PRODUCTIVITY AND WELFARE EFFECTS OF CLIMATE-SMART ADAPTATION PRACTICES OF CROP FARMING HOUSEHOLDS IN THE SAVANNA REGION OF NIGERIA

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MARCH, 2021

CERTIFICATION

This is to certify that this thesis has been read and approved as meeting the requirement of the Department of Agricultural Economics and Farm Management, University of Ilorin, Ilorin, Nigeria, for the award of Doctor of Philosophy (Ph.D.) degree in Agricultural Economics.

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DEDICATION

This thesis is dedicated to my beloved parents, Mr. and Mrs. Bartholomew Edeh, who believed and supported my life dreams.

DECLARATION

I, **EDEH,HYACINTH ONUORAH**, a Ph.D. student in the Department of Agricultural Economics and Farm Management, University of Ilorin, Ilorin hereby declare that this thesis entitled "Productivity and Welfare Effects of Climate-Smart Adaptation Practices of Crop Farming Households in the Savanna Region of Nigeria" submitted by me is based on my actual and original work. Any materials obtained from other sources or work done by any other persons or institutions have been duly acknowledged. In addition, the research has been approved by the University of Ilorin Ethical Review Committee.

EDEH,HYACINTH ONUORAH (15/68AJ002)	DATE

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ABSTRACT

Climate change distorts agricultural production and impacts negatively on the welfare of farming households in Nigeria. The climate-smart adaptation (CSA) strategies have the potential to mitigate the effects of climate change while preserving the natural resource-base. However, there is limited empirical knowledge on the impacts of usage of such strategies on the productivity and welfare of farmers. The study assessed the productivity and welfare effects of CSA practices on crop farming households in the savanna region of Nigeria. Theobjectives of the study were to: (i) identify crop specific CSA strategies; (ii) examine the factors that influence the choice of CSA strategies; (iii) assess the determinants of the use intensity of CSA; (iv) determine the productivity and welfare effects of the usage of CSA strategies; and (v) identify the constraints to the use of CSA strategies.

A structured questionnaire was used to collect data for the study through a three-stage sampling technique involving the selection of 391 households from 33 Enumeration Areas (EAs) constituting about 6% of the rural-based EAs in Benue and Niger States. Descriptive statistics, tetrachoric correlation, multivariate probit regression, Ordinary Least Square (OLS) regression, heterogenous treatment effects (HTE), conditional recursive mixed process (CMP) for sequential joint estimations, and Garrett ranking score were used to analyse the data at 5% level of significance.

The findings of the study were that:

i. crop rotation and intercropping with legumes, green manure, and farmyard manure were the common CSA strategies used in the production of cereals, pulses as well as roots and tubers. In addition, minimum tillage and improved varieties of seeds were used for cereals;
ii. tetrachoric correlation coefficients showed that 80% of the pairs of CSA strategies have between 17 and 74% relationships in the simultaneity of usage;
iii. farmer’s age and education, group membership, credit constraint, risk perception, risk experience and household perception of effectiveness of strategiesare factors that influence the choice of the CSA strategies;
iv. usage of the CSA strategies reduced with age of the farmers, but increased with farm size, soil fertility perception, market distance, number of livestock owned, and years of continuous use of farm;
v. usage of fertilizer deep placement and cover cropping increased the yields of cerealsby 65% and 31% respectively, while improved crop varieties as well as crop rotation with legumes increased yield of pulses by 43%and 63% respectively. Mulching increased yield of roots and tubers by 43%;
vi. Based on CMP estimate, a percentage increase in yields of cereals, pulses, and roots and tubers improved household welfare by 340%, 1.15% and 0.43% respectively; and
vii. the use of CSA strategies is constrained by the initial establishment and labour costs, farm tenure security status,and market distance to purchase of relevant CSA inputs.

The study concluded that CSA strategies had positive impacts on crop productivity and household welfare. The study recommended the use of farmer groups as platform for promotion of the use of CSA and provision of on-lending facilities for farmers.

CHAPTER ONE

INTRODUCTION

1.1.Background to the Study

Poverty and climate change are two daunting challenges facing households in developing countries. While poverty, a manifestation of human deprivation, is attributable to several factors including social, economic, political, individual, community and historical factors (Leichenko &Silva, 2014), it is often exacerbated by increased climate variability and change.Like many other developing countries, Nigeria is contending with high levels of poverty alongside increasing negative effects of climate variability and change. Reports on Nigeria by the United Nations Development Programme (UNDP-MDGs, 2013), the World Bank (2014) and the British risk consultancy, Maplecroft Report (2013; 2015), have shown that the country is faced by these twin challenges of poverty and climate change. The World Bank (2014) and the UNDP-MDGs Report (2013) show that the per capita poverty rate in Nigeria remained staggeringly high at about 62% in 2009/2010, just about 2% lower than the 2003/2004 figure. Similarly, Corral Rodas, Molini, andOseni (2019) indicates that around 60% of the Nigeria population live below the established poverty line of $2 per capita per day as at 2012/2013. More recently, Nigeria has the highestnumber of extreme, growing by six people every minute in 2018 (Kharas, Hamel & Hofer, 2018). Also, Ojewale andAppiah-Nyamekye (2018) argue that about half of Nigeria population live in poverty. The Oxford Poverty & Human Development Initiative and UNDP Report (2019)indicates that multidimensional poverty incidence and intensity in Nigeria is 51.4% and 56.6% respectively. These figures are indications that poverty is still a serious developmental problem in Nigeria. It makes households highly vulnerable to shocks, particularly those associated with changes in climate variables (Winsemius, Jongman, Veldkamp, Hallegatte, Bangalore & Ward, 2015).

With respect to climate change, Nigeria ranks sixth among 193 most vulnerable countries on the 2013 climate change effect index report (Maplecroft Report, 2013). This situation has worsened in recent times as Nigeria ranks fourth out of 32 extreme risk countries in the Maplecroft's Climate Change Vulnerability Index Report (2015). The vulnerability of Nigeria to shocks, especially to those that are related to climate change is due to the country's tropical geographical location and long coastline, the dependence of its economy on agriculture, and households' poor capacity to adapt to climate change

(Tambo & Abdoulaye, 2012). Maplecroft Report (2015) indicates that countries vulnerable to climate change depend heavily on agriculture; and according to the World Bank General Household Survey Report (2016), “agriculture is the most prevalent income-generating activity in many Nigerian households”. This, therefore, makes rural livelihoods highly vulnerable to climate change. Changing weather patterns in the forms of changesin temperature and rainfall patterns, and variations in frequency and intensity of climatic events such as floods and droughts are already impacting poverty, migration, social stability and food production, especially cereal production including rice, wheat, sorghum, and maize (McCarthy &Brubaker, 2014; Maplecroft Report, 2015; Khatri-Chhetri, Aggarwal, Joshi, & Vyas, 2017).

According to Khatri-Chhetri *et al.*(2017), climate change distorts agricultural production through changes in the suitability of crops cultivated and agricultural biodiversity. It also leads to a decrease in input use efficiency, and increased incidenceof pests and diseases. Further to these changes in agro-ecological conditions, climate change impacts on economics of food production by influencing income generation and distribution, and how agricultural produce are demanded (Schmidhuber &Tubiello, 2007). These impacts are however higher among the rural households, threatening their farm productivity and welfare. The poor are mostly located in the rural areas with less developed markets (Kapoor &Ojha, 2006) and are typically dependent on climate-sensitive, rainfed agriculture as a major source of livelihood, hence, they are more exposedto climate change-related shocks (Abdelhak, Sulaiman & Mohd, 2012; Below, Mutabazi, Kirschke, Franke, Sieber, Siebert, & Tscherning, 2012; Tesso, Emana & Ketema, 2012).

Coping with the outcomesof climate change requires farmers to adopt strategies that use inputs efficiently, preserve the natural resource base, sustainably increase farm productivity while ameliorating the effects of climate change through resilience to risks, shocks and climate variability; and consequently, improving household welfare status. Agricultural production systems that integrate such strategies are known as climate-smart agriculture (CSA). Characteristically, climate-smart agriculture is built on three pillars: sustainable increase in farm productivity, enhanced resilience of agricultural and food security ecosystems to climate change at various levels, and reduced greenhouse gas emissions (Behnassi, Boussaid, & Gopichandran, 2014; Khatri-Chhetri *et al.*, 2017; Rioux, Gomez San Juan, Neely, Seeberg-Elverfeldt, Karttunen, Rosenstock, Kirui, Massoro, Mpanda, Kimaro, Masoud, Mutoko, Mutabazi, Kuehne, Poultouchidou, Avagyan, Tapio-Bistrom, & Bernoux,, 2016; Shirsath, Aggarwal, Thornton, & Dunnett, 2017). Strategies capable of achieving these pillars either wholly or partly are therefore, known as; climate-smart agriculture strategies.

And as Douxchamps, Van Wijk,Silvestri, Moussa, Quiros, Ndour, ...& Ouedraogo(2016) noted, most of the climate-smart agriculture strategies have been in existence and would continue to evolve from traditional/indigenous practices. The literature of (Magombo, Kanthiti, Phiri, Kachulu, & Kabuli, 2012;Yegbemey, Yabi, Tovignan, Gantoli, & Kokoye, 2013; Barnard, Manyire, Tambi &Bangali, 2015; Khatri-Chhetri *et al.*, 2017) have identified various water, nutrient, energy, carbon, and knowledge-based climate-smart adaptation strategies usedby farmers to respond to climate change variability. These include the use of new and improved crop varieties, irrigation, crop diversification, changeof planting dates for crops, livelihood diversification (especially from farm to non-farm activities), water and soil conservation techniques, tree planting, mulching, composting, intercropping, improved animal feeding, and climate-risk insurance among others.

Adopting theforegoing identified strategies means that; households will benefit from increased farm productivity and cash income, and consequently, household welfare status will improve. However, the extent to which these benefits will accrue to the household depends on various conditions, including the types of climate-smart technologies adopted and the intensity of adoption. It is therefore argued that,theuseof CSA strategies will increase farm productivity and welfare of arable crop farmers.It will also depend on crop types and the intensity of the use of these strategies, with a higher intensity able to drive higher farm productivity and household welfare.

1.2.Statement of theProblem

Climate change poses a serious threat to agricultural development, household welfare, food and nutrition security outcomes and poverty reduction in Nigeria, where around 70% of its active population are engagedin agriculture for their livelihood. However, several policies to address the impacts of climate change in Nigeriacontinue to emerge. In 2013, for instance, the Nigerian government developed its National Agricultural Resilience Framework (NARF) document. This was towards the implementation of climate-smart agriculture that is based on “innovative agricultural production strategies and risk management mechanisms” and bothare aimed at promoting resilience in the agriculture sector. Similarly, the 2016 Nigeria agriculture policy roadmap (the Agriculture Promotion Policy) shows a renewed thrust “towards the promotion of climate-smart agriculture in Nigeria”. This is also aimed at boosting farmers’ productivity and increased agricultural earnings.

On the research front, there are several empirical evidences of the impact of climate change on agriculture at various levels (Wood, Jina, Jain, Kristjanson, & DeFries,2014). Also, research evidences (Oparinde & Hodge, 2011; Nzeadibe, Egbule, Chukwuone, Agwu, & Agu, 2012; Ofuoku & Agbamu, 2012; Tambo &Abdoulaye, 2012; Arimi, 2014) show that rural households adopt several strategies to cushion the effects of climate change and other shocks. In their case study on “State of knowledge on climate-smart agriculture in Africa; Nigeria, Cameroon and Democratic Republic of Congo”, Nwajiuba, Emmanuel & Bangali (2015) identified and recommended for scale-up of several agroecology-specific but crop-generic agricultural practices in Nigeria that qualify as climate-smart adaptation practices.

Despite the aforementioned policy and research outputs,knowledgebase is still thin on climate-smart adaptation strategies on several fronts. Of interest are those related to crop specific, intensity of usage, and effectiveness of these strategies in relation to farm productivity and the type of climate risks farmers face, in Nigeria. There seems to be limited information about the types of climate-smart adaptation strategies that smallholder staple farmers use, vis-à-vis the crops produced. Such information is critical for both farmers and policymakers for crop targeting, since the use of wrong strategies would have negative cost, yield and welfare implications for the farmer.

Similarly, variations in quantity and method of use (solely or combinations) of climate-smart adaptation strategies could have varying production implications. In the production of a given staple cropfor instance, the use of multiple strategies is likely to be more productive when compared with the use of single strategy. Staple crop yield under improved crop varieties, proper manure application, and efficient irrigation system is more likely to be higher than under single strategy application. It, therefore, implies that strategies or interventions which recognize and incorporate these variations are more likely to be effective for climate change management, yield and welfare improvement among smallholder staple farmers. However, empirical results quantifying these variations to guide farmers’ decisions seem non-existent.

Though several climate-smart adaptation strategies abound, the level of adoption by farmers seems low and unstable. This may not be unconnected with constraints associated with technology adoption. Where these strategies are used, choices vary by farmer and crop. The knowledge about what drives farmers' usage of climate change adaptation strategies across available farmlandis limited. Poor understanding of these underlying factors, particularly farmers' motivations or goals, which determine these choices and the extent of use of these strategies by farmers can hamper the design of appropriate interventions to increase farm productivity and consequently, household welfare outcomes.

Findings in literature indicate that the use of climate-smart strategies among farmers is not new. However, empirical evidences of the impacts of these strategies on farm productivity and how this translates to improve farmer welfare remain scanty.

Against the foregoing background, this study answers the following research questions:

i. What type of climate-smart adaptation strategies do staple crop farmers use vis-à-vis the type of crops produced?
ii. What factors are responsible for the choices of climate-smart adaptation strategies used by staple crop farmers?
iii. What factors determine the use intensity of climate-smart strategies by farmers and the crops produced?
iv. How does the use intensity of climate-smart adaptation strategies affect farmers' welfare level via impacts on crop productivity?
v. What constraints limit the use of available climate-smart adaptation strategies by farmers in the study area?

1.3.Objectives of the Study

The broad objective of this study is to examine how farm productivity and welfare of smallholder staple crop farmers in Savanna Agro-Ecological Zone of Nigeria vary with the heterogeneity of climate-smart adaptation strategies adopted.

Specifically, the study objectives are to:

i. describe the types of climate-smart adaptation (CSA)strategiesused by farmers vis-à-vis staple crops produced;
ii. examine the factors influencing the choice(s) of CSA strategies of small-holder arable crop farming households;

iii. analyse the determinants of use intensity of CSA strategies among staple crop farmers;
iv. determine the productivity and welfare effects of usage of CSA strategies; and
v. identify constraints on the use of CSA strategies among smallholder staple crop farmers in the study area.

1.4.Justification for the Study

Climate-smart agriculture is identified as a means towards achieving sustainable agricultural production, and improving household food and nutrition security outcomes, particularly under a changing climate. Currently, there is renewed interest in the promotion of climate-smart strategies by both government and international agencies with the aim of reducing poverty, increasing household resilience, and engendering economic prosperity. Therefore, information to guide government and international organizations in developing and implementing policies towards climate-smart agriculture in Nigeria is important. Findings from this study will provide such valuable information.

In addition, understanding the productivity and welfare effects of farmers' adaptation practices could provide stakeholders with the needed incentive to spur the adoption of adaptation strategies that can increase household farm productivity, profitability, and resilience in the most cost-effective (economic and environmental) ways. For instance, providing generic adaptation options to farmers may not usually be cost-effective and sustainable; and could hamper government and donor organizations' efforts towards a hunger-free society. Findings of this study will be useful in this regard by providing tailored adaptation strategies, that are capable of increasing farm productivity alongside environmental benefits.

This study adds to the limited knowledgebase on climate change adaptation and welfare. It adopts a more comprehensive view of poverty that is likely to be more informative of the experience of rural smallholders in many developing countries like Nigeria. It adopts a multidimensional approach to poverty which considers poverty to extend beyond income and expenditure which are the focus of traditional measures of poverty (Okunmadewa, Olaniyan, Yusuf, Bankole, Oyeranti, Omonona, Awoyemi & Olayiwola, 2005; Adetola&Olufemi, 2012). Using a multi-dimensional poverty measure will inform how various socio-economic units suffering from deprivations other than income make adaptation decisions. It will also encourage targeting of development interventions to aim at promoting resilient livelihood systems.

Further, this is one of the few studies that specifically addresses households' motivations in response to adaptation to climate change in Nigeria. Though several studies have analyzed household responses to climate change adaptation, there is very little information, at least in Nigeria that have addressed the motivations behind adaptation strategy usage among rural households. Motivation has been identified as a critical factor that explains why some individuals show adaptive behaviour while others do not (Grothmann &Patt, 2005; Patt &Schröter, 2008; Frank, Eakin &Lopez-Carr, 2011). Literature has identified four motivation perceptual processes – climate risk perception, perception of adaptive capacity, risk experience, and social identity – to explain individual adaptive behaviour. Empirical adaptation studies have often used one or two of these alternative motives to explain adaptive behaviours. For instance, Frank *et al.* (2011) used scenario analysis to evaluate risk perception and social identity effects on adaptive behaviour. In their work, Grothmann and Patt (2005) developed a socio-cognitive model to understand private proactive adaptation to climate change, including risk perception and adaptive capacity to explain adaptation. However, these perceptual processes are not mutually exclusive when households make adaptation decision. Hence, this work constructed and empirically tested a model that contains these processes with a view to understanding the contributionof this variable in climate-smart adaptation decision and consequently, the welfare of households.

Further, the choice of the savanna agro-ecological region of Nigeria as the study area is premised on fact that it covers the largest geographical area in Nigeria, with most people engaged in rain-fed farming. This makes the zone and its people especially, vulnerable to climate change. Generally, the zone is noted for intense staple crop production under inter-annual rainfall variability (Odekunle, Orinmoogunje, & Ayanlade, 2007), and the probabilities of adaptation to climate-related vagaries is high. In view of the importance of staple crops in rural household welfare, understanding crop specific and intensity of use of climate-smart adaptation strategies in addition to their productivity effects, remains of great interest to both researchers and policymakers.

1.5.Plan of the Study

The remaining part of this thesiscomprises chapter two, the conceptual and analytical frameworks in addition to the review of relevant empirical literature on climate change, climate-smart strategies, farm input intensification and productivity. In addition, multidimensional poverty index isdiscussed. The methodology for the study is presented in chapter three and includes description of the study area, sampling procedure, and the analytical techniquesemployed for each of the objectives. In chapter four, the results based on the stated objectives of the study are presented and discussed. Chapter five presents the summary, main conclusions, and policy recommendations as well as suggestions on areas for further study.

CHAPTER TWO

LITERATURE REVIEW

2.1. Concepts of climate change and climate-smart adaptation

This section focuses on the review of the concepts of climate change and climate-smart adaptation as they relate to farm productivity and household welfare.

Climate change resulting from both anthropogenic and natural climate cycle activities alters rainfall pattern (intensity and duration) and temperature levels causing increased intensity of such natural hazards as storms, floods and droughts. Several studies including Enete et al. (2011), Arimi (2014), Asafu-Adjaye (2014), Barnard et al. (2015) and Sanogo, Binam, Bayala, Villamor, Kalinganire and Dodiomon(2017)have identified climate change as a major threat to human socio-economic and environmental development, particularly in developing economies. According to Asafu-Adjaye (2014), and Abidoye and Odusola (2015), the economic landscape of most African countries exposes them to the vagaries of climate. These studies premised that the vulnerable countries in Africa have a significant proportion of their population employed in agriculture, water and forestry which are climate-sensitive; and account for the largest number of the world's poor, who have weak climate change adaptive capacity. For instance, developing countries including Nigeria are adjudged to be at risk of climate change (Ayanlade, Odekunle & Orimoogunje, 2010; Tambo &Abdoulaye, 2012; Nwajiuba et al., 2015; Ayanlade, Radeny & Morton, 2017). In 2011, Nigeria is one of the five countries in the world where about 60% of the world poor live (UNDP-MDG Report, 2015). Its agriculture is mostly rain-fed and spatial analysis show that, the share of the poor remains higher in the rural than the urban areas (Nwalieji &Uzuegbunam, 2012; World Bank, 2014). These characteristics indicate that, changes in climate variables drastically affects ecosystem services, human health, water supply, agricultural production and productivity, market dynamics, and by extension, the socio-economic status of the rural dwellers,particularly in Nigeria.

Studies across sub-Sahara Africa have identified and assessedthe effect of climate change on agriculture using various approaches. For instance, a process-based crop model at a West Africa regional scale indicates that,without agricultural intensification for climate adaptation, crop yield in the long-term would significantly decrease and show inter-annual variability. This is because of increasedvariability in inter-annual growing season temperature and/or precipitation in future climate scenarios (Ahmed, Wang, Yu, Koo &You, 2015). Nwalieji and Uzuegbunam (2012) in their study of impact of "effect of climate change on rice production in Anambra State, Nigeria" analysed the perception of 100 rice-based rural farmers and identified the impact of climate change to include,"reduction in crop yield, reduction in grain quality, destruction of farm land by flood, food unavailability, instability, inaccessibility and poor utilization, incident of pests and diseases, surge of infectious diseases such as malaria, cholera on farmers, decrease in soil fertility, incidence of droughts in rice field, and high incidence of weed". A perception study of 400 farmers from southern Mali on the effects of climate change on ecosystem services of parklands shows that climate change in the forms of reduced rainfall (drought) and excessive wind impacts negatively, the ecosystem service delivery, particularly, the yield of trees (Sanogo*et al.*, 2017). Furthermore, Asante, Acheampong, Kyereh and Kyereh (2017) explore the manifestations of climate impacts among cocoa farmers in Ghana and show that climate change has increased incidence of pests and diseases, wilting of cocoa leaves, high mortality of cocoa seedlings with impacts on farm expansion and rehabilitation, and wilting of young cocoa pods resulting in low yield. On the economic impacts of climate change on 1000 rural households in Ethiopia using a Ricardian approach, a time-dependent negative effects of cropping season rainfall and temperature on net revenue was also found (Deressa &Hassan, 2009).

Regardless of the approach used, the consensus remains that climate change has strongly affected agriculture, and invariably, the livelihood outcomes of farmers. Adaptation is considered one of the options for reducing the negative impacts of climate change, particularly on agriculture (Watson, 2001; Adger,Huq, Brown, Conway, & Hulme, 2003; Smit &Wandel, 2006; Adger, Agrawala, Mirza, Conde, O'Brien, Pulhin, Pulwarty, Smit & Takahashi, 2007; Esham &Garforth, 2013; Tambo &Abdoulaye, 2012). This is because adaptation strategies have the potential to modify and ease the consequencesof climate change (Smit *et al.*, 1999) while complementing climate change mitigation efforts to achieve the sustainable development goals (SDGs) (Watson, 2001). According to these scholars, the term adaptation has several dimensions ranging from ecology/environmental to social science/human dimension, but with the common denominator that adaptation is response-based. Accordingly, Smit, Burton, Klein andStreet, (1999) defined adaptation as "adjustments in ecological-social-economic systems in response to actual or expected climatic stimuli, their effects or impacts".

Similarly, Smit and Wandel (2006) describe adaptation as a "process, action or outcome in a system (household, community, group, sector, region, country) in order for the system to better cope with, manage or adjust to some changing condition, stress, hazard, risk or opportunity". In their work, Adger et al. (2007) refer to adaptation as "actual adjustments, or changes in decision environments, which might ultimately enhance resilience or reduce vulnerability to observed or expected change in climate". In climate change adaptation context, Smit *et al*. (1999) defined adaptation to climate change variability as "the process by which stakeholders make adjustments aimed at reducing the actual and expected adverse effects of climate on their livelihood". This nature of conceptualization of adaptation allows for a better understanding of the pathway through which households and communities use their adaptive capacities and various assets toreduce adverse impacts of climate change and variability on food systems and livelihoods (Antwi-Agyei et al., 2014).

Variability in the frequency and magnitude of occurrence of climate variables is an age-long phenomenon with farmers continuously adapting to the changes through several strategies (Tambo and Abdoulaye, 2012). Some of these strategies have been identified in several studies (Farauta, Egbule, Idrisa, & Agu, 2011; Magombo et al., 2012; Tambo & Abdoulaye, 2012; Baez et al., 2013; Falaki,Ajayi,Akangbe, & Akande 2013; Yegbemey et al., 2013; Jost,Kyazze, Naab, Neelormi, Kinyangi, Zougmore, Aggarwal, Bhatta, Chaudhury, Tapio-Bistrom, Nelson, & Kristjanson,2016) toinclude; planting of trees to provide windbreaks and shades for livestock and crops, adjusting dates for land preparation, planting and harvesting, crop diversification, mulching, planting drought tolerant and early maturing crop varieties, using several cropping methods (mixed, relay, intercropping), adopting water conservation practices, changing from farming to non-farming activities, migration to avoid floods or drought; and insuring against weather-related asset losses. Others are small-scale irrigation farming, application of organic manure, inter and intra-household's transfers, consumption smoothing, and reduction in social capital investment. These strategies are usually not taken to combat the immediate or short-term negative impacts of climate variability but are long-term strategies that are forward-looking (Antwi-Agyei et al., 2014).

In addition to contributing to reduced vulnerability of farmers to the consequencesof climate change, each of these strategies has varying degrees of contribution to costs (or negative externalities) of the users. For instance, improper irrigation practices have the potential of impacting negatively on the environment through depletion of ground and surface waters and improper application of fertilisers havenegative consequences on the environment even while increasing crop yield. Similarly, the reduction in social capital investment such as pulling of children out from school as climate change adaptation strategy portends socio-economic danger to human capital development. This follows that climate change responses alsohave negative consequences for food security and measures taken to increase food security can as well exacerbate climate change (CCAFS, 2009). It is, therefore, crucial for farmers to adopt adaptation strategies that are environmentally friendly, sustainable, and economically viablewhile helping households and communities adapt to the impact of climate change within their locality (Sekaleli & Sebusi, 2013). The concept of climate-smart agriculture (CSA) provides a framework to describe types of adaptation strategies.

