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Adoption of Stress Tolerant Maize for Africa Varieties and Resilience to Climate Change among Maize Farmers in Derived Savannah Zone, Nigeria

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DECLARATION

I, Phillips Chimezie FRANCIS hereby declare that this thesis titled "*Adoption of Stress Tolerant Maize for Africa Varieties and Resilience to Climate Change among Maize Farmers in Derived Savannah Zone, Nigeria*" which was submitted in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy (PhD) in Economics, specialty in Climate Change Economics at the Université Cheikh Anta Diop de Dakar is the product of my own work and that no part or whole of it has been submitted for the award of a degree or diploma at any level in the university or any other university or institution. All materials used for this thesis have been duely acknowledged both in the text and in the reference section.

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DEDICATION

I dedicate this research to God, my wife Abisoye Phillips-Francis, my daughter Asher Phillips-Francis and my late mother Catherine Francis-Egbuaba.

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ABSTRACT

The decline in maize yield in Nigeria is largely attributed to droughts and floods. Farmers' ability to anticipate, prepare for, adapt to, and recover from the impacts of climate changes and extreme weather is crucial to mitigate the attendant economic losses This study examined the effect of adoption of the new Stress Tolerant Maize Varieties of Africa (STMA) on the resilience of smallholders maize farmers to climate change in the Derived Savanah zone of Nigeria. A multistage stratified random sampling procedure was used to select 520 maize farming households from 13 villages and data was elicited using a well-structured questionnaire. Descriptive statistics, Heckman Selection Model, Resilience Index Measurement and Analysis II (RIMA-II) and Endogenous Switching Regression Model (ESRM) were employed to analyse the data. Results reveal that majority of the maize farmers are in their productive age, cultivating an average of 3.94 ha of farmland, most of whom perceived the incidence of all the climate change indicators considered in the study. Results of the Heckman two-staged selection model show that the age of household head, farming experience, income sources, and location are significant variables influencing household food security of the maize farmers, while schooling years, household size, and market distance are significant in influencing the productivity of maize farmers in the study area. The first stage of the ESRM reveals that farmers' awareness of both improved maize varieties and the STMA varieties, gender, and household size are positive and statistically significant in determining the adoption of STMA varieties. The second stage reveals that farming experience, income sources, and awareness of improved maize varieties are negative and statistically significant in explaining the variation in resilience to climate change among the farmers that adopted the STMA varieties, while schooling years, dependency ratio, off-farm income, income sources, market distance, extension access and awareness of improved maize variety are negative and statistically significant in explaining the variation in resilience to climate change among the non-adopters. Adoption of STMA varieties has a significant positive impact on resilience to climate change. Thus, awareness of STMA varieties and easy access to certified STMA seeds should be included in any agricultural development programmes and extension communication in Nigeria.

Keywords: Resilience Capacity, Climate Change, STMA, Switching Regression, Nigeria.

RESUME

La baisse du rendement en maïs au Nigeria est largement attribuée aux sécheresses et aux inondations. L'aptitude des agriculteurs à anticiper, se préparer, s'adapter et se remettre des effets des changements climatiques et des conditions météorologiques extrêmes est cruciale pour atténuer les pertes économiques qui en découlent. Cette étude a examiné l'effet de l'adoption des nouvelles variétés résistantes au stress de maïs de Afrique (STMA) sur la résilience des petits producteurs de maïs face à la variabilité climatique dans la zone de Savanah Dérivée au Nigeria. Une procédure d'échantillonnage aléatoire stratifié à plusieurs degrés a été utilisée pour sélectionner 520 ménages producteurs de maïs dans 13 villages; les données ayant été obtenues à l'aide d'un questionnaire bien structuré. Des statistiques descriptives, le modèle de sélection Heckman, la mesure et l'analyse de l'indice de résilience II (RIMA-II) et le modèle de régression à commutation endogène (ESRM) ont été utilisés pour analyser les données. Les résultats révèlent que la majorité des producteurs de maïs, de par leur âge, sont à une période active de leur vie, cultivant en moyenne 3,94 ha de terres agricoles. La plupart des producteurs ayant perçu l'incidence de tous les indicateurs de variabilité climatique pris en compte dans l'étude. Les résultats du modèle de sélection en deux étapes de Heckman montrent que l'âge du chef de ménage, l'expérience agricole, les sources de revenus et la localisation sont des variables importantes qui influent sur la sécurité alimentaire des producteurs, tandis que les années de scolarisation, la taille des ménages et la distance par rapport au marché sont déterminants de la productivité des producteurs de maïs dans la zone d'étude. La première étape de l'ESRM révèle que la connaissance des variétés améliorées de maïs et des variétés STMA par le producteur, le sexe et la taille du ménage ont un effet positif et statistiquement significatif sur l'adoption des variétés STMA. La deuxième étape révèle que l'expérience agricole, les sources de revenus et la connaissance des variétés améliorées de maïs ont un effet négatif et statistiquement significatif sur la variation de la résilience à la variabilité climatique chez les producteurs qui ont adopté les variétés STMA. Quant aux non-adoptants, les variables années de scolarisation, ratio de dépendance, revenu hors-ferme, sources de revenu, distance par rapport au marché, accès aux services d'extension et connaissance de la variété améliorée de maïs ont un effet négatif et statistiquement significatif sur la variation de leur résilience à la variabilité climatique. L'adoption des variétés STMA a un impact positif et significatif sur la résilience à la variabilité climatique. Ainsi, la connaissance des variétés STMA et l'accès facile aux semences certifiées STMA devraient être inclus dans tous les programmes de développement agricole et de communication de vulgarisation au Nigeria.

Mots-clés: Capacité de résilience, variabilité climatique, STMA, régression par commutation, Nigeria.

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ACRONYMS AND ABBREVIATIONS

ABS	Access to Basic Services
AC	Adaptive Capacity
AI	Artificial Insemination
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AST	Assets
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
BIC	Bayesian Information Criterion
BRACE	Building Resilience against Climate Effects
CA	Conservation Agriculture
CIMMYT	International Maize and Wheat Improvement Center
COP	Conference of the Parties
CSA	Climate-Smart Agriculture
CSAT	Climate-Smart Agricultural Technologies
DDT	Dichlorodiphenyltrichloroethane
DiD	Difference in Difference
ESR	Endogenous Switching Regression
ESRM	Endogenous Switching Regression Model
ETR	Endogenous Treatment Effect
FA	Factor Analysis
FotF	Farms of the Future Approach
GHG	Greenhouse Gas
HFIAS	Household Food Insecurity Access Scale
IFA	Income and Food Access
IITA	International Institute for Tropical Agriculture

IMR	Inverse Mills Ratio
MESR	Multinomial Endogenous Switching Regression
MIMIC	Multiple Indicator Multiple Causes
ML	Maximum Likelihood
MLM	Multinomial Logit Model
OLS	Ordinary Least Square
PCA	Principal Component Analysis
PEOU	Perceived Ease of Use
PSM	Propensity Score Matching
PU	Perceived Usefulness
RCI	Resilience Capacity Index
RCT	Randomized Control Trials
RDD	Regression Discontinuity Design
RIMA II	Resilience Index Measurement Analysis II
RSM	Resilience Structure Matrix
SAPs	Sustainable Agricultural Practices
SDG	Sustainable Development Goals
SEM	Structural Equation Model
SSA	sub-Saharan Africa
SSN	Social Safety Networks
STMA	Stress Tolerant Maize for Africa
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action

GENERAL INTRODUCTION

1.1 Background Information

The impact of climate change on agriculture and food security cannot be overemphasized and it is well established in literature (Mendelsohn, 2009; Calzadilla *et al.*, 2013; Wiebe, Robinson and Cattaneo, 2019; Kogo, Kumar and Koech, 2021). Changes in temperature, precipitation, surface water runoff, carbon dioxide fertilization, and increased climate change are recognised as five main factors through which agricultural productivity is affected by climate change (World Bank, 2007). Temperature and precipitation have more direct effect on crop production (Battisi and Naylor, 2009). Precipitation is an important determinant of soil moisture content which is vital for crop growth (Calzadilla *et al.*, 2013). It is evident that extreme temperature and rainfall affect crop output, pest incidence, pasture availability and stimulates hazardous fire outbreak (Tubiello, Soussana and Howden, 2007; Schlenkera and Roberts, 2009; Aragón, Oteiza and Rud, 2021). Floods destroys crops, food system infrastructure and washes off productive top soil (Anyamba *et al.*, 2014).

Although the socioeconomic impact of these events vary regionally, climate change engenders the unpredictability of agricultural production, food prices and consumption which in turn leads to a disproportionate demand and supply of food and hampers food security. Despite the efforts and progress made in combating climate change, projections spell out uncertainties. The frequency of droughts is projected to increase in most regions of the world especially in drought prone areas (Malhi, Kaur and Kaushik, 2021). The yield of major crops is expected to decline by more than 50% by 2050 and close 90% in 2100 (Li *et al.*, 2009). Globally, yield losses in rice, maize and wheat are predicted to decline 10-25% with a 1^0C rise in the mean surface temperature (Deutsch *et al.*, 2018) and average crop yield is projected to plunge by 6-24% as a result of climate change (Waha *et al.*, 2013). Substantial investments in adaptation and mitigation strategies should be gears towards "climate-smart food systems" that is resilient to the effects of climate change on food security and welfare.

According to the famous Stern report, climate change is the greatest and wide-ranging market failure the world have ever seen, which affords economics and economist a distinctive challenge (Stern, 2007). The 1960s and 1970s witnessed notable environmental campaigns which heralded a dispensation of the application of economic theory to finding solution to negative externality problems (Bergstrom, 2022). An important contribution to the recognition of the externality problem was Rachel Carson's book, *Silent Spring*. In this book, Carson revealed how DDT spraying for mosquitoes instigated an unintended consequence for birds' reproduction which eventually led to a silent spring (Carson, 1962). The DDT negative externality problem is a typical example of market failure, which is defined as the inability of private markets to meet the conditions necessary and sufficient for a competitive market equilibrium to be Pareto efficient (Bergstrom, 2022). On the other hand, market failure can ensue in an instance of positive externalities such as public goods. Examples include clean air and clean water.

The literature contains several views of authors with respect to the concept of externality. A situation where a private economy does not have enough incentives to create a potential market for a good which result in a loss of efficiency can be referred to as externality (Arrow, 1969). According to (Tietenberg and Lewis, 2014), externality ensues when the welfare of an economic agent is dependent on both its activity and the activity of another economic agent's activity without any transaction taking place fix the damages or take out benefits created. More so, when public goods have non-rival consumption that is everyone can consume the same amount, the "free-rider" problem engenders difficulty in measuring consumer true willingness to pay for public goods - this is case of the global climate (Samuelson, 1954). Climate change results from the externality associated emission of greenhouse-gas (GHG), it entails costs that are not paid for by those who create the emissions (Harris, Roach and Codur, 2017). As revealed in Stern report, since the industrial revolution, the trend of GHG emissions has been on the increase, thereby amplifying the heat-trapping capability of the earth system. Hence, this questions the inclusiveness and sustainability of economic growth and development (Stern, 2007).

From an economic perspective, global warming is caused by the accumulation of GHG as a negative environmental externality and an over-usage of a common property resource which also occurs as a result of absence of market and lack of defined property rights (Harris, Roach and Codur, 2017). This leads to unintended consequences for present and future generations. This instance flaws the first fundamental theorem of welfare economics of Pareto Efficiency as a group of individuals are more adversely affected than others (Laffont, 1989; Stiglitz, 1991; Baujard, 2013). There is no doubt that climate change has impacted, is impacting, and will continue to impact the welfare of individuals globally if conscious efforts are not made to tackle it. Several approaches has been proposed to reduce the emission of greenhouse gasses which includes command and control regulation, market-based incentives, hybrid approaches and voluntary initiatives (U.S. Environmental Protection Agency, 2010). With the increasing awareness of the consequences of environmental pollution, it is possible that businesses and/or governments remain unwilling to reduce emission of pollutants. Some economists have recommended the use of command and control mechanisms to compel economic actors to reduce their pollution and shift focus to clean development (Hanley, Shoregon and White, 2007; Tietenberg and Lewis, 2014). In other words, policies should be geared towards compelling risk-generating businesses to take full cost of their operations by incurring social cost to offset marginal benefits (Stone, 1992) . Hence, government intervention becomes expedient in regulating problems of externalities. Such intervention include pollution abatement technologies, subsidies, taxes, and fines (Tietenberg and Lewis, 2014).

Several market-based policies have been employed to regulate pollution while taxes and tradable permits are the widely or commonly used (Muller and Mendelsohn, 2009; Wang and Zhang, 2022). Tradable permit programs set specific targets on total emissions and auction required number of pollution permits to polluters who are mandated to abide by such target (Stavins, 2003; Tietenberg, 2006). Emission tax is a controlling system where tax provides an incentive for polluters to pursue more cost efficient solutions to control pollution (Parry, 1995; Norregaard and Reppelin-Hill, 2000). Pigou's seminal contribution on the use of taxes as efficiency enhancing mechanism to correct for negative externalities provoked insights and debate on the choice of instruments for environment policies (Norregaard and Reppelin-Hill, 2000; Tietenberg, 2006). In a competitive market, introducing a tax equal to a marginal damage can internalize the negative externality resulting from an environmental pollution (Pigou, 1932). In other words, tax is placed on production and/or consumption of goods that have negative externality effects. Decentralised price mechanism is in consonance with the instrumentation of Pigouvian taxes (Feldman and Serrano, 2006). Putting a suitable price on GHG emissions is of vital importance to internalize the external cost of climate change in the widest range of economic decision making and in initiating economic incentive for clean development (World Bank, 2017). The presence of externality is an indication of a gap between private and social returns. Different authors have argued that carbon price intervention can correct market failure resulting from native externality and reinstate market efficiency (Millar *et al.*, 2016; van der Ploeg, 2018; Dietz and Venmans, 2019).

From another perspective, a government intervention may not be necessary for correcting market failure in instances where there are defined property rights and no transaction costs (Coase, 2013). This implies that stakeholders could negotiate and arrive at a consensus on dealing with the environmental challenge. In case where stakeholders and actors involved in decision making are not many, voluntary negotiation and compensations can easily ensue. Compensations can be made by the actor to the affected and vice versa to achieve optimality. Market-based mechanisms have been generally preferred because they are more cost effective in practice (Norregaard and Reppelin-Hill, 2000; Wang and Zhang, 2022). However, a major setback the battle against climate change is facing is the lack of global consensus in tackling climate change among the governments and business (Harris, 2007; United Nations Development Programme, 2007). Individual actions will always have insignificant impact on the attendant consequences of climate change. This informs the recurrent climate change negotiations and conferences at the global level. The Paris Agreement adopted in 2015 by 175 parties aims at limiting global warming to well below 2^0C compared to pre-industrial levels (UNFCCC, 2015; Savaresi, 2016). For some governments, it is now a priority to formulate economic policies that are appropriate to contain environmental degradation and consequently improving the quality of the environment (Kahuthu, 2006; Garnett and Godfray, 2012). Though efforts have been made to tackle global warming, the period 2010-2020 has been the planet's hottest decade and the predicted long-term trend is increasing (Hochrainer-stigler *et al.*, 2020).

The current patterns of development are largely ecologically and economically unsustainable (Kahuthu, 2006). Resource-intensive development led to problems of inadequate worker and consumer protection, poverty and exclusion (Kemp, Parto and Gibson, 2005; Kahuthu, 2006). Although economic progresses have improved some sort of environmental values and accrued environmental gains, the overall result mostly include persistent development failures and burgeoning ecological depletion (Kemp, Parto and Gibson, 2005). The quest for economic growth and development while considering the environmental implication led to the concept of sustainable development (Zilberman, 2013). Given the evident deteriorating environmental conditions, sustainable development has become a widely recognised agenda for the human society. The theory of sustainable development has evolved over three periods: The embryonic period before 1972, the molding period 1972 - 1987, and the developing period 1987 – present (Shi *et al.,* 2019). From pursuing the single goal of sustainable use of natural resource, to Millennium Development Goals and now, Sustainable Development Goals (SDG). The issues of food security, climate change, adaptation, resilience to climate change are well spelt out in the SDG 2 (No Hunger) and 13 (Climate Action). SDG 2 talks about ending hunger, achieving food security, improving nutrition and promoting sustainable agriculture (Mugambiwa and Tirivangasi, 2017; Banik, 2019; United Nations, 2022).

Specifically, SDG 2 seeks to double agricultural productivity and incomes of small-scale producers, promote sustainable food production systems and implement resilient agricultural practices that increase productivity and production, maintain genetic diversity of seeds (United Nations, 2022). SDG 13 pursues an urgent action to fight climate change and its impacts (Maupin, 2016; Doni, Gasperini and Soares, 2020). Specifically, this goal talks about strengthening resilience and adaptive capacity to climate-related hazards, integrated climate measures into policies, strategies and planning, and improving education, awareness-raising and institutional capacity on climate change mitigation, adaptation, impact reduction (United Nations, 2022). However, climate change can undermine the achievement of sustainable development goals despite the commitments of the international community. Synergies and trade-offs in evidence and governance between the SDG commitments, and suggests a deeper interdisciplinary collaboration and well-connected climate change and sustainable development governance (Fuso Nerini *et al.*, 2019). Relationship between sustainable development and adaptation resilience to climate change. Sustainable development is typically perceived as a socially established process of adaptive change in which innovation is a necessary element (Kemp, Parto and Gibson, 2005; Mekonnen *et al.*, 2015).

Innovation has a central role to play in African agricultural development (Lipper *et al.*, 2014). Agricultural development is more than agricultural growth fostered by research and dissemination services, it involves a set of processes of agricultural transformation, elements, causes and mechanism through it is achieved (Boserup, 2005). In other words, agricultural development involves a steady change of the agricultural production process through advanced farming location, tools, organic materials, farm work settings and gratification of social need. Essentially, in agriculture, innovation refers to a new agricultural practice, method, technique, variation in farming system or a modification of an existing farming methods that is capable of increasing productivity and income (Feder, Just and Zilberman, 1985; Badiane, 2012). Increase in productivity is a requisite factor for agricultural transformation. A new technology or an innovation characterizes one of the paths of raising productivity in agriculture that is producing more output for a particular amount of labour (Bosc *et al.*, 2012). It is therefore evident that innovation and/or new technology is crucial for development, be it agricultural development or sustainable development.

Agriculture played significant roles in different tales of industrialisation. The industrial revolution of the 1750s in England and that of the 1880s in Japan were spurred by agricultural revolutions (Bezemer and Headey, 2008). The Green Revolution of the 1960s in the developing countries secured most of its successes from a combination of intensive investment in crop research, infrastructure, market development and appropriate policy support (Pingali, 2012). These instances suggests that the agricultural sector supplies labour and other inputs to industrial sector requisite for industrialization. Agricultural growth is a pathway to pro-poor and sustainable economic development in sub-Saharan Africa (SSA) as it has the potential of reducing poverty, food insecurity and vulnerability especially to climate change (Dawson, Martin and Sikor, 2016). It can further instigate reduction in income inequality, gender inequity, and rural-urban migration, releasing scarce resources and delivering many environmental services (De Janvry, 2010). The classical paradigm of development thinking provides a meritorious pathway through which agricultural growth can accelerate Gross Domestic Product growth. However, the underperformance of agriculture for development is linked in particular with continual low and/or mis-investments in agriculture by governments and international donors (De Janvry, 2010).

The world is currently bedeviled by mounting environmental challenges which includes pollution, biodiversity loss, land degradation, climate change among other problems that compromises the achievement of the sustainable development goals by 2030 (Arslan *et al.*, 2015). From the environment, social and economic perspective, climate change is proving to be the most daunting of these challenges (Tesfaye and Seifu, 2016; Destaw and Fenta, 2021) . This is because of the deleterious effects of climate change on livelihoods and its projected impacts under the business as usual scenario. Climate change have a wide ranging effects across resources such as water, land, soil, biodiversity, coastal resources ; sectors such as agriculture, energy, health; and welfare indicators such as income, poverty and food security (Deubelli and Mechler, 2021). Climate change has been described as long-term variations in the trend of weather (Vijayavenkataraman, Iniyan and Goic, 2012; Al-Ghussain, 2018). West Africa is one of the most vulnerable regions to climate change due to the abundance of low-income populations in this region. With the existing exponential population growth, the region is facing the consequences of climate variability through steady land degradation, loss arable lands, ecosystem services, high water stress in addition to recurrent droughts and floods (Sylla *et al.*, 2016; Palazzo *et al.*, 2017). It is also predicted that the warming and increased variability in climate are likely to be exacerbated in future climate (Anyamba *et al.*, 2014; Adefisan, 2018).

1.2 Statement of the Problem

The effect of climate change is peculiar to the savannah region (Ayedun, 2018). The region is a grassland ecosystem characterised by trees that are widely spaced so that the canopy does not close, characterised by periodic water availability, and receives most of rainfall confined to one season (Werner, Walker and Stott, 2009). Based on intensity of rainfall and temperature, savannah is divided into; Derived savannah which is sun stressed with less water; the Guinea savannah which consists of Northern guinea savanna and Southern guinea savannah, and the Sudan savannah which is the most water stressed (Alahira, 2013). Consequently, climate change effects like drought, flood, irregular rainfall patterns in these areas negatively affects the yield, income, food security, and nutrition of millions of maize-dependent smallholders farming households (Fisher *et al.*, 2015). An estimated 70% of economic losses in SSA are attributed to droughts and floods whose impact translates to a substantial decline of about 22% in yields of maize (Shikuku, Mwungu and Mwongera, 2019). Increased temperatures and more erratic rainfall by 2050 has been predicted in the Derived Savannah zone of Nigeria (Steward *et al.*, 2018).

Over the last three decades, climate change has resulted in a reduction in global maize production by 0.17 MMT per year, translating to an annual 0.7% decrease in consumable food calories available from maize globally (Wossen et al., 2017). Erratic precipitation and increase in temperature due to climate change has had the greatest effect on maize production and productivity rendering the smallholder farmers particularly vulnerable. Climate change is further projected to reduce maize yields by an average of 7.4% for every 1°C increase in mean global temperature (Zhao et al., 2017; Tigchelaar et al., 2018). Maize yield losses from drought stress are estimated to increase by 10–25% for every 1°C warming through increased population growth and metabolic rates with 25% of maize production suffering from a frequent drought that causes losses of up to 50% of the harvest (Steward et al., 2018). Furthermore, production of maize would decline by 22% in SSA by 2050 due to climate change (Schlenker and Lobell, 2010; Wossen et al., 2017). In the Derived Savannah zone of Nigeria drought and irregular rainfall are not only the problems posed by climate change; an increase in temperature and heat waves has seriously affected productivity of smallholder maize farmers (Simtowe et al., 2019; Chikulo, 2021).

In SSA, more than 176 million people depend on maize-based agriculture for their food security and economic well-being (Baiyegunhi, Akinbosoye and Bello, 2022). Maize is one of the major staple crops in Nigeria, second to Cassava, based on the land area covered and production indices (FAOSTAT, 2019). It is predominantly cultivated in the savanna zone due to the presence of high radiation which is favourable for its growth, therefore, becoming a dependable source of food security and livelihood for millions of smallholder farmers (Worku *et al.*, 2020). Nigeria is arguably Africa's second-largest producer of maize after South Africa. Ethiopia occupies the third-place position on the chart of largest producers of maize in Africa. Together, the three countries (i.e., South Africa, Nigeria, and Ethiopia) accounted for about 39% of the continent's total maize output in 2019 (PWC, 2021). In Nigeria, the top ten maize-producing states (Borno, Niger, Plateau, Katsina, Gombe, Bauchi, Kogi, Kaduna, Oyo, and Taraba) account for nearly two-thirds (64%) of maize produced in the country (Adeagbo, Ojo and Adetoro, 2021). It is cultivated on about 4.9 million hectares of land (FAOSTAT, 2019). Apart from human consumption, maize demand is diversified into livestock feed. There is growing utilization of maize by food processing industries and livestock feed mills. In developing countries, more than fifty percent of the maize demand is for livestock feed.

Maize farmers' resilience to climate change is a fundamental concept in climate risk management (Alvar-Beltrán *et al.*, 2021). In this context, resilience refers to the ability of an agricultural system to anticipate and prepare for, as well as adapt to, absorb and recover from the impacts of changes in climate and extreme weather (Prasanna *et al.*, 2021). Resilience can be enhanced by implementing short and long-term climate mitigation and adaptation strategies, as well as ensuring transparent and inclusive participation of multiple actors and stakeholders in decision-making and management processes (Adger *et al.*, 2011; Simonson *et al.*, 2021). Recognizing the need for improving resilience among maize farmers in Africa to adapt to various abiotic and biotic stresses, the International Maize and Wheat Improvement Center (CIMMYT), in collaboration with public and private partners, embarked on intensive maize-breeding programmes in the region (Worku *et al.*, 2020). The Stress Tolerant Maize for Africa (STMA) project aims to diminish devastating constraints in maize production across Sub-Saharan Africa by producing an estimated 54,000 tonnes of certified seeds to put into the hands of more than 5.4 million smallholder farmers' households (CIMMYT, 2017).

The STMA project develops improved maize varieties with resistance and tolerance to drought, low soil fertility, heat, diseases such as maize lethal necrosis and fall armyworm, and other pests affecting maize production areas in the region. The STMA operates in eastern (Ethiopia, Kenya, Tanzania, Uganda), southern (Malawi, South Africa, Zambia, Zimbabwe), and West Africa (Benin, Ghana, Mali, Nigeria). These countries account for nearly 72 percent of all maize areas in Sub-Saharan Africa (Ayinde, 2021). In Nigeria, the project covers the savannah and forest areas (NAERLS, 2019). Stress tolerant maize germplasm is one component of climate-smart agriculture (CSA) that, when used in combination with other components, can sustainability increase production and resilience of agriculture systems (Setimela *et al.*, 2018; Adnan *et al.*, 2020). For agricultural technologies to be labeled “climate-smart”, they have to deliver on three aspects; adapt to the negative effects and impacts of climate change, mitigate its effects by reducing greenhouse gas emissions and sequestering carbon, and increase productivity and profitability (Setimela *et al.*, 2018). By early 2016, over 200 distinct drought-tolerant maize varieties had been released in 13 Sub-Saharan countries, with reportedly more than 2 million farmers growing them adoption of stress-tolerant maize varieties is expected to increase (Wossen *et al.*, 2017; Simtowe *et al.*, 2019).

In 2018, 3.5 million smallholder farmers planted stress-tolerant maize varieties in 10 African countries. Nigeria has produced over 40 improved maize varieties (STMA) that are tolerant to stresses of various degrees. Out of these, about 17 were released into the market between 2014 and 2019. Maize production in Nigeria has significantly increased over the decades from 931,000 tonnes in 1971 to 10,000,000 tonnes in 2020 growing at an average annual rate of 7.29% (World Bank, 2021). Assessing stress-tolerant maize varieties combined with additional climate-smart agriculture technologies has been efficient to reap the benefit of several climate-smart interventions and make farming systems more resilient (Setimela *et al.*, 2018). Farmers are demanding stress-tolerant varieties (STMA) as the harsh realities of climate change bite harder. Striga and drought as well as other production stresses-related to maize cultivation are no more causing nightmares to farmers in Nigeria due to laudable achievements of the STMA introduction (CIMMYT, 2017). With the aforementioned, the adoption of STMA varieties provides several features beyond mitigating drought, however, there has been very low demand and variation in adoption.

Hence, it suffices to say that there is lack of adequate information because of scanty research on the relationship among adoption of STMA varieties, resilience to climate change, maize productivity and household food security (Gebre *et al.*, 2021). Hence, an adequate understanding of the effect of STMA varieties on resilience to climate change will increase the adoption of STMA varieties, meet the food needs of the populace and improve farm households' welfare. Despite the adoption of different adaptation strategies to improve resilience, farmers experience major difficulties in making changes toward more sustainable practices (Ayinde, 2021; Gebre *et al.*, 2021). This calls for a deeper investigation of farmers' adoption of STMA varieties and understanding resilience to climate change of the farmers for a sustainable practice. There is therefore a requirement of an evidence based action of deliberately, and with urgency encouraging the dissemination, diffusion, adoption and continuous use of stress-tolerant maize varieties among farmers by identified effect of STMA adoption on maize farmers' resilience to climate change. Based on the foregoing, the overall research question was, what is the effect of STMA varieties adoption on resilience to climate change among maize farmers? Specifically, the following research questions were studied;

1. What is the perceived evidence of climate change?
2. What effect does adoption of STMA varieties have on productivity and household food security?
3. What effect does adoption of STMA varieties have on resilience to climate change?

1.3 Research Objectives

The broad objective of this study is to examine the effect of adoption of STMA varieties on resilience to climate change among maize farmers in derived Savannah zone, Nigeria.

The specific objectives of the research are to:

1. Investigate the perceptions of maize farmers on climate change.
2. Examine the effect of adoption of STMA varieties on productivity and household food security.
3. Determine the effect of adoption of STMA varieties on resilience to climate change.

1.4 Hypothesis

1. Maize farmer perceive increased evidence of climate change given the past and current weather conditions.
2. STMA varieties adoption influences productivity and household food security.
3. Adoption of STMA varieties affects the resilience of maize farmers to climate change.

1.5 Justification of the study

The relevance of this study is justified from empirical and methodological perspectives. The importance of farmers' adoption of new agricultural technologies has long been of interest to agricultural economists, extensionists, and rural sociologists (Adeagbo, Ojo and Adetoro, 2021). The adoption decision is divided into three phases: acceptance, actual adoption, and continued use. Generally, this multistage process is undertaken most often sequentially and is influenced by a wide range of economic, social, physical, and technical aspects of farming (Cairns *et al.*, 2021). It is believed that an effective way to increase productivity in maize in Nigeria is the adoption of the broad spectrum STMA (CIMMYT, 2017). Adoption of STMA implies the decision to apply an STMA technology and to continue its use. STMA adoption by smallholder farmers has not been alluded the appropriate attention since the end of the project in 2019. This study assesses the adoption rate of STMA and its impact on maize yield, food security and resilience to climate change. It also provides important insights into the extent to which smallholder farmers are adapting to climate variability and change through adoption of stress-tolerant maize varieties (STMA). According to Manyong et al 2001, impact assessment studies are vital in providing vital evidence to research organisations, guiding technology transfer personnel and policy makers to better understand technology dissemination, acceptance, assimilation and adoption in rural communities

Technology acceptance and adoption play a significant role in agricultural transformation, poverty alleviation and food security in the developing countries (Adenle, Wedig and Azadi, 2019). Although there is an abundant empirical evidence on the determinants of adopting agricultural technologies, such as improved crop varieties, studies that links agricultural technology adoption to climate change perception are limited. Some authors have argued that there is a need to have a broader spectrum when investigating the impact of agricultural technology development and promotion (Glover, Sumberg and Andersson, 2016). In other words impact assessment should consider social, economic and environmental effects of an investment. According to (Setimela *et* *al.*, 2018) The performance of STMA maize under farmer management is relatively documented. More so, after the completion of the STMA project in 2019, not many studies have been done on the STMA farm and household level economic performance and its impact on productivity, and household food security. To the best of the author's knowledge, no previous study have directly linked the adoption of STMA to climate change resilience.

