; Becerril and Abdulai, 2010). Alternative methods accounting for unobserved differences can also be used. The sensitivity analysis of insignificant ATT was trivial (Caliendo and Kopeinig, 2008).

Table 4-13: Manure sensitivity analysis

Matching algorithm	Adopters	Non-adopters	ATT	Bootstrapped standard errors	t-stat	Critical level hidden bias (Γ)
NNM^{P}	50	129	0.340	0.179	1.89*	1.30
Radius^{P}	50	324	0.371	0.169	2.20**	1.45
Kernel^{P}	50	324	0.361	0.172	2.10**	1.35
NNM^{Y}	50	130	0.392	0.159	2.47**	1.45
Radius^{Y}	50	322	0.320	0.150	2.14**	1.30
Kernel^{Y}	50	322	0.345	0.154	2.23**	1.35
NNM^{I}	45	125	0.309	0.223	1.39	-
Radius^{I}	45	281	0.252	0.218	1.16	-
Kernel^{I}	45	281	0.246	0.220	1.12	-

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

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4.7 Impact evaluation of residue retention adoption

This section discusses the empirical results for the impact of residue retention on household maize production quantity, yield, and crop income.

4.7.1 Residue retention adoption

Table 4-14 shows the sampled population, with 32.68% and 67.2% of the respondents adopting or not adopting residue retention respectively. The results confirmed the assertion that technology adoption among smallholder farmers remains low in the sub-Saharan region (Dinar et al., 2012; Shongwe, 2014). (See Adeoti (2008) for a detailed discussion of the factors that influence technology adoption.)

Table 4-14: Residue retention adoption

Household adopted crop residue retention in 2018/2019	**Yes**	**No**
	100 (32.86%)	206 (67.20)

Source: TLC household survey 2019

Residue retention is one of the three principles of CA, and has the potential to preserve moisture and add fertility to the soil. Farmers practise technologies, especially those of CSA, only in a small proportion of the total planted area. Technologies might require labour to adopt, which might discourage farmers. Additionally, farmers use small sections of their farms as ‘demo plots’ to compare the effects of different technologies.

4.7.2 Residue retention propensity score estimation

The results from the estimated probit model for propensity scores on crop residue retention adoption are presented in Table 4-15. The variable for adoption was indicated as ‘1’, and as ‘0’ if the respondent did not adopt. The covariates used in the model affected adoption and its outcomes. As stated earlier, propensity scores reflect the probability of adoption. In estimating the propensity scores, access to extension services was found to positively and significantly influenced the adoption of residue retention at ($p<0.000$) (Prokopy et al., 2015). According to (Akerele, 2014), the rate at which farmers adopt agricultural technologies depends on contact with extension services. The results from Table 4-15 further show that legume farmers are more

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likely to adopt residue retention. Legumes are often intercropped with maize, or are rotated; the residues from legumes can also be used as mulch (residue retention). Farmers producing their seeds are likely to adopt residue retention (5%). Involvement in seed multiplication improves farmers' production, as they can produce seeds that suit the environment and match their personal objectives.

Climate change awareness positively associated with the adoption of residue retention. In a study by Ayal and Leal Filho (2017), on farmers' perception of climate change in Ethiopia, they reported that farmers' perceptions were formed by their experiences; and the way in which farmers adapt depends on their awareness of climate change. Livestock ownership (e.g., cattle, goats) negatively influenced residue retention adoption. Farmers often practise mixed farming, and during the dry seasons crop residues (fodder) are fed to the livestock (FAO, 2015). However, livestock ownership was expected to have positive effect on adoption of manure. Farmers with large farms have been found to be less likely to adopt residue retention. However, the literature provides inconclusive findings on the influence of farm size on technology adoption. For example, (Idrisa et al., 2010) reported that farm size negatively influenced the adoption of agricultural technology. Small farms are easier to manage than large farms; thus, the adoption of technology is fast. Often happens when the results of adopting that technology are positive. In contrast, (Ayinde et al., 2010; Melisse, 2018) reported a positive effect of farm size on the adoption of technology. Larger farm sizes are seen as a sign of wealth, of individuals who have access to agricultural inputs. Conservation agriculture principles (e.g., residue retention) are often practised in small areas, as they are often aimed at smallholder farmers. Further, households headed by males had a higher probability of adopting residue retention than those headed by females, although the difference was not significant. Males are thought to be able to adopt CSA technologies, as these technologies are often labor-intensive (Afolami et al., 2015).

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Table 4-15: Residue retention probit estimates

Variable	Coefficient	Z	P > | z |
Gender, 1 – Male	0.242	1.19	0.233
Climate change awareness, 1 – Yes	0.403	1.61	0.107
Aware of GAPs, 1 – Yes	0.023	0.11	0.912
Maize area	-0.018	-0.28	0.777
Extension access, 1 – Yes	0.673	3.66	0.000***
Input access, 1 – Yes	0.249	1.42	0.156
Market access, 1 – Yes	0.144	0.48	0.630
Livestock, 1 – HH owned goats or cattle	-0.065	-0.38	0.707
Treadle pump, 1 – Yes	0.034	0.09	0.929
Legumes	0.398	2.16	0.031**
Seed multiplication, 1 – Yes	0.423	2.35	0.019**
Knapsack sprayer, 1 – Yes	-0.116	-0.53	0.593
Agribusiness	0.093	0.42	0.672
Constant	-2.118	-5.38	0.000
Summary			
Number of observations	306		
Pseudo R^2	0.115		

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

The estimated propensity scores for the whole sample varied from 0.0023428 to 0.6683763, with a mean of 0.3285803. For adopters, the propensity scores ranged from 0.0351126 to 0.6683763, while the estimated propensity scores for non-adopters varied from 0.0023428 to 0.6651842. The region of common support was defined; thus adopters with propensity scores outside the minimum and maximum propensity scores of non-adopters were removed from the sample (Leuven and Sianesi, 2003). The distribution of propensity scores within the common support region shows adopters and non-adopters who shared similar observable characteristics. Figure 4-2 illustrates the distribution of the propensity scores.