Lipper, Mann, Meybeck and Sessa (2010) defined climate-smart agriculture (CSA) as “agriculture that sustainably increases productivity, enhances resilience (adaptation), reduces/removes greenhouse gases (GHGs) (mitigation) where possible, and enhances achievement of national food security and development goals”. Again, Gibbon (2012) considers CSA as an “ecosystem farming approach characterized by minimal disturbance of natural environment, plant nutrition from organic and non-organic sources, and the use of both natural and managed biodiversity to produce food, raw materials and other ecosystem services”. This farming system provides for improved farmland health and encourages the regeneration of already degraded soils, while ensuring that the pillars of climate-smart agriculture are achieved. Ideally, CSA aims at achieving these multi-objective functions/goals simultaneously. However, Notenbaert, Pfeifer, Silvestri, & Herrero (2017) argued that this is rarely possible but that trade-offs between various goals can be observed. Following this, adaptation options that aim to achieve any of the pillars (sustainable increase in productivity, resilience enhancement, reduction in greenhouse gases) of climate-smart agriculture are known as climate-smart adaptation strategies (Khatri-Chhetri, et al., 2017). These strategies are often location-or-context specific (Asfaw, Di Battista, & Lipper, 2016) and their implementation involves the integration of both traditional and innovative farm strategies that are capable of increasing productivity, efficiency, resilience, and mitigation potentials of the farm (Khatri-Chhetri *et al.*, 2017).

Many agricultural practices and technologies used by farmers or promoted by national governments in Africa in response to climate change threats often qualify as climate-smart adaption strategies (Nwajiuba*et al.*, 2015). There is vast literature on the different climate-smart adaptation strategies, which Khatri-Chhetri *et al.* (2017) grouped as water, energy, nutrient, carbon, weather, and knowledge-smart technologies. Water-smart technologies are those with the goal of promoting water-use efficiency by addressing variability in rainfall patterns, managing water quality and water-related erosion and degradation. They include improved rainwater harvesting and retention technologies (Behnassi *et al.*, 2014), precision irrigation and laser-assisted land-levelling (Gill, 2014), cover crops method (Khatri-Chhetri *et al.*, 2017). Technologies that are considered energy-smart are those that ensure minimum soil disturbance like the zero or minimum tillage, direct sowing, permanent vegetative cover and crop rotation practices (Arslan, Jian, Lipper, & Tuong, 2014). Although zero tillage is noted to change the distribution of carbon in the soil profile significantly (Luo, Wang & Sun, 2010), reduce soil erosion and compaction, conserve soil moisture and provide a good habitat for soil fauna which build soil porosity and structure (Palombi & Sessa, 2013). Gattinger, Jawtusch, Müller and Mäder (2011) argue that it could lead to reduced or no-yield outcome, increased use of herbicide and poor contribution to carbon sequestration particularly in developing countries. This is because of its low ability to significantly contribute to soil organic carbon when compared with the conventional tillage practices (Luo *et al.*, 2010; Martinsen, Shitumbanuma, Mulder, Ritz & Cornelissen, 2017). However, it contributes to a higher carbon sequestration, increased soil moisture and sustainable crop yield when combined with increased cropping frequency, residue retention, permanent crop cover, and elimination of agrochemicals (Witt *et al.*, 2000; Luo *et al.*, 2010; Palombi & Sessa, 2013; Khatri-Chhetri, *et al.*, 2017). This implies that benefits of zero or minimum tillage as energy-smart agricultural practice is heterogeneous. Crop rotation is "the practice of alternating the crops planted on land, ideally incorporating nitrogen-fixing plants in the crop cycle to increase soil fertility" (McCarthy & Brubaker, 2014). It is considered very effective for achieving controlled weed and soil-borne diseases (Al-Kaisi & Kwaw-Mensah, 2016) and higher crop yields and reduced production risks (Azevedo, Landivar, Vieira & Moseley, 1999; Nel & Loubser, 2004), and increased resilience to crop production under climate variability and change (Debaeke, Pellerin & Scopel, 2017).

Furthermore, intercropping with legumes, green manuring, composting, and leaf colour chart are considered very effective nutrient-smart farming technologies under climate change (Palombi & Sessa, 2013; Arslan, McCarthy, Lipper, Asfaw, Cattaneo & Kokwe, 2015; Khatri-Chhetri, *et al.*, 2017). Intercropping with legumes, a cropping pattern that involves the cultivation of at least one legume crop with other crop genotypes together, in time and space, is a practice that controls insect vectors and weed (Gibbon, 2012), increases soil carbon sequestration (Steenwerth, Hodson, Bloom, Carter, Cattaneo, Chartres,…Jackson, 2014), improves soil health and saves labour demand (Nyasimi, Amwata, Hove, Kinyangi & Wamukoya, 2014), and allows farmers to maximize productivity per land area using only few external inputs (Himanen, Mäkinen, Rimhanen & Savikko, 2016). The useof compost particularly farm compost made of wood chips and bark, organic manure, straw, crop residues, mowed grass and soil contributes to increased soil organic carbon content, micro and macro-fauna population and crop yield in a sustainable manner (D'Hose,Cougnon, De Vliegher, Van Bockstaele, & Reheul, 2012). On its part, green manuring plays significantadaptation and mitigation rolesinclimate change and crop productivity by improving soil moisture content, reducing water stress during dry season, improving soil physical and chemical characteristics, reducing nitrogen fertilizer needs, by fixing atmospheric nitrogen, and consequently, improving farm productivity.

The carbon-smart climate change adaptation strategies constitute several options that facilitate carbon sink. Notably, options such as integrated pest management and sustainable land use management strategies like agroforestry and crop-livestock integration, fall into this category. According to FAO (2012), integrated pest management (IPM) is an "ecosystem approach to crop production and protection that combines different management strategies and practices to grow healthy crops and minimize the use of pesticides". Gan, Liang, Chai, Lemke, Campbell, andZentner (2014) and FAO (2015) indicate that pesticides generate greenhouse gases (GHG) throughout their value chain: manufacturing, transportation and application. For instance, Heimpel, Yang, Hill, andRagsdale (2013) estimated the release into the environment of between 6 – 40 million of CO_2 equivalent GHGs because of pesticides used to treat soybean aphid infestation in the United States of America within a decade. However, the study concluded that the use of biological control (a component of IPM) to check soybean aphid infestation can reduce the annual GHG emission by about 200 million Kg of CO_2

equivalent. Similarly, replacing chemical control with improved farm practices in wheat production reduces GHG emission by 256 kg CO_2 equivalent per hectare per year (Gan *et al.*, 2014). These highlight the potentials of integrated pest management (IPM) in climate change adaptation and mitigation. It is considered a means to sustainably increase agricultural productivity in Africa under reduced pesticide use (Hoeschle-Zeledon, Neuenschwander & Kumar, 2013)

Sustainable land use management practices including agroforestry and crop-livestock integration have been predicted to contribute significantly to climate change adaptation and mitigation goals, particularly those that increase soil organic carbon content (Pender, Ringler, Magalhaes, & Place, 2012). For instance, agroforestry, the deliberate cultivation of woody perennials and annual crops on agricultural land (Gibbon, 2012), is a climate-smart practice useful in smallholder agricultural production in many agroecological zones in Africa (Neufeldt, Kristjanson, Thorlakson, Gassner, Norton-Griffiths, Place, & Langford, 2011; Mbow, Smith, Skole, Duguma & Bustamante, 2014). As a good substitute for the slash-and-burn system prevalent in most developing countries, its potentials lie in the ability to increase climate resilience of agricultural production to such weather events such as; flooding, drought, and pest/disease, and to decrease GHG emissions (Palombi & Sessa, 2013). The benefits of agroforestry also includes; improvement of soil fertility, enhancement of local climate conditions, contribution to ecosystem services, reduction of human impacts on natural forests, promotion of carbon sequestration, improvement of agricultural productivity, and reduction in yield variability (Mbow *et al.*, 2014; Sanogo et al., 2017). According to World Bank (2012) and Khatri-Chhetri *et al*. (2017), those interventions such as livelihood diversification, crop and weather index insurance whichprovide income security and weather advisories to farmers constitute weather-smart strategies. The knowledge-smart technologies are those that combine science and local knowledge to combat the impacts of climate change. They include the use of improved crop varieties tolerant to weather extremes like drought, flood, heat and cold stresses, and input-intensification such as the use of urea deep placement technology.

2.2. Theoretical and conceptual frameworks

In this section, the maximum utility theory as it relates to agricultural household's decision-making processes is discussed. This theory highlights the behaviours of farming households towards the use of production inputs. Furthermore, the linkages between farmers' adaptation decisions and the outcomes of the decisions are illustrated under the conceptual framework sub-section (Fig. 1), and the need to account for the influence of farmers' decisions on production outcomes was identified and discussed.

Generally, farmers either purchase or provide their production inputs and produce for sale or for own consumption. Therefore, agricultural households would make separate or joint decisions on these activities particularly as they relate to their well-being. The agricultural household model provides the theoretical framework to assess the behaviours of farming households towards production, consumption, and labour allocation decisions. As Findeis, Swaminathan & Jayaraman (2003) argue, the core of this model is that household's decisions are not separable, including production and consumption decisions particularly under the existence of imperfect market and risks situations prevalent in developing countries. Hence, household decisions involving production and consumption need to be jointly or simultaneously determined either through the reduced-form or systems approach since farm enterprise activities contribute to household income, and therefore affect household consumption (Singh, Squire & Strauss, 1986; Findeis *et al.*, 2003). However, Singh, *et al.* (1986) opined that under the situation where income is the main linkage between the household's production and consumption activities, the production activities can be analyzed separately from the consumption activities: production as a profit maximizing activity and consumption as utility maximisingcomponent, following the assumption that the household is a price taker for every commodity, including family labour, which is both consumed and produced, and that commodities are homogenous. Furthermore, Singh *et al*. (1986) noted that if the production and consumption side errors are correlated, joint estimation of both sides is needed to account for endogeneity issues. Estimation can be done, using a system of equations, involving structural and reduced forms or single equations.

Climate change adaptation decisions of households can be considered utility maximizing decisions,in the form ofreduction in downside risk or yield stability, in addition to increased yield derived from adopting a climate-smart practice (Mulwa, Marenya & Kassie, 2017). Hence, decisions to adapt and the choice of adaptation strategies (input variables) made by farmers would indicate that, the net benefit/utility from such decisions/choices is significantly greater than the situationwithout it (Deressa & Hassan, 2009). Following Train (2009), the outcome of the farmer's decision denoted as A, indicating the chosen climate-smart adaptation option or sequence of options, and if the outcome variable is discrete, the observed factors x and the unobserved factors ε which influence the choice(s) made by the farmer can be represented through a function:

$$A = f(x, \varepsilon) \quad \ldots\ldots 1$$

Since ε constitute several unobserved factors in the model, the farmer's choice cannot be predicted exactly;instead, the outcome of the farmer's decision can be derived based on probability. The unobserved factorsare considered random with density *f*(ε). The likelihoodthat the farmer choosesan outcome from the set of all possible outcomes is the probabilitythat the unobserved factors in the behavioural process results in that outcome:

$$Prob(A|x) = Prob(\varepsilon\ s.t. f(x, \varepsilon) = A) \quad \ldots\ldots 2$$

Given an indicator function $I[f(x, \varepsilon) = A]$ that takes the value of 1 ifthe statement in brackets is true and 0 ifotherwise, i.e. $I[\,.\,] = 1$ if the value of ε combined with x induces the farmerto choose outcome A, and $I[\,.\,] = 0$ if the value of ε combined with x induces the farmerto choose some other outcomes. The probability that the farmer observesoutcome A is the expected value of theindicator function, where the expectation is over all possible values of the unobserved factors:

$$P(A|x) = Prob(I[f(x, \varepsilon) = A] = 1) \quad \ldots\ldots 3$$

$$= \int I[f(x, \varepsilon) = A] f(\varepsilon)\, d\varepsilon \quad \ldots\ldots 4$$

The probability of whether a farmer adopts an adaptation strategy given the net benefit or observed utility can be determined from the integral function in equation (4). The behavioural model specifying the farmer's action is a function of observed farmer characteristics x and unobserved factors ε such that:

$$U = \beta x + \varepsilon \quad \ldots\ldots 5$$

A farmer adopts a given climate-smart adaptation option if such decision provides a net benefit, i.e. the utility U is positive. Therefore, the probability that a farmer adopts an option (practices and technologies), given the observables, will be:

$$P = \int I[\beta x + \varepsilon > 0] f(\varepsilon)\, d\varepsilon \quad \ldots\ldots 6$$

where$f$ is the density of ε, which can be assumed to have either logistic or probit distribution. The distributions mostly used are those that assume$\varepsilon$to beindependently and identically distributed with mean zero.

In the context of adaptation, farmers are more likely to adopt several practices simultaneously to deal with climate change-related production constraints, than to adopt a single practice (Asfaw *et al*., 2016). As such, the probability function in equation (6), would need to account for possible interdependency of decision outcomes and simultaneity (Cameron &Trivedi, 2005). A multivariate discrete outcome model which allows the errors terms to be correlated because of complementarity or substitutability between different adaptation options is considered adequate for this nature of outcomes (Asfaw *et al*., 2016; Mulwa *et al*., 2017; Tarekegn, Haji & Tegegne, 2017). Following these authors, the multivariate probit model consists of a set of simultaneous binary dependent variables A_i that equals 1 if farmer i adopts a practice j such that:

$A_{ij} = \beta_{ij}x_{ij} + \varepsilon_{ij} > 0$ ……………………………………………………………..7

otherwise,

$A_{ij} = \beta_{ij}x_{ij} + \varepsilon_{ij} \leq 0$, for each j = 1, 2, 3, ……, n, ………………………………..8

where, x_{ij} is setof the explanatory or independent variables including household demographic and motivation, plot and climate change-related variables, β_{ij} are the parameter vectors, and ε_{ij} are the error terms assumed to exhibit multivariate normal distribution with zero mean, unitary variance and an *n x n* correlation matrix.

Impact analysis requires that endogeneity resulting from self-selection and treatment issues are considered since estimations which do not account for these problems will generate bias and inconsistent estimates. In this study, for instance, adaptation decision variable(s) in the productivity (outcome) model is not exogenous but endogenous and would, therefore, require endogeneity consideration. The methods of instrumental variables (IV), for a single instrument, or two-stage least squares (2SLS), for multiple instruments, and the use of structural specifications are common estimation approaches in literature for handling endogeneity issues (Greene, 2012; Wooldridge, 2012). The IV and 2SLS methods have been used in several impact studies (Di Falco, Veronesi & Yesuf, 2011; Simtowe, Kassie, Asfaw, Shiferaw, Monyo & Siambi, 2012; Liverpool-Tasie, Adjognon & Kuku-Shittu, 2015; Dzanku, 2015; Manda, Alene, Gardebroek, Kassie & Tembo, 2016; Makate, Wang, Makate & Mango, 2016; Arslan *et al*., 2016). Again, the endogenous issues can be handled by matching methods, especially the propensity score matching (PSM) (Mendola, 2007; Liverpool-Tasie *et al*., 2015; Ali & Erenstein, 2017;Makate, Wang, Makate & Mango, 2017).

Also, structural equations have been applied to jointly estimate sets of the equation to account for selectivity bias and correlated error terms in impact models. Studies (Rahman, 1999; Perz, 2002; Blanc, 2011; Kaminski, Kan & Fleischer, 2012) have either suggested or used the Zellner's Seemingly Unrelated Regression Estimator (ZSURE) to obtain consistent estimates under this condition. More recently, Roodman (2011) proposed the "conditional recursive mixed-process (CMP)" modelling framework which is based on the seemingly unrelated regressions (SUR) setup and allows mixing of different multi-equation systems such that each dependent variable of the different equationscanbe ofdifferentkinds. The various components of the framework are described as follows: "Multi-equation means that CMP can fit Seemingly Unrelated (SUR) systems, instrumental variables (IV) systems, and some simultaneous-equation systems". "Mixed process" means that the different equations can have different dependent variables: continuous, censored, discrete binary variable. A dependent variable in one equation can appear as an independent variable of another equation. "Conditional" means that the model can vary by observation such that an equation is modelled only if observations are relevant. "Recursive" means, however, that "CMP can only fit sets of equations with clearly defined stages, not the ones with simultaneous causation" (Roodman, 2011; Baum, 2016).

CMP, which is appropriate for two types of models can be used for (i) those models which a truly recursive data-generating process is hypothesizedand fully modeled, and (ii) those in which there is simultaneity, but instruments allow for the construction of a recursive set of equations, as in two-stage least squares, that can be used to consistently estimate structural parameters in the final stage. In the first case, CMP is a full-information maximum likelihood estimator and all estimated parameters are structural. In the second case, CMP is a limited-information maximum likelihood estimator, and only the final stage's coefficients are structural, the rest are reduced-form parameters (Asfaw *et al.*, 2016; Baum, 2016). Maximum likelihood (ML) SUR estimators, including CMP, are appropriate for the class of simultaneous equation models in which endogenous variables appear on the right side of structural equations as well as on the left (Asfaw *et al.*, 2016).

The CMP framework differs from the SUR framework. In the SUR setup, the equations for each dependent variable is specified and can be estimated by ordinary least squares (OLS) such that each equation satisfies the zero-conditional mean assumption,

$E[U_j|X_j] = 0$, ruling out either simultaneity or presence of endogenous variables in the X_j (Baum, 2016). Though based on seemingly unrelated regression algorithm, the CMP modelling framework, using a systems approach, allows for joint estimation of two or more equations whose dependent variables may or may not be related but with linkages among their error processes, accounting for multiple endogeneity in a structural model (Asfaw *et al*., 2016; Ergano, 2017). That is, the CMP analyseseach equation as independent from one another, but models their underlying errors as jointly and normally distributed.

Hence, the CMP framework produces more consistent and efficient estimates than either the instrumental or two-stage least squares estimation technique. Asfaw *et al*. (2016) further explains that CMP differs from instrumented regressions by not automatically including the first stage exogenous regressors (included instruments) from the second stage. However, the major challenges associated with the implementation of CMP approach arecomputational burden and those with achieving convergence, especially for a large and varying multi-equations. Asfaw *et al*. (2016) applied it to analyse the impacts of three climate-smart technologies on-farm productivity and net crop income in Niger while Ergano (2017) used this estimation technique to estimate adoption decisions for four dairy technologies in Ethiopia.

The CMP framework is therefore considered most appropriate in this study where the decision to use, the intensity of use, the productivity, and welfare effects of use of climate-smart adaptation strategies are sequentially connected and the unobserved factors are likely to impact the dependent variable at each sequence.

In this study, a major concern is on the climate-smart adaptation choices and productivity/welfare linkages. The conceptual frameworks proposed by Selvaraju, Subbiah, Baas and Juergens (2006) and Eisenack andStecker (2012) are adapted in this study because they adequately explain the linkages by emphasizing the households as the pivot of adaptation decision and the receptor of decision outcomes.

At the centre of the frameworks are human systems, which are individuals or households, who adjust (adapt) in response to changes in climatic variables. Specifically, agricultural households are key in the frameworks not only because they are usually affected by changes in the climatic variables, but also because they are at the centre of where adaptation strategies are developed, and decisions taken to develop and maintain livelihoods, by means of the livelihood portfolio (Selvaraju *et al*., 2006) and because they are the receptors of these livelihood decisions.

In the framework, climate change events (floods, drought, high temperature, pest and diseases), biophysical (agriculture) unit, socio-economic units (households) and the actions/strategies taken by them with the purpose to achieve intended ends are part of a simple system as shown in Figure 1. Climate change could influence the biophysical (agriculture) and households' socio-economic variables, impact resources and assets, including social capital; and affecting the resource management strategies and decision-making potential of the households (Eisenack & Stecker, 2012). Households, however, respond to these impacts by adjusting (adapting) to achieve target livelihood outcomes, including productivity and welfare. The adjustments (adaptations) can be made to target biophysical (crops) and social (households) units; and would require the use of different livelihood resources (means) to achieve the intended outcomes(Eisenack & Stecker, 2012). These livelihood resources could be natural resources (e.g. land), economic/financial resources, human resources (e.g. labour, skills, knowledge and expertise), and social capital (e.g. formal and informal networks, strong social and legal institutions) (Scoones, 1998; Brooks & Adger, 2005). The availability and ability to effectively use these resources to achieve adaptation,reflects the adaptive capacity of the households (Brooks & Adger, 2005). Furthermore, some external factors are hypothesisedto influence the extent of use of the climate-smart adaptation strategies (Figure 1). For instance, the prevailing climatic risk evident in the crop production process, availability or access to required climate-smart technologies and market access, could influence the type and number (diversification) of climate-smart technologies, used by households, to adapt to climate change and variability.

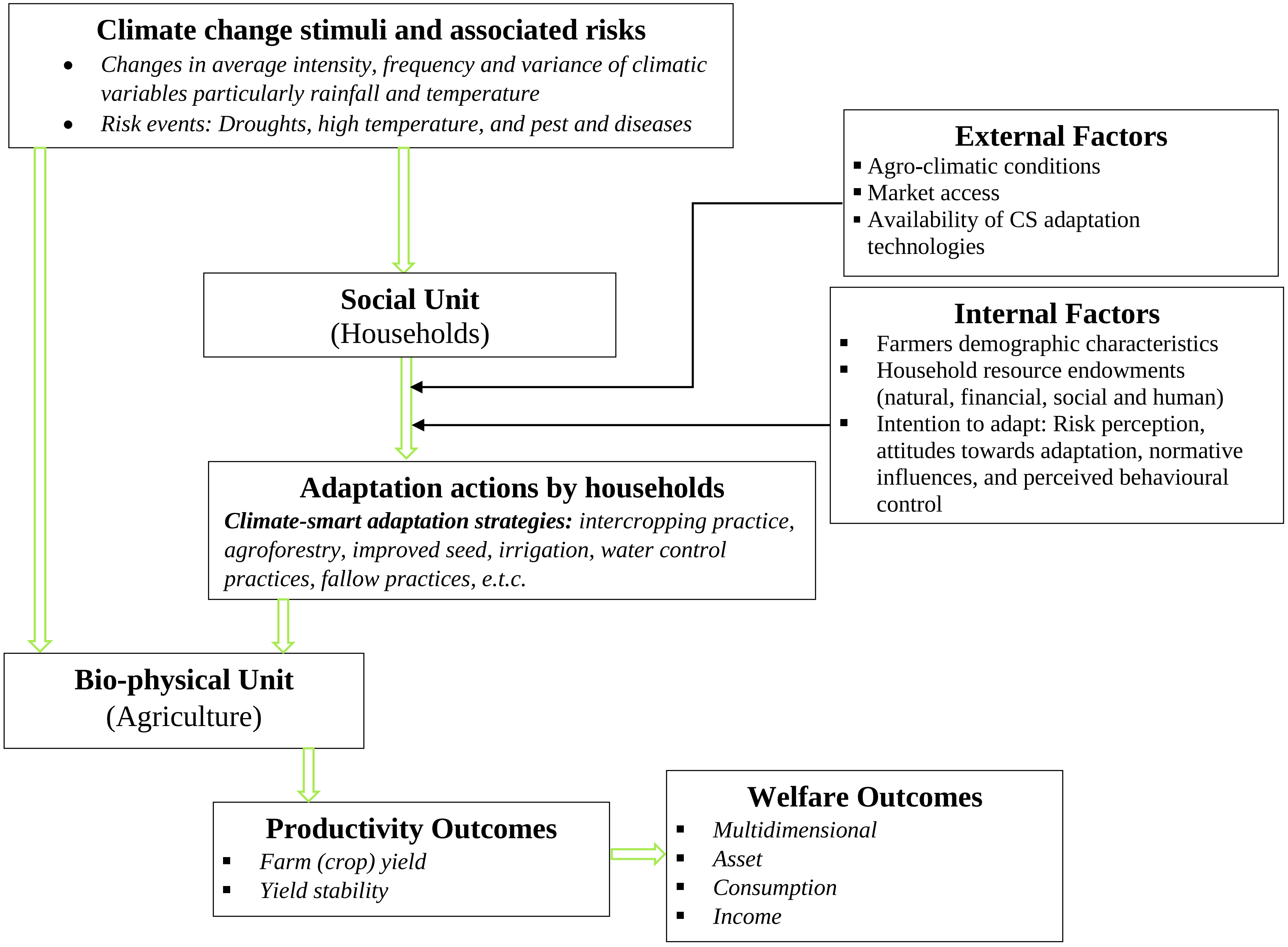

Figure 1: Conceptual framework for productivity and welfare impacts of climate-smart adaptation practices

Source: Adapted from Selvaraju *et al*. (2006) and Eisenack and Stecker (2012)

2.3. Analytical/methodological Review

This section deals with the different approaches to measuring the various indices of concern in this study, such as; productivity, welfare outcomes, intensification indices, and motivational processes.

2.3.1. Approaches to indicator measurement

2.3.1.1. Farm productivity

One of the most fundamental insight of the climate-smart adaptation practices is that they are to increase farm productivity. The term productivity has received different interpretations, including the ability of production factors to produce the output (Latruffe, 2010), “the ratio of a volume measure of output to a volume measure of input use” (OECD, 2001), the value of farm output per worker (Dzanku, 2015), and the rate of output produced per unit of input used for a given production process (Burja, 2012). It is also considered as the overall efficiency with which inputs are transformed into output within a production process. Liverpool-Tasie, Kuku & Ajibola (2011) defined it as “theratio of final output, in appropriate units, to some measure of inputs”. In each case, therefore, productivity infers an input-output relationship which shows the extent to which input(s) used in a production process generate the desired amount of output. Three indicators of agricultural productivity (partial factor, total factor and total resource) which are defined on the basis of ratio of quantity-based output to input in a production process are mentioned in literature (Fuglie, Benton, Sheng,Hardelin,Mondelaers, & Laborde, 2016).

Partial factor productivity is the ratio of output and any one of the inputs, particularly labour or land (Nyangito&Odhiambo, 2003). If labour is the input used, it is called labour productivity, while land input will generate land productivity. According to FAO (2001) in Dzanku (2015), output per cultivated land area is used for measuring the effect of new production practices while farm labour productivity is often used to compare welfare effects of farm and nonfarm productivity. As Nyangito and Odhiambo(2003) mention, the major weakness of the partial factor productivity is its inability to account for the role of otherinputs used during a givenproduction process. The total factor productivity, however, corrects for this weakness, because it is the ratio of total output and all factor inputs (Christensen, 1975). Fuglie *et al.* (2016) define it as “a ratio of the total marketable outputs to total marketable inputs in a production process”. It is developed to measure production efficiency, which involves understanding how economic resources are used to produce economic outputs. They, however, noted that the weakness of the total factor productivity is that it does not account for the environmental inputs or outputs whether priced in the marketplace or not. The total resource productivity which in addition to the total factor productivity includes the various non-market environmental outputs and inputs used foragricultural production and therefore developed to account for this shortcoming (Fuglie *et al*., 2016). However, studies (Nyangito&Odhiambo, 2003; Liverpool-Tasie *et al*., 2011) limit productivity metrics to partial and total factor productivity with the latter regarded as superior to others.

