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ADDIS ABABA UNIVERSITY SCHOOL OF GRADUATE STUDIES

ADOPTION OF CLIMATE SMART AGRICULTURAL PRACTICES IN RAYA KOBO WOREDA.

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A Thesis Submitted to Collage of Business and Economics Department of Economics for Partial Fulfillment of the Requirements for the Degree of Masters of Science in Economics (Natural Resource and Environmental Economics)

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This is to certify that the thesis prepared by **Iyasu Hailu** entitled: **Adoption of Climate Smart Agricultural Practices in Raya Kobo Woreda** and submitted in partial fulfillment of the requirements for the degree of Master of Science (Natural Resource and Environmental Economics) aligned with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Iyasu Hailu

Dedication

This thesis is dedicated to my father **Hailu Demeke** and my mother **Tadelech Baye**.

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Table of Contents

Acronyms.....	i
Tables and Figures.....	iii
Abstract	iv
CHAPTER ONE: INTRODUCTION	1
1.1. Introduction.....	1
1.2. Background of the Study	1
1.3. Statement of the Problem.....	3
1.4. Research Questions.....	5
1.5. Objective of the Study	5
1.5.1. General Objective	5
1.5.2. Specific Objectives	5
1.6. Significance of the Study	6
1.7. Scope of the Study	6
1.8. Organization of the Study	7
CHAPTER TWO: LITERATURE REVIEW.....	8
2.1. Review of Theoretical Literature	8
2.1.1. Why Climate Smart Agricultural Practices.....	8
2.1.2. Current Adoption of CSA Practices in Ethiopia	10
2.1.3. Innovation Adoption System and Theoretical Framework.....	11
2.1.3.1. Diffusion of Innovation (DOI) and Expected Utility Theory (EUT).....	12
2.1.3.2. The Theory of Planned Behavior (TPB).....	15
2.1.3.3. Integrated Framework Development	17
2.2. Empirical Literature Review	19
2.2.1. Exogenous variables	19
2.2.2. Endogenous variables	20
CHAPTER THREE: RESEARCH METHODOLOGY	27
3.1. Area of the study	27
3.2. Sampling techniques	28
3.3. Model Specification	29

3.3.1.	Partial Least Square-SEM (PM)	30
3.3.2.	Estimation procedures: Econometric Framework.....	35
CHAPTER FOUR: RESULT AND DISCUSSION.....		38
4.1.	PLS-SEM Prediction.....	38
4.1.1.	PLS: Descriptive Statistics.....	38
4.1.2.	PLS-SEM Prediction Result	41
4.1.2.1.	Results Evaluation: Reflective (outer) Measurement Model.....	42
4.1.2.2.	Results Evaluation: Inner (Structural Equation) Model.....	50
4.2.	Estimation Results with Econometrics	53
4.2.1.	MNL: Descriptive Statistics.....	53
4.2.2.	Multinomial Adoption Selection Model and Marginal Effect	59
CHAPTER FIVE: CONCLUSIONS AND POLICY IMPLICATIONS.....		74
References		76
Appendix:		i
Questioner.....		iv

Acronyms

ATT	Attitude
AVE	Average Variance Extracted
CR	Composite Reliability
CRGS	Climate Resilient Green Economy Strategy
CSA	Climate Smart Agriculture
CSAPs	Climate Smart Agriculture Practices
CSI	Climate Smart Initiative
DOI	Diffusion of Innovation
EC	Ethiopian Calendar
EUT	Expected Utility theory
F	Organic Fertilizer
FAO	Food and Agricultural Organization
GDP	Gross Domestic Product
GHG	Green House Gas
GNP	Gross National Product
GR	Green Revolution
GTP	Growth and Transformation Plan
I	Improved Crop Varieties
IIA	Independence of Irrelevant Alternatives
ISP	Input Subsidy Program
LVs	Latent Variables
MERET	Managing Environmental Resources to Enable Transitions
MNL	Multinomial Logit Model
MNP	Multinomial Probit Model
P	Push-Pull pest management strategy
PBC	Perceived Behavioral Control
PLS-SEM/PM	Partial Least Square-Structural Equation Modeling/ Path Modeling
PSNP	Productive SafetyNet Programme
REDD+	Reduce Emissions from Deforestation and Forest Degradation in Developing Countries

SAPs	Sustainable Agricultural Practices
SEM	Structural Equation Model
SLM	Sustainable Land Management
SN	Subjective Norm
SSA	Sub-Sahara Africa
TLU	Tropical Livestock Unit
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
VIF	Variance Inflation Factor
WAO	Woreda Agricultural Office

Tables and Figures

Tables

Table 1: Sample size distribution

Table 2: Descriptive statistics of measurement model analysis

Table 3: Results Summary for Reflective Outer (Measurement) Models

Table 4: Outer (reflective measurement) and Inner (Structural) model bootstrapping PLS predicted path coefficient results

Table 5: Fornell–Larcker Criterion analysis for checking discriminant validity

Table 6: Packages of Climate-Smart Agricultural Practices

Table 7: Explanatory Variables by Combination of Climate-Smart Practices

Table 8: Table Parameter Estimates for the Selection Model of Various Combinations of Climate-Smart Practices

Table 9: Marginal effect for various combinations of packages of explanatory variables

Figures

Figure 1: Integrative Model.

Figure 2: Map of the study area

Figure 3: Indicator loadings and path coefficients of key constructs.

Figure 4: Bootstrap Partial Least Square T values and R square with relative results

Figure 5: Bootstrap Partial Least Square P values and R square with relative results

Abstract

This thesis takes an integrative approach how variation decision predicts adoption via technology attributes and behavioral features, and synthesize with other socioeconomic variables to investigate how these factors influence the uptake of CSA practices. The study applies both Partial Least Squares Structural Equation Model (PLS-SEM) for prediction as well as the Multinomial Logit model to determine adoption decisions. Except observed trialability constructs the bootstrapped measurement model results shows a significant relation with their latent variables, as well as, the inner structural model technological attribute was highly explained negatively by technological complexity (-40.5%), intention by 39% by personal attitude. CSA adoption was highly and directly by usefulness, technological attribute, cost, and intention respectively by 35.4%, -26.5%, -22.7%, and 22.4%, supporting for specified hypothesis. Moreover, technology attributes and behavioral latent constructs were also simulated in the MNL model along with socioeconomic factors. Results show that education, large land size, access to CSA information, extension, and credit services, inconsistent rainfall, and occurrence of pests and diseases increase the likelihood of adopting one or more CSA practices. While, livestock unit, non-farm income activities, and high temperature reduce the probability of adaptation decisions. These results imply that efforts to promote the widespread adoption of CSAPs by farmers in the study area should focus on enhancing farmers' educational level, create awareness regarding CSAPs, addressing liquidity constraints and deliver extension services. The adoption of CSAPs can also further be enhanced by raising farmers' awareness, and skill and knowledge to ease technological attributes, and change their perceptions and attitudes towards sustainable farming practices.

Key words: Climate-smart agricultural practice, Partial least square structural equation, Multinomial logit, Ethiopia.

CHAPTER ONE: INTRODUCTION

1.1. Introduction

The need to develop climate-smart agriculture (CSA) has become a national and international agenda. Beyond unsustainable agricultural practices; climate change can exacerbate current social and economic problems, particularly for those parts of society that depend on that climate-sensitive resources, where risks are evident in rainfed agriculture (James et al., 2012). FAO (2017) suggests that the impacts of climate change on agriculture and food security are occurring in vulnerable areas, as a result of increased unpredictable weather conditions and the spread of extreme events, resulting in reduced production and lower incomes.

Improving agricultural sustainability, which is one of the most important goals of Ethiopian Growth and Transformation Plan (GTP), taking into account climate change under the strategic of environment and climate change building, such as Climate-Resilient Green Economy (CRGE), are made so far to develop policies and strategies appropriate to climate change (Jirata et al., 2016). Additionally, adopting of CSA practices, such as high-yield varieties and improved production technologies, is at the top of the government's agenda for its five-year GTP achievement (Fentie and Beyene, 2018). Hence, the agricultural system, which is the backbone of the national economy, needs to be smart against climate change by generating incomes at acceptable levels for sustainable production and promoting environmental management. efforts to achieve sustainable production requires an understanding adaptation mechanism where agriculture is more vulnerable to climate change. It is not yet clear whether non-socioeconomic factors predict the adoption of CSA practices at the farmer level, along with other important socio-economic features. Thus, the study takes into account factors such as psychological and technological attribute factors, as well as key socioeconomic factors, in order to provide a clear understanding of the practices adopted and feedback to policy makers.

1.2. Background of the Study

Nowadays, there is growing consensus about climate changes in transforming conditions of rural development, changes in physical and socio-economic landscapes, and changes the environment to make the development of smallholder farmers more expensive. On the other hand, there is little agreement on how to adopt smallholder farming practices to adapt to climate variability (Grainger-

Jones, 2011). Over the last decades, farmers have been using a wide range of synthetic agricultural inputs to improve agricultural productivity, yet the benefits they drive have become difficult due to the negative environmental externalities in the long run. Accordingly, CSA practices have been accepted as eco-friendly methods and have emerged as alternative farming system that addresses many of the obstacles faced by resource-poor farmers and at the same time ensure environmental sustainability. Also, Fentie and Beyene (2018) noted that adopting of climate-smart farming practices can lead to steady increase in farm productivity and income and, therefore, build resilience to shocks, including the effects of climate change.

Long-term adaptation measures and sustainable agricultural practices need to be aligned with local vulnerabilities. In drought-prone lowlands areas such as Raya Kobo, in addition to the habits of using traditional farming methods such as slow-raining varieties, fertilizer application and pest control, experience more intense and irregular rainfall affecting yields of agricultural production. CSA-related efforts have been focused to restore degraded lands and improve production through stress-tolerant varieties (I), organic fertilizers (O), and biological pest control (push-pull (P)). The government and its development partners are largely support such most common climate-smart agricultural technologies through research and development, rural extension services as well as direct implementation (Gelaw, 2017).

Improved seeds are a key input to improve crop production and productivity. Increasing the quality of seeds, which tolerates high temperature and inadequate rainfall, can significantly increase the yield potential of crops and thus, is one of the most economical and efficient inputs of agricultural development (Girma and Amanuel, 2017). Organic fertilizers are fertilizers obtained from animal substances, animal excrement (manure), human excrement, and vegetable matter (for example compost and crop residues). Naturally occurring organic fertilizers include animal wastes, peat, and manure. Furthermore, the push and pull strategy is biological and involves the behavioral manipulation of insect, pests and their natural enemies via the integration of stimuli that act to make the protected resource unattractive or unsuitable to the pests (push) while luring them toward an attractive source (pull) from where the pests are subsequently removed (Cook et al., 2007).

The study focused on the adoption of climate-smart agricultural practices in Raya Kobo woreda in four selected 'kebeles' (sub woreda); Aradum, Addis Kign, Abourie, and Addis Alem. Raya Kobo woreda is located in North Wollo zone, eastern part of Amhara region. The adoption of CSA practices to increase crop productivity has been applied with conventional and non-climate-smart agricultural practice. This can increase farmers' income, suggesting to improve food security and reduce poverty. Therefore, to improve the sustainable agricultural system, adoption of climate-smart agricultural practice needs to be increase. This, in turn, requires understanding the power of behavioral and technological attributes in predicting adoption decision, and knowing the basic determinants of adopting CSA practice using a multidisciplinary approach. Hence, this study sought to predict, and explore the determinants of the adoption of three CSA practices (i.e., combinations of improved seeds, organic fertilizers, and push-pull techniques) in Raya Kobo woreda as a case study.

1.3. Statement of the Problem

While significant progress has been made in household livelihoods and food security through agricultural development, this has consistently happened at the expense of environmental sustainability, overwhelming the very foundations of our long-term capacity. As a result, there is an urgent need to enhance the ongoing research activities with a sound research to investigate the drivers and effectiveness of the innovations associated with adopting CSA practices as a cornerstone to help control environmental degradation and climate change adaptation. So far many attempts have been made to understand what factors determine the adoption of CSA practices and as to why the level of adoption is limited (Fazio et al., 2014). Still, such scattered results obtained testify to the lack of research in this domain. Farmers' choices to embrace an innovation¹ has been studied by different lines of research, like economics, sociology and psychology (Joao et al., 2015). However, such literature cannot capture the complete and complex picture of farmers' decision-making, since it fails to recognize that farmers' behavior is not driven only by the maximization of economic profit (Joao et al., 2015; Mutyasira et al., 2018; Tey, 2013). Since most of the theoretical models on the adoption of innovations have tended to present discipline-guided clarifications in the choice of selection, despite that, adoption is subjected to a combination of social, economic,

¹ Followed Rogers (2003) definition of innovation as an idea, practice, or object that is perceived as new by an individual or other unit of adoption. Following this we will use innovation and practices interchangeably.

psychological, as well as cultural factors. Thus, the adoption decision needs to be analyzed and examined from a holistic perspective and justifies the significance of expected utility theory (EUT), the theory of planned behavior (TPB) and diffusion of innovation (DOI) by providing evidences from past literatures; yet current knowledge concerning CSA practices remains scarce and decision to adopt can be contemplated as a multidisciplinary. Thus, to fill the gap, this study attempts to identify the significance of multidisciplinary approach to find out whether the joint factors predict and determine adoption of CSA practices through integrative framework.

Another research gap arises from examining the level of adoption level of a single CSA practice and typically fail to take into account psychological, economic and technology attribute together with socioeconomic factors. For example studies (D'souza et al., 1993) estimated the extent to which individual components and environmental characteristics of the environment influence the adoption of sustainable agriculture in West Virginia. On the other hand, Aryal, Jat, et al. (2018) have attempted to estimate the probability and intensity of multiple CSAPs adoption in India using socioeconomic factors. And numerous studies, Knowler and Bradshaw, (2007) and Mutyasira et al., (2018) have assessed the level of SAPs adoption using psychological synthesized with socioeconomic variables; however fail to include expected utility profit variables (such as associated perceived usefulness, costs and risk of innovation) and other latent perceived innovation attributes from theories of DOI. Turning to those studies that have attempted to estimate the level of multiple adoption practices econometrically most of them are limited with socioeconomic factors in investigating between adoption and non-adoption decision behavior. While, adoption behavior is also predicted and determined by other factors, like, perceived economic, psychosocial and perceived innovation attribute. Consequently, from a theoretical point of view, there is still a research gap in providing the formal integration of the economic, psychological, and technical aspects of attributes synthesized with socioeconomic variables to assess the level of adoption multiple CSA practices in the relevant models. To fill this gap, this thesis will apply an integrative framework for determining and estimating multiple adoption level by including the latent economic, psychological and perceived characteristics made from EUT, TPB and DOI as exogenous variables in the model along with a set of socio- economic variables and related studies (Joao et al., 2015), while CSA practices adopted by the farmer is used as the endogenous variables in the model.

In addition to theoretical literatures, there are still gaps in empirical literature on the adoption of CSA practices that contribute to the desired effect in Ethiopia. Despite this, few empirical studies (Mutyasira et al., 2018) have reported an empirical analysis of the factors influencing SAPs adoption using economic and non-economic or intrinsic factors among stallholder farmers' in Ethiopia. Most of the empirical studies focuses on the economic factors that adopt agricultural technologies (Admassie and Ayele, 2010; Aryal, Jat, et al., 2018; Kassie, Zikhali, Manjur, et al., 2009). Thus, this study seeks to fill the existing empirical literature by incorporating technological attribute, psychological stewardship, and perceived economic factors influencing adoption decisions.

1.4. Research Questions

The intent of this thesis is outlined in the following research questions:

1. Which factors from DOI, EUT, and PBT at most predict (made large variation) farmer's decision to adopt CSA practices?
2. Which factors of (perceived economic, psychosocial, and technological attribute) together with other socioeconomic factors most determine adoption of multiple CSA practices?

1.5. Objective of the Study

1.5.1. General Objective

The main objective of the study is to predict, and investigate the determinant of adoption of CSA practices using an integrative approach in Raya Kobo woreda.

1.5.2. Specific Objectives

Specifically, the study intends to:

- 1st. Show how variation of technological attributes and psychological factors predict adoption decision.
- 2nd. Identify the key determinants of adoption of multiple CSA practices using multidisciplinary approach.