A rich body of literature is available on the adoption of climate-smart technologies and sustainable agricultural practices. However, empirical evidence shows that there is a dearth in the studies of the relationship between climate-smart agricultural technologies and their impact on welfare and climate change adaptability, the available evidence is mixed (Mossie, 2022). To the best of the author's understanding, there is a shortage of research on the effect of adopting STMA varieties on the welfare and resilience of maize farmers especially in Nigeria (Prasanna *et al.*, 2021). Consequently, a knowledge gap persists in examining the adoption of STMA on the resilience of maize farmers to climate change. Noticeably, adoption effects vary with the scale of the adoption because different levels of adoption scale are expected to trigger outcome responses of different magnitudes (Baiyegunhi, Akinbosoye and Bello, 2022). Therefore, this study will highlight and emphasize the benefits of adopting STMA varieties to maize farmers to increase their resilience to climate change, increase productivity and food security. This study is not intended to break an entire new ground, rather, it is undertaken on the premise that it will add to the existing literature on the farmers' adoption of STMA varieties and climate change. The study aims at understanding the level of resilience of maize farmers to climate change and what role technological innovation has played to help farmers come out of biotic and abiotic stress elements of climate change. It will provide policy-relevant information that is needed for developing robust and effective adaptation strategies for smallholder farmers across the region and mainstreaming smallholder farmer adaptation into climate change and sustainable development policies.

Previous studies have used Logit regression, Probit regression model and Heckman selection model to measure the effect of the technology adoption on resilience to climate change. However, considering that the data available of this study is a cross-sectional data, that is, information elicited on several variables at a particular point in time, it will be impossible to observe individuals at both factual and counterfactual states. In addition, we cannot use a non-treatment group as a control group dues to self-selection problems. Hence, the study employs the Endogenous Switching Regression Model (ESRM) to account for self-selection that comes from observable and unobservable characteristics of the respondents, in a bid to consistently estimate the impact of technology adoption on the outcomes of interest. The ESRM is generalization of Heckman's model where a sample selection is treated as a problem of specification error or omitted variable which can be corrected by explicitly using information obtained from selection equation for the reliable estimation of the outcome equation (Abdulai, 2016; Abdoulaye, Wossen and Awotide, 2018; Workineh, Tayech and Ehite, 2020). The primary advantage of ESRM is that information is provided on determinants of technology adoption, the differential impact of the independent variable on the dependent variables for adopters and non-adopters as well as the treatment effects of adoption. This study uses ESRM to correct the potential endogeneity of adoption of STMA varieties and resilience to climate change.

1.6 Plan of Study

This thesis is organised into five sections. The first section is the General introduction which contains the introduction, problem statement, research questions, research objectives, research hypothesis and justification of the study. The second section is the chapter one which provides the theoretical, empirical, conceptual reviews of relevant literature and the conceptual framework of the study. Chapter two in the third section and it presents details of the methodological review, study design, data collection and analysis of the socioeconomic characteristics. The fourth section contains chapter four which provides the empirical findings of each objective outlined in chapter one. The fifth section is the chapter five which comprises of the summary, conclusions and recommendations arising from the study.

CHAPTER ONE

THEORETICAL, EMPIRICAL AND CONCEPTUAL ANALYSIS OF AGRICULTURAL TECHNOLOGY ON CLIMATE CHANGE

Introduction

This chapter presents the theoretical, empirical and conceptual reviews of the subject matters in the study. From the theoretical standpoint, the adoption and diffusion theory, and reasoned action theory, the technology acceptance model, and resilience theories were reviewed. Empirical review was presented in a thematic structure with discussion on themes that are closely intertwined with the general topic, which is followed by the review of the concepts of climate change impacts, agricultural innovation, climate-smart agriculture and climate resilience.

2.1 Theoretical framework

2.1.1 Theory of Adoption and Diffusion of innovation

For over three decades, the adoption of new ideas have been studied. A significant publication by Rogers, "*Diffusion of Innovations*", describes an aspect of the most widespread adoption models. The model has been utilized as a framework in a wide range of studies from several fields (Sahin, 2006). Public health, Political science, Education, Technology, Communications, Economics, and History are among the disciplines made known by (Stuart, 2000), who defines Rogers' theory as an extensively adopted theoretical framework in the aspect of technological acceptance and diffusion. Given the prevalence of headways in technological diffusion research, (Rogers, 2003) regularly used the terms "innovation" and "technology" in place of one another. Adoption, in accordance with (Rogers, 2003), is "total use of an invention as the best course of action available," while rejection implies "not accepting an innovation". Diffusion was defined by (Rogers, 2003) as "the process by which an innovation is shared over time among members of a social system through specified routes". This theory began in communication to clarify how a thought or item acquires force and diffuses (or spreads) through a particular populace or social framework over the long haul.

The outcome of the hypothesis is that individuals, as a feature of a social framework embrace a groundbreaking thought, conduct, or item. Adoption implies that an individual accomplishes something else than what they had beforehand, in other words, they purchase and utilize innovation and play out another way of behaving, and so on. The way to reception includes the view of the thought, behavior, or item as new or creative. The fact that diffusion is possible sustains this. The response of novel thought, conduct, or item (i.e., "rice-fish culture innovation or framework") does not occur all the while in a social framework; rather it is an interaction by which certain individuals have more reasons to take on the advancement than others. Analysts have observed that individuals who embrace an advancement or innovation early have unexpected attributes in comparison to individuals who take on it later. When introducing an innovation to an objective populace, it is critical to comprehend the qualities of the objective populace that will help or thwart the reception of such innovation. According to (Rogers, 2003), There are five adopter classifications; innovators, early adopters, the early majority, late majority, and laggards. Generally, most people will fall in the center category or classes (the early majority), it is as yet important to understand the qualities and characteristics of the objective populace.

Agricultural technology or innovation is any substance that is planned at advancing a given circumstance or changing the state of affairs to a more positive level (Bonabana-Wabbi, 2002). It is also the information or data which allows a few tasks to be achieved more advantageously or new ways or techniques for delivering labor and products inside a specific spot or among a group of farmers (Lavison, 2013). Innovation reception is the fusing of innovation into existing practice to supplement it, or the utilization or non-utilization of new or further developed innovation by an individual or farmer at a given moment (Loevinsohn *et al.*, 2013), and is normally continued by a time of 'endeavoring' and some level of transformation. Innovation reception can be separated into two; the rate of reception and the intensity of reception. The rate of reception is the overall speed at which farmers embrace a development or thought and has "time" as one of its points of support. The intensity of reception implies the degree of the use of a given technology or innovation in any period (Bonabana-Wabbi, 2002). Innovation detachability and inseparability is a proportion of the portion of farm under the innovation or amount of information utilized per hectare, these actions the degree of reception of the innovation.

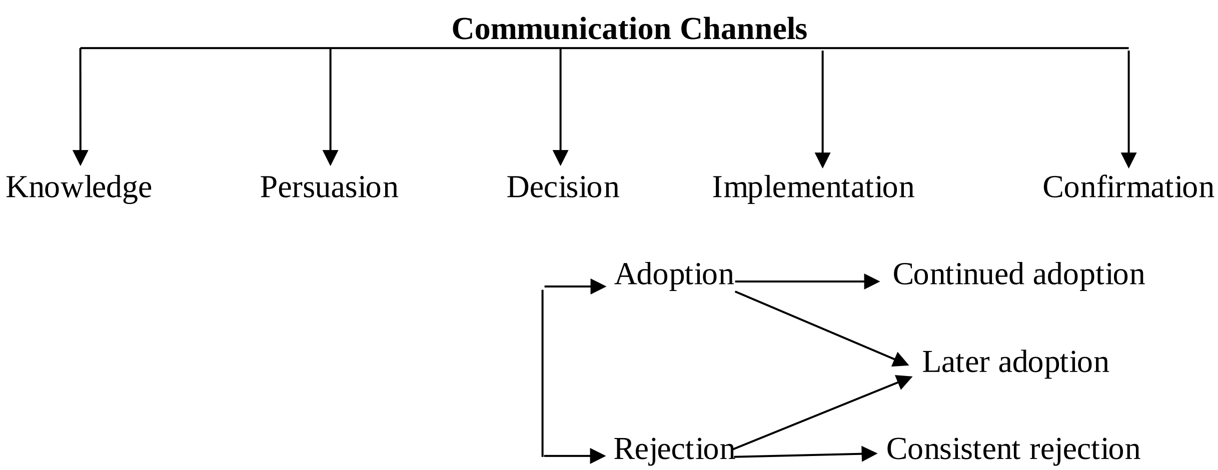
The degree of reception for unified rural innovations at the farm level at a given timeframe is dichotomous (use or no use), and the total measure becomes consistent. In this manner, the reception rate can be gotten by ascertaining the number of farmers utilizing the innovation in a given region/locale. A farmer is relied upon to pick regardless of whether to take on innovation in view of the match between her resources, the innovation's prerequisites, and her impression of that innovation's appropriateness for her necessities. As such, the dissemination of developments relies upon the qualities, inclinations, and climate of individual adopters (Rogers, 2003). The four main elements in this model are communication channels, innovation, social systems and time. Communication Channel is an important constituent in the innovation process of diffusion is communication. Communication can be defined as the modes in which information is created and shared among participants in order to reach a shared perception (Rogers, 2003). Localized channels and cosmopolite channels are two types of communication channels that connect a person in a social system to outside sources. Almost all mass media channels are cosmopolite, although interpersonal channels might be local or cosmopolite. Due to the characteristics of these communication channels, mass media and cosmopolitan channels are more relevant at the knowledge stage of the innovation-decision process, whereas localized and interpersonal channels are more important at the persuasion stage (Rogers, 2003).

In spite of an innovation being around for a period of time, if considered as fresh to people, it would still be considered an innovation. The steps involved in the innovation-choice process which are knowledge, persuasion and decision which would be explored later are more closely attached to the originality feature of an adoption. Rogers suggested that has been incidences of shortage of studies on diffusion on technological clusters. He defined technological clusters as that which is made up of at least one (which can be more than one) exclusive aspect of technology that is observed to be strongly interrelated. Uncertainty is a fact of life which acts as an impediment to the adoption of innovations. According to Rogers, consequence refers to the results that occur in an individual or a social system as a result of the adoption or rejection of an innovation (Rogers, 2003). Innovation benefits and drawbacks should be made known to individuals in order to lessen their doubt about adopting it. This will ensure that they are aware of all of the repercussions. Furthermore, Rogers asserted that outcomes might be characterized as desired vs. unpleasant (functional vs. nonfunctional), anticipated vs. unplanned (recognized and intended or not) and direct vs. indirect (immediate result vs. effect of instantaneous result).

Social system has been defined as a group of interconnected persons involved in jointly providing solutions to problems in order to accomplish a mutual objective. Rogers further claimed that the nature of the social system affects the innovativeness of individuals, which is the main measure for categorizing adopters. Majority of behavioral research, according to (Rogers, 2003), ignores the aspect of time. He claims that a benefit of diffusion research is that it incorporates the time dimension. Time is incorporated into the invention dissemination development, categorization of adopters and rate of adoption. A set of models required for the diffusion process was identified by

(Wolfe, 1994) . Considering that the sets of stages in these models can differ and there has been a considerable overlap, (Rogers, 2003) created a model which constitute of five stages which is cited most recently by (Nutley, Davies and Walter, 2002). First is Knowledge which has to do with being open to the innovation's existence and gain understanding of how it functions. The second is Persuasion where favorable or unfavorable approach is formed towards the innovation. This may involve matching the innovation to a perceived problem and appraisal of the benefits of adoption. Thirdly, Decision refer to activities that lead to choosing to adopt or reject the innovation. This may include interaction with forces of support or opposition that influences the process. The fourth has to do with Implementation where an innovation being put into use by an individual or unit. The last stage is Confirmation where an individual or unit seeks reinforcement for an innovation-decision already made, but may reverse this decision if exposed to conflicting messages about the innovation.

Figure 2.1: A Model of Five Stages in the Innovation-Decision Process



Source: Adapted from Diffusion of Innovations by (Rogers, 2003)

This model, or variations on it, is commonly regarded as the classic technology transfer model. Some scholars, however, extend the concept to address factors of the re-utilization of innovation and infusion issues (Nutley, Davies and Walter, 2002). Initial conditions such as innovativeness and previous practice are influenced by characteristics of the decision-making unit, perceived innovation characteristics, communication channels involved and the role of change agents and opinion leaders in promoting an innovation, according to (Nutley, Davies and Walter, 2002) .

2.1.2 Theory of Reasoned Action (Fishbein's hypothesis)

The theory of reasoned actionl (TRA) and planned behavior (TPB) with its modern incarnation, are in the list of the most important approaches in predicting and understanding intentional conduct from its commencement in the 1970s by Icek Ajzen and Martin Fishbein. A broad range of behaviors, situations and populations have incorporated these theories. The theories centralize on individuals' views about the potential performance of a precise behavior. Intention which has been considered as a motivational construct that is regarded as the most proximal driver of behavior is the primary component of the theory (Fishbein and Ajzen, 1975). The amount to which a person intends to achieve something and puts out effort to do it is showcased in their intention. Two variables that are based on beliefs that are used to demonstrate intention are attitudes and norms which are subjective. Subjective norms are represented by thoughts that significant parties would expect that they execute the conduct while attitudes are positive or negative assessments of executing the behavior (Ajzen and Fishbein, 1977). The theory of reasoned action has been very useful in predicting behavioral variability in demographics, choices of circumstances and behaviors. Ajzen reinvented the thought of reasoned action to account for activities that are not totally under one's control. Perceived behavioral control was incorporated as an extra forecaster of intents in the theory of planned behavior (Ajzen, 1991). When people's expectation of control is closely equivalent to their actual control, the strength of the Intention-Behavior Relationship is determined by perceived behavioral control. When individuals feel that they have a lot of control over their actions, they would be more prone to act on their intentions.

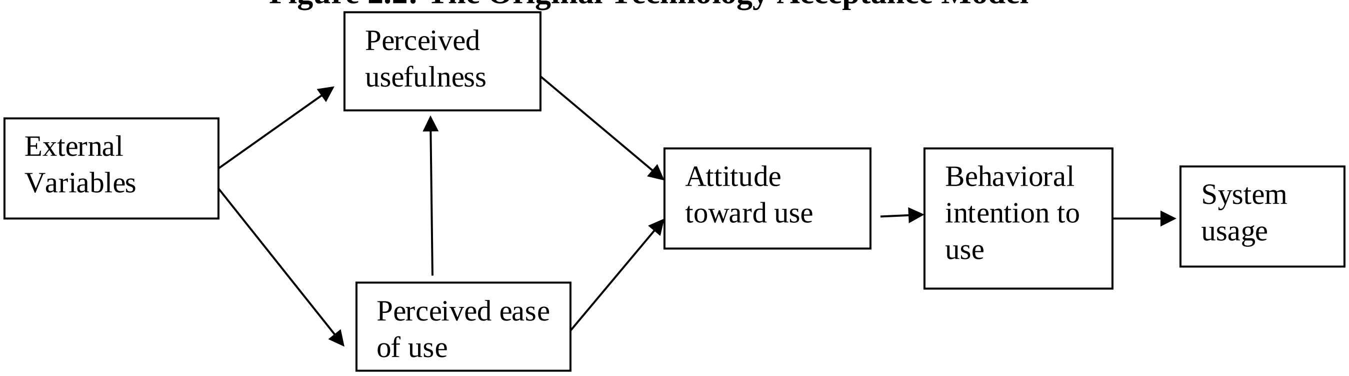
Ajzen further noted behavior is predicted directly when alleged behavioral control closely indicates actual control (Ajzen, 2005). The initiative of premeditated behavior is made comprehensive by the reasoned action approach, which differentiates multiple subcomponents of the attitude, perceived behavioral control constructs and subjective norm (Ajzen, 2005). The reputation of the theory has its roots from its relative straightforwardness and flexibility along with its ability to account for noteworthy disparity in behavior. The theory has also been used to generate more comprehensive explanations of behavior by incorporating additional constructs into the theory and examine important determinants of action. Generally, TRA is a prediction model that claims that the best forecaster of people's conduct in a given situation is their intention to carry out the behavior. Predictably, when people intend to carry out an act is the best pointer of whether they will really get it done. The intention to execute the action is influenced by a person's personal outlook towards the behavior, as well as the attitudes of key persons in the person's life and the resulting perceived social pressures (subjective norms). Behavioral intention which can be what one intends to do or not do is the most proximate source of conduct. Attitude is the assessment of conduct and subjective norm taken as one's assessment of what people believe one should do determines behavioral intention, with any of these potentially being the most important determinant of any behavior. The beta weights obtained from numerous regression studies, where behavioral intention is regressed on to attitude and subjective norm, usually demonstrate this empirically.

Subjective norms are dictated by one's ideas about what is expected to be done in the perspective of others and how motivating it is to follow advice from the others. Summative processes are thought to determine both attitude and subjective norm. In this manner, to shape a mentality, individuals are accepted to total conduct conviction assessment items for example mentality $=\sum b_i e_i$, whereas to frame an emotional standard, individuals are expected to total standardize conviction inspiration to go along items for example abstract standard $=\sum n_i m_i$). Many people have attacked the premise of reasoned action. The contrast between subjective norm and attitude has arguably received most attention (Liska, 1984). Though there have been empirical arguments, the main problem is largely conceptual. Recall that attitudes are generated by the beliefs on outcomes (assessments of those results), while subjective norms are presumably as a result of normative beliefs (to act in accordance with motivations). But, what if normative and behavioral beliefs are just unlike labels for the similar thing? This exactly is the question addressed by (Miniard and Cohen, 1981) who opined that the definition and operationalization of these concepts leads to inappropriate differentiation between personal and normative reasons for engaging in a behavior. Attitude is a cognitive variable, according to the idea of reasoned action: it is a judgment based on anticipated consequences and their values (Ajzen and Fishbein, 1980). Other scholars, on the other hand, feel that attitude has an emotive and cognitive element (Triandis, 1980). Researchers have utilized factor logical research paradigms to explore these possibilities.

2.1.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) was established by Davis in 1986, which has been identified as a comprehensively used model adopted to illustrate user acceptance behavior. The model is reliant on the social psychology theory which is the Theory of Reasoned Action (Fishbein and Ajzen, 1975). Theory of Reasoned Action states that attitudes are driven by beliefs, which in turn influences intentions and consequently conduct. Originally TAM by Davis (Davis, 1986, 1989; Davis, Bagozzi and Warshaw, 1989) recognized the categories as follows: perceived usefulness (PU), perceived ease of use (PEOU), attitude and behavioral intention to use. PEOU and PU are elements which create an end-view to users about a technology and predict the resulting approach towards it and this forecasts its acceptance. Perceived ease of use and perceived use were used as independent variables and system usage as the dependent variable in a series of experiments to validate TAM. Davis discovered that perceived usefulness was extensively associated with self-reported current usage and self-predicted future usage (Davis, 1986).

Figure 2.2: The Original Technology Acceptance Model



Source: Technology acceptance model adapted from (Davis, 1986)

PEOU was discovered to be linked to both present and future usage. In general, it was revealed that PU had a more compact association with system usage than PEOU. Perceived ease of use can be mentioned as the precursor of perceived use instead of an undeviating determining factor of system utilization. Perceived ease of use therefore has an indirect impact on technological acceptance through perceived use (Davis, 1989; Davis, Bagozzi and Warshaw, 1989).

Figure 2.3: A Validated Technology Acceptance Model

Source: Validated acceptance model adapted from (Davis, 1986)

A lot of attention and empirical evidence has been given to TAM (Taylor and Todd, 1995). TAM was extensively evaluated using different sample sizes and user groups within and across enterprises, examined with various statistical tools and compared to contending models in earlier studies (Gefen and Straub, 2000). Earlier before the study by (Davis, 1986, 1989; Davis, Bagozzi and Warshaw, 1989), quite a number of studies have highlighted the usefulness of perceived ease of use and perceived usefulness in the prediction of people's behavior. For example, an explanatory study was carried out by Schultz and Slevin where it was revealed that PU made available a dependable forecast for self-predicted use of a decision model (Davis, Bagozzi and Warshaw, 1989). A replication was later made by (Robey, 1979) and it was established that there was a high correspondence that existed between perceived usefulness and system usage. Meanwhile, in supporting the importance of perceived ease, meta-analysis of (Tornatzky and Klein, 1982) on innovation adoption was carried out. This research involved studying the association between characteristics of an innovation and its adoption; it was revealed that the complex nature of an innovation was among the factors that had the most consistent significant relationships among a broad series of innovation types. Also, (Bandura, 1982)made known the importance of considering both PEOU and PU in forecasting behavior. Here it was noted that in several instances, behavior would be best predicted by outcome judgments and self-efficacy. Self-efficacy is comparable to PU and is referred to as the level to which a behavior which once successfully executed is believed to be linked to prized results.

The research by (Swanson, 1982) reported that PU and PEOU are both key determinants of behavior. Swanson hypothesized that possible users opt for and utilize reports which are reliant on a tradeoff between associated cost of access and perceived information quality. In his study, information value was found to be related to perceived usefulness while cost linked to access was similar to PEOU (Swanson, 1982) . Finally, it was resolved by (Davis, 1986) that people are likely to adopt or not adopt a scheme to the level of believing it would assist them in carrying out their activities more efficiently (PU) and that the belief of the efforts required to use a system can directly affect system usage behavior (PEOU). Davis' research has been modified and made comprehensive in different ways. Till this moment, several propositions have been recorded to explain results from the study. The most updated of all is by (Yousafzai, Foxall and Pallister, 2007a, 2007b) who carried out a meta-analysis of a hundred and forty-five articles published on Technology Acceptance Model.

2.1.4 Resilience Framework and Theories

The resilience theory was first introduced by C.S. Holling in 1973, who concentrated on how populaces work inside natural system, especially after some kind of biological pressure. Natural examination preceding Holling's work had been focused on system balance, yet C.S. Holling argued that a framework might have numerous equilibria that shift during pressure (Holling, 1973). In concentrating on hunter-prey connections and populace models, C.S. Holling opined that there were different stable states conceivable (Folke, 2006) . This acknowledgment moved environmental work from zeroing in exclusively on a solitary balance to system eccentrics and more factor ways of behaving. Consequently, from C. S. Holling's work, resilience is characterized as a system's capacity to adapt to pressure or shock while protecting its current capacity and association for example without moving to another balance (Bahadur, Ibrahim and Tanner, 2013). This strong viewpoint moves the concentration from attempt to seclude a system from change to an attempt to construct the limit of a system to endure change; to cite Holling, "the important spotlight is not on consistency however on inconstancy" (Folke, 2006). Holling and his kindred scientists presented work in 1995 that associated the association and conduct of environments with the association and conduct of individuals who live in and work with these biological systems (Folke, 2006). This work focused on the certainty of vulnerability and started to drive ecological administration procedures from the straightforward "order and-control" strategies that attempt to stay away from framework change.

Holling further argued that these strategies might give the ideal impact temporarily, yet as they do not consider everything factors, they can leave systems more helpless against unsettling influences over the long haul. Holling's disclosure of different stable states additionally prompted his work on the versatile environment of the executives and the possibility of the versatile cycle. Resilience is considered as the capacity of people, networks, associations, or nations that are exposed disasters, and crises given inherent vulnerability; to anticipate, lessen the effect of, adapt to, and recuperate from the impacts of adversity without undermining their future prospects (IFRC, 2012). It is the capacity of a system or a society to convey its flow level of cultural prosperity, without compromising that of people in the future, by responding to shocks and tireless underlying changes. This should be possible by either opposing (absorptive limit) or by taking on a level of adaptability and rolling out little improvements to the system (adaptive limit). At the breaking point, when aggravations are serious, it is the capacity to go through a more profound change or change (transformative limit) (Manca, Benczur and Giovannini, 2017). Households that have access to financial associations are privy to systems to acquire their own technique for adapting and thus might accomplish various degrees of adaptability to food security (Ahmed, 2011). The resilience system is moored on the accompanying hypotheses panarchy and the adaptive hypothesis, designing hypothesis, biological hypothesis, and socio-ecological hypothesis. The panarchy and the adaptive hypothesis form the structure squares of the resilience hypothesis. The versatile cycle is a pattern of unsettling influence and recuperation that frameworks go through as they answer stresses.

Panarchy is the possibility that these cycles are settled, rather than progressively or directly coordinated (Holling and Gunderson, 2002), it additionally versatile cycles as intricately connected both spatially and transiently in manners that might cause "falling" occasions where a disappointment of one level can influence an assortment of different levels (Van Apeldoorn *et al.*, 2011). The versatile cycle has four principal stages: abuse, protection, delivery, and redesign. Abuse and preservation are the fronts of the circle, while delivery and redesign are the rear of the circle (Holling and Gunderson, 2002), and furthermore shows how much change is a vital piece of social-environmental frameworks. Under the adaptive hypothesis, rather than portraying strength in light of the capacity to keep a steady harmony, the regular pattern of progress should be represented, and the certainty of changes to the framework implies that adaptability and *resilience* are critical to a tough framework. Along these lines, the meanings of strength have advanced to consolidate patterns of progress, as well as changes starting with one condition of harmony then onto the next. The designing hypothesis of adaptability, as per (Folke, 2006) is how much time is taken by a framework to get back to its past state after an unsettling influence had happened. This hypothesis is simply material to more modest unsettling influences where the framework doesn't wind up a long way from the underlying harmony. The more complicated definitions contend that this consistent state definition doesn't matter to environment conduct in a temperamental express this sort of conduct requires a definition that utilizes a viewpoint of intricate versatile frameworks as opposed to corralling states (Folke, 2006).

Form a complex adaptive system perspective, system is seen as being subject to natural cycles and criticisms that work on various spatial and transient scales. According to this viewpoint of mind-boggling adaptive system and different conditions of equilibria, came the ecological resilience and social resilience ideas, which drive a stage past designing stability. Ecological resilience and social resilience center on the support capacity, which alludes to the capacity of a system to adjust to a shock without changing its capacity or construction (Darnhofer, 2014). These ideas relate more to "industriousness" than the designing versatility thoughts of framework recuperation and consistency (Folke, 2006) . They can be utilized with regards to an environment retaining a shock without changing its capacity or with regards to a social framework or local area engrossing a shock while keeping up with its association. The social-ecological resilience strength coordinates the ideas of recuperation and industriousness while likewise moving past these to a more versatile thought of framework *resilience*. Here, three extra definitions were joined: the capacity to self-put together; the capacity to learn and adjust; and the capacity to change into a better state. The capacity of the system to self-sort out is portrayed as essential to how the framework will arise following a shock and has clear ramifications for social systems (Folke, 2006; Altieri *et al.*, 2015; Quinlan *et al.*, 2015). In social-ecological frameworks, this implies tracking down a feasible harmony between human guidelines and environmental guidelines. Socially, a farmer should have the option to self-coordinate, as does the customer. The association can be through farmer cooperatives, nearby organizations, and more modest administration structures, all of which empower generally high levels of farmer support and self-association.

A self-coordinated system will be stronger than one that either is not coordinated or has a constrained arrangement of association, for instance, one directed by a political body (Folke, 2006). Additionally, integral to the social-environmental strength idea, and firmly interrelated to networks is the ability to learn and change. This connects with the idea of adaptive limit, characterized as the capacity of a system to change by learning and growing, yet without including extremist changes to the system's capacity or construction (Darnhofer, 2014). (Cabell and Oelofse, 2012) allude to this limit as reflected and shared getting the hang of, implying that partners inside the system can learn and change, put together both with respect to previous encounters and on data from one another. Nearby organizations can give a helpful strategy to this sort of information sharing. By gaining from the past or by sharing prescribed procedures, the framework can adjust and be more ready for future shocks, rather than basically responding to them as they occur. Social-ecological resilience likewise consolidates the idea of moving forward to a better state instead of just returning to the past stable state (Cabell and Oelofse, 2012). For instance, (Engle *et al.*, 2014) characterize resilience as "the possibility to assimilate and adapt to effects of environmental shocks and limits for the time being, and to learn, redesign, and redevelop, desirable over a superior state, in the more drawn out term." This definition contends that for a framework to be tough, it should have the option to adapt to prompt anxieties as well as make itself less helpless against future burdens. This connects to the third strength capacity called the transformative capability. This denotes to the ability of a system to react to shock by drastically changing its system or function (Darnhofer, 2014). This is a discovery from Holling’s work here; a movement from one state of equilibrium to another is seen as resilient, so long as the move is advantageous in the long term.

2.2 Empirical Review

2.2.1 Determinants of awareness, adoption and sustained use of agricultural technology and climate smart practices

The importance of agricultural innovation in agricultural development cannot be over emphasized as revealed in literature both theoretically and empirically. Over the years, it is evident that adoption of agricultural innovations among smallholder farmers are usually very low especially in sub-Saharan Africa and also depends on several factors which have been extensively studied in literature. Limited and slow adoption of improved agricultural technologies among smallholder farmers have hampered development and promotion of technology. Several studies have been done on the determinants of sustained utilization of agricultural innovation adoption. Understanding the factors influencing the choice to take on the innovation is significant in getting a crucial change in the development of the agricultural area and the business of the farm households. Also, understanding the variables influencing a scope of supported utilization of rural innovation is essential for improvement specialists chipping away at fostering the agricultural area and makers entrapped in the creation of rural advancements (Hall and Khan, 2003).

(Bayan and Dutta, 2018) attempted to identify the factors that influences the adoption decision and use intensity of artificial insemination (AI) technology among smallholder dairy farmers in India. They found different farm, farmer, physical, natural, and perception characteristics, for example, schooling and experience of the family head, awareness about AI innovation, government support, distance to AI Center, all-weather road and market, and herd size significantly impact the decision to adopt the AI innovation.(Donkor, Owusu and Owusu-Sekyere, 2014) analyzed the determinants of adoption of improved cassava varieties among cassava farmers in Ashanti area, Ghana. Results showed that extension access, credit access, education, marital status, farmer-based association, and family size have a significant effect on the likelihood of farmers adopt improved cassava varieties. (Awotide *et al.*, 2014) evaluated the degree and determinants of improved cassava varieties adoption in south-western Nigeria. Estimates revealed that adoption intensified with the age, gender, hired labour, land cultivated, and access to credit. Outcomes further showed that the adoption intensity is affected by hired labour and farm size; awareness of the improved cassava varieties is determined by the age, gender, and education of the family head, and by off-farm income.

(Asfaw, Di Battista and Lipper, 2014b) examined the food security effect of adoption of agricultural innovation in Niger, utilizing multivariate probit and instrumental variable procedures to show the choice choices and their effect. The investigation discovered that the determinants of modern inputs use can be different from determinants of climate adaptation practices such as crop residues. Proximity to extension services and markets are identified as two major determinants of adoption of modern inputs. They found that effects of climate change are vital factors which determine farmers' selection of farm practices. In studying the perception and determinant of agricultural innovation adoption in Ethiopia, (Massresha *et al.*, 2021) found that the probability of embracing improved seed varieties, chemical fertilizer, and irrigation is higher among families with higher household age, more schooling years, larger farm size, higher livestock ownership, and more extension visits. Likewise, the probability of taking on these agricultural technologies is higher for families taking part in non-farm income activities, belong to a social group, and credit access. The probability of taking on the predominant agricultural technologies was seen as higher for male-headed families compared to female-headed ones. Distance to the closest market adversely influences the decision to adopt different agricultural advancements.