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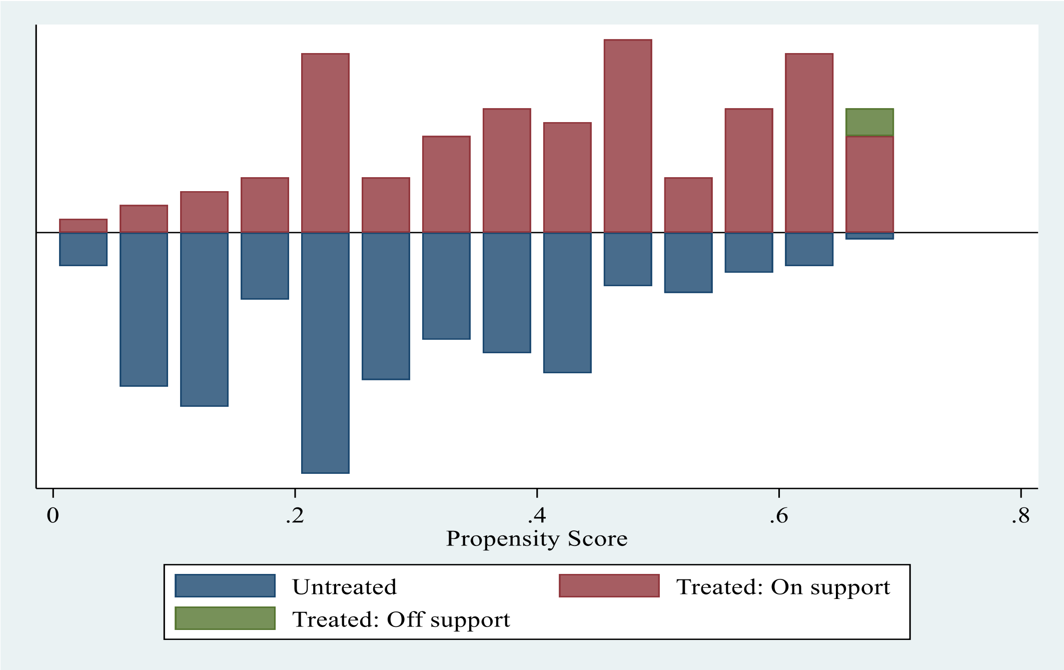

Figure 4-2: Residue retention propensity score distribution
Source: Own calculations. Stata version 15.1 output

4.7.3 Average treatment effect of residue retention adoption

What would have been the situation if residue retention adopters had not adopted? Table 4-16 shows the results of the effect of adopting residue retention on farmers' welfare. Alternative matching algorithms were used. These included the most common matching estimator, the nearest neighbour method (NNM) with replacement (five neighbours). According to Caliendo and Kopeinig (2008), this type of NNM improves the average quality of matching and decreases bias. The other algorithms used were kernel-based and radius calliper matching. The results were consistent for all the matching algorithms: residue retention adoption had a positive and significant effect on the household maize that was produced. The ATT estimates of 31.9% and 34.8% with radius and kernel matching respectively suggested that residue retention adopters were better off in maize produced in the 2018/2019 season than they would have been if they have had not adopted. Residue retention also positively and significantly impacted maize yield at a 10% level of significance in two matching algorithms (i.e., NNM and kernel matching). The positive and significant effect on maize production and yield was consistent with studies evaluating the impact of CSA technologies (Hailu et al., 2014; Kuntashula et al., 2014; Nkhoma et al., 2017). Manda et al. (2016) reported similar findings in Zambia with sustainable agricultural practices having positive effect on farmers welfare. The increase in yield improves food security situation in society and farmers may sell surplus and

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be able to generate income to invest in farming and other household activities. However, the effect on maize yield was less than with manure adoption. In contrast, the results of the effect of residue retention on income were insignificant. These results contradict previous studies which reported significant impact on income (Mendola, 2007; Khonje et al., 2018). The results of an insignificant negative or positive effect on income are consistent with previous studies, as often smallholder farmers practise subsistence farming, and rarely sell their surplus produce (Kuntashula et al., 2014). Furthermore, the lack of bulking facilities hampered group marketing in some communities, affecting farmers' income (TLC, 2019). The standard errors were bootstrapped by 100 replications. The psmatch2 program that was used to estimate the treatment effect assumes that standard errors do not take into account that the propensity scores are estimated (Leuven and Sianesi, 2003).

Table 4-16: Effect of residue retention on welfare outcomes

Matching algorithm	Adopters	Non-adopters	ATT	Bootstrapped standard errors	t-statistic
NNM^{P}	98	161	0.352	0.163	2.16**
$Radius^{P}$	98	206	0.319	0.144	2.22**
$Kernel^{P}$	98	206	0.348	0.152	2.29**
NNM^{Y}	98	161	0.253	0.137	1.84*
$Radius^{Y}$	98	206	0.195	0.135	1.45
$Kernel^{Y}$	98	206	0.248	0.141	1.75*
NNM^{I}	91	143	-0.039	0.171	-0.23
$Radius^{I}$	91	173	0.051	0.163	0.31
$Kernel^{I}$	91	173	0.021	0.171	0.12

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

4.7.4 Matching quality estimation

Before matching, 69.23% (9 out of 13) of the covariates were significantly different between adopters and non-adopters of residue retention (see Table 4-6). After matching, as shown fully in Table 4-17, climate change awareness was no longer significantly different between adopters and non-adopters compared with before matching, with a reduction in the standardised bias of 88.3%. This was the case with all the other covariates regarding systematic differences between the two groups before and after matching. Matched observations should not have remaining observable differences (Rosenbaum and Rubin, 1985).

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Table 4-17: Residue retention matching quality indicators[17]

Variable	Mean		Bias		P > | z |
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.827	0.845	4.6	79.7	0.725
Climate change	0.918	0.903	4.3	88.3	0.713
Aware of GAPs	0.796	0.779	4.0	77.6	0.770
Maize area	1.107	1.042	1.7	70.0	0.769
Extension access	0.827	0.810	3.7	92.1	0.770
Input access	0.643	0.654	2.2	92.9	0.873
Market access	0.939	0.939	0.0	99.9	0.999
Livestock	0.398	0.393	1.0	86.9	0.947
Treadle pump	0.071	0.111	18.3	2.6	0.336
Legumes	0.776	0.778	0.5	98.6	0.967
Seed multiplication	0.500	0.507	1.3	97.0	0.932
Knapsack sprayer	0.194	0.180	3.5	46.1	0.810
Agribusiness	0.857	0.834	6.0	78.2	0.651

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.
%Bias = standardised bias after matching; |**Bias**| = bias reduction percentage

Additionally, the standardised bias percentage for most covariates was below 20%, which validated the efficiency in matching quality between adopters and non-adopters. Moreover, the pseudo R^2 was significantly lower after matching (0.008) than before matching (0.115), as shown in Table 4-18. This was to be expected, as matching eliminates selection bias on observable characteristics. All the variables used in the model were balanced, thus satisfying the balancing property condition. The covariates were well-distributed between adopters and non-adopters, validating the evaluation estimates.