1.6. Significance of the Study

Agricultural technologies have been extensively promoted to mitigate the effects of drought as well as improving agriculture productivity for over a decade. Despite widespread extension and investment on agriculture, climate smart technologies have been less widely used by farmers. Understanding adoptive behavior at the farm-level will offer a clear policy direction for supplementing the adoption of CSA practices, which will shift from conventional farming methods to more sustainable and climate adaptive agricultural practices. Such pattern of shifting scheme should critically examine the behavior of farmers from different angles for long term planning. Predicting and estimating the level of adoption behavior based on a multidisciplinary approach (TPB, EUT, and DOI) allows a somehow thorough study of what factors lead to significant changes in the way CSA practices are adopted. It is also highly valuable to leverage resources to facilitate this aspect and to provide empirical evidences for future policy campaigns and for researchers to focus on key features that matter to farmers.

Moreover, this study gives much credit for the unforeseen human behavior synthesized with the observed socioeconomic factors to examine the relationship between adoption decision level and examine the correlation among selected multiple CSA practices. Nevertheless, major limitation in the literature remains in stressing CSA practices and informing policy makers of the results of such understanding to. To the researchers' knowledge, no research is conducted in Ethiopia using an integrative framework in the decision to adopt CSA practices. In addition, this study seeks to add some value to previous efforts by reducing existing research gaps and satisfying the above research objectives.

1.7. Scope of the Study

The study is being carried in Raya Kobo woreda of Amhara region. The result cannot represent Ethiopia as a whole. The study connotes CSA approach in general, however, it is limited to only three selected CSA practices, namely: improved crop varieties (stress-resistance), organic fertilizer and excrement, and push-pull biological pest control; which creates a compelling need to ensure comprehensive integration of these effects into the local agricultural system in order to improve income at smallholder level. Since agriculture encompasses many different activities, the study

only focused on crop farming, while improved seeds are key inputs for improving crop yield and improving soil fertility through organic fertilizer, and control pests through push-pull strategies. When examining the adoption of agricultural practices, farm land is an important variable in this study. Therefore, individuals are excluded from the study who do not rely on land (either own or tenured land) for a living, but who are perceived as ‘farmers’ in the area. Lastly, this study is limited to a one –shot survey of cross-sectional data collected from respondents. Since the adoption is mainly a dynamic process, trends in overtime are not discussed in this study.

1.8. Organization of the Study

The study is organized under the following chapters. The first chapter starts with introduction and chapter 2 reviews theoretical and empirical literature regarding adoption behavior on CSA practices. In Chapter 3, suitable models were specified to analyze the study. The next chapter discuss the main findings of the study and the final chapter concludes and recommend policy implications.

CHAPTER TWO: LITERATURE REVIEW

Following, Feder et al. (1985) suggestions of theoretical studies allow to define adoption variables rigorously, to determine the exact relationship for estimation, to lead to a better understanding of the association among selection decisions, and consequently to adopt them simultaneously. This helps to decide appropriate determination for simultaneous adoption models and suggest hypotheses which can be-tested empirically. This chapter focuses on a review of both the theoretical and empirical literature on the concepts of adopting selected CSA practices and develops an integrated framework using TPB, EUT and DOI. The theoretical literature focuses on the basic elements of planned behavior, expected utility and diffusion of innovation, whereas the empirical literature focuses on some comparable empirical evidences on our selected CSA methods.

2.1. Review of Theoretical Literature

2.1.1. Why Climate Smart Agricultural Practices

Climate-Smart Agriculture (CSA) was launched by FAO in 2010 and has gained rapid and widespread interest and attention. FAO estimates that agricultural production needs to grow by 60 percent by 2050 to meet expected demands for food and feed (McCarthy et al., 2011). As a result, farming system must change itself to take care of the growing global population and provide the basis for economic growth and poverty reduction. Yet, environmental change will make this task more troublesome under the same situation due to adverse effects on agriculture, requiring spiraling adaptation and related costs (Lipper et al., 2014). Thus, the responsibility lies on CSA practices and techniques that sustainably increase productivity, support farmers' adaptation to climate change, and lessen greenhouse gases levels (James et al., 2012).

Climate-smart agriculture has become a powerful concept to focus on the climate change–agriculture nexus and has combined the agricultural system with climate change and development communities under one brand. Most researchers attribute climate adaptation strategies as CSA practices while others typically use the phrase SAPs. However, Neufeldt et al. (2013) refers in principle to the fact that only agricultural practices that encompass all components of the CSA should be branded as “climate-smart”, which is a triple win for all without regrets, losers and trade-offs. Consequently, in order to assess the global problem of climate change, we additionally name

the selected agricultural practices as CSA, disregarding the difference between SAPs and CSA practices where applicable.

In Asia and Latin America, under the banner of 'Green Revolution'², there was a dramatic increase in production in the 1960s and 1970s in the use of high-yield crop varieties, chemical packages and irrigation expansion. Despite a significant increases in agricultural productivity through extensive use of pesticides and fertilizers, it was recorded as unsustainable (Tey, 2013). However, significant progress was made at a significant cost. Soil quality has degraded, biodiversity reduced and pest resistance diminished (Kassie et al., 2009; Tey, 2013) and both the environment and human health at risk (Grainger-Jones, 2011). Still, it should be noted that merely exhaustive agricultural production that ignores environmental issues is no longer considered as sustainable practices. With an introduction of CSA practices, including natural biological inputs and process-dependent agricultural productivity and natural resources. Recent studies, Aryal, Jat, et al. (2018) suggested that the adoption of CSA approach was accepted as a way to address such challenges.

Most farmers in Africa's, where their farming systems remain with rain-fed, with insufficient technical inputs; small-scale or sustainable level is characterized by persistent poverty, lack of access to infrastructure and information, and challenges related to policy and governance. As a result, climate change is expected to have a significant negative effect on the livelihoods and food security of such ranchers (Girvetz et al., 2019). Studies in India by Ansari & Tabassum (2018) confirms that climate change may reduce national gross domestic product (GDP) by 8–10 percent by 2050, though there may be a significant reduction in adaptation activities in the agriculture system. Following this rationale, agricultural development is currently at the center of both research and policy communities (Neufeldt et al., 2013). This forces the emergency of climate smart agriculture, which was first used in 2009 (FAO, 2017) to increase global agricultural productivity, increasing resilience of farming systems and mitigating greenhouse gas (GHG) emissions.

² Green Revolution': Between 1970 and 2008 India and China increased their rice and wheat production resulted in spectacular achievements. For example, farmers increased cereal food production from 800 million tons to over 2.2 billion tons between 1961 and 2000. While an estimated one billion people were saved from famine and malnutrition. However, in many countries, decades of intensive cropping have degraded fertile land, depleted groundwater, triggered an upsurge in pests, eroded biodiversity and polluted the air, water and soil.

Furthermore, in Ethiopia as weather variability and changes in climate have continued to affect the agricultural sector, people's livelihoods and the wider economy, the CSA approach has gained significance institutional and policy attention over the years to reduce climate impacts and to help build an extra resilient, food-secure and economically competitive agriculture sector (Gelaw, 2017).

2.1.2. Current Adoption of CSA Practices in Ethiopia

Climatologically, Ethiopia has a very irregular rainfall distribution, which is exacerbated by climate change. Given the limited change in the economy and the reliance on rain-fed agriculture, Ethiopia's development prospects is closely associated with climate (Fentie and Beyene, 2018). Moreover, the dominance of rain-fed agricultural systems and challenges related of adopting climate friendly agricultural practices exacerbate the situation. In addition, climate smart agricultural farming practices have been limited in different countries (Aryal, Jat, et al., 2018; Chalak et al., 2017; Tey, 2013) and likewise, Ethiopia is remained below expected level (Gelaw, 2017; Teklewold et al. 2013). Thus, adoption of a sustainable farming system is one of the policy options to mitigate the negative impact of climate change, which aims to increase sustainable agricultural production by adapting and building resilience to climate change (Aggarwal et al., 2018).

Over the past few decades, Ethiopia government has set up various policies and strategies aimed at helping to adapt climate change, as well as supporting sustainable development. Such agricultural practices include integrated watershed management, integrated soil fertility management, agricultural conservation, crop residue management, composting, promotion of improved livestock grazing and rangeland management (Jirata et al. 2016). To support the green economy, several initiatives related to CSA and climate change have been undertaken in Ethiopia. Some of these initiatives include Managing Environmental Resources to Enable Transitions (MERET), Productive SafetyNet Program (PSNP), Sustainable Land Management (SLM), Climate Resilient Green Economy Strategy (CRGS) and Climate Smart Initiative (CSI), aimed at conservation and afforestation practices. The REDD+ project to reduce emissions from deforestation and forest degradation and Push-Pull strategy designed to reduce striga and stalk borer infestation of crops with Napier grass were launched recently (Jirata et al. 2016), a mechanism to improve fodder and for biological control of weeds and pests. These initiatives

encourage farmers to introduce different innovation system, such as appropriate methods of fertilizer application, improved seeds and biological pest and diseases management. In many cases, however, these methods have not featured climate- friendly agriculture innovations as a mechanism for addressing issues on climate change and variability problems.

2.1.3. Innovation Adoption System and Theoretical Framework

As farmers adopt technology, the agricultural system continues innovatively. This is a typical occasion in which farmers do not adopt innovations at the same time as they appear (Diederer et al., 2003). On the contrary, they may not adopt a single practice to boost production. As a result, not all the potential farmers adopt new technologies that have better qualities than their predecessors. Farmers often compare technology/ practice with conventional one and adopts it if the expected utility exceeds the traditional (Adesina & Zinnah, 1993). Consequently, the issue of adoption of new technologies is fundamental for agricultural development (Edwards-Jones, 2006). Knowing the factors that impact adoption will allow for development of strategies, policies and plans that exploit the main implication of adoption of appropriate practices. Shea et al. (2018) reported that technology adoption researches through a better understanding of the individual adoption decision helps policymakers better understand climate variability and their ability to adapt to climate change.

Adaptation to climate change is not a new process, even if different strategies are adopted. According to (Fentie and Beyene, 2018), adaptation is a complex phenomenon comprising different practices that may play an important role in reducing the food insecurity of farm households. There are various measures on a fundamental level farmer can adopt as supplements and substitutes to address climate change and other overlapping production restraints. Farmers also gave constant applause to adapt to the irregularities of climatic conditions. Predicting farmers' behavior and understanding the decision to adopt different mechanisms for climate change adaptation can help to assess the importance of strategies in the event of future climate change. Thus, the study is guided by an integrative framework encompassing elements of DOI, TPB and EUT of non-socioeconomic factors (that is, psychological, perceived economic and innovation attributes) jointly with farmers' socioeconomic features to address adoption as a complex behavior.

Previous efforts lacked theoretical support to enable sufficiently a comprehensive review. Adoption of CSA practices is a specific type of behavior like other types of social phenomena and become apparent through perceived character of practices and expected economic profit and behavioral intention towards the actual adaptation behavior. Adoption of agricultural practice research uses a number of theoretical frameworks and methodologies to better understand the adoption decision behavior at farm level. Although such research is not limited to a single framework (Shea et al., 2018), there are several theoretical literatures on personal decision-making behavior in different disciplines. Studies on the acceptance of innovations often ignores the basic psychological constructs that influence farmers' choices behavior, for example, attitudes³, perceptions, social norms, and intention⁴. Yet, integrated theoretical models have been used in different disciplines. For instance, (Mutyasira et al., 2018; Tey 2013) applied an integrated behavioral model to predict the adoption of sustainable agricultural practices. In addition, Tey (2013) argued that the collective findings of different studies suggest that their adoption is the result of multi-dimensional considerations of socioeconomic, agro-ecological, institutional, informational, and psychological factors. Consequently, this study provides a unified framework for the adoption of CSA agricultural practices in which TPB, EUT, DOI and other socioeconomic parameters are integrated to influence the decision to adopt. In this integrative framework, it tries to apprehend farmers' psychological constructs from the theory of planned behavior (TPB), perceived characteristics of innovation from DOI, and expected economic profit factors from the theory of expected utility (EUT) of traditional economics are used together for investigating farmer's decision-making behavior for adoption of CSA practices.

2.1.3.1. Diffusion of Innovation (DOI) and Expected Utility Theory (EUT)

Diffusion⁵ of innovation (DOI) has been addressed for almost 60 years (Rogers, 2003). DOI's Rogers theory seeks to provide a theoretical basis for understanding the perceptual characteristics of innovation. According to Rogers, an innovation may not be a recent invention, apart from its widespread adoption, the form in which it is recognized or made available is new to farmers of the

³ Attitude refers to individual's way of thinking or feeling; a self-evaluation, either positive or negative, of performing a behavior.

⁴ Intention refers to the likelihood of taking-action to perform a specific behavior.

⁵ Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system.

present generation except it is widely adopted it will fail to make any effective social or economic impact. According to Rogers et al. (2004) the perceived characteristics of innovations are formed by four attributes (*compatibility, complexity, trialability* and *observability*)⁶. Also, Rogers et al. (2004) suggests that the less compatibility and the more complex an innovation, the more difficult it is for potential adopters to incorporate it in to their lifestyle, which is the farming system in this case.

CSA practices must be compatible with existing farming systems, less complex, easily verifiable and observable. The farmer's choice of technology (refusal) refers to the optimal decision from the farmer's perspective on the appropriateness (non- appropriateness) of the characteristics of the technology under investigation (Adesina and Zinnah, 1993). In addition, Adesina & Zinnah (1993) and Ansari & Tabassum (2018) provide strong evidence that farmers' perceptions of agricultural technology determine observed adoption choices and significantly influence adoption behavior of farmers. Accordingly, omission of such factors in the adoption models may confuse the outcome of key factors that determine the farmer's choice for adoption. From the technical standpoint, farmers' perception of using technology must be taken into account in evaluating the determinants of adoption decisions for agricultural innovation. Thus, the three attributes of technology: compatibility, complexity, and trialability are displayed as precursors technology characteristics.

The EUT concept is used to clarify decisions in terms of economic value; for example, usefulness, cost and risk of introducing certain technologies associated with agricultural innovations. Joao et al. (2015) found that farmers' choice decisions are studied by two main methods: one based on simple economic models, where EUT plays a central role, and the other approach based on ideas from socio-psychological theories. This is where psychological constructs make it clear to farmers' behavior. EUT's main assumption is that farmers seek to maximize their income. This theory will be used to study the innovations necessary to increase profitability by increasing profitability and reducing the costs and risks of implementation and innovation. Utility theory is used not only to

⁶ *Compatibility*, which refers to degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters; *complexity* refers the degree to which an innovation is perceived as relatively difficult to understand and use; *trialability* describes how easily potential adopters can easily trial innovations, and *observability* is the extent to which the results or benefit of using an innovation are visible to potential adopters.

explain the introduction of innovation that anticipate to increase profitability with one hand, but also to adopt sustainable agricultural practices (Mutyasira et al., 2018).

Utility is extremely difficult to use in a more practical manner because it is more difficult to measure in real world situations (Edwards-Jones, 2006). however, economists say that money can work to such an extent that any change in innovation/ practice affect the usefulness of individual. When farmers value utility as much as possible, profit is used as a substitute for utility (since actual utility is so difficult to measure) hence the rationale for maximizing farmer Abadi Ghadim & Pannell (1999) assume expected utility of profit, instead of expected profit. Thus, observable variables between CSA practices (such as consideration of usefulness, risks, and costs associated with the innovation) are formulated as linear functions of vectors.

It is expected that sustainable agricultural technologies and methods will be used if farmers achieve more and more stable income and consumption opportunities (OECD, 2001). A study from Lebanon (Chalak et al., 2017) showed that farmers who find conservation agriculture useful prefer large areas of their land. Thus, technological features, such as visibility of results, are useful for meeting existing needs and low capital investment promotes its final adoption and should be taken into account in technology transfer (OECD, 2001). Hence, in our model, we can expect a number of studies that the farmer's perception of the usefulness of a particular technology is one of the most important factors influencing his/her adoption through its direct impact on economic utility of profit. Furthermore, the transition from of conventional to CSA practice can also be determined by the costs and risks associated with certain practices. In any case, a rational decision maker is a profit maker and at the same time reduce its costs. Accordingly, SAPs should lead to profitability or at least long-term economic stability in farms to ensure smooth transformation (Tey, 2013). Many farmers can easily switch to organic technologies with very low entry costs (Kelley and Läpple, 2010).