Either total or partial, price-based farm productivity is most preferred for productivity studies in developing countries where most household plots are under the mixed or intercropping system. It is usually measured by multiplying the quantity of each crop produced per hectare by either farmgate or market price of the produce (Peterman, Quisumbing, Behrman & Nkonya, 2011). This study, however, adoptsthe measure of quantity-based plot-level total farm productivity for each household.

2.3.1.2. Welfare outcomes

Literature suggest numerous proxies of household welfare which are measured through objective or subjective methodology. Objectively, household welfare is proxied as monetary variables, including; consumption expenditure, asset, and income. Of these metrics, consumption expenditure remains the preferred welfare metric because it is less prone to fluctuations compared with income metrics particularly in agricultural economies (Deaton & Zaidi, 2002), captures long-run welfare, less vulnerable to under-reporting bias, accounts for relative price changes with a single deflator, reflects in-kind transfers, and easier to measure than the income measure of welfare (Filmer & Pritchett, 2001; Pradhan, 2001; Meyer & Sullivan, 2003). In addition, Arndt &Mahrt (2016) note that this metric is more relevant in the African context, where self-employment in the agricultural sector is predominant. The consumption expenditure welfare measure is usually constructed from expenditures on food and non-food household items, using information on purchases, imputed values (using market prices) of own produce consumption, receipts-in-kinds as well as the values of durable goods and the imputed rent of owner-occupied housing (Arndt & Mahrt, 2016). For comparability in a food-based measure, consumption values obtained are usually adjusted to account for seasonal food price fluctuations, using intra-temporal price index, especially, when different recall periods are involved (Dzanku, 2015; Arndt &Mahrt, 2016). The estimation of welfare as per capita consumption expenditure to account for household composition is common (Dercon, Hoddinott & Woldehanna, 2005; Arndt &Mahrt, 2016). Other consumption indicators of household welfare include; consumption per adult equivalent, calorie consumption per person per day, and food consumption expenditure as a proportion of total household expenditure. Though consumption expenditure is favoured in welfare measurement, its use as an indicator of welfare is limited by measurement errors, the prohibitive cost of data collection, and spatial location of respondents, among others.

The use of income as welfare indicator abound in literature. Income refers to the earnings from productive activities and current transfers includelabour services (wage income), the supply of assets (rental income), self-employment income, and transfers from government, non-government agencies, other individuals and households (World Bank, 2003). Although used as a living standard measure, income dimension is seen to be conceptually and practically inadequate (World Bank, 2003) particularly among agricultural households and those involved in self-employed labour activities (Finan, Sadoulet & De Janvry, 2005). This is because income-related questions constitute more sensitive issues to respondents, than those based on consumption or asset (Moratti&Natali, 2012). Consequently, responses are likely to be underestimated and biased as well as fraught with recollection and measurement errors (Moser & Felton, 2007). Again, income earnings do not necessarily translate to increased welfare for every member of the households, since its spending can be biased towards male members (Kumar, 1989). These observations, therefore, indicate that the use of income as a measure of welfare should be with caution.

Asset-based welfare measure reflects household stock that indicates the accumulation and use of economic value and income over time (Cohen & Little, 1997). This metric expressed as an index is usually constructed from several assets the household owns using various methodologies, including; 1) simple asset score constructed by assigning equal weight to each asset (World Bank, 2003); 2) principal component analysis (PCA) if the asset variable is continuous and linear constraint is assumed (Browne, Ortmann & Hendriks, 2014; Dzanku, 2015); 3) factor analysis (FA) (Carletto & Zezza, 2006); and 4) multiple correspondence analysis when fewer assumptions are made about the underlying distributions of the indicator variable and the indicator variable is either discrete or categorical (MCA) (Booysen, Van Der Berg, Burger, Von Maltitz& Du Rand, 2008). As a welfare measure index, asset index is adjudged to be better because it "reflects long-term welfare, less volatile, than both income and consumption, and more suitable to analyse multi-dimensional poverty" (Filmer & Pritchett, 2001). Furthermore, asset measure of welfare is less prone to measurement errors (Moser & Felton, 2007). However, the index is considered a specific indicator, which cannot be compared to the income or expenditure measures of economic status (Moratti & Natali, 2012) and does not properly reflect current household welfare status, in addition to being urban bias (Filmer & Pritchett, 2001), and unable to account for spatial price level differences and asset quality (Moratti & Natali, 2012; Dzanku, 2015).

Subjective measure of welfare is non-monetary, and it is often constructed using simple qualitative assessments of individuals or households' perceptions about the state of well-being (Pradhan & Ravallion, 2000). This approach accounts for the unobservable and the difficult-to-measure effects of some factors, which the objective measures are unable to capture. Consequently, it provides additional information, particularly, on the poor, which could help for effective policy design and implementation (Carletto & Zezza, 2006; Lokshin, Umapathi & Paternostro, 2006). Approaches to constructing this index identified in literature include; 1) Minimum Income Question (MIQ) approach which is appropriate in developed countries (Lokshin *et al*., 2006); 2) Consumption Adequacy Question (CAQ); and 3) Economic Ladder Question (ELQ) suited for developing countries, where income concept is not well defined (Pradhan & Ravallion, 2000; Roberts, 2009). The MIQ approach is well described in Deaton & Zaidi (2002) and the MIQ approach can be achieved following Ravallion (2012).

In recent studies (Finan *et al*., 2005; Alkire & Foster, 2011; Justino, 2012; Dzanku, 2015; Ardnt *et al*., 2018), multidimensional welfare measurement, which combines the strengths of the various unidimensional welfare indicators and the simultaneous multiple deprivations faced by households, has been advocated. This involves the construction of welfare index by aggregating multiple dimensions, including consumption expenditure, income, and those related to sanitationaccess, water and dwelling features. Finan *et al*. (2005) note that this approach helps to integrate accumulated welfare, associated with durables, the current flow of welfare associated with consumption and income, and access to public goods into a single welfare index and consequently, captures the multidimensionality of welfare. Several approaches have been used to construct this index. Using the principal component technique, Finan *et al*. (2005) constructed a multidimensional household welfare index from various dwelling characteristics;(running water, electricity, has a bathroom, number of rooms, and dirt floors) and household durables (ownership of a blender, refrigerator, television, and truck). This is in addition to the short-term measures of consumption expenditure and non-farm labour income. Following this approach, Dzanku (2015) also constructed an individual welfare index by aggregating consumption, income, household durable assets, and dwelling characteristics including;number of bedrooms per adult equivalent, type of roof and walls, electricity connection and toilet facilities). The Alkire-Foster multidimensional poverty indicator is a context-specific index, thatconsiders the joint distribution of deprivations, reflecting the extent of association between the several dimensions of welfare. In addition, its flexibility in terms of dimensions and their cut-offs, weights and poverty cutoff makes it adaptable to various levels; (households, village, state and national) and purpose (Alkire& Foster, 2011). It uses the counting approach (Ajakaiye, Jerome, Olaniyan, Mahrt, & Alaba,2014) based on a weighting scheme usually applied on cardinal and ordinal indicators grouped along three dimensions: living standard, health and education. The living standard dimension has assets, cooking fuel, floor types, drinking water, sanitation and access to electricity as indicators. The indicators of health include nutrition and mortality while those for education are school attendance and years of schooling. Under the Alkire-Foster index, a person or household is identified as multidimensionally poor, if such person or household experiences deprivation in at least 30% of the weighted indicators. Tran, Alkire & Klasen (2014) applied this approach in their work on “disparities between the monetary and multidimensional measurement of poverty” in Vietnam choosing indicators based on available data. The recent first-order dominance (FOD) approach to multidimensional welfare analysis developed by Ardnt *et al*. (2012) has been operationalized in several developing countries, including Tanzania and Nigeria. The features of the FOD approach include use of binary indicators and does not require weighting scheme, but relies on non-restrictive assumptions; and unlike the Alkire-Foster methodology, which focuses on deprivation in any dimension of analysis, the FOD approach measures non-deprivation status on any dimension under consideration (Arndt, Mahrt, Hussain &Tarp, 2018). Examining five dimensions including access to water, sanitation, energy, housing and education at the household level, Ajakaiye, Jerome, Olaniyan, Mahrt andAlaba(2016) use this approach to estimate a non-monetary multidimensional poverty for Nigeria at sectoral (rural and urban) level, across the six geopolitical zones and state levels. Following Alkire-Foster methodology, this study constructs a multidimensional welfare index for each households by aggregating the various indicators of these welfare dimensions: education (years of schooling and school attendance by school-age children), living standards (source of drinking water, sanitation or toilet facilities, types of cooking fuel, electricity access, types of roof, floor and wall, number of bedroom per adult equivalent, access to motorable roads, land, livestock, and asset ownership) and health (food security and child mortality).

2.3.1.3. Intensification index

Various indices have been used to measure the intensity of use of agricultural technologies, including the number of technologies/strategies adopted (Mazvimavi & Twomlow, 2009; Pedzisa, Rugube, Winter-Nelson, Baylis, & Mazvimavi, 2015) and land area allocated to a given technology/practice (Shiferaw, Kebede & You, 2008; Tambo & Abdoulaye, 2012; Ngwira, Johnsen, Aune, Mekuria & Thierfelder, 2014; Arslan *et al*., 2014). However, these approaches do not account for variations in the rate and extent of application of these technologies (Kunzekweguta, Rich & Lyne, 2017). Consequently, Kunzekweguta *et al*. (2017) constructed and used a conservation agriculture index which is based on these components: number, relative importance, rate and extent of application of technologies. According to the authors, the index is a "continuous variable that accommodates partial adoption and analytical techniques that cannot be used with binary or ordinal dependent variables". The index is expressed as:

$CAI_i = \sum W_{ir} R_{ir} P_{ir} S_{ir}$………………………………..……………………………...9

The yield weights, W_{ir}represents the perceived contribution of each or a combination of conservation agriculture strategies to yield. It accounts for differences in the perceivedimportance of the conservation agriculture strategies. It either can be estimated from field experiments, expert opinions, or through regression estimations. R indicates the rate of application of the conservation agriculture strategy (or combination of strategies) compared to the recommended application rate of the strategy. It is a ranking score based on farmer perceptions and takes the value of one (1) for a farmer who adheres to the recommended practices of the technology and zero (0) otherwise. P is the proportion of the total land area cultivated using conservation agriculture strategies. S, which accounts for the absolute differences in the extent to which households apply conservation agriculture techniques, is the area of the individual i_{th} plot relative to largest plot in the data set. This approach is adapted in this study to measure the intensity of use of climate-smart adaptation practices, at plot and household levels, by using weighted perception index to measure the contributions of each climate-smart adaptation practice. This is considered adequate to better capture the unobserved extent of contributions of adaptation strategies compared to using dummies to generate such contributions.

2.3.1.4. Behavioural intention to adapt to climate change

The indicator for intention to adapt to climate change is based on the outcomes of the risk and adaptation assessments(Grothmann & Patt, 2005). These are measured based on four predictors: risk perception, perception of adaptive capacity, risk experience and social identity (Blennow & Persson, 2009; Frank *et al*., 2011; Truelove, Carrico & Thabrew, 2015; Roesch-McNally, 2016). Risk perceptions are based on subjective assessment of risk (Doss *et al*., 2005). When faced with external pressures especially those associated with climate change, individuals would act only after assessing the perceived probability and magnitude hence, potential consequences of occurrence of climate risks (Alam, Alam & Mushtaq, 2017), and availability of capacities to avert or reduce the impacts of such pressures (Grothmann & Patt, 2005; Truelove *et al*., 2015). These perceptions concerning climate risks and capabilities strongly and positively influence farmer's support for adaptation (Roesch-McNally, 2016). The extent of farmer's risk perception can be determined using the risk perception index, which combines farmer's perceived expectancy of climate risk exposure and severity of such exposure if they occur (Grothmann & Patt, 2005). As such, risk perception measures the anticipatory behaviour of farmers. Operationalizing this, Frank *et al*. (2011) measured perceived risk index as sum of the product of frequency (f) of experienced climate event types identified by the farmer and the perceived severity (s) of the impact of each event type [i.e. risk perception index =sum (frequency, f_i * severity, s_i)]. Similarly, perceived adaptive capacity has been found to significantly explain farmers' adaptation behaviours (Blennow & Persson, 2009). Grothmann andPatt (2005) identify three independent predictors of perceived adaptive capacity, namely; perceived adaptation efficacy, which highlights the extent of farmer's belief in the effectiveness of adaptive responses to climate risks (Frank *et al*., 2011); perceived self-efficiency, which shows how confident the farmer is with his/her knowledge and skill to implement the adaptive responses; and perceived adaptation cost which represents the anticipated cost associated with the adaptive action (Grothmann & Patt, 2005).

Furthermore, risk experience as a predictor of intention to adopt measures the severity of a risk experienced in the past. Unlike risk perception, which is based on uncertainty in risk occurrence and behaviour, risk experience captures the intention to adopt associated with previous individual experiences with hazard events and thus, explains behaviours based on events, which had previously occurred (Grothmann & Patt, 2005). In recent times, the social dimensions of intention to adopt has been considered in the cognitive assessment of intention to adopt. This is because individuals do not act independently of cultural/social influences, but continually refer their behaviour back to the important reference group(s) (Burton, 2004 cited in Borges *et al.*, 2015). Social identity construct refers to behaviours exhibited, based on the influence of group membership (Frank *et al*., 2011; Borges, Foletto & Xavier, 2015). Justifying this construct as a predictor of climate change adaptation behaviour, Patt and Schröter (2008) and Frank *et al*. (2011) argue that if it can apply to actors' perception in other areasof climate-related information, social capital can also influence adaptation behaviour. It is operationalized using participation or membership to cultural/social or farmer organizations/groups such as farmers' cooperative societies (Herath & Takeya, 2003; Borges *et al*., 2015), and occupation of leadership position. The roles of social networks in predicting adaptation decision making, have also been identified in Roesch-McNally (2016). For each of these behavioural outcomes and following relevant literature discussed above, this study constructed an indicator based on farmer responses.

2.4. Determinants of climate change adaptation practices: A review of empirical studies

There are numerous empirical literature on the factors that explain farmers' adaptation behaviour towards agricultural innovations. These factors are usually selected based on theory and test (Knowler & Bradshaw, 2007) and analysed using any of the parametric and non-parametric statistical methods, including the ordinary least square (OLS) method, probit/logit regression, random effects generalized least square (RE – GLS), and linear probability model (LPM). The choice of estimation technique, however, depends on the nature of the dependent variable (categorical or continuous). For instance, the normality distributional assumptions often associated with continuous dependent variables that can take large range of values, make the OLS regression technique adequate for continuous variables. The use of probit/logit model is adequate, when dichotomous/binary dependent variables are involved and the normality assumptions of the dependent variable is not needed, the relationship between the dependent and independent variables is assumed to be non-linear, and the error term is not normally distributed. Poisson estimation technique is suited for analysis of a count data dependent variable. A count variable does not have normal distribution, but, Poisson distribution, which is entirely determined by its mean (Wooldridge, 2012, 2016)

Farmers' socioeconomic and behavioural factors, farm and climate variables, as well as ecological factors, have been identified as influencers of choice of climate change adaptation practices used by farmers. These socio-economic influencersinclude; education, experience, farm income/wealth status, extension and credit access,availability of market services, and social capital (Temesgen*et al*., 2008; Hisali *et al.*, 2011; Komba & Muchapondwa, 2012; Yegbemey *et al.*, 2013; Hadgu *et al.*, 2015). The nature of the influence of these factors, however, differs across adaptation methods. For instance, farmers' educational level has significant positive effect on the use of such adaptation measures assoil conservation practices, adjustment of plantingtime, drought-tolerant varieties, irrigation and crop varieties (Temesgen*et al*., 2008; Hadgu *et al*., 2015; Ali & Erenstein, 2017). These differ from Komba & Muchapondwa (2012) and Shikuku, Winowiecki, Twyman, Eitzinger, Perez, Mwongera and Läderach (2017), which for instance, reveal a significant negative impactof education on useof drought-tolerant varieties and the changing of planting dates, as climate change adaptationstrategies. Uddin *et al*. (2014) however show that education favours the use of climate change adaptation strategies in general.

In Northern Benin, farmers' choice of crop diversification, farming practices and timeadjustment, and land use practices as climate change adaptation strategies are significantly and positively influenced by gender, credit access and experience, respectively (Yegbemey *et al*., 2013). Ahmed (2016), Ali andErenstein (2017) and Mulwa *et al*. (2017) show that extension contactshas a significant positive effect on such adaptation strategies as adjustment in plantingtime, drought-tolerant and disease/pest-tolerant varieties and change to new crops. Also, Hisali *et al*. (2011) study in Uganda identifies a significantly positive effect of age of household head on the choice of labour supply as drought coping option. Labour availability would significantly encourage the use of crop diversification, soil and water conservation measures, but decreases the probability of the adoption of early planting and use of disease/pest-tolerant varieties as adaptation practices(Mulwa *et al.,* 2017). The effect of various indicators of social networks also varies across adaptation strategies. For instance, Mulwa *et al*. (2017) show that, membership to farmer groups would significantly reduce the probability of farmers' useof drought-tolerant crop varieties, while group cohesiveness has a significantly positive relationship with the adoption of climate change adaptation methods (Ofuoku & Agbamu, 2012; Uddin *et al*., 2014). Shikuku *et al*. (2017) reveal that, group membership has a significant positive effect on terracing strategy but negativelyaffects the use of pest-resistant variety. This is consistent with Mulwa *et al*. (2017). Other socio-economic factors thatsignificantly and positively influence the use of climate change adaptation strategies include asset/livestock ownership, food security status of household, and credit access (Temesgen*et al*., 2008; Hadgu *et al*., 2015; Ahmed, 2016). Those with significant negative effect include; household distance to the market, plot distance to farmers' home, social responsibility, household head's civil status, and poor access to amenities like water (Arimi, 2014; Ahmed, 2016).

The behavioural factors which determine farmers' choiceof climate change adaptation strategies include; the level of perceived risk, beliefs, risk assessment, and adaptation abilities (Grothmann& Patt, 2005; Patt & Schröter, 2008;Hisali *et al*., 2011; Mulwa *et al*., 2017;). According to Grothmann& Patt (2005), these socio-cognitive or psychological factors have a significant effect on farmers' general decision-making processes on the use of climate change adaptation strategies. Mulwa *et al*. (2017), for instance, show that drought experience by farmers would significantly favour the use of such adaptation methods, as; drought-tolerant varieties, early planting, crop diversification, and soil and water conservation measures.

Further studies such as; (Hassan & Nhemachena, 2008; Yegbemey *et al*., 2013; Uddin *et al*., 2014; Ali & Erenstein, 2017; Mulwa *et al*., 2017) have suggested various farm factors including farm size, soil fertility and tenure status as influencers of the use of climate change adaptation strategies. For instance, Hassan andNhemachena (2008) observe a significant positive effectof farm size on farmers' use of multiple cropping and mixed farming as adaptation strategies, while Uddin *et al*. (2014) reveal a significant negative relationship between farm size and adaptation to climate change. Shikuku *et al*. (2017) specifically indicate a negative relationship between farm size and the use of pest-resistant variety. In their studies, Di Falco *et al*. (2011) and Mulwa *et al*. (2017) indicate that when farms are perceived to be highly fertile, there is significant decrease in the use of adaptation strategies, including; drought-tolerant varieties, early planting, and crop diversification strategies.

Weather variables also affect farmer's choice of adaptation strategies. Temperature and precipitation, for instance, have significant positive and negative effects, respectively, on soil conservation, as choice of adaptation practice, while average temperature has a significant positive effect on the use of short-season crops, crops resistant to drought and irrigation choices asadaptation methods (Temesgen*et al*., 2008; Komba & Muchapondwa, 2012). Average rainfall has a significant positive influence on irrigation on drylands (Hassan & Nhemachena, 2008), but a negative effect on changing crop planting dates and tree planting methods of climate change adaptation. (Komba & Muchapondwa, 2012). Bezabih *et al*. (2013) indicate that changes in climate variables is a significant determinant of soil conservation, while farmer access to weather information has a significant positive effect on the use of climate change adaptation practices (Di Falco *et al*.,2011; Arimi, 2014; Ndamani & Watanabe, 2016). Further, Shikuku *et al*. (2017) show that erratic and delayed rainfall have significant positive effects on farmers' choice of climate-smart adaptation strategies, with erratic rainfall decreasing the use of mulching, as an adaptation method.

2.5. Farm productivity and welfare implications of climate-smart adaptation strategies

This subsection focuses on existing literature onimpacts of climate-smart adaptation strategies on farm productivity and household welfare. Many studies have evaluated these outcomes vis-à-vis farmers' decision to adopt several strategies.

Di Falco *et al*. (2011) assessment onadaptation impacts oncropyieldin Ethiopia,shows that, such adaptation strategies as varying crop varieties and usingsoil and water conservation methodshave significant positive impacts on crop yields. Both strategies are most likely to support increased resilience levels of farming.A recent follow-up study in the same country by Di Falco andVeronesi (2013) show that, a significant net revenue increase is achieved, when adaptation strategies are implemented as a basket rather than in isolation. Specifically, the study shows that, combining knowledge-smart technology (changing crop varieties) with either water (water conservation) or sustainable soil conservation – smart strategies resulted in significantly higher farm net revenue compared with the application of any of these strategies in isolation. In cost-benefit terms, the study also indicates that, the higher the intensity of usage of these adaptation strategies, the lower the returns to their investments. As such, cost threshold resulting from adaptation of multiple and complex strategies could be exceeded, such that, negative monetary returns is accrued to the farmer.

Similarly, adaptation strategies implemented simultaneously increase net farm income on a maize farm compared with those used in isolation (Teklewold, Kassie & Shiferaw, 2013). The use of three climate-smart adaptation strategies, namely; improved crop varieties, land levelling using, laser technology and no-till method by farmers, in the Indo-Gangetic plains of India, under rice-wheat farming system, indicates that, though each strategy can contribute to increase in net income, their combinations significantly improve yield and net income in the farming system and are recommended for national scale-up (Khatri-Chhetri *et al*., 2017). Furthermore, Arslan *et al*. (2016) examined the productivity impacts of selectedclimate-smart agricultural practicesused by smallholder maize farmers in Zambia. These strategies include; reduced or minimum tillage, crop rotation, and legume intercropping. Certain combinations of these inputs were jointly used,with improved seeds and inorganic fertiliser. While reduced tillage and crop rotation in combination with improved seeds and chemical fertilisershow no significant impact on maize yield, legume intercropping with these modern inputs but improves both yield and yield variability on maize farms. Welfare analysis of zero or no-till practice among small and medium scale farmers in Karak Governorate, Jordan by Akroush, Yigezu & Hadi (2015) show that, the significant increase in farmers' net farm income is attributable to the adoption of the technology.

Douxchamps *et al*. (2016) assessed the linkage between crop diversity, soil and water conservation, agroforestry, small livestock herding, improved crop varieties, fertilizers, and households' food security levels in three West Africa countries of Burkina Faso, Ghana and Senegal. Their findings show that, intensity of usage and impacts of these strategies on productivity and vulnerability vary, depending on households' market orientation. Households with diversified and intensive farming systems with high market orientation, tend to achieve significantly higher farm productivity with the implementation of climate change adaptation strategies, compared with households practising subsistence and extensive farming systems, but with low market orientation. As such, this study concludes that, the adoption of agricultural practices does not have a homogenous effect on farm productivity and consequently, there is food security status of households. The study of Asfaw, Di Battista & Lipper (2016) in Niger show the time variable effect of adaptation strategies on crop productivity under climate change.Following this study, the use of such technologies as inorganic fertilisers and improved inputs results in higher crop productivity increase, in the short term, compared with the use of crop residues of which yield returns are experienced slowly. In astudy, Arslan *et al*. (2016) also determined the effects of intercrop of maize and legume, conservation agricultural practices, use of fertilisers (organic and inorganic), and high-yielding seed varieties on maize yield in Tanzania and posit a similar explanation for the non-significant relationship between organic fertilizers and maize yield. In addition, they opine that, for the use of improved seed to achieve yield increase, it must be combined with inorganic 35ommercial. This highlights the need to adopt some productivity-enhancing technologies as a portfolio rather than in isolation, if the intended result is to be achieved. Furthermore, the study reveals that the application of the characteristically climate-smart technologies, namely,intercrop of maize and legume, and conservation agricultural practices can increase maize yield by an average of 10 and 14 percent, respectively. In Malawi, Asfaw *et al*. (2015) show that, the implementation of modern land management practices has significant positive impacts on the productivity of maize. However, the level of impact depends on climate risk exposure and sensitivity of the farm. They conclude that, crop productivity of farms in areas of higher climate risk exposure and sensitivity can be increased using sustainable land management strategies, whereas inorganic fertilisers and improved seeds contribute significantly to crop yield in areas with lower climate risks, implying the need to consider farm vulnerability to climate change before adaptation decisions. A similar result was obtained for rice in Ghana where promotion and adoption of high yielding, disease and pest-resistant rice varieties facilitated the using of knowledge-based strategies including; demonstrations, training courses, community seed production, etc. showed evidence of increased rice yield (Buah *et al*., 2011). Also, Sain, Loboguerrero, Corner-Dolloff, Lizarazo, Nowak, Martínez-Barón, and Andrieu (2017),evaluateseveral climate-smart agricultural technologies focusing mainly on water (contour ditches, stone barriers, water reservoirs/ponds and drip irrigation), carbon (agroforestry), energy (crop rotation and conservation tillage with mulch), and knowledge (improved seed varieties) – smart technologies in Dry Corridor in Guatemala indicated that, the cost-benefit analyses of the private profitability of the adoption of these practices on the average are profitable, with a payback period of about four years, reflecting their time influence on productivity and income.