(Oyetunde-Usman, Olagunju and Ogunpaimo, 2021) looked at the factors influencing the adoption of different Sustainable Agricultural Practices (SAPs) and drivers of adoption intensity of these practices. The empirical outcomes show that farmers' adoption of various SAPs and their intensity of use rely fundamentally age of family head, gender, education, family size, extension access, and family wealth status. From the study of determinants of agricultural technologies adoption in the Niger republic, (Djibo and Maman, 2019) argued that age, education level, farm size, agricultural co-operative membership, number of plots owned, plot size, plot location, plot soil type, tenure status and income determined the decisions to adopt agricultural technology. Specifically, (Milkias and Abdulahi, 2018) investigated determinants of adoption of improved high country maize varieties in Ethiopia, using censored Tobit regression. Farm size, household income, credit access, extension service, training participation, age and market distance influenced adoption and intensity of use of improved maize variety. (Ponguane and Mucavele, 2018) in their study on the determinants of agricultural technology adoption in Mozambique using bivariate probit regression found that education, farm size, purchasing power ad market access had vital roles to play in improved seed and mechanization adoption. Surprising, extension access reduces the likelihood to adopt improved seed.

(Challa and Tilahun, 2014) investigated the determinants and effects of modern agricultural technology adoption in Ethiopia. Result showed that education level, farm size, credit access, cost of inputs, off-farm income, and household size significantly affect adoption decisions of farmers. The result of the propensity score matching result revealed an improvement in the average income and consumption expenditure of adopters compared to non-adopters. While (Cavane, Cunguara and Jorge, 2013) found that an expansion in farm size improves the probability of a family taking on agricultural innovation since farmers with large farm size ownership gain from economies of scale and are market-oriented. In another study, (Tiamiyu *et al.*, 2017) examined farmers' adoption of climate-smart agricultural practices in Northern Nigeria. The descriptive outcomes showed that adoption of the most of selected climate smart practices was by and large low. Agronomic practices were the most embraced practice, however, practices like integrated pest management, agro-forestry, soil fertilization, and water management were not profoundly taken on. Bush burning posed a significant impediment towards the resilience building. They argued that farmers need continuous sensitization about the reality of climate change and the need for adoption climate smart practices.

(Amadu, McNamara and Miller, 2020) reviewed the adoption of climate-smart agriculture, by developing a typology of farm-level CSA practices to facilitate analyses of CSA adoption in southern Malawi. The typology classifications are buildup expansion, non-woody plant development, helped recovery, woody plant development, actual foundation, and blended measures. The review observed a positive impact of program participation or support on the adoption of CSA practices with the strongest effects on resource-intensive CSA subgroups. (Ntshangase, Muroyiwa and Sibanda, 2018) determined the factors that influence the adoption of no-till conservation agriculture (CA), farmers' perceptions of CA, and the impact of CA on maize yield in South Africa. Findings revealed that farmers' positive perceptions were correlated with higher maize yields. Increased extension visits, age, education, and farmers' positive perceptions improved the probability of a farmer adopting CA, larger size of land was negatively related with CA adoption. They further highlighted the critical role played by extension service in the promotion of CA.

(Yigezu *et al.*, 2018) in their review on the adoption of zero tillage among wheat and barley producers in Syria using the double hurdle and duration analysis models. The review figured out that the overall grounds of farmland devoted to wheat creation is a vital determinant of span to take on rather than the simple all-out farmland. Likewise, farmers with huge Wheatland are probably going to take on zero culturing prior to comparison with little wheat regions. The results show that increasing exposure and awareness of the zero tillage technology through organized field days and demonstration trials, complemented with providing free access to costly zero tillage seeders for first-time users, increases the propensity, speed, and intensity of adoption. The intensity of adoption is also positively influenced by wheat acreage and farmers' access to credit. (Abay *et al.*, 2016) studied farmers’ multidimensional technology adoption decisions in the presence of heterogeneities among households in Ethiopia with respect to input complementarity and Heterogeneity employing a longitudinal datasets. Authors observed significant complementarities among agricultural technologies, presence of heterogeneity in preferences for agricultural technologies among farmers and highlighted that the dissemination of agricultural technologies can be enhanced by providing these technologies as a bundle.

Similarly, (Ogada *et al.*, 2020) investigated multidimensional agricultural technology adoption decisions in the existence of farm households’ heterogeneities. They estimated the complementarities among alternative agricultural technologies while controlling for unobserved heterogeneities. The outcomes show that based on the unobservable heterogeneity impacts, adoption choices exhibit complementarity for the technologies considered. There was also presence of unnoticed heterogeneity impacts prompting the heterogeneous effect of explanatory factors on adoption choices among farmers with similar observable attributes. These heterogeneities could represent varieties in preferences and inclinations among households for agricultural technologies conditioned by the degree of risk avoidance or rate of return to technology adoption. Subsequently, any compelling agricultural innovation reception and dispersion procedures and arrangements should consider the complementarity of the advances and heterogeneity of the families, and it very well may be advanced as a bundle while thinking about family and farm level requirements to reception. Form these two studies, a vital insight is the fact the current efforts towards technology diffusion in sub-Saharan Africa which assume an identical production function among farm household can be alluded to the existing and continuing low adoption of agricultural technologies.

2.2.2 Adoption of climate-smart technology and productivity

The variation on climate conditions in the past decades have rendered the agricultural communities in developing countries greatly uncertain thereby increasing the risk exposure in agricultural production. Several studies have investigated the potency of adopting climate smart practices and technology as a solution to impact of climate change. (Tesfaye, Bedada and Mesay, 2016) studied the effect of wheat technology adoption on productivity and income in Ethiopia and found that it increased the productivity of the farmers by about 1 to 1.1 per hectare while the income of adopters on average was increased by 35 to 50% higher than non-adopters. This demonstrates that agricultural innovation adoption can add to further developing efficiency and raising the income of farming households. (Issahaku and Abdulai, 2020a) examined the drivers of individual and joint adoption of crop choice and soil and water conservation practices, and effects on crop income and skewness of crop yield in Ghana. The empirical outcomes showed that farmers' adoption of crop choice and soil and water preservation prompts higher yield incomes and decreased uncertainty in crop production, with the biggest effect on crop incomes coming from joint adoption. More so, education, extension and climate information access were important determinants of adoption these practices.

(Imran *et al.*, 2018) analyzed the effect of CSA adoptions on cotton production and the living condition of Farmers in Pakistan. The study identified water-smart, energy-smart, carbon-smart and knowledge-smart practices of CSA, as embraced by the cotton farmers to forestall the adverse impact of the climate change. Empirical outcome shows that there was uniform cotton growth, significant increase in yield and financial returns, and increase in resource use efficiency. This result shows the evident benefit of adopting CSA practices in agricultural production. (Sardar, Kiani and Kuslu, 2021) assessed the intensity of CSA adoption and its attendant benefit on crop yield and farm income. Result from a multinomial logistic regression model showed that institutional factors, financial resources, farm and farmers; characteristics significantly explained adoption. More so, farmers who adopted multiple CSA practices gained higher yield and higher income that their counterpart who did not adopt CSA practices. To analyse the adaptation benefits of climate-smart agricultural practices in the Blue Nile Basin, (Asrat and Simane, 2017) employed Heckman selection model and nearest-neighbour matching techniques. They argued that physical, natural and social factors influence farmers decision to adopt CSA while adopting households experienced higher productivity by 22% over non-adopters. This implies that risks associated with climate change are significantly reduced.

(Shahzad and Abdulai, 2020) analyzed the heterogeneous impacts of the adoption of climate-smart farm practices on farm performance in Pakistan. The outcomes show significant heterogeneity in the benefits from the adoption of climate-smart farm practices with respect to observed and unobserved family characteristics. Besides, results showed that adoption of climate-smart practices contributes to higher farm net returns and adoption of these practices had significant negative effect on the unpredictability of the farm net returns and farmers' risk exposure. (Arslan *et al.*, 2015) used panel data from the Rural Incomes and Livelihoods Surveys merged with a set of climatic variables based on geo-referenced historical rainfall and temperature data to explore the changing effects of farm practices with climatic conditions in Zambia. The study appraises the effects on maize yields as well as yield resilience of the maize farmers while controlling for household characteristics. Empirical outcomes showed that legume intercropping increased yields and reduced the probability of low yields even under critical weather stress during the growing season. Besides, the average positive effects of modern input use were significantly conditioned by climatic variables. Prompt fertilizer access appears as one of the most robust factors that influenced yields and their resilience. (Mossie, 2022) examined the impact of climate-smart agriculture practices on rural household productivity. Employing the propensity score matching and semi-parametric local instrument variable, result revealed that that wheat row planting has a statistically significant positive effect on productivity of wheat. Hence, he poised that increased adoption of technology, increase in productivity will significantly contribute to the resilience of farmers to the uncertain effects of climate variability.

2.2.3 Adoption of climate-smart technology and welfare

(Awotide *et al.*, 2022) investigated the distributional impact of the Climate-Smart Agricultural Technologies (CSAT) on-farm households' welfare in Mali. Using the Instrumental Variable Quantiles Regression model addressing potential endogeneity from selection bias and the heterogeneity of the impact across the quantiles of outcome variables. Results revealed that adoption of climate-smart agricultural technologies positively influenced household welfare. Also, credit access, extension contact, training participation, information access, belonging to a group positively impact adoption of these climate-smart technologies. They further argued that the impact of the adoption of these climate-smart practices can be pro-poor given that impact of the adoption of technologies on households' welfare is generally higher for the poorest farmers at tail end of the welfare distribution. (Tesfaye, Blalock and Tirivayi, 2020) examined the welfare effects of climate-smart agricultural practice specifically conservation agriculture. Results showed that conservation agriculture practices play a crucial role in addressing the issues of rural poverty.

These practices fosters decrease in the incidence and depth of poverty in areas that are susceptible to heavy rainfall. Also, they found the combination of minimum tillage and mixed cropping can greatly augment efforts to reduce rural poverty, serving as climate risk mitigation and management.

(Martey *et al.*, 2020) provided novel evidence of the impact of row planting and drought-tolerant maize varieties on farm output and welfare by computing a multinomial endogenous switching regression model which corrected for selection bias and heterogeneity in CSA selection. They found that adoption of the considered CSA practices increased yield and commercialization of maize production, however, negatively affects the individual consumption of individual household. They further argued that there is a possibility that the extent of the effect of a CSA may differ than another. (Ali *et al.*, 2022) discovered the potency of CSA practices in combating poverty, they found that CSA adopter households have a lower deprivation score in multidimensional poverty that their non-adopter counterparts. Hence, it is expedient to know that advancing adoption of CSA practices by out and up scaling incentives is quite important.

2.2.4 Adoption of climate-smart technology and food security

In the face of climate variability and change, there is a growing concern about increasing agricultural productivity and meeting food security demands. Climate-smart agriculture have been progressively used as an approach to inclusive development with a wide range of technological, institutional and policy interventions (Radeny *et al.*, 2018). Several authors have looked into the impacts of CSA technologies on food security, nutrition and dietary diversity. Using a quasi-experimental approach, (Radeny *et al.*, 2018) analysed adoption and effect of CSA on livelihood outcomes in East Africa. Results from the study show an increase in take-up of CSA technologies and innovations, combined with better agronomic and livestock. Farmers that adopted stress-tolerant crop varieties and improved breeds of livestock, were seen to have access to more types of food and accrued more household assets than the non-adopting farmers. Dietary diversity, asset index and household income of adopters were also seen to be higher than their non-adopters. Also, adoption of improved and better breeds of livestock increased household dietary diversity scores and increased household dietary diversity scores. The authors further argued that the adoption of crop and livestock related CSA practices impacts food security, asset index, and income.

(Teklewold *et al.*, 2013) in their study of the impact of crop system diversification, conservation tillage and modern seed adoption on income, agrochemical and labour demand, found that CSA practices increases maize income and the highest payoff is accrued when the practices are adopted in combination than in isolation. Interestingly, it was shown that adoption of the package approach to CSA practice may raise the workload on women hence widening the gender inequity gap. Authors argued that promoting a combination of CSA technologies can foster income, reduce production costs and food security of farm households. (Ali *et al.*, 2022) considered impact of climate-smart agriculture adoption on food security of rural farm households and found that adopter households on average showed more food consumption score, dietary diversity score, and less food insecurity experience scale than non-adopters, hence, CSA adoption improves households' food security and contributes to the achievement of SDG 1, 2 and 13 goals. (Issahaku and Abdulai, 2020b) found that adoption of climate-smart technologies positively and significantly impacts food and nutrition security. These impacts of adoption were greater in the lower quantiles of the distributions of food and nutrition security.

2.2.5 Adoption of climate-smart technology and resilience to climate change

From a cross-sectional data of cotton farmers from cotton-developing areas of Punjab Pakistan, (Jamil *et al.*, 2021) investigated the adoption of CSA practices, factors that influence farmer adoption decision, and its impact on poverty, income, and yield using logistic regression and propensity score matching (PSM). The outcomes showed that education, access to credit, ownership of tube well, farm experience, and extension visits determined farmers' adoption. Empirical results revealed that the reception of CSA practices is economical, financially and ecologically attractive, and favorable to the poor. Authors proposed that adoption of CSA would help in diminishing the adverse consequence of climate change on the cotton production crop by guaranteeing benefits, eliminating the barriers to adoption, spreading information about CSA, rigorously implementing the guidelines for CSA and promoting resilience to climate change. Using the Endogenous Switching Regression model, (Teklewold *et al.*, 2017) investigated the role played by adoption of multiple climate smart practices (agricultural water management, improved crop seeds and fertilizer) on improving farmers' climate resilience in the Nile Basin of Ethiopia. The study showed that farmers are less inclined to take on fertilizer (either alone or in the mix with improved crop varieties) in areas of greater precipitation fluctuation. However, farmers are more probable to adopt fertilizer and improved varieties even when there is high variability in rainfall only when they are able to include water management practices to the bundle. Authors argued that a package approach rather than a piecemeal approach to deal with maximizing the collaborations in different climate smart practices. (Nyasimi *et al.*, 2017), in their study of the adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania, found that farmers were embracing a variety of CSA practices, technologies, and institutional developments in the wake of taking part in the Farms of the Future Approach (FotF). Furthermore, result showed that farmers' minimize their risks and reduce vulnerabilities by diversifying and integrating five to ten CSA practices in one season. This study emphasizes the vital roles of training, access to information and "package" approach to adoption of CSA practices and the impacts of adoption on resilience to climate change.

2.3 Conceptual Review

2.3.1 Technology Innovation in Agriculture

Technological development has made the general agribusiness process simpler. Over time in rural area, technology advancement has been changing, overhauled or enhanced reliably on different sustainability fronts (Luo, Guob and Jia, 2017). Agriculture might probably be the most seasoned business, however with the turn of events and utilization of rural apparatus, there has been a sensational drop in the quantity of individuals who can be depicted as farmers (Fielke *et al.*, 2019; Odame *et al.*, 2020). With proceeding with progresses in agricultural advancement, the job of the farmer will turn out to be progressively particular. The impact of technology advancement on farming has prompted the idea of agricultural innovation. Rural innovation is among the most progressive and significant areas of current innovation, driven by the key requirement for food and for taking care of a consistently developing populace (Fielke *et al.*, 2019; Curry *et al.*, 2021). It has opened a time in which fueled apparatus accomplishes the work previously performed by individuals, and creatures (like bulls and ponies). The advantages of innovation advancement in agribusiness firm, and tank-farming cultivating to augmenting crop yield with decreased work costs and improving the practicality of activity. Technology advancement in agriculture has greatly expanded farm yield and significantly had an impact on the manner in which individuals have utilized and produced food around the world. Motorized agribusiness likewise includes the utilization of planes and helicopters (Curry *et al.*, 2021).

Currently, there is technology advancement for essentially every phase of the farm operation. Machines are incorporated for plowing the soil, sowing seeds, watering the land, developing yields, safeguarding them from bugs and weeds, collecting, sifting grain, taking care of domesticated animals, and arranging and bundling the items. Developing technology advancement has made consolidates to remove the gathering position from farm haulers, however farm vehicles actually do most of work on a cutting edge farm (Knickel *et al.*, 2009; Fujun *et al.*, 2018). Aside utilizing grower, a few yields are planted by drills, which put out significantly more seed in columns under a foot separated, covering the field with crops. Present day water system likewise depends on a lot of technology development. An assortment of motors, siphons and other particular stuff is utilized to give water rapidly and in high volumes to enormous areas of land. Comparable kinds of gear can be utilized to convey manures and pesticides (Knickel *et al.*, 2009) . Technology development in rural goes past agricultural production to management, dissemination, and capacity, which brings about more prominent efficiencies and lower costs, more secure developing circumstances and more secure food varieties, decreased natural, and biological effect.

2.3.2 Climate Change Impact on Agriculture

The effects of climate change and variability on farming has been well research in literature. Climate change have seriously impacted the farming systems, which are the significant sources of employment for rural households in developing countries (Keshavarz and Moqadas, 2021). In spite of the fact that agribusiness is basic to Africa's development and improvement, climate change could weaken neighborhood markets, control monetary development, and uplift risk for rural financial backers. While agricultural questions were basically omitted from the United Nations Framework Convention on Climate Change that took on in 1992, a door opened for their incorporation in the environment plan at the Conference of the Parties of Durban in 2011 (Figueiredo, Nunes and Brito, 2021). As farmers are regularly adaptable in managing climate and year-to-year variability, there is in any case a serious level of variation to the nearby environment as laid out foundation, neighborhood cultivating practice and individual experience. Climate change thus impacts agriculture, possibly compromising laid out parts of farming systems yet in addition giving opportunity to upgrades. Climate and environmental change has contributed significantly to food insecurity, expanding food costs and diminishing food production, and made water expected for food production scanty because of expanded crop water utilized and droughts (Keshavarz and Moqadas, 2021).

Sub-Saharan Africa specifically West Africa seems defenseless in light of the fact that for large numbers of its harvests, it is at the edge of actual edges past which yields decline. Additionally, a significant part of the region's economy relies upon agriculture. Outrageous climate events, related with environmental change has brought about abrupt decreases in agricultural efficiency, prompting fast augmentations. While progressive increase in temperature and carbon dioxide might bring about better circumstances that could build the yields of certain areas, these potential yield increments are probably going to be limited by outrageous occasions, especially outrageous hotness and dry season, during crop blooming. Atmospheric conditions are turning out to be less great in many examples, expanding the unpredictability of harvest and animals yields. The recurrence or potentially seriousness of outrageous occasions is expanding as temperatures are projected to keep rising and precipitation design expected to move more than they have as of now. Crop creation is projected to diminish in numerous region during the 21st century due to climatic changes. Heat waves which are projected to increment under climate change could straightforwardly compromise domesticated animals (Antwi-agyei *et al.*, 2021). Dry spell might undermine field and feed supplies, environmental change might build the pervasiveness of parasites and infections that influence the animals. Many weeds, vermin, and growths flourish under hotter temperatures, wetter environments, and expanded CO_2 levels.

2.3.3 Climate-Smart Agriculture

Agriculture's outrageous vulnerability challenge keeps on heightening because of climate change's adverse consequence. Agricultural areas should become climate smart to effectively handle current food security and climate change difficulties (Autio *et al.*, 2021). Climate-Smart Agriculture (CSA) is a methodology that helps guide activities to change agri-food frameworks towards green and environment versatile practices. CSA has been inserted in conventional agricultural practices that have been utilized to cushion the antagonistic effects of environmental change and changeability (Antwi-agyei *et al.*, 2021). CSA upholds arriving at globally concurred objectives like the Sustainable Development Goals and the Paris Agreement. It intends to handle three principle targets: reasonably expanding agricultural usefulness and wages; adjusting, and constructing versatility to environmental change; and, decreasing, or potentially eliminating ozone harming substance emanations, where conceivable. Environment savvy agribusiness adds to a cross-cutting scope of advancement objectives. There are numerous valuable open doors for catching cooperative energies between the mainstays of environment brilliant farming, yet additionally numerous circumstances where compromises are inescapable (Hrabanski and Le Coq, 2022).

Working at the scene level with an environments approach, consolidating ranger service, fisheries, yields, and domesticated animals frameworks are pivotal for answering the effects of environmental change and adding to its moderation. Between sectorial approaches and steady arrangements across agrarian, food security, and environmental change are vital at all levels (Waaswa *et al.*, 2021). Institutional and monetary help is required for farmers, fishers, and timberland subordinate people groups to make the progress to environment shrewd farming. Some powerful environment brilliant practices as of now exist and could be increased, yet this must be finished with genuine interests in building the information base and creating innovation (Autio *et al.*, 2021). Interests in environment savvy agriculture should connect finance valuable open doors from public and private areas and furthermore coordinate environment finance into reasonable advancement plans.

2.3.4 Resilience to Climate Change

Resilience is the ability of a social-environmental framework to go on after a shock, re-put together while supporting an essentially comparative capacity (Mekuyie, Jordaan and Melka, 2018). In a bid to foster adaptability against climate change, the Center for Disease Control and Prevention laid out a system known as Building Resilience against Climate Effects (BRACE). Climate resilience is the capacity to expect, get ready for, and answer perilous occasions, patterns, or aggravations connected with environment. Further developing climate resilience includes surveying how environmental change will make new, or modify current, environment-related dangers, and finding a way ways to all the more likely adapt to these threats (Keshavarz and Moqadas, 2021). Environment strength is regularly connected with intense occasions - like heat waves, heavy floods, storms, or violent fires - that will turn out to be more incessant or serious as the environment changes. Notwithstanding, great strength arranging likewise represents persistent occasions, such as rising ocean levels, deteriorating air quality, and populace movement. Indeed, even as we work to turn away the most awful likely effects of climate change, we should turn out to be stronger to those impacts that are presently unavoidable. These effects regularly excessively influence low-pay networks and networks of shading, supporting the requirement for evenhanded and proactive strength arranging and asset portion (Guo *et al.*, 2021).

Organizations get ready for gambles consistently and can factor environment takes a chance into existing gamble the board structures to turn out to be more environment strong. States has a significant part to play in refreshing foundation and assisting networks with adapting to outrageous climate, ocean level ascent, and other environmental impacts. As ozone harming substance emanations keep on rising, environmental change will keep on speeding up. Regardless of whether emanations were to stop today, the environment would keep on changing for quite a while as the Earth's framework answers the warming currently in progress. It's a good idea to expect changes and act now to limit future monetary and social dangers. Urban areas and nearby networks are answering by putting resources into foundation updates and environment brilliant intending to alleviate the effects of intense and persistent occasions. For instance, a mix of nature-based arrangements and building upgrades, such as establishing road trees and introducing green rooftops, can assist with alleviating extreme heat (Fujun *et al.*, 2018). Activities like these are particularly significant in generally underestimated networks, where environmental effects can worsen existing disparities. Baltimore and Minneapolis are among urban areas that have executed Resilience Hubs, housed in believed local area offices that offer everyday types of assistance and work as asset focuses during and after risk occasions like floods or outrageous heat waves.

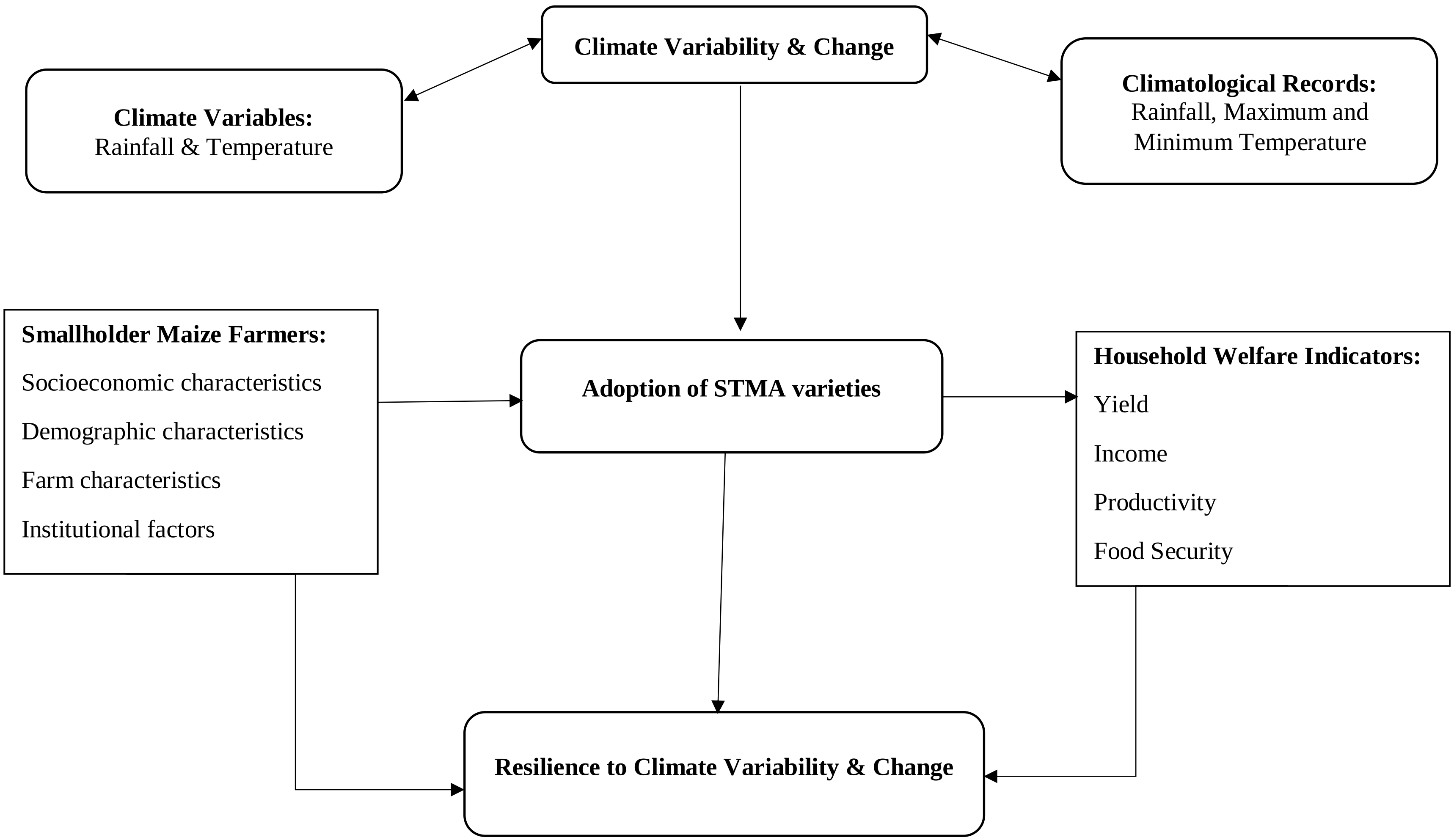
2.3.5 Conceptual Framework

A conceptual framework that integrates the major components of the study is developed in order to guide the discussion of findings of this research. Figure 2.6 presents the conceptual framework of the study.

Partial Conclusion

The first part of this section expounded on the theoretical framework of the study. The theories of adoption and diffusion of innovation, reasoned action, technology acceptance model, resilience theories were explained. Technology diffusion and adoption has a strong theoretical background which has evolved over the years in the works of several authors. The second part of this section presents a thematic review of relevant empirical studies which include determinants of awareness, adoption and use of agricultural technologies, effect of adoption of climate-smart technology on productivity, welfare, poverty, food security and resilience to climate change. These studies emphasize the various benefits of agricultural technological adoption. The last part looked into the concepts relevant to the study and a conceptual framework for the study was hewed out.

Figure 2.6: Conceptual framework for the study



Source: Authors' Representation

CHAPTER TWO

METHODOLOGY AND HOUSEHOLDS' CHARACTERISTICS

Introduction

This chapter presents the methodology approach and an overview of the characteristics of households sampled for the study. The popular impact evaluation measures which include randomized control trial, quasi-experimental, regression discontinuity design, difference in difference, propensity score matching, endogenous treatment impact model and endogenous switching regression are reviewed. The general econometric approaches to analysing the determinants of technological adoption which are abundant in literature are also reviewed. Information on the study area, sampling design, data used and data collection procedure, tools of data analysis are provided. The chapter further presents an overview of the descriptive statistics of the farm households surveyed with the profile of these characteristics are profiled by food insecurity categories and STMA adoption status.

3.1 Methodological Review

3.1.1 Review of impact evaluation measures

Impact evaluation positions among a wide scope of corresponding techniques that help evidence-based approach. There are two primary ways to deal with impact assessment; Experimental (Randomized Control Trials) and Non-Experimental (Quasi-exploratory/Observational examinations) approaches. The various sorts of impact assessment techniques are investigated in this part.

Randomized Control Trials (RCT)

Randomized Control Trials (RCTs) are regularly alluded to as the best quality level of effective assessment and are the most thorough examination technique for deciding if a reason impact connection exists between a treatment and an outcome (Bhide, Shah and Acharya, 2018). (Cook and Payne, 2001) opposed that while RCTs might be reasonable for estimating basic, momentary improvement treatments, they are less appropriate for more complicated, long-haul interventions, where many variables try to deliver change. Since RCTs try to quantify a counterfactual (correlation bunch), they frequently require information assortment before the beginning of an treatment, which makes it hard to apply this methodology after treatment has started and how much the innovations of one review can be summed up to different settings (Hutchison and Styles, 2010) In particular, with a sufficiently enormous number of perceptions, the randomized task cycle will deliver bunches that have measurably identical midpoints for every one of their qualities (Ashraf, Giné and Karlan, 2008; Awotide *et al.*, 2012) . The RCTs enjoys the benefit of guaranteeing that the two gatherings of subjects are matched similarly on all variables even prior to figuring out what these elements might be; it is great for making causal derivations. It doesn't rely upon molding on the observed covariates and can adjust for both observed and unobserved covariates. In any case, it has inconveniences in that it is costly; Randomization may not be feasible or logical in view of moral concerns; there are issues of generalizability of study plans; Subjects may not be representative of everybody. Preferably, a plan would incorporate the arbitrary choice of subjects and an irregular portion of the treatments to subjects (Hutchison and Styles, 2010).

Non-experimental Method or Quasi-Experimental

Without a completely randomized preliminary, semi-trial error has been taken on to gauge sway. This is more significant in sociology where individuals are the unit of perception and produce results that are of higher outer legitimacy since they occur in genuine settings rather than in the fake setting of trials (Bärnighausen *et al.*, 2017). It is an observational review with an exogenous illustrative variable that the specialist doesn't control (King, Keohane and Verba, 1995).The various techniques for observational examinations are distinction in-contrasts (DiD), Propensity Score Matching (PSM), and regression irregularity plans. (RDD) and so on The premise of these methodologies is to lay out a correlation bunch that is as like the treatment bunches as could be expected (Shahidur, Samad and Koolwal, 2010; White and Raitzer, 2017). A portion of these strategies are talked about as follows:

Regression discontinuity design (RDD)

This impact evaluation technique is satisfactory for programs that utilization a persistent file to rank expected members and that have an endpoint along with the record that decides if potential members get the program (Moscoe, Bor and Bärnighausen, 2015). The gauge can't really be summed up to units whose scores are further away from the removed score and the technique cannot process a normal treatment impact for all program members (White and Raitzer, 2017). Determination might be touchy to the practical structure utilized in displaying the connection between the qualification score and the result of interest (Filmer and Schady, 2009). Notwithstanding, the benefit is that regression brokenness strategy permits us to effectively gauge the effectiveness of a program without barring any qualified populace.