Furthermore, the perceived risk of introducing conservation practices was seen as a major barrier to adoption in the African situation (McCarthy et al., 2011). Risks and uncertainties affect adoption behavior, with some farmers avoiding adoption and disliking it, while others are willing to take it. With this justification, Abadi Ghadim & Pannell (1999) argued that the adoption of innovations with relatively high risks and uncertainties would be less likely or limited. Risk aversion generally

negatively impacts the speed of adoption, given that high uncertainty is a common feature of innovation before it is tested. To this end, the attributes of agricultural innovation are not only affected by their compatibility, complexity, trialability, and observability. But also, about the economic perception of usefulness, risk and cost. To avoid redundancy, it contains a component of recognized attributes (observability) and is merged under perceived economic usefulness component.

2.1.3.2. The Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) was first proposed in 1985 by Icek Ajzen in his article "From intentions to actions: A theory of planned behavior". This theory was, in fact, an extension of the Theory of Reasoned Action (TRA), proposed by Martin Fishbein with Icek Ajzen in 1980 (Ajzen I., 1991). The TRA seeks to explain behavior through behavioral intention based on attitude and subjective norms under the control⁷ of the will. However, the TPB solves the issue of incomplete volitional control over the behavior in question and therefore adds another component - perceived behavioral control. Behaviors that is not completely under volitional control does not lead to goal achievement, either because of a change in intention or because the performance of the behavior cannot be achieved. A good example is that a farmer who intends to apply a certain farming practice may not accept it for several reasons, or change his intentions, or, when he tries, may not to achieve his goal. Since adopted behavior is not an easy task in itself, for example, we like grab a coffee all the time and act under voluntary control. A closer look reveals, unlike TRA, that even the most mundane action, which can usually be done (or not) at will, are sometimes influenced by factors beyond one's control and we can never be absolutely such that we will be able to achieve our intentions.

Understanding certain contextual characteristics (personal attitude, subjective norms, and perceived control of behavior⁸) can help explain and predict an individual's behavior in relation to adopting CSA practices. While many people may initially find that these psychological and social dimensions are important in bringing changes in agricultural practices, many economists have not

⁷ Volitional control refers to circumstances which are under individual control and can be performed with no need of special skill or ability. Like we do things, simply if we want.

⁸ Behavioral beliefs refer an individual's perception of a behavior and its likely consequences.

really taken these dimensions into consideration when addressing climate change adaptation and traditional agricultural practices. This greatly reduces their chances of success, especially in the long run. This study, however, lists some of the major social and psychological factors that play the role of farmers in adopting CSA practices in line with Ajzen's TPB and hypothesis the study.

Generally speaking, a person who believes that performing a given behavior will have fundamentally positive results will have a favorable attitude towards the behavior, while a person who believes that his behavior will lead to a negative outcome there will be an offensive attitude towards it. Beliefs that strengthen a person's attitude towards behaviors are called behavioral beliefs⁹. The attitude of potential adopters is an important factor influencing this decision (Shea et al., 2018). We therefore expect a positive Correlation between a positive attitude and behavior towards adoption decision.

In the same context, it is also assumed that subjective norms¹⁰ are a function of beliefs, but beliefs of a different kind of beliefs, i.e. individual beliefs or certain individuals or groups that believe they should or should not behave. These beliefs under the subjective norm are called normative beliefs (Ajzen, 1985). The ultimate harbinger of intent, behavior control, relates to the degree to which a person believes they control a certain behavior (methods of adoption). Planned behavior theory suggests that people intend to enact certain behaviors if they think they can do it successfully. While positive attitudes and social pressures motivate a farmer to adopt the CSA practices, the farmer may lack knowledge, skill and adoption ability. Hence, the individual farmer behavior does not achieve the intended goal. According to Ajzen (1991), perceived control can have a direct effect on behavioral intention. As a result, we can expect farmers with social pressure from expert, friends, families and neighbors to do things, and good skills and confidences are likely intending to be aimed at adopting them.

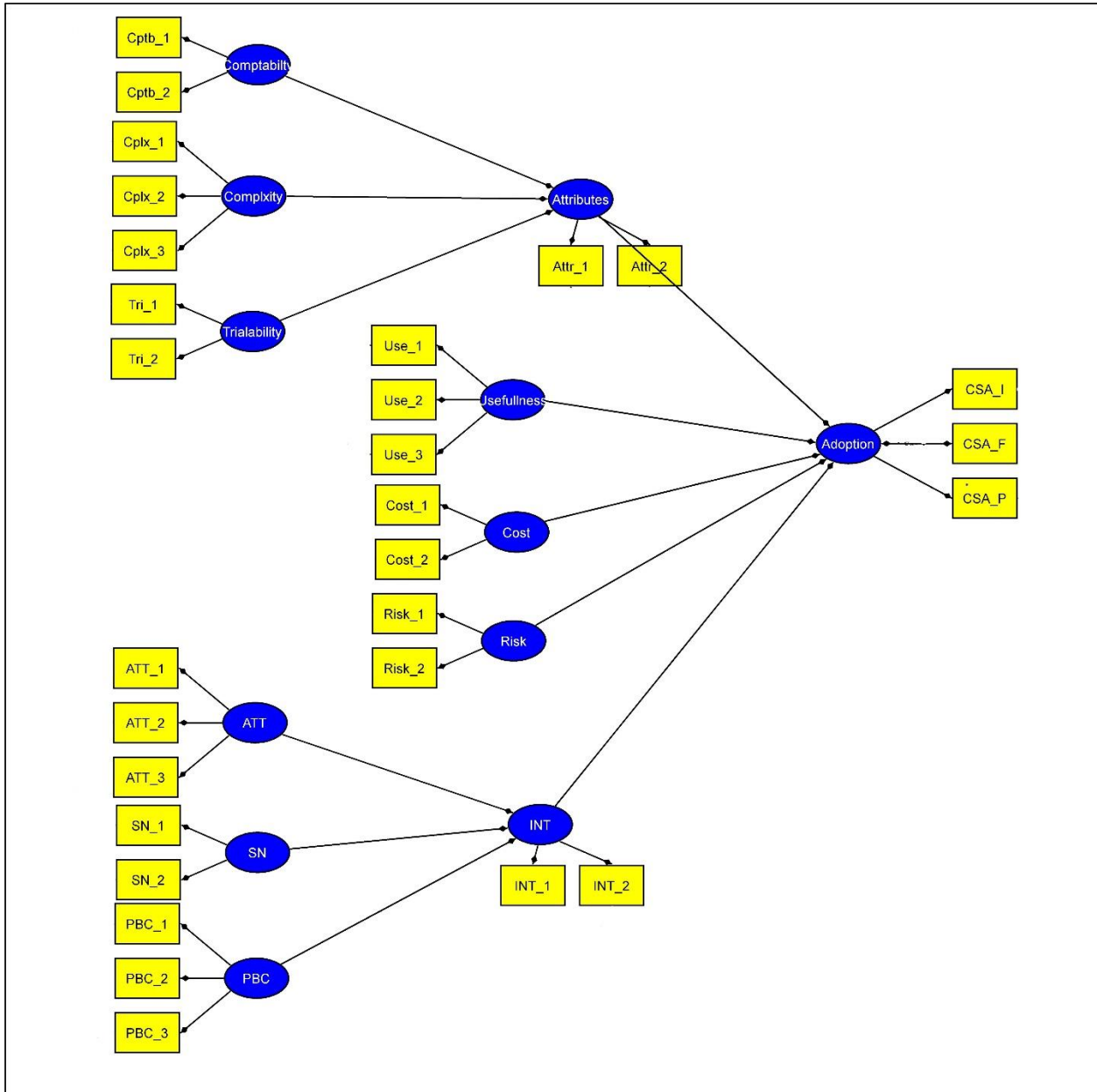
In this study, the farmer's behavioral objective is taken into accounts as per the farmer's expectation when adopting CSA practices. In general, the motive for adopting a practice is stronger when the attitude and subjective norm are more favorable and when the control behavioral is

greater. Thus, we expect that a strong behavioral objective from the farmer increases the likelihood of using CSA practices.

2.1.3.3. Integrated Framework Development

Although TPB provides a general framework to explain behavior, it has been criticized in some cases that other factors could be included to fully improve prediction comprehensively (Ansari and Tabassum, 2018). So, previous studies have called for new perspectives on the adoption of sustainable agriculture adoption studies that focus on the perception of innovation and economic factors, as well as the attitudes of farmers. Following this consensus, the basic theories of DOI, TPB and EUT were used to create an integrated model that is a good predictor of adoptive behavior. This framework integrates various factors such as perceived compatibility, complexity, and perceived trialability to influence the attributes of innovations that are synthesized with economic values such as the perceived usefulness, risks, and costs of technologies that influence adoption behavior. While the attitude, the subjective norm and the behavioral control constructs (beliefs) of the farmers influence the intention of the behavior towards an adoption decision. Thus, the elements of DOI, TPB and EUT together form an integrative framework, which is estimated in structural modeling to allow better prediction of farmer adoption behavior, are of increasing importance in the agricultural sector. It also explains the adoption decisions as a dynamic process, assuming a complex interaction of groups of variables coming from both theories. The combination of DOI, EUT and TPB overcomes some restrictions that arise when just one theory is used to study the adoption decision.

Figure 1: Integrative Model.



Source: Own Formulation

Figure 1 above shows a unified model developed using SmartPLS 3 software for the study based on the principles of DOI, EUT, and TPB forming measurements and structural models which will be estimated using the PLS-SEM (Partial Least Square Structural Equation Model). The measurement model is characterized by an external relationship between the yellow and blue colors. Yellow rectangular colors reveal variables for which respondents responded in a

reflective¹¹ manner on the Likert scale. For instance, Cptb_1 represents the questioner “as to whether climate – friendly farming agricultural practices are compatible with all aspect of farming experience.” While the structural model is only shown by the inner relationship between the blue colors. For example, characteristics of innovation may be due to their perceived compatibility, complexity, and trialability. In the same way, the behavioral intention of farmers is influenced by personal attitudes, subjective norms and behavioral control. Since individual utilities are difficult to measure directly, the study uses perceived economic variables, namely, the usefulness, risks, and costs of presenting technologies that directly influence the decision to adopt. Figure 1 therefore shows that adopting CSA practices predicts farmers’ behavioral intentions, technical characteristics, perceived usefulness, perceived risks, and perceived costs of adopting technology.

2.2. Empirical Literature Review

The theoretical models discussed so far suggest a number of important concepts regarding to the adoption of CSA farming practices and have shown that it is determined by key technical features, economic and psychological factors. Most climate-based farming methods have long been practiced, while others (improved crop varieties, organic fertilizers and pest control) have recently gained traction in Ethiopia, particularly in the study area. Despite the benefits of CSA’s economic and climate change adaptation, its adoption by farmers is diverse and relatively limited.

2.2.1. Exogenous Variables

The need for chemical fertilizers and pesticides can be reduced by adaption to climate change, insufficient rainfall, and improved varieties of crops resistant to pests and diseases. This will increase crop yield and reduce crop losses due to pests and diseases during adverse weather conditions (Jirata et al. 2016). This can increase crop yield and quality of harvest; reduce crop losses due to pests and diseases during adverse weather conditions (Gelaw, 2017). On the other hand, adoption of organic farming in the semi-arid region of Ethiopia (Kassie et al., 2008) has led to the use of compost compared to chemical fertilizers, in comparison, the use of compost has shown a clear advantage. Furthermore, the use of high yielding, stress-tolerant seed varieties/breeds, and better management practices have stabilized and increase agricultural

¹¹ In reflective case the latent variable is considered as the cause of the manifest variables because the manifest variables are “reflecting” the latent variable.

productivity even under adverse production conditions. A study in India (Khatri-Chhetri et al., 2016) has confirmed that farmers can increase the net farm yield of farms by INR¹² 15,712 ha⁻¹ yr⁻¹ through improved crops in rice–wheat system. Such a cropping system reduces the risk of complete crop failure, given the next crop the benefit of rotation as it can help increased soil nitrogen through biological nitrogen fixation (FAO, 2017). Another new technology that will be useful in controlling the weed parasitic *Strega* in corn and sorghum fields and which has been tried to be adopted and implemented is the push–pull technology. Rapidly dry and hot conditions associated with climate change, as well as to identify, test and select new drought-tolerant crops and plants that can be incorporated into the push–pull system (Jirata et al., 2016). The contribution of this CSA practice, using a variety of organic pest control methods in addition to legumes, cover crops and green manures, has doubled the bean and groundnut yields in western Kenya from 300 to 600 kg per hectare (Kassie and Zikhali, 2009).

2.2.2. Endogenous Variables

Social and economic factors influencing adoption decisions include the characteristics of farmers and farms, organization and credit; and an understanding of technical and psychological factors. Although the characteristics of the farmer, such as the age of the farmer is an important factor, even though, there is no black and white results have been found in the empirical literature; many agricultural technology adoption studies revealed conflicting results of age in adoption effect. Some empirical studies have shown that age is negatively associated with adoption. Thus, younger farmers are more likely to adopt new and/ or early adopters of sustainable farming (D’souza et al., 1993). Similarly, Kassie et al. (2008a) has also had a negative and significant effect on the possibility of adopting conservation tillage as well as combining it with compost, where younger farmers are more likely to try with newer innovations than older farmers. On the contrary, another researcher argues that even if older farmers often have short-term planning horizons in the face of energy shortage and high risk, they are more experienced with farming methods and often more accumulation of physical and social capital. National studies have also shown that such attributes can be considered as an opportunity to promote organic farming (Soltani et al., 2014). Others argued that decision to adopt the average age of the household head has no effect, although the

¹² INR- is an Indian Rupee currency used as a medium of exchange, equivalent with 69.70INR=1\$, in the 2019 exchange rate.

was a positive relationship with the adoption conservation agriculture status of the households (Mlenga, 2015). From these empirical studies, the results are inconclusive, but we can expect that the younger the farmer the more likely he is to adopt CSA practices.

The gender differential between household heads is also an important explanatory variable in the study of adoption decision, as female farmers are often overlooked in agricultural statistics. However, as they play a key role in the agricultural system, it is important to consider the adoption study to what extent a new technology reaches women farmers. Admassie & Ayele (2010) found that women-led households are usually less likely to adopt new technologies. In view of this, due to cultural norms and traditions, male heads have more access to information to use innovation than female heads, it is likely that men adopt practices than female heads. In line with this, a study by Melesse (2018) concluded that have a women with a head has a negatively impact on decisions to adopt technology. Thus, we can expect male farmers to be more likely to adopt the CSA approach.

Education is believed to increase the probability of access to information and various studies have confirmed that it has a positive impact on technology adoption. For instance, Aryal, Rahut, et al. (2018) and D'souza et al. (1993) examined the adoption of CSA practices and found that educated household heads with at least school education have more ability to access and process income and new information from non-farm agriculture. In addition, Melesse (2018) strongly argues that education has a positive and significant relationship with adoption of agricultural technology, as education has the potential to change farmers' knowledge, skills and attitudes.

Households are seen as a source of labor and the family size can be used an alternative to the availability of HH labour. The size of farming families, particularly the active labour force, including hired labour, are engines to agricultural activities and issues related to adoption decisions (Fazio et al., 2014). Most agricultural activities in Ethiopia are labor intensive and capital input is limited, which underscores the need to shift from traditional to CSA practices. CSA practices such as making manure and compost require manpower. Farmers can use the available labor for the production and use of organic manure or use additional labor to improve soil fertility. Mlenga (2015) results show that members of households that contribute to agricultural work were 1.65 times more likely than households to initiate conservation agriculture. Similarly, Admassie &

Ayele (2009) found that the coefficient of agricultural work represented by household size is statistically significant and has a positive association with technology adoption. Therefore, we hope that the decision to adopt CSA practices on a large scale will have a positive impact.

The number of migrated HH has a strong positive impact on remittances in several studies and provides evidence of an increasing debate on the role of migration and remittances in productive agricultural investments in the homeland with immigration background (Kpadonou et al., 2017). Although immigration reduces household employment, it improves access to alternative sources of income. Therefore, migration is believed to facilitate the adoption of CSA.