Gill (2014) identified the advantages of land levelling,using lasser techniques as a climate change adaptation strategy to include; improvement in crop yields, decreasein water requirement for both land preparationand irrigation, increase in natural resource conservation and reduction in emissions that exacerbate climate change. The adoption of this strategy improved yield increase of both rice and wheat by an average of 330 kg/ha through efficient use of fertilizer and water, in addition, to increase in farm income and a reduction in time (pumping and cultivation) and energy spent on irrigation. Afolami, Obayelu and Vaughan (2015) as Simtowe *et al*. (2012) showedevidence of a positive effect of different crop varieties on household welfare by comparing the use of improved and local groundnut varieties and found that improved groundnut varieties returned higher yields to adopters than farmers using local groundnut varieties. This consequently results in higher net income among adopters of improved groundnut varieties compared with non-adopters. Evaluating the adoption impacts of high-yielding rice varieties on farm households' wellbeing in rural Bangladesh, Mendola (2007) argue that, theincrease in rural incomes through the diffusion of modern farming technology is important, as shown by the significant positive effect of improved rice varieties on yield. Similar yield and consumption expenditure effects were reported by Amare, Cissé, Jensen & Shiferaw (2017) for farmers in Tanzania who adopted maize – pigeon pea intercropping system. Furthermore, Makate *et al*. (2016) observed that; crop productivity, income, food security and nutrition at household level improve alongside an increase in the rate of adoption of crop diversification. The study therefore suggests crop diversification as a viable climate-smart agriculture practice, that can significantly enhance crop productivity and consequently, aid resilience in rural smallholder farming systems. In their recent study of the productivity effects of urea deep placement technology in rice production in Niger State, Nigeria, Liverpool-Tasie *et al*. (2015) found that this inorganic fertilizer intensification practice has the potential to raise rice yield by up to 15% with possible additional increases, under good management practices, including adopting the recommended application rate at the prescribed placement depth. Rahman andBarmon (2015) observed similar result in Bangladesh where an average of 13% increase in yield is achieved for rice farms under urea deep placement technology compared with those under the conventional urea fertiliser. The study by Arslan *et al*. (2018) in Zambia identify livelihood diversification as having the potential to contribute to the componentsof climate-smart agriculture particularly, food security, through the increase in household income and decrease in poverty incidence.

2.6. Insights from literature

The in-depth review of literature in the preceding sections is done to understand what has been done and highlights various methodologies and techniques, including the emerging ones that improve empirical findings and policy recommendations. The review shows that though several empirical studies have been carried out in climate change thematic area, research gaps especially, those associated with use of adaptation strategies and returns to farmers' use decision, still exist.

Generally, strategies to adapt to climate change are not new, but continue to evolve.Their use by farmers and differential effects are often influenced greatly by socioeconomic, environmental and biophysical factors. Literature identifies outcomes of risk and adaptation appraisal processes as major determinants of farmers' use of adaptation strategies. However, the predictors of these constructs have been separately studied. This study intends to analyse models under joint interactions of these predictors and improve on their policy information. On methodological front, the review indicates the various strengths and weaknesses associated with welfare and productivity measurement, particularly, under developing country smallholder scenario. For instance, literature abound on welfare measurement by income, consumption expenditure, and asset approaches, but the multidimensional welfare indicators are considered better due to their insulation to the challenges in the use of the former proxies. This informs the choice of the indicator in this study. In addition, the choice of weighted perception index improves on the strength of intensification index constructed by Kunzekweguta*et al*. (2017).

The emerging analytical technique, the conditional recursive mixed-process (CMP) modelling framework based on the seemingly unrelated regressions (SUR) setup is discussed. This technique allows for the mixing of different systems of equation, where the dependent variable of each equation canhave differentcharacteristics. Unlike other frameworks, this allows for sequential modelling and analysis of several multi-equations without instrumentation.

It is, therefore, evident that this section provides an understanding of climate-smart adaptation strategies, and the basis for the choice of both conceptual and analytical frameworks necessary for this study.

CHAPTER THREE

METHODOLOGY

This section discusses the study area, sampling techniques, and the analytical tools used to achieve the objectives of the study.

3.1. Study area

This study wascarried outin the Southern Guinea Savanna (SGS) and the DerivedSavanna (DS) agroecological zones (AEZs) of Nigeria. These zones express distinct climatic conditions that influence their capacity to support rainfed agriculture. However, staple crop production remains a significant agricultural activity in both AEZs. The zones also represent the transition corridors between the southern and northern parts of Nigeria. The derived savanna is found immediately north of the humid forest, southern Nigeria and it is characterized by regular bush burning particularly during the dry season, reduced tree cover, and fallow areas with predominantly matured woodland, relics of patches of high forest or forest tree, and climbers growing on relatively dry ground, which receives water only from rain (Adegbola &Onayinka, 1976). Dominantsoil types in the zone are Ferrasols, Luvisols, Nitosols, Arenosols, Acrisols and Lithosols (Salako, 2004). The southern Guinea savanna zone lies to the immediate north of the derived savanna and it is covered with open savanna woodland and tall grasses. Its soil types include; Luvisols, Acrisols, Ferralsols and Lithosols. Salako (2004) and Wada, Kehinde, Ukwungwu, Adagba& Usman (2013) describe the soil types in the zones, as low in organic matter and chemical fertility and would require soil conservation measures, inorganic and organic fertilizers to improve their soil physical qualities.

The derived savanna agroecological zone runs across states of Kogi, Nasarawa, Ekiti,Enugu and Benue, while the states of Niger and Adamawa are predominantly within the southern Guinea savanna. Both the SGS and DS zones run across the states of Oyo, Kwara and Taraba, while Plateau has three agroecological zones of northern and southern guinea savannas, derived savanna, and mid-altitude zones across its landscape (Figure 2).These AEZs in addition to the northern guinea savanna (NGS) constitutethe most extensive agroecological zone in Nigeria – the savanna. The SGS and the DS zonescombine the grains (cereals and pulses) production potentials of the north and the root/tuber production potentials of the southern part of Nigeria and therefore have great opportunities for farmingactivities (Adegbola &Onayinka, 1976). The zones are noted for the farming of crops including; maize, millet, rice, sorghum, ginger, cowpea,groundnut, cassava and yam which are either in themonocropping or intercropping system (Ajeigbe, Singh, Musa, Adeosun, Adamu & Chikoye, 2010; Foli, 2012).

The prevailing environmental and cropping characteristics in the AEZs can be described in terms of length of growing period, amount of rainfall received, and cropping system. For instance, the length of growing period in the southern Guinea savanna is 181-210 days and 211-270 days for the derived savanna/coastal savanna (Jagtap, 1995), and the amount of rainfall received is 1000 mm in the northern end of the southern Guinea savanna and 1800 mm in the southern end of the derived savanna (Adegbola &Onayinka, 1976). The cropping system is intensive in the SGS,while increased crop diversity is dominant in the SGS zone (Foli, 2012).

The zones are characterized by large year-to-year rainfall variability (Odekunle *et al*., 2007; Ogungbenro &Morakinyo, 2014) and drought-prone (Woomer*et al*., 2014) leading to differences in crop yield rates (Odekunle *et al*., 2007). The coefficient of rainfall variation is between 15 – 20 percent in the guinea savanna zones and between 10 – 24 percent in the derived savanna zone, with increasing flood risk in both agroecological zones (Aremu, Bello, Aganbi & Festus, 2017). Also, Oladipo (2010) perceivesreduced soil moisture, because of less rainfall and increasedtemperature in the savanna areas particularly in the northern parts of Nigeria. These environmental anomalies are responsible for most crop failures in the zone (Nwajiuba*et al*., 2015).

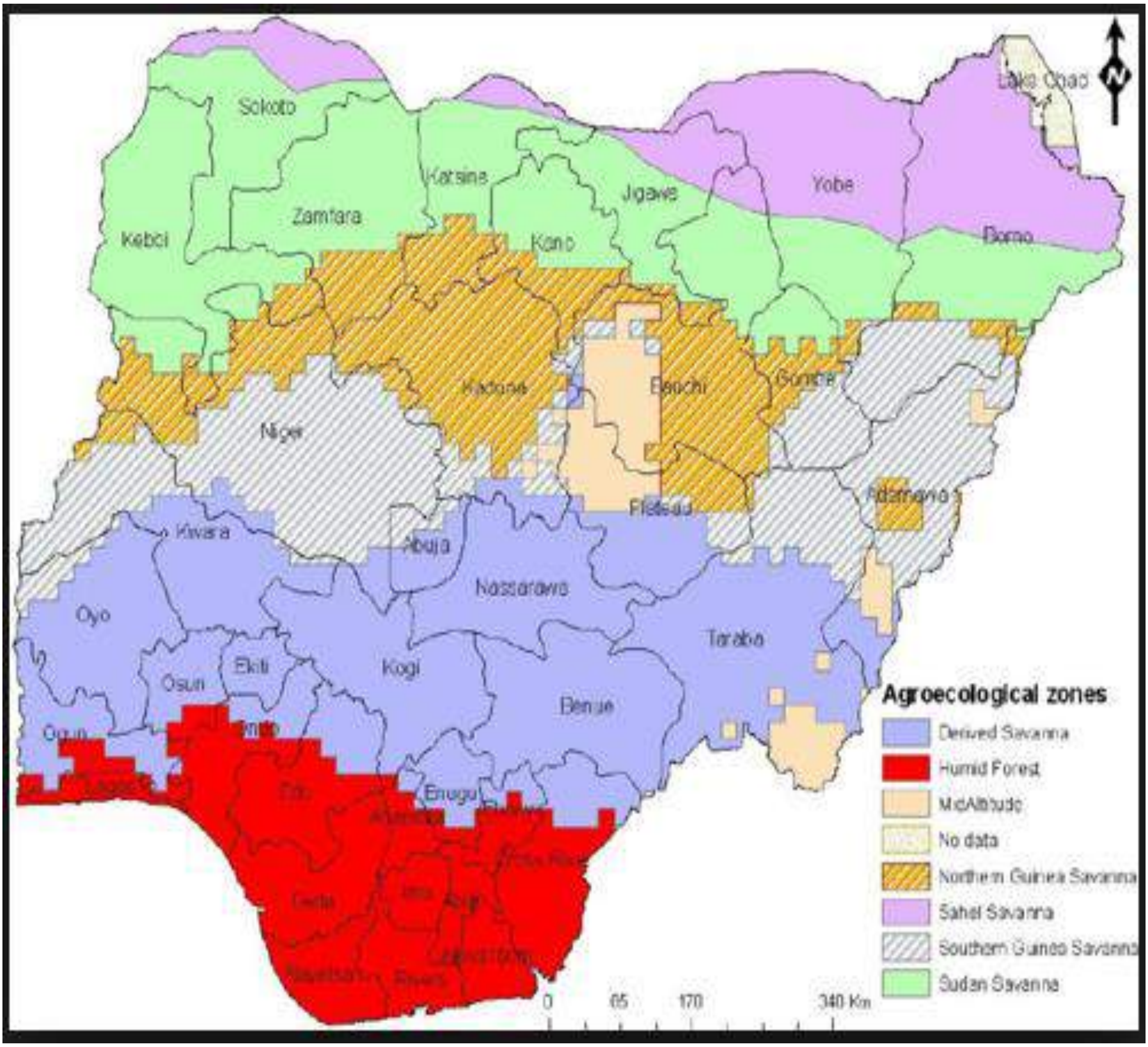

Figure 2: Map of Nigeria showing the agro-ecological zones and their states
Source: Salako, 2004

3.2. Sources and types of data

Primary data,using a structured interview schedulewas collected and used for this study.The interview instrumentwas pre-tested for appropriateness and revised based on the pre-test feedbacks, before it was administered on the sample respondents. Information collected include those relating to demographic andsocio-economic characteristics,plot level data on farm inputs including CSA strategies, crops-based CSA strategies, agricultural production, climate-related risks and farmers' risk experiences and perceptions, etc. Table 1 shows the data needs by objectives of the study.

3.3. Sampling procedure

A three-stage sampling procedure stratified by two well-defined agroecological zones (SouthernGuinea Savanna and Derived Savanna)was used in this study. It involved the use ofstratified and simple randomsamplingtechniques,to select required respondents for this study. The States that are distinctly located in each of the two agroecological zones (AEZs) (SGS and DS) were grouped as a stratum. Hence, the two AEZs were considered as two different strata. The use of strata allows for smaller error of estimation to be produced and allows for precise information inside the subpopulations, about the variables under study (Barreiro & Albandoz, 2001). Hence, this sampling allows for identification of distinct spatial characteristics between the two zones (SGS and DS) within the same region.The probability proportional to size accounts for population differences (assigning self-weights) andit is adequate for indicating the number of enumeration areas (Eas) selected, while the simple random sampling technique was used to physically select the Eas and the households interviewed. Administratively, each state isdivided into Local Government Areas (LGA) and each LGA divided into localities. Each locality was further divided into enumeration areas (Eas) by the National Population Commission (NPC) for population census purposes.In the states selected for this study, the frame of Eas used underthe National Integrated Survey of Household (NISH) system by the National Bureau of Statistics (NBS) to conduct its household-based survey was adapted. In this system, 30 Eas had randomly been pre-selected from each of the 774 LGAs in Nigeria through systematic sampling.

In this study, the sampling stages were as follows: First, a simple random sampling technique was used to select astate per stratum. Accordingly,Niger State with 25 LGAs was randomly selected from the SGS and BenueState with 23 LGAs from the Derived savanna zone.Following this selection, the rural LGAs in each of the states were identified with the assistance of states ministry of agriculture and natural resources staff specifically from Department of Planning, Research and Statistics (DPRS) and the Agricultural Development Programme (ADPs) as follows:

i. **Benue State Rural LGAs (n=16)**:

Ushongo, Konshisha, Logo, Gwer East, Gwer West, Buruku, Tarka, Apa, Ado, Obi, Oju, Agatu, Aogbadibo, Okpokwu, Ohimini and Guma

ii. **Niger State Rural LGAs (n=18)**:

Agaie, Gbako, Edati, Katcha, Lavun, Bosso, Gurara, Munya, Paikoro, Shiroro, Rafi, Tafa, Agwara, Magama, Mariga, Mashegu, Rijau, and Wushishi

Due to high level of insecurityassociated withconflicts and violence, and the difficult terrain in some locations of both states, the above identified rural LGAs were further evaluated, with the help of staff of the state ADPs and informal interactions with security operatives in the state, for accessibility for data collection.

In the second stage, a total of 33 EAs were randomly selected for this study. The sample of EAs picked allows for concentration of the study within focused geographically delineated area.

In the last stage, a purposive selection of representative farming households from the sampled Eas was carried out. At this stage, purposive sampling was used because not all the people in the Eas are engaged in the crops (rice, maize, millet, sorghum, yam, cassava, groundnut, soybean, and cowpea) of interest to the study. It is important to focus directly on farmers cultivating these crops, so the type of crops cultivated by farmer is the main criteria of selecting respondents for the study.

Using the Cochran (1977) formula, the statistically relevant number of respondents for the study was determined as follows:

$$n_{hhd} = \frac{z^2pq}{e^2} \, ,$$

where,

n_{hhd}= the number of households (sample size) required for this study; z = the selected critical value of desired confidence level usually at 95% level (z =1.96); p = the estimated proportion of farming attribute (smallholder crop farming) that is present in the population. This is assumed to be a maximum variability of 50% (p = 0.5); q=1 – p; and e = the desired level of precision of ±5% (e = 0.05), a total of 384 representative households were required for the study. However, 450 households were selected and interviewed across the Eas (Table 1).

3.4. Analytical techniques and models

This section describes the analytical tools employedfor analysis of the stated objectives. These tools include; descriptive statistics, Ordinary Least Square (OLS)multiple regression, multivariate (MV) probit estimation, heterogeneous treatment effect(I) based on propensity score matching (PSM) technique, and the conditional recursive mixed-process (CMP) modelling framework (CMP) involving, probit and OLS estimation. The analytical tool(s) for each objective is presented in Table 1.

Table 1: Analysis of objectives of the study

S/No	Objective	Analytical tool(s)/ level of analysis	Data used
1	describe the types of CSA strategies used by staple crop farmers	Descriptive statistics (Household level)	Various climate-smart technologies used by households and crops produced
2	examine the factors that determine the choices of CSA strategies of small-holder arable crop farming households	Multivariate probit estimation (Household level) Tetrachoric correlation	Various climate-smart technologies used by households, socio-economic and behavioural intention variables
3	analyse the determinants of intensity of use of CSA strategies	Ordinary least square (OLS) estimation Poisson estimation* (Household level)	Climate-smart intensification index, farmer, and households' socio-economic and demographic characteristics
4	determine the productivity and welfare effects of usage of CSA strategies	CMP modelling framework involving probit and OLS regression estimation	Climate-smart intensification index, crop yield and its production inputs, household welfare status constructed

		Heterogeneous treatment effects based on propensity score matching technique (Plot/household level) Seemingly Unrelated Regression Analysis*	using the indicators of the three dimensions (education, living standard, and health), households' socio-demographic,spatial and plot characteristics
5	Identify the constraints to the use of CSA among staple crop farmers	Descriptive statistics, mainlyGarrett ranking score (Household level)	Farmer-identified and ranked constraint variables

NB: *Alternative estimation technique for robustness check

3.4.1. Descriptive statistics

The descriptive analyses employed include; frequencies, proportions, means,standard deviation, and the Garrett's ranking technique.

The Garrett's ranking technique is based on normality assumption in the trait for which ranking is made. The formula is given as:

Percent position $= \frac{100(R_{ij}-0.5)}{N_j}$,

whereR_{ij} is the rank assignedto *i*th constraintby the *j*th farmer and N_j is the number of constraintsranked by the *j*th farmer. The calculated percent position of each assigned rank was converted into scores,using the table developedby Garrett and Woodworth (1969). This table assigns to each constraint a "problem weight" on a scale of 100 points. For everyconstraint (factor), the score of respondents were summedtogether and then divided by the total number of the respondents. The authors explained that, such scores define the contribution of constraints better than a rank of 1, 2, 3, etc will.

3.4.2. Multivariate probit (MVP) estimation model

Following Mulwa *et al*. (2017) and Asfaw *et al.* (2016), the basic multivariate probit model is specified as:

$$CS_i = \alpha_0 + \alpha_1 hhdage + \alpha_2 depratio + \alpha_3 hhdgender + \alpha_4 hheduc + \alpha_5 hhsize +$$
$$\alpha_6 hhdgrpmemb + \alpha_7 plottopo + \alpha_8 crdtconst + \alpha_9 hhdriskexp +$$

$\alpha_{10}hhdriskpercep + \alpha_{11}hhdadaptcap + \alpha_{12}plotfertpercep + \alpha_{13}tenurestat + \alpha_{15}agrozone + \varepsilon_i$…...………………………………………………………………………….10

$CS_i$are the dependent variables measured as binary outcomerepresenting the list of climate-smart adaptation strategies a farmer used in the last 10 years to combat climate-related shocks such as;drought, flood, crop pests and diseases, among other shocks. To ensure that these strategies are based on climate shocks, respondents were asked about their personal perceptions on changes in local climate over the last decade (ten years) and probable future concerns, and their experiences with climate-related shocks. Following this, farmers were requested to identifystrategies they had used and those they intend to use to reduce the effects of the shocks.The former responses were used as outcome variables in the multivariate probit analysis.α_i $(i = 0, 1, 2, 3, \ldots\ldots, 15)$ are unknown parameters, and ε_i $(i = 1, 2, 3, 4, 5, \ldots\ldots\ldots, n)$ are the random errors in each outcome model distributed as a zero mean, unitary variance multivariate normal distributionand an $n\ x\ n$vector correlation matrix. The independent variables and their *apriori*expectations arepresented in Table 2.However, these variables were subjected to principal component analysis (PCA) after standardization to summarize their variability. PCA, a useful technique for transforming many variables, is often used in data analysis to obtain smaller and clearer set of uncorrelated (orthogonal) factors known as principal components (Krishnan, 2010). Using the eigenvalue-one criterion (Kaiser criterion), any component with an eigenvalue greater or equal to one (1) was retained, since such component accounts for a greater amount of variability than had been contributed by singlevariable.Further, the tetrachoric correlation, which is a Pearson correlation estimate that assumes a latent bivariate or joint normal distribution for each pair of variables, was used to assess and describe the nature of the combinations of the CSA strategies by farmers. Adaptation strategies are considered simultaneously used by farmers, if the coefficient of the tetrachoric correlation is significantly high and positive. If the coefficients are significantly high and negative, the use of both technologies are considered to be mutually exclusive (Rauniyar & Goode 1992; Sharma, Kumar & Yadav, 2014).

Table 2: Description of explanatory variables used in the various models (multivariate probit, OLS, and CMP estimations)

Variable	Definition	measurement	Expected sign/explanation

Variable	Definition	measurement	Expected sign/explanation
hhdage	Age of household head	Years	(+/-)Age as a proxy for experience and if correlates with risk aversion, older farmers are more likely to adopt climate-smart strategies due to possible experiences of climate-related hazards.
depratio	Household dependency ratio which relates to the number of children (0 – 14 years old) and older persons (65 years or over) to the working-age population (15 – 64 years old) (UN-DESA, 2006)	Per 100 persons aged –5 - 64	(+/-) Households with high dependency ratio are less likely to adopt and use local climate-smart technologies since there would be less available person-day. However, the probability of using modern labour saving strategies may be higher.
hhgender	Gender of household head	Dummy (1=Male)	(+) The likelihood of male headed households to adopt climate-smart technologies is more,since they are expected to have more control of resources. If female households are risk averse, adoption of CSA practices, would also be favoured.
mstat	Marital status of the household head	Dummy (1 = Married and living with spouse)	(+) Married household heads living with their spouse(s) are more likely to use climate-smart technologies, due to possible joint decision making.
hheduc	Educational level of household head	Years of schooling	(+) Better educated households are more likely to apply CSA technologies
hhsize	Adjusted household size	Adult equivalent	(+/-) Small-sized households are less likely to adopt labour-intensive technologies,but they will readily adopt labour saving strategies.
hhdnature	Nature of households indicating monogamous or polygamous category of the household	Dummy (1 = Monogamous household)	Monogamous households are expected to have better level of multidimensional welfare level, due to reduced competition for familial resources
hhdgrpmemb	Membership of social/cultural/farmer group of one or more household members	Dummy (1=Member of group)	(+) This variable is a proxy for farmers' social capital and provides opportunity for human capital and information sharing, which are likely to promote

Variable	Definition	measurement	Expected sign/explanation
			technology adoption
plotcultyr	Years of cultivating plot	Years	(+) Use intensity of climate-smart adaptation strategies is expected to increase on plots, that have been under cultivation for several years
mktdist	Distance of household to the nearest input/output market	Km	(+/-) Nearness to markets (input or output) increases market information and access to modern farm technologies, but may tend to decrease the use of local technologies.
roadaccess	Walking distance to the nearest major road	Dummy (1 = less than 30 minutes walk)	(+/-) Nearness to motorable road is likely to increaseaccess to information and farm technologies; and consequently, increases intensity of use of CSA strategies
plottopo	Plot topography	Dummy (1 = Flat; otherwise = 0)	(+) Plots that are not flat are likely to need adaptation strategies, particularly, those that improve water retention and uptake and reduce erosion
crdtconst	A credit constrained household is one which was unable to access the amount of credit it intended in the last 5 years	Dummy (1= No credit constraint, otherwise=0)	(-) Credit access relaxes liquidity constraints of households, thus, increasing technology adoption
extaccess	Frequency of extension contact in last five years	Number	(+) Households with more visit of extension officers are more likely to be informed and therefore, use smart technologies that are risk reducing.
hhdriskexp	Drought/flood/pest and disease experience in last 10 years	Number of risk events experienced	(+) The higher the frequency of climate risk events, the more likely households would adopt CSA strategies, to ameliorate the impacts of such events
hhdriskpercept	Risk perception of household head	Risk perception index (sum of the product of risk frequency and severity)	(+) The higher the risk perception index, the more likely households would adopt CSA strategies
hhdadaptcap	Perceived adaptation efficacy of the household head	Weighted effectiveness of household's adaptive responses	(+) Climate-smart technologies perceived by the farmer as more effective in increasing farm yield, are more likely to be adopted.

Variable	Definition	measurement	Expected sign/explanation
plotfertpercep	Farm plot fertility perception (Weighted average soil fertility perception per household)	Soil fertility index (5=Very fertile, …..,1=Not at all fertile)	(-) Households are less likely to invest to improve the fertility of farm plots, that they perceive to be fertile.
tenurestat	Extent of household's perceived plot tenure security	Dummy (1=Secure, 0=Insecure)	(+) Households are more likely to invest in long-term strategies on plots, perceived to be better secured.
farmsize	Average size of farm cultivated per household[a]	Hectare	(+/-) The larger the farm size, the higher the probability of use of CSAstrategies,since farmers can use part of their land to experiment new adaptation strategies. However, those with small farms mightbe more likely to usestrategies that involve intensive management.
agrozone	Agroecological zone location of household	Dummy (1=SGS, 0=DS)	(+/-) The apriori expectation here is indeterminate since adaptation behaviour may depend on severity of climate-related risks in the area

[a]Average farm size was used for household level analysis while actual farm size was used for plot-level analysis

3.4.3. Climate-smart intensification index (CSI)

This index is the measure of usage and was constructed following the approach of Kunzekweguta *et al*. (2017) in equation (9).The equation highlights the need to account for thenumber, their relative importance, and variations in household's rate and extent of application of agricultural technologies on a given land. The variables for the construction of the index are presented in Table 3. Kunzekweguta*et al.* (2017) used econometric analysis to generate the contributions of conservation agriculture to crop yield.This study, however, used weighted perception index to achieve these contributions. This is considered adequate to better capture the unobserved extent of contributions of adaptation strategies,compared to using dummies to generate such contributions.

Table 3: Components of climate-smart intensification index construction

Variable	Definition	Measurement

W_{ir}	Perceived contribution of CSA strategy (or their combination) to crop yield	Weighted household perception of adaptation strategI, i, contribution to crop yield
R_{ir}	Perceived rate of application of the conservation agriculture strategy (or combination of strategies) compared to the recommended application rate of the strategy.	Ranking score (5=strictly adhered, …., 1=Not at all adhere)
P_{ir}	Proportion of the total land area cultivated, using conservation agriculture strategies.	Percentage (%)
S_{ir}	Area of the individual i_{th} plot relative to largest plot in the data set	Percentage (%)

3.4.4. Ordinary Least Squares (OLS) regression technique

Furthermore, objective 3 wasanalysed at thehousehold level, using the ordinary least square (OLS) estimation procedure following that, the dependent variable, climate-smart intensification index CSI_i per farming household,isa continuous one. This variable was generated by adapting Kunzekweguta *et al*. (2017) methodology presented in Equation 9. The independent variables were those related to plot and households' demographic and socio-economic variables and those defined in Table 4. The basic econometric model is:

$$CSI_i = \gamma_0 + \gamma_1 hhage + \gamma_2 hhgend + \gamma_3 mstat + \gamma_4 depratio + \gamma_5 hhdnature + \gamma_6 extaccess + \gamma_7 crdtconst + \gamma_8 hhdgrpmemb + \gamma_9 TLU + \gamma_{10} plotcultyr + \gamma_{11} mktdist + \gamma_{12} roadaccess + \gamma_{13} farmsize + \gamma_{14} plottopo + \gamma_{15} tenurestat + \gamma_{16} soilfertpercep + \gamma_{17} hhdriskpercep + \gamma_{18} agrozone + \varepsilon_i \ldots\ldots\ldots\ldots..11$$

Table 4: Description of explanatory variables in the OLS model

Variable*	**Definition**	**Measurement**	**Expected sign**
livestock	Number of livestock owned perhousehold	TLU**	+/-
CSAfreq	Number of years of use of strategies	Year	+

*****Other included variables are as defined in Table 3

**TLU is tropical livestock unit

3.4.5. CMP modelling framework with Probit and OLS regression estimation

In addition to the indicator of usage of CSA strategies, crop productivity and household-level welfare indicators were needed in the analysis of this objective. In this study, crop productivity was measured as the yield per hectare of the various staple crops under study. The indicator of household welfare,the multidimensional welfare, was measured as weighted deprivation score. The score is used to determine the welfare cut-off, which shows the proportion of weighted deprivations a household would experience,to be classified asmultidimensionally poor or otherwise. The dimensions of the multidimensional welfareare the global dimensions for multidimensional poverty index (MPI): education, health and living standard. Their respective indicators are as shown in Table 5.Eight of the indicators are same as the international MPI, while household food security was used as proxy indicator for nutrition indicator in the health dimension. Four additional indicators – number of persons (measured in adult equivalent) per bedroom, access to motorable roads, land ownership, and livestock ownership, were included as measures of living standard. These are considered adequate in the Nigeria rural setting.