Table 4-18: Residue retention summary of matching quality indicators

Sample	Pseudo R^2	p>chi2	Mean bias	Median bias
Before matching	0.115	0.000	25.2	22.9
Matched	0.008	1.000	3.9	3.5

Source: Own calculations

[17] Tables 4-17 and 4-18 are based on the kernel matching method. See the Appendix, pages 75 to 76, for the quality indicators for other matching algorithms.

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4.7.5 Sensitivity analysis for residue retention models

The study proceeded to run a sensitivity analysis to check how the study results might change if farmers or households that looked comparable (based on observables) were somewhat different in their unobservable characteristics. The Rosenbaum bounds sensitivity analysis was used for its suitability with the continuous outcome variables – i.e., maize production, yield, and income (Caliendo and Kopeinig, 2008). As presented in Table 4-19, the critical gamma, Γ, ranged from 1.25 to 1.55 across matching estimators. If individuals with similar observable characteristics differed by 55% in their likelihood of adopting residue retention, the results would have to be revised. This percentage is fairly high; thus, the results showed the true effect of residue retention on welfare outcomes, as the covariates used were checked to have an association with the adoption and outcome variables. A sensitivity analysis of the effect on crop income was not necessary because of the insignificant impact.

Table 4-19: Residue retention sensitivity analysis

Matching algorithm	Adopters	Non-adopters	ATT	Bootstrapped standard errors	t-stat	Critical level hidden bias (Γ)
NNM^{P}	98	161	0.352	0.163	2.16**	1.40
$Radius^{P}$	98	206	0.319	0.144	2.22**	1.50
$Kernel^{P}$	98	206	0.348	0.152	2.29**	1.55
NNM^{Y}	98	161	0.253	0.137	1.84*	1.25
$Radius^{Y}$	98	206	0.195	0.135	1.45	
$Kernel^{Y}$	98	206	0.248	0.141	1.75*	1.30
NNM^{I}	91	143	-0.039	0.171	-0.23	-
$Radius^{I}$	91	173	0.051	0.163	0.31	-
$Kernel^{I}$	91	173	0.021	0.171	0.12	-

Source: Own calculations. *Significant at 10%, **significant at 5%, and ***significant at 1%.

4.8 Summary of the tested hypotheses

The study tested the different hypotheses listed in Chapter 1 to achieve the related study objectives. The study first tested the null hypothesis, that there is no significant difference in observable characteristics between adopters and non-adopters of manure and residue retention. The study used the t-test to check separately for statistical differences in observable

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characteristics between adopters and non-adopters. In manure adoption, the study found that access to agricultural inputs ($p>0.002$), province ($p>0.003$), whether a farmer cultivated legumes ($p>0.001$), whether a farmer had access to a water source ($p>0.029$), having adopted minimum tillage in the past ($p>0.000$), and whether the farmer received training on running a farm as a business ($p>0.031$) to be statistically different between adopters and non-adopters. In addition, access to agricultural inputs ($p>0.011$), having contact with extension services ($p>0.000$), gender ($p>0.074$), whether the household cultivated legumes ($p>0.002$), whether the HH was involved in seed multiplication ($p>0.000$), whether a farmer used a treadle pump in production ($p>0.097$), whether a farmer had received training on running the farm as a business ($p>0.031$), whether farmers had access to a market ($p>0.076$) and whether a farmer was aware of climate change ($p>0.004$) were all statistically different between adopters and non-adopters in residue retention. Consequently, we could not accept the null hypothesis that there is no statistically significant difference in observable characteristics between adopters and non-adopters in manure and residue retention adoption.

The second hypothesis was tested using the PSM method (specifically, psmatch2, Stata 15 program). The study's results showed that manure had a positive and significant effect on household maize yield, at 5%. Therefore, we could reject the null hypothesis of there being no positive and significant difference in household maize yield between adopters and non-adopters of manure. The third hypothesis was also tested using PSM, and residue retention had a positive and significant effect on farmers' yield at 10%. Thus, we rejected the null hypothesis of there being an insignificant difference in household maize yield in 2018/2019 between adopters and non-adopters of residue retention. Robustness was ensured in testing both hypotheses by using alternative matching algorithms and checking for quality matching. The null hypothesis of no positive significant effect of manure on maize income was accepted, as the results of the study showed that manure did not have a significant effect on income. The last hypothesis tested was that there was a no significant effect of residue retention adoption on maize income between adopters and non-adopters. The results showed no significant effect of residue retention on income; thus, the null hypothesis was accepted.

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4.9 Summary of the results and discussion

Chapter 4 presented the results of the study according to its objectives, and tested the hypotheses. The summary of the descriptive statistics was discussed, as well as farmers' awareness of climate change. The chapter then estimated the impact of manure and residue retention on household maize yield and crop income, and both technologies were found to have a positive and significant effect on the quantity of maize produced and yield. However, these technologies had an insignificant effect on crop income. Manure adoption had the greater impact on welfare indicators than residue retention.

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CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Overview

Chapter 5 presents the main findings of the study by providing a summary of the key results, aligned with the study's objectives and hypotheses. The chapter also presents policy recommendations arising from the results of the study, as well as the limitations encountered during the course of this study.

5.2 Conclusion

Maize is the staple crop for Zambia's population; therefore, an increased household maize yield and income might improve the country's food security situation. To identify ways to improve farmers' welfare, the study used the PSM method to estimate the effect of adopting either manure or residue retention on farmers' welfare indicators – i.e., household maize production, maize yield, and maize income – in 2018/2019. These technologies require less capital and skill, making them ideal for smallholder farmers. The results showed the existence of systematic differences between observable characteristics in the adoption of either manure or residue retention. In manure adoption, there were systematic differences between adopters and non-adopters: whether a farmer received agribusiness training, whether a farmer had access to agricultural inputs, the location of the farmer, whether the farmer planted legumes, and whether the farmer was able to access a water source. In residue retention adoption, the characteristics that were statistically different between adopters and non-adopters were whether the household was headed by a male, whether a farmer was aware of climate change, whether farmers had contact with extension services, and whether farmers had access to agricultural inputs. The study accounted for the potential existence of selection bias in the adoption of both technologies in the analysis by using the PSM method.