The overall equation for assessing impacts utilizing regression brokenness is given as:

$$Y_i = \beta_0 + \beta_1 + \delta(cutoff) + \varepsilon_i \quad (1)$$

Difference in Difference (DiD)

This impact valuation strategy assesses the counterfactual for the adjustment of result for the treatment bunch by working out the adjustment of result for the examination bunch, subsequently, considering any distinctions between the treatment and correlation bunches that are steady over the long haul (Di Tella and Schargrodsky, 2004). It settles the issue to the degree that numerous attributes of units or people can sensibly be thought to be steady after some time (or time-invariant). Assuming some other elements are available that influence the distinction in patterns between the two gatherings, the assessment will be invalid or one-sided (Galiani, Gertler and Schargrodsky, 2005). However, DiD is not difficult to carry out and is straightforward, yet, information is typically not accessible to test model legitimacy. Thus, it is more thorough to utilize a matching procedure or to apply a fixed-impacts model. The model creates a normal treatment impact on the treated (ATT), which is helpful for understanding consequences for those generally taking part yet isn't a proportion of the impacts of the mediation on the general populace (White and Raitzer, 2017).The implied model of the distinction in contrast gauge is given as:

$$Y_i = \alpha + \beta T_i + et_i + \gamma T_i t_i + \mu_i \quad (2)$$

Propensity Score Matching (PSM)

The propensity score matching measures the likelihood of being in the treatment bunch given the detectable attributes from a regression model of investment (Rosenbaum and Rubin, 1983). Matching basically utilizes measurable procedures to build a fake examination bunch by distinguishing for each conceivable perception under treatment a non-treatment perception (or set of non-treatment perceptions) that has the most comparative attributes conceivable (Rosenbaum, 2002). The treatment impact is assessed from the penchant score, and the normal treatment impact arrived at the midpoint of over the conveyance of the affinity score is given as:

$$E(Y_1 - Y_0) = E[Y_1 - Y_0/e(X)] \quad (3)$$

The impacts of unmistakable inclination (brought about by choice on observables) and secret predispositions (brought about by determination on undetectable), and the issue of rebelliousness or endogenous treatment variable can be eliminated/limited through contingent autonomy suspicion (Rosenbaum and Rubin, 1983) and the instrumental variable-based strategies (Abadie, 2003; Imbens, 2004). The upside of affinity score matching is that it is generally feasible for a double treatment assuming adequate information are accessible (thus should be visible as a "strategy for final retreat") and it can likewise produce an ATT and a normal treatment impact (ATE) that is legitimate for the general populace. The disadvantage is that PSM depends on matching observables. In the event that choice (investment) is impacted by inconspicuous, PSM will yield one-sided sway gauges for ex-post single distinction gauges (White and Raitzer, 2017).

Endogenous Treatment Impact (ETR) Model

The endogenous treatment impact model was created by (Heckman, 1976) to assimilate the impacts of imperceptible determinants of treatment, so fair-minded treatment impacts can be assessed. It includes a two-stage assessment where the principal stage models a probit condition of investment (like how it helped PSM aside from that the probit contains at least one instrument for support). In the subsequent stage, the fitted qualities for interest from the principal model are utilized as a regressor in the OLS assessment for the result variable. The effect is estimated as the coefficient on the fitted program variable. The test for determination is not set in stone by the meaning of lambda in the second stage regression. Notwithstanding, in contrast to the instrumental variable, covariates that influence both choice and the result can be utilized in the two phases. A significant downside of this model is the recognizable proof of a solid covariate that can fill in as an instrument. The ETR gauges the normal treatment impact (ATE) which is reasonable for summed approach (Danso-Abbeam *et al.*, 2021; Oyetunde-Usman, Olagunju and Ogunpaimo, 2021).

The model is given as;

$$P_t^* = \theta X_t + \varphi W_t + \mu_t,\ P_t = \begin{cases} 1\ if\ P_t^* > 0 \\ 0, otherwise \end{cases} \quad (4)$$

$$Y_t = \alpha P_t + \beta_t X_t + \varepsilon_t \quad (5)$$

$$ATE = E(Y_{1i}|P_i = 1) - E(Y_{0i}|P_i = 0) \quad (6)$$

Where, P_t is the treatment variable (sham) which rises to 1 for members and 0 for non-participants. W is the instrumental variable utilized for model recognizable proof, $\theta, \varphi, \alpha, \beta$ are the boundaries to be assessed. μ and ε are the bivariate blunder terms with mean zero and covariance grid.

Endogenous Switching Regressions (ESR)

This model is an impact evaluation approach that gauges two result conditions (two systems), one for treatment and one for correlation, considering the endogeneity of choice into treatment (Maddala and Nelson, 1975). The endogenous exchanging model is assessed utilizing logit or probit and executes the full data Maximum Likelihood (ML) strategy to all the while gauge the parallel determination and the double result portions of the model to yield steady standard mistakes of the evaluations. It represents endogeneity predisposition and the impact of the imperceptible covariate (Lokshin and Sajaia, 2004).

$$Y_i^* = \beta_0 + \gamma Z_i + \mu_i \;\; with \;\; T_i = \begin{cases} 1 \;\; if \; Y_i^* > 0 \\ 0 \;\; if \; Y_i^* \leq 0 \end{cases} \tag{7}$$

Endogenous switching is said to happen to assume there is a communication or connection between the choice to develop and any covariate in the resulting work.

$$Regime1: Y_{1i} = \gamma_1 x_{1i} + \varepsilon_{1i} \quad if \quad T_i = 1 \tag{8}$$

$$Regime2: Y_{2i} = \gamma_2 x_{2i} + \varepsilon_{2i} \quad if \quad T_i = 0 \tag{9}$$

Multinomial Endogenous Switching Regression (MESR)

This is utilized to assess the reception of various or different interrelated rehearses (Bourguignon, Fournier and Gurgand, 2007). The strategy first purposes a multinomial Logit model (MLM) to decide factors that impact selection of practices, and besides gauges sway utilizing the result condition. This technique enjoys triple benefits of tending to biasness that emerges from inconspicuous covariate, getting reliable and proficient gauges, and figures the effect of both discrete and joined rehearses all the while (Wekesa, Ayuya and Lagat, 2018).

The result condition is given as;

$$
\begin{cases}
Regime\ 1: \Omega_{1i} = \alpha_1 Z_{1i} + \sigma_1 \lambda_{1i} + \theta_1 \bar{Z}_{1i} + e_{1i} \quad if\ I = 1 \\
\quad \vdots \\
Regime\ J: \Omega_{Ji} = \alpha_J Z_{Ji} + \sigma_J \lambda_{Ji} + \theta_J \bar{Z}_{1i} + e_{Ji} \quad if\ I = J
\end{cases} \tag{10}
$$

The MESR is a subset of ESR and will be utilized to assess the effect of various practices. It additionally creates gauges on ATT, ATU, and ATE. This technique controls for test choice inclination and heterogeneity which different strategies (RDD, DiD, PSM, ETR) can't represent aside from the RCT plan.

3.1.2 Econometric approaches for the analysis of the factors of adoption and diffusion of Agricultural technology

Literature is loaded up with various systemic methodologies utilized in assessing the adoption intensity of agricultural technologies and/or innovations. A portion of these incorporates Count Data models like Poisson regression, Negative Binomial regression; Probit regression, Multivariate probit regression, Tobit regression; and Double regression model. They are additionally talked about as follows:

Probit Regression

The Probit model is one of the ways to deal with fostering a likelihood model for a double reaction variable (Gujarati, 2003). The Probit system registers the greatest probability assessments of the boundaries of the Probit condition utilizing a changed Newton-Raphson calculation. At the point when the response Y is double, with values 0 and 1, the Probit model is frequently preferred over the standard bivariate Probit approach as a result of its oversimplified nature which functions admirably by and by. The Probit model likewise gives a fairly straightforward and efficient split of the difference between the standard bivariate Probit model and other elective factors that halfway change as indicated by the given situation. Despite the fact that the Probit model can end up being extremely effective, execution in functional circumstances can end up being truly challenging. It likewise doesn't assist with controlling the predisposition that might happen during test determination.

The Probit regression model can be indicated as below;

$$Y_t^* = X_t \beta + \varepsilon_i \tag{11}$$

$$Y_i = \begin{Bmatrix} 1 if Y_t^* \geq 0 \\ 0 if Y_t^* < 0 \end{Bmatrix} \tag{12}$$

Where, Y_t^* = observed dichotomous dependent variable.

Count Data Models

Count data models are utilized in the event that where the reliant variable is the quantity of advancements chose as a proportion of the degree of purpose of accessible innovations. For example, (Mensah-Bonsu *et al.*, 2017) observationally evaluated the reception and force of land and water the board (LWM) works on utilizing considered models such Poisson and Negative binomial models. They in the long run involved Poisson regression for the investigation because of lower upsides of AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion).

Tobit Model

This alludes exclusively to models with either censored, controlled, or shortened subordinate factors and it fuses elements of microeconomic information with zero qualities or crimps focuses (Lung-fei, 1993). Studies such as (Adesina and Baidu-Forson, 1995) and (Owusu and Donkor, 2012) both dealt with the reception power of further developed rural innovations utilizing the Tobit model. Nonetheless, as brought up by (Cragg, 1971), (Lung-fei, 1993), (Smith and Brame, 2003) one significant downside of the Tobit model is the supposition that the choices on regardless of whether to embrace and the amount to take on are together made and thus, the elements influencing the two choices are thought to be same. To address this inadequacy, (Cragg, 1971) proposed the Double Hurdle model.

Double hurdle Model

The double hurdle presented by (Cragg, 1971) is to control for test sample selection bias and endogeneity issues. He recommended that singular choice on the degree of investment in action is the after-effect of two interactions. First to decide if the individual is a zero sort and also, deciding the degree of investment (non-zero worth) and incorporation of extra regressor (reverse plant proportion). The twofold obstacle model was additionally changed by (Mullahy, 1986) to oblige count information with Poison, mathematical, and negative binomial (Amadu, McNamara and Miller, 2020; Hlatshwayo *et al.*, 2021).

It is given as:

$$P_i^* = \beta' Z + \varepsilon_i \; with \; P_i = \begin{cases} 1, & if \; P_i^* > 0, \\ 0, & otherwise \end{cases} \tag{13}$$

$$y_i = \beta' Z + \delta_i \tag{14}$$

Where, P_i^* is the inactive degree of utility of investment (faker result), β' are the coefficient to be assessed, Z are the vectors of free factors, y_i is the count factors (showing power or degree) ε_i and δ_i are the arbitrary factors.

3.1.3 Methodological tools in resilience assessment measures

Structural Equation Models (SEMs)

The SEM is an expansion of general straight demonstrating system like investigation of change (ANOVA) and various regression examination. The model estimates every one of the parts all the while and expects that residuals are conveyed ordinarily. Thus, it is restricted to the ordinarily disseminated noticed factors in consistent structure (Lei and Wu, 2013). In any case, information gathered at the family level is either ordinal or all out, which restrains the utilization of SEM to gauge strength. Estimation of inert factors with the assistance of multivariate strategies is beneficial. As indicated by (Wuensch, 2016), the SEM enjoys benefits in distinguishing immediate and circuitous impacts, for example the immediate connection between the reliant variable (the most recent one) and the free factors connected with it, while the backhanded impact happens when one variable affects one more factor through a third reliant or autonomous variable. A roundabout impact demonstrates, for instance, that the age of family heads could indirectly affect Resilience Capacity Index. Additionally, the chance of having different markers in clarifying the dormant variable implies that it is feasible to assess the impact of single pointers on the reliant variable, holding different pointers. Ultimately, the consideration of estimation error in the model is the primary contrast with way investigation. Way investigation incorporates error terms in the expectation yet tragically doesn't control for estimation error during the interaction. SEM examination, in representing estimation blunders, gives a superior comprehension of how great the model predicts the genuine result, limiting the irregularity between the covariance grid of the noticed factors, and the hypothetical covariance network anticipated by the model construction (Bollen, 1989, 2007).

Multiple Indicator Multiple Causes (MIMIC)

A Multiple Indicator Multiple Causes (MIMIC) model clarifies the connection between perceptible factors and the imperceptible variable by limiting the distance between the example covariance matrix and the covariance lattice anticipated by the model. The recognizable factors are separated into connects of the inert variable and its pointers. The correlates are important for the design of the model, while the pointers are estimated. The MIMIC model expects that the factors are estimated as deviations from their means and that the error term is not related with the correlates (Buehn and Schneider, 2008). MIMIC models are embraced to get estimation invariance and heterogeneity (Flora and Curran, 2004). They are essentially utilized in psychometrics and sociology. They are causal models which permit one dormant variable with numerous basic pointers and different causes. It has two estimation models, intelligent and developmental models (Edwards and Bagozzi, 2000). The developmental model considers the noticed factors to be the reasons for an idle variable model while the intelligent model considers an inert variable to be the reason for noticed factors. For a direct form of the MIMIC, the connection between the inactive variable and its causes, the pointers and the dormant variable are straight in the boundaries. The dependent variable (which is regression on the developmental markers) is the common fluctuation of the reflected factors or builds. The mistake term is the common change between the results (for example the at least two intelligent parts) not represented by the developmental pointers.

Figure 3.1: Multiple Indicator Multiple Causes Model Estimation

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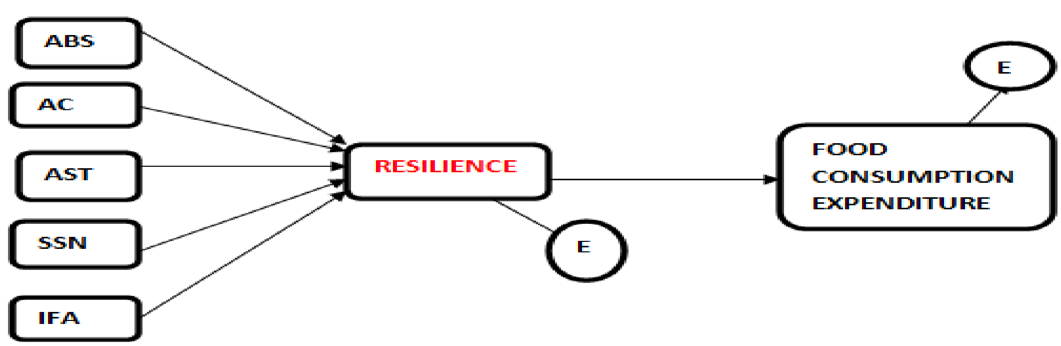


Source: Hypothesized Relationships in the MIMIC Model Adapted from (Buehn and Schneider, 2008)

The Resilience Incidence Measurement Analysis (RIMA II) Approach

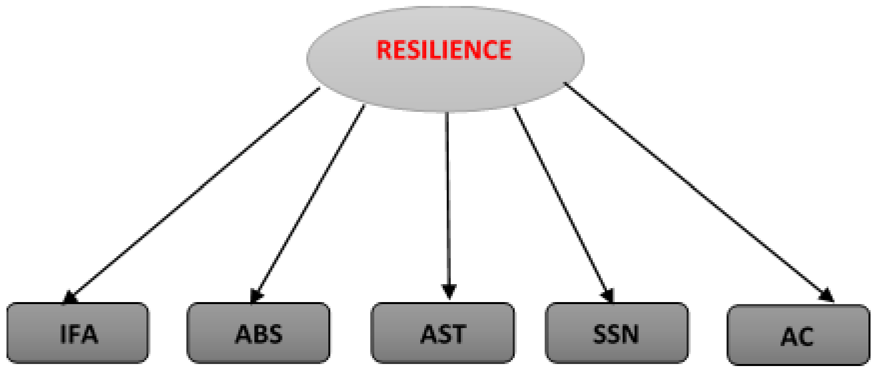
The Resilience Index Measurement Analysis (RIMA II) approach centers on two related yet unmistakable investigations of *resilience* for example construction and limit. The investigation of Resilience Structure Matrix (RSM) targets distinguishing the determinants of strength, by first surveying the noticed variable loads. This is trailed by distinguishing their general commitments in deciding the points of support and inspecting loads of the support points to recognize their overall commitment in deciding the Resilience Capacity Index. The examination of the Resilience Capacity Index (RCI) matches the strength list of Female-Headed Households across rural families at various levels in this way making it conceivable to comprehend which profiles show a sequential limit of adapting to shocks and stressors (D'Errico, Garbero and Constas, 2016). Resilience, considered as an imperceptible list, is determined as a component of five points of support: Income and Food Access (IFA), Access to Basic Services (ABS), Assets (AST), Social Safety Networks (SSN), and Adaptive Capacity (AC), as below;

$$R_{i,t} = f\left(IFA_{i.t}, ABS_{i,t}, AST_{i,t}, SSN_{i,t}, AC_{i,t}\right) + \varepsilon_{i,t} \qquad (15)$$

Resilience Index of the i-th family relies upon the degrees of IFA, ABS, AST, SSN and AC at time t, in addition to the mistake term. The assessment cycle comprises of two stages.

To start with, resilience pillars of support are assessed through Principal Component Analysis (PCA) and they are hence utilized in the assessment of family strength limit. During factor extraction, the common change of the factors is isolated from their one of a kind fluctuation and mistake difference to uncover the basic component structure; just shared fluctuation shows up in the arrangement. Adequate quantities of variables are viewed as to ensure they represent something like 95% of the clarified fluctuation (Preacher *et al.*, 2013). RIMA II uses Structural Equation Model (SEM), despite many number of unobserved variable models, which includes correlation between residual errors and a number of formal statistical tests and fit indices

Figure 3.2: Resilience Analysis

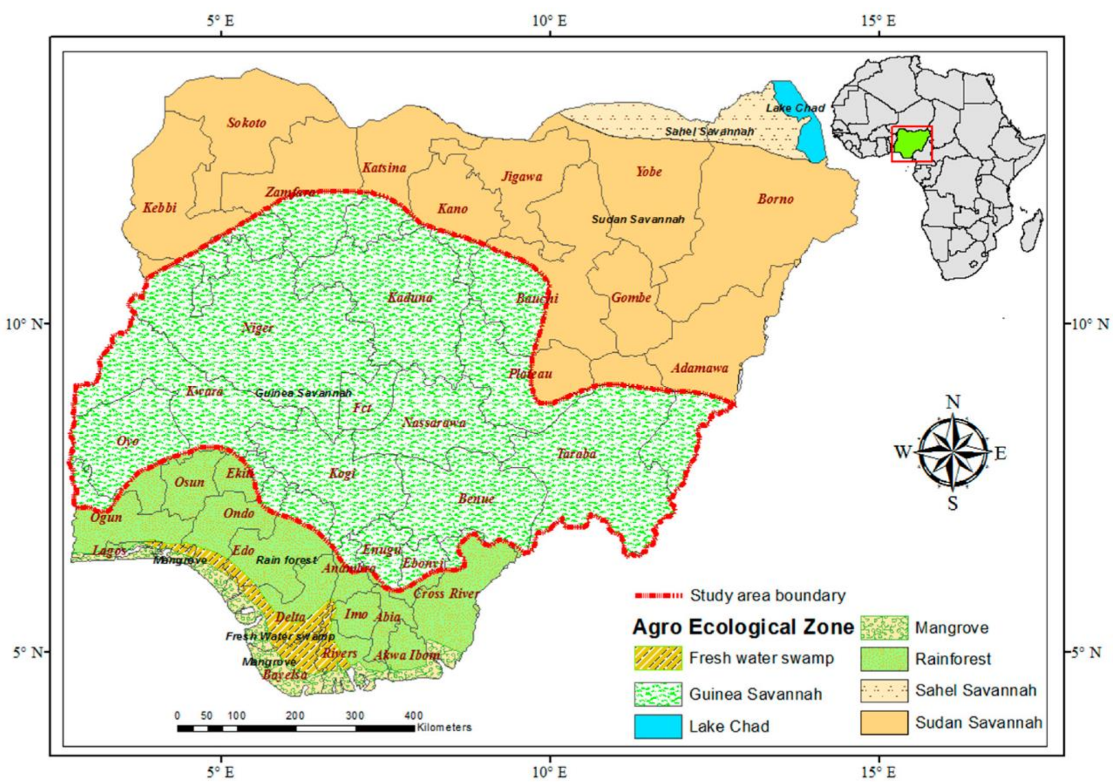


Source: Resilience Analysis adapted from (D'Errico, Garbero and Constas, 2016)

3.2 Study Area

The Federal Republic of Nigeria is a constitutional entity of thirty-six (36) States and has Abuja as the Federal Capital Territory Nigeria. It has a total area of 923,768 km^2 (356,669mi^2) and lies between latitude, 9° 04' 39.90" N and longitude, 8° 40' 38.84" E in the western part of Africa on the Gulf of Guinea. Nigeria is a large country with diverse climate and terrain. It has six (6) agro-ecological zones (Fig 3.3). The climate is humid and semi-arid in the Southern and Northern regions respectively.

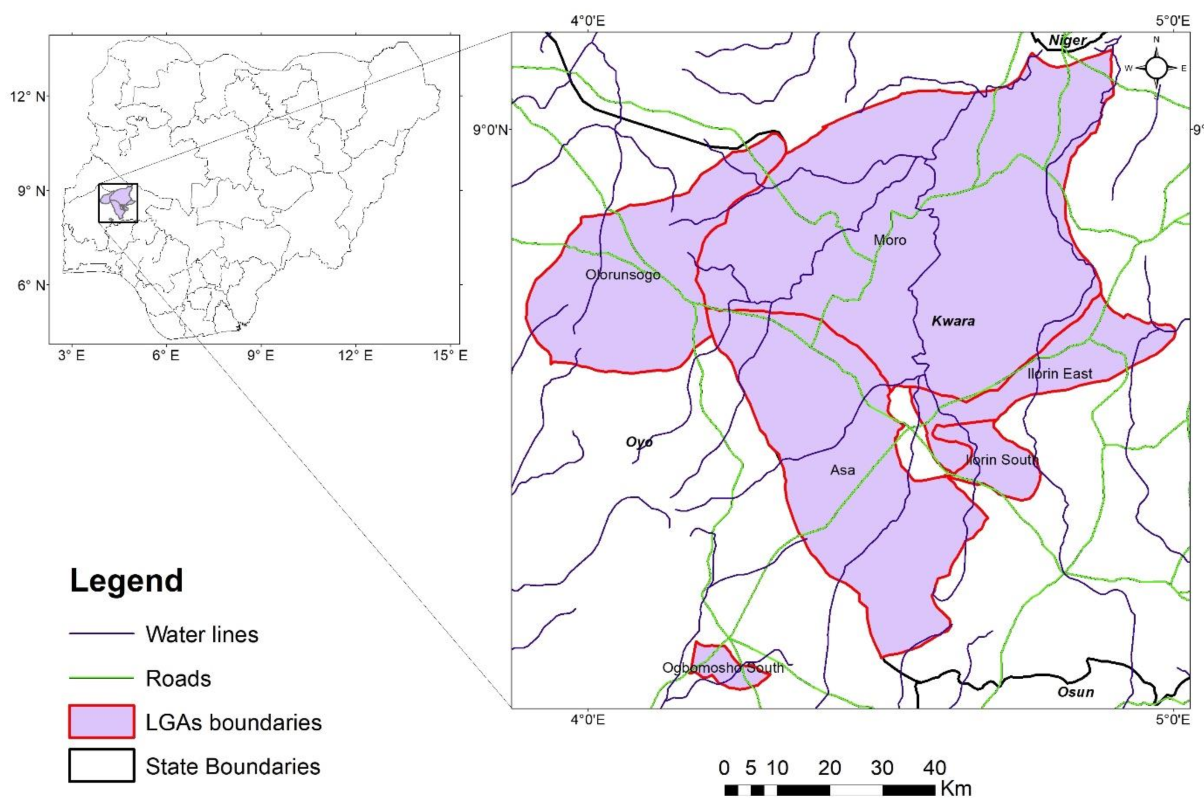
Figure 3.3: Map of Nigeria showing the Agro-ecological Zones



Source: Country pastures/forage resource profiles 2009

The climate ranges from the equatorial climate of the southern lowlands (Adebayo *et al.*, 2011) through the tropical central hills and plateau, to the arid northern plains which mark the southernmost extent of the Sahara desert (AbdulKadir, Usman and Shaba, 2015).The interaction among climate variables such as rainfall, temperature, soil and humidity gave Nigeria her natural vegetation zones (Oyenuga, 1967; Iloeje, 2001). The soil types and climate in the Northern and Southern states are mostly well adapted to cereal and grains production which accounts for the reason bulk of grains and cereals are produced in the Guinea savannah zone of the country. The STMA programme for adaptation to climate change was conducted in the Northern Guinea Savannah and Derived Savannah of the country. The study area selected for this study is the Derived Savannah Zone of Nigeria.

Figure 3.4: Map of Nigeria showing the study area



Source: Authors' representation using shape file data

3.3 Sample determination and Sample size

Due to the unavailability of the population size of farming households in the study area, the only reliable statistic is the proportion of active population involved in agriculture. Therefore, relying on approximately 70% proportion of agricultural households, the sample size was estimated using single population proportion approach (Cochran, 1977; Tessema, 2017). The sample size for the study was determined as:

$$n = \frac{Z^2 * \hat{p}(1-\hat{p})}{\mathcal{E}^2}$$

Where Z = Z score (1.96); $\hat{p}$ = population proportion (70%); Ɛ = margin error (5%).

$$n = \frac{1.96^2 * 0.70(1-0.70)}{0.05^2} = 322$$

Hence, the minimum number of farming households that should be selected is 322. However, since 0.70 proportion assumed in the sample determination was for 2014 and this might have changed in the past eight years, the computed sample was adjusted upward to 520. Therefore, the sample adjustment is necessary to increase the sample size, where ultimately, larger samples gets closer to the true population.

3.4 Sampling Design

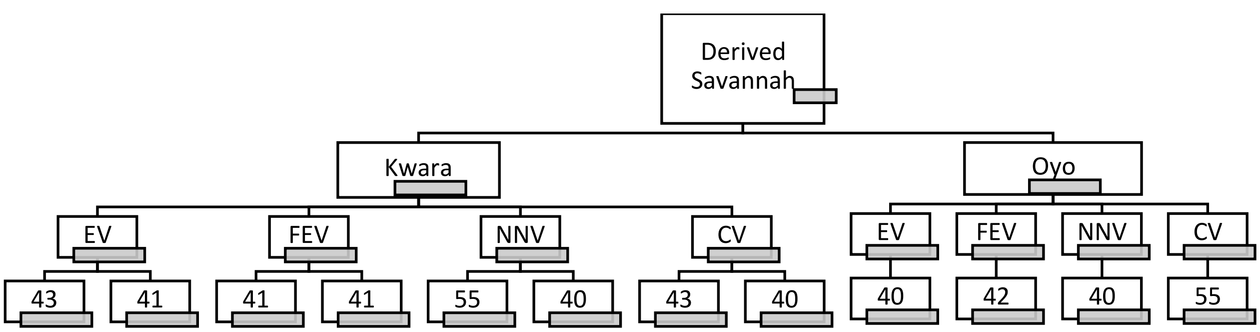
From the agro-ecological zone where the STMA programme was conducted, the Derived Savannah zone was selected for this study. Furthermore, two states were randomly selected from the Derived Savannah zone namely, Kwara and Oyo States. Villages in these two states were further stratified to four categories based on the IITA Stress Tolerant Maize experimental activities and adoption of the Stress Tolerant Maize Varieties (Ajewole *et al.*, 2021). The first stratum is the Experimental Villages; these are villages where STMA varieties have been tried and still being used for trials. Farmers in these villages are actively growing STMA varieties. The second stratum is the Near-neighbour villages; these are villages where trials were not done but are likely to use the STMA varieties by virtue of their proximity to the experimental villages and expected technology spillage from the experimental villages into neighbouring villages. The Former experimental villages is the third stratum; these are villages where experimental trials of the STMA varieties have been carried out in the past but have been discontinued officially by the IITA. These villages were included to help understand if these villages are still currently cultivating STMA varieties or they have discontinued growing the STMA varieties. The fourth stratum is the control villages; these villages are measured for at least 35km away from the experimental villages. They have no knowledge of STMA varieties. Sampling these villages based on these strata provides a detailed knowledge of maize farmers' behaviours as regards adopting the STMA variety. The sampling distribution is presented in Table 3.1. From the distribution, 8 villages were selected in Kwara State while 4 villages were selected in Oyo State. This is because a proportionate sampling was done in Kwara State due to the intensity of STMA activities compared to Oyo State.

Table 3.1: Sampling distribution

State	Villages	Category	Number
Kwara	Oke Oyi	Experimental village	43
	Gambe	Near-neighbour	55
	Lajiki	Former experimental village	41
	Asomu	Control	43
	Alapa	Experimental village	41
	Ohoro	Near-neighbour	40
	Apaola	Former experimental village	41
	Shao	Control	40
Oyo	Igbeti	Experimental village	40
	Tesi Garuba	Near-neighbour	40
	Tesi Apata	Control	55
	Ogbomoso	Former experimental village	42
	TOTAL		**520**

Source: Survey and Author's computation, 2022

Figure 3.5: Figure showing the sampling distribution



Survey: Survey and Author's computation, 2022**.** Where, *EV = Experimental village; FEV = Former experimental village; NNV = Near-neighbour village; CV = Control village*

3.5 Data types and Data collection

The study used both primary and secondary data. For the evidence of climate change, meteorological data were sourced from National Meteorological Agency of Nigeria and were compared with farmers' perception of climate variability and climate. This was done so as to understand the historical climatic patterns of the study area and also compare with the responses that were obtained from farmers in the study area. The primary data (cross-sectional) for this study were obtained from farming households using structured survey questionnaire.

3.6 Data Analytical Techniques

The data collected were subjected to parametric and non-parametric analytical procedures. Descriptive statistics were used to investigate the perceived evidence of climate change while the Heckman selection model was used to achieve the second objective of the study. The Resilience Index Measurement Analysis (RIMA II) and the Endogenous Switching Regression analysis was employed to achieve the third objective.