Table 5:Multidimensional welfare dimensions and indicators

Dimension (Weight)	Indicator (weight)	Deprivation cutoff *Household is deprived if:*
Education (1/3)	Years of schooling (1/6)	No member has completed six years of schooling
	School attendance by school-age children (1/6)	Any school-aged child (5 – 14 years) in the household is not attending school. A household without school-aged children is considered non-deprived
Living standard (1/3)	Source of drinking water (1/30)	It does not have access to piped water, public tap, borehole, protected well, or safe water is more than 30-minute walk (round trip)
	Sanitation or toilet facilities(1/30)	It does not have ventilated improved pit, flush toilet/latrine,or improved toilet available is shared with other households
	Type of cooking fuel (1/30)	It cooks with animal dungs, charcoal or wood
	Electricity access (1/30)	It has no electricity (either from public or private sources)
	Roof, floor and wall types (1/30)	If the materials for the floor, roof, and walls are not modern
	Number of persons (measured in adult equivalent) per bedroom (1/30)	It has more than 2 persons per bedroom (Based on Canadian National Occupancy Standard; Adebayo and Iweka (2013))
	Access to motorable road (1/30)	It is more than 30-minute walk from the nearest major road
	Land ownership(1/30)	It owns less than 0.5 ha of farmland(Based on 2015/2016 Nigeria LSMS-ISA Household Survey Report)
	Livestock ownership (1/30)	It does not own more than three cattle, goat, sheep, pig, chicken, duck, guinea fowl.
	Asset ownership (1/30)	It does not own more than one radio set, TV, mobile phone, bicycle, motorcycle, or refrigerator; and does not own a car or truck
Health (1/3)	Food security (1/6)	Household suffers food shortage as indicated by the food consumption coping strategy index
	Child mortality (1/6)	Any child has died in the household

NB: A household is in good food security standing if it has a food consumption coping strategy score of less than 4.

Following Santos and Alkire (2011), the deprivation score, C_i for each household wasbe computed as:

$$C_i = w_1 I_1 + w_2 I_2 + \cdots + w_i I_i \text{..} 12$$

Where w_i = indicator weight, I_i = number of deprivations.

NB: Household is multidimensionally poor, if it experiences deprivation in at least 30% of the weighted multidimensional indicators.

Following equation 12, the multidimensional welfare indices of relevance to this study include;

i. Headcount ratio (H) – this identifies the percentage of the respondents that are deprived, at least eitherall the indicators of a single dimension or a combination across dimensions;
ii. Intensity of deprivation among the poor (A), which describes the average number of deprivations a poor person suffers and
iii. Adjusted headcount ratio (M_0), which indicates the share of the respondents that is multidimensionally poor adjusted by the intensity of deprivation suffered. It reflects the proportion of deprivations that the poor experiences in the study area, out of all the overallor potential deprivations that the study area could experience.

The modelling of the relationship between household welfare and crop productivity requires that endogeneity and potential simultaneity issues be accounted for. This will normally require the use of instrumental variables to identify anexogenous source of variations in the regressors. However, the CMP modelling framework will allow for sequential joint estimation of the welfare,productivity, and climate-smart intensification equations, while accounting for these issues (i.e., it will allow the error terms –unobserved and unmeasured variables– to be freely correlated and yield unbiased estimates).Theoutcome (welfare, W_i) of CSA decisions of the households is assumed to be achieved in a sequential manner. First, the decision and extent of use (CSI_i^*) of any CSA strategy in the face of weather-related threats is expected to be influenced by several factors. Next, the effect of the farmer's adaptation decisions (use and intensity) is expected to influencehousehold's farm yield, Y_i^*; therefore, the decision and/or extent of use variable will enter the yield (productivity) equation as an endogenous variable. Household farm productivity is again expected to translate to improved household welfare,W_h^* - little or no deprivations.Hence, adaptation decision and farm productivity will enter the welfare equation as endogenous variables. Therefore, the recursive systems of equations are stated implicitly as:

$W_i^* = f(Y_{ic}, CSI_i) + \varepsilon_3$ ……………………………………………………………………13

$Y_i^* = f(CSI_i) + \varepsilon_2$ ………………………………………………………………………...14

$CSI_i^* = f(X_i) + \varepsilon_1$……………………………………...…………………………..…………..15

Explicitly,

$W_i^* = \alpha_0 + \alpha_1 Y_i + \alpha_2 hhgend + \alpha_3 eduyrs + \alpha_4 hhgend * eduyrs + \alpha_5 hhdage + \alpha_6 hhdcrdstat + \alpha_7 depratio + \alpha_8 hhtlu + \alpha_9 mroad + \alpha_{10} tenurestat + \alpha_{11} locationI$ ......……………………………………………16

$Y_i^* = \delta_0 + \delta_1 CSI_i + \delta_1 farmsize + \delta_2 totpday + \delta_3 agrochem + \delta_4 fertcost + + \delta_5 tenurestat + \delta_6 plottopo + \delta_7 farmsize * fertcost + \delta_8 farmsize * totpday + \delta_9 farmsize * agrochem + \delta_{10} farmsize * CSI + \delta_{11} totpday * fertcost + \delta_{12} totpday * agrochem + \delta_{13} totpday * CSI + \delta_{14} agrochem * fertcost + \delta_{15} agrochem * CSI + \delta_{16} CSI * fertcost + \delta_{17} hhdage + \delta_{18} hhsize + \delta_{19} extaccess + \delta_{20} hhdgrpmemb + \varepsilon_y$……………………………………………….………17

$CSI_i = \gamma_0 + \gamma_1 hhage + \gamma_2 hhgend + \gamma_3 mstat + \gamma_4 depratio + \gamma_5 hhdnature + \gamma_6 extaccess + \gamma_7 crdtconst + \gamma_8 hhdgrpmemb + \gamma_9 TLU + \gamma_{10} plotcultyr + \gamma_{11} mktdist + \gamma_{12} roadaccess + \gamma_{13} farmsize + \gamma_{14} plottopo + \gamma_{15} tenurestat + \gamma_{16} soilfertpercep + \gamma_{17} hhdriskpercep + \gamma_{18} agrozone + I$…………...….18

Whereγ_i, $\delta_i$and $\alpha_i$are matrix of coefficients while ε_{cs}, ε_y and ε_w are random error terms representing both equation-level unobservables and choice-specific unobservables, whose correlation coefficient measures the indirect effect of first-level outcome on the second-level outcome, after the endogenous influence of the first-level outcome is accounted for, and so on. $\alpha_1$and$\delta_1$measure endogeneity of the endogenous variable(s) on the outcome variable at a given system level (Bhat, Castro & Pinjari, 2015; Ergano, 2017). The explanatory variables are as explained in Tables 2,3, 4 and 5.

Further, the study employed the propensity score-based heterogenous treatment effect technique to analysethe treatment effect of use of CSA strategies on crop yield. The potential of this technique,lies in its ability to account for variability across units of analysis

(Xie, 2007) since individuals differ not only in their background characteristics, but also, in how they respond to any treatment or intervention (Xie, Brand & Jann, 2012). The research and policy implications of using this technique are documented in Xie et al. (2012).

3.5. Limitations to the Study

As with any other scholarly work, this dissertation was challenged by several limitations, though several steps were taken to reduce or eliminate their influences on the results. Generally, climate change analyses are best done, using panel series data, since climate-relate risk events are observed over time. In this study, however, data on climate risk variables were collected during a one-round survey from the household head, who was presumed to be well-informed about the climate change events within the study reference period of ten (10) years. The survey round and timeframe considered may not have allowed for information on some major climatic events outside the period to be captured. Therefore, the responses might not have reflected every climate change eventas closely as possible. This is because the data on several variables, particularly, those related to climate risk events used for this study, were based on farmer recall (memory) and perception. These methods are often associated with inaccurate information and could haveimpact on response precision.

This study is limited to dichotomous choices, made by farmers in the use of the CSA strategies and did not consider the cost of use of these strategies. As such, cost-related data were not collected for analysis.

Often, several factors,including climate change events,simultaneously affect farm household outcomes such as farm productivity and welfare. When this happens, attribution of these outcomes to climate change events,becomes difficult for the farmer and responses can be biased.

Another limitation is that associated with sampling methodology, since biases were expected under a disproportionately sized sample, as used in this study. However, this was corrected by using cluster (weights), in the various regression analyses carried out.

In this study as well, selection bias resulting from both observables and unobservables was assumed and therefore requires that a valid instrument, which is often difficult to identify be used (Angrist &Krueger, 2001). Similarly, adaptation and impact route of farmers' use of CSA strategies is considered recursive, which implies that,it requires various equations with defined stages, rather than simultaneous relationship. Considering these difficulties, the study estimated impact of CSA strategies, following the conditional recursive mixed-process (CMP) modelling framework, which helps to circumvent these methodological constraints, often associated with the well-known impact evaluation methods.

CHAPTER FOUR

RESULTS AND DISCUSSION

This chapter presents the results of data analysis to examine productivity and welfare effects of climate-smart adaptation (CSA) practices of smallholder staple crop farmers in Savanna Agro-Ecological Zone of Nigeria. These results are presented and discussed in two parts: background information of the respondents and results based on the study objectives.

4.1. Background information of respondents

These are presented and discussed under characteristics of sample respondents and the impacts and severity of climate risks events in the study area.

4.1.1. Characteristics of sample respondents

The socio-economic characteristics of the respondents on various variable groups are presented in Table 6. The characteristics presented and discussed include;age, gender, educational level, marital status, and household size. Others considered,were dependency ratio, incidence of child mortality, extension visits, membership of groups, food security level, and credit status, among others. Asset (land and livestock) ownership and various indicators of household living standards, were used to measure household wealth/infrastructure status.Distance of household from nearest market and access to motorable road were indicators of community level variables,

Table 6: Socio-economicattributes of respondents (n=391)

Socioeconomic Variables	Frequency	Percentage	Mean (SD)
Age of household head			
30 – 44	189	48.34	
45 – 59	150	38.36	45.60
60 – 74	46	11.76	(±10.87)
75 – 89	6	1.53	
Gender of household head			
Female	46	11.76	
Male	345	88.24	
Educational level of household head			
No formal education	98	25.06	
Primary education	68	17.39	9.21 (5.99)
Secondary education	172	43.99	
Above Secondary education	53	13.55	
Civilstatus of head			
Married and living with spouse	344	87.98	
Married and living without spouse	47	12.02	

Socioeconomic Variables	Frequency	Percentage	Mean (SD)
Household size (AE)			
1 – 6	187	47.83	
7 – 12	148	37.85	
13 – 18	36	9.21	7.91 (4.94)
19 – 24	14	3.58	
25 – 30	5	1.28	
31 – 37	1	0.26	
Dependency ratio			
Low dependency (Less than 1)	259	66.24	
Moderate dependency (1 – 2)	117	29.92	0.85 (0.98)
High dependency (3 – 5)	12	3.07	
Very high dependency (above 5)	3	0.77	
Incidentof child mortality			
Yes	156	39.90	
No	235	60.10	
Numberof extension contacts in last 5 years			
None	111	28.39	
1 – 7	170	43.48	
8 – 14	46	11.76	5.84 (7.83)
15 – 21	44	11.25	
22 – 28	11	2.81	
29 – 35	9	2.30	
Extension visit on climate change issues			
Yes	138	35.29	
No	253	64.71	
Group membership of household			
Yes	327	83.63	
No	64	16.37	
Food security status			
Very good	175	44.76	
Good	84	21.48	
Fair	54	13.81	
Poor	78	19.95	
Household mobile phone ownership			
Yes	372	95.14	
No	19	4.86	
Credit status of household			
Constrained	265	67.77	
Unconstrained	126	32.23	
Community level Variables			
Distance of household from nearest market			
Less than 1	169	43.22	
1 – 3	79	20.20	
4 – 6	45	11.51	5.88 (16.24)
7 – 9	21	5.37	
Above 9	77	19.69	

Socioeconomic Variables	Frequency	Percentage	Mean (SD)
Access to motorable road less than 30minutes walk			
Yes	353	88.69	
No	45	11.31	
Wealth/infrastructural indicators			
Number of livestock owned (TLU)			
None	23	5.88	
0.01 – 1.00	162	41.43	
1.01 – 2.00	96	24.55	1.51 (1.35)
2.01 – 3.00	59	15.09	
3.01 – 4.00	20	5.12	
4.01 – 5.00	31	7.93	
Asset ownership quintile			
Poor	74	18.93	
Fair	85	21.74	
Good	88	22.51	
Very good	63	16.11	
Excellent	81	20.72	
Access to safe water			
Yes	358	91.56	
No	33	8.44	
Access to improved sanitation/toilet			
Yes	250	63.94	
No	141	36.06	
Use of efficient cooking fuel			
Yes	7	1.79	
No	384	98.21	
Access to electricity			
Yes	305	78.01	
No	86	21.99	
Dwelling place of modern floor, roof and wall types			
Modern dwelling	146	37.34	
Local dwelling	245	62.66	
Adult equivalent per rooms			
Adequate	351	88.24	
Inadequate	46	11.76	
Average farmsize			
0.1 – 0.5	117	29.92	
0.6 – 1.0	131	33.50	
1.1 – 1.5	64	16.37	
1.6 – 2.0	33	8.44	1.06 (0.75)
2.1 – 2.5	27	6.91	
2.6 – 3.0	19	4.86	

Source: Field survey, 2018

The overall averageage of the household heads, who are mostly (88%) male, is 46 years with about 9 years of formal education (equivalent to completion of Junior Secondary School level). The age distribution shows that most (48.34%)of the respondents were between the ages of 30 – 44 years old followed by those within the age bracket of 45 – 59 years. About 2% of the respondents were older than 74 years. About 44% of the respondents had up to secondary education, while a quarter is shown to have no form of formal education. Those with primary and above secondary education were about 17% and 14%, respectively. Further on Table 6, the civil status of the respondents shows that majority (88%) of the household heads live with their spouse(s), providing opportunity for possible joint adaptation decision-making. Household size proxied for labour accessibility and based on adult equivalent, the average is eight (8) with most (47.83%) of the households having a household size of 1 – 6 persons. This is followed by those with 7 – 12 and 13 – 18 persons representing 38% and nine per cent, respectively. Some evidence in literature suggest that greater labour availability are associated with increased adaptation practices (Ali & Erenstein, 2017; Arslan *et al.*, 2017; Mulwa *et al.*, 2017). Overall, households in the study area had high low dependency ratio with each person in their prime or working age, supporting about 0.85 children or elderly persons. The distribution of households' dependency ratios indicates that, those with low and moderate dependency are 66% and 30% respectively, while about three per cent and one per cent of the households had high and very high dependency.

On the average, respondents had about six contacts with extension agents in the last five years, approximately one per year with about 43% having between 1 – 7 contacts in the last five years. The percentage of households decreased with increased number of extension contacts within the period. However, about 35% of the households in the last five years received climate change related information, due to their contact with extension agents in their areas. This could have implications on the use of adaptation practices, since extension contacts could increase availability of information and technical assistance needed to foster climate-smart adaptation practices. Social capital or networks among farmers had been shown to play significant positive role in agricultural technology adoption (Knowler & Bradshaw, 2007). Majority (84%) of the respondents are members of different social/cultural/farmer groups. Based on food consumption coping strategy index,households with lower mean scores are considered more food secure. The quantile distribution of these scores indicates that,two-third (66%) of the households are in good food security standing.Majority (95%) of the households in the study area had mobile phone mostly used for communication and which could have aided in climate change information dissemination. In terms of access to credit, 68% of the households where considered to be credit (either formal or informal) constrained, which can limit farmers' resilience to shocks (Elias, Ayele & Ferede, 2017).

Distance-related variables are often considered as determinants of farm input use decision, since to a considerable extent, they influence travel time and transaction costs (Asfaw *et al*., 2016). Proxied by distance of household's residence to the nearest market and walk time to nearest access road, farmers on average travel about 6km to the nearest market with great variability shown by the distribution of the households. About 43% of the households travel less than a kilometer to the nearest market while about 20% must travel more than nine kilometers to access the nearest market in their location. Another 20% of the respondents showed that they travelledbetween 1 – 3 km to access the nearest market while 12% travelled 4 – 6 km. Generally, the closer a farmer is to the market, the more access to market information and lesser transportation cost. Access to motorable roads is very high in the study area as indicated by 89% of the respondents, who opined that, these roads are less than 30 minutes' walk from their homes. It is imperative to note that, these results are indicative, since the quality of the roads were not considered.

The availability of various resources, including physical, human, institutions, technological and social means, have been identified to affect distributional impact and adaptation behaviours of households (Burton, Diringer & Smith, 2006; Devereux, 2007; Ayanlade*et al*., 2017). The wealth and infrastructure indices of the sampled households indicate similarity in livestock ownership and use of efficient cooking fuel, with respondents having about two (2) livestock and 98%, using such cooking method, respectively. Ninety percent (92%), 64%, 78% and 88% of the respondents had access to save water, improved sanitation, electricity and adequate household size-room ratio, respectively; indicating a relatively high living standard. Land-based asset proxied by average plot size shows that, respondents own an average of one hectare (1 ha) with 34% having between 0.6 – 1.0 ha followed by about 30%

of the respondents with 0.1 – 0.5 ha. Households with 1-6 – 2.0 ha, 2.1 – 2.5 ha, and 2.6 – 3.0 ha are about eight, seven and five per cent, respectively. Non-land asset quintile distribution of households indicates a relatively similar distribution across the levels. For instance, about 19% of the respondents are in the poor non-land asset category, 22% in the fair category while 23% were in the good non-land asset group. 16% and 21% of the respondents fall into the very good and excellent non-land asset ownership category (Table 6).

The perceptions about farm plot fertility, nature of topography, and perceived plot-level tenure security status are presented on Table 7. Also presented, are the length of use of plot for farming activities and the efficacy of adaptation strategies, used by farmers on the plots.

Table 7: Respondents' plot characteristics

Plot biophysical and perceived tenure security variables	Frequency	Percentage	Mean (SD)
Farm-plot fertility perception			
Fertile	832	65.00	
Non-fertile	448	35.00	
Nature of farmtopography			
Flat	1080	84.38	
Non-flat	200	15.63	
Leave farmempty with no fear of loss			
Secure plot	933	72.89	
Insecure plot	347	27.11	
Likelihood of ownership/use dispute			
Secure plot	398	31.01	
Insecure plot	882	68.91	
Length of farm-plot use for farming activities			
1 – 10	412	32.19	
11 – 20	445	34.77	
21 – 30	187	14.61	19.50 (13.71)
31 – 40	121	9.45	
41 – 50	115	8.98	
Perceived adaptation efficacy of the household head			
None	86	6.72	
0.01 – 0.09	514	40.16	
0.1 – 0.19	420	32.81	0.13 (0.09)
0.2 – 0.29	187	14.61	
0.3 – 0.39	73	5.70	

Source: Field survey, 2018

NB: Biophysical and plot variables were measured at plot level (number of plots = 1,280)

Sixty-five per cent of the respondents perceived their farmland to be fertile; thus, requiring small amount of fertilizer to increase crop production, even after about 20 years of farming activities of such lands. Indicators of tenure insecurity, proxied by the possibility of the farmer to leave farmland empty with no fear of loss and the likelihood of occurrence of ownership or use dispute with 73% and 69% respectively, show that, tenure insecurity is a concern in the agroecological zone. The perceived efficacy of adaptation practices ranges between zero (0) and one (1) or 0 and 100 per cent with zero indicating no adaptation efficacy and 1 or 100% showing full efficacy of adaptation practices. The median score of perceived efficacies of the climatesmart adaptation strategies used by farmers is 0.13 (±0.09). This indicates that these strategies as used by farmers contribute poorly to the yield of the crops compared to their potentials. This may not be unconnected with the use intensity among other factors. The distribution of the perceived efficacy scores indicates that plots with 0.01 – 0.09 efficacy score were about 40% of the total plots. This is followed by 33% and 15% of plots with scores between 0.1 – 0.19 and 0.2 – 0.29, respectively.

On Table 8, climate risks experiences of households,over the last ten (10) years,are presented and include those associated with fluctuations in temperature, rainfall characteristics and incidences of climate risk events.

Table 8: Climate change experience/perception of respondents

Climate Risk Variables	Frequency	Percentage	Mean (SD)
Temperature changes			
Yes	376	96.16	
No	15	3.84	
Changes in rainfall quantity			
Yes	382	97.70	
No	9	2.30	
Changes in rainfall distribution			
Yes	382	97.70	
No	9	2.30	
Changes in rainfall duration			
Yes	383	97.95	
No	8	2.05	
Number of drought incidences			
None	236	60.36	1.24 (2.09)
1 – 5	139	35.55	
6 – 10	16	4.09	
Number of delayed rainfall incidences			
None	4	1.02	3.33

Climate Risk Variables	Frequency	Percentage	Mean (SD)
1 – 5	233	59.59	(3.32)
6 – 10	133	34.02	
11 – 15	13	3.32	
16 – 20	8	2.05	
Number of earlier onsets of rainfall incidences			
None	9	2.30	
1 – 5	211	53.96	6.42 (4.62)
6 – 10	107	27.37	
11 – 15	48	12.28	
16 – 20	16	4.09	
Number of erratic rainfall pattern incidences			
None	43	11.00	
1 – 5	238	60.87	4.30 (3.17)
6 – 10	98	25.06	
11 – 15	12	3.07	
Number of too much rain incidences			
None	23	5.88	
1 – 5	242	61.89	5.11 (3.79)
6 – 10	102	26.09	
11 – 15	16	4.09	
16 – 20	8	2.05	
Number of less rain incidences			
None	22	5.63	
1 – 5	226	57.80	5.05 (3.29)
6 – 10	124	31.71	
11 – 15	15	3.84	
16 – 20	4	1.02	
Number of higher temperatures incidences			
None	32	8.18	
1 – 5	221	56.52	5.17 (4.38)
6 – 10	94	24.04	
11 – 15	33	8.44	
16 – 20	11	2.81	
Number of hailstorm/windstorm incidences			
None	11	2.81	
1 – 5	295	75.45	3.98 (2.85)
6 – 10	75	19.18	
11 – 15	10	2.56	
Number of increased pests/diseases incidences			
None	9	2.30	
1 – 5	254	64.96	5.04 (3.89)
6 – 10	104	26.60	
11 – 15	15	3.84	
16 – 20	9	2.30	

Climate Risk Variables	Frequency	Percentage	Mean (SD)
Number of climate risks incidences in last 10 years			
None	2	0.51	
1 – 3	153	39.13	
4 – 6	158	40.41	4.66
7 – 9	64	16.37	(2.49)
10 – 12	10	2.56	
13 – 15	4	1.02	
Climate risk perception index of respondents			
0.1 – 1.9	172	43.99	
2.0 – 3.9	114	29.16	
4.0 – 5.9	65	16.62	2.96
6.0 – 7.9	29	7.42	(2.11)
8.0 – 9.9	8	2.05	
10 – 11.9	3	0.77	

Source: Field survey, 2018

It is evident from Table 8that climate variability/change exist as more than 90% of the respondents acknowledge observing changes in temperature and rainfall characteristics in the last decade, or since when they started farming. In terms of number of incidences of climate anomaly,60% of the respondents indicated that no drought incidence has occurred in the last 10 years or since when they started farming activities. Thirty-six (36%) and four (4) per cent of the households opined that drought occurred between 1 – 5 and 6 – 10 times respectively in the study area in the last 10 years.The incidence of early onset of rains is more with an average of six (6) occurrences within the same period. About 54% and 27% of the respondents noted that this climatic anomaly has happened between 1 – 5 and 6 – 10 times, respectively, in the last 10 years. Only 2% of the households have not witnessed any occurrences, while those who witnessed the occurrences of this climatic deviation between 11 – 15 and 16 – 20 times in the last 10years were about 12% and 4%, respectively. Similar distribution pattern exists across other climate risk events, with modal observations within 1 – 5 times in the last 10 years. This is followed by 6 – 10 times occurrences over the study period. On average, households in the study area have had about five incidences of one climate risk event or the other in the last 10 years. About 39%,40% and 16% of the respondents had witnessed the occurrence of at least one of the climate-risk events between 1 – 3, 4 – 6, and 7 – 9 times, respectively. This portends some implications on the adaptation behaviours of farmers, who are more likely to be involved in anticipatory/proactive, rather than reactive adaptation behaviours. Furthermore, the distribution of respondents based on perceived climate risk index shows that 44%, 29%, and 17% of the households have 0.1 – 1.9, 2.0 – 3.9, ad 4.0 – 5.9 index scores while about 10% of the households recorded 6% and above. This indicates that, multiplicative effects of the number of incidence and the severity of climate risk events arelow in majority of the households.

4.1.2. Climate risk events: impacts and severity

The results in this sub-section are presented and discussed under the followings: outcomes/impacts and perceived severity of climate risk events. The results,as presented in Table 9, show varied outcomes of the different climatic risk events, with most of the outcomes yield based.