Most of the respondents (more than 80%) were aware of climate change and of the impacts associated with it. Most farmers reported having noticed a decline in crop yield in recent years; others noted the prevalence of diseases as a result of climate change. Farmers also indicated that climate change caused fluctuations in the planting season, such that they were no longer certain when the planting period began, as it varied year on year. The study empirically analysed the impact of manure and residue retention on household maize production, yield, and

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income. The results showed that the adoption of manure significantly improved farmers' maize production (by 34% to 37.1%) and yield (by 32% to 39.2%). In contrast, manure had an insignificant but positive effect on crop income (by 21.8% to 22.3%). The adoption of residue retention resulted in a significant and positive improvement in the quantity of maize produced (by 31.9% to 35.2). The effect on maize yield was positive and significant at 10% with NNM and kernel matching (i.e., by 19.5% to 25.3%). Furthermore, residue retention adoption did not improve crop income significantly; using nearest neighbour matching, the effect was found to be negative. The adoption rate of manure and residue retention was low at 13.6% and 32% respectively.

Overall, the findings of this study corroborate previous studies that CSA technologies have a positive effect on farmers' welfare outcomes, especially crop yield. However, there is still a need to improve farmers' income through participation in markets.

5.3 Recommendations and policy implications

Based on the results of the study we can draw two policy implications for the food security situation in Zambia. First, the promotion of CSA technologies – i.e., manure and crop residue retention – in northern Zambia must be intensified, as these technologies positively improve farmers' welfare, especially their maize yield. CSA technologies have mainly been promoted by NGOs and international agencies, and there is a greater need for government of Zambia and other countries to integrate promotion of such technologies in their national budgets. As shown by the results, the technologies improved productivity significantly contributing to the objective for the Zambian NAPA and NPCC policies and programs. However, impact on income for both technologies was insignificant, highlighting the need to encourage and improve farmers' market participation, and to improve farmers' incomes. Income is used by farmers to acquire the agricultural inputs that are needed to improve their agricultural production. Secondly, the analysis showed that extension services encourage farmers to adopt production-improving technologies. Therefore, agricultural institutions should ensure that their strategies give greater attention to the provision of extension services to farmers. Farmers' access to agricultural inputs (seeds and fertiliser) needs to be improved to increase the probability that they will adopt these technologies. The study also found that training farmers to run farms as businesses increases the probability that they will adopt technology. Therefore, farmers should be provided with incentives or encouraged to acquire the necessary business training to run their farms profitably.

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5.4 Limitations of the study

The study faced several limitations, including missing values in the dataset. The dataset used for the study had missing values in some variables, which decreased the sample size. In impact evaluation studies, like most other observational studies, more is better when it comes to the number of observations. Farmers' experience in farming was not captured, the distance to the input source, the costs of production (i.e., input costs), and markets were also not captured during the survey, although they would have been a good addition to the study.

For further research, a similar study could be carried out to account for the unobservable characteristics of farmers by complementing PSM with methods such as the difference-in-difference method or the instrumental variable method (Heckman et al., 1997). Furthermore, future studies could investigate the intensity of technology adoption as a result of intervention programmes.

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APPENDIX A: TABLES

Table A-1 Manure Quality Indicators Nearest Neighbour Matching

Variable	Mean		Bias		Pr(|T| > |t|)
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.520	0.527	1.3	91.0	0.947
Age	0.820	0.909	23.9	48.2	0.195
Agribusiness	0.880	0.892	3.1	91.3	0.852
Extension access	0.740	0.732	1.8	88.9	0.929
Inputs access	0.800	0.808	1.8	96.5	921
Market access	0.900	0.912	4.0	15.5	0.839
Livestock	0.880	0.916	10.5	7.2	0.557
Aware of GAPs	0.800	0.796	1.0	62.7	0.961
Province	0.800	0.764	8.0	83.2	0.667
Legumes	0.880	0.884	1.0	98.2	0.951
Water source	0.260	0.225	8.5	71.9	0.690
Tillage	0.440	0.476	8.1	86.9	0.721

Sample	Pseudo R^2	p>chi2	Mean Bias	Median Bias
Before Matching	0.154	0.000	28.3	23.2
Matched	0.021	0.996	6.1	3.6

Source: Author's analysis *Significant at 10%, ** Significant at 5% and *** Significant at 1%
%Bias = standardised bias after matching |**Bias**| = Bias reduction percentage

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Table A-2 Manure Quality Indicators Radius Matching

Variable	Mean		Bias		Pr(|T| > |t|)
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.520	0.514	1.2	91.2	0.953
Age	0.820	0.844	6.4	60.7	0.754
Agribusiness	0.880	0.860	5.2	85.5	0.768
Extension access	0.740	0.720	4.5	71.7	0.820
Inputs access	0.800	0.758	9.4	81.6	0.615
Market access	0.900	0.901	0.2	15.1	0.992
Livestock	0.880	0.890	3.0	68.9	0.872
Aware of GAPs	0.800	0.819	4.8	79.7	0.809
Province	0.800	0.765	7.9	83.5	0.672
Legumes	0.880	0.837	10.6	80.6	0.541
Water source	0.260	0.226	8.3	72.7	0.698
Tillage	0.440	0.396	9.9	93.9	0.658

Sample	Pseudo R^2	p>chi2	Mean Bias	Median Bias
Before Matching	0.149	0.000	28.3	23.2
Matched	0.010	1.000	5.9	5.8

Source: Author's analysis *Significant at 10%, ** Significant at 5% and *** Significant at 1%
%Bias = standardised bias after matching |**Bias**| = Bias reduction percentage

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Table A-3 Residue Retention Quality Indicators Nearest Neighbour

Variable	Mean		Bias		P > | z |
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.827	0.804	5.5	75.6	0.687
Climate Change	0.918	0.900	5.3	85.7	0.657
Aware of GAPs	0.796	0.731	15.3	14.9	0.285
Maize Area	1.107	1.024	2.2	61.7	0.560
Extension access	0.827	0.829	0.5	99.0	0.970
Market Access	0.939	0.955	5.6	75.3	0.612
Input access	0.643	0.653	2.1	93.4	0.882
Livestock	0.398	0.345	10.9	48.9	0.445
Treadle Pump	0.071	0.129	2.63	39.8	0.184
Legumes	0.776	0.789	2.7	93.1	0.837
Seed Multiplication	0.500	0.488	2.5	94.1	0.865
Knapsack sprayer	0.194	0.153	10.6	63.6	0.453
Agribusiness	0.857	0.818	9.9	64.0	0.464