3.6.1 Household Food Insecurity Access Scale (HFIAS)

The Household Food Insecurity Access Scale (HFIAS) was used to measure the food insecurity of the farming households (INDDEX Project, 2018) First, the HFIAS score is calculated for each household by summing the codes (between 0 and 3) for each frequency-of-occurrence question. The maximum score for a household is 27 (the response of the household was 'often' to all 9 questions, coded with 3) and the minimum score is 0 (the household responded 'no' to all occurrence questions, and therefore the frequency-of-occurrence questions could be skipped). The higher the score, the more food insecure the household is considered. According to this classification method, the food security status of the households is presented below:

Table 3.2: Classification of food security status based on the HFIAS

Score	Food Security Status
0 – 1	Food Secure
2 – 8	Mildly Food Insecure
9 – 16	Moderate Food Insecure
17 – 27	Severely Food Insecure

Source: Coates et al., 2007

3.6.2 Heckman Selection Model

The model was used to examine the effect of the adoption of STMA varieties on productivity and household food security. The selection model is explicitly stated as follows; the first stage (selection equation) of deciding whether a farmer adopted the STMA variety or not is empirically specified as:

$$\mathrm{A_i} = \alpha_0 + \sum_{k=1}^{14} \alpha_k X_k + \mu_i \tag{16}$$

Where;

A_i = Adoption status of the i-th farmer (1 = Yes, 0 otherwise)

X_1 = Gender of household head (1 = Male, 0 otherwise)

X_2 = Marital status (1 = married, 0 otherwise)

X_3 = Household size (headcount)

X_4 = Years spent in school (years)

X_5 = Farm size (hectares)

X_6 = Off-farm income (1 = Yes, 0 otherwise)

X_7 = Social group membership (1 = member, 0 otherwise)

X_8 = Access to Credit (1 = Yes, 0 otherwise)

X_9 = Income Sources (count)

X_{10} = Access to Extension Services (1 = Yes, 0 otherwise)

X_{11} = Awareness of an improved seed variety (1 = Yes, 0 otherwise)

X_{12} = Awareness of STMA (1 = Yes, 0 otherwise)

α_0 = constant term

α_k = coefficients of the explanatory variables

μ_i = random error term

The second stage (outcome equation), which assesses the effect of adoption of STMA varieties on productivity, is specified as follows:

$$\mathrm{G_i} = \gamma_0 + \sum_{k=1}^{15} \gamma_k X_k + \varepsilon_i \tag{17}$$

Where;

G_i = Yield of the i-th farmer (kg/hectare)

X_1 = Gender of household head (1 = Male, 0 otherwise)

X_2 = Age of household head (years)

X_3 = Household size (headcount)

X_4 = Years spent in school (years)

X_5 = Household Dependency Ratio

X_6 = Farming Experience (years)

X_7 = Off-farm income (1 = Yes, 0 otherwise)

X_8 = Access to Credit (1 = Yes, 0 otherwise)

X_9 = Income Sources (count)

X_{10} = Market distance (kilometre)

X_{11} = Access to Extension Services (1 = Yes, 0 otherwise)

X_{12} = Awareness of an improved seed variety (1 = Yes, 0 otherwise)

X_{13} = Inverse Mills Ratio (IMR)

γ_0 = constant term

γ_k = coefficients of the explanatory variables

ε_i = random error term

Also, the second stage (outcome equation), which assesses the effect of adoption of STMA varieties on food security, is specified as follows:

$$G_i = \gamma_0 + \sum_{k=1}^{15} \gamma_k X_k + \varepsilon_i \qquad (18)$$

Where;

G_i = HFAIS score of the i-th farming household

X_1 = Gender of household head (1 = Male, 0 otherwise)

X_2 = Age of household head (years)

X_3 = Household size (headcount)

X_4 = Years spent in school (years)

X_5 = Household Dependency Ratio

X_6 = Farming Experience (years)

X_7 = Off-farm income (1 = Yes, 0 otherwise)

X_8 = Access to Credit (1 = Yes, 0 otherwise)

X_9 = Income Sources (count)

X_{10} = Market distance (kilometre)

X_{11} = Access to Extension Services (1 = Yes, 0 otherwise)

X_{12} = Awareness of an improved seed variety (1 = Yes, 0 otherwise)

X_{13} = Inverse Mills Ratio (IMR)

γ_0 = constant term

γ_k = coefficients of the explanatory variables

ε_i = random error term

3.6.3 Resilience Index Measurement and Analysis (RIMA II)

The FAO Resilience Index Measurement and Analysis (RIMA) II was used to analyse the resilience capacity of farming households in the study area (FAO, 2016). RIMA II estimates resilience using direct and indirect measurement as well as long and short-term measurement approaches. Direct measurement gives descriptive information on resilience capacity which aims at targeting and ranking households while indirect measurement can be adopted as a predictor tool for intervention that builds and strengthens resilience i.e. it looks at its main determinants.

Resilience Capacity Index (RCI) was estimated using a two-stage Factor Analysis (FA) with Bartlett's prediction technique (Alinovi, Mane and Romano, 2010). In the first stage, resilience pillars were estimated through factor analysis of observable variables on each pillar. This can be specified as:

$$X_i = A_{i1}F_i + A_{i2}F_i + \ldots + A_{in}F_i \qquad (19)$$

Where:

X_i = Constructed i-th pillar

A_{in} = n-th component that made up i-th pillar.

F_i= Factor of i-th component

In the second stage, RCI was estimated through factor analysis of the overall pillars by adopting a Structural Equation Model (SEM), and each pillar is considered an observable index. Following (Constas, Frankenberger and Hoddinott, 2014):

$$RCI_i = W_iX_1 + W_iX_2 + W_iX_3 + W_iX_4 \qquad (20)$$

Where:

RCI_i = Resilience Capacity Index of i-th household

W_i = Factor of i-th pillar

X_1 = Access to Basic Service (ABS)

X_2 = Assets (AST)

X_3 = Social Safety Nets (SSN)

X_4 = Adaptive Capacity (AC)

The Resilience Capacity Index (RCI) of the ith household depends on the levels of ABS, AST, SSN, and AC. The following are the variables used to construct the pillars:

Table 3.3: Variables used to construct the pillars

Pillar	Definition
ABS	**Access to basic services:** proximity to main services, proximity to a water source, safe drinking water, sanitation, and housing index.
AST	**Household assets:** per capita land used (ha), financial assets, per capita number of livestock owned, household wealth perception, and agricultural wealth index.
SSN	**Social Safety Nets:** formal transfers (per capita, Naira), Informal transfers (per capita, Naira), access to credit.
AC	**Adaptive Capacity:** diverse Income portfolio, number of training attended by a household, crop diversification index, household head with a university degree.

Source: FAO, 2019

Following (Nakuja *et al.*, 2012), farmers were classified into low, moderate, and high resilience capacity based on the computed resilience capacity index.

Table 3.4: Classification of Resilience Capacity Index

Index	Status
0.00 – 0.33	Low resilience capacity
0.34 – 0.66	Moderate resilience capacity
0.67 – 1.00	High resilience capacity

Source: Adapted from (Nakuja *et al.*, 2012)

3.6.4 Endogenous Switching Regression Model

The Endogenous Switching Regression model (ESRM) was used to determine the effect of the adoption of STMA varieties on farmers' resilience to climate change. Past studies have investigated the effect of adoption of improved varieties on many outcomes by estimating separate production and/or supply functions for adopters and non-adopters separately then comparing the estimates. A major weakness of this approach is the implicit assumption that all farmers that adopt and those that did not adopt are identical based on their intrinsic characteristics. There is also an endogeneity problem that results from that fact that adoption of improved varieties is either voluntary or some farmers are in a better position than others to adopt improved varieties. For instance, a wealthy educated and informed farmers is more likely to adopt an improved varieties than others. Hence, self-selection into adoption improved varieties is a source of endogeneity in the study. One of the best solution into explicitly account for such endogeneity is to use simultaneous models (Hausman, 1983). ESRM was used in this study to correct for any sample selection bias that may have resulted from other interventions to farmers that may influence their adoption decisions (Freeman, Ehui and Jabbar, 1998).

The ESRM is an econometric model that specifies a decision process and the regression models associated with each decision option, and it is used to address issues of self-selection and the estimation of treatment effects when there is a non-random allocation of subjects to treatment and non-treatment groups as is generally the case with observational (as opposed to experimental) data (Awotide *et al.*, 2015). Therefore, an ESRM is chosen to control for the selection bias. Using the ESRM, the direction and degree of non-random selection of farmers for adoption of STMA and the selection biases that are implicit in Ordinary Least Square (OLS) estimates of adoption of STMA can be evaluated.

The binary decision choice of farmers to adopt STMA is conditional on observed covariates using a Probit model is first specified as follows:

$$\left.\begin{aligned} P_i^* &= \beta Z_i + \varepsilon_i \\ P_i &= 1 \;\; if \;\; P_i^* > 0 \\ P_i &= 0 \;\; if \;\; P_i^* \leq 0 \end{aligned}\right\} \tag{21}$$

Due to the selection biases, the farmers are believed to experience two regimes as follows:

Regime 1 (Adopters of STMA): $G_{1i} = \lambda_1 H_i + \varphi_1 C_{1i} + v_{1i} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$ (22)

Regime 2 (Non-adopters of STMA): $G_{2i} = \lambda_2 H_i + \varphi_2 C_{2i} + v_{2i} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$ (23)

Where G_{1i} and G_{2i} are the resilience capacity of the farmers in regimes 1 and 2, respectively. H_i represents a vector of exogenous variables which are hypothetically assumed to determine the resilience capacity function. ϕ_1 and ϕ_2 are the parameters to be estimated. v_1 and v_2 are the error terms.

According to (Maddala, 1986) when there are unobservable factors associated with selection bias, the important implication of the error structure is based on the fact that the error term (ε_i) of the selection equation (21) is correlated with the error terms (v_1, v_2) of the outcome functions 22 and 23, the expected values of v_{1i}, v_{2i} conditional on the sample selection are non-zero:

$$E(v_{1i}|P_i = 1) = E(v_{1i}|\varepsilon_i > -Z_i\beta) = \sigma_{1\varepsilon}\left[\frac{\theta\left(\frac{Z_i\beta}{\sigma}\right)}{\phi\left(\frac{Z_i\beta}{\sigma}\right)}\right] \equiv \beta_{1\varepsilon}\gamma_1 \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (24)$$

$$E(v_{2i}|P_i = 0) = E(v_{2i}|\varepsilon_i \leq -Z_i\beta) = \sigma_{2\varepsilon}\left[\frac{-\theta(Z_i\beta/\sigma)}{1-\phi(Z_i\beta/\sigma)}\right] \equiv \beta_{2\varepsilon}\gamma_2 \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (25)$$

Where θ and φ are the probability density and cumulative distribution functions of the standard normal distribution, respectively. The ratio of θ and φ evaluated at $Z_i\beta$, represented by γ_1 and γ_2

in equations 26 and 27 is referred to as the Inverse Mills Ratio (IMR) which denotes selection bias terms. The IMR provides the correlation between the adoption of STMA and the resilience capacity of farmers. In the first stage, a Probit model of the criterion equation is estimated and the IMRs γ_1 and γ_2 are derived according to definitions in equations 26 and 27. In the second stage, these predicted variables are added to the appropriate equation in 22 and 23, respectively to yield the following sets of equations.

$$G_{1i} = \lambda_1 H_i + \beta_{1\varepsilon}\gamma_1 + \varphi_1 C_{1i} + n_{1i} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{(26)}$$

$$G_{2i} = \lambda_2 H_i + \beta_{2\varepsilon}\gamma_2 + \varphi_2 C_{2i} + n_{2i} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{(27)}$$

The empirical equation of the ESRM to be estimated consists of a probit regression and a resilience capacity function. The adoption of STMA decision equation, which is equivalent to equation (21), is specified as follows:

$Y_i = f(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12})$ ……………………………………… (28)

Where;

Y_i = Adoption status of the i-th farmer (1 = Yes, 0 otherwise)

X_1 = Gender of household head (1 = Male, 0 otherwise)

X_2 = Marital status (1 = married, 0 otherwise)

X_3 = Household size (headcount)

X_4 = Years spent in school (years)

X_5 = Farm size (hectares)

X_6 = Off-farm income (1 = Yes, 0 otherwise)

X_7 = Social group membership (1 = member, 0 otherwise)

X_8 = Access to Credit (1 = Yes, 0 otherwise)

X_9 = Income Sources (count)

X_{10} = Access to Extension Services (1 = Yes, 0 otherwise)

X_{11} = Awareness of an improved seed variety (1 = Yes, 0 otherwise)

X_{12} = Awareness of STMA (1 = Yes, 0 otherwise)

The separate resilience capacity function for the farmers that have adopted STMA and those that did not, similar to equation (3.9), is as follows:

$Y_i = f(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12})$ ……………………………………….(29)

Y_i = Resilience Capacity Index of the i-th farming household

X_1 = Gender of household head (1 = Male, 0 otherwise)

X_2 = Age of household head (years)

X_3 = Household size (headcount)

X_4 = Years spent in school (years)

X_5 = Household Dependency Ratio

X_6 = Farming Experience (years)

X_7 = Off-farm income (1 = Yes, 0 otherwise)

X_8 = Access to Credit (1 = Yes, 0 otherwise)

X_9 = Income Sources (count)

X_{10} = Market distance (kilometer)

X_{11} = Access to Extension Services (1 = Yes, 0 otherwise)

X_{12} = Awareness of an improved seed variety (1 = Yes, 0 otherwise)

3.7 An overview of the descriptive statistics of the farm households surveyed

This section presents the descriptive statistics for some selected socio-economic variables used in the analysis of farmers' adoption of STMA varieties and the impact of this adoption on productivity, food security and resilience to climate change. The socioeconomic characteristics of the maize farmers are presented in this section elicit background information of the sampled maize farmers. The maize farmers' characteristics, farm characteristics and institutional factors were examined.

Gender

Table 3.5 presents the gender distribution of the maize farmers. It shows that about three-quarters (74.23%) of the farmers are male while only one-quarter (25.77%) are female farmers. This depicts that there is male dominance in maize farming in the study area. This gender distribution is typical of several agricultural production activities because it requires a considerably large amount of energy which is biologically available in the male gender. Also, this distribution could be a result of the cultural background where it is prestigious to have a male as the representative of a household at the community level. This result is consistent with (Oyekale *et al.*, 2017) who reported that the majority of smallholder maize farming households were male-headed.

Table 3.5 Distribution of Respondents by Gender

Gender	Frequency	Percentage (%)
Female	134	25.770
Male	386	74.230
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Age

Table 3.6 shows that more than a quarter (26.4%) of the maize farmers are 60 years and above. About 24.0% of the respondents fall within the age range of 30 – 49 years of age and 5.4% of the maize farmers are below 30 years. The mean age of the maize farmers is 43 years and the majority (73.6%) of them are below the age of 60 years. This implies that respondents involved in maize production are not very aged and they are expected to have relatively high productivity on farm works. A similar result was reported by (Awotide *et al.*, 2015), who found that most maize farmers are below 50 years old. Age has been revealed to be relevant in agriculture since it could serve as a determinant of how active and productive a farmers could be (Oyekale *et al.*, 2017) while (Jansuwan and Zander, 2022) asserted that young farmers are more risk-lovers than old people hence, tends to be productive in the agricultural sector.

Table 3.6 Distribution of Respondents by Age

Age (years)	Frequency	Percentage (%)
< 30	28	5.380
30 – 39	112	21.540
30 – 49	125	24.040
50 – 59	118	22.690
≥ 60	137	26.350
Total	**520**	**100.000**
Mean = 43.23 (±15.03)		

Source: Survey and Author's computation, 2022

Marital Status

Table 3.7 shows that 90.8% of the farmers were married, 5.4% of them were widowed and 0.6% were divorced. This suggests that maize production is a viable enterprise in helping farming households to generate income and increase living standards. Marriage is an institution that confers responsibilities on individuals that are involved to take care of their families and participate in other communities' activities.

Table 3.7 Distribution of Respondents by Marital Status

Marital status	Frequency	Percentage (%)
Divorced	3	0.580
Married	472	90.770
Single	17	3.270
Widowed	28	5.380
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Household Size

Table 3.8 reveals that the majority (35.4%) of the respondents have between 5 – 7 persons in their households. About 31.9% of the respondents have household size between 8 – 10 members, while 7.1% of the maize farmers have at least 14 members in their households. The average household size is 8 persons. This average household size is larger than the recommended national average of four as reported by (Alabi and Aruna, 2006) . This high household size might be a result of a polygamous family system which is prevalent among most rural dwellers. This result is in line with (Oyetunde-Usman and Olagunju, 2019), who reported an average agricultural household size including household head of about 8, which indicates a large household and possibly serve as a plus for family labour use on farmlands.

Table 3.8 Distribution of Respondents by Household Size

Household size	Frequency	Percentage (%)
1 – 4	49	9.420
5 – 7	184	35.380
8 – 10	166	31.920
11 – 13	84	16.150
≥14	37	7.120
Total	**520**	**100.000**
Mean = 8.54 (± 3.77)		

Source: Survey and Author’s computation, 2022

Household Religion

Table 3.9 presents the distribution of maize farming households by religion. It reveals that majority (81.73%) are Muslims while the rest (18.27%) are Christians. This implies that the study area is Muslim dominated as about four in every five maize farmers in the study area are of the Islamic religion. Religious beliefs and inclination of the maize farmers are not expected to influence their adoption status and the realisation of the outcome variables.

Table 3.9 Distribution of Respondents by Religion

Religion	Frequency	Percentage (%)
Christianity	95	18.270
Islam	425	81.730
Total	**520**	**100.000**

Source: Survey and Author’s computation, 2022

Farming Experience

Table 3.10 shows that 73.9% of the maize farmers have farming experience of at least 10 years while 18.1% have 6 – 10 years of experience. Only a few (1.2%) of them have maize farming experience of fewer than 2 years. The mean years of experience stood at 22 years. This implies that the farmers in the study area are well-experienced in maize farming.

Table 3.10 Distribution of Respondents by Farming Experience

Farming Experience (Years)	Frequency	Percentage (%)
< 2	6	1.150
2 – 5	36	6.920
6 – 10	94	18.080
≥ 10	384	73.850
Total	**520**	**100.000**
Mean = 22.05 (± 13.08)		

Source: Survey and Author's computation, 2022

Educational Status

Table 3.11 indicates that 41.9% of the farmers have primary education, followed by those who have no formal education (24.4%) with a few (10.0%) of the respondents who have tertiary education. The average number of years spent in school is 7 years thereby affirming that the average maize farmer in the study area is fairly educated. Such level of education could enhance the easy diffusion and adoption of new and improved maize farming techniques among the farmers. (Awotide *et al.*, 2015) reported that this characteristic could enhance productivity and technology adoption.

Table 3.11 Distribution of Respondents by Educational Status

Educational status	Frequency	Percentage (%)
No Formal Education	127	24.420
Primary Education	218	41.920
Secondary Education	123	23.650
Tertiary Education	52	10.000
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Off-farm Income

Table 3.12 presents the distribution of the maize farming households according to engagement in off-farm activities. The result reveals that about two in every three (64.42%) maize farmers in the study area engaged in off-farm activities while about one in every three (35.58%) maize farmers in the study area did not engage in off-farm activities.

Table 3.12 Distribution of Respondents by Off-farm Income

Off-farm Income	Frequency	Percentage (%)
Yes	335	64.420
No	185	35.580
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Income Sources

Table 3.13 reveals that most of the respondents (45.4%) have 4 sources of income while only 3.7% of them are not engaged in any enterprise apart from farming. This suggests that the majority (69.6%) of the respondents are moonlighters since about two out of every three maize farmers have some other income sources apart the farming.

Table 3.13 Distribution of Respondents by Income Sources

Sources of Income	Frequency	Percentage (%)
0	19	3.650
1	139	26.730
2	80	15.380
3	46	8.850
4	236	45.380
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Farm Size

Results in Table 3.14 shows that the majority (45.6%) of the maize farmers have between 1.01 – 3.0 hectares of farmland. About 25.4% of the respondents have a farm size between 3.01 – 5.0 hectares while 7.7% of the farmers have between 5.01 – 7.0 hectares of farmland. The average farm size stood at 3.9 hectares which suggests that the average maize farmer in the study area is a small-scale producer. The economic implication of producing on this scale is that the average farmer can minimize his operating expenses and perform better due to the economies of scale. This finding is consistent with that of (Awotide *et al.*, 2015) who reported a larger share of maize farmers using less than 4 hectares of farmland.

Table 3.14 Distribution of Households by Farm Size

Farm Size (Hectares)	Frequency	Percentage (%)
< 1.00	58	11.150
1.01 – 3.00	237	45.580
3.01 – 5.00	132	25.380
5.01 – 7.00	40	7.690
≥ 7.01	53	10.190
Total	**520**	**100.000**
Mean = (3.94 ± 3.12)		

Source: Survey and Author's computation, 2022

Access to Credit

Table 3.15 reveals that majority (85.8%) of the respondents do not have access to credit facilities leaving only 14.2% of the farmer with access to credit facilities. Given that the average farmer is young at 48 years and fairly literate with at least a primary education, despite this endowment, only one out of every seven maize farmers was able to access credit for agricultural production purposes. This is similar to the report of (Awotide *et al.*, 2015) where only a few of the farmers who demanded credit were able to acquire credit for their agricultural production.

Table 3.15 Distribution of Respondents by Access to Credit

Access to Credit	Frequency	Percentage (%)
Yes	74	14.230
No	446	85.770
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Group Membership

Table 3.16 presents the distribution of respondents by group membership, the result shows that the majority (63.85%) of the farmers are members of particular groups, organisations, and/or associations while about 36.15% are non-members of cooperative societies. It is expected that the high percentage of group membership could foster awareness and adoption of agricultural innovation/technology.

Table 3.16 Distribution of Respondents by Group Membership

Membership	Frequency	Percent
Yes	332	63.850
No	188	36.150
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Access to Extension Services

Table 3.17 presents the distribution of respondents by access to extension services, the results show that the majority (88.27%) of the farmers have access to extension services while about one-tenth of the respondents do not have access to extension services. It is expected that the high access to extension services would increase their awareness and eventual adoption of improved agricultural technologies targeted at making them more resilient to climate change.

Table 3.17 Distribution of Respondents by Access to Extension Services

Access to Extension	Frequency	Percentage (%)
Yes	459	88.270
No	61	11.730
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

3.8 Analysis of Awareness and Adoption of Maize Technology

Awareness of Improved Maize Varieties

Table 3.18 presents the distribution of the maize farming households according to awareness of improved maize varieties. The result reveals that about four in every five (82.31%) maize farmers in the study area are aware of improved maize varieties while only one in every five (17.69%) maize farmers in the study area are ignorant of the improved maize varieties. This shows that the majority of the maize farmers in the study area are aware of improved maize varieties.

Table 3.18 Distribution of Respondents by Awareness of Improved Maize Varieties

Awareness	Frequency	Percentage (%)
Yes	428	82.310
No	92	17.690
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Awareness of STMA Maize Varieties

Table 3.19 presents the distribution of the maize farming households by the awareness of STMA maize varieties. The result reveals that about three in every four (76.54%) maize farmers in the study area are aware of the STMA maize varieties while about one in every four (23.46%) maize farmers in the study area are not aware of the STMA maize varieties. These results imply that the majority of the maize farmers in the study area are aware of STMA maize varieties.

Table 3.19 Distribution of Respondents by Awareness of STMA Maize Varieties

Awareness	Frequency	Percentage (%)
Yes	398	76.540
No	122	23.460
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

Adoption of STMA Maize Varieties

Table 3.20 presents the distribution of the maize farming households by the adoption of STMA maize varieties. The result reveals that about two in every three (64.96%) maize farmers in the study area have not adopted the STMA maize varieties while only one-third (35.96%) of the maize farmers have adopted the STMA maize varieties. This result indicates that there is a low level of adoption of STMA maize varieties among the maize farmers in the study area.

Table 3.20 Distribution of Respondents by Adoption of Improved Maize Varieties

Adoption	Frequency	Percentage (%)
Yes	187	35.960
No	333	64.960
Total	**520**	**100.000**

Source: Survey and Author’s computation, 2022

Sources of STMA Maize Varieties

Table 3.21 shows that more than half (59.30%) of the maize farmers buy the STMA maize varieties from agro-dealers, while cooperative societies accounted for the least with 0.50% of the maize farmers’ patronage. The result also shows that about 11.81%, 9.55%, 9.55%, and 3.552% sourced their STMA maize varieties from extension agents, fellow farmers, research institutes, and the government respectively. While the remaining 5.78% of the maize farmers sourced their STMA varieties from other sources.

Table 3.21 Distribution of Households by Sources of STMA

Sources of STMA	Frequency	Percentage (%)
Cooperative societies	2	0.500
Extension agents	47	11.810
Fellow farmers	38	9.550
Government	14	3.520
Markets (Agro dealers)	236	59.300
Research institute	38	9.550
Others	23	5.780
Total	**520**	**100.000**

Source: Survey and Author’s computation, 2022

3.9 Profile of Adoption of STMA Varieties by Farmers Characteristics

Distribution of STMA Adoption by Gender

Table 3.22 reveals that a larger proportion (82.89%) of the STMA varieties adopters are male. Similarly, a larger percentage (69.37%) of the non-adopters are male. However, the result reveals that for the adopters, only about one of every six female respondents adopt the STMA varieties, while four of every five male respondents adopt the STMA varieties. This result implies that a larger proportion of male adopts the STMA varieties compared to their female counterpart. In Sub-Saharan Africa, farm resources are usually owned and managed by men, which gives men more access to information than women. The expectation is that households headed by men have a higher likelihood of adoption.

Table 3.22 Distribution of STMA Adoption by Gender

Gender	No	Yes	Total
Female	102 (30.630)	32 (17.110)	134 (25.770)
Male	231 (69.370)	155 (82.890)	386 (74.230)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution of STMA Adoption by Age

Table 3.23 shows that majority (78.1%) of the STMA adopters are young farmers. Among the young maize farmers, those belonging to the age cohort of 40 – 49 constitute the major (24.0%) STMA adopters, followed closely (22.7%) by those in the age bracket of 50 – 59, while farmers with ages below 30 years constitute the least STMA adopters with about 4.8%. The result further reveals that farmers above 60 years of age constitute the major STMA non-adopters with about 28.8%, while farmers with ages below 30 years constitute the least STMA non-adopters with about 5.7%. This suggests that the percentage of the non-adopters of the STMA maize varieties tends to increase as the ages of farmers increase. Farmer's age can either increase or decrease the probability of adopting an innovation. This is because as a farmer ages, his level of risk averseness increases or decreases depending on his/her confidence level, hence, we expect a positive or negative relationship (Danso-Abbeam *et al.*, 2021) (Danso-Abbeam et al., 2017).

Table 3.23 Distribution of STMA Adoption by Age

Age group	No	Yes	Total
<30	19 (5.710)	9 (4.810)	28 (5.380)
30-39	59 (17.720)	53 (28.340)	112 (21.540)
40-49	84 (25.230)	41 (21.930)	125 (24.040)
50-59	75 (22.520)	43 (22.990)	118 (22.690)
≥60	96 (28.830)	41 (21.930)	137 (26.350)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution of STMA Adoption by Marital Status

Results presented in Table 3.24 reveals that a larger percentage (92.51%) of the STMA adopters are married while the least adopters (0.53%) are divorced. The results also show that a greater proportion (89.79%) of the STMA non-adopters are found to be married, while the least non-adopters (0.60%) are divorced. The results further reveal that the married category is the highest for both adopters and non-adopters however a closer look shows that the proportion of married adopters is greater than the proportion of married non-adopters.

Table 3.24 Distribution of STMA Adoption by Marital Status

Marital Status	No	Yes	Total
Divorced	2 (0.600)	1 (0.530)	3 (0.580)
Married	299 (89.790)	173 (92.510)	472 (90.770)
Single	12 (3.600)	5 (2.670)	17 (3.270)
Widowed	20 (6.010)	8 (4.280)	28 (5.380)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution STMA Adoption by Educational Level

Table 3.25 presents the distribution of the respondents' educational status by the adoption of STMA maize varieties. The results show that majority (41.92%) of the STMA adopters have primary education, while 19.25%, 28.34%, and 12.30% have no formal education, secondary education, and tertiary education, respectively. On the other hand, the result for the STMA non-adopters shows that majority (42.94%) of the STMA non-adopters have primary education, while the least percentage (8.71%) of the STMA non-adopters have tertiary education. A critical look at the table shows that there are more adopters compared to non-adopters at higher educational levels. This result gives little insight into the relationship between educational level and the adoption of STMA varieties.

Table 3.25 Distribution of STMA Adoption by Educational Level

Education Level	No	Yes	Total
No formal education	91 (27.330)	36 (19.250)	127 (24.420)
Primary education	143 (42.940)	75 (40.110)	218 (41.920)
Secondary education	70 (21.020)	53 (28.340)	123 (23.650)
Tertiary education	29 (8.710)	23 (12.300)	52 (10.000)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution of STMA Adoption by Household Size

Table 3.26 reveals that the largest percentage (35.83%) of the STMA adopters have household sizes between five and seven members, while the least adopters of STMA maize varieties have household sizes between one and four members. Similarly, the result reveals that the majority (35.14%) of STMA non-adopters have household sizes between five and seven. The result further reveals that the percentages of the adopters and non-adopters of the STMA maize varieties tend to decrease with an increase in household size. A more significant number of adults in a household provides the family labor force for the farm business since the adoption of Improved Varieties requires extra labor inputs. Thus, farmers' adoption of Improved Varieties is strongly associated with the amount of labour force available.

Table 3.26 Distribution of STMA Adoption by Household Size

Household size	No	Yes	Total
1 – 4	36 (10.810)	13 (6.950)	49 (9.420)
5 – 7	117 (35.140)	67 (35.830)	184 (35.380)
8 – 10	111 (33.330)	55 (29.410)	166 (31.920)
11 – 13	47 (14.110)	37 (19.790)	84 (16.150)
≥ 14	22 (6.710)	15 (8.020)	37 (7.120)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution STMA Adoption by Income Source

Table 3.27 reveals that about one-third (36.90%) of the STMA adopters have about four other income sources apart from farming, while the least adopters of STMA maize varieties are respondents who have farming as their only source of income. On the other hand, about half (50.15%) of the non-adopters of the STMA maize varieties have four or more income sources while the least non-adopters of STMA maize varieties are those with farming as their only source of income.

Table 3.27 Distribution of STMA Adoption by Income Source

Income Sources	No	Yes	Total
0	11 (3.300)	8 (4.280)	19 (3.650)
1	86 (25.830)	53 (28.34)	139 (26.730)
2	46 (13.810)	34 (18.180)	80 (15.380)
3	23 (6.910)	23 (13.300)	46 (8.850)
4	167 (50.150)	69 (36.900)	236 (45.380)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution STMA Adoption by Farming Experience

Table 3.28 reveals that majority of adopters (66.2%) and non-adopters (60.1%) of the STMA varieties are those maize farmers with 10 or more years of farming experience. Similarly, farmers who have between 6 – 10 years of experience constitute a high proportion of adopters (24.3%) and non-adopters (26.7%). This profiling suggests that there is a weak relationship between farmers' experience and adoption of an improved maize variety, hence, a positive or negative correlation may be observed from farmer to farmer. The farm business requires more field work hence farmers with longer years in farming are expected to adopt innovation faster than farmers with fewer years of farming. Knowledge gained over time can also help farmers to evaluate the merits of a new technology thereby influencing their decisions on the new product (Simtowe *et al.*, 2011). Moreover, farmers who have spent some years cultivating the local variety of maize may find it difficult to switch to Improved Varieties as they have become accustomed to the local variety (Danso-abbeam *et al.,* 2017).

Table 3.28 Distribution of STMA Adoption by Farming Experience

Farming Experience	No	Yes	Total
< 2	5(2.180)	1 (0.740)	6 (1.150)
2-5	34 (10.480)	12 (8.830)	36 (6.920)
6-10	61 (26.640)	33 (24.260)	94 (18.080)
>10	139 (60.700)	90 (66.180)	384 (73.850)
Total	**333**	**187**	**520**

Source: Survey and Author's computation, 2022

Distribution of STMA Adoption by Credit Access

Table 3.29 show that maize farmers who do not have access to loan facilities are major adopters of the STMA maize varieties (81.82 %) compared to their counterpart (18.18%) who has access to loan facilities. Similarly, about nine of every ten non-adopters of the STMA maize varieties do not have access to loan facilities. This implies a dearth of credit facilities in the study area. This distribution does not agree with (Danso-abbeam *et al.*, 2017), who opined that having access to credit provides a means for farmers to purchase the required inputs to implement a new farm technology.