Table 9: Descriptive summary of climate change risk events (Percentages)

	Climate Risk Events								
	Agricultural Drought++	Delayed onset of rain	Early onset of rain	Erratic rainfall pattern	Too much rain	Less rain	Higher temp.	Hailstorm/windstorm	Increased pests/disease incidence
Climate event outcomes/impacts+									
No effects	36.07	0.26	2.06	7.85	6.44	5.43	5.40	2.08	2.06
Decrease in crop yield	39.07	64.01	4.88	52.09	26.29	50.13	4.11	5.97	42.67
Increase in crop yield	2.19	1.54	77.12	10.47	22.94	2.07	0.51	0.00	1.29
Food scarcity/insecurity	30.05	35.48	3.60	24.87	9.79	37.47	3.34	5.71	28.02
Increase in food prices	12.84	26.22	4.37	8.12	5.93	21.96	1.80	0.78	15.17
Decrease in food prices	0.82	1.29	28.02	3.14	7.99	1.81	0.51	0.00	2.83
Increased conflict among resource users	1.91	1.29	0.00	1.57	1.80	6.98	0.51	0.26	0.00
Death/disability of a household member	1.64	0.51	0.00	0.26	0.77	0.00	1.29	4.68	0.51
Dwelling damaged/demolished	0.55	0.51	0.77	1.83	38.40	0.26	3.08	85.45	0.77
Decreased livestock productivity	1.91	1.29	0.26	2.36	9.02	3.10	14.65	0.52	8.48
Increase in livestock productivity	0.00	0.00	6.17	0.52	2.84	0.26	0.26	0.26	0.00
Death of livestock	7.65	0.77	0.00	0.26	6.96	1.55	33.42	7.79	28.02
Reduced water availability	16.94	11.57	1.03	1.57	0.77	17.31	26.48	2.60	0.51
Health-related problem	1.09	0.26	1.29	1.05	2.32	1.03	37.53	1.82	10.28
Incidence of pest and diseases	1.91	1.26	2.31	2.36	3.35	3.36	10.03	1.30	22.88
Negative changes in vegetation	1.09	2.31	0.77	6.81	5.93	6.20	15.94	4.68	4.63
Severity of climate change events									
None	45.36	1.54	22.05	11.31	5.90	5.64	7.69	3.59	1.03
Little	12.30	22.88	27.18	30.59	18.72	18.46	10.26	22.82	9.25
Somewhat	22.95	41.13	35.64	35.48	34.10	29.23	23.59	30.51	30.59
Much	7.10	26.74	12.05	20.31	18.72	25.64	25.13	25.13	23.39
A great deal	12.30	7.71	3.08	2.31	22.56	21.03	33.33	17.95	35.73

Source: Field survey, 2018

+Multiple responses recorded, and number reported are percentages based on farmers' experiences in the last ten (10) years or since started farming, ++ 2 – 3 months of little or no rainfall characterized by insufficient soil moisture resulting in lack of crop growth and production (Wilhite, 2000).

The decreasein crop yield over the past ten years was attributed by the respondents to delayed onset of rainfall, unpredictable (erratic) rainfall pattern, limited quantity (amount) of rain, increased incidences of pests/diseases, and drought incidence by 64%, 52%, 50%, 43%, and 39%, respectively. Usually, yield decline has spiral effects. Hence, these risk events except excessive rainfall (about 10%) were also indicated to lead to food shortage/insecurity while food price increases were attributed partly to delayed onset of rainfall (26%), limited quantity of rainfall (22%), pest/disease (15%) and drought incidences (13%). A positive outcome of decrease in food prices was observed only for early onset of rain. This could be that, when such occurred, it remained stable or at intervals and that, supports crop growth and development. Non-farm asset loss (damaged/demolished dwelling place) was attributed to excessive rains (38%) and the occurrence of hail/windstorm (85%), while the decline in livestock productivity, livestock death, reduced water availability, human health-related problems, and negative changes in vegetation cover, were associated with incidences of high temperatures.

In addition, about 23% and 10% of the respondents noted that, pests and diseases incidences led to proliferation of more pests/diseases incidences and some human health-related issues. Though drought, defined in this study following Wilhite (2000), was identified to impact welfare of respondents, 36% of the respondents noted that, it had no economic/welfare effects on them. This probably reflects the frequency of its incidence, which is highly limited to about one occurrence in the last ten years (see Table 8). Other events with higher frequencies of incidence did not follow this pattern as less than 10% of the respondents noted that they had no economic effect, when they occurred. The multiple responses of respondents show that the impacts/outcomes of these climate risk events are not mutually exclusive and as such, could not be solely attributed to anevent. For instance, a decline in crop yield could be a manifestation of anomalies in multiple climate risk events occurring, simultaneously. High variability in rainfall could trigger increased pest/disease incidence, and increased temperature could favour reproductive/productivity failure in livestock, animal migration, and reduced photosynthetic activity in plants (Haynes, 1964). Overall, the severity of the incidences of the climate risk events is heterogeneous. For instance, about 55% of the respondents opined various levels of severity ranging from little to a great deal of severity for drought incidence in their locality. About 99% of the respondents indicated similar severity distribution for pests and diseases incidences.

4.1.3. Crop-based climate-smart adaptation strategies used by farmers

Table 10shows the distribution of the use of various climate-smart adaptation practices for staple crops farming and their length of usage in the study area, over the last decades. These strategies are presented and discussed according to the crops cultivated by the respondents. Crops like rice, maize, millet, and sorghum are collectively discussed under cereals; yam and cassava constitute root/tuber crops; while groundnut, soybean, and cowpea belong to pulses group.

Table 101: Percentage Distribution of CSA strategy use by major crops and years of usage

	Climate-smart adaptation strategies										
Crop Type	Irrigation	Cover crops	Minimum tillage	Mulching	Crop rotation with legumes	Intercropping with legumes	Green manuring	Agroforestry	Farmyard manure	New/improved crop variety	Fertilizer deep placement
Rice	1.25	2.58	7.66	2.34	3.98	3.59	7.50	0.86	6.09	9.53	3.67
Maize	0.47	16.17	15.23	9.84	25.86	22.03	25.16	2.89	19.77	20.00	9.84
Millet	0.23	12.42	14.38	3.75	15.70	11.95	13.05	2.34	14.84	7.03	2.19
Sorghum	0.55	13.67	15.47	3.83	16.33	13.20	13.83	2.42	16.64	8.13	2.58
Yam	0.08	7.97	7.81	13.98	19.22	16.41	18.91	2.50	12.19	13.28	11.33
Cassava	0.31	8.13	9.38	7.97	19.14	16.02	21.95	2.81	10.00	16.09	6.56
Groundnut	0.16	14.77	13.59	8.91	25.31	20.16	24.38	2.81	15.63	14.61	7.19
Soybean	0.08	6.02	5.55	4.45	12.89	10.86	12.66	1.56	6.95	9.69	3.98
Cowpea	0.31	8.44	9.45	2.42	10.23	7.27	8.52	1.80	9.61	5.86	0.82
Years of usage											
1 – 5	68.97	83.16	53.89	60.31	83.75	74.06	59.84	90.54	66.98	90.24	90.88
6 – 10	31.03	16.84	35.49	37.02	16.25	24.87	35.04	9.46	25.28	9.76	9.12
11 – 15	0.00	0.00	2.33	1.15	0.00	0.00	0.67	0.00	0.94	0.00	0.00
16 – 20	0.00	0.00	2.07	1.15	0.00	1.07	1.48	0.00	1.70	0.00	0.00
21 – 25	0.00	0.00	0.00	0.38	0.00	0.00	0.13	0.00	1.13	0.00	0.00
26 – 30	0.00	0.00	6.22	0.00	0.00	0.00	2.83	0.00	3.96	0.00	0.00
Mean year of usage	4.30	3.71	7.18	5.45	4.14	4.75	7.04	3.01	11.39	3.52	3.34

Source: Field survey, 2018

Choice of use of any strategy is dependent on several factors, including; frequency of climate risk incidence, crop physiology, cost of use, technical know-how, local knowledge/experience, and their perceived contributions to yield. While some of the practices are readily applicable at individual/household levels, others require support from government, private organizations and donors, due to the limitations posed by some of these factors. Across all crop types under study, irrigation and agroforestry are least practiced. Only about 1% of rice is produced under irrigationfollowed by sorghum, maize and millet. The share of these crops in irrigation practice reflects their water requirements, with rice noted as "thirstier" compared toother crops. Drought stress or water-limited condition is a major constraint to rice and maize production (Zhang, Zhang, Cheng, Jiang, Zhang, Peng, Lu, Zhang &Jin, 2018;Zhao, Xue, Jessup, Hao, Hou, Marek, Xu, Evett, O'Shaughnessy& Brauer, 2018) while sorghum and millet are more drought tolerant. Irrigation use is also capital intensive, which could limit its use by smallholder farmers.

The use of cover crops follows expected and similar trend as seen under irrigation practice. About 16%, 14% and 12% of maize, sorghum and millet respectively were produced under cover cropping practices,while rice has the least share of about 3%. This observation buttresses the traditional farming systems associated with maize, millet, and sorghum under subsistence/small scale levels, where mixed/intercropping is predominantly practiced for risk impact mitigation, labour saving, and output per area maximization. In most cases, rice is cultivated under sole cropping system, probably, due to agronomic practices required for its cultivation. Furthermore, the use of minimum tillage, crop rotation,legume intercropping, green manuring, agroforestry, farmyard manure, improved crop variety and fertilizer deep placement follow similar trend across the cereal crop types; (rice, maize, millet, and sorghum) and this is indicative of the production system, prevalent in the study area. Maize compared to other cereal crops continues to be the predominant cereal crop, that farmers use these strategies forits production.

Under yam and cassava production, irrigation is the least practiced. Green manuring (19%), crop rotation with legumes (19%), intercropping with legumes (16%) and mulching

(14%)were most practiced for yam, while green manuring (22%), crop rotation with legumes (19%), and use of improved variety (16%) were dominant for cassava farming. Table 11 further shows that the use of crop rotation with legumes (25%), green manuring (24%), intercropping with legumes (20%), farmyard manure (16%) and use of new/improved crop variety (15%) were dominant under groundnut production compared with soybean production where such strategies as crop rotation with legumes (13%), green manuring (24.38%), intercropping (11%) and use of improved varieties (10%) were mostly used. For cowpea production, the use of crop rotation with legumes, farmyard manure, minimum tillage, and cover crops were indicated by 10.23%, 9.61%, 9.45% and 8.44% of the households, respectively. Across crops under pulses category, the use of the climate-smart strategies is most pronounced for groundnut, compared tosoybean and cowpea.

The foregoing observations show that, smallholder crop farmers in the study area are more inclined to the use of nutrient (green manuring, farmyard manuring and intercropping with legumes), energy (crop rotation with legumes) and knowledge (use of better crop varieties) smart adaptation strategies, with limited use of those strategies associated with water and carbon smart adaptation strategies. These choices indicate farmers' preference for low external inputs, which are readily accessible, since they are available locally or at relatively cheap costs compared with external inputs, such as, fertilizers and efficient irrigation practices. Other reasons for these choices could be associated with those identified byHimanen, Mäkinen, Rimhanen & Savikko, (2016), and Nyasimi, Amwata, Hove, Kinyangi andWamukoya (2014).

While majority of the farmers have used these strategies for between 1 – 5 years, Table 10further shows that the use of some of the strategies arerecent and others had been in use in the last decades. For instance, the use of strategies such as; irrigation, cover cropping, crop rotation, intercropping with legumes, agroforestry, new/improved crop variety and fertilizer deep placement is relatively new; mostly in the last five years. The practices of minimum tillage, mulching, green manuring and farmyard manuring span over the last five years with farmyard manure had been most used (over a decade). This, in addition to other factors, could be attributed to local knowledge and awareness level of these strategies among the farmers.

4.2. Determinants of choice(s) of climate-smart adaptation strategies of arable crop farming households

The individuals/groups,who influenced the respondents and reasons for use of identified strategies for climate change adaptation, association or mix of strategies used and the multivariate estimates of the determinants of choice of strategy used on farmers' plots are presented and discussed in this sub-section.

4.2.1. Sources of information for farmers' choice of CSA strategies

The results of those, who were identified by respondents as being responsible for their actual use of the strategy on a given plot are presented in Table 11. Though farmers can get information from different sources, the results presented are those showing the sources, that influenced their actual use of strategies.

Table 2: Distribution of sources of information for farmers' choice of climate-smart adaptation strategies (Proportion=100%)

Influencing source of information for CSA use	Climate-smart adaptation strategies										
	Irrigation	Cover crops	Minimum tillage	Mulching	Crop rotation with legumes	Intercropping with legumes	Green manuring	Agroforestry	Farmyard manure	New/improved crop variety	Fertilizer deep placement
Household member	27.78	18.89	17.41	10.91	18.40	16.67	9.93	11.32	19.56	4.98	0.96
Fellow farmer	5.56	34.14	17.41	25.45	34.13	27.50	17.88	39.62	21.25	28.91	22.19
Extension agent	50.00	17.19	30.08	5.82	10.96	10.83	9.40	9.43	5.23	39.00	47.27
Electronic media	0.00	0.24	0.53	0.36	0.42	0.17	0.13	0.00	1.01	1.66	0.00
Paper media	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.17	0.14	0.00
NGOs	0.00	0.24	0.26	0.73	0.42	0.50	0.00	3.77	0.51	3.32	0.32
Cooperative associations	0.00	0.22	0.79	0.73	1.69	1.67	0.66	0.00	1.18	4.98	0.32
Community meetings	0.00	0.00	0.00	1.09	0.70	1.50	0.66	1.89	0.67	5.53	0.32
Agric service providers	5.56	0.73	0.00	1.82	0.00	0.00	0.26	0.00	0.17	5.53	1.29
Agricultural	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.28	0.00

shows											
Personal indigenous knowledge	11.11	28.57	33.51	53.09	33.14	41.00	61.05	33.96	50.26	5.67	27.33

Source: Field survey, 2018; Figures are percentages

The respondents opined that their use of perceived efficient irrigation practices, including; stream diversion, drip/spot irrigation, and manual water extraction on about 50%, 28% and 11% of their plots was due to persuasion by extension agents, members of the household and indigenous knowledge respectively. Those who used this as an adaptation strategy, following fellow farmer information and agricultural service providers,were only six percent each. About 11% however, used irrigation, following their personal indigenous knowledge. The use of green manure, mulches, farmyard manure, intercropping with legumes and agroforestry on 61%, 53%, 50%, 41% and 34% of plots, where these strategies are practiced was based on generational local knowledge. Other adaptation strategies influenced by this knowledge included legume-based crop rotation and minimum tillage practiced on about 33% and 34% of plots, respectively. The influence of indigenous knowledge supports the assertion of Douxchamps *et al.* (2016) that most climate-smart strategies have evolved from traditional or local practices. Further, social network effects tend to play roles in the choices of practicing cover cropping, crop rotation with legumes, intercropping with legumes and agroforestry as climate change adaptation strategy. These strategies were practiced on about 34%, 34%, 28% and 40% of the plots in the study area, respectively, due to the influence of fellow farmers. The advice and conviction by extension agents in the study area is very important in the use of modern adaptation technologies, including; irrigation practices, new/improved crop varieties, and fertilizer deep placement as climate change adaptation strategies. Overall, the influence of media (electronic and paper), NGOs, cooperative, community associations, agricultural service providers and agricultural shows, played limited roles in promoting the use of climate-smart adaptation strategies.

4.2.2. Farmers reasons for use of CSA strategies

The reasons for using certain adaptation strategies, as adduced by the respondents are shown in Table 12. Generally, the reasons for use of these strategies are not mutually exclusive (more than one reasons possible for a strategy) and discussions of results are based on strategies with at least a quarter response rate, across each observed reason.

Table 3: Reasons for plot use of climate-smart adaptation strategies by famers

Climate-smart adaptation strategies	Reasons for use+									
	Labour saving		Higher crop yield		Soil moisture retention		Soil erosion control		(pest & diseases control, good soil microbe develop ment	
	Freq	%	Freq	%	Freq	%	Freq	%	Freq	%
Irrigation	6	2.08	15	5.21	9	3.13	0.00	0.00	10.00	3.47
Cover crops	89	18.86	69	14.62	111	23.52	168	35.59	79	16.74
Minimum tillage	108	24.05	79	17.59	154	34.30	83	18.49	33	7.35
Mulching	27	5.59	46	9.52	187	38.72	25	5.18	21	4.35
Crop rotation with legumes	80	10.43	162	21.12	90	11.73	111	14.47	432	56.32
Intercropping with legumes	197	27.29	126	17.45	109	15.10	48	6.65	195	27.01
Green manuring	85	10.35	127	15.47	19	2.31	52	6.33	608	74.06
Agroforestry	11	3.82	7	2.43	19	6.60	16	5.56	0	0.00
Farmyard manure	84	13.17	248	38.87	17	2.66	54	8.46	412	64.58
New/improved crop variety	124	14.32	568	65.59	7	0.81	25	2.89	44	5.08
Fertilizer deep placement	26	4.68	92	16.58	2	0.36	61	10.99	211	38.02

Source: Field survey, 2018; + Multiple responses recorded

The labour- saving potentials of intercropping with legumes, minimum tillage, and cover cropping were indicated as the most reason for use of these strategies by about 28%, 24% and 19% respondents, respectively, underpinning Arslan, McCarthy, Lipper, Asfaw andCattaneo (2014) and FAO (2016) classification, particularly for minimum tillage and cover cropping practices. However, the responses of the respondents reflect smallholder farmers' view that, these practices can reduce the amount of labour (mandays) needed for weeding (Al-Kaisi and Kwaw-Mensah, 2016) and other related activities. Respondents also noted that, their use of farmyard manure and new/improved crop varieties help in labour-saving with irrigation, agroforestry practices, and fertilizer deep placement contributing the least to the benefit of labour -saving. All except agroforestry and irrigation practices were used by farmers for their yield increasing potentials, especially the use of new/improved crop varieties (66%), farmyard manure application (39%) and crop rotation with legumes (21%). These strategies are noted by several scholars, including D'Hose, Cougnon, De Vliegher, Van Bockstaele,andReheul(2012), Arslan, McCarthy, Lipper, Asfaw, Cattaneo & Kokwe (2015), Khatri-Chhetri *et al*. (2017), to enrich soil nutrients through increased soil organic carbon and moisture contents, water stress reduction during dry season, among others. These are precursors for good soil health and consequently, increase in crop yield. Similarly, the practices of mulching (39%) and minimum tillage (34%) also contribute to soil moisture retention by reducing or limiting evapotranspiration, while the cover crops considered are able to ensure soil moisture retention and soil erosion control by 24% and 36% of the respondents, respectively. Furthermore, the strategies of crop rotation and intercropping with legume provide other ecosystem services likepests and disease control and development of soil micro-organisms as reported by 56% and 27%, respectively. The use of manures (green and farmyard) and fertilizer deep placement as indicated by 74%, 66%, and 38% of the respondents respectively was based on their ability to contribute to pests/diseases reduction on farms, development of micro-organisms, and reduction in economic wastage accruing to efficient fertilizer use.

4.2.3. Tetrachoric correlation for CSA strategy mix by respondents

Following Sharma *et al*. (2014), Ergano (2017) and Mensah-Bonsu, Sarpong, Al-Hassan, Asuming-Brempong, Egyir, Kuwornu & Osei-Asare (2017) tetrachoric correlation was used to assess the association or mix (either simultaneously or exclusively) of the climate-smart adaptation strategies by farmers in the study area (Table 13). Correlation coefficients which lie between 0.25 and 0.50 are described as moderate (Mensah-Bonsu *et al*., 2017) and those above 0.5 regarded as high (Sharma *et al*., 2014). Overall, 78.26% of the significant correlation coefficients are less than 0.5 (Table 13); comparable to Mensah-Bonsu *et al*. (2017) observation for maize farmers in Ghana. Following their conclusion, the estimated correlations among smallholder farmers' selection of climate-smart adaptation strategies are not high.

The estimated positively high correlation coefficients between cover cropping and either crop rotation with legumes or farmyard manure shows that, farmers select the pairs simultaneously due to their potentials to improve soil fertility, at reduced labour needs, while controlling for crop pests and diseases incidences on the farms. Similarly, the pairs of minimum tillage and farmyard manure and green manure and crop rotation with legumes are simultaneously used by farmers for same reasons. Crop rotation with legumes and intercropping with legumes are also simultaneously used by farmers to adapt to climate change incidences. Observed agroforestry practices in the study area, commonly involves cultivation of multiple arable crops on either cashew, mango, or orange plantations. This reduces the impacts of production risks, ensure efficient use of farm plot, and increases farmer's income streams. The correlation coefficient between agroforestry and intercropping with legumes is significantly high and positive.

By defining correlation coefficient between 0.10 and 0.24 as low indicates that 39% out of the 78% significant correlation coefficients fall within this category, while the remaining 39% falls within the moderate group (Table 13). Moderately and positively correlated pairs of climate-smart strategies used by farmers for climate change adaptation include, irrigation and either of mulching, agroforestry, or fertilizer deep placement practices; cover cropping and either of minimum tillage, intercropping with legumes, green manuring, agroforestry, new/improved crop variety, or fertilizer deep placement; and mulching with either of green manuring or fertilizer deep placement. Other moderately and simultaneously used strategies were crop rotation with legumes and green manuring or use of new/improved crop variety, green manuring and agroforestry or fertilizer deep placement, among others. The pair of significantly and mutually exclusively moderate strategies used by farmers for climate change adaptation are irrigation and cover cropping; mulching and cover cropping; while the pair of significantly and mutually exclusively low strategies include; minimum tillage and any of deep placement of fertilizer or use of improved crop types/varieties; irrigation and crop rotation with legumes and mulching and use of new/improved crop variety.

Table 4: Tetrachoric correlation estimates of climate-smart adaptationpractices

Climate-smart adaptationpractices	Irrigation	Cover crops	Minimum tillage	Mulching	Crop rotation with legumes	Intercropping with legumes	Green manuring	Agroforestry	Farmyard manure	New/improved crop variety	Fertilizer deep placement
Irrigation	1.000										
Cover crops	-0.297**	1.000									
Minimum tillage	0.237**	0.493***	1.000								
Mulching	0.365***	-0.312***	-0.048	1.000							
Crop rotation with legumes	-0.234**	0.608***	0.224***	0.211***	1.000						
Intercropping with legumes	-0.062	0.501***	0.071	0.217***	0.741***	1.000					
Green manuring	-0.178	0.484***	-0.038	0.248***	0.524***	0.463***	1.000				
Agroforestry	0.389***	0.382***	0.193***	0.169**	0.337***	0.664***	0.317***	1.000			
Farmyard manure	0.145	0.710***	0.542***	-0.216***	0.255***	0.218***	0.098***	0.114	1.000		
New/improved crop variety	0.025	0.245***	-0.150***	-0.195***	0.203***	0.313***	0.222***	0.262***	-0.023	1.000	
Fertilizer deep placement	0.338***	0.174***	-0.212***	0.447***	0.179***	0.229***	0.243***	0.291***	-0.055	0.310***	1.000

Source: Field survey, 2018
*** denotes 1% significance and ** denotes 5% significance

4.2.4. Determinants of choice of CSA strategies by respondents

The results on parameter estimates from the analysis of the multivariate probit model are presented in Table 14. It highlights the factors responsible for farmer's choice of climate-smart adaptation strategies. The model results indicatethat decisions of farmers to use different climate-smart adaptation strategies on a given plot are distinct. To a significant extent, the factors central to the decision to use any of the strategies are also different, indicating heterogeneity in the adaptation decisions of smallholder crop farmers in the study area. The model diagnostics show that, it fits the data to a significant extent, following that the Wald Chi square statistic is statistically significant and therefore, rejects the hypothesis of independence of use of climate-smart adaptation strategies by farmers. This as a resultvalidates the use of multivariate probit model for assessing farmers' use decisions of the various climate-smart adaptation strategies in the last ten (10) years. Overall, the test of null hypothesis that the error terms across equations are uncorrelated is also rejected; thus, supporting the hypothesis that at plot level, the use of climate-smart adaptation strategies is dependent and simultaneous. The correlation coefficients (rho) are different statistically from zero in 37 of the 55 cases. The signs of the correlation coefficients indicate interdependency of use of the strategies, either as substitutes or complements (Asfaw *et al*., 2016). While farmers use a combination of strategies to adapt to climate change, the preference of a strategy over the other,is influenced by several factors and these are discussed below.