Sample	Pseudo R^2	p>chi2	Mean Bias	Median Bias
Before Matching	0.115	0.000	25.2	22.9
Matched	0.028	1.000	7.7	5.5

Source: Author's analysis *Significant at 10%, ** Significant at 5% and *** Significant at 1%
%Bias = standardised bias after matching |**Bias**| = Bias reduction percentage

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Table A-4 Residue Retention Quality Indicators Radius Matching

Variable	Mean		Bias		P > | z |
	Adopters	Non-adopters	%Bias	|Bias|	
Gender	0.827	0.825	0.5	97.9	0.972
Climate Change	0.918	0.899	5.6	85.0	0.642
Aware of GAPs	0.796	0.777	4.3	75.9	0.754
Maize Area	1.107	1.033	2.0	66.1	0.731
Extension access	0.827	0.800	6.2	86.8	0.630
Market access	0.939	0.936	0.9	96.0	0.939
Inputs access	0.643	0.603	8.1	74.2	0.566
Livestock	0.398	0.372	5.3	27.5	0.712
Treadle Pump	0.071	0.843	5.9	68.6	0.739
Legumes	0.776	0.764	2.6	93.3	0.843
Seed Multiplication	0.500	0.502	0.4	99.0	0.977
Knapsack sprayer	0.194	0.171	5.9	9.9	0.686
Agribusiness	0.857	0.845	3.0	89.0	0.817

Sample	Pseudo R^2	p>chi2	Mean Bias	Median Bias
Before Matching	0.115	0.000	25.2	22.9
Matched	0.006	1.000	3.9	4.3

Source: Author's analysis *Significant at 10%, ** Significant at 5% and *** Significant at 1%
%Bias = standardised bias after matching |**Bias**| = Bias reduction percentage

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APPENDIX B: QUESTIONNAIRE

Total LandCare (TLC) S3P EndLineSurvey Household Questionnaire

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Questionnaire Number: …………………………..

Enumerator Name: ………………………………………………………………………..

Supervisor Name: …………………………………………………………………………

Date of Interview: ………………………………………………

Start Time:………………………………………….

Please indicate your voluntary consent by participating in this TLC S3P end line survey and note everything you say will be treatedas confidential. If have questions about this survey, you may contact EliSil Environmental Consulting, Plot 1259 Chendauka Road, Chelstone, Lusaka elisilconsulting@yahoo.com, 097 7 748335

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Note: *For the data like* ***length/distance, area, weight, price, etc.*** *please take answers in local units then convert them into international units as, meters, hectares, and kg etc.*

Household Identification Details	**Coding**
1.What is your status in the household?	*1=head of household, 2= spouse, 3=child, 4= worker,5= mother,5= father, 6=other relative*
2.Name of Household Head/Respondent	
3.Sex of household head	*1= Female 2=Male*
4.District	*1=Kasama 2=Mungwi3=Luwingu4=Mbala (Senga)5=Kawambwa6=Mansa 7=Samfya (Chifunabuli)*
6.Agricultural Block	
7.Camp	
8.Village	

Basic Household Information	**Coding**
9.Educational Level of Head of HH	*1. Never been to School* *2. Primary* *3. Secondary* *4. Tertiary*
10.Age of the head of Household (years)	………………. Years
11.Marital Status of Household head	*1. Married* *2. Widow* *3. Widower* *4. Bachelor* *5. Spinster* *6. Divorced*

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Household Composition								
	Under 5		**Children (617)**		**Adults (1859)**		**Elderly (60+)**	
	M	**F**	**M**	**F**	**M**	**F**	**M**	**F**
12.No. of people living in homestead:								
13.No. of chronically ill								

"living" is defined as someone who stays there at least for three months in a year) chronically ill is defined as, *sick and unable to work for a total of 3 months over the last 12 months*

13. Are you aware of Smallholder Productivity Promotion Programme (S3P)? 1) Yes 2) No

14. Are you a beneficiary of the S3P project? 1) Yes 2) No

Adoption of Good Agricultural Practices for the production of priority crops among smallholder farmers in the targeted district sites.

15.Which of the following crops did you grow in the following seasons (2016/2017, 2017/2018 and 2018/2019)				
	2016/2017 Season			
	Crop	***Varieties*** *(codes below)*	***Source of seed*** *(codes below)*	***Area Planted (Ha)***
	Cassava			
	Beans			
	G/ Nuts			
	Rice			
	Maize			

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Codes for Varieties			***Codes for Seed source***
G/Nuts *1.MGV 4* *2.MGV 5* *3.Chishango* *4.Chalimbana* *5.Makuru red* *99.Other (specify)*	***Rice*** *1.Kilombero* *2.Nerica 1,2,3,4* *3.Super* *4.Zianxhou* *5.Other (specify)*	***Beans*** *1.Kabulangeti* *2.Liyambai* *3.Mbereshi* *4.Solwezi* *5.Lusaka* *6.Lukupa* *7.Luangeni* *8.Mixed* *99.Others (specify)*	*1.TLC* *2.GRZ* *3.Agro-dealers* *4.Local Seed Multipliers* *99.Other (specify)*

16.Which of the following crops did you grow in the following seasons (2016/2017, 2017/2018 and 2018/2019)

	2017/2018 Season			
	Crop	***Varieties*** *(codes below)*	***Source of seed*** *(codes below)*	***Area Planted (Ha)***
	Cassava			
	Beans			
	G/ Nuts			
	Rice			
	Maize			

Codes for Varieties			***Codes for Seed source***
G/Nuts *6.MGV 4* *7.MGV 5* *8.Chishango* *9.Chalimbana* *10.Makuru red* *99.Other (specify)*	***Rice*** *6.Kilombero* *7.Nerica 1,2,3,4* *8.Super* *9.Zianxhou* *10.Other (specify)*	***Beans*** *9.Kabulangeti* *10.Liyambai* *11.Mbereshi* *12.Solwezi* *13.Lusaka* *14.Lukupa* *15.Luangeni* *16.Mixed* *99.Others (specify)*	*5.TLC* *6.GRZ* *7.Agro-dealers* *8.Local Seed Multipliers* *99.Other (specify)*