The characteristics of the farm (size of agricultural land) affect the adoption of CSA practices. Better access to the plot increases the probability of adoption as it affects the availability of innovation. Empirical evidence validating this hypothesis is inconclusive because of a measurement problem, and several studies found no significant differences between landlords and tenants (Feder et al., 1985). On the other hand, the tenure of unsecured land can present an additional risk for the farmer who invests long enough to get a positive return on investment in sustainable land management (McCarthy et al., 2011). When it comes to renewing agricultural leases, farmers expect not to receive it and this will result in the termination of farming activities on those lands and reduce the likelihood of adopting SAPs (Tey, 2013). The size of the is an indicator of the level of economic resources held by the farmer. Some studies (Mutyasira et al., 2018) have shown that farm size has a negative effect on the number of SAPs adopted by farmers. However, many researchers have found that farmers with a larger farm size will be more likely to adopt a new technology. For instance, (Admassie and Ayele, 2010; Aryal, Jat, et al., 2018; Teklewold et al., 2013) found that farm size was strongly and positively related to technology adoption.

off-farm activities (Fentie and Beyene, 2018) can increase family income and influence households adoption decisions. Access to off-farm income has also had positive impact on the number of SAPs adopted by farmers, although its minor effects have been minimal (Mutyasira et al., 2018). Fazio et al. (2014) concluded that off-farm income has given farmers the financial flexibility to turn to sustainable practices than who are being economically affected farmers. On the other hand, the possibility of a farmer having off-farm employment is negatively associated with his or her

decision to adopt CSA. Its inverse relationship suggests a trade-off between farm efforts and off-farm incomes, as this extra income reduces farm work time as well as diminished mental and physical abilities for farming adoption of SAPs (Tey, 2013).

Livestock in Ethiopia is important as a source of social protection, food and nutrition security and a source of income for the country (Gelaw, 2017). The positive contribution of livestock to sustainable farming practices is most likely due to the increasing availability of traction for animals (Mutyasira et al., 2018). Many empirical literatures found that similar results from families with more livestock were more likely to use CSA practices (Aryal, Jat, et al., 2018; Teklewold et al., 2016). Wealthy households may have the necessary resources to take appropriate adjustment measures (Teklewold et al., 2016). On the other hand, Tropical Livestock Units (TLU¹³) were quite negative and only somewhat associated with the adoption of CSA practices. As the animal size increases (an equivalent increase in weight of livestock), farmers have to devote more time on livestock management. Both of these explanations suggest direct competition between livestock and farming (Tey, 2013). However, TLU had a positive and significant effect on the number of SAPs offered by farmers; where there is an increased likelihood of household adopting two or more SAPs (Mutyasira et al., 2018). Livestock ownership also has a positive effect on farming because animal waste is the main source of manure for small farms in most parts of Ethiopia (Teklewold et al., 2013).

The conventional wisdom is that limitations to the adoption process include the lack of credit and a number of studies have found that lack of credit, and several studies have shown that lack of credit is a major factor limiting the adoption of technology, such as high-yield varieties (Feder et al., 1985). In Ethiopia, access to credit in rural areas is generally low, and commercial bank coverage in these areas is low: about 1% of the rural population has a bank account (Gelaw, 2017). Therefore, the availability of credit should have a positive impact on the adoption decision. The results confirm the importance of credit and labor restrictions to prevent the adoption of CSA practices (Lipper et al., 2018). This result was inconsistent with (Aryal, Jat, et al., 2018), where access to credit has a negative and significant effect on the CSA practices used. Since credit taken for agricultural purposes is often used for other social purposes, for example, to cover marriage,

¹³ Tropical livestock unit (TLU) standardizes the body weight of livestock: one TLU is equivalent to 250 kg of live weight (FAO, 1999).

dowry and medical expenses. On the other hand, a study by (Mutyasira et al., 2018) revealed that the variation in the adoption of SAPs by farmers due to access to agricultural credit was (20%), which shows the influence of decisions of SAPs implementation in their farm. The influence of incentives or rewards can have an important effect on the behavior change of farmers. Direct financial incentives or input subsidies to adopt particular behaviors are often necessary because there is a cost associated with the change (Rose et al., 2018). The evidence available to date suggests that in most cases potentially CSA practices in SSA smallholders' have not effected or reduced the use of input subsidy programs (Lipper et al., 2018). However, their study in Malawi was identified that the input subsidy program (ISPs) system provides a potentially useful means of promoting comprehensive integration and farmer behavior that enhances CSA practices and contributes to climate resilience.

The agricultural advisory service also greatly improves the adoption of CSA practices (Aryal, Rahut, et al., 2018). We therefore expect that farmers with less extension services will use the CSA method less. In Ethiopia, recent studies (Kassie and Zikhali, 2009) have found that use of agricultural advisory services has a positive effect on the introduction of CSA methods, especially compost, and reduced farming. Studies conducted by (Admassie and Ayele, 2010; Mlenga, 2015) also showed that the introduction and uptake of new technologies was influenced by the farmer's contact with the advisory services and was significantly influenced by the decision-making advisory services.

As noted earlier, in addition to socioeconomic factors, elements of non-socioeconomic factors of perceived attributes of innovations are believed to affect adoption behavior. This is done through subjective evaluations of the relative compatibility, complexity, and trialability of agricultural innovation. These characteristics of innovation are subjectively perceived before adoption. Empirical studies (Tey, 2013) consider SAPs to be compatible with farmer behaviors, physical farming conditions and acceptance of agricultural operations; easy to understand and use (less complex); and is practically designed on a divisible basis (trialability). Fifty-eight articles showed a history of compatibility, complexity, and trialability, with a propensity for adoption by meta-analysis (Weigel et al., 2014). They found a positive correlation of compatibility (0.43), and complexity (0.32), and with a negative correlation of trialability of (-0.27). If farmers subjectively

assess the characteristics of the innovation that are less complex and compatible, and consistent with their farming system, it will probably be more adapted.

Perceived economic usefulness is also important in determining the economic viability of sustainable agriculture. The profitability of sustainable agriculture practices (both in the short and long term) affects their wider diffusion (Kassie and Zikhali, 2009). On the other hand, the perceived risks of adopting decisions are highly influenced by the changing conditions of the agricultural economy. For example, (Fazio et al., 2014) shows that farmers do not want to risk they may lose money if labor and input costs are high. Also, good prices for conventional products reduce financial risk by increasing profit potential, thus reducing the incentive to adopt sustainable practices. Similarly, farmers' perceptions (actual or perception) of costs negatively impact the adoption of the CSA approach. According to Nowak (1991), farmers cannot adopt sustainable practices because they are either unable or unwilling, "unable" referring to expenses. This means the costs and costs associated with adopting practices that farmers cannot afford, and "unwillingness" means refusing to take actions with the risk of negative financial consequences (Fazio et al., 2014) .

TPB has received considerable attention in the literature. A meta-analytic review by Armitage and Conner (2010) found that TPBs accounted for 27% and 39% of the variance in behavior and intention, respectively. While the PBC construct showed significant differences in intention and behavior. It is also generally said that SN construct is a poor predictor of intent. A study on farmers' motivation to adopt SAPs (Menozzi et al., 2015) showed that attitudes, subjective standards, PBC and other characteristics of farms with an objective of at least 55% and 81% of the variance in the intention, respectively, to maintain the arable land as an ecological focus area. Empirical data show that attitudes have a significant effect on farmers' adoption decisions when they are included as descriptive variables in the adoption study (Shea et al., 2018). Similarly, Mutyasira et al. (2018) found attitudes and individual norms that influence the adoption of SAP by small holder in Ethiopia.

On the other hand, the influence of other people on the individual behavior of farmer has also been observed very often, and the behavior farmers is sensitive to a range of social pressures. Studies have shown that the opinions of family members, friends, peers and counselors have a major

influence on the decision-making behavior of farmers when adopting. The study suggested that behavior is not only influenced by individual traits, but rather is also heavily affected by family, peer, and counselor networks (Rose et al., 2018). Likewise, Mutyasira et al. (2018) found that personal norm is positively and significantly related to the number of SAP adopted by farmers. Furthermore, when a person has a high PBC, they have an increased confidence that they can successfully perform the specific behavior (Icek Ajzen, 1985). Rose et al. (2018) reported that farmers feel that they are being told what to do rather than being in control, or that they do not have the skills, knowledge or practical conditions to do so when implementing a management practice, the action unlikely to take place. Farmers must therefore be sure that they can adopt a certain behavior. As a result, PBC also directly affects the adoption behavior of farmers. Mutyasira et al. (2018), in their estimate of the path coefficients of the inner model, suggest that PBC has the strongest influence on farmers' intentions to implement SAPs (0.51), followed by ATT (0.26), and SN (0.03). Therefore, PBC of a farmer is a moderately strong predictor of farmer's intentions to adopt SAPs.

In general, the intention of an action is stronger when the individual is positive, faces favorable social pressure, and trusts in their ability to perform a particular action behavior (Fishbein and Ajzen, 2009). However, the stronger the will to carry out the behavior, the better its performance would be. Yet, since we do not have full control over social consequences and implementation, attempting to perform the action may not necessarily result in the actual action (Kelley and Laple, 2010). In contrast, many studies have confirmed a high correlation between attitudes and subjective norms to behavioral intention and subsequent behavior. For instance, Borges (2015) found that farmers' intentions to perform certain actions were mainly correlated with their subjective attitudes and norms, and less with perceived behavioral control.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1. Area of the Study

The research area, referred to as Raya Kobo woreda, is located in Amhara Region of north Wollo zone. It is part of the Great Rift Valley, located in an area of 185,262 km², 1360-3000 m asl, surrounded by Tigray and Afar regions from the north and east, respectively. The average annual rainfall is 500-800 mm. Long rains begin in late July to late September. Teff, maize and sorghum are the most common crops, and small-scale irrigation projects produce cash crops such as mangoes, onions, tomatoes, and other vegetables. The average annual yield is about 249,731 quintals of teff, 22,540 quintals of maize and 362,682 quintals of sorghum (Raya Kobo WAO, 2019). The area was chosen because of its high potential for food production, but it is under threat of high temperature and massive soil erosion, causing the area the most drought prone. Thus, this study is an excellent case study for investigating the adoption of CSA practices by farmers.

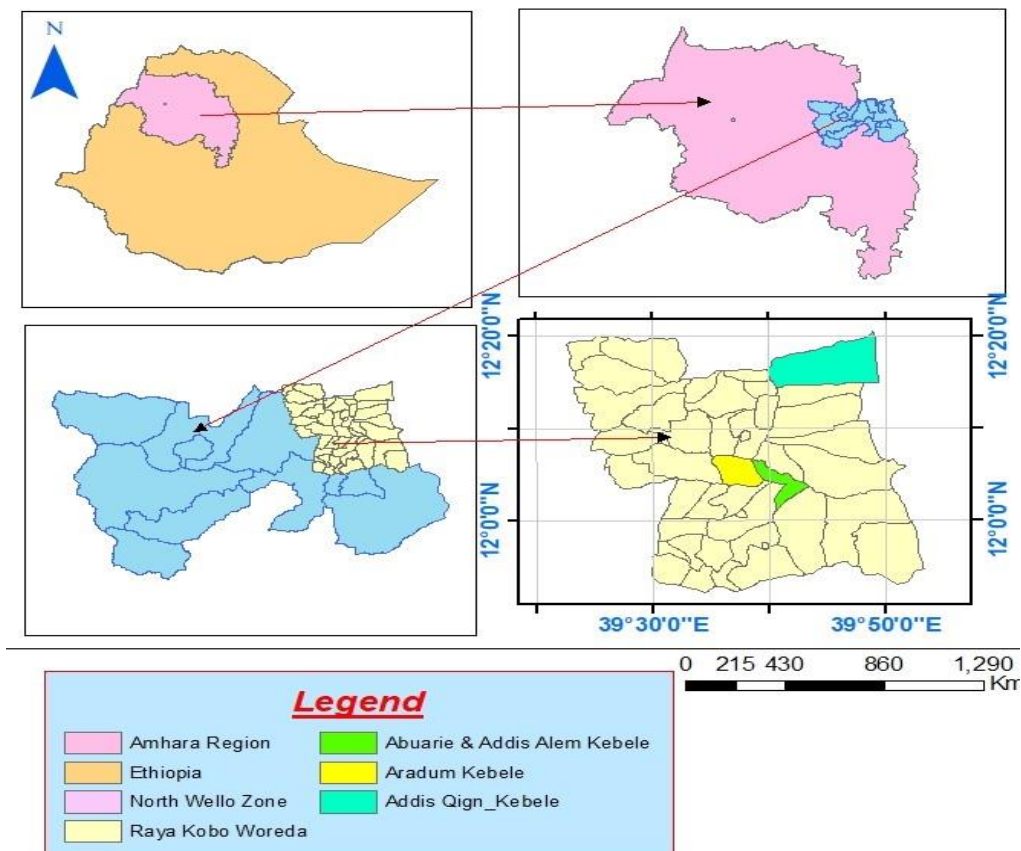


Figure 2: Map of the study area

There are 43 rural and semi-urban kebeles in the woreda, however the survey was studied in only asl, surrounded in four kebeles, namely Aradum, Addis kign, Addis Alem and Abourie, which rely more on agronomic practices, where agricultural production is predominantly a potential source of livelihood for the adjoining areas. For these reasons, it has become an important research area for CSA practice to investigate what adoption factors to improve household farm productivity and address climate change effects.

3.2. Sampling Techniques

Multistage sampling methods were used to select farmers who provide information survey participants. The first phase, out of 43 homogenous kebeles, four kebeles have been deliberately selected, which are suitable for agronomic practices through discussion with the experts of district's agricultural department. The second step involves determining the sampling size based on Kothari (2004), taking into consideration the nature of the population, degree of accuracy, and type of study. This method allows a margin of error and an accuracy level of 0.045454545¹⁴, and estimated under the 95% confidence interval. Kothari formula is appropriate when the population is finite. From this the ideal sample size can be calculated based on the exact level of traits present in the population, the desired level of confidence, and the estimated ratio. The Kothari formula is as follows:

The Kothari formula is given by:

$$n = \frac{Z^2pqN}{e^2(N - 1) + Z^2pq} \dots \dots \dots (1)$$

Where:

n = sample households

Z-value is the desired confidence level of 95% found in a Z table (=1.96).

p is the (estimated) proportion of the population which has the attribute in question (0.5),

q is $1 - p$ (0.5); N is the total number of households in the four administrative kebeles and;

e is the desired level of precision (i.e. the acceptable error) ($e=100/22*0.01=0.045454545$), this was calculated based on having at least 22 independent variables in the regression analysis.

¹⁴ 0.045454545, shows the level of precision (acceptable error), $e=100/22*0.01$, based on at least 22 independent variables are used in the regression analysis.

Using this formula, a total sample size of 433 households was obtained. And a proportional sampling method was used to obtain the exact number of respondents from each kebeles. This means that the total number of households in each community was divided by the total number of households multiplied by the total population of the study area (5952) and the total sample size (433). The study is based on primary data collected in 2012 EC on four selected kebeles based on 2011 EC agronomic activities. As shown in Table 1 below, 129 sample households from Aradum, 28 from Addis Alem, 62 from Abourie and the remaining 214 from Addis Kign were selected according to their respective household size.

Table 1: Sample size distribution

Kebeles	Total Household			Total Sampling	Percentage
	M	F	T		
Aradum	1244	527	1771	129 (=1771/5952 *433)	29.8%
Addis Alem	278	107	385	28 (=385/5952 *433)	6.5%
Abourie	480	366	846	62 (=846/5952 *433)	14.3%
Addis Kign	1644	1306	2950	214 (=2950/5952 *433)	49.4%
Total	3646	2306	5952	433	100%

Source: Raya Kobo worda agricultural office (2011/2012 E.C)

3.3. Model Specification

As noted in the literature review section, the decision to accept is not always perceived from a same discipline. Hence, multi-disciplinary research can help to address the essence of the whole research by combining human behavior from social, psychological, and economic perspectives with technological attributes to achieve a common objective in a holistic and integrative way. To capture such complex behavior, such study needs a better and more flexible model that is based on theoretical principles and includes multi-disciplinary approach. Traditional statistical approaches specify standard models, assuming that the measurement is error-free and somewhat inflexible. Moreover, we need to provide a suitable model for each target, as these are of different in nature and require different models.

PLS-SEM is one of the most suitable models used for prediction. Most commonly defined, Structural Equation Modelling (SEM) is one of a multivariate technique that incorporates measured variables and latent constructs, and clearly defines measurement error. Researchers (Chin, 2010; Sanchez, 2013) suggest that SEM can provide a powerful framework for the synergy

of multidisciplinary research around major challenge and clarify the relationship between the complex variables associated with observable (measured) and unobserved variables (latent constructs). While traditional techniques only analyze measured variables. Recently, Mutyasira et al. (2018) applied an integrated approach using PLS-SEM to predict the adoption decisions of Ethiopian farmers. The second most powerful model used to study key factors determining the decision to adopt is the multinomial logit model. Thus, the study applied a two-step estimation method, in which PLS-SEM was used in the first stage to predict which latent variables cause the most variation in the adoption decision, and multinomial logit model was applied in the second step applies to estimating what factors determine the adoption decision.