Table 3.29 Distribution of STMA Adoption by Access to Credit

Credit Access	No	Yes	Total
Yes	40 (12.010)	34 (18.180)	74 (14.230)
No	293 (87.990)	153 (81.820)	446 (85.770)
Total	**333**	**187**	**520(100)**

Source: Survey and Author's computation, 2022

Distribution of STMA Adoption by Off-Farm Activities

Table 3.30 presents the distribution of the respondents' off-farm activities vis a vis adopting STMA maize varieties. The result reveals that a large percentage (64.17%) of the STMA adopters engaged in off-farm activities. However, about one out of every three maize farmers who do not engaged in off-farm activities adopts the STMA maize varieties. On the other hand, about two out of every three maize farmers who engage in off-farm activities were found to be non-adopters of the STMA maize varieties. Result shows that a large percentage of the non-adopters (64.56%) engaged in off-farm activities. This result is an indication that there may not be a correlation between engaging in off-farm activities and adoption of STMA adoption in the study area.

Table 3.30 Distribution of STMA Adoption by Off-Farm Activities

Off Farm Activities	No	Yes	Total
Yes	215 (64.560)	120 (64.170)	335 (64.420)
No	118 (35.440)	67 (35.830)	185 (35.580)
Total	**333**	**187**	**520(100)**

Source: Survey and Author's computation, 2022

3.10 Profile of Food Insecurity Status by Farmers Characteristics

Distribution of Respondents Food Insecurity by Gender

Results in Table 3.31 reveals that male-headed households are more food secure than their female-headed counterparts. Likewise in terms of food insecurity status, 76.9% of female-headed farming households were plunged into MiFI to SFI while 71.5% of male-headed households are found to be MiFI to SFI. MoFI to SFI is more pronounced in female-headed farming households than among their male-headed counterparts. This may be due to their huge responsibility at the home front, from taking care of the children and other tasks which necessitates their reduced involvement in farming activities, which may result in limited access to productive assets. These findings were supported by (Obayelu, Akpan and Ojo, 2021; Otekunrin *et al.*, 2021).

Table 3.31 Distribution of Household Food Insecurity by Gender

Gender	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
Female	31 (21.990)	36 (26.280)	52 (25.240)	15 (41.670)	134 (25.770)
Male	110 (78.010)	101 (73.720)	154 (74.760)	21 (58.330)	386 (74.230)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author's computation, 2022

Distribution of Respondents Food Insecurity by Age

Table 3.32 shows that a larger proportion of older maize farmers have food-secure households while a lesser percentage of younger maize farmers have food-secure households. This implies that food security increases as age increases. For food insecure categories, cumulatively, the result reveals that more than fifty percent of younger maize farmers have food insecure households, in other words, a lesser percentage of the older age groups have food insecure households. This finding is not in agreement with that of (Otekunrin *et al.*, 2021) who reported that household heads that are 41–50 years and older (>50 years) are more likely to be severely food insecure because of limited resources owing to reduced energy to engage in farming activities leading to a reduction in productivity and income.

Table 3.32 Distribution of Household Food Insecurity by Age

Age	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
< 30	6 (4.260)	7 (5.110)	13 (6.310)	2 (5.560)	28 (5.380)
30 – 39	26 (18.440)	33 (24.090)	42(20.390)	11 (30.560)	112 (21.540)
40 – 49	27 (19.150)	35 (25.550)	56 (27.190)	7 (19.440)	125 (24.040)
50 – 59	35 (24.820)	26 (18.980)	51 (24.760)	6 (16.670)	118 (22.690)
≥ 60	47 (33.330)	36 (26.280)	44 (21.360)	10 (27.780)	137 (26.350)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author’s computation, 2022

Distribution of Household Food Insecurity by Marital Status

Table 3.33 reveals that 73.1% of the married household heads are reported to be experiencing different levels of food insecurity (from MiFI to SFI), while only 26.9% of them are food secure. This suggests that being married may not reduce food insecurity among farming households, especially those with a large family size, which demands a higher expenditure on food. This result is similar to that of (Obayelu, Akpan and Ojo, 2021), which reported that 82.7% of married household heads are food insecure in an urban slum of Ibadan.

Table 3.33 Distribution of Household Food Insecurity by Marital Status

Marital Status	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
Divorced	1 (0.710)	1 (0.730)	0 (0.000)	1 (2.780)	3 (0.580)
Married	127 (90.070)	126 (91.970)	192(93.200)	27 (75.000)	472 (90.770)
Single	3 (2.130)	5 (3.650)	7 (3.400)	2 (5.560)	17 (3.270)
Widowed	10 (7.090)	5 (3.650)	7 (3.400)	6 (16.670)	28 (5.380)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author’s computation, 2022

Distribution of Household Food Insecurity by Educational Level

The incidence of MoFI to SFI is prominent among household heads with no formal education (51.8% and 33.3%) and those with primary education (44.1% and 50.0%). Moreover, 69.9% of household heads with secondary school education are also found to be experiencing moderate-to-severe food insecurity within the recall period of 30 days. With these findings, it is suggested that the level of education may not necessarily reduce food insecurity among maize farming households because only 10.0% of the household heads had a tertiary school education, while 67.3% of them experienced mild-to-severe food insecurity within the recall period. This result is consistent with the findings of (Otekunrin *et al.*, 2021) but contrary to the findings of (Obayelu, Akpan and Ojo, 2021), who found that the majority of household heads with no formal education are food secure.

Table 3.34 Distribution of Household Food Insecurity by Educational Level

Educational Level	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
No formal education	38 (26.950)	26 (18.980)	51 (51.760)	12 (33.330)	127 (24.420)
Primary education	49 (34.750)	60 (43.800)	91(44.170)	18 (50.000)	218 (41.920)
Secondary education	37 (26.240)	31 (22.630)	52 (25.240)	3 (8.330)	123 (23.650)
Tertiary education	17 (12.060)	20 (14.600)	12 (5.830)	3 (8.330)	52 (10.000)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author’s computation, 2022

Distribution of Household Food Insecurity by Income Sources

Table 3.35 revealed that 60.1% of the household heads with at least 2 sources of income are food secure, while those with at most one income source account for only 39.9% of those that are food secure. About 63.3% of the household heads with one source of income are revealed to be experiencing different levels of food insecurity (from MiFI to SFI), while only 36.7% of them are food secure. Contrary to expectation, majority (75.9%) of the households whose heads have four different sources of income apart from farming experienced mild-to-severe food insecurity within the recall period. This result implies that having several income sources may not necessarily translate to household food security in the study area.

Table 3.35 Distribution of Household Food Insecurity by Income Sources

Income Source	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
0	5 (3.550)	10 (7.300)	4 (1.940)	0 (0.000)	19 (3.650)
1	51 (36.170)	63 (45.990)	23 (11.170)	2 (5.560)	139 (26.730)
2	22 (15.600)	33 (24.090)	18 (8.740)	7 (19.440)	80 (15.380)
3	6 (4.260)	9 (6.570)	27 (13.110)	4 (11.110)	46 (8.850)
4	57 (40.430)	22 (16.060)	134 (65.050)	23 (63.890)	236 (45.380)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author’s computation, 2022

Distribution of Household Food Insecurity by Farming Experience

The results also show that households with more than 10 years of farming experience had the highest percentage (76.6%) of food secure households, however, about 77.8% of the occurrence of severely food-insecure households also have at least 10 years of farming experience. This result is an indication that the maize farmers are well experienced in maize farming, nonetheless, this may not influence their household food security. This result does not agree with that of (Otekunrin *et al.*, 2021) who opined that an increase in household heads' farming experience is likely to reduce the food insecurity (access) of the households.

Table 3.36 Distribution of Household Food Insecurity by Farming Experience

Farming Experience	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
< 2	1 (0.710)	0 (0.000)	5 (2.430)	0 (0.000)	6 (1.150)
2 – 5	8 (5.670)	9 (6.570)	17 (8.250)	2 (5.560)	36 (6.920)
6 – 10	24 (17.020)	25 (18.250)	39 (18.930)	6 (16.670)	94 (18.080)
> 10	108 (76.600)	103 (75.180)	145 (70.390)	28 (77.780)	384 (73.850)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author's computation, 2022

Distribution of Household Food Insecurity by Household size

Results in table 3.37 reveal that 33.3% of the households with 11 – 13 members and 27.8% of farm households with 5 – 7 members experienced severe food insecurity within the 30-day recall period. These findings indicated that severe food insecurity is common among households with 11 – 13 and 5 – 7 members. A cursory at these results give an insight into a probable connection between higher household size and higher severity of food insecurity. This result is consistent with the findings of (Otekunrin *et al.*, 2021) but contrary to the findings of (Obayelu, Akpan and Ojo, 2021) who found only 6.4% food-insecurity incidence among maize farming households with ≤ 5 members in Ogun State.

Table 3.37 Distribution of Household Food Insecurity by Household size

Household size	Food Secure	Mildly Food Insecure	Moderately Food Insecure	Severely Food Insecure	Total
1 – 4	19 (13.480)	16 (11.630)	10 (4.850)	4 (11.110)	49 (9.420)
5 – 7	59 (41.840)	45 (32.850)	70 (33.980)	10 (27.780)	184 (35.380)
8 – 10	45 (31.910)	41 (29.930)	72 (34.950)	8 (22.220)	166 (31.920)
11 – 13	12 (8.510)	19 (13.870)	41 (19.900)	12 (33.330)	84 (16.150)
≥ 14	6 (4.260)	16 (11.680)	13 (6.310)	2 (5.560)	37 (7.120)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author's computation, 2022

Distribution of Household Food Insecurity by Off Farm Activities

Table 3.38 reveals that 61.0% of the household heads that are engaged in an off-farm activity are food secure, while those without an off-farm activity are only 39.0% of those that are food secure. About 70.3% of the household heads who do not have an off-farm activity are revealed to be experiencing different levels of food insecurity (from MiFI to SFI), while only 29.7% of them are food secure. Contrary to expectation, the majority (74.3%) of the household heads with an off-farm activity experienced mild-to-severe food insecurity within the recall period. This result implies that combining farm activity with an off-farm activity may not necessarily translate to household food security in the study area.

Table 3.38 Distribution of Household Food Insecurity by Off-Farm Activities

Off-Farm Activities	Food Secure	Mildly Food Insecure	Moderately Food Secure	Severely Food Insecure	Total
Yes	86 (60.990)	92 (67.150)	133 (64.560)	24 (66.670)	335 (64.420)
No	55 (39.010)	45 (32.850)	73 (35.440)	12 (33.330)	185 (35.580)
Total	**141**	**137**	**206**	**36**	**520**

Source: Survey and Author's computation, 2022

3.11 Selection of the Variables Based on Literature and A-priori Expectation

Based on literature, various farmers' characteristics, households' characteristics, plots' characteristics and institutional factors are selected, described and included as variables that can help to explain the maize technology adoption, maize productivity of farmers, their household food security and resilience to climate change. These variables are as follows:

Gender – In the rural agriculture context, the gender of a household head can have a positive effect on technology adoption and mixed effects on productivity and household food security. Generally, men tends to have more access to production inputs compared to women. This invariably implies that men can have more profitable farms which may translate to better household welfare. However, woman may be more efficient in cultivating smaller plot sizes thereby recording similar outcomes as their male counterparts.

Age – Usually, the age of farmers is often link with better experience and know-how. Hence, it is expected that older farmers will be associated with higher yield performance. On the other hand, older farmers may not have enough strength and agility to cultivate large expanse of land compare to the younger folks. The age variable can also have mixed effects depending the outcome variable of interest.

Table 3.39: A-priori expectations on explanatory variables on the outcomes variables

Variables	Expected Signs			References
	P	FS	R	
Age	+	±	±	(Asfaw, Di Battista and Lipper, 2016; Andrianarison, Kamdem and Kameni, 2022)
Gender	+	±	+	(Asfaw, Di Battista and Lipper, 2016; Andrianarison, Kamdem and Kameni, 2022)
Marital status	+	±	±	
Household size	+	_	+	(Asfaw, Di Battista and Lipper, 2016; Gebre *et al.*, 2021; Andrianarison, Kamdem and Kameni, 2022)
Education	+	+	+	(Asfaw, Di Battista and Lipper, 2016; Mohammed, Ojo and Mohammed, 2019; Andrianarison, Kamdem and Kameni, 2022)
Farm size	+	+	±	(Asfaw, Di Battista and Lipper, 2016; Mohammed, Ojo and Mohammed, 2019; Andrianarison, Kamdem and Kameni, 2022)
Farm Experience	+	+	+	(Mohammed, Ojo and Mohammed, 2019)
Off-farm income	±	+	+	
Group Membership	+	+	+	(Abdoulaye, Wossen and Awotide, 2018)
Credit access	±	+	+	(Mohammed, Ojo and Mohammed, 2019; Andrianarison, Kamdem and Kameni, 2022)
Extension services access	+	+	+	(Jenrola, 2021)
Adoption of IMV	+	+	+	(Asfaw, Di Battista and Lipper, 2016; Wossen *et al.*, 2017; Mohammed, Ojo and Mohammed, 2019; Gebre *et al.*, 2021; Koudjom, 2022)

Source: Author’s Compilation

Educational status – Formal education affords farmers a greater consciousness of yield and profitability issues. It also fosters awareness of available agricultural technology and further encourages technology acceptance and continued use. Based on this, it is expected education be positively correlated with productivity and adoption of technology.

Marital status – Being married comes with responsibilities of taking care of the household. More so, depending on household size there may be availability and cheap labour for farm activities. Hence, it is expected that being married should have a positive impact of productivity. However, being married could have mixed effects on household food security and resilience to climate change.

Household size – Skills and knowledge are different for every member of a farming household. Members of a farming household typically provides available and cheap labour supply for maize production. Based on this premise, it is expected that larger households may have higher yield and productivity, however, incidence of food insecurity may be higher in larger households.

Farm size – Larger farm sizes attracts more production inputs and more outputs. Due to scale effects, farm size is likely to have a positive relationship with productivity and household food security. However, the effect of farm size may be mixed for resilience to climate change.

Group membership – Groups and Associations are strong social networks for polling resources and disseminating information and innovations. From such groups, farmers can obtain information that would improve yield, productivity and resilience to climate change. Hence, organisation membership is assumed to be positively associated with productivity, food security and

Extension access – Extension services serves as a platform through information on profitable farming practices and technologies are passed to farmers from research and government bodies. Therefore, it is expected that access to extension services be positively related with productivity, household food security and resilience to climate change.

Partial Conclusion

This chapter provided details of the methodological approach implemented in the study. The high points of this chapter were the choice of the study area, study design and household survey. The household survey was conducted with 522 maize farming households. Demographic and socio-economic data were elicited from the farming households. This chapter presents the descriptive analysis of this socio-economic data. More so, data was collected on the adoption of STMA and other maize varieties, respondents' perceptions of and adaptations to climate change, food security measurements. The collected data are analysed empirically in the following chapter to answer the specific research questions and objectives of the study.

CHAPTER THREE

RESULTS AND DISCUSSION

Introduction

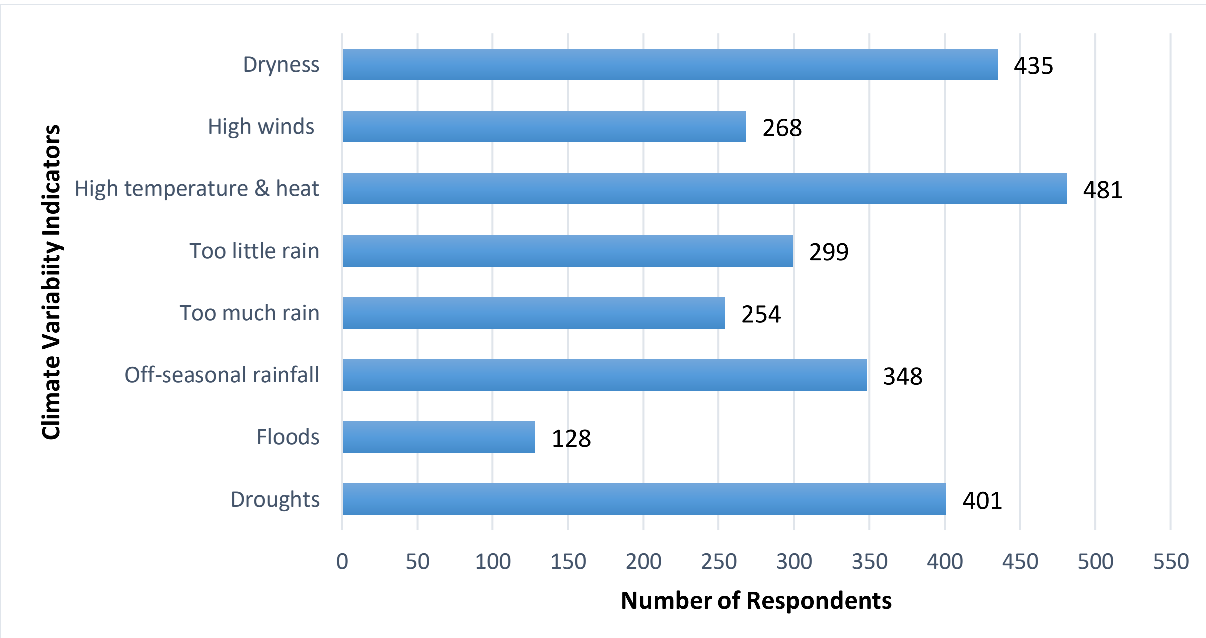
Several studies have analysed the determinants of adoption agricultural technology and climate smart innovation, specifically improved varieties of maize. Socioeconomic characteristics, farm characteristics, and institutional factors among others, are identified as major factors that influence adoption of improved varieties. In the same vein, different studies have considered the impact of adoption of agricultural technology on farming households' income, yield, and welfare status. That being said, the determinants of adoption of the agricultural innovations remain a field of research to be further explored in Nigeria particular the Derived Savanah region. More so, the determinants and impacts of the adoption the new STMA varieties has not been well explored since the conclusion of the STMA programme in 2019. This chapter consists five section which presents the results and discussions of the research findings. Section 4.1 presents the descriptive results of maize farmers' perception of climate change. Section 4.2 presents the empirical results of the effect of adoption of STMA on productivity. Likewise, the empirical results of the effect of STMA adoption on household food security is presented in section 4.3. Section 4.4 shows the empirical results of the evaluation maize farmers level of resilience while the results of effects of adoption of STMA varieties on resilience to climate change is presented in section 4.5.

4.1 Perceived Evidence of Climate Change

4.1.1 Occurrence of climate change indicators

In developing nations, farmers have proved to be the right people to inquire about climate change and its impacts on their livelihood because they have always lived with variations in climate conditions over time (Chalchisa and Sani, 2016). According to (Maddison, 2006), awareness about climate change is a pre-requisite for mitigation and adaptation to climate change. Figure 4.1 shows the distribution of the occurrence of climate change indicators as indicated by respondents in the study area. The climate change indicators considered include; dryness, high winds, high temperature and heat, too little rain, too much rain, off season rainfall, floods and drought. The result shows that more than half of the respondents perceived the occurrence of all these climate change indicators except floods which was reported by less than one hundred and fifty respondents. However, high temperatures and heat, dryness and drought were the top three perceived climate change indicators observed by the maize farmers to occur most in the list of the climate change indicators, while floods, too much rain and high winds were the three least perceived climate change indicators in the study area. Generally, farmers perceived an increase in temperature and reduction in rainfall. This result is similar to the findings of researchers over last two decades. (Maddison, 2006; Nhemachena and Hassan, 2007) reported that substantial numbers of farmers in African countries had the opinion that temperature has increased and precipitation has declined. Specifically in West Africa, (Akponikpè, Johnston and Agbossou, 2010) revealed in their study that farmers bemoaned change in rainfall pattern with delayed rains, early cessation and increase in the number of hot days. Results of studies of (Chalchisa and Sani, 2016; Rapholo and Makia, 2020; Guodaar, Bardsley and Suh, 2021) found that farmers perceived increased temperatures, decreased rainfall, seasonal changes and extreme climate events.

Figure 4.1: Occurrence of climate change indicators



Source: Survey and Author's computation, 2022

4.1.2 Perceived occurrence of climate change indicators

To gain an understanding of the perceived severity of the climate change, farmers were asked to rate the following indicators: drought, floods, off-season rainfall, too much rain, too little rain, high temperatures and heat, high winds, and dryness based on their frequency of occurrence; once in two years, once in a year, twice in a year, and thrice in a year. Farmers' responses were further ranked to obtain a clearer picture of the most frequent climate change indicators in the study area. Table 4.1 shows that drought, high temperatures & heat, and dryness were ranked first, second and third respectively in order of perceived frequency and severity. About 56%, 51%, and 45% of the cases of drought, high temperatures & heat, and dryness, respectively, were reported to have occurred between twice a year and thrice a year. On the other hand, floods, off-season rainfall, and too little rain were the least perceived climate change indicators. Where about 74%, 59%, and 62% of the cases of floods, off-season rainfall, and too little rain, respectively, were reported to have occurred between once in two years and once in a year. The warming trend perceived by the maize farmers in the savannah region may have a shortage of water effect on agricultural production and farmers may experience exposure of their crops to heat stress. This is consistent with the findings of (Ademe *et al.*, 2020) who reported that farmers perceived the rise in temperature and a decline in rainfall. This phenomenon has negative implications for crop production on account of exposure to high-temperature stress, increasing the evaporative demand of the atmosphere, and reducing water availability. It will also reduce the number of chill hours that some crops grown in Nigeria require to initiate flower buds thereby lowering their productivity.

Table 4.1: Rank of climate change indicators

Climate change indicators	Once in two years	Once a year	Twice a year	Thrice in a year	Mean	Rank
Droughts	5%	39%	43%	13%	2.63	1
Floods	37%	37%	23%	2%	1.90	8
Off-seasonal rainfall	18%	41%	39%	2%	2.25	7
Too much rain	16%	47%	31%	6%	2.27	5
Too little rain	19%	43%	32%	7%	2.26	6
High temperature & heat	3%	46%	46%	5%	2.52	2
High winds	16%	44%	32%	8%	2.32	4
Dryness	4%	51%	40%	5%	2.47	3

Source: Survey and Author's computation, 2022

4.1.3 Perceived shift in the Rainy Season

Table 4.2 shows that nearly all (98.05%) of the maize farmers in the study area perceived that there has been a change in rainfall patterns in the last decade. The farmers explained that rainfall occurrence becomes shorter every year, which is consistent with the findings of a similar survey done in the savannah area which reported that farmers perceived a decline in rainfall (Alemayehu and Bewket, 2017)

Table 4.2: Distribution of Respondents by the observed shift in the rainy season

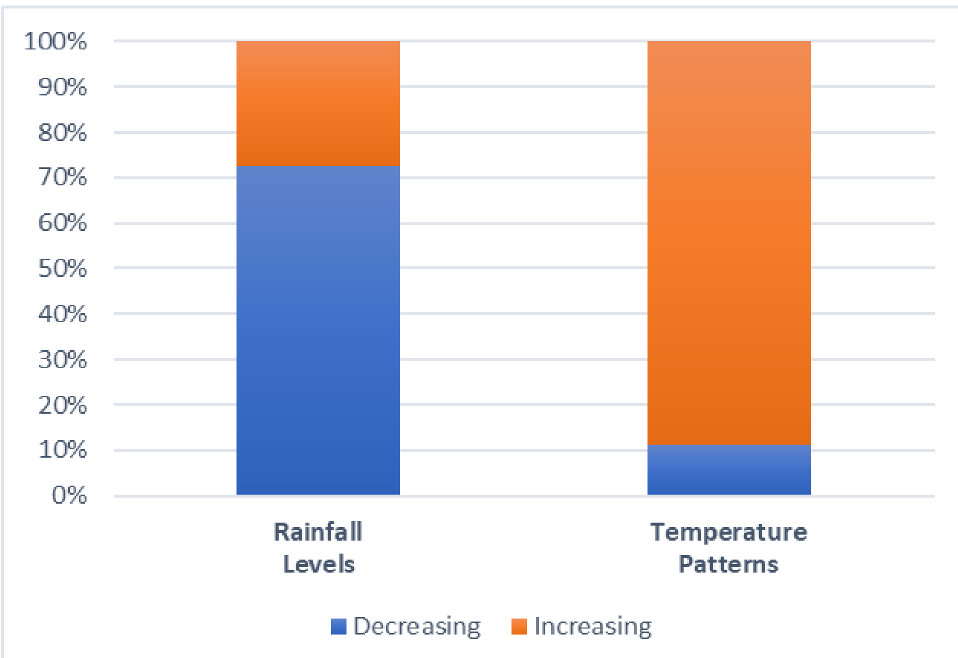
Shift in Rainy Season	Frequency	Percentage (%)
Yes	504	98.050
No	10	1.950
Total	**514**	**100.00**

Source: Survey and Author's computation, 2022

4.1.4 Perceived shift in Rainfall and Temperature

Figure 4.2 shows that all the maize farmers observed variability in both the rainfall levels and the temperature patterns in the last decade. According to the farmers, changes in rainfall and temperature has been occurring in opposing directions. Majority (88.85%) of the respondents observed that there has been an increase in the temperature in the last decade, while about three-quarters (73.05%) of them observed a decrease in rainfall over the same period. Conversely, only one of every nine maize farmers and less than one-third (27.5%) of them experienced a drop in temperature and increasing rainfall respectively. Since most of the participants in the present study reported that total rainfall is decreasing and the temperature is increasing, this suggests that the savannah region is getting hotter and drier. Many previous studies in this region (Asfaw, Di Battista and Lipper, 2014a; Alemayehu and Bewket, 2017; Ademe *et al.*, 2020) also confirmed the presence of significant warming trends, with spatial variability.

Figure 4.2: Variability in Rainfall and Temperature

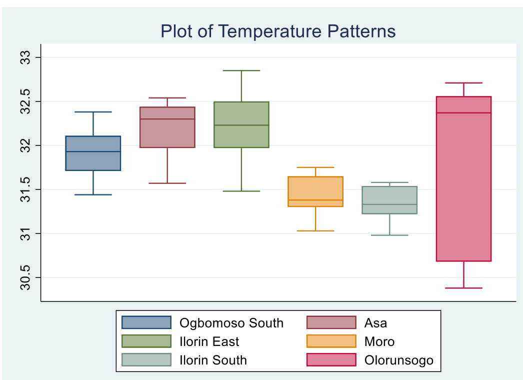


Source: Survey and Author’s computation, 2022

4.1.5 Observed temperature patterns in the study area

Observed variability of weather conditions is of critical importance. A descriptive analysis of meteorological data obtained from the European Centre for Medium – Range Weather Forecasts (ECMWF) Re-analysis 5 is presented in box plots. Figure 4.3 shows the variability in the temperature patterns both within and between the selected farming communities in the study area over 11 years. The median temperature is higher in Olorunsogo (32.37^{0}C) and Asa (32.30^{0}C) while the temperature in Moro (31.38^{0}C) and Ilorin South (31.33^{0}C) had the lowest median values. The interquartile range (IQR) is relatively large for Olorunsogo (1.89^{0}C) while Ilorin South (0.34^{0}C) has the smallest range. This implies that farmers in Olorunsogo experienced high variability in the temperature patterns with half of all years falling within the IQR while those in Ilorin South experienced relative stability in their temperature pattern. The temperature in Moro and Ilorin South are positively (upward) skewed to the median value, hence cooler while Asa and Olorunsogo exhibits a downward movement (negative skewness) from the median value making them relatively hotter over the period. Ogbomosho South and Ilorin East have middle clustering of temperatures over the years, however, the short and balanced whiskers of the former suggests that its temperature is relatively more stable than the latter. Asa and Ilorin East were relatively the hottest communities while Moro and Ilorin South were the coolest.

Figure 4.3: Box plots of temperature patterns in the study area



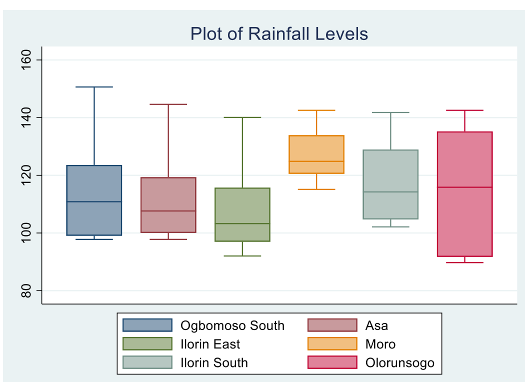
Source: Survey and Author’s computation, 2022

4.1.6 Observed rainfall levels in the study area

Figure 4.4 reveals the variability in the rainfall levels both within and between the selected farming communities in the study area over 11 years. The median rainfall is higher in Moro (124.84 mm) and Olorunsogo (115.86 mm) while the rainfall in Asa (107.64 mm) and Ilorin East (103.26 mm) have the lowest median values. The interquartile range (IQR) is relatively large for Olorunsogo

(43.71 mm) while Moro (15.44 mm) has the smallest range. This implies that farmers in Olorunsogo experienced high variability in the rainfall levels with half of all years falling within the IQR while those in Moro experienced relative stability in their rainfall levels. The rainfall in Asa, Ilorin East, Moro, and Ilorin South are positively (upward) skewed to the median value making them relatively dry over the period, while Ogbomosho South and Olorunsogo exhibit a middle clustering (zero skewness) of rainfall levels over the years suggesting that they are neither relatively wetter nor dryer. However, the long and imbalanced whiskers of Ogbomosho South, Asa, Ilorin East, and Ilorin South indicate that they are prone to cases of extremely high rainfall levels. Moro was relatively wetter among the selected communities while Ilorin East was dryer than the others. Hence, it can be induced from Figures 4.3 and 4.4 that Moro has been relatively cool and wet while Ilorin East has been hot and dry over the years. However, farmers in Olorunsogo experienced the highest climate variability in both their temperature patterns and rainfall levels. The result of this analysis confirms the variation in weather and climate as perceived by maize farmers in study area.

Figure 4.4: Box plots of rainfall levels in the study area



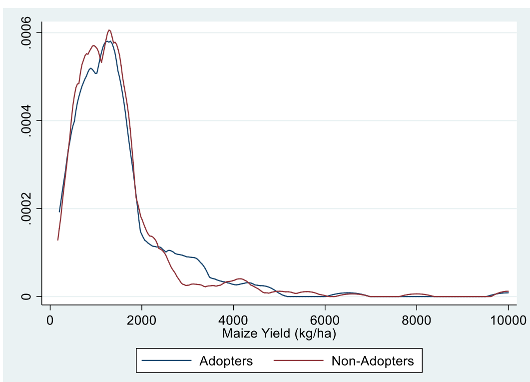
Source: Survey and Author's computation, 2022

4.2 Adoption of STMA Varieties on Productivity

4.2.1 Distribution of Maize Farmer's Productivity

The Kernel density graph, presented in Figure 4.5, shows that at the lower tail of the distribution of the maize yield, the mass of maize farmers that had not adopted the STMA varieties had higher yields than those that adopted it. This may be attributed to the competing effect of adoption of the STMA varieties on other input factors used by small scale maize farmers who are mostly resource-constrained. However, as the distribution moves into the upper tail, the yield of the adopters becomes higher than the non-adopters. This result is consistent with the findings of (Awotide *et al.*, 2015; Olagunju *et al.*, 2020) This provides an additional reason to examine the distributional effect of STMA adoption.