17.Which of the following crops did you grow in the following seasons (2016/2017, 2017/2018 and 2018/2019)

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	2018/2019 Season			
	Crop	***Varieties*** *(codes below)*	***Source of seed*** *(codes below)*	***Area Planted (Ha)***
	Cassava			
	Beans			
	G/ Nuts			
	Rice			
	Maize			

Codes for Varieties			***Codes for Seed source***
G/Nuts	***Rice***	***Beans***	*9.TLC*
11.MGV 4 *12.MGV 5* *13.Chishango* *14.Chalimbana* *15.Makuru red* *99.Other (specify)*	*11.Kilombero* *12.Nerica 1,2,3,4* *13.Super* *14.Zianxhou* *15.Other (specify)*	*17.Kabulangeti* *18.Liyambai* *19.Mbereshi* *20.Solwezi* *21.Lusaka* *22.Lukupa* *23.Luangeni* *24.Mixed* *99.Others (specify)*	*10.GRZ* *11.Agro-dealers 12.Local Seed Multipliers* *99.Other (specify)*

18. Which of the below listed sustainable soil management practices did you use and area of use?

Practice	**Used in 2016/17**	**Area**	**Used in 2017/18**	**Area**	**Used in 2018/2019**	**Area**
	1 = Yes 2=No	**Ha**	**1 = Yes 2=No**	**Ha**	**1 = Yes 2=No**	**Ha**
Crop rotation						
Agroforestry						
Manure						
Liming						
other (specify)						

19. Did you have a Good Agricultural Practices (GAP) demo plot in 2018/2019 season?1) Yes 2) No

20. If yes, which month was it established? ______________________________

21. Did you receive any training on Good Agricultural Practices (GAP)? 1) Yes
2) No

If Yes, which type of training(s) did you receive?

1) Crop residue management 2) Minimum tillage 3) manure use
4) Intercropping 5) Planting 6) Weeding 7) Fertilizer application
8) Liming 9) Pesticide use and handling 10) Other (specify)

……………………

22.	Which of these GAP practices have you adopted/are you practicing in your own field? And for how long have you been practicing them?	***GAP Practice***	***Years in practice***
		1. Crop residue management	
		2. Minimum tillage	
		3. Crop rotation	
		4. Inter-cropping	
		5. manure use	
		6. Planting methods	
		7. Fertilizer application	
		8. Herbicide use	
		9. Weeding	

23. Were any members of the household trained in any seed multiplication techniques?

a. Yes 2) No

22. If yes, for which crop(s) and when was the training done?

....

....

24. Is your household involved in seed multiplication? 1) Yes 2) No

25. If yes, when did the household get involved in seed multiplication (month and year)? ………….

26. Which crop(s) are you specifically multiplying the seed

a. Cassava (2) Beans (3) Groundnuts (4) Rice (5) Maize (6) Other (specify)…………………

27. Do you use a treadle pump for seed multiplication? 1) Yes 2) No

28. Give reason for your answer above?

………………………………………………………………………………………….

…………………………………………………………………………………………

……

29. Did you have access to extension services in 2018/2019 season? 1) Yes 2) No

30. If yes, what was the source of extension services? 1) GRZ 2) Private 3) NGOs 4) Other (specify)

…………………………………………….

31. Wereyou satisfied with the extension services provided? 1) Yes 2) No

32. Did you have access to extension services in 2018/2019season? 1) Yes 2) No

33. If yes, what was the source of extension services? 1) GRZ 2) Private 3) NGOs 4) Other (specify)

…………………………………………….

Improved access and linkages to markets

34. Do you belong to an agricultural group? 1) Yes 2) No

35. What is the type of group?

1) Cooperative 2) Farmer club 3) Association 4) Other

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(specify)..………

36. If yes, what is the main purpose of the group?

…………………………………………………

……………………………………………………………………………………………….

1= Easy access to credit, 2= Aggregation of produce, 3= Collective transportation of commodities, 4= Group selling of produce, 5= Easy access to inputs, 6= Other, (specify)____

37. When did you join the group?

....

38. Have you ever been trained in running farming as a business? 1) Yes 2) No

39. If yes, has this training made you start running farming as a business? 1) Yes 2) No

40. If yes, in what ways?

………………………………………………………………………...

………………………………………………………………………………………………….

41. Do have access to market information? 1) Yes 2) No

42. If yes, since when (month and year)

…………………………………………………………….

43. What mode do you use to access agricultural information? *1) Radio (2) TV (3) Newsletters (4) Extension staff (5) Mobile phones (6) Seed dealers (private seed company, agro-dealers) (7) Fellow farmer (8) Project/ Institution (name………………………) (9) Other (specify)…………………….....*

44. What challenges do you have in selling your agricultural produce?

……………………………………………………………………………………………….

…………………………………………………………………………………………….

45. Where do you often sell your agricultural produce?

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1= Individual consumers, 2= traders/bulking agents, 3= processing plant, 4= Urban markets, 5=Local markets, 6= Zambian Breweries, 7= FRA, 8 = Government institution (school, hospital, prisons), 7=Other (specify)____

46. Are you able to sell whatever quantity of products you want at this market? 1) Yes 2) No

47. Fill in the following Table about your 2016/17marketing of agricultural produce

Crop/products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Groundnuts					
Beans					
Rice					
Maize					
Other (specify)					
Other (specify)					

***Conversion data

48. Have you retained food (not sold) in 2018/2019? 1) Yes 2) No

49. Is thefood retained (not sold) in 2018/2019 season able to last the whole year? a) Yes b) No

50. If No, how many months on average do you stay without the retained food?

....

51. Fill in the following Table about your 2017/18 marketing of agricultural produce

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Crop/products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Groundnuts					
Beans					
Rice					
Maize					
Other (specify)					
Other (specify)					

***Conversion data

52. Fill in the following Table about your 2018/2019marketing of agricultural produce

Crop/products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Groundnuts					
Beans					
Rice					
Maize					
Other (specify)					
Other (specify)					

53. Did food retained (not sold) in 2017/18 last the whole year? 1) Yes 2) No

54. If no, how many months on average did you stay without this retained food?

....