3.3.1. Partial Least Square-Structural Equation Modeling

In the first stage of this thesis, a partial least square method has been adopted because it does not perform assumptions about distribution of the data; and maximizes the explained variance and minimizes the overall error. PLS is moving away from strict data assumptions while maintaining a focus prediction-oriented. In contrast to the classical theory of statistical inference, PLS-PM offers a different approach, which imposes no data distribution assumptions that are difficult to fulfil in real life, especially for non-empirical data (Sanchez, 2013). The ultimate goal of PLS-PM is to provide a practical summary of how the set of dependent variables is systematically described by a group of their sets in the inner and outer model.

In this first stage, unobserved perceived attributes, economic and psychosocial that influence the adoption of CSA practices, along with components in the farming context using partial least square (PLS) includes predicting multidisciplinary latent variables by evaluating PLS-path modeling. This allows to use the Likert scale to estimate latent variables based on their respective observable constructs (beliefs). This prediction method can show which latent variables (that is, antecedent of adoption decision) have changed more when explaining (predicting) the farmer's decision to adopt CSA practices.

In addition, each PLS Path Model consists of two sub-models. A Structure that links latent variables (inner model) and dimensions that define the relationship between latent variable and their manifest blocks (observed variables) in the outer model (Chin, 2010; Sanchez, 2013).

1. The Measurement Model (Outer Models)

The measurement or outer model indicates the relationship between the latent variable and its manifest variables. In Figure 1 above, the measurement model shows the relationship between the blue circle (LVs) and their observable constructs (the yellow rectangular boxes). The relevant aspect of the outer model is that there are two main measurement options: reflective blocks and formative (structural) blocks. The formative blocks, which are not considered in this study, show that observed constructs are the cause of their latent variables.

Reflective Way: The most common type of measurement is the reflective mode. In this case, the latent variable is considered to be the cause of the manifest variables. This is why it is called reflective because the manifest variables “reflect” the latent variable. The reflective blocks are represented by outward arrows starting with long the latent variables. For example, the adoption of CSAPs has resulted in improved farming conditions, improving soil fertility, reduce the adverse effects of excessive chemical fertilizers, and reduce negative effect of pesticides and increase productivity.

The linear mathematical notation, we have that:

$$\text{Reflective: } X_{jk} = \lambda_{0jk} + \lambda_{jk}LV_j + e_{jk} \dots \dots \dots 2$$

where X_{jk} =observed constructs and λ_{jk} are their loadings. LV_j =latent variable, and λ_{0jk} and e_{jk} are their respective intercepts and error terms.

Consequently, the unobserved variables in the external measurement model are estimated using their manifest variables weighted with Likert scales as follows. According to TPB theory, attitudes toward a behavior are determined by salient beliefs about that behavior, and each salient belief associates the behavior with an estimated outcome. For example, a farmer may believe that "the use of organic fertilizer" behavior "increase soil fertility", "leads to a higher production", and so forth (results). Therefore, attitudes toward adopting certain CSA practice (behavior) are determined by the individual's assessment of the outcomes associated with the adoptive behavior and by the strength of those associations. In particular, the evaluation of each outcome contributes to the attitude relative to the person's subjective probability that the behavior will produce the outcome in question. By multiplying the strength of the belief and rating the result and adding the

$$P_{\text{Comptbl}} \propto \sum_{j=1}^n p_{\text{Comptbl}_j} \text{Comptbl}_j \dots \dots 10; P_{\text{Complex}} \propto \sum_{j=1}^n P_{\text{Complex}_j} P_{\text{Complex}_j} \dots \dots \dots 11;$$

$$P_{\text{Tria}} \propto \sum_{j=1}^n p_{\text{Tria}_j} \text{Tria}_j \dots \dots \dots 12; \text{ and } P_{\text{Attri}} \propto \sum_{j=1}^n P_{\text{Attri}_j} \text{Attri}_j \dots \dots \dots 13$$

The perceived adoption of CSA practice is also estimated in the outer model with its manifested reflective constructs.

$$CSAPs \propto \sum_{j=1}^n CSAPs_j CSAPs_j \dots \dots \dots 14$$

Regression Specification: In addition, we have the concept of predictor description or regression specification: in terms of predicting linear relationships, the conditional expected values (either manifest or latent) of the response variables are conceptualized in terms of standard regression as follows. $E(X_{jk} | LV_j) = \lambda_{0jk} + \lambda_{jk} LV_j \dots \dots \dots 15$

The other extra assumption is that there is no correlation between dependent latent (LV_j) with its error term. i.e $cov(LV_j, e) = 0$. Notice that in PLS-PM, we are assuming nothing about the distributions of the variables and error terms. We are just requiring the existence of first and second order moments in the variables.

2. The Structural Model (Inner Models)

The second aspect of PLS-SEM is the estimation of structural (internal) model. We consider all the structural relations as linear relations which are shown in in Figure 1 above depicts the relation between the blue circle (latent variable). The structural relations expression in mathematical notation as:

$$LV_j = \beta_0 + \sum_{i \rightarrow j} \beta_{ij} LV_i + error_j \dots \dots \dots 16$$

The subscript i of LV_i refers to all the latent variables that are supposed to predict LV_j . The coefficients β_{ij} are the path coefficients and they represent the “strength and direction” of the relations between the response LV_j and the predictors LV_i . β_0 is just the intercept term, and the $error_j$ term accounts for the residuals (Sanchez, 2013).

From Chin (2010) and Sanchez (2013), we can also express the structural relationships in mathematical notation. The first inner model of behavioral intention (BINT) is estimated in the

inner structural equation with their respective antecedent latent variables, attitude (ATT), subjective criterion (SN), perceived behavioral control (PBC). In addition, the perceived technical characteristics (PT_{Attri}) are estimated with the respective antecedent latent variables: perceived compatibility ($P_{Comptbl}$), perceived complexity (P_{Complx}), and perceived trialability (P_{Tria}). Nevertheless, the perceived usefulness, cost and risk of technological adoption in the structural equation model are estimated by multiple regression.

Therefore, the intent to behavior is influenced by three components: ATT, SN and PBC. Thus, from the three components of the TPB which are derived after the expectancy-value model, the model explaining the behavioral intention (BI) becomes:

$$BINT = f(ATT, SN, PBC) \Rightarrow BINT = \beta_4 ATT + \beta_5 SN + \beta_6 PBC + \varepsilon \dots \dots \dots 17$$

Similarly, technological attribute is influenced by three components: perceived compatibility, complexity, and trialability. Thus, perceived attribute is given by the structural equation as follows;

$$PT_{Attri} = f(P_{Comptbl}, P_{Complx}, P_{Tria}) \Rightarrow \beta_7 P_{Comptbl} + \beta_8 P_{Complx} + \beta_9 P_{Tria} + \varepsilon \dots \dots \dots 18$$

Finally, the CSA practices latent variable is given in equation 19 as a function of all latent antecedents;

$$\begin{aligned} CSAPS = f(P_{Use}, P_{Cost}, P_{Risk}, INT, ATT, SN, PBC, PT_{Attri}, P_{Comptbl}, P_{Complx}, P_{Tria}) \\ = \beta_1 P_{Use} + \beta_2 P_{Cost} + \beta_2 P_{Risk} + \beta_4 ATT + \beta_5 SN + \beta_6 PBC + \beta_7 P_{Comptbl} \\ + \beta_8 P_{Complx} + \beta_9 P_{Tria} + \beta_{10} INT + \beta_{11} PT_{Attri} + \varepsilon \dots \dots \dots 19 \end{aligned}$$

where the β 's are empirically estimated weights or path coefficients depicting the relative importance of each of the constructs and ε is the error term. The parameters can be derived from multiple regression in a structural equation model.

The first stage in the modeling process is to evaluate the partial least square structural equation modeling (PLS-SEM) to evaluate the relationship between latent constructs and their explicit indicators. Therefore, the structural equation model contains an external sub-model that defines the relationship between the latent variables and its observable. Next, an internal sub-model is added to estimate the relationship between the dependent and independent latent variables and their respective path coefficients (Sanchez, 2013).

Regression Specification: Inner relationships is something called predictor specification which is an imaginary term for expressing a linear regression. The idea behind this description is that linear relationships are considered from the point of view of standard regression:

$$E(LV_j|LV_i) = \beta_{0i} + \sum_{i \rightarrow j} \beta_{ij}LV_i \dots \dots \dots 20$$

Eq 20 shows the conditional expected values of the response LV_j determined by its predictors LV_i . The only extra assumption is: $cov(LV_j, e_j) = 0$, indicates that a latent variable LV_j is uncorrelated with the residual e_j . Nothing is assumed about the distributions of the variables and error terms, but requiring the existence of first and second order moments in the variables.

3.3.2. Estimation Procedures: Econometric Framework

The second stage of estimation involves an econometric model for an integrative approach and uptake of CSA practices to assess the relative importance of perceived characteristics, socioeconomic and psychological variables in explaining farmers’ behavior. Developing the constructs from the structural equation (path) model described previously, the DOI, EUT, and TPB constructs are included as independent variables synthesized with a set of socio- economic variables from related studies in economic theory (Knowler and Bradshaw, 2007; Mutyasira et al., 2018). At this stage of the estimation, the latent variables are included in estimating the main determinants of adoption selection for multinomial logistic regression. The latent variables were taken from average (mean) values of their observed constructs and would be synthesized with other exogenous socioeconomic variables.

Under the adoption of multiple agricultural technologies, bundle of practices is used to adopt farmers’ innovation rather than adopting a single practice in their parcels. Thus, applying an appropriate model that can simultaneously estimate the effect of explanatory variables on various adoption decision is important to understand the potential relationship between explanatory variables and the adoptions of different CSA methods. Farmers were supposed to maximize their income. The two most widely used multinomial probability selection models are the multinomial logit (MNL) and multinomial probit (MNP) models, which are distinguished only by the distribution of error term. The distribution of the error term in MNL is independently and

assumption of independence of irrelevant alternatives (IIA) to hold. More specifically, the IIA assumption requires that the probability of using a certain adaptation method by a given household needs to be independent from the probability of choosing another adaptation method (that is, P_j/P_k is independent of the remaining probabilities). The premise of the IIA assumption is the independent and homoscedastic disturbance terms of the basic model in Eq. (21). The parameter estimates of the MNL model provide only the direction of the effect of the independent variables on the dependent (response) variable, but estimates do not represent either the actual magnitude of change nor probabilities. Differentiating Eq. (21) with respect to the explanatory variables provides marginal effects of the explanatory variables given as

$$\frac{\partial P_j}{\partial X_k} = P_j \left(\beta_{jk} - \sum_{j=1}^{j-1} P_j \beta_{jk} \right) \dots \dots \dots 22$$

The marginal effects or marginal probabilities are functions of the probability itself and measure the expected change in probability of a particular choice being made with respect to a unit change in an independent variable from the mean (Greene, 2012).

CHAPTER FOUR: RESULT AND DISCUSSION

4.1. PLS-SEM Prediction

4.1.1. PLS: Descriptive Statistics

This study aims to predict latent variables based on the theoretical foundation of DOI, UT and TPB and examine how the attributes of a climate-friendly innovation, its perceived economic utility and its psychosocial behavior may influence the acceptance of CSAPs behaviors by farmers on their farm. In the first step, measurement model of the PLS algorithm comprises the prediction of latent antecedents of the attributes of innovation, antecedent intention and the linear prediction of usefulness, costs and risk latent variables with their respective manifested beliefs. While, in the second stage the structural model of the PLS algorithm was confined by the inner relationship between the latent variable (as a cause) and the dependent variable, the adoption of CSA practices (as a result). Then a total of 433 respondents rated the questions about related to the manifested items on a 5-point Likert scale, which ranged from 1 = low magnitude to 5 = high, and indicated the extent to which they agree with the statements. The following Table 2 below provides descriptive statistics for the measurement items used in the study.

There are three exogenous core variables in DOI theory, namely compatibility, complexity, and trialability. Compatibility was measured directly on the instrument by the two questions (Cptb1, Cptb2). For both questions, the farmer was asked if the chosen method was appropriate to his/ her farming experience and the value of the communities. Technological complexity was captured by three elements (cplx1, cplx2, cplx3) which indicates the technical simplicity and ease of understanding with less mental and physical efforts. Whereas the trialability was predicted by two clear points (Tri1 and Tri2) to determine whether the described practices are possible under the current farming conditions and whether the farmers have so far been able to cultivate their land and they have a great opportunity to try.

Based on the linear relationship of expected economic factors, such as perceived usefulness, cost, and risk of adopting multiple CSA practice. The perceived usefulness was measured by three beliefs (Use1, Use2 and Use3) that denote the technological usefulness to promote production and for the environment; interrupt the appearance of pests and improves soil fertility; and in control stem borers and striga and fodder improves respectively. The cost of the adaptation strategy was

evaluated in terms of labor and other input costs compared to the conventional agricultural system by cost elements of cost1 and cost2. likewise, risk adaptation was estimated from two items (risk1 and risk2), which address adaptation by reducing the risk to the health of the associated farmer and the risks derived from crop failure.

Table 2: Descriptive statistics of measurement model analysis

Latent Variables	Indicators	Descriptions	Mean	Std. Dev.
Compatibility	Cptb_1	The compatibility of CSA practices with all aspect of my farming experience.	4.05	0.908
	Cptb_2	The appropriateness of adopting CSA practices with my farming communities' value.	4.3	0.736
Complexity	Cplx_1	Adopting CSA practices can be easily understood without external help.	3.28	1.147
	Cplx_2	CSA practices are complex and requires a lot of mental and physical effort, which makes adoption cumbersome.	3.7	1.079
	Cplx_3	CSA practices can easily be carried out, which makes adopting relatively technically simple.	3.63	0.958
Trialability	Tri_1	The trialed of CSA practices can be straightforwardly do-able under my current farm condition without modifying my farm operation.	3.26	0.905
	Tri_2	I have had a great deal of opportunity to try CSA practices in my farm land so far.	3.97	1.019
Attributes	Attr_1	The attributes of these agricultural innovations can consume much time when adopting in farm land than conventional.	3.73	0.994
	Attr_2	The attributes of CSA innovations seem they can be carried out at farm level.	3.13	1.024
Usefulness	Use_1	The beneficial of adopting climate smart agricultural practices to my production and to the environment.	4.27	0.844
	Use_2	The usefulness of adoption of CSA to disrupts pest outbreak and improves soil fertility than the advantage of conventional practices.	3.98	0.833
	Use_3	The benefit of adopting climate smart agricultural practices on my farming activity in controlling stemborers and striga weed and improves fodder.	3.15	1.312
Cost	Cost_1	The associated labor cost in adopting CSA practices is less than conventional farming.	2.01	0.825
	Cost_2	The associated input costs (e.g. improved seeds, inputs used to prepare organic fertilizer and to purchase Rodus grass) of adopting CSA practices are less than conventional farming (e.g. local seeds).	1.86	0.744

Latent Variables	Indicators	Descriptions	Mean	Std. Dev.
Risk	Risk_1	Adoption of CSA practices (e.g. food produced by organic farming) reduces my associated health risk than non-CSA farming (or using chemical pesticides).	3.49	0.913
	Risk_2	The reduction of risks arises from crop failure (by tolerating stress, fix nitrogen, and controls pests and disease) from adoption of CSA practices.	4.47	0.649
Attitude	ATT_1	My adoption of CSAPs for my agricultural system are convenience.	4.07	0.782
	ATT_2	My practical adoption of CSA practices can enhance my agricultural production over time.	4.32	0.88
	ATT_3	The effectiveness of my adoption of CSAPs in my farming system.	3.98	0.848
Subjective Norm	SN_1	Most of my friends, families and neighbor's approval (recommendation) my decision to adopt CSA practices	3.54	0.942
	SN_2	Agricultural agents' recommendation on my decision to adopt CSA practices.	4.03	1.082
Perceived Behavioral Control	PBC_1	My skill and knowledge to adopt CSA practices in my farm land.	3.43	0.888
	PBC_2	The decision and responsibility to adopt CSA practices is entirely depending on me.	4.38	0.676
	PBC_3	I have the necessary resource which allows me to adopt CSA practices.	2.34	0.841
Intention	INT_1	My regular use of CSA practice so far.	2.79	0.923
	INT_2	My intention to use CSA practices in the future.	4.34	0.794

Source: Own calculation

The final measurement model bond is expressed by the TPB, where attitude (behavioral beliefs) is directly measured by three questions on the instrument (ATT1, ATT2, ATT3). The three questions asked the farmer to the extent he/ she agreed with the view that it was convenient to adopt CSAPs, and how the farming system could affect farm production over time. The adoption of the theme captures the Subjective norm (normative beliefs) was captured by two items (SN1, SN2.), which refers to the views of agricultural agents and recommendations of key people (friends, families and neighbors) and fellow farmers. In addition, the PBC (control beliefs) are measured by three items (PBC1, PBC2, PBC3), to the extent that farmers are confident (gain sufficient skill and knowledge). The responsibility for the decision and adoption of CSA practices depends entirely on him/ her; and their ability to conduct CSAPs in the farm business should have the necessary resource. Finally, intentionality is measured by a two of statements (INT_1 and INT_2) that

capture farmers' past involvement and future intentions to adopt CSA practices. These questions are worded following (Icek Ajzen, 2013) sample TPB questionnaire recommendation.