Table 54: Multivariate estimates of determinants of CSA strategies choice (Plot-level analysis)

Variables	Dependent variables: climate-smart adaptation strategies										
	Irrigation	Cover crops	Minimum tillage	Mulching	Crop rotation with legumes	Intercropping with legumes	Green manuring	Agroforestry	Farmyard manure	Improved crop variety	Fertilizer deep placement
hhdage	-0.339***	0.237***	0.151***	-0.041(0.057)	0.190***	-0.013	-0.089*	0.080	0.212***	0.005	0.152***
	(0.110)	(0.054)	(0.054)		(0.051)	(0.049)	(0.050)	(0.084)	(0.055)	(0.047)	(0.052)
hhgender	0.057	0.098*	0.357***	-0.088**	0.050	-0.034	-0.181***	-0.043	0.338***	-0.068*	-0.133***
	(0.122)	(0.053)	(0.072)	(0.043)	(0.040)	(0.041)	(0.046)	(0.068)	(0.053)	(0.40)	(0.045)
hheduc	-0.204**	-0.092*	-0.259***	0.001	0.084*	0.138***	0.107**	-0.115	-0.421***	0.245***	0.192***
	(0.083)	(0.047)	(0.047)	(0.046)	(0.045)	(0.045)	(0.043)	(0.071)	(0.049)	(0.042)	(0.047)
depratio	0.118	0.076*	0.005	0.030	0.027	-0.038	-0.114**	0.102**	0.033	0.076*	0.088**
	(0.078)	(0.044)	(0.051)	(0.045)	(0.037)	(0.040)	(0.051)	(0.050)	(0.041)	(0.039)	(0.040)
hhsize	0.164**	0.073	-0.016	0.400	-0.034	-0.026	0.039	0.030	0.091*	-0.118***	0.071
	(0.078)	(0.049)	(0.049)	(0.050)	(0.046)	(0.043)	(0.043)	(0.068)	(0.047)	(0.044)	(0.049
hhdgrpmemb	-0.412***	-0.452***	-0.275***	-0.500	-0.194***	-0.110**	-0.224***	-0.317***	-0.052	-0.000	-0.463***
	(0.152)	(0.060)	(0.058)	(0.056)	(0.049)	(0.048)	(0.051)	(0.095)	(0.052)	(0.047)	(0.054)
crdtconst	0.103	0.167***	0.388***	0.091*	0.067	-0.098**	0.023	0.200**	0.047**	-0.078*	-0.254***
	(0.093)	(0.048	(0.047)	(0.49)	(0.044)	(0.044)	(0.043)	(0.080)	(0.046)	(0.042)	(0.045)
hhdriskpercep	-0.585***	-0.619***	-0.592***	0.135	0.301***	0.029	-0.085	-0.542***	-0.952**	-0.113*	-0.050
	(0.156)	(0.113)	(0.112)	(0.106)	(0.093)	(0.093)	(0.098)	(0.143)	(0.115)	(0.093)	(0.099)
hhdriskexp	0.571***	0.050	0.314***	0.083	-0.204**	0.093	0.205**	0.494***	-0.145	-0.009	0.202**
	(0.170)	(0.107)	(0.107)	(0.105)	(0.094)	(0.095)	(0.097)	(0.157)	(0.114)	(0.096)	(0.102)
hhdadaptcap	0.212***	0.534***	0.217***	0.053	0.568***	0.515***	0.523***	0.390***	0.502***	0.346***	0.045
	(0.082)	(0.052)	(0.045)	(0.043)	(0.049)	(0.045)	(0.048)	(0.063)	(0.051)	(0.042)	(0.044)
plottopo	0.071	0.343***	0.074*	-0.071	-0.266***	0.095**	0.086*	-0.006	0.230***	0.063	0.119**
	(0.084)	(0.052)	(0.043)	(0.044)	(0.045)	(0.044)	(0.044)	(0.062)	(0.049)	(0.040)	(0.047)
tenurestat	-0.032	0.007	0.033	-0.004	-0.010	0.108***	-0.180***	-0.133**	-0.046	0.057	-0.009
	(0.091)	(0.047)	(0.45)	(0.046)	(0.041)	(0.042)	(0.043)	(0.061)	(0.046)	(0.040)	(0.046)
Constant	-2.431***	-0.626***	-0.587***	-0.946***	0.100**	-0.184****	0.241***	-1.981***	-0.134***	0.054	-0.789***
	(0.171)	(0.046)	(0.047)	(0.045)	(0.040)	(0.039)	(0.040)	(0.087)	(0.043)	(0.038)	(0.045)

Log pseudolikelihood = -5372.633, Wald chi2(132) = 1703.26; Prob>chi2 = 0.00; LR test of rho_{xy}: Chi2 (55) =744.288; Prob>chi2 = 0.000

Source: Generated by author from field survey, 2018 data using STATA 16 software

*** 1% significance; **5% significance and *10% significance. Figures in parentheses are robust standard errors

The effects of respondents' demographic and socio-economic characteristics are heterogenous on the use decision of the climate-smart adaptation strategies. Consistent with He, Cao & Li (2007) and Chuchird, Sasaki and Abe (2017), the likelihood to adopt irrigation technology as an adaptation strategy is significantly and inversely related with the age of household head; thereby, suggesting that young household heads are more likely to use modern irrigation facilities, which could be a little complex in operation, to adapt to climate change. Thus, targeting young farmers under climate-smart technology promotion can increase adoption. However, the positive coefficients of age variable indicate that, older household heads have higher likelihood to usesuch practices as crop rotation with legumes, new/improved crop variety, minimum tillage, farmyard manure, and fertilizer deep placement as climate change adaptation strategies. Knowledge of climate change/variability and skills to reduce its consequences increase with age. Therefore, older farmers who understand and or have experienced the effects of climate change/variability and have moreresource endowment are likely to use these strategies, to reduce the impacts of climate change. This result is consistent with findings of Ahmed (2016) and Simtowe, Asfaw & Abate (2016).

The effect of gender is significantly positive for the decisions to use cover crops, minimum tillage and farmyard manure. This shows that, the likelihood of use of these climate-smart adaptation strategies are significantly higher for male than female household heads. Resource ownership and labour requirements are expected to account for farmyard manure use. Farmyard manure are mostly animal-based, and livestock ownership is male-dominated which gives them more access to animal dungs/manure than their female counterparts. Similarly, manure application is labour-intensive, which male-headed households can afford because they command most of the household resources, including the use of cash income (Waithaka, Thornton, Shepherd& Ndiwa 2007). As Marenya, Kassie, Jaleta, Rahut & Erenstein (2015) noted, male headed households are typically dual adults (husband and wife) households. Such households are likely to have more adult residentswith more capacity to implement labour demanding practices. The practice of fertilizer deep placement is more likely among female-headed households compared totheir male counterparts. This agrees with the findings of Liverpool-Tasie *et al*. (2015) that, female plot managers were more likely to adopt improved method of urea application for rice production, than male plot managers.

The educational level of household head proxied by years of schooling has heterogenous effects on decision to use the climate-smart adaptation strategies. It has significant positive effect on the use of crop rotation with legumes, intercropping, new/improved crop variety, and fertilizer deep placement; significant negative influence on practices of irrigation, use of cover crops, minimum tillage and farmyard manure; while it has no effect on the use mulch, and agroforestry in the study area. Earlier study by Knowler andBradshaw (2007) acknowledges these mixed results. Education, as a human capital, enables farmers to critically anayse and use technical information to understand the causes and consequences of climate change, prepares them to live with the impacts of climate change and empowers them to take appropriate actions (UNESCO, 2015; Tripathi &Mishra, 2017). Here, crop rotation with legumes, intercropping, new/improved crop variety, and fertilizer deep placement practices are considered information-intensive strategies, which can easily be used by educated farmers. Generally, previous studies have found that education effect on farmers' adaptation to climate change is positiveand significant (Below *et al.*, 2012; Chukwuone, 2015; Lokonon& Mbaye, 2018). However, Komba and Muchapondwa (2012),Tanellari, Kostandini, Bonabana-Wabbi andMurray (2014) and Shikuku, Winowiecki, Twyman, Eitzinger, Perez, Mwongera and Läderach (2017) found a significantly negative nexusbetween education and climate change adaptation decisions.

The likelihood of farmer's use of cover crops, agroforestry, new/improved crop variety, and fertilizer deep placement as strategies to adapt to climate change is increased with higher dependency ratio. These strategies, which can boost crop productivity in short and medium term, are relatively modern farm inputs whichAsfaw *et al*. (2016) opined that their use is favoured by higher dependency ratio. However, dependency ratio is likely to significantly decrease the decision to use green manuring at plot level. Asfaw *et al*. (2016) posited similar negative effect on the use of crop residues, though not statistically significant. Household size (in adult equivalent) is statistically significant and positively signed for the practice of irrigation and use of farmyard manure as strategies for adaptation. This implies that the likelihood of use of these strategies would increase with farmers that have larger household sizes. This agrees with earlier study by Hassan andNhemachena (2008) that the choice of anadaptation measure depends on household endowments, including household size at the disposal of farming households. Large family size is a potential indicator of adequate labour availabilityfor production activities, especially for use of adaptation strategies (Yegbemey *et al.*, 2013; Asfaw *et al.*, 2016). The use of improved crop varieties, however, decreases with large household size. This partly may be due to the consumption pressure on the household, which could lead to diversion of financial resources from the purchase of improved crop varieties to food consumption.

Social capital, which is also a constituent of adaptation appraisal processes, plays a critical positive role in sustainable technology adoption among farmers (Lokonon &Mbaye, 2018). However, the finding of this study shows the contrary as the coefficient of farmers' membership of any group, measured as number of years of membership, is significant and negatively signed for irrigation, cover cropping, minimum tillage, crop rotation with legumes, intercropping with legumes, green manuring, agroforestry, and use of fertilizer deep placement. This negative correlation is supported by the work of Mponela, Tamene, Ndengu, Magreta, Kihara, andMango (2016). One possible explanation for this observation is that farmers do not discuss or access information on climate change through these groups. Other reasons advanced for this negative relationship, include; marketing and dealing with specific constraints, that do not depend on social networks (Asante, Afarindash & Sarpong, 2011).

In this study, households, that are not able to borrow against future income in the last five (5) years are categorized as being credit constrained. Credit access relaxes liquidity constraints of household and therefore, increases the odds of technology adoption (Temesgen*et al.*, 2008; Hadgu, Fantaye, Mamo & Kassa, 2015). This study found that farmers using cover crops, minimum tillage, mulching, agroforestry, and farmyard manure are probably credit constrained, while those who are not credit constrained, used intercropping with legumes, improved crop varieties and fertilizer deep placement strategies. The latter strategies are capital intensive, thus, requiring households with strong financial capability to adopt.

The variables used in this study to measure households' behavioural intention to adapt to climate change, include; risk perception, risk experience, and perceived adaptation efficacy of identified strategies. The coefficient and sign of household risk perception index indicate that, it has a significantly negative effect on the likelihood of use of all the strategies except crop rotation with legumes. This observation depicts the risk attitudes of the farmers and the potentials of the strategies for minimizing climate change risk. As risk averse, the probability of use of strategiessuch as; irrigation, cover cropping, green manuring, agroforestry, and farmyard manure will decrease significantly. However, as risk takers, the probability of crop rotation with legumes would significantly increase as risk-taking farmers considers the strategy as climate risk minimizing.

Further, the number of actual climate risks experienced is seen to have mixed effects on farmers' probabilities of use of adaptation strategies. With increase in climate risk experienced, farmers are more likely to adopt the use of irrigation, minimum tillage, green manuring, agroforestry, and fertilizer deep placement technology as adaptation measures. However, this is not the case with the use of crop rotation with legumes, which would experience a significant decrease in use. Generally, the farmers believe that, the climate-smart adaptation strategies can helpthem out of the negative consequences of climate change as indicated by the significantly positive coefficient of perceived adaptation. This is in line with the studies by Grothmann &Patt (2005) and Mase, Gramig& Prokopy(2017). From the result in Table 15, this adaptation appraisal variable is positive for all strategies, but not statistically significant for mulching and fertilizer deep placement.Knowing the problems associated with soil degradation often influences farmers' decisions about improved soil fertility management practices (Pulido &Bocco, 2014; Bwambale, 2015). Also, Pulido &Bocco (2014) observed that farmers choose to invest in soil conservation technology if the cropping system becomes more productive within a short period.

Plot topography has a significantly positive effect on the respondents' likelihood use of cover crops, minimum tillage practices, intercropping involvinglegumes, green manuring, farmyard manuring, and the practice of fertilizer deep placement technology as climate-smart adaptation strategies. The use of these strategies tends to increase on farmlands, with relatively flat topography, serving as effective water retention, soil-nutrient saving, and limited soil disturbance strategies adequate for increased fam yield. Although the use of these strategies is expected for plots with topographical diversity (concave and convex slopes) due to increased leaching losses, infiltration, and runoff potentials(Brouwer & Powell, 1998; Senthilkumar, Kravchenko & Robertson, 2009) and high yield variability (Beehler, Fry, Negassa, & Kravchenko,2017), the results show that these strategies are not limited to such topographic features. This is probably because such soil degradation features affect relatively flat farmlands.

Perceived plot tenure security status has a significant positive effect on farmers' likelihood of using nitrogen-fixing cropping method (intercropping with legumes). Surprisingly, the likelihood of use of organic manures (green and farmyard) and agroforestry tend to decrease with secure tenure security. This is a deviation from Arslana *et al*. (2015) who found that, improved tenure security is an incentive to investments in strategies, that increase productivity and improve soil health in the long run. This finding could be a result of farmers' preference for strategies, that can bring quick returns on investment within the shortest period considering that climate change events and impacts are unpredictable.

4.3. Determinants of use intensity of climate-smart adaptation strategies among staple crop farmers

This section is aimed at presenting the analysis forobjective three of the study. Hence, the results discussed are those on climate-smart intensification index and its determinants.

4.3.1. Intensification of climate-smart strategies by crop category

The distribution of plot-level climate-smart intensification level is shown in Table 15. Following that the respondent farmers practice intercropping generally and the use of adaptation strategies are not mutually exclusive for crops in each plot, the distribution of the intensification level follows similar pattern across the three crop categories.

Table 6: Percentage distribution of climate-smart intensification level

Household	**Pooled**		**Cereals**		**Root/Tubers**		**Pulses**	
Climate-smart intensification level	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage

Low	499	38.98	310	36.95	273	44.54	273	39.57
Medium	272	21.25	177	21.10	134	21.86	153	22.17
High	509	39.77	352	41.96	206	33.60	264	38.26
Total	**1,280**	**100.00**	**839**	**100.00**	**613**	**100.00**	**690**	**100.00**

Source: Field survey, 2018

NB: Multiple responses across columns

Overall, the intensity of use of climate-smart adaptation strategies is relatively low, given that only about 40% of the plots were under high use intensity of these strategies. Across crop categories, the intensity of use of these strategies is higher in cereals (42%) than in

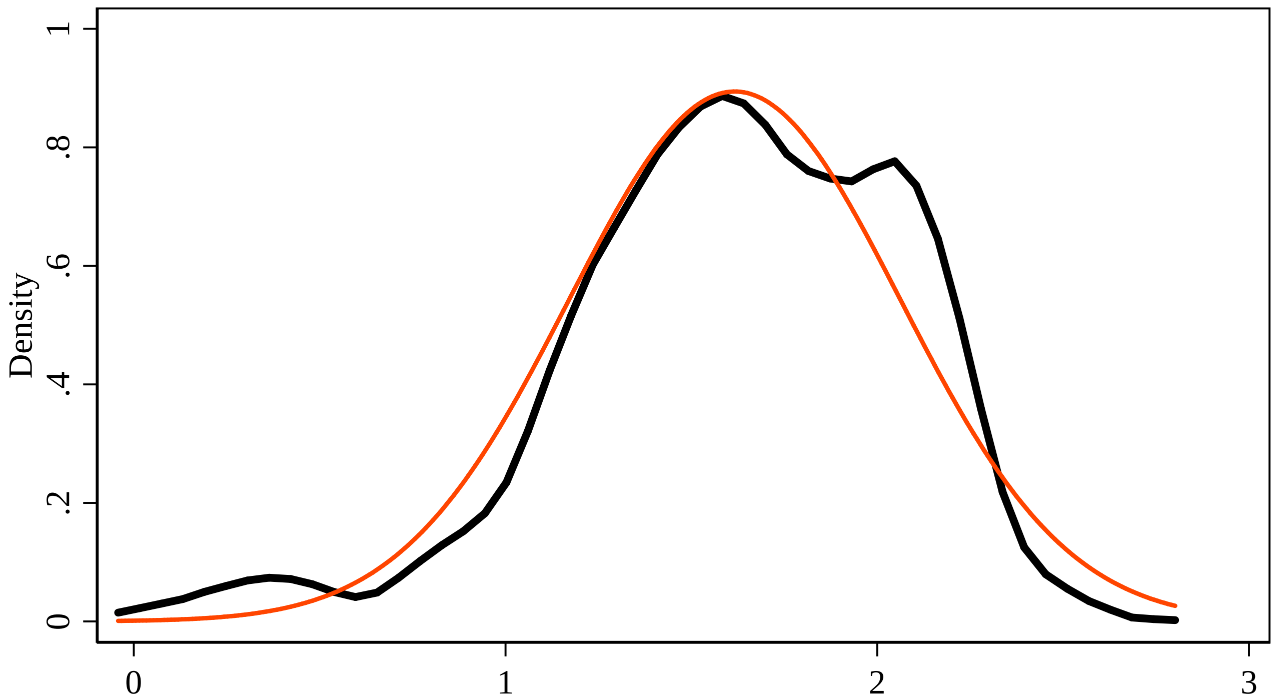

Fig. 1: Kernel density estimate of plot-level CSA intensification index

either pulses (38%) or root and tuber crops (34%), suggesting that higher production investment is made in this crop category compared to others, probably d87ommercializationialisation potentials. Furthermore, the distribution of CSA intensification index among the respondents is presented in Figure 1. The distribution of the index shows, homogeneous variations in use intensity of CSA strategies, among the respondents except for two distinct group of farmers: high intensity and low intensity users. Following this pattern, the number of farmers is likely to decrease, with increasing use intensity of CSA strategies.

4.3.2. Determinants of the use intensity of climate-smart adaptation strategies

Table 16shows the results of the clustered OLS and Poisson regression analyses (for robustness check). The use of clustered option helps to account for possible correlation within an enumeration area. Based on model performance criteria (model specification, collinearity, and smaller standard error), the OLS model was chosen for further discussions. The model exhibits a high explanatory power,with the coefficient of multiple variation, R^2 = 0.6155 and thus, explains 61.55% of the total variations in intensity of adaptation. The F-statistic of joint significance of the explanatory variables was 156.96 with a probability =0.000 indicating that, the model parameters were jointly significant at 1% level and adequate in fitting the data.

Table 76: Estimates of determinants of use intensity of climate-smart strategy (Dependent variable = households' climate-smart intensification index)

Variables	OLS estimate DV= CS intensification index		Poisson estimate DV=Number of strategies used	
	Coefficient	Robust Std. Error	Coefficient	Std. Error
hhdage	-0.003**	0.001	0.001	0.003
hhgender	0.041	0.030	0.066	0.081
Mstat	0.045*	0.022	0.146*	0.085
depratio	0.002	0.008	0.014	0.022
hhnature	-0.012	0.018	-0.087	0.058
extaccess	0.015*	0.008	0.038	0.024
crdtconst	-0.001	0.016	0.056	0.082
hhdgroupmemb	0.028	0.029	-0.012	0.082
TLU	0.005**	0.002	0.018	0.012
plotcultyr	0.002**	0.001	-0.0001	0.004
lnmktdist	0.023**	0.011	0.090***	0.029
roadaccess	-0.012	0.022	0.026	0.087
lnfarmsize	0.376***	0.028	-0.403***	0.069
plottopo	-0.029	0.018	0.305***	0.106
tenurestat	0.030	0.024	0.013	0.061
soilfertpercep	0.124***	0.021	0.399***	0.090
hhdriskpercep	-0.002	0.003	-0.006	0.017
agrozone	0.005	0.065	0.271**	0.116
Constant	0.053	0.059	0.610***	0.213
Number of observations	1, 151		1, 151	
R^2	0.6155		Log pseudolikelihood (-2275.79)	
F – statistic	156.96		Wald chi2(18) (219.27)	
Prob > F	0.000		Prob>chi2 (0.000)	

Source: Generated by author from field survey, 2018 data using STATA 16 software

*** denotes 1% significance; ** denotes 5% significance and * denotes 10% significance; NB: Standard error adjusted for clusters in enumeration areas

Age of household head had a significant and negative effect on intensity of use of climate-smart adaptation strategies; signifying that a year increase in age of household head decreasing intensity of use by 0.3%. This impliesthat, the younger the farming household head, the more the practice of climate-smart intensification. This could be an indication of younger farmers disposition to experiment with several strategies,that are capable to help them reduce the consequencesof climate change. This supports the finding of Olarinde, Adepoju andJabaru (2014) but deviates from the findings of Belay, Recha, Woldeamanuel andMorton (2017) which shows that, the decision to intensify agricultural practices increases with age.

The influence of joint decision making within the household is shown by the significant and positive relationship between household heads living with their spouse and intensification index. The increase in climate-smart intensification is about 5% higher among farmers living with their spouse compared with those who do not or that are single. This shows that, some level of intra-household bargaining or deliberation for resource use between spouses exist in intensification of adaptation strategies; consistent with the conclusions of Bomuhangi, Nabanoga, Namaalwa, Jacobson andGombya-Ssembajjwe(2016) and Kunzekweguta *et al*. (2017). Earlier, Doss (2013) opine that, intrahousehold bargaining is likely to influence the adoption of new agricultural technologies.

As expected, the coefficient of extension contacts shows that, it increases intensification of adaptation strategies by 1.5%. Access to extension services enables farmers to make informed decisions on the type, number, and frequency of use of adaptation strategies. This corroborates the works of Mazvimavi and Twomlow (2009), and Kunzekweguta *et al*.(2017)which conclude that intensity of adoption is significantly and positively influenced by farmer’s access to extension services.A one-kilometer increase in distance between farmers’ place of residence and the nearest market will significantly increase intensification of adaptation strategies by 0.2%. Access to market has been identified to increase the intensity of use of inputs like; fertilizers, pesticides, and improved crop varieties (Olarinde *et al.*, 2014; Belay *et al.*, 2017). However, when farmers greatly depend on locally available adaptation strategies, for intensification practices and are not commercial-oriented, intensification of adaptation strategies could deviate from these earlier findings, such that, it increases with increasing market distance.

Livestock are store of wealth often measured in tropical livestock unit, a weighted sum of large and small livestock (Kunzekweguta *et al.*, 2017). From Table 16, a percentage increase in the numbers of livestock owned by a household would lead to 0.5% increase in the intensification of climate-smart adaptation strategies in the study area. This suggests that the wealthier the farmer, the more the use of multiple strategies on plots cultivated. Chen, Wichmann, Luckert, Winowiecki, Förch, andLäderach(2018) found similar result in their study of diversification and intensification of agricultural adaptation strategies from global to local, where livestock ownership increases adaptation intensity by about 0.6%. Use intensity of climate-smart adaptation strategies would increase by 0.2% as plot is put into cultivation for an extra year. Continuous farming on a piece of land for a prolonged period, impacts on its characteristics, including; structure, fertility status, biodiversity and vegetative biomass. This has tendency to reduce the natural capital of the soil and distort the flow of environmental services. To avoid this, farmers would tend to employ several strategies, simultaneously, to renew this stock on a continuous basis. The intensity of use climate-smart adaptation strategies tends to increase with increasing distance of households from the nearest market. Generally, many of the climate-smart strategies considered in this study are traditional strategies which can be sourced locally. This tends to agree with Asfaw *et al.* (2016) whoobserved that, farm households that reside far away from periodic or permanent markets, tend to use more of locally sourced inputs such as; organic fertilizers and less of modern inputs.

Households' average farm size has a significant and positive effect on the intensity of use of climate-smart adaptation strategies with a hectare increase, leading to an increase in plot intensification index by about 37%. Thus, the larger the farm size, the more the share of intensification practices by farmers. Studies (Mazvimavi & Twomlow, 2009; Tongruksawattana, 2014;Kassie, Teklewold, Jaleta, Marenya, & Erenstein, 2015) have observed similar trend, which they attribute to influence of household's endowment and response to productivity gains. Furthermore, the results in Table 16indicate that intensification of use of adaptation strategies increases even when farm-plots are perceived to be fertile. Though it is expected that intensification would increase with less soil fertility, farmers might however, be concerned with sustaining or improving the current soil fertility status for increased productivity; suggesting that they are aware that climate change can cause depletion in soil fertility. Hence, they would increase the use intensity of the climate-smart adaptation strategies to prevent this loss in the future.

4.4. Productivity – welfare effects of climate-smart adaptation strategies

Results discussed in this sub-section are to answer the fourth research question and hence, achieve the objective of determining the productivity and welfare effects of usage of climate-smart adaptation strategies. Results discussed include those related to crop productivity under different climate-smart adaptation practices, household multidimensional welfare level, and the nexus between welfare – productivity – use intensity of climate-smart adaptation strategies.

4.4.1. Crop productivity under climate-smart adaptation practices

As described earlier, climate-smart adaptation strategies are promoted as means to improve sustainable crop productionin the presenceof climate variability and change. The heterogenous treatmenIffect (HTE) results of use of various climate-smart adaptation strategies are shown in Table 17. Evident from the table is the varied contributions/effects of the climate-smart adaptation (CSA) strategies to crop yield.

Table 8: Estimated average treatment effect on the treated (ATT) for use of CSAstrategies

Crop category	CSA strategy	Sample	Treated	Control	difference	t-stat
Cereals	Irrigation	Unmatched	2453.24	1668.79	333.89	2.35
		ATT	2453.24	2189.73	416.43	0.63
	Cover cropping	Unmatched	2030.92	1663.18	367.74	2.10
		ATT	2030.92	1396.36	634.56**	**1.93**
	Minimum tillage	Unmatched	1763.97	1677.25	86.72	0.57
		ATT	1763.97	1768.67	-4.50	-0.02
	Mulching	Unmatched	2009.88	1681.39	328.49	1.18
		ATT	2009.88	2442.72	-432.83	-0.72
	Crop rotation with legume	Unmatched	2110.37	1640.20	470.17	2.74
		ATT	2110.37	1619.13	491.24	1.34
	Intercropping with legume	Unmatched	2383.76	1610.09	772.67	4.25
		ATT	2383.76	1844.83	537.93	1.10
	Green manuring	Unmatched	2076.24	1513.32	562.93	4.09
		ATT	2076.24	1822.24	254.01	1.09
	Agroforestry	Unmatched	2239.97	1691.04	548.93	1.16
		ATT	2239.97	2561.98	-322.01	-0.36
	Farmyard manure	Unmatched	1683.60	1775.34	-91.74	-0.64
		ATT	1683.60	1177.69	505.89	0.38

Crop category	CSA strategy	Sample	Treated	Control	difference	t-stat
	Improved crop variety	Unmatched	1984.30	1325.52	658.78	4.87
		ATT	1984.30	1665.30	319.00	1.43
	Fertilizer deep placement	Unmatched	2049.91	1649.80	400.11	2.37
		ATT	2049.91	726.13	1323.78**	**2.16**

	CSA strategy	Sample	Treated	Control	difference	t-stat
Pulses	Cover cropping	Unmatched	465.73	506.92	-41.19	-0.63
		ATT	465.73	417.58	48.15	0.33
	Minimum tillage	Unmatched	380.30	568.89	-188.55	-2.92
		ATT	380.30	107.97	272.34	0.60
	Mulching	Unmatched	311.56	524.27	-212.70	-2.71
		ATT	311.56	518.14	-206.57	-1.51
	Crop rotation with legume	Unmatched	554.92	350.38	204.54	3.11
		ATT	554.92	203.26	351.66**	**3.00**
	Intercropping with legume	Unmatched	506.22	458.87	47.35	0.76
		ATT	506.22	419.96	86.25	0.82
	Green manuring	Unmatched	462.96	526.93	-63.97	-0.96
		ATT	462.96	578.80	-115.84	-0.55
	Agroforestry	Unmatched	229.41	508.97	-279.55	-2.51
		ATT	229.41	273.67	-44.26	-0.24
	Farmyard manure	Unmatched	389.57	587.07	-197.50	-3.24
		ATT	389.57	398.69	-9.12	-0.05
	Improved crop variety	Unmatched	516.72	450.80	65.91	1.03
		ATT	516.72	293.61	223.11**	**2.10**
	Fertilizer deep placement	Unmatched	427.56	500.71	-73.15	-0.87
		ATT	427.56	747.01	-319.45	-1.65

Roots and Tubers	Cover cropping	Unmatched	6327.78	13694.83	-7367.06	-2.41
		ATT	6327.78	5339.63	988.15	0.48
	Minimum tillage	Unmatched	6661.77	12997.48	-6335.71	-1.60
		ATT	6661.77	9582.56	-2920.78	-0.50
	Mulching	Unmatched	23729.39	8485.99	15243.40	6.19
		ATT	23729.39	13486.51	10242.88**	**2.24**
	Crop rotation with legume	Unmatched	10929.04	12877.14	-1948.10	-0.78
		ATT	10929.04	26846.08	-15917.04	-2.13
	Intercropping with legume	Unmatched	11487.72	12077.53	-589.81	-0.22
		ATT	11487.72	3466.62	8021.10	1.02
	Green manuring	Unmatched	15014.08	6975.52	8038.56	3.27
		ATT	15014.08	29077.77	-14063.69	-1.57
	Farmyard manure	Unmatched	7362.77	16121.65	-8758.88	-3.79
		ATT	7362.77	7059.15	303.63	0.04
	Improved crop variety	Unmatched	12749.25	11884.38	864.87	0.36
		ATT	12749.25	11560.07	1189.18	0.17
	Fertilizer deep placement	Unmatched	15788.32	10641.63	5146.69	2.06
		ATT	15788.32	12949.21	2839.11	0.51

Source: Generated by author from field survey, 2018 data using STATA 16 software
** denotes 5% significance

Climate-smart adaptation strategies with statistically significanteffect on crop yield includecover cropping, fertilizer deep placement, crop rotation with legume, improved crop variety and mulching.On the average,the treatment effect on the treated of the use of cover croppingis positive and increased the yieldof cereal crops by 45%.Similarly, the percentage change in cereal yield,as a result of fertilizer deep placement practice is182% over non-use of the strategy. Still on cereal production, the impacts of the use of irrigation, crop rotation and intercropping with legumes, green manure, farmyard manure, and improved varieties is positive though not statistically significant. These are indications that the use of these strategies positively impacted yields of cereal crop.Under pulsesproduction, the average treatment effects on the treated of use of crop rotation, with legumes as well as improved varieties as CSA strategies increased yield by 75% and 76%, respectively. However, minimum tillage and intercropping with legumes had positive, though not statistically significant, effect that indicatessuch practices may not be adequate for this crop category. Quantitatively, the use of mulch in roots and tubers increased yield by 76%compared to non-use. Though, the use of cover cropping, intercropping with legumes, farmyard manure, improved crop variety and the practice of fertilizer deep placement on root and tuber crops production had positive effects on yield, the effects are statistically non-significant.