Figure 4.5: Kernel density of maize yield (kg/ha) by adoption status



Source: Survey and Author's computation, 2022

4.2.2 Effect of Adoption of STMA Varieties on Productivity of Maize Farmers

Table 4.3 presents the results for the effect of the adoption of STMA varieties on the productivity of maize farmers using the Heckman two-staged selection regression model. The dependent variable of the fitted regression model is the maize yield per hectare of land cultivated. Results for the first and second stages were evaluated using the relevant diagnostic statistics of the fitted Heckman selection model. The model diagnostics summarized in the last rows of Table 4.3 showed that the lambda (λ) value ($-$ 0.038) was insignificant, indicating that there was no evidence of selection bias, which could not be established a priori. In other words, unobservable factors did not affect farmers' adoption of the STMA varieties. The significant Wald test ($\chi^2 = 27.57$, $p<0.05$) reveals that the model has a good fit and is significant in determining the effect of the adoption of STMA varieties on the productivity of maize farmers in Nigeria. The estimated Rho ($\rho = -0.0599$) suggests that a good proportion of variation in the dependent variable has been explained by individual specific terms and the rest is due to idiosyncratic error.

The result of the first stage of the Heckman selection model presents the factors that determine the adoption of the STMA maize varieties. The significant determinants of STMA adoption with a positive sign were gender, schooling years, awareness of improved maize varieties, and awareness of the STMA maize varieties while the number of income sources contributes negatively to the likelihood of adopting the STMA varieties. The estimated coefficient for gender which is positive and significant at 10% shows that there is a positive relationship between the gender of maize farmers and their adoption status. The result suggests that male-headed farming homes are more likely to adopt the STMA varieties than their female counterparts. This result is consistent with previous findings of (Munyua *et al.*, 2012; Oluwayemisi, Olarinde and Fatunbi, 2017; Ayinde, 2021; Sigigaba, Mdoda and Mditshwa, 2021) who found that gender of the household head matters in explaining adoption of improved crop varieties. This emphasizes the evidence that female-headed household are less likely to adopt agricultural technologies.

Schooling years are positively related to adoption status, implying that an extra year of schooling increases the likelihood of adopting the STMA varieties. A higher level of education could enhance the easy diffusion of new and improved maize farming techniques among farmers. The result reveals that an increase in the number of schooling years of household head will increase the probability of adoption of the STMA maize varieties. This result corroborates the findings of (Jaleta *et al.*, 2013; Akinbode and Bamire, 2015; Danso-abbeam *et al.*, 2017; Ayinde, 2021; Chete, 2021) who reported statistically significant influence of education on the adoption of improved maize varieties.

Farmer's awareness of improved maize varieties and awareness of the STMA maize varieties positively and significantly increase the likelihood of adoption of the STMA maize varieties at a 1% level of significance. This suggests that the maize farmers in the study area are well informed on the significance of improved maize varieties. This can also be a result of good extension service in the study area. On the other hand, income sources negatively influence the adoption of the

STMA maize varieties at a 5% level of significance. This implies that having more income sources decreases the likelihood of adopting the STMA maize varieties. This result is contrary to findings of some studies such as (Akinbode and Bamire, 2015; Chete, 2021; Zegeye, Fikire and Meshesha, 2022) who found that adopting improved maize varieties is positively influenced by access to off-farm income and off-farm income can also spur the intensity of use of the improved maize varieties. Off-farm income-generating activities are known to improve the overall economic performance and welfare of a farm household however in this case it poses a barrier to adoption of technologies. This result is in consonance with (Zegeye, 2019) who found that off-farm activities has a negative effect on the adoption decision since engagement in off-farm activities reduce working hour allotted to agriculture.

The result of the second stage of the Heckman selection model presents the factors that determine the productivity of the farmers that adopted the STMA varieties. The result shows that schooling years, household size, and market distance are statistically significant in influencing the productivity of maize farmers in the study area. The level of education in years and household size are significant at 5% level, while the distance to the nearest market was significant at 10% level. The result reveals that as schooling years increases by a unit, there is decrease the productivity of the average maize farmer by 2.9%. This result is not consistent with a-priori expectation as an increase in years of education should enhance the acquisition and utilization of information on improved technology and thus increase maize yield. This result is a variance from the findings of (Tefaye and Beshir, 2014) who found a positive relationship between education and maize yield. This may be tethered to the fact that maize production is field work that requires relevant training and cognitive practical experiences, hence, school years may not have the expected relationship with productivity as the study is not related to agribusiness.

The estimated coefficient of household size reveals that an additional person to the household size will increase the maize farmer's yield by 3.9%. Maize production is labour intensive and requires high labour for land preparation, planting, weeding, and harvesting. Since many smallholder farmers depend on family labour, families with large numbers of household members were able to provide labour in the farms resulting in increased yield. This finding is in line with the findings reported by (Chune, 2022), who found a positive relationship between household size and maize production in Western Uganda.

Similarly, the result shows that a kilometer increase in the distance to the market increases the average maize farmer's yield by 1.3%. This is contrary to the expectation that farther markets could demotivate farmers due to limited market access. Studies such as (Buckmaster, 2012; Fungo, Krygsman and Nel, 2017; Teferra *et al.*, 2018) found that farmers who have access to markets produce higher crop yield and that higher distance undermines the incentive to produce. However, a far market distance may serve as a preconditioning for the agribusiness-minded maize farmers who would rather cultivate a larger expanse of land for higher productivity and scale efficiency to enjoy economies of scale in the agricultural value chain and spend less on the transportation of inputs and output. In addition, with the general increase in prices and transportation cost, farmers with farms far from market increase their yield to cushion the effect of higher transport cost on their overall profit.

Table 4.3: Heckman Two-Step estimates of the effects of STMA adoption on Productivity

Variable	**Maize Yield**		**STMA Adoption**	
	Coefficients	**se**	**Coefficients**	**se**
Age	-0.004	0.006		
Dependency ratio	-0.029	0.022		
Farming experience	-0.007	0.006		
Market distance	0.013	0.008*		
Gender	0.236	0.149	0.307	0.165*
Schooling years	-0.029	0.013**	0.024	0.014*
Household size	0.0399	0.017**	0.029	0.019
Off-farm income	-0.143	0.121	0.191	0.144
Income sources	-0.015	0.048	-0.128	0.051**
Credit access	0.175	0.133	0.157	0.185
Extension access	0.017	0.184	0.163	0.224
IMV awareness	0.151	0.456	0.816	0.268***
Oyo State	0.131	0.112	-0.181	0.138
Marital status			-0.089	0.239
Farm size			0.016	0.022
Group membership			0.183	0.140
Awareness of STMA			2.125	0.363***
Constant	7.010	0.889***	-3.617	0.542***
Lambda	-0.038	0.334		
Rho	-0.059			
Sigma	0.638			
Wald Test	27.570**			
Observations	520			

se = standard error *** p<0.01, ** p<0.05, * p<0.1
Source: Survey and Author's computation, 2022

4.3 Adoption of STMA varieties on Household Food Security

4.3.1 Food Insecurity Prevalence among Maize Farming Households

Table 4.4 presents the HFIAS module of nine occurrence questions of food insecurity conditions among maize farming households in the study area. It reveals that about 36.7%, 35.0%, 37.3%, and 42.5% of the farming households did not experience questions 1 – 4 (responded "no" to the occurrence questions), while 43.7%, 45.8%, 71.5%, 84.0%, and 84.2% of them responded "no" to questions 5 – 9. The remaining farming households' responded affirmatively (saying "yes") to the nine HFIAS questions, as indicated in Table 4.4. Additionally, result indicates a consistent increase in the percentage of households that responded "no" to the questions, while there was a downward trend in the percentage of households that responded affirmatively to the nine HFIAS questions with a recall period of four weeks. This conforms to the findings of (Otekunrin *et al.*, 2021) who found that most farming households had varying levels of food insecurity.

Table 4.4 Distribution of farming households based on the incidence of food insecurity conditions.

		No	**Yes**
	Incidence Question (N = 520)	Frequency (%)	Frequency (%)
1	Concerned about not enough food to eat?	191 (36.730)	329 (63.270)
2	Eating food you did not desire?	182 (35.000)	338 (65.000)
3	Eating monotonous foods?	194 (37.310)	326 (62.690)
4	Eating foods you did not want to eat?	221 (42.500)	299 (57.500)
5	Eating smaller size of meals?	227 (43.650)	293 (56.350)
6	Skipping some meals in a day?	238 (45.770)	282 (54.230)
7	No food to eat at all?	372 (71.540)	148 (28.460)
8	Go to bed hungry?	437 (84.040)	83 (15.960)
9	Not eating anything throughout the day (24 h)?	438 (84.230)	82 (15.770)

Source: Survey and Author's computation, 2022

Table 4.5 presents only households that responded affirmatively to all the nine HFIAS occurrence questions while revealing the numbers of households based on their responses to the repetitiveness of the conditions. Based on households' responses, Table 4.5 shows that more than three-quarters (78.1%) of 329 households responded they rarely worry about not having enough food (Q1a), while only 4.6% and 17.3% of the households responded they experience the Q1a condition sometimes and often, respectively. Likewise, about 73.6% of the farming households confirmed they rarely eat monotonous food (Q3a), while only 3.1% and 23.3% of the households responded that this food insecurity (access) condition occurred sometimes and frequently, respectively. Confirming the resilience of farming households to the hard economic reality in Nigeria, only about 27.0% of the households responded that they skip meals (Q6a) sometimes or often while about 73.0% of the households confirmed that they rarely experience this condition (Q6a) within the 30-day recall period. The results equally revealed that majority (64.6%) of farming households affirmed that they rarely go the whole day and night without eating anything (Q9a), indicating that as farmers, they may always find something to eat, though it may not be nutritious food, which is common in low- and middle-income countries, as also found by (Otekunrin *et al.*, 2021).

Table 4.5 Distribution of farming households based on the repetitiveness of food insecurity conditions.

		Repetitiveness of Food Insecurity Condition			
	Incidence Question	Rarely	Sometimes	Often	Total (N)
		Freq. (%)	Freq. (%)	Freq. (%)	
1a	Concerned about not enough food to eat?	257 (78.120)	15 (4.560)	57 (17.330)	329
2a	Eating food you did not desire?	276 (81.660)	9 (2.660)	53 (15.680)	338
3a	Eating monotonous foods?	240 (73.620)	10 (3.070)	76 (23.310)	326
4a	Eating foods you did not want to eat?	218 (72.910)	11 (3.680)	70 (23.410)	299
5a	Eating smaller size of meals?	208 (70.990)	13 (4.440)	72 (24.570)	293
6a	Skipping some meals in a day?	206 (73.050)	12 (4.260)	64 (22.700)	282
7a	No food to eat at all?	97 (65.540)	7 (4.730)	44 (29.730)	148
8a	Go to bed hungry?	50 (60.240)	3 (3.610)	30 (36.140)	83
9a	Not eating anything throughout the day?	53 (64.630)	4 (4.880)	25 (30.490)	82

Source: Survey and Author's computation, 2022

4.3.2 Food Insecurity Incidence among Maize Farming Households

Presented in table 4.6 is the result of the food security status of farming households in the study area. The result shows that the majority (72.9%) of the farming households in the study area suffers food insecurity even though the level of food insecurity varies. This is consistent with similar studies in Nigeria that reported a high prevalence of food insecurity cases in Nigeria (Sholeye, Animasahun and Salako, 2019; Aboaba, Fadiji and Hussayn, 2020). There is evidence of a high level of hunger among maize farming households which implies that being engaged in agriculture does not guarantee food security as agricultural households are most affected by prevailing food insecurity issues despite being food producers (Ogunniyi *et al.*, 2016). The extent of food insecurity reveals that two out of every five maize farming households (39.6%) were moderately food insecure, similarly, more than one-fourth of the respondents (26.4%) are mildly food insecure while about 6.9% suffered food insecurity with severe hunger. This high food insecurity might be attributed to various factors, for instance, (Oyetunde-Usman and Olagunju, 2019) reported that households' efficiency, age of household heads, household size, number of assets, and land size have significant effect on the food insecurity status of agricultural households in Nigeria.

Table 4.6: Food Security Status of farm households

Household Food Insecurity	Frequency	Percentage (%)
Food Secure (FS)	141	27.120
Mild food insecure (MiFi)	137	26.350
Moderate food insecure (MoFI)	206	39.620
Severely food insecure (SFI)	36	6.920
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

4.3.3 Effect of Adoption of STMA Varieties on Food Security of Farming Households

Table 4.7 presents the results for the effect of the adoption of STMA varieties on household food security of farming households using the Heckman two-staged selection regression model. The dependent variable of the fitted regression model is the Household Food Insecurity Access Scale (HFIAS). Results for the first and second stages were evaluated using the relevant diagnostic statistics of the fitted Heckman selection model.

The model diagnostics summarized in the last rows of Table 4.42 showed that the lambda (λ) value (1.4235) was insignificant, indicating that there was no evidence of selection bias, which could not be established a priori. In other words, unobservable factors did not affect farmers' adoption of the STMA varieties. The significant Wald test (χ^2 = 98.94, $p<0.01$) reveals that the model has a good fit and is significant in determining the effect of the adoption of STMA varieties on household food security in Nigeria. The estimated Rho (ρ = 0.3966) suggests that a good proportion of variation in the dependent variable has been explained by individual specific terms and the rest is due to idiosyncratic error.

The result of the first stage of the Heckman selection model presents the factors that determine the adoption of the STMA maize varieties. The significant determinants of STMA adoption with a positive sign are: gender, schooling years, awareness of improved maize varieties, and awareness of the STMA maize variety while the number of income sources contributes negatively to the likelihood of adopting the STMA varieties. The estimated coefficient for gender which is positive and significant at 10% shows that there is a positive relationship between the gender of maize farmers and their adoption status. The result suggests that male-headed farming homes were more likely to adopt the STMA varieties than their female counterpart. This result is consistent with previous findings of (Fisher *et al.*, 2015).

Schooling years is positively related to adoption status, implying that an extra year of schooling increases the likelihood of adopting the STMA varieties. A higher level of education could enhance the easy diffusion of new and improved maize farming techniques among farmers (Otekunrin *et al.*, 2021). The result also revealed that an increase in the number of household members will increase the probability of adoption of the STMA maize varieties. This result corroborates the findings of (Khonje *et al.*, 2015; Amondo *et al.*, 2019) who found a positive effect of household size on the adoption of improved maize varieties.

Farmer's awareness of improved maize variety and awareness of the STMA maize varieties positively and significantly increase the likelihood of adoption of the STMA maize variety at a 1% level of significance. This suggests that the maize farmers in the study area are well informed on the significance of improve maize varieties this can be a result of good extension service in the study area. On the other hand, income sources negatively influence the adoption of the STMA maize varieties at a 5% level of significance. This implies that having more income sources decreases the likelihood of adopting the STMA maize varieties.

The result of the second stage of the Heckman selection model presents the factors that determine household food security given the farmers adopt the STMA varieties. The result shows that the age of the household head, farming experience, income sources, and location are the significant variables influencing the household food insecurity of the maize farmers in the study area. The location of the farming households is significant at 10%, the age of the household head and farming experience are significant at 5% level, while the income source is significant at 1% level.

The result reveals that a unit increase in the age of the household will decrease the household food insecurity of the average maize farmers by 0.1144 points. This implies that a farming household becomes less vulnerable to food insecurity with an increase in the age of the farmers. This finding agrees with (Ogunniyi *et al.*, 2021) who found a positive relationship between the age of male-headed smallholder maize farmers and household food security in rural Nigeria. The estimated coefficient for location suggests that the food security incidence of the average maize farming household located in Oyo state is 1.6925 points better off than their Kwara State counterparts in other words farmers living in Oyo state experience less food insecurity.

On the other hand, a unit increase in farming experience will increase the household food insecurity of the maize farmers by 0.1112 points on average. This may be because maize farmers are currently being plagued by the vagaries of the climate elements thereby reducing their farm productivity and the ability to adequately meet the food needs of the household. This is in line with previous studies by (Ogunniyi *et al.*, 2021) that found a similar relationship between farming experience and food security.

Similarly, an increase in the number of income sources will increase the household food insecurity of the average maize farmer by 2.476 points. This result is contrary to expectation because it is expected that higher number of income sources will lead to more household income which will eventually influence food security. However, the reason for this relationship is not farfetched in the study area since majority (75.9%) of the households whose heads have four different sources of income apart from farming experienced mild-to-severe food insecurity within the recall period. This result implies that having several income sources may not necessarily translate to household food security in the study area.

Table 4.7: Heckman Two-Step estimates of the effects of STMA adoption on Food Security

Variable	**HFIAS**		**STMA Adoption**	
	Coefficients	**se**	**Coefficients**	**se**
Age	-0.114	0.045**		
Dependency ratio	-0.216	0.168		
Farming experience	0.111	0.048**		
Market distance	-0.049	0.060		
Gender	-1.803	1.160	0.307	0.165*
Schooling years	-0.086	0.098	0.024	0.014*
Household size	-0.013	0.129	0.029	0.019
Off-farm income	-0.461	0.947	0.191	0.144
Income sources	2.476	0.377***	-0.128	0.051**
Credit access	1.398	1.038	0.157	0.185
Extension access	-1.399	1.436	0.163	0.224
IMV awareness	2.381	3.527	0.816	0.2684***
Oyo State	-1.693	0.875*	-0.181	0.138
Marital status			-0.089	0.239
Farm size			0.016	0.022
Group membership			0.183	0.140
Awareness of STMA			2.125	0.363***
Constant	6.7386	(6.8837)	-3.617	0.542***
Lambda	1.424	(2.578)		
Rho	0.281			
Sigma	5.063			
Wald Test	98.940***			
Observations	520			

Se = Standard errors *** p<0.01, ** p<0.05, * p<0.1
Source: Survey and Author’s computation, 2022.

4.4 Level of Resilience of Maize Farmers to Climate Change

4.4.1 Distribution of Resilience Pillars by STMA adoption status of farmers

Table 4.8 shows that adopters of the STMA varieties outperform their counterparts in majority of the resilience capacity indicators. They are better off by 34% and 5% on the Social Safety Nets (SSN) and Household Assets (AST) indicators respectively. However, the Adoptive Capacity (ACC) of the adopters are worse off by 8%. The overall resilience capacity of the adopters is 6% higher than that of their counterparts thereby suggesting that the adoption of STMA varieties positively affects the ability of maize farmers to be more resilient to the observed climate change.

Table 4.8: Distribution of Resilience Pillars by STMA Variety Adoption

STMA Adoption	ABS	AST	SSN	ACC
No	0.769	0.111	0.120	0.519
Yes	0.779	0.116	0.182	0.482
Total	**0.773**	**0.113**	**0.142**	**0.505**

Source: Survey and Author's computation, 2022

4.4.2 Resilience Capacity and Resilience Pillars

The Resilience Capacity Index (RCI) is estimated from the pillars, taking into account the indicators of climate change using the Multiple Indicators Multiple Causes (MIMIC) model. The climate change indicators are considered outcomes of resilience. The results of the MIMIC model are shown in Table 4.9. The model presents a good fit to the data using the relevant diagnostic statistics; all the pillars' coefficients are positive and statistically significant.

Table 4.9: MIMIC estimates of Farmers' Resilience capacity to climate change

Variables	RCI
Access to Basic Services (ABS)	1.741*** (0.146)
Household Assets (AST)	1.668*** (0.104)
Social Safety Nets (SSN)	0.122*** (0.008)
Adoptive Capacity (ACC)	1.226*** (0.368)
Climate Change Trends (index)	1 (0.000)
Vulnerability (index)	0.391*** (0.145)
Chi-Squared	19.900**
RMSEA	0.053
CFI	0.869
SRMR	0.042
Observations	520

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Survey and Author's computation, 2022

4.4.3 Correlation between Resilience Capacity Index and its pillars

The correlation matrix (Table 4.10) shows that most of the variables are weakly or moderately correlated to each other with a correlation coefficient of less than 50%. The only pair of variables with a correlation coefficient greater than 50% are Resilience Capacity Index (RCI) and Adaptive Capacity (ACC). RCI and ACC have the largest negative correlation coefficient of 91.7%. Correlation scores above 0.80 may suggest a high degree of collinearity between the variable pair. However, (Gujarati, 2003) stipulates that high zero-order correlations are a sufficient but not a necessary condition for the existence of multi-collinearity because they can exist even though the zero-order correlations are comparatively low (say, less than 0.50).

Table 4.10: Correlation between resilience capacity index and its pillars

	RCI	ABS	AST	SSN	ACC
RCI	1.000				
ABS	0.502	1.000			
AST	0.124	0.039	1.000		
SSN	-0.069	0.046	0.129	1.000	
ACC	-0.917	-0.236	-0.059	0.060	1.000

Source: Survey and Author’s computation, 2022.

4.4.4 Resilience Capacity of Maize Farmers to Climate change

Results in table 4.11 show that approximately 96% of the maize farmers have either a moderate resilience (55.58%) or a low resilience (40.19%) to climate change in the study area. The International Food Policy Research Institute asserts that agricultural resilience means implementing farmers absorb and recover from shocks and stresses to their agricultural production and livelihood (Béné *et al.*, 2016). This result implies that the majority of farming households would be affected by climate shocks since their capacity to bounce back when hit by climate shocks is low. This can also mean that majority of maize farming households in the study area are vulnerable to climate shocks which might be a result of the low level of adoption of climate adaptation strategies as stated in the previous result and in line with the findings of (Fatoki *et al.*, 2020) who asserted that small-holder farmers’ vulnerability to climate change in Ogun State is high and dependent on loss of coping or adaptive capacity in the zone. The implication of this is that any slight variation in climate will influence the output and productivity of farmers as well as the farmers’ food security status.

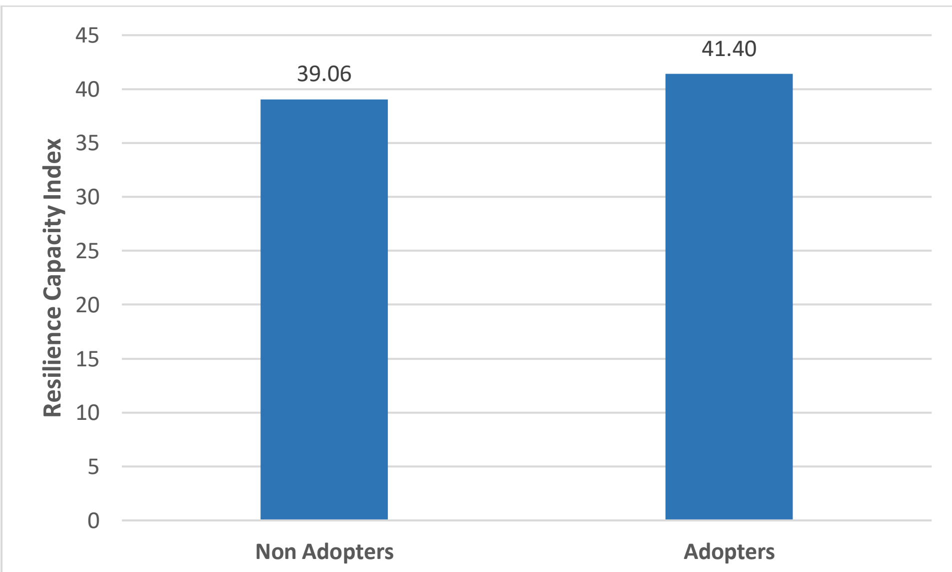
Table 4.11: Distribution of Farmer's Resilience to Climate Change

Resilience	Frequency	Percentage (%)
Low Resilience	209	40.190
Moderate Resilience	289	55.580
High Resilience	22	4.230
Total	**520**	**100.000**

Source: Survey and Author's computation, 2022

While majority of the maize farmers do not exhibit a high resilience, the resilience capacity of the average farmer (Figure 4.6) indicates that the adopters of the STMA varieties are more resilient to climatic variability and shocks than their non-adopter counterparts.

Figure 4.6: Resilience capacity by Adoption status



Source: Survey and Author's Computation

4.4.5 Test of mean differences in farmers' endowment between Adopters and Non-Adopters of STMA

This section presents the test of the mean differences in some selected endowment variables of the maize farmers. The summary statistics in Table 4.12 reveals that more than one out of every three maize farmers, approximately 36%, have used STMA varieties in the planting season when the survey was carried out. There is no observable differences in the adoption across the two sampled states in Nigeria. The low adoption rates of about 36% per state show that there is a need to improve the seed supply chain to broaden STMA varieties adoption and use in Nigeria.

The results show that maize farmers that adopted the STMA varieties are not entirely similar to those that did not adopt the STMA varieties. Adopting farmers have statistically significantly higher food insecurity, income sources, credit access, and extension services, and are more aware of the existence of both an improved maize varieties and the STMA varieties than the non-adopting farmers. However, the results show no significant difference in yield and resilience capacity index (RCI) between the two farmers, although the kernel density graph (Fig. 4.5) of the maize output per hectare of cultivated land reveals that the adopting farmers have a higher yield compared with the non-adopting farmers.

Table 4.12: Test of mean differences in farmers' endowment between Adopters and Non-Adopters of STMA

Variable	Total	Adopters	Non-Adopters	Mean Difference	t-test
Outcome variables					
Yield (kg/ha)	1475.69 (52.30)	1494.68 (85.32)	1465.03 (66.22)	29.65 (109.07)	0.27
HFIAS	7.53 (0.27)	8.30 (0.46)	7.10 (0.32)	1.20 (0.55)	2.20**
RCI	0.40 (0.01)	0.42 (0.01)	0.40 (0.01)	0.02 (0.02)	1.52
Other covariates					
Age (years)	43.23 (0.66)	41.93 (1.07)	43.96 (0.83)	-2.04 (1.37)	-1.49
Household size (number)	8.54 (0.17)	8.84 (0.27)	8.38 (0.21)	0.46 (0.34)	1.33
Farming experience (years)	22.05 (0.57)	21.56 (0.92)	22.33 (0.73)	-0.77 (1.20)	-0.65
Income sources (number)	2.66 (0.06)	2.49 (0.10)	2.75 (0.08)	-0.26 (0.13)	-2.04**
Credit access (yes = 1, 0 = otherwise)	0.14 (0.02)	0.18 (0.03)	0.12 (0.02)	0.06 (0.03)	1.94*
Extension access (yes = 1, 0 = otherwise)	0.88 (0.01)	0.92 (0.02)	0.86 (0.02)	0.06 (0.03)	1.97**
IMV awareness (yes = 1, 0 = otherwise)	0.82 (0.02)	0.97 (0.01)	0.74 (0.02)	0.24 (0.03)	7.03***

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Survey and Author’s computation, 2022

These findings are not a reflection of the impact of STMA adoption on any outcome of interest; neither do they indicate that those maize farmers that have adopted the STMA varieties are better in output or in other variables than those that did not. This result is only a pointer to the fact that there is selection bias in the sample, and any conclusion on the impact of STMA adoption on any outcome of interest based on the mean differences will be biased and generate erroneous policy recommendations. Thus, the observed differences in yield and output between the adopting and non-adopting farmers have no causal interpretation. Therefore, to empirically determine the impact of STMA adoption on our outcome of interest, we adopted other econometric models such as the Heckman two-staged selection regression model and Endogenous Switching Regression model that conveniently eliminate observable and unobservable biases in the sample and provide a consistent estimate of the impact.

4.5 Impact of adoption of STMA varieties on farmers' resilience to climate change

This section presents the empirical evaluation of the impact of the adoption of STMA varieties on resilience to climate change. The basic impact model adopted is the Endogenous Switching Regression model (ESRM) capable of controlling for all possible biases that could confound our results. The results of the estimation are presented in Table 4.13. The result of the estimates is in three parts, one part consists of the Probit model of the determinants of adoption of STMA varieties. The result of the Probit model reveals that farmers' awareness of the existence of both an improved maize varieties and that of STMA varieties, gender, and household size are positive and statistically significant in determining the adoption of STMA varieties. This can be explained by the fact that awareness is the first stage of the adoption process, a larger household size guarantees a constant supply of farm labour, then maize farming is dominated by the male gender, hence fostering healthy competition leading to the early and rapid adoption of STMA varieties to stay ahead of counterparts in both social status and wealth creation.

The estimated coefficient for gender which is positive and significant at 1% shows that there is a positive relationship between the gender of maize farmers and their decision to become an adopter of new technology. The result shows that the probability of a male-headed household adopting the STMA varieties is about 0.45 points higher than that of their female counterparts. This result is consistent with previous studies (Nhemachena and Hassan, 2007; Sadiq *et al.*, 2019) that being in a male-headed household positively influenced the adoption decision of climate-related strategies. This could be because a switch to a new technology involves changes that may require a lot of energy in the implementation phase, hence, it becomes easier for the male gender to be an adopter.

Household size is significant and positively related to the probability of adopting the STMA varieties. The estimated coefficient shows that there are 0.04 points as much probability of adopting the STMA varieties among larger households than among smaller households. In other words, increasing the household size by one person will increase their probability of adoption of STMA varieties by 0.04 points with other variables held constant. Indeed, the adoption of new improved varieties is labor-intensive. Hence, large households tend to have labour supply toward the adoption of innovation more than smaller households. In similar studies by (Belay *et al.*, 2017; Ojo and Baiyegunhi, 2020; Danso-Abbeam *et al.*, 2021) farming families with a substantial number of persons adopt improved maize varieties than those with a smaller number of persons.

Table 4.13: Full Information Maximum Likelihood Estimates of the ESRM

Variable	STMA Adoption		RCI (Adopters)		RCI (Non-Adopters)	
	Coef.	**se**	**Coef.**	**se**	**Coef.**	**se**
Gender	0.445	0.161***	-0.052	0.025**	0.001	0.014
Age	0.000	0.008	0.003	0.001**	0.001	0.001*
Schooling years	0.020	0.015	0.001	0.002	-0.003	0.001**
Household size	0.043	0.019**	-0.005	0.003	-0.002	0.002
Dependency ratio	-0.007	0.029	0.002	0.004	-0.019	0.003***
Farming experience	-0.007	0.007	-0.002	0.001	-0.001	0.001
Off-farm income	0.064	0.143	-0.001	0.021	0.039	0.013***
Income sources	-0.106	0.054*	-0.079	0.008***	-0.101	0.004***
Market distance	0.003	0.011	0.002	0.002	-0.002	0.001**
Credit access	0.194	0.180	-0.039	0.025	-0.028	0.017
Extension access	0.117	0.215	-0.031	0.032	-0.051	0.017***
IMV awareness	0.895	0.271***	-0.164	0.046***	-0.036	0.018**
Oyo State	-0.218	0.147	-0.077	0.021***	-0.030	0.013**
Marital status	-0.131	0.173				
Farm size	-0.016	0.014				
Group membership	0.186	0.117				
Awareness of STMA	1.872	0.291***				
Constant	-3.229	0.569***	0.921	0.082***	0.784	0.036***
/lns1	-1.918	0.097***				
/lns2	-2.326	0.04***				
/r1	-1.945	0.475***				
/r2	-0.149	0.475***				
sigma_1	0.147	0.014***				
sigma_2	0.098	0.004***				
rho_1	-0.960	0.037***				
rho_2	-0.149	0.258				
LR Test	15.410***					
Observations	520		520		520	

Coef. = Coefficients; se = Standard errors *** p<0.01, ** p<0.05, * p<0.1

Source: Survey and Author's computation, 2022

The estimated coefficient of the number of income sources is negative and statistically significant at 10%. The negative sign as expected implies that farmers with multiple sources of income are less likely to adopt STMA varieties. For a unit change in the number of income sources, there is a 0.1059 points decrease in the probability of becoming an adopter of the STMA varieties. This may be because involvement in more income sources means that less attention would be given to the farm business.