The descriptive statistics from Table 2 suggests that there was a strong level of agreement with the farmers for relevant questions, which is higher than the expected mean of constructed items. As shown in the table, the overall average of Cptb_1 and Cptb_2 indicate 4.048 and 4.296 respectively, which is close to the strong agreement of the 5-point Likert scale. This reveals that CSA technologies are considered more compatible in terms of farmers' experience and societal value. Likewise, farmers insist that CSA adoption practice disrupt the spread of pest and improve soil fertility. The result shows that these practices help to reduce the risk of crop failure; and practically enhance agricultural production over time. Furthermore, households believed that the decision and responsibility rests entirely depend on him/ her and the recommendation of the agricultural agent also helps him/ her to adopt the methods. However, cost constructs reflect strong disagreement and less responses to constructs, which shows the cost of labor and other input of climate smart technologies are higher compared to other non-climate smart agricultural practices. Similarly, in this case farmers lack the necessary resources, which negatively affects their adaptation experience. Standard deviation also show less variation in opinion among farmers. However, in some cases, there is little difference in the response among farmers as to whether the adoption of CSA practices can be easily understood without the need of external assistance.

4.1.2. PLS-SEM Prediction Result

On the recommendation of a two-step analytical method for path modeling, we tested the measurement model (validity and reliability of the measures) and then examined the structural model. The evaluation of the PLS-SEM results begins with the evaluation of the measurement model and continues with the evaluation of structural model. These guidelines provide rules of thumb to explain the adequacy of the results. This involves assessing of the reliability and validity of the key latent constructs and indicators to complete the study of the structural models. This preliminary analysis step showed that all the indicators used had a high reliability of the individual indicator, indicating that they were more loaded in their respective constructs than the other constructs.

4.1.2.1. Results Evaluation: Reflective (Outer) Measurement Model

For an exploratory research, the reliability of the indicators and the reliability of the internal consistency measure the reliability and relevance of the indicators. Measurement is completely reliable if the error of random measurement is zero and equally, the measurement is perfectly valid if both error parts are zero (Churchill, 1989). From this basic definition, the literature discusses some of the criteria for validating reflective constructs. The following paragraphs describe a detailed procedure for evaluating reflective constructs with respect of the PLS approach. When the reflective indicator loadings and CR are 0.4 and 0.6 or higher, respectively, shows items are a good measurement of the latent constructs and have adequate consistency among all the constructs (Hair et al., 2014; Hulland, 1999). When checking for convergent validity, each latent variable's Average Variance Extracted (AVE) is evaluated and if the AVE values exceed the accepted threshold of 0.5, the convergent validity is confirmed. In general, the closer these values are to 1, the greater the internal consistency of the indicators (items) in the constructs.

The first step of PLS path modeling involves predicting the latent factors along with their respective indicators. Table 3 shows an evaluation of the Average Variance Extracted (AVE) measure for each of the indicator loadings and composite reliability. Hulland (1999) shows that items are a good measure of the latent constructs with reflective indicator loadings of 0.4 or more. This initial diagnostic step showed that all the indicators used had low reliability of the individual indicator reliability, which indicates that they loaded higher in their respective constructs than in other constructs. Thus, the result shows that all the reflective measures construct except the indicators Tri_1, Attri_1 and PBC_3 meet the evaluation criteria related to the constructs of the model, so the indicator indicates an adequate level of reliability (i.e., >0.4). Furthermore, AVE shows a high level of convergent validity except for latent constructs Attri, SN and PBC, which is slightly below the accepted threshold of 0.5. Yet, from the result (Table 3 and Fig. 3 indicated by the numbers in the blue circle) all the average variance extracted (AVE) are above 0.5, which provides the basis for the convergent validity of the measurement (Hair et al., 2014). The Composite Reliability (CR) values of 0.735 and above for compatibility, usefulness, risk, attitude and intention constructs, which is clearly above the expected minimum level of 0.60. However, both attributes and subjective norm latent variables do not meet convergent validity and composite

reliability, indicating that these construct measures do not show sufficient levels of convergent validity and internal consistency.

Table 3: Results Summary for Reflective Outer (Measurement) Models

Latent Variables	Indicators	Loadings ^a	AVE ^b	CR ^c
Compatibility	Cptb_1	0.887 ^{**}	0.733 ^{**}	0.846 ^{**}
	Cptb_2	0.824 ^{**}		
Complexity	Cplx_1	0.905 ^{**}	0.712 ^{**}	0.382
	Cplx_2	-0.894 ^{**}		
	Cplx_3	0.720 ^{**}		
Triability	Tri_1	0.149	0.508 ^{**}	0.572
	Tri_2	0.997 ^{**}		
Attributes	Attr_1	-0.365	0.435	0.177
	Attr_2	0.858 ^{**}		
Usefulness	Use_1	0.745 ^{**}	0.598 ^{**}	0.816 ^{**}
	Use_2	0.854 ^{**}		
	Use_3	0.716 ^{**}		
Cost	Cost_1	0.936 ^{**}	0.544 ^{**}	0.681 ^{**}
	Cost_2	0.46		
Risk	Risk_1	0.76 ^{**}	0.581 ^{**}	0.735 ^{**}
	Risk_2	0.765 ^{**}		
Attitude	ATT_1	0.739 ^{**}	0.634 ^{**}	0.838 ^{**}
	ATT_2	0.861 ^{**}		
	ATT_3	0.784 ^{**}		
Subjective Norm	SN_1	0.466	0.396	0.554
	SN_2	0.758 ^{**}		
Perceived Behavioral Control	PBC_1	0.842 ^{**}	0.427	0.669 ^{**}
	PBC_2	0.668 ^{**}		
	PBC_3	0.355		
Intention	INT_1	0.845 ^{**}	0.612 ^{**}	0.758 ^{**}
	INT_2	0.714 ^{**}		

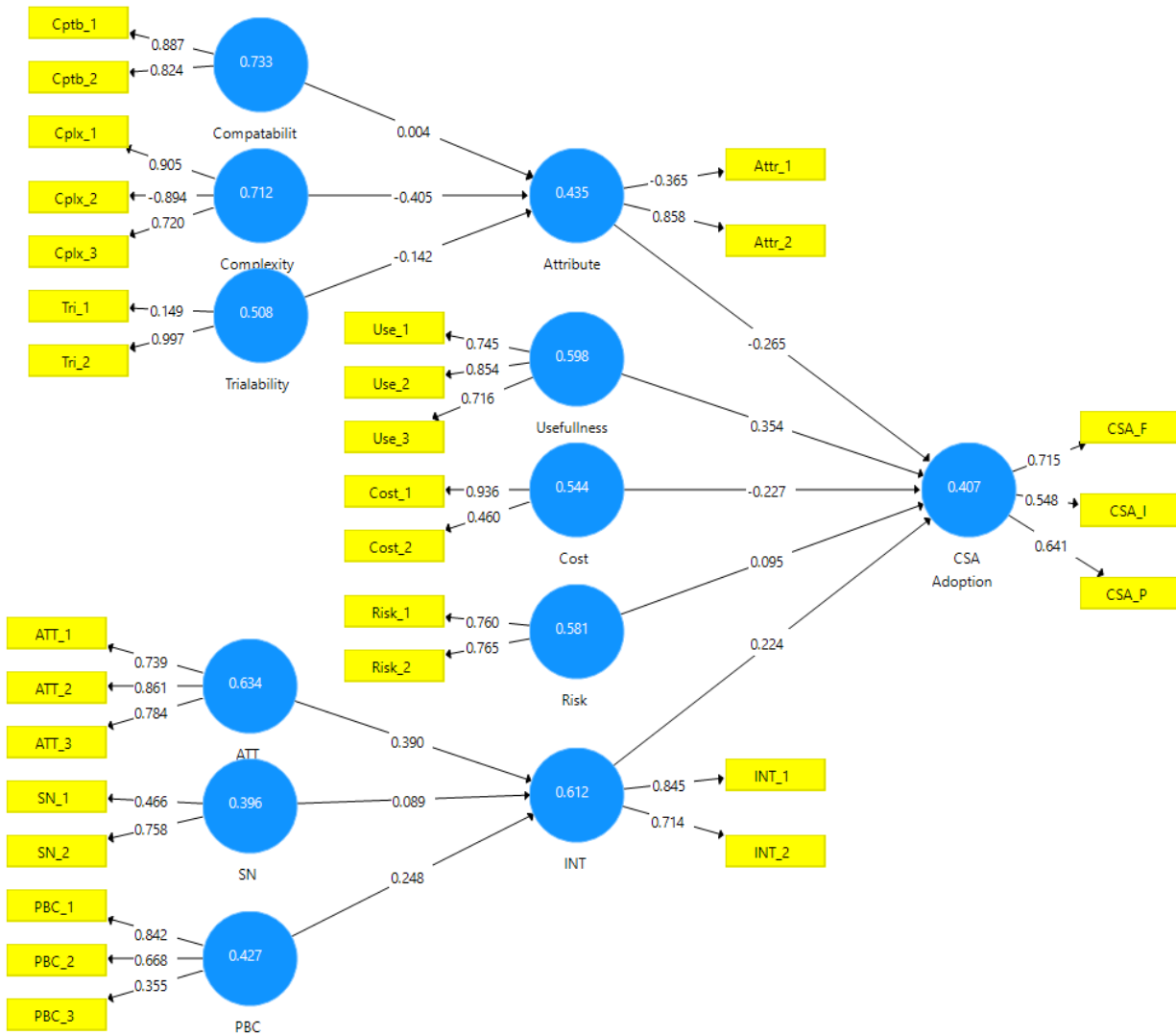
a. ^{**}Indicator Loadings>0.4 indicates Indicator Reliability (Hulland, 1999)

b. ^{**}Average Variance Extracted (AVE)>0.5 indicates Convergent Reliability (Fornell and Larcker, 1981)

c. ^{**}Composite Reliability (CR)>0.6 indicates Internal Consistency (Gefen et al., 2000)

Figure 3 below, correspondingly, shows indicator loadings of path coefficients and AVE of key constructs before bootstrapped procedure. The out-point arrows are called the path coefficients. They explain how strong the effect of the latent variable cause changes in the assigned indicators of another variable. Path coefficients vary between -1 and +1. Higher absolute values denote stronger (predictive) relationships between constructs. As stated in the table 3 above, the path coefficients (also in fig. 3) indicates measurement constructs (Tri_1, Attr_1, Cost_2, SN_1 and PBC_3) confirms a lower value of (0.149, -0.365, 0.46, 0.466 and 0.355 respectively) reveals insignificant predictive relationship between the manifested and their respective latent constructs.

Figure 3: Indicator loadings and path coefficients of key constructs.



As indicated in Table 4, SmartPLS can generate T-statistics and P-values and use a procedure called bootstrapping to test the significance of both the inner and outer model, respectively (see in the appendix Fig. 4 and Fig. 5). This procedure takes and replaces a number of subsamples (e.g., 5000) from the original sample to get the bootstrap standard errors, which in turn gives approximate T-values for significance testing of the structural path. Bootstrap results are approximating the normality of data. Once the bootstrapping procedure is completed, T-Statistics, P values, and R square results are reported to see if the path coefficients of the outer and inner models are significant or not. Using a two-tailed t-test with a significance level of 5%, the path coefficient is significant if the t-statistic is greater than 1.96. In Table 4 below, if you look at the result of the outer model (also shown in Fig. 4 and 5), it can be seen that only the “Tri_1 and Tri_2 <- Trialability” linkage is not statistically significant.

Table 4: Outer (reflective measurement) and Inner (Structural) model bootstrapping PLS predicted path coefficient results

Measurement Model					Structural Model						
Outer relationship	Coefficients	Bootstra SE	t-value	VIF	Inner relationship	Coefficients	Bootstra. SE	t- value	R ²	VIF	Decision
Cptb_1 <- Compatibility	0.881***	0.103	8.594	1.284	H3=Compatibility -> Attribute	-0.003	0.052	0.082	0.004	1.00	Not supported
Cptb_2 <- Compatibility	0.8***	0.128	6.444	1.284							
Cplx_1 <- Complexity	0.806**	0.408	2.217	2.239	H4=Complexity -> Attribute	-0.356**	0.193	2.097	-0.41	0.71	Supported
Cplx_2 <- Complexity	-0.796**	0.404	2.213	1.952							
Cplx_3 <- Complexity	0.645**	0.324	2.224	1.489							
Tri_1 <- Trialability	0.137	0.245	0.61	1.005	H10=Triability -> Attribute	-0.091	0.124	1.143	-0.14	0.71	Not supported
Tri_2 <- Trialability	0.6	0.762	1.308	1.005							
Attr_1 <- Attribute	-0.343**	0.153	2.381	1.028	H2=Attribute -> CSA Adoption	-0.264***	0.039	6.784	-0.27	0.79	Supported
Attr_2 <- Attribute	0.854***	0.094	9.169	1.028							
Use_1 <- Usefulness	0.744***	0.037	20.363	1.327	H11=Usefulness -> CSA Adoption	0.350***	0.039	9.064	0.354	1.55	Supported
Use_2 <- Usefulness	0.854***	0.016	54.826	1.495							
Use_3 <- Usefulness	0.715***	0.034	21.27	1.225							
Cost_1 <- Cost	0.935***	0.024	38.803	1.014	H5=Cost -> CSA Adoption	-0.228***	0.031	7.234	-0.23	0.82	Supported
Cost_2 <- Cost	0.454***	0.091	5.045	1.014							
Risk_1 <- Risk	0.763***	0.058	13.049	1.027	H8=Risk -> CSA Adoption	0.098**	0.031	3.059	0.095	1.11	Supported
Risk_2 <- Risk	0.755***	0.09	11.059	1.027							
ATT_1 <- ATT	0.735***	0.041	17.877	1.357	H1=ATT -> INT	0.391***	0.041	9.485	0.39	1.64	Supported
ATT_2 <- ATT	0.862***	0.017	50.275	1.427							
ATT_3 <- ATT	0.784***	0.025	31.362	1.439							
SN_1 <- SN	0.439*	0.259	1.801	1.053	H9=SN -> INT	0.094**	0.045	1.987	0.089	1.1	Supported
SN_2 <- SN	0.731***	0.19	3.98	1.053							
PBC_1 <- PBC	0.837***	0.04	21.068	1.061	H7=PBC -> INT	0.251***	0.037	6.745	0.248	1.33	Supported
PBC_2 <- PBC	0.662***	0.07	9.52	1.059							
PBC_3 <- PBC	0.35**	0.116	3.068	1.021							
INT_1 <- INT	0.846***	0.025	34.503	1.055	H6=INT -> CSA Adoption	0.227***	0.038	5.858	0.224	1.29	Supported
INT_2 <- INT	0.711***	0.05	14.318	1.055							

Note: Asterisks: *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

From the DOI theoretical framework presented in Table 4 above, the compatibility latent variables and their explicit constructs (cptb_1 and cptb_2) indicate the type of the relationship between the constructs. The path coefficient (cptb_1 and cptb_2) shows that a slight improvement in the compatibility of CSA technologies improves the compatibility of these technologies by 88.1% and 80% with all aspect of farming experience and societal value. This shows a positive and strong relationship between the latent variable with its manifested construct variables at a significance level of 1% (see also Fig. 4 and 5). Cplx_2 has a strong negative prediction of -0.796 loading coefficient with its latent complex variable. This reflects that the adoption of CSA practices is more complex for farmers, leading directly to a negative change in the farming practices. The result shows that while the complexity of CSA practices is high, farmers require a lot of physical and mental effort to adopt the technologies, as a result, adoption is reduced by 79.6% as it become cumbersome. However, once they try, Cplx_1 and Cplx_3 have a positive and significant relationship with the latent complexity variable. As a result, adoption can be easily understood without outside help, and relatively simple to carried out with significance level of 5% with an indicator loading of 80.6% and 64.5%, respectively. Attr_1, indicating that the attributes of these agricultural innovations are very time consuming, farmers prefer to adopt the conventional system to 34.3%, which shows a strong negative correlation with its latent attribute variable. The other technological construct was measured by outer linkage Attr_2 <- Attribute. The result was indicated by a strong and positive prediction at significant level of 1%. Since CSA attributes of innovations seem to be carried out at farm land, the adoption process for farmers will increase by 85.4%. This suggests that the easiness of the characteristics of the innovation can help to adoption behavior.