Crop yields under the practices of minimum tillage and farmyard manure use were significantly less likely to contribute to increased crop yield, compared to plots without such practices. Minimum tillage for instance can lead to reduced or no yield (Gattinger, Jawtusch, Müller, & Mäder, 2011) and the effects of farmyard manure on crop yield are usually not immediate. Studies (Witt, Cassman, Olk, Biker, Liboon, Samson, & Ottow, 2000; Luo, Wang & Sun, 2010; Khatri-Chhetri, et al., 2017) have shown that, climate-smart adaptation strategies are more effective, when applied in combinations.

4.4.2. Nature of multidimensional welfare deprivation in the study area

The figures in Table 18indicate that,overall, the respondent households are multidimensionally deprived, since none of the scores is zero (0) under any of the dimensions (or indicators). However, the level of multidimensional deprivation varies across the dimensions/indicators.

Table 98: Summary of household multidimensional welfare dimensions

Dimension	Weight	*Deprived (%)
Education		
Years of schooling	0.17	9.45
School attendance by school age children	0.17	45.67
Living Standard		
Source of drinking water	0.03	8.40
Sanitation/toilet facilities	0.03	37.27
Type of cooking fuel	0.03	98.69
Electricity access	0.03	22.31
Quality of dwelling place	0.03	62.99
Adequacy of bedrooms	0.03	11.81
Access to motorable road	0.03	11.81
Land ownership	0.03	22.57
Livestock ownership	0.03	70.87
Asset ownership	0.03	39.90
Health		
Food security	0.17	56.69
Child mortality	0.17	40.42

Source: Calculated from field survey data (2018) using Stata 16software

* Percentage of households whose indicator values are below the threshold

From Table 18, it is evident that households in the study area, suffer multiple welfare deprivations particularly across the use of environmentally degrading cooking methods (99%), level of livestock ownership (71%), quality of dwelling place (63%) and food security (57%). The high level of use of firewood, charcoal, and other environmentally degrading cooking fuel may relate to their cheapness and availability, since they can be locally sourced. According to Anozie, Bakare, Sonibare & Oyebisi (2007), the use of this type of cooking fuel is due to poverty factors and often decreases with increase in income level. Other areas of deprivation include high out-of-school children (school attendance by school age children) (46%), child mortality (40%), asset ownership (40%) and sanitation/toilet facilities (37%). The study households are least deprived in sources of drinking water with about 92% of the households under study having access to protected drinking water sources (piped water, public tap, borehole, protected well, etc.), which are typically less than 30-minute walk (round trip). This is followed by years of schooling, which shows that about 91% of the households in the study area had at least a member that completed a minimum of six years of schooling.

Table 19: Multidimensional welfare levels

Headcount Ratio (H): % Population in multidimensional deprivation (poverty)	**0.575(0.025)**
Intensity of deprivation among the poor (A): Average % of weighted deprivations	**0.510 (0.008)**
Adjusted Headcount Ratio (M0* = MPI = H x A): Mean of censored deprivation matrix	**0.293(0.014)**
Dimension and indicator	**Contribution to M0**
Dimension	
Dimension 1: Education	**0.258**
Dimension 2: Living standard	**0.262**
Dimension 3: Health	**0.480**
Indicator	
Dimension 1: Education	
Years of schooling	0.04
School attendance by school age children	0.22
Dimension 2: Living Standard	
Source of drinking water	0.008
Sanitation/toilet facilities	0.033
Type of cooking fuel	0.064
Electricity access	0.017
Quality of dwelling place	0.043
Adequacy of bedrooms	0.004
Access to motorable road	0.005
Land ownership	0.013
Livestock ownership	0.051
Asset ownership	0.025
Dimension 3: Health	
Food insecurity	0.273
Child mortality	0.207

Source: Calculated from field survey data (2018) using Stata 16software

*M0 is the multidimensional welfare index of households

Figures in parentheses are standard errors

The multidimensional welfare indices reported in Table 19include the headcount ratio (H), intensity of deprivation among the households (A) and adjusted headcount ratio (M0 = H*A).Following Alkire-Foster methodology, a household is multidimensionally deprived, if it experiences deprivations in at least 30% (deprivation cut-off) of the weighted indicators (Alkire & Foster, 2011; Alkire, Conconi & Seth, 2014). Multidimensional headcount ratio or incidence of deprivation (poverty) is the proportion of household who experience multiple deprivations in the welfare dimensions: education, living standard, and health. About 58% of the households show that, they are deprived at least either in all the indicators of a single dimension or in a combination across dimensions and thus, in acute poverty.

Overall, the multidimensional welfare index indicated by the adjusted headcount ratio, which capturesboth the incidence and intensity of deprivation (i.e. adjusts headcount ratio by the number of deprivations) and depicts the multidimensional welfare level in the study area, shows that 29% out of the 58% of the welfare-deprived household respondents suffer larger deprivation on the average. This implies that, a poverty intervention aimed at reducing intensity rather than proportion of the poor would be more effective if this 29% of the poor is targeted while the 58% deprived households would be the target if the aim of the intervention is change in proportion rather than intensity of poverty.

The health dimension, consisting of the food security and child mortality indicators, made the largest contribution of 0.48 (48%) to households' welfare deprivation. This is followed by the living standard dimension with 0.262 (26.20%) and the education dimension with a contribution of 0.258 (25.80%). The results, therefore,show that, the households in the study area are more deprived, in the indicators of health dimension compared to others.

4.4.3. Crop productivity and welfare effects of usage of climate-smart adaptation strategies

The results in this sub-section are presented in three parts: household welfare, crop productivity, and use intensity of climate-smart adaptation strategies. These were jointly estimated with maximum likelihood (ML) employing OLS and probit models and implemented with the *cmp*Stata command. The estimation was done, while accounting for cluster heteroscedasticity standard error, at enumeration area level. Based on OLS regression, the estimation of the determinants of use intensity is the first stage of the joint estimation process, followed by the estimation of the effects of use intensity on crop yield.The third stage involved a probit analysis of the effects of yield on household welfare category, defined as deprived (1) or not deprived (0). The estimated modelsfor the crop categories haveX^2 goodness-of-fit statistic significant at the 1% level. Also, the models yield significant correlation coefficients, among the error terms between CSA intensity and productivity equation and between production and welfare model. The correlation is shown by *atanhrho* parameter estimates (a measure of selection bias) which indicates that, joint recursive estimation was adequateunder each crop model (Table 20). A positive *atanhrho* value implies that, there are unobserved factors, that positively affectsthe selection and outcome equations and that individual models ignoring the correlation would be biased. The reverse can be said about observed negatively signed *atanhrho* (Makate *et al.*, 2016).

Table 10: Estimates of effects of CSA use intensity on crop-based farm productivity and household welfare using CMP analysis

Variables	Crop category		
	Cereals	Root and tubers	Pulses
	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)
Welfare model (DV1 = Welfare status (MPI non-poor=0))			
ln of yield	0.480** (0.218)	-0.455***(0.127)	-1.881*** (0.467)
ln of yield squared	-0.076*** (0.025)	0.028** (0.013)	0.062** (0.031)
hhdgroupmemb	0.276 (0.290)	0.122 (0.228)	-0.337 (0.244)
Dratio	-0.130 (0.116)	-0.058 (0.053)	-
Crdstat	0.066 (0.440)	-0.584*** (0.202)	-
Hhgend	0.718** (0.286)	-	-
Hhdnature	-0.236 (0.415)	-	-
hhdnature* crdstat	-0.274 (0.536)	-	-
ln mktdist	-	0.152 (0.147)	0.912*** (0.226)
Hhdage	-	-0.010 (0.009)	-
Mstat	-	-	-0.367 (0.270)
Location	-	-	-2.249*** (0.532)
Constant	-0.093 (0.490)	1.707*** (0.519)	11.313*** (2.261)
Productivity model (DV2 = Log of yield (kg/ha))			
CSI intensity	3.378** (1.590)	6.347*** (1.364)	2.842** (1.220)
ln farmsize	-2.648** (1.151)	-4.001*** (0.975)	0.012 (0.167)
ln farrmsizesq	0.289 (0.243)	-0.192*** (0.057)	-0.096*** (0.032)
ln totpday	-0.329 (0.257)	-1.223*** (0.452)	-

Variables	Crop category		
	Cereals	Root and tubers	Pulses
	Coefficient (Std. error)	Coefficient (Std. error)	Coefficient (Std. error)
ln agrochemqty	-0.267 (0.213)	-	-
ln fertcost	0.238 (0410)	-0.972*** (0.369)	-
hhdgroupmemb	0.038 (5.83)		-
Plotcultyr	-0.016 (0.019)	-	0.018* (0.010)
Extaccess	-	0.094 (0.316)	0.033 (0.067)
Hhdage	-		-0.006 (0.011)
Fertstat	-		1.213** (0.569)
ln mktdist	-		-0.3002 (0.272)
crdtconst	-0.137 (0.440)	-	-
flattop	-	0.841 (0.556)	-
Location	-0.612 (0.635)	-	-1.011 (0.807)
Constant	5.051 (4.684)	11.354*** (3.033)	2.447 (1.853)
CSA use intensity model (DV3=CSA intensity)			
Hhage	-0.004* (0.003)	-	-0.004*** (0.002)
Roadacess	0.057 (0.051)	-	0.115*** (0.042)
ln farmsize	0.647*** (0.075)	0.595*** (0.036)	-
Tenuresec	-	0.161*** (0.058)	0.116** (0.059)
Extaccess	0.015 (0.021)	-	-
Hhgend	0.202 (0.133)	-	-
hhdgroupmemb	-0.058 (0.058)	-	-
Tlu	0.0361*** (0.011)	-	-
Plotcultyr	0.006** (0.002)	-	-
Mstat	-	0.245*** (0.043)	-
Hhdnature	-	-	-0.066* (0.035)
ln mktdist	0.091*** (0.033)	0.044 (0.032)	0.154*** (0.050)
plotfertpercep	0.115* (0.064)	0.092* (0.052)	-0.101 (0.106)
hhdriskpercep	-0.010 (0.011)	-0.015 (0.012)	-0.032*** (0.005)
Location	-0.100 0.112)	0.073 (0.062)	0.114 (0.157)
Constant	0.883*** (0.123)	0.737*** (0.067)	1.691*** (0.164)
/atanhrho_12	0.421** (0.171)	0.868*** (0.245)	0.643*** (0.225)
/atanhrho_13	-0.096 (0.112)	0.275** (0.121)	-0.064 (0.138)
/atanhrho_23	-0.511*** (0.195)	-0.480*** (0.134)	-1.112*** (0.424)
/lnsig_2	0.698***(0.183)	1.245*** (0.116)	0.261 (0.328)
/lnsig_3	-1.293*** (0.093)	-1.352***(0.197)	-1.129*** (0.128)
Log likelihood	-348.662	-282.981	-196.694

Wald chi2(31; 21; 24)	40937.52	14531.28	303155
Prob > chi2	0.000	0.000	0.000
Number of observations	255	164	134

Source: Generated by author from field survey, 2018 data using STATA 16 software
*** denotes 1% significance; ** denotes 5% significance and * denotes 10% significance

Although several covariatesare included in the models (Table 20) to capture the adjusted effects of the outcome variables, the causal relationships between household welfare, crop productivity and use intensity of climate-smart adaptation strategies are the focus in this section.The individual joint estimation models show that, household welfare is likely to improve, with increase in yield of the crop categories. This collaborates the findings by Dzanku (2015) that an increase infarm productivity increases the probability of being non-poor in all indicated welfare dimensions.However, the pathto achieving the increase differs with crop category. For instance, a percentage increase in cereal yield, is likely to increase household welfare by 48%. However, the significant positive sign of the linear coefficient of yield and its significant negative nonlinear coefficient in the cereal model, implies that, household welfare is likely to first increase at the indicated rate and then decrease with size of yields of cereal crops. In the case of roots and tubers and pulses, a reverse observation is noted. In both models, household welfare is likely to first decrease and then increase by 2.8% and 6.2% with respective yield increase. This observation is associated with the significant negative linear and the positive non-linear relationship between the household welfare and the yields of roots and tubers and pulses.

Overall, increase in yields of cereals and pulses are significantly more likely to make significant positive contributions, to household welfare improvement, than roots and tubers (yield coefficients: cereals = 0.48; pulses = 0.062; roots and tubers = 0.0.028). One possible explanation for this, is that, cereals and pulsesare high-value crops,which can be sold for high prices, at local or international market (Rahmanian et al., 2018) and therefore,could contribute more to household income than roots and tubers.Furthermore, the higher contribution of cereals to household welfare compared with pulses is consistent with Amare, Mavrotas & Edeh(2018). Their study noted that, the share of cereal crops in Nigeria farm households' net crop income have been consistently higher than that of pulses in the last decade.

The results of the productivity models show that, the responses of crop yields to intensity of use of climate-smart adaptation strategies,are significantly positive and exceed proportionate increases. This indicates increasing returns to scale (at 1% roots and tubers and 5% level of significance for cereals and pulses). This is consistent with the findings of Roco, Bravo-Ureta, Engler, & Jara-Rojas (2017). The negative term associated with both farm size and square of farm size collaborate earlier empirical findings in literature.

4.5.Constraints to use of CSA strategies by farmers in the study area

Following the responses of the sampled respondents, the constraints to use of CSA strategies by farmers were ranked and prioritized, by using the Garrett's ranking method and reported in Table 21. Overall, the most important constraint to the use of CSA strategy by smallholder arable crop farmers, is the initial establishment cost without immediate benefits (62.17 Garrett score). Following that CSA strategies are long term investments, they often require huge investments to establish and maintain, if the needed returns are to be achieved. However, the time lapse to achieve these returns tends to be an impediment to their use by smallholder farmers who are often credit constrained. This constraint mostly affects the practice of fertilizer deep placement, improved crop varieties, green manuring, and minimum tillage. This constraint is followed by plot tenure security status (61.76 Garrett score), which mostly affects the use of legume-based practices, mulching and cover cropping. Constraints related to markets to purchase the inputs for strategy implementation occupies the third position with 60.69 Garrett score, which is the most important constraint to the use of irrigation and agroforestry, while cost of labour for strategy use, followed with a Garrett score of 59.93. This constraint is mostly an impediment to farmyard manure use by smallholder farmers.

Knowledge of climate-smart adaptation strategy seems to be high among the respondents considering that, information-related constraints have relatively low Garrett scores across the strategies, with overall Garrett score of 58.66. Similarly, the respondents identified access to product market as an important constraint to use of agroforestry (61.81 Garrett score) and cover crops (62.70 Garrett score). However, it has on overall Garrett score of 57.33 for all the constraints. The least scored constraint is that related to credit access (52.40 Garrett score). Across the strategies, this constraint is almost the least scored, except for irrigation, where it ranked the fourth most impeding constraint.Generally, the rank of this constraint is an indication that,respondents do not depend on external financial source to use CSA strategies.

Table 111: Garrett mean score distribution of constraints affecting use of CSA strategies

Nature of constraints	Overall Garrett Mean score	Garrett mean ranking of constraints: Irrigation	Cover crops	Minimum tillage	Mulching	Crop rotation with legumes	Intercropping with legumes	Green manuring	Agroforestry	Farmyard manure	New/improved crop variety	Fertilizer deep placement
Initial establishment cost without immediate benefits	62.17 (1)	56.06 (3)	64.06 (2)	65.43 (1)	64.60 (4)	63.67 (2)	65.59 (2)	64.88 (1)	53.29 (7)	62.96 (2)	63.06 (1)	62.31 (1)
Land ownership status of plot	61.76 (2)	52.04 (7)	65.13 (1)	59.04 (5)	67.40 (1)	66.81 (1)	65.97 (1)	61.46 (3)	61.19 (3)	56.00 (6)	60.98 (2)	61.24 (2)
Markets to purchase the inputs for the strategy	60.69 (3)	61.94 (1)	57.17 (6)	64.34 (2)	66.42 (2)	62.30 (3)	57.63 (5)	62.91 (2)	61.93 (1)	61.63 (3)	57.99 (4)	53.32 (6)
Cost of hired labour for technology application	59.93 (4)	52.24 (6)	61.45 (4)	63.08 (3)	64.78 (3)	59.02 (4)	58.39 (4)	59.26 (4)	58.03 (5)	64.31 (1)	58.89 (3)	59.80 (3)
Limited access to information on CS practices	58.66 (5)	61.05 (2)	59.86 (5)	58.21 (6)	58.46 (5)	58.61 (5)	58.87 (3)	58.33 (5)	60.92 (4)	57.34 (5)	56.24 (5)	57.37 (4)
Access market to sell farm products	57.33 (6)	53.13 (5)	62.70 (3)	61.87 (4)	52.51 (7)	56.56 (6)	57.53 (6)	53.51 (7)	61.81 (2)	61.12 (4)	55.85 (6)	54.00 (5)
Credit access	52.40 (7)	53.83 (4)	49.97 (7)	50.91 (7)	53.55 (6)	52.42 (7)	53.33 (7)	55.22 (6)	53.88 (6)	53.00 (7)	51.04 (7)	49.28 (7)

Source: Field survey, 2018

NB: Figures in parentheses are in order of merit of constraints.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Summary

It is evident in literature that improving farm productivity, using climate-smart agricultural technologies,has positive implications for rural household wellbeing. However, the extent to which these benefits will accrue to households, depends on various conditions, including the types of climate-smart technologies adopted and the intensity of adoption; with a higher intensity able to drive higher farm productivity and consequently, household welfare. Empirical evidence of this nexus remains scanty. In the absence of such evidences, the extent of agricultural enhancement of the poor and the incentive to promote the use of climate-smart adaptation strategies, among farmers, will be limited. This study, therefore, examines how productivity and welfare of smallholder staple crop farmers in Savanna Agro-Ecological Zone of Nigeria vary with intensity of use of climate-smart adaptation strategies, by addressing five important policy questions. Firstly, what type of climate-smart adaptation strategies do staple crop farmers use vis-à-vis the type of crops produced? Secondly, what factors are responsible for the choices of climate-smart adaptation strategies among staple crop farmers? Thirdly, what factors determine the intensity of use of climate-smart strategies by farmers and crops produced? Fourthly, how does the intensity of use of climate-smart adaptation strategies affect farmers' productivity/welfare level? Fifthly, what constraints limit farmers use of available climate-smart adaptation strategies in the study area?

Using a cross-sectional data collected through a survey of smallholder crop farming households in Benue and Niger States, the first and fifth questions were addressed using descriptive statistics. The econometric methods,including multivariate probit, heterogenous treatment effect, based on propensity score matching, and conditional recursive mixed-process (CMP) modelling framework, involving probit and OLS estimations, were employed to address questions two, three, and four, respectively. The use of CMP framework allows for joint estimation of two or more equations, whose dependent variables may or may not be related, but with linkages among their error processes, account for multiple endogeneity, while producing more consistent and efficient estimates than either the instrumental or two-stage least squares estimation method.

The descriptive analysis of the sample respondents indicates that, the household heads are predominantly male with mean age of 46 years; overseeing a household size of 8 persons with low dependency ratio. These household heads, on average, spent about 9 years in formal education with an average of six extension contacts in five years mostly on non-climate change related issues. Social network among household heads is high with 84% belonging to at least a farmer/social group. Farmers on average travel about 6km to the nearest market with great variability shown by the distribution of the households; while majority are credit constrained.

On wealth and infrastructural indicators, 37 percent of the respondent households are in the upper non-land and livestock asset quintile, and had, on average, 2 animal units and cultivate one hectare of farmland. Majority of the households had accesses to safe drinking water, improved sanitation, and electricity, but, no efficient cooking fuel and modern dwelling place.

Descriptive analysis of plot biophysical and perceived tenure security variables shows that, most farmers perceive their farms to be fertile, though these farms have been in use for an average of 20 years. The results for land tenure security are mixed. Though respondents do not fear loss of their farmland, there are likelihood of ownership and use disputes occurring.The adaptation strategies used by the households received only 13 percent perceived efficacy score, even as climate change occurrence is evident, as perceived by more than 90% of the respondent households. The outcomes of climate change events were manifested in yield decline, loss of dwelling places, and health-related problems with varying degree across the events.

Irrigation and agroforestry are least practiced climate-smart adaptation strategies across all crop types, while the use of the climate-smart strategies is dominant for maize farming. The use of these strategies varies for yam and cassava, butmost pronounced for groundnut compared with soybean, and cowpea under pulses. The use of these strategies is, however, a reflection of local knowledge and awareness among farmers.

Empirical results show that majority of the climate-smart strategies are used simultaneously. The mix and the intensity of use of these strategies isrelatively low,overall, while the determinants of choice(s) of these strategies,arestrategy specific.Furthermore, the results show that; marital status, access to extension services, livestock ownership, years of plot cultivation, distance to market, farm size and perceived soil fertility level, significantly, encourage intensity of use of climate-smart strategies, while aged farmers are less likely to increase the use of these strategies.

Additionally, the study found out that mulching has significant impact on yields of roots and tubers,while the use of improved crop varieties and the practice of crop rotation with legumes significantly increased the yields of pulses. In addition, thepractice of fertilizer deep placement and cover cropping have significant positive impact of cereal yield compared with other climate-smart technologies. Overall, the effect of intensity of use of these strategies on household welfare, through the yields of crops is significantly positive. Butthe intensity – productivity nexus is linear, the linkage between productivity – welfare is non-linear.

On the multidimensional welfare, multidimensional headcount ratio or incidence of deprivation is 58% while the adjusted head count ratio is 29%. The health dimension contributed most to household deprivation, followed by living standard and the education dimensions. In all, initial cost of establishment, plot tenure security, input and output markets, and good knowledge of climate-smart adaptation strategies remain challenges to intensity of use. Surprisingly, access to finance had the least Garrett score, which is an indication though a challenge, farmers may not depend solely on external financial source to use CSA strategies.

5.2. Conclusion

A clearevidence from this study is the differential contributions of the crop yields to household welfare improvement. Also, the effects of intensity of use of climate-smart adaptation strategies on crop yields, is heterogenous across the crop categories. Both observations indicate that, promoting crop-specific use of CSA strategies is likely to be more effective in improving the wellbeing of smallholder crop farmers in Nigeria.

The study further showssimultaneity and low intensity of use of climate-smart adaptation strategies by smallholder farmers across crop categories. Despite the low intensity of use, climate-smart adaptation strategies contribute positively to crop productivity in a non-linear relationship, exceeding proportionate increases. This, therefore, suggests an increasing return to scale. Though the impact of intensity of use of climate-smart adaptation strategies is lower in cereals and pulses, both crops are pro-poor, since they significantly contribute to household welfare improvement compared with root and tuber crops.

The positive impacts of marital status, livestock ownership, farm size, tenure security among others on intensity of use of climate-smart adaptation strategies supports the consideration of gender-inclusive outreach activities, in policy design to stimulate increased intensification of climate-smart strategies. This follows literature evidence that, female-headed households and farmers are often more disadvantaged than the male counterparts in resource allocation.

The depth of contribution of health dimension to multidimensional deprivation suggests that policies targeting household welfare need to pay attention to its components, to reduce the intensity of deprivation in the study area.

5.3. Policy Recommendations

The conclusions from this study provide strong evidence that, farmers acknowledge the existence of climate change and are adapting to it, using various strategies. These strategies are impacting positively on the livelihood and welfare of the farmers. However, the depth of deprivations evident is the study area suggests that, policy interventions,addressing the right use of climate-smart adaptation strategies in terms of mix, intensity and crop can be a pathway to improving crop productivity and consequently, household welfare levels.

Key recommendations from this study include:

- Use of farmer groups as platform for promoting the use of CSA strategies and providing on-lending facilities for farmers.
- Yield decline is mainly associated with delayed or less frequent or amount of rainfall. A smart approach shouldbe provision of artificial water source through promotion of affordable and less sophisticated irrigation facilities.
- The government’s ongoing National Home-Grown School Feeding Programme (NHGSFP), which promotes enrolment among school-age children, should be vigorously pursued and encouraged. In addition to improving school enrolment, this also would encourage local farm production and subsequently, the use of farm production technologies, that are climate smart.
- With more than half of the population under multidimensional deprivation, policy interventions which seek to promote the use of improved cooking fuel, improve children school enrolment, encourage backyard livestock production, asset ownership and reduce any form of child illness and mortality can be an effective way to bring more households out of deprivation, in the short term. Such policy interventions need to be vigorous pursued, by all the tiers of government.

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