The term for IMV awareness and Awareness of STMA variables has a slightly different interpretation. The predicted probability of STMA adoption is 0.895 points higher for the farmers that are aware of the existence of improved maize varieties than for those who are not. In the same vein, the predicted value probability of STMA adoption for the farmers that know about the STMA varieties is 1.8721 points higher for those farmers with this knowledge than for those that are not aware.

The coefficient estimates, of the second stage of the switching regression model, for the resilience to climate change (RCI), are shown in the second and third columns of Table 4.48. The results of the resilience to climate change regressions among the farmers that adopted the STMA varieties are reported in the RCI (Adopters) column and the resilience to climate change among the farmers without the STMA varieties is presented in the RCI (Non-Adopters) column.

The estimated coefficient of gender, age, number of income sources, IMV awareness, and location are statistically significant in explaining the variations in resilience to climate change among the farmers that adopted the STMA varieties. Similarly, the coefficient of schooling years, dependency ratio, off-farm income, market distance, and extension access are significant in explaining the variations in the resilience capacity of the non-adopters with different relationship directions.

The estimated coefficient of gender is negative and significant at 5%. This implies that the resilience capacity of a male maize farmer who adopted the STMA variety is lower than that of their female counterpart. Conversely, the estimated coefficient of gender for the non-adopting male farmers is the reverse of their adopting counterparts. The positive and non-significant for the non-adopters may be because the pillars of the resilience capacity index are mostly gender neutral, hence, a male-headed farming household may not necessarily be more resilient to climate change than their counterparts.

Age is significant and positively related to the resilience capacity to climate change of the adopters of the STMA varieties. Although non-significant for the non-adopters of the STMA varieties, the estimated coefficients imply that a year increase in the age of the farmer will bring about 0.0027 points increase in the adopting farmer’s ability to manage climate variability while that of the non-adopting farmer would increase by 0.0011 points. This finding is variance with (Issahaku and Abdulai, 2020a) who found a negative relationship between age and adoption of climate-smart practices among smallholder farmers in Ghana. Older farmers have seen and persevered through a lot of changes in the climate, hence, they are better equipped to anticipate and prepare for, as well as adapt to, absorb and recover from the impacts of climate changes and extreme weather.

The coefficient of income sources is negative and significant at 1% for both adopters and non-adopters, showing that there is an inverse relationship between the number of income sources of maize farmers and their capacity to be resilient to climate change regardless of their adoption status. Additional income source to the adopting farmer reduces his resilience by 0.0791 points while the non-adopting farmers experience a 0.1008 points reduction in their resilience to climate change. However marginal (27.4%), the adopters of STMA tend to give up less resilience capacity when they venture into an income source. This is consistent with the findings of (Legesse, Ayele and Bewket, 2013; Issahaku and Abdulai, 2020a) who found that farmers' engagement in extra income-generating activity negatively influence adoption of all climate-smart practices, alluding to the fact that off-farm activity engagement and adoption of these practices may be competing for household labour resulting in the labour-loss effect. Similarly, the more income sources farmers have, the less devoted to farm production they would likely become, hence, the reduction in their capability to be resilience to climate change.

Awareness of improved maize varieties reduces farmers' resilience to climate change. The estimated coefficient is negative and significant at 1% and 5% for the adopters and the non-adopters respectively. For the adopting farmer, this knowledge reduces his resilience capacity by 0.1643 points compared with another adopter who is not aware of any other improved maize varieties. The resilience of the non-adopting farmer reduces by 0.0355 points compared with another non-adopter who only knows local maize varieties. Awareness of improved maize varieties means that, without technical guidance, farmers may choose other local maize varieties or improved maize varieties over the STMA varieties as they would likely prioritize other features over the climate-stress tolerance of the chosen improved variety.

Locational differences in the resilience to climate change of the adopters show that the maize farmers in Oyo state have a relatively lower capacity of about 0.0774 points compared to their counterparts who are in Kwara state of Nigeria. The non-adopting farmers in Oyo state experience a 0.0301 points reduction in their resilience to climate change compared with the base state. This may be due to the higher density of maize-adopting farmers in Kwara state whose clustering may have afforded them higher diffusion of the STMA technology in the region.

The correlation coefficients rho_1 and rho_2 are both negative but are statistically significant only for the correlation between the STMA adoption choice equation and the resilience to climate change of those farmers who adopted the STMA varieties. Since rho_1 is negative and statistically significantly different from zero, the model suggests that farmers who choose to adopt the STMA varieties have higher resilience to climate change than a random farmer from the sample would have obtained. Those farmers who are non-adopters of the STMA varieties are not better or worse than a random farmer. The likelihood ratio test for joint independence of the three equations is statistically significant at 5%, this implies that these three models are not jointly independent and should not be estimated separately.

Table 4.14 reveals that the mean Average Treatment effect on the Treated (ATT) is 2.54×10^{-2} and the t-test of the ATT shows that it is statistically and significantly different from zero. This implies that those farmers that adopted the STMA varieties have higher resilience to climate variability than the non-adopters.

Table 4.14: One-sample t-test

Variable	Mean	t-value	Df
ATT	0.0254	1.9872	518

Source: Survey and Author's computation, 2022

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Summary

This study was conducted to examine the effect of the adoption of STMA varieties on resilience to climate change among maize farmers in the derived savannah agroecological zone of Nigeria. This zone of the country was purposively selected because of the introduction, experimentation, and adoption of STMA varieties in this zone. A multistage stratified sampling procedure was employed to select 520 maize farming households from Oyo and Kwara states. Data were collected using a well-structured questionnaire. The data were analyzed using descriptive statistics, cross-tabulation, Household Food Insecurity Access Scale (HFIAS), Heckman Selection Regression Model, Resilience Index Measurement and Analysis (RIMA II), and Endogenous Switching Regression Model.

Analysis of the socioeconomic characteristics of respondents indicates that 74.2% are male and 90.8% of the sampled farmers are married. The average maize farmer has a household size of 8 persons, is 43 years old, cultivates 3.9 hectares of land, and has obtained an average of 7 years of formal education indicating that the maize farmers are fairly educated. Although, 73.8% of the farmers have spent at least 10 years in the farming business, only one-third (35.9%) of the maize farmers have adopted the STMA maize varieties and about two out of every three maize farmers have some other income source apart from farming.

Profile of adoption of STMA varieties by farmers characteristics show that a larger proportion (82.89%) of the STMA adopters are male who are young farmers (78.1%) below the age of 60 years. There are more adopters compared to non-adopters at higher educational levels although the ratio of adopters to non-adopters tends to decrease with an increase in household size. Profiling suggests that there is a weak relationship between farmers' experience and adoption of an improved maize variety but maize farmers who do not have access to credit facilities are major adopters of the STMA maize varieties.

The top three climate change indicators perceived by maize farmers in the last decade are high temperatures and heat, dryness, and drought while floods, too much rain, and high winds are the three least perceived climate change indicators. Farmers have perceived a warming trend in the savannah region as about 56%, 51%, and 45% of the cases of drought, high temperatures & heat, and dryness, respectively, are reported to have occurred between twice in a year and thrice in a year while about 74%, 59% and 62% of the cases of floods, off-season rainfall, and too little rain, respectively, are reported to have occurred between once in two years and once in a year. This suggests that the savannah region is getting hotter and drier.

The HFIAS module of nine occurrence questions of food insecurity conditions among maize farming households reveals that 36.7%, 35.0%, 37.3%, and 42.5% of the farming households did not experience questions 1 – 4, while 43.7%, 45.8%, 71.5%, 84.0%, and 84.2% of them responded “no” to questions 5 – 9. There is a consistent increase in the percentage of households that responded “no” to the questions, while there is a downward trend in the percentage of households that responded affirmatively to the nine HFIAS questions with a recall period of four weeks. Only 27.0% of the households responded that skipping meals sometimes or often happened to them while about while majority (64.6%) of farming households affirmed that they rarely go the whole day and night without eating anything, indicating that as farmers, they may always find something to eat, though it may not be nutritious food. However, majority (72.9%) of the farming households suffers food insecurity even though the level of food insecurity varies. This evidence of a high level of hunger among farming households implies that being engaged in agriculture does not guarantee food security as agricultural households are most affected by prevailing food insecurity issues despite being food producers.

Profile of the food security status by farmers' characteristics shows that male-headed households are more food secure than their female-headed counterparts. Food security increases as age increases since a larger proportion of older maize farmers have food-secure households. About 73.1% of the married household heads are reported to be experiencing different levels of food insecurity (from Mildly Food Insecure to Severely Food Insecure). Although there is a positive connection between higher household size and higher severity of food insecurity, the findings suggested that the level of education may not necessarily reduce food insecurity among maize farming households and that having several income sources may not necessarily translate to household food security.

The Resilience Index Measurement and Analysis (RIMA) II was used to analyze the resilience capacity of farming households to climate change. Three categories of level of resilience to climate change were obtained, namely low resilience, moderate resilience, and high resilience. From the results of the descriptive analysis, more than half of the farmers are moderately resilience while only 4.2% of the maize farmers have high resilience to climate change. For the adoption of STMA varieties and the resilience capacity of the respondents, the result shows that the adopters of the STMA varieties are more resilient to climatic shocks than their non-adopter counterparts.

Results of the Heckman two-staged selection model show that age of the household head, farming experience, income sources, and location are the significant variables influencing the household food security of the maize farmers. While school years, household size, and market distance are significant in influencing the productivity of maize farmers in the study area. Impact of the adoption of STMA varieties on the resilience to climate change using the Endogenous Switching Regression model (ESRM). The coefficient estimates of the first stage reveal that farmers' awareness of the existence of both an improved maize varieties and that of STMA varieties, gender, and household size is positive and statistically significant in determining the adoption of STMA varieties.

The coefficient estimates of the second stage show that gender, age, number of income sources, IMV awareness, and location are statistically significant in explaining the variations in resilience to climate change among the farmers that adopted the STMA varieties. Similarly, the coefficient of schooling years, dependency ratio, off-farm income, market distance, and extension access are significant in explaining the variations in the resilience capacity of the non-adopters with different relationship directions. The negative and statistically significant estimate of rho_1 suggests that farmers who choose to adopt the STMA varieties have higher resilience to climate change than a random farmer from the sample would have obtained. Those farmers who are non-adopters of the STMA varieties are not better or worse than a random farmer. The significant t-test of the ATT affirms that those farmers that adopted the STMA varieties have higher resilience to climate change than the non-adopters.

5.2 Conclusion

Conventionally, maize is produced with limited inputs and less attention to management. However, heat, dryness, drought, declining soil fertility, pest, and diseases are the most persistent challenges that maize farmers face. A vital strategy to reduce the stresses posed by these factors necessitates advancing agricultural technology development in terms of improved seeds like the STMA varieties. In place of this, improved seeds provide greater benefits because of their higher productivity potential, ability to withstand drought, and resistance to heat, pests, and diseases.

From the results of the study, it can be concluded that awareness of technologies in maize production in terms of improved maize varieties is prevalent, however, adoption of the STMA varieties is low. Regression analyses revealed that the adoption of the STMA varieties positively affects farmers' productivity, household food security, and resilience capacity to climate change. In conclusion, the adoption of the STMA varieties is an important factor in the quest to achieve an increase in farmers' realization of the aforementioned outcomes.

5.3 Recommendations

Based on the findings and the conclusions of this research, the following recommendations are made;

1. Policy makers should back maize farmers through the provision of adult education which should empower them to understand new agricultural technologies such as STMA varieties. This will foster the age-long and persistent challenge of low technological adoption in African agriculture.
2. Attention should be given to extension and dissemination programmes and training, especially the younger and agile farmers who still have the strength to take a risk that can in turn help in boosting their production through the adoption of STMA technology.
3. A well-functioning community-based seed provision system should be promoted to enhance maize farming households' accessibility to certified STMA seeds. Likewise, there is a need for policymakers and stakeholders to improve the seed supply chain to broaden STMA varieties use in Nigeria.
4. The cooperative system has been well-researched and known to advance adoption of agricultural technologies in many African communities. However, this institution is seen to be weak in the study area which may be tethered to frailty of embracing this seed technology. It is therefore recommended that the cooperative system be improved in the study area and other locations in order to enhance agricultural productivity, food security and farmers' resilience to climate change.
5. Further studies should consider applying the methodology of this study to panel data to make a recommendation that will address the persistent low adoption of improved maize varieties sustainably. There is also an avenue to study maladaptation and specifically the maladaptive practices of maize farmers which may be negatively influencing their resilience to climate change.

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APPENDIX

Analysis of Climate Data

Summary of the Temperature Patterns in the study area

Year	Ogbomosho South	Asa	Ilorin East	Moro	Ilorin South	Olorunsogo
2011	31.48	31.57	32.85	31.33	31.27	30.38
2012	31.44	32.30	32.23	31.04	30.98	30.68
2013	31.74	31.90	31.91	31.35	31.33	30.61
2014	31.78	32.10	32.22	31.30	31.22	32.37
2015	31.93	32.25	32.22	31.38	31.27	32.53
2016	32.18	32.49	32.53	31.69	31.54	32.71
2017	32.11	32.44	32.50	31.65	31.57	32.66
2018	32.03	32.32	32.43	31.48	31.43	32.54
2019	31.71	31.97	31.97	31.03	30.98	32.24
2020	32.08	32.34	32.38	31.48	31.40	32.56
2021	32.38	32.54	31.48	31.75	31.58	31.03
Mean	**31.89**	**32.20**	**32.25**	**31.41**	**31.32**	**31.84**
Coefficient of Variation	**6.94%**	**7.63%**	**7.80%**	**7.37%**	**7.61%**	**7.44%**
Cumm. Annual Change	**0.03%**	**-0.01%**	**-0.05%**	**0.01%**	**-0.02%**	**-0.02%**

Source: Author's computation, 2022

Summary of the Rainfall Levels in the study area

Year	Ogbomosho South	Asa	Ilorin East	Moro	Ilorin South	Olorunsogo
2011	110.84	107.64	96.98	120.52	107.07	140.38
2012	115.95	114.58	107.89	131.68	117.45	123.39
2013	109.28	104.81	92.03	118.03	102.12	129.68
2014	123.58	119.34	115.73	133.91	119.53	111.39
2015	98.08	97.93	94.01	121.78	104.71	89.73
2016	99.06	100.01	100.52	131.85	114.25	91.72
2017	111.17	107.14	100.88	124.84	107.47	100.04
2018	124.45	126.00	114.37	140.06	128.95	115.86
2019	150.63	144.60	119.13	142.53	132.38	135.23
2020	97.77	97.78	103.26	122.30	102.73	91.36
2021	103.26	115.86	140.06	115.11	141.78	142.53
Mean	**113.09**	**112.34**	**107.71**	**127.51**	**116.22**	**115.57**
Coefficient of Variation	**77.88%**	**78.40%**	**82.65%**	**75.60%**	**78.44%**	**77.82%**
Cumm. Annual Change	**0.76%**	**0.98%**	**-1.84%**	**-1.52%**	**0.88%**	**-0.63%**

Source: Author's computation, 2022

Survey Questionnaire

My name is FRANCIS Phillips, I am PhD student of Climate Change Economics from the above institution. I am writing a thesis on *Building Resilience of Smallholder Maize Farmers to Climate Variability and Change: A Case Study of Stress Tolerant Maize Variety (STMA)*. I need your support by giving me accurate information on your farming activities. The information that will be collected from you will serve only for academic purpose and will be kept confidential. Thank you in advance for your cooperation.

Date: ______/_______/______ Name of Enumerator: _________________________________
State: ___________________Village: _____________________ Location: ____________________

Personal and Household Information

1. Gender 1. Male 0. Female
2. Age of the Household head ___________years
3. Marital status 1. Married 2. Single 3. Divorced 4. Widowed
4. Educational level of household head 1. No formal education 2. Primary 3. Secondary 4. Tertiary 5. Others (specify) _______________________
5. Total number of schooling years ___________years
6. Religion: 1. Christianity 2. Islam 3. Traditional worship
7. Household size: Male members______ Female members________ Total __________
8. How many members of your household are dependents on your income? __________
9. Farming experience of household head__________ years
10. Do you engage in off-farm income generating activity? 1. Yes 0. No
11. How many sources of income do you have? ______________
12. Please specify the income received from the following activities last year

	Income source	How many HH members worked	Monthly Income (N)
a	Farm labour		
b	Off-farm labour		
c	Business		
d	Artisan		

Farm characteristics and production information

13. How much farmland do you have in total? _________hectares
14. How much of the land do you own? _____________hectares
15. How much of the land is rented/leased? ____________hectares
16. What other types of crops do you cultivate? 1. Cassava 2. Yam 3. Maize 4. Sorghum 5. Rice 6. Millet 7. Others (specify) ____
17. Is maize a major crop in your farm enterprise? 1. Yes 0. No
18. Approximately, how much land do you use for maize cultivation each year? __________hectares
19. How much land did you use last year for maize cultivation? __________hectares
20. What source of labour do you use in your farming? 1. Family labour 2. Hired labour 3. Both
21. How much did you use of purchased inputs for maize varieties cultivation in the last year?

Variety Planted	Land area (ha)	Seeds		Fertilizer	
		Qty. (kg)	Cost (₦)	Qty. (bags)	Price/bag (₦)

Variety Planted	Herbicide		Pesticide	
	Qty. (lit.)	Price/lit. (₦)	Qty. (lit.)	Price/lit. (₦)

22. Do you use mechanized means for cultivation? 1. Yes 0. No. if yes, fill the table below

Machine used	Total land area mechanized (Ha)	Total expenditure (₦)

23. Use of hired labour and expenditure

Variety Planted	Clearing (man days)	Planting (man days)	Weeding (man days)		Fertilizer application	Harvesting (man days)	Total (man days	Rate (₦)	Total (₦)
			1st	2nd					

24. Use of family labour

Variety Planted	Clearing (man days)	Planting (man days)	Weeding (man days)		Fertilizer application	Harvesting (man days)	Total (man days	Rate (N)	Total (N)
			1st	2nd					

25. Total amount of money spent on maize farming last season? _________________________ ₦
26. What was your maize output in the last year?

Variety Planted	Land area (Ha)	Self-consumption (kg)	Seed for next (kg)	Sale (kg)	Sale price (₦/kg)	Storage (kg)	Total yield (kg)

27. Total yield of Maize (kg) in the last two seasons? _______________ kg
28. Total yield of Maize (kg) in the last three seasons? _______________ kg
29. How much did you sell a bag of maize last season? ______________ ₦

Institutional factors

30. How far is the market where you buy your inputs in terms of: Distance ____________km; Time taken to get there __________hours
31. How far is the market where you sell your maize output in terms of: Distance ____________km; Time taken to get there __________hours
32. Have you ever faced shortage of finance in farming activities? 1. Yes 0. No
33. If yes, did you take a loan/credit? 1. Yes 0. No
34. If yes, how did you source the loan for your farming activities?

	Sources of loan	Loan amount taken (Naira)	Year taken
a	Commercial bank		
b	Microfinance		
c	Cooperatives		
d	Money lenders		
e	Friend/relative		
f	Others (specify)		

35. If No, what challenges did you face in accessing the credit/loan? 1. Lack of collateral 2.High interest rate 3. Absence of lending institution 4. Low producer prices, 5. Others (specify) ____
36. Are you a member of any groups, organisation or associations? 1. Yes 0. No
37. If yes, which one do you belong? 1. Co-operative 2. Farmer's group 3. Professional association 4. Religious group 5. Youth group 6. Women group 7. Trade union 8. Village association 9. Political group 10. Others (specify)____
38. For the groups of which you are member, please choose

	Group type	Degree of participation (1. Leader 2. Very active 3. Active 4. Not active)	Frequency of meeting (1. Once a week 2. Once every two weeks 3. Once a month 4. Two times a year or less 5. Never
a			
b			
c			

39. What are the reasons that made you to join? 1. Access to extension services 2. Access to loans 3. Access to help from colleagues, 4. Access to land 5. Bargaining power 6. Others (specify)____
40. To what extent do these groups benefit you? 1. Not at all 2. A little 3. Average 4. A lot 5. Completely
41. To what extent has membership given you knowledge to improve farm system? 1. Not at all 2. A little 3. Average 4. A lot 5. Completely
42. To what extent has membership given you knowledge to withstand/cope with climate challenges? 1. Not at all 2. A little 3. Average 4. A lot 5. Completely
43. Do you have access to extension services? 1. Yes 0. No
44. How often do you have extension visits? 1. Once a week 2. Once in two weeks 3. Once a month 4. Once a year
45. What is the source of extension service? 1. Government extension officers 2. NGO extension officers 3. Others (specify) ____
46. What extension message did you receive? 1. Climate information 2. Land preparation 3. Seed rate 4. Use of improved maize varieties 5. Weeding 6. Plant spacing 7. Fertilizer application 8. Post-harvest management 9. Pesticide and disease control 10. Others (specify) __________

Awareness, Adoption and Continued Use of Maize Technology

47. Have you heard of the any improved maize varieties? 1. Yes 0. No
48. Do you grow special or improved maize varieties? 1. Yes 0. No
49. If yes (in Q48), where is the source of supply of the maize seed? 1. Government 2. Research Institute 3. Cooperative society 4. Market 5. Extension agents 6. Fellow farmers 7. Others (specify)_____
50. If No (in Q48), what is the reason for non-usage? 1. I have not heard about it 2. Not available here 3. Not accessible here 4. It is expensive 5. I prefer the old varieties 6. Others (specify) _________
51. If yes, kindly specify the improved maize varieties you grow.

	Name	Colour	Specific characteristic
a			
b			
c			

52. Have you heard of the Stress Tolerant Maize Variety (STMA)? 1. Yes 0. No
53. If yes (in Q52), from what source did you hear about STMA? 1. Government 2. Research Institute (PSA) 3. Cooperative society 4. Market (agro-dealers) 5. Extension agents 6. Fellow farmers 7. Others (specify)____
54. If no (in Q52), why haven't you heard? ____
55. Do you grow STMA variety? 1. Yes 0. No
56. If yes (in Q55), what are the types of STMA varieties you grow?

	Name	Colour	Specific characteristic
a			
b			
c			

57. How long have you been growing STMA variety? _______year(s)
58. What attributes of the STMA variety do you perceive important to you? ____
59. Will you continue to grow STMA variety? 1. Yes 0. No
60. If yes (in Q59), why______________________________
61. If no (in Q59), why not____________________________
62. If no (in Q55), have you grown it before? 1. Yes 0. No
63. If yes (in Q62), why did you stop growing? 1. Not available 2. Not accessible 3. It is expensive 4. I prefer the old varieties 5. Others (specify) _________
64. How long did you grow it before you stopped? ___________________year(s)
65. If No (in Q62), why haven't you grown it? 1. I have not heard about it 2. Not available here 3. Not accessible here 4. It is expensive 5. I prefer the old varieties 6. Others (specify) ______
66. If No (in Q62), will you want to grow STMA variety? (*for farmers who do not grow STMA*) 1. Yes 0. No
67. If yes (in Q66), can you state the reason? ____
68. If no (in Q66), can you state the reason? ____

69. Where do you source your STMA maize seeds? 1. Government 2. Research Institute (PSA) 3. Cooperative society 4. Market (Agro dealers) 5. Extension agents 6. Fellow farmers 7. Others (specify) ____
70. What is your general comment as regards the STMA maize varieties? ____

Evidence of climate variability and change and coping mechanisms

71. In the last 10 years, have you noticed any change in the rainfall patterns? 1. Yes 0. No
72. If yes, specify the pattern of the change in rainfall. 1. Decreasing rainfall 2. Increasing rainfall
73. In the last 10 years, have you noticed any change in temperature? 1. Yes 0. No
74. If yes, specify the pattern of the change in temperature. 1. Decreasing temperature 2. Increasing temperature
75. In the last 10 years do you observe any shift in the rainy season? 1. Yes 0. No
76. If yes, tick as appropriate the table below

Observation	Responses	
	1. Yes	0. No
has it come later than usual		
has is it come earlier than usual		
has it gone later than usual		
has it gone earlier than usual		

77. Have you experienced any of the following climate variability and change indicators?

	Climate change indicators	1. Yes	0. No	How often? 1. Three times in a year 2. Twice in a year 3. Once in a year 4. Once in two years
a	Droughts			
b	Floods			
c	Off-seasonal rainfall			
d	Too much rain			
e	Too little rain			
f	High temperature & heat			
g	High winds			
h	Dryness			
i	Others (specify)			

78. Have you observed the following climate related impacts in the last decade?

	Climate change impacts	1. Yes	0. No
a	Decline in crop yield		
b	Increase in crop yield		
c	Shortage of water		
d	Food shortage		
e	Increased weed and pest pressure		
f	Higher risk of crop damage due drought		
g	Others (specify)		

79. In response to above climate variability and change, have you taken adaptation measures to reduce their impacts? 1. Yes 0. No
80. If no, why?

	Reasons for not adapting	1. Yes	0. No
a	Lack of information		
b	Lack of capital		
c	Shortage of farming land		
d	Not experiencing climate related challenges		
e	Others (specify)		

81. If yes, which of the following adaptation strategies have you employed?

	Adaptation strategies	1. Yes	0. No	If No, why not?
a	Change of crop variety			
b	Mixed farming			
c	Mixed cropping			
d	Mono-cropping			
e	Change of crop cultivated			
f	Soil & water conservation system			
g	Soil fertilization system			
h	Early planting			
i	Off-farm employment			
j	Agroforestry (tree planting)			
k	Irrigation			
l	Buying insurance			
m	Relatives and Friends financial support			
n	Obtaining loan			
o	Others (specify)			

82. Has the government done anything to help you cope with losses due to climate variability? 1. Yes 0. No If yes, what? ____
83. Have private organizations done anything to help you cope with losses due to climate variability? 1. Yes 0. No. If yes, what? _____________________________________
84. Do you think the assistance from government, organizations and your own efforts have been useful and sufficient? 1. Yes 0. No
85. If yes, how? ____
86. If no, what do you expect from the government to help you to cope with climate variability and change effects? ____
87. What do you suggest to be done to reduce the impacts of climate variability and change in your area? ____
88. What are your comments on the climate conditions overtime? ____
89. Do you think you will be able to cope with future adverse climatic conditions? ____

Resilience to the effect of climate variability and change

Access to Basic Services

90. Do you have access to health care services? 1. Yes 0. No
91. How far is it? In terms of distance ______km; time taken to get there _______hours
92. Do you have access to primary school? 1. Yes 0. No
93. How far is it? In terms of distance ______km; time taken to get there _______hours
94. What is the distance of the major road from your house? In terms of distance ________km; time taken to get there _________hours
95. Do you have good farm feeder roads? 1. Yes 0. No
96. Do you have access to improved drinking water? 1. Yes 0. No
97. How far is the water source in terms of distance ____km, time taken to get there ____hours
98. Do you experience conflict due to water scarcity? 1. Yes 0. No
99. How often do you have electricity supply? 0. Never 1. Rarely 2. Sometimes 3.Frequently

House assets profile

100. Please indicate which asset you have and their values in the following table

	Items		Quantity Owned	Year Purchased	Value/1
a	Television				
b	Radio				
c	Car				
d	Motorcycle				
e	Bicycle				
f	Mobile phone				
g	Land owned (Ha)				
h	Livestock	1.Chicken			
		2.Small ruminants			
		3.Cow			
i	Farm equipment	1.Hoe			
		2.Machete/Cutlass			
		3.Axe			
		4.Spade			
		5.Wheel barrow			
		6.Sprayer			
		7 Farm Boot			
j	Other durables (Specify)				

Social safety nets

101. Do you receive assistance in cash and kind from association, colleagues, friends, relatives and children not living with you? 1. Yes 0. No
102. In the last year, how many times did you received this assistance? ______________________

Absorptive capacity

Natural disaster & climate variability

103. Do you have access to climate information? 1. Yes 0. No
104. Do you have access to early warning information about an impending climate shock? 1. Yes 0. No

105. If yes, from what source do you get early warning information? 1. Extension agents 2. Farmers groups 3. Media 4. Others (specify) ___________________________________

106. Do you prepare or get ready for sudden shocks due to climate variability? 1. Yes 0. No

107. How do you prepare for climate shocks? ____

Stability

108. Do you consider much of your farmland to be gentle slope or undulating? 1. Yes 0. No

109. Do you consider much of your farmland to have good soil quality? 1. Yes 0. No

110. How much of your farmland is under soil and water conservation system? ___hectares

111. Can you say your farmland is protected against climate variability extremes such as flood, droughts, dryness and heavy wind? 1. Yes 0. No

Food expenditure & consumption

112. How much do you spend on feeding monthly on the average? __________________ ₦

113. What proportion of your income do you spend on food? _______________

114. In the past 4 weeks, did you worry that your household would not have enough food? 0. No 1. Yes

115. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

116. In the past 4 weeks, were you or any member not able to eat the kinds of foods you preferred because of lack of resources? 0. No 1. Yes

117. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

118. In the past 4 weeks (30 days), did you or any household member have to eat a limited variety of foods due to a lack of resources? 0. No 1. Yes

119. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

120. In the past 4 weeks (30 days), did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food? 0. No 1. Yes

121. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

122. In the past 4 weeks (30 days), did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food? 0. No 1. Yes

123. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

124. In the past 4 weeks (30 days), did you or any household member have to eat fewer meals in a day because there was not enough food? 0. No 1. Yes

125. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

126. In the past 4 weeks (30 days), was there ever no food to eat of any kind in your house because of lack of resources to get food? 0. No 1. Yes

127. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

128. In the past 4 weeks (30 days), did you or any household member go to sleep at night hungry because there was not enough food? 0. No 1. Yes

129. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

130. In the past 4 weeks (30 days), did you or any household member go a whole day and night without eating anything because there was not enough food? 0. No 1. Yes

131. If yes, how often did this happen? 1. Rarely 2. Sometimes 3. Often

Health

132. How many times were you or anyone in the household sick in the last month? ________

133. How much do you spend on health-related issues monthly on the average? _____ ₦

Transformative capacity

134. I have changed the way I practice farming due to climate variability? 1. Yes 0. No

135. If yes, what did you do? ____

Farmers' perception of resilience to climate variability and change

136. Choose the extent to which you agree or disagree with the following statements

	Questions	Responses				
		SA	A	I	D	SD
a	Your household can bounce back from any climate-related challenge that comes					
b	During times of hardship, your household can change its primary income or source of livelihood if needed					
c	If climate change threats to your household became more frequent and intense, you would still find a way to get by					
d	During times of hardship your household can access the financial support you need					
e	Your household can rely on the support of family and friends when you need help					
f	Your household can rely on the support from government when you need help					
g	Your household has learned important lessons from past hardships that will help you better prepare for future threats					
h	Your household is fully prepared for any future climate change extreme that may occur in your area					
i	Your household receives useful information warning you about future risks					

SA – strongly agree A - agree I - indifferent D - Disagree SD – Strongly disagree