Furthermore, the expected economic factors from the integrated adoption model also affect adoption behavior. These factors are reflected by three latent constructs in the outer measurement model. For example, the perceived usefulness of whether the adopting of the CSA practices would benefit farmers' productivity and to the environment (Use_1 <- Usefulness); to disrupts pest outbreak and improves soil fertility (Use_2 <- Usefulness); and in controlling stemborers and striga weed and improves fodder (Use_3 <- Usefulness). The results shown in the Table 4 and in Fig 4 and 5 in the appendix, also confirmed that the advantage of adopting the CSA practices is superior than the conventional practices, since all the constructs were statistically significant at 1% and positively correlated with usefulness latent variable. Moreover, farmer believed that if

improvement on the usefulness of CSA was made, it could improve production and to the environment by 74.4%. Prevent pest infestation and improves soil fertility; and controlling stemborers and striga weed and improves fodder with 85.4% and 71.5% respectively compared to the conventional. From the relative values shown in Fig. 4 and 5 (in the appendix) adoption was more beneficial in controlling stemborers and striga weed and improves fodder than other uses.

The perceived cost of adopting CSA practices are also contributes its share whether farmers can adopt a specific technology and was predicted strongly and positively through two manifested constructs (Cost_1 <- Cost and Cost_2 <- Cost). The indicator item Cost_1 was systematically measured if the associated labor cost in adopting CSA practices is less than conventional farming and similarly Cost_2, if associated input costs (e.g., improved seeds, inputs used to prepare organic fertilizer and to purchase rodus grass) of adopting CSA practices are less than conventional farming (e.g., local seeds). The result established shows that both items were significant at 1% level and a unit change in the cost of labour lead to dropped adoption of CSA practices by 93.5%. By the same token if cost of input (for example improved seed) is higher than the traditional local seed, farmers will fell to adopt CSA practices by 45.4%.

Farmers also consider the associated risk with adoption of CSA practices to conventional farming. Risk variable was reflectively measured by two constructs. The perceived health risk (Risk_1 <- Risk) and risks of crop failure (Risk_2 <- Risk). As the result suggest, all constructed elements were significantly and positively related to the latent risk variable. Consequently, if farmers face health risks of adopting CSA practices, for example when using chemical fertilizers or pesticides, adoption of these practices will be felt by 76.3% and shift to practice the conventional system (non-CSA practices). However, CSA adoption will only be increased by 76.3% if and only if the perceived risk of adopting CSA practices reduces the risk of farmers' health. Equally, the perceived risks from crop failure can be reduced by adopting CSA practices, which can tolerate stress, fix nitrogen, and controls pests and disease farmers adoption of CSA practices will rise by 75.5%.

Finally, psychosocial factors such as attitude were measured by three behavioral beliefs that dictates the convenience of adoption of CSAPs for agricultural system (ATT_1 <- ATT); the attitudinal belief of practical adoption of CSA practices can enhance farmers' agricultural production over time (ATT_2 <- ATT); and whether adoption of CSAPs in farming system are effective (ATT_3 <- ATT) than usual farming practice. The result of the PLS path model shown

in Table 4 complemented the fact that all attitude beliefs were statistically significant at a level of 1%. Table 4 shows that if farmers had a positive attitude towards the introduction of non-traditional system, then it can be assumed that the ease of adopting with the farming system of farmers could be 73.5%. Same way, a positive attitude towards farmers adopting the practice lead to an 86.2% enhancement of farmers' agricultural output over time. Confidence in the effectiveness of introducing CSA practices in the farming system can be also promoted among farmers with a positive attitude.

Subjective norms latent variable was measured by two main normative beliefs SN₁ <- SN and SN₂ <- SN. The direct linkage of SN₁ <- SN item was indicated whether a farmer get most recommendations / or approval from his/her friends, families and neighbors for his/ her decision to adopt CSA practices. Likewise, SN₂ <- SN reflective relation also signposts whether the source of approval emerged from agricultural development agents to help farmer's decision in adopting CSA practices. From the result recommendation will enhance farmers' decision to adopt as shown by a positive relation of construct items with latent SN variables. SN₁ linkage is only significant at 10% level, however, SN₂ was strongly predicted SN with 1% significance level. The PLS prediction result shows most farmers decided to adopt the practices after the recommendation of agricultural agents. Consequently, adoption will be increased by 43.9% after farmers get friends, families and neighbors' approval, however, farmers' adoption decision risen at 73.1% soon they are recommended through agricultural agents, who are more technically educated.

Adoption decision also not only determined by personal attitude and other recommendations but also once control over (example, resource, responsibility, skill and knowledge) to do the activities. For this reason, perceived behavioral control, which is the prominent psychological variables, was measured by three control beliefs; PBC₁, PBC₂ and PBC₃. The association between control items and latent PBC variable shows that positively and significantly predicting PBC variable. The correlation of PBC₁ <- PBC dictates whether a farmer has the required skill and knowledge to adopt CSA practices in his/her farm land. This was confirmed in Table 4, (and in fig 4 and 5) such that, as farmers acquired the necessary skill and knowledge adoption practice would be advanced by 83.7%. Whereas, PBC₂ <- PBC indicates whether decision and responsibility to adopt CSA practices is entirely depending on individual farmers. The result also shows when the decision and responsibility reside only a single headed farmer then adoption of CSA practices will be only raised

by 66.7%. Likewise, the necessary resource which allows farmers to adopt CSA practices display by PBC_3 <- PBC relationship shows merely a 35% increment towards helping in adoption decision with control of resources.

The intention to adopt was measured by two things, whether the farmer regularly uses the CSA practice until now (INT_1) or intends to use the CSA practices in the future (INT_2). The regression result shows that both items are significant and positively consistent with intention variable. The first item to show is that regular past experience of farmers can help them adopt practices through 84.7. Whereas, the intention of the farmer to use CSA practices in future only motivates farmers to adopt CSA practices by 71.1%. In addition, the VIF value for the measurement model, as indicated in Table 4 below, also illustrates collinearity issues of all set manifested variables. Since all VIF values are less than the threshold of 5, we can conclude that collinearity is not an important issue (K. Wong, 2011).

4.1.2.2. Results Evaluation: Inner (Structural Equation) Model

By examining the bootstrapped path coefficient for the outer model, we can find out whether the internal relation (hypothesis) is supported or not. As presented in table 4, all of the T-Statistics except for the structural relationship between Compatibility -> Attribute and Trialability -> Attribute are greater than 1.96, so we can say that the internal model loadings are very significant. In contrast to the outer (measurement) model, which defines the relationship between a construct and its observable indicators, the structural model determines the relationship between exogenous and endogenous constructs. It is assumed that the values of exogenous constructs (previously estimated in the measurement model) are given from outside the model. Thus, these exogenous variables (for instance, compatibility, complexity...) are not explained by other constructs in the model, and the structural model should not contain arrows pointing to exogenous constructs. In contrast, endogenous constructs (such as attributes and intention) are at least partially explained by other constructs in the model. The relationships between the constructs are usually viewed to be linear (Henseler et al., 2016).

After reviewing the measurement model in stage 1, which indicates a satisfactory quality, as indicated by indicators of reliability and internal consistency in Table 3 above, we are encouraged to assess the structural model in stage 2 of the PLS- SEM evaluation process. Thus, we should first

need to check the structural model for collinearity problem by examining the VIF values of all the predictor in the model shown in Table 4. From the table we can conclude that all VIF values are below the threshold of 5. Consequently, this is not a critical issue and there is a lack of collinearity in the predictor constructs. The next step involves testing the coefficient of determination (R^2), indicating the variance described in each of the endogenous constructs (Table 4). The R^2 ranges from 0 to 1, indicating the accuracy of predictive high values (Henseler, Hubona, and Ash 2016). As a rough rule of thumb, the R^2 values of 0.75, 0.50, and 0.25 can be considered respectively as substantial, moderate and weak (Hair et al., 2014).

$VIF_k = 1/(1-R^2_k)$, where R^2_k is the R^{2th} of the k^{th} latent variable.

In analyzing the estimated path coefficient of the structural model indicated in Table 4, we will focus only on the coefficients among the latent variables, which are also shown their T statistics, P values and R^2 values in Fig. 4 and 5. According to the results of the model in Table 4, we observe that the technological attributes were determined by three variables (technology compatibility, complexity and trialability) from the DOI theory. Compatibility correlated positively with the characteristics of the innovation, however, the complexity and the trialability were correlated negatively with attributes of agricultural practices. The standardized complexity coefficient (-0.356) was only statistically significant at a significance level of 5%. This shows that farmers have failed to adopt CSA agricultural practices on their plot as these practices are more complex and require mental and physical effort. Furthermore, the complexity problem has a strong influence on the technological attributes of other factors of the attribute variables and explains the attributes negatively by about $R^2 = 40.5\%$.

The theory of planned behavior shows that three core variables: individual attitude, subjective norm, and perceived behavioral control mainly affect farmers willingness to adopt CSA methods. The results of Table 4 show that the standard path coefficients for these latent variables are 0.391, 0.094, and 0.251, and pass the significance test at 1%, 5%, and 1%, respectively. It also shows strong positive connection between farmers' intention to adopt the practices. This suggests that attitude is a strong predictor of intent and as a result positive attitude can motivate farmers to adopt climate- friendly agricultural practices. Perceived behavioral control (skills, knowledge, and self-determination, and responsibility) are strongly associated with the recommendation and approval of others also helps to engaged in adoption decisions.

Additionally, the perceived exogenous economic factors are associated as a linear relationship with the endogenous adoption variable, specifically, the perceived economic usefulness, cost, and risk of adopting CSA practices. As indicated in Table 4, the estimated standard coefficients are respectively 0.350, -0.228, and 0.098 and satisfy the significance level at 1% for both usefulness and cost and at 5% for the risk variable. The result illustrates that the variables of economic usefulness and risk reduction have a strong and positive linkage with adoption behavior. This further suggests that non-traditional adoption practices are being developed among farmers as long as their economic benefit is to improve crop production, soil fertility, control weeds, pests and diseases, it also reduces the associated risk of health and poor harvest. Although, farmers failed to adopt if the associated input costs are greater than the conventional practices. In general, the endogenous adoption variable is strongly and positively determined by perceived use, intention, and risk factors. On the opposite, the attributes of the technology, due to its extreme negative complexity loading, have a negative influence on the adoption behavior followed by the perceived cost of inputs. The coefficient of determination (R-squared) also confirms that the proportion of the variance of adoption was positively explained with 35.4%, 22.4% and 9.5% exogenously, and respectively, by usefulness, intention to adopt and risk reduction variables. Whereas, it was negatively explained by attributes and cost variables only by 26.5 and 22.7%, respectively.

The Fornell–Larcker criterion Table 5 (Fornell and Larcker, 1981) shows that the discriminant validity is obtained when the square root of the AVE exceeds its inter-construct correlations. Furthermore, Fornell and Larcker (1981) suggest that the square root of AVE in each latent variable can be used to establish discriminant validity, if this value is larger than other correlation values between the latent variables. To do this, Table 5 has been prepared in which the square root of AVE can be calculated manually and written in bold on the diagonal of the table. The correlations between the latent variables are copied from the “Latent Variable Correlation” section of the default report and are placed in the lower left triangle of the same table. This result (Table 5) shows that constructs, except INT and PBC, remains valid. For example, the average extracted value (AVE) of latent variable compatibility is found to be 0.733 (from Table 3) hence its square root becomes 0.856. This number is greater than the correlation values in the compatibility column (0.34, -0.172, 0.386, 0.343, 0.141 and 0.464) and is also larger than those in the row of compatibility (0.507 and -0.153). The results indicate that discriminant validity is well established except for latent variables INT and PBC.

4.2. Estimation Results with Econometrics

4.2.1. MNL: Descriptive Statistics

Table 6 below displays the frequency and percentage of packages of climate-smart agricultural packages. In this study, three categorical variables were included, such as improved crop seeds adoption, organic fertilization, and push-pull biological pest management, providing eight mutually exclusive interrelated practices (2³). Table 6 also shows the proportion of growing area under different combinations of CSA practices. Of the sample of 433 farmers, only about 8.31% of the farmers did not adopt any of the specified practices (IoFoPo), while only 22.40% of the farmers adopted all three alternative practices (IIF1P1) simultaneously. The minimum percentage of technology packages adopted is 3.93% (IoFoP1) and 4.85% (IoF1P1) respectively. The table further illustrates how farmers prefer to adopt technologies in combination rather in isolation. Most farmers adopt separately improve seeds as an adaptation mechanism, but at least 15.5% of farmers of the sample size have implemented more than two packages of CSA practices to increase agricultural productivity.

Table 6: Packages of Climate-Smart Agricultural Practices

Choice (j)	Package of CSAPs (m)	Improved Seeds (I)		O. Fertilizer (F)		Push-Pull (P)		Frequency	%tage	Cumulative
		Io	I1	Fo	F1	Po	P1			
1	I ₀ F ₀ P ₀	*		*		*		36	8.31	8.31
2	I ₁ F ₀ P ₀		*	*		*		79	18.24	26.56
3	I ₀ F ₁ P ₀	*			*	*		28	6.47	33.03
4	I ₀ F ₀ P ₁	*		*			*	17	3.93	36.95
5	I ₀ F ₁ P ₁	*			*		*	21	4.85	41.8
6	I ₁ F ₁ P ₀		*		*	*		88	20.32	62.12
7	I ₁ F ₀ P ₁		*	*			*	67	15.47	77.6
8	I ₁ F ₁ P ₁		*		*		*	97	22.4	100

^m Each combination of packages consists of a binary variable for a practice (Improved crop varieties (I), Organic fertilizer (F) and Push-pull pest management (P)), where the subscript refers 1= if adopted and 0 = otherwise. Source: own calculation

Table 7 presents a full sample and the eight selection packages that describe and summarize the control variables used in the empirical analysis of the sub-groups. The specification of our empirical model is based on a review of theoretical work and previous similar empirical adoption

models (D'souza et al., 1993; Feder et al., 1985; Knowler and Bradshaw, 2007; Teklewold et al., 2016). Studies showed that factors that affect farmer's climate smart adaptation practices include farmer characteristics (gender, age, educational level, number of migrated and family size, and access to off-farm activities) and farm characteristics (land size and total livestock unit), agricultural extension service (access to CSA information, extension and credit service). Ecological factors such as, temperature, rainfall, and pest and diseases are also included. Other non-socioeconomic factors include perceived economic factors (usefulness, cost and adaptation risk), psychological factors (household attitudes, norms, behavioral control and intention), and technological attributes (compatibility, complexity, trialability and attributes of innovation). In the MNL model, non-socioeconomic latent variables were generated as explanatory variables, taking into account the mean values of their particular observed constructs. Thus, Table 7 below focuses on explaining these variables at their mean values in connection to adopting each CSA packages synthesized with socioeconomic explanatory variables. The asterisks denote dummy variables.