55. Fill the below Tables on cassava and its products during the 2016/17 season

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Cassava products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Flour					
Chips					
Whole Dried Roots					
Leaves					
Fresh Roots					

***Conversion data

56. Fill the below Tables on cassava and its products during the 2018/2019 season

Cassava products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Flour					
Chips					
Whole Dried Roots					
Leaves					
Fresh Roots					

***Conversion data

57. Fill the below Tables on cassava and its products during the 2017/18 season

Cassava products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Flour					
Chips					

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Whole Dried Roots					
Leaves					
Fresh Roots					

58. Fill the below Tables on cassava and its products 2016/17

Cassava products	Quantity produced (Kg)	Quantity sold per Kg	Place sold/Name of buyer	Price per Kg	Were you happy with price?
Flour					
Chips					
Whole Dried Roots					
Leaves					
Fresh Roots					

***Conversion data

59. Did you access your inputs through the agro dealers in 2018/2019? 1) Yes 2) No

60. If yes, which inputs and from which agro-dealer?

…………………………………………..

………………………………………………………………………………………………

No.	Type of Inputs Accessed	Name of Agro-dealer
1		
2		
3		

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4		
5		

61. Did you have access to financial services for your agricultural activities?

1) Yes 2) No

2016/17			**2017/18**			**2018/2019**		
Access to Financial Services		**Who linked you?**	**Access to Financial Services**	**Who linked you?**		**Access to Financial Services**	**Who linked you?**	
Yes	**No**		**Yes**	**No**		**Yes**	**No**	

Resilience of smallholder farmers to the impact of climaticvariations/shocks

62. Kindly answer the following climate change related questions

Are you aware of climate change issues and their consequences? ***1= Yes*** ***2= No***	When did you become aware?	Who shared climate change information with you?	What MAIN effect has CC had on your crop/livestock activities**?** ***Use codes below***	What have you done to deal with the negative consequences of CC?	When did you start using the practice mentioned in 13? *Enter* ***Year***	Who influenced you to take up the practice? *1= Relative* *2=NGO/Church* *3= Extension worker 4= Others (specify)*	Is the measure working for you? *1= Yes* *2= No*
63.	65.	66.	67.	68.	69.	70.	71.

Codes(22) 1= Decline in yields2= Decline in livestock production3= Difficult to time seasons

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4= Increased weeds 5= Increased diseases 6= Decrease in soil quality 7= decrease in water availability 8= Scarcity of pastures 9= Increase in yields 10= Others(Specify)

72. Do you access messages/ information about risks of climate change in 2018/2019?	*1. Yes* *2. No*		
73. What messages do you access?	*1. Visible effects of climate change (floods, droughts, dry spells, drying of rivers etc.)* *2. Climate change mitigation measures (planting trees, natural regeneration etc.)* *3. Climate smart technologies (conservation agriculture, Irrigation, cook stoves, natural tree regeneration, etc.)* *4. Drought tolerant crop varieties* *5. Weather forecasts and rainfall projections* *6. Others* *(specify)………………………………………………….*		
74. Where did you access these messages/ information from?	*1. Radios 6. Other NGOs* *2. TVs 7. Others source*		
	3. TLC Extension Workers specify…………………….. *4. GRZ Extension Workers* *5. Mobile phones*		
75. Which of the above mentioned media channels do you prefer to get messages from?	*1. Radios* *2. TVs* *3. TLC Extension Workers* *4. Mobile phones* *GRZ Extension Workers*	*5. Other NGOs* *6. Others source* *specify……………………………*	
76. Do you get assisted with the messages you receive?	*1. Yes* *2. No*		
77. How do the messages you receive assist you?	*1. To make informed decisions in adopting Climate smart technologies* *2. They assist in planning for the farming season* *3. Assist in understanding the weather and rainfall patterns* *4. Help to learn adaptation and mitigation measures of climate change* *6. Others specify…………………………………………….*		

79. Which of the below conservation agriculture activities did you practice?

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Practice	Area in ha (2016/17)	Area in ha (2017/18)	Area in ha (2018/2019)
Minimum tillage, crop rotation and residual retention			
Minimum tillage and crop rotation			
Minimum tillage and residual retention			
Crop rotation and residual retention			
Minimum tillage			
Crop rotation			
Residual retention			

Adoption of processing, preparation, cooking and consumption of nutritious foods

80. Where you trained in the following activities related to the different crops in the table below? Indicate **Yes** or **No**

Food product	**Improved processing**	**Improved preparation**	**Improved cooking**	**Consumption of product**
1, Cassava				
2. Beans				
3. Groundnuts				
5.Rice				
6.Maize				
7.Other (specify) ……………………				
8.Other (specify) ……………………				

81. Do you practice what you were trained in the following activities related to the different crops in the table below? Indicate **Yes** or **No**

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Food product	**Improved processing**	**Improved preparation**	**Improved cooking**	**Consumption of product**
1, Cassava				
2. Beans				
3. Groundnuts				
4.Rice				
5.Maize				
6.Other (specify) ……………………..				
7.Other (specify) ……………………				

82. Household consumption of various food stuff Table

Food item names	**(a)In a typical week between October 2017and October 2018, how often did the household members consume the following foods?**	**On average how much did the household consume per week?**	**(b)In a typical week between October 2018and October 2019, how often have the household members consumed the following foods?**	**On average how much did the household consume per week?**

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1.	Cassava				
2.	Beans				
3.	Groundnuts				
4.	Rice				
5.	Maize				
	6.Orange maize				
	7.Orange fleshed potato				
	8.Soy beans				
	9.Vegetables				
	10.Other (specify) …………………..				
11. (specify)	Other …………………..				

83. What cooking structures do you use for preparing your meals? 1) Three stones (2) Blazier (3) Others

(specify)…………………

84. Are you aware about the TLC rocket stove? 1) Yes 2) No

85. If yes in 56, does the household own and use a TLC rocket stove? 1) Yes 2) No

86. How often do you use a TLC rocket stove?
1) Once a day 2) Twice a day 3) Thrice a day 4) More three times a day 5) Every time when cooking 6) Don't use it at all

87. If, don't use at all what are the reasons?
……………………………………………………………………………………

88. If yes, what are the advantages of the rocket stove? 1) Use less fuel wood (2) Produces less smoke (3)

Saves on time (4) Other (specify) ……………………………………………………..

Pass-on scheme

LIVESTOCK

89.	Are you participating in livestock pass-on?	*1.Yes* *2.No*	

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90.	Do you belong to a pass-on group?	*1. Yes* *2. No*	
91.	Why don't you belong to a livestock group?	*1. Never existed* *2. Group failed* *6. Other (specify)…………*	
92.	How was the group formed?	*1. Through a community meeting* *2. By the village headman* *3. By TLC Extension worker* *4. By GRZ Extension worker* *99. Other (specify)……………………………………*	
93.	Who is in charge of the pass-on process?	*1. CAC* *2. FC* *3. CEO* *4. Headman/Traditional leadership* *5. Livestock group committee* *99. Other (specify)……………………………………..*	
94.	Do you think it is important to have a group for the pass-on process?	*1. Yes* *2. No*	***State the reason***
95.	Why do you think it is important, or is not important? **EXPLAIN**		
96.	Is each member of the group making any monetary contribution to the group?	*1. Yes* *2. No*	
97.	What is the money used for? **EXPLAIN**		
98.	How was your household selected as a beneficiary?	*1. CAC* *2. FC* *3. CEO* *4. Headman/Traditional leadership* *5. Fellow farmers* *6. Other (specify)…………………………………………..*	

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99.	Are you a primary or secondary beneficiary?	*1. Primary beneficiary* *2. Secondary beneficiary* *8. Don't know*	
100.	What type of livestock did the household receive from the project?	*1. Chickens* *2. Goats*	
	CHICKEN FARMERS ONLY		
101.	How many chickens did you receive?	*No. of hens……………* *No. cocks……………..*	
102.	What is the current number of livestock owned?	*No. of Chickens…………………*	
103.	Did any of the chickens die after receiving them before they multiplied?	*1. Yes* *2. No*	
104.	How many chickens died?	*No. of Chickens…………………*	
105.	Have any of the chickens died after they started multiplying?	*1. Yes* *2. No*	
106.	How many chickens have died	*No. of Chickens…………………*	
107.	Have you managed to pass on the chickens you received?	*1. Yes* *2. No*	
108.	How many chickens did you pass on?	*No. of Hens…………………* *No. of Cock……………………*	
109.	How often do you consume your chickens or chicken products?		

110.	***Livestock / Product***	***Consumption Frequency In A Week (number)***	***Consumption Frequency In A Month (number)***	***Consumption Frequency In A Year (number)***	
	Chickens				
	Eggs				

111.	How often do you sell your chickens or chicken products?						
	Livestock / Product	***Sales Per Week***		***Sales Per Month***		***Sales Per Year***	
		Quantit	***Amount ZMK***	***Quantit***	***Amount***	***Quantit***	***Amount***

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		y		***y***	***ZMK***	***y***	***ZMK***
	Chickens						
	Eggs						
	GOAT FARMERS ONLY						
112.	How many Goats did you receive?			*No. of goats…………………*			
113.	What is the current number of livestock owned?			*No. of Goats…………………*			
114.	Did any of the goats die after receiving them before they multiplied?			*1. Yes* *1. No*			
115.	Have any of the goats died after they started multiplying?			*1. Yes* *2. No*			
116.	Have you managed to pass on the goats you received?			*1. Yes* *2. No*			
117.	How many goats did you pass on?			*No. of goats……………………………..*			
118.	How often do you consume your goats or goat products?						
	Livestock/ Product	***Consumption Frequency In A Week***		***Consumption Frequency In A Month***		***Consumption Frequency In A Year***	
	Goats						
	Goat milk						
119.	How often do you sell your goats or goat products?						
	Livestock /Product	***Sales Per Week***		***Sales Per Month***		***Sales Per Year***	
		Quantity	***Amount ZMK***	***Quantity***	***Amount ZMK***	***Quantity***	***Amount ZMK***
	Goats						

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	Goat milk							
120.	Were you trained in livestock management before you received the livestock?	*1. Yes* *2. No*						
121.	Who trained you	*1. TLC Extension workers* *2. GRZ Extension workers* *99. Other (specify)……………….*						
122.	What livestock management practices were you trained in?	*1. Housing* *2. Feeding* *3. Breeding* *4. Pest and disease control*						
123.	Does the household have a proper housing structure for the livestock received? **OBSERVE TO CONFIRM**	*1. Yes* *2. No*						
124.	Why did the household not build a proper housing structure for the livestock received?	*1. No construction materials* *2. Not trained in shelter construction* *3. Fear of theft and predators, livestock are kept in the same house that the farmer puts* *99. Other (specify)…………………………….*						
125.	What challenges, if any has the household experienced in managing the livestock received?	*1. Disease and pests out breaks* *2. find feed for the livestock* *3. straying into other crop fields* *4. Theft* *5. Attacks by wild animals* *99. Other (specify)……………………..*						

126. Tick the following assets owned by the household and indicate the number owned now

Does household possess any of the following physical assets? (tick all that apply)	**Quantity Owned**
1. ☐ Local Cattle	
2. ☐ Improved Cattle	

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3.	☐	Local Oxen	
4.	☐	Improved Oxen	
5.	☐	Local Goats	
6.	☐	Improved goats	
7.	☐	Local Chicken	
8.	☐	Improved Chicken	
9.	☐	Local Pigs	
10.	☐	Improved Pigs	
11.	☐	Donkeys	
12.	☐	Ox carts	
13.	☐	Ox drawn ploughs	
14.	☐	Ox drawn harrows	
15.	☐	Cultivators	
16.	☐	Ridging plough	
17.	☐	Knapsack sprayers	
18.	☐	Bicycles	
19.	☐	Radios	
20.	☐	TV set	
21.	☐	Iron roofed house	
22.	☐	Grass thatched house	
23.	☐	Open water source	
24.	☐	Water well	
25.	☐	Borehole	
26.	☐	Ordinary	
27.	☐	VIP	

127. Fill the household source of income for the two seasons as indicated in the Table

Does household receive income from the following livelihood strategies? (tick all that apply)	**Approximate how much per year (ZK)** Oct 2017–	**Approximate how much per year (ZK)** Oct 2018 – Sept 2019

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Sept 2018		
1. ☐ Petty trading (Specify)		
2. ☐ Gardening activities/Off season farming		
3. ☐ Chicken rearing		
4. ☐ Goat rearing		
5. ☐ Cattle rearing		
6. ☐ Remittances		
7. ☐ Sale of rain fed food crops (specify crops)		
8. ☐ Sale of rain fed cash crops (specify crops)		
9. ☐ Piece work		
10. ☐ Sale of charcoal		
11. ☐ Other (Specify)		

Thank you so much for your participation!

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