Table 7: Explanatory Variables by Combination of Climate-Smart Practices

Variables	Variable Description	Mean values for CSA packages								All Mean	All Std. Dev.
		IoFoPo	IIFoPo	IoF1Po	IoFoP1	IoF1P1	IIF1Po	IIFoP1	IIF1P1		
<i>Farmer's characteristics</i>											
Gender*	Sex of the head	0.53	0.56	0.57	0.71	0.71	0.65	0.72	0.78	0.66	0.47
Age	Age of household head (years)	52.97	47.9	43.89	46.94	42.48	48.19	45.66	44.19	46.6	11.17
Edu*	Educational level of HH head	0.33	0.54	0.68	0.47	0.71	0.74	0.69	0.75	0.65	0.48
HHfamsize	Total family size (number)	5.42	5.01	4.89	5.47	5.05	5.28	5.01	4.99	5.11	1.5
MigHH	Number of migrated households	0.36	0.41	0.54	0.76	0.43	0.35	0.33	0.52	0.43	0.62
Offarm*	Access to off-farm activities	0.5	0.32	0.25	0.12	0.14	0.2	0.15	0.16	0.23	0.42
<i>Farm characteristics</i>											
Lsize	Land size (hectare)	1.09	1.03	0.9	1.51	0.77	1.05	1.1	1.04	1.05	0.52
TLS	Total Livestock Unit	4.54	3.36	2.62	3.87	3.15	3.32	3.26	2.05	3.1	1.44
<i>Agricultural services</i>											
CSAinfo*	Access to CSA information	0.25	0.46	0.36	0.53	0.57	0.69	0.55	0.68	0.55	0.5
Aagriex*	Access to agricultural extension service	0.53	0.61	0.71	0.82	0.9	0.82	0.85	0.79	0.77	0.42
Acredit*	Access to credit service	0.39	0.61	0.89	0.88	0.86	0.76	0.96	0.86	0.75	0.43
Subs*	Availability of government subsidy	0.14	0.51	0.25	0.53	0.62	0.48	0.57	0.69	0.51	0.5
<i>Ecological factors</i>											
Temp*	Existence of high temperature	0.69	0.71	0.96	0.76	0.81	0.83	0.78	0.82	0.79	0.41
Rain*	Occurrence of decreasing and erratic rainfall	0.67	0.76	1.00	1.00	0.9	1.00	0.97	0.96	0.91	0.29
Soilero*	Occurrence of soil erosion	0.39	0.59	0.54	0.82	0.86	0.64	0.73	0.69	0.65	0.48
Pestdes*	Occurrence of pest and disease	0.78	0.84	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.22
<i>Perceived economic utility</i>											
Use	Usefulness of adopting CSA practices	2.58	3.34	3.74	4.18	4.56	3.58	4.11	4.41	3.8	0.77
Cost	Cost of adopting CSA practices	2.24	2.34	1.98	2.06	1.76	1.77	2.03	1.58	1.94	0.59
Risk	Risk of adopting CSA practices	3.1	3.69	4.2	4.62	3.86	4.04	4.12	4.25	3.98	0.6

Variables	Variable Description	Mean values for CSA packages								All Mean	All Std. Dev.
		IoFoPo	IIFoPo	IoF1Po	IoFoP1	IoF1P1	IIF1Po	IIFoP1	IIF1P1		
<i>Psychological factors</i>											
Attitude	Farmer's attitude towards CSA practices	2.67	4.11	4.19	4.02	4.32	4.28	4.3	4.36	4.12	0.67
SN	Subjective Norm	3.01	3.76	3.75	3.79	3.5	3.96	4.02	3.85	3.79	0.63
PBC	Perceived Behavioral Control	2.89	3.26	3.39	3.55	3.49	3.34	3.2	3.78	3.38	0.53
INT	Farmer's Intention	2.54	3.5	3.45	3.38	3.52	3.59	3.53	4.06	3.56	0.67
<i>Innovation characteristics</i>											
Comptbl	Compatibility of Technology	2.76	4.24	4.41	4.62	3.98	4.18	4.27	4.46	4.17	0.71
Complx	Complexity of Technology	3.2	3.38	3.58	3.78	3.3	3.54	3.58	3.76	3.54	0.47
Tria	Trialability of Technology	2.79	3.47	3.52	3.65	3.83	3.8	3.67	3.81	3.62	0.7
Attri	Attributes of Technology	4.1	3.03	4.23	3.44	3.5	3.28	3.51	3.33	3.43	0.77
Number of obs = 433		36	79	28	17	21	88	67	97		

FP-represent combination of technologies and 1 = Adopted; 0 = Not adopted. (*) represent dummy variables

Source; Own calculation

Considering the mean values of each independent variables over selection of CSA packages shows that out of a total sample of 433 household, 66% were male households, with the highest percentage, 78% and 72% of male household having IIF1P1 and IIFoP1 adaptation method respectively relative to female headed. Similarly, compared to female heads, the result shows that out of a total sample size of 433 households, 36 household heads were non-adopters, of whom 53% were male households. This indicates that the combination of packages was adopted by male than female headed, and at least 65% of male households use a combination of CSA practices as adaptation methods. Table 6 also shows that in the sample, the average age is about 66 years with average family size of five of which 43% of the family members are migrated out of their country. The data revealed that relatively young farmers, aged between 42 and 48, use at least one technology, while older farmers (over 52) are limited to adopt any of the CSA practices. In the adoption literature, the level of education of farmers was generally discussed as a factor influencing technology adoption. Education can increase an individual's ability to acquire, understand, and apply knowledge-intensive adaptation practices and use these practices to increase returns compared to the conventional (non-climate-smart) practices. Thus, from the total sample size, 65% of the households are educated and on average IIF1P1, IIF1Po, and IoF1P1 are applied at highest level respectively. Household refuse to adopt any of CSA technologies, despite 33% of them are literate. The total average family size is about five, which is similar across all CSA choices. About 23% of farmers participates in off-farm agricultural income activities. The average values for each CSA package indicate that households with off-farm activities are less likely to implement adaptive strategies. On average, the less accessible farmer has access to non-farm activities, the more likely they are to use a combination of packages on their farm.

Household farm characteristics revealed that the majority of the households in the sample can be characterized as small-scale farmers, with average farm size of 1.05 ha. Most of them adopt biological pest management which can also serve as a fodder for their animals. Similarly, the sample data indicates an average of three livestock units per head of household. Nevertheless, there are farmers in the livestock sector who are unlikely to adopt CSA practices on average.

Agricultural services (like, access to CSA information, extension and credit services, and the provision of government subsidies) are major source through which many practices of climate-related adaptation can be adopted. Researcher control for access to CSA information, extension, credit, and subsidy services, by including a dummy variable for whether the farmer has had

information source regarding climate-smart agricultural practices, either has contacted with the extension agent or credit supply and subsidy during the last cropping season. As a result, the average farmers who receives CSA information, access to agricultural extension service, access to credit, and received government subsidies apply CSA practices at a rate of 55%, 77%, 75%, and 51% respectively. This shows that more than half the size of sample obtain information and government subsidy when applying climate-smart agriculture technologies. Furthermore, according to Teklewold et al. (2013) the result in Table 6 show that the more farmers have access to climate smart information as they experience climate change, consequently, the more likely they are to respond to climate change by implementing adaptation strategies. Similarly, the result is also the same side with Feder et al. (1985) where the follow up of agricultural extension service and the provision of government subsidy strategy, as well as the availability of credit, encourages ways to adopt CSA practices.

Environmental factors such as high temperature, low and erratic rainfall, occurrence of soil erosion, and pest and disease increases the average adaptation strategy compared to non-adopters. The result shows highest occurrence of pest and disease with decreasing and erratic rainfall, and high temperature. It further sheds light on the need to adopt CSA technologies alone or as a package for ways to adapt to climate change.

Although non-socioeconomic factors are used in other areas of social science, recently, they also receive much concern in the adoption decision. Recent literature suggest that the perceived economic efficacy in determining the economic viability of sustainable agricultural practice will affect their wider diffusion (Kassie and Zikhali, 2009) and therefore the perceived risk of adoption decision and the expected cost of inputs in the agricultural economy are highly influenced (Fazio et al., 2014). The potential role of farmers' view on economic efficacy variables (usefulness, cost, and risk); psychological factors (ATT, SN, PBC, and INT); and the innovation characteristics (compatibility, complexity, trialability, and attribute) were included in the questionnaire via a 5-point Likert scale, "from low to high" or "strongly disagree to strongly agree". The aggregate average values derived from these latent variables in the table above indicate that the average farmers agreed to a rate above the default mean of a 5-point Likert scale (i.e., 3.00, indicating neutrality of response). Yet, the result in table 7 (i.e., Mean = 3.80) shows that on average households agreed that the expected usefulness of adopting CSA practices are far more

economically profitable for his/ her production and the environment, to disrupt pest outbreak and improve soil fertility and fodder, and control stemborers and striga weeds compared to the reference category. Moreover, since production risks are high in a climate change environment, CSA technology is more likely to be adopted with an average of 3.98, showing that strong agreement on adaptation strategies can reduce household's health risks and risks arises from crop failure. However, farmers did not agree that the associated labour and other inputs associated with the CSA practices are less than conventional (non-climate-smart) practice. Due to these cost differentials, on average, most farmers do not choose to adopt CSA methods.

In addition, there is a growing evidence in the literature on the role of psychological factors in the adoption of agricultural techniques (Armitage and Conner, 2010; Knowler and Bradshaw, 2007). A farmer who has a positive attitude, he / she had or perceived to believed adoption of CSA adaptation technologies are convenience for his/ her farming method and therefore can improve agricultural production over time shows an overall average rate of 4.36, which shows a strong agreement or closer to higher magnitude of a 5-point Likert scale. The effects of adopting adaptation practices are also captured on the basis of subjective norms (neighbor's and agricultural agents' recommendation), farmers perceived behavioral control (skills and knowledge, responsibility and resources), and his past and future adoption intention shows a good response of 3.79, 3.38, and 3.56, respectively, which is relatively higher than the default mean of 5-point Likert rate. This revealed that farmers' positive attitude, who have approval of friend's, neighbor's and agricultural development agent's, who take self-responsibility, skillful and relatively rich in resource, and intent to adopt in the future are high likely to adopt a given practice on their plots.

4.2.2. Multinomial Adoption Selection Model and Marginal Effect

In this second stage, multinomial logit was used to analyze the determinants of CSA package selection. Hence, we will begin to discuss the results with the choice analysis. Table 8 reports the estimation results of the multinomial logit model for a combination of climate-friendly agricultural practices that are including mean of perceived economic and psychological explanatory variables previously predicted by PLS path model. As shown in the table, the model rejected the null hypothesis that all coefficients of different combinations of CSA practices are jointly statistically equal to zero. Thus, the results suggest that the estimated coefficients sufficiently different in the alternative package, confirming the existence of a correlation between the observed explanatory

and dependent choice variables. Assuming non-adoption of all practices (IoFoPo) as the base category to which results are compared relative to other seven packages (i.e., at least one package is adopted, each regarding mutually exclusive combination of practices). The estimation results display on the difference between adopting different combinations of adaptation practices. The Wald test that all regression coefficients are jointly equal to zero is rejected [Wald χ^2 (161) = 747.31; $p = 0.000$]. Thus, we can infer that at least one population slope is different from zero.

Table 8: Table Parameter Estimates for the Selection Model of Various Combinations of Climate-Smart Practices

Variable	IIFoPo		IoFIPo		IoFoP1		IoF1P1		IIF1Po		IIFoP1		IIF1P1	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
<i>Household Characteristics</i>														
Gender	-0.463	0.930	0.074	0.985	0.080	1.065	0.936	1.204	-0.159	0.964	0.193	0.960	-0.033	1.066
Age	0.044	0.041	-0.010	0.042	-0.018	0.047	-0.063	0.074	0.010	0.040	-0.013	0.039	-0.018	0.049
Edu	0.694	0.892	1.778	0.931**	0.291	0.991	0.518	1.362	1.302	0.895	1.195	0.886	1.549	0.944*
HHfamsize	-0.511	0.378	-0.592	0.386	-0.439	0.405	-0.256	0.483	-0.588	0.365	-0.559	0.372	-0.555	0.434
offarm	-0.742	1.116	-2.243	1.152**	-1.912	1.442	-3.491	1.619**	-2.169	1.152*	-2.419	1.188**	-2.939	1.251**
<i>Household farm Characteristics</i>														
Lsize	0.743	0.914	-0.576	0.914	1.739	0.878**	-1.325	1.031	0.813	0.863	0.636	0.878	-0.039	0.900
TLS	-0.169	0.269	-0.857	0.327***	-0.094	0.316	-0.738	0.395*	-0.386	0.276	-0.322	0.278	-1.564	0.332***
<i>Agricultural information and extension service</i>														
CSAinfo	0.508	0.758	0.142	0.796	0.740	0.828	0.089	1.020	1.782	0.745**	1.056	0.734	1.502	0.795**
Aagriex	-0.534	0.899	0.763	1.053	1.354	1.143	4.501	1.323***	0.733	0.940	0.783	0.982	1.758	1.113
Acredit	0.361	0.796	1.831	1.072*	1.035	0.950	3.217	1.005***	1.098	0.751	3.078	0.941***	1.972	0.891**
<i>Agro-ecological factors</i>														
Temp	-2.222	0.932**	0.496	1.436	-2.593	1.223**	-1.622	1.355	-1.008	0.908	-1.795	0.938**	-2.023	0.984**
Rain	-1.044	0.993	2.278	1.027**	1.226	1.207	-1.612	1.312	4.191	1.316***	0.900	1.140	0.716	1.107
Pestdes	-0.931	1.130	1.026	1.886	-1.267	1.213	16.664	4.448***	3.773	1.719**	1.271	1.452	0.667	1.597
<i>Perceived Economic Utility</i>														
Use	-0.839	0.858	-0.041	0.941	2.043	1.166*	4.552	1.090***	-0.890	0.843	1.641	0.878*	2.010	0.947**
Cost	2.070	0.606***	-0.038	0.634	0.501	0.639	-0.068	0.767	-0.991	0.578*	0.321	0.585	-1.285	0.609**
Risk	-0.315	1.089	0.426	1.154	2.027	1.172*	-0.875	1.465	0.450	1.107	0.301	1.090	0.779	1.205
<i>Psychological Factors</i>														
ATT	2.864	0.899***	1.272	0.907	0.246	0.919	0.526	1.065	1.853	0.938**	1.471	0.894*	1.115	0.928
SN	0.176	0.884	-1.014	0.935	-2.012	1.174*	-2.665	1.160**	-0.076	0.896	-0.153	0.932	-1.170	0.988
PBC	-0.677	0.536	-0.796	0.680	-0.972	0.670	-0.286	1.027	-0.749	0.486	-1.763	0.510***	1.189	0.649*

Variable	IIFoPo		IoF1Po		IoFoP1		IoF1P1		IIF1Po		IIFoP1		IIF1P1	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
<i>Technological Attributes</i>														
Comptbl	2.482	0.638***	1.900	0.671***	1.860	0.803**	-0.508	0.953	1.161	0.616*	1.184	0.635*	1.196	0.704*
Complx	-3.288	1.425**	-2.528	1.462*	-2.332	1.549	-4.081	1.590***	-2.787	1.430**	-2.606	1.444*	-2.569	1.491*
Tria	1.142	0.936	0.737	0.949	0.748	1.017	2.009	1.175*	1.829	0.931**	1.258	0.936	1.704	0.985*
Attri	-1.806	0.534***	0.156	0.599	-1.804	0.627***	-2.247	0.768***	-1.668	0.547***	-1.482	0.551***	-2.047	0.625***
Sample size = 433 Wald χ^2 (161) = 747.31; Prob > χ^2 = 0.0000														

Note: SE is robust standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level; IoFoPo is the reference category.

Source: Own calculation

Table 8 allows us to determine the independent variables that significantly predict between farmers who adopted different packages versus the ‘non-adoption’ (i.e., base outcome) category. In the initial MNL regression, migrant households, government subsidy, farmers’ intention and soil erosion were added to the model, but they were dropped because they were insignificant. Moreover, the comparison category has at least one package been adopted, against the reference category shows that there is no significant relationship between the adoption of climate-friendly agricultural packages and the age and gender of the head of household. However, when using organic fertilizer is applied (IoF1Po), there is a significant and positive correlation between the level of education of the head of household and the adoption of climate-smart farming practice compared to less - educated farmers. It is also true that more educated farmers are more likely to use organic fertilizers in combination with more advanced crop seed varieties and push-pull pest management techniques (IIF1P1). Education increase an individual’s ability to obtain information related to climate variability and various farm management practices. This result was also associated with Melesse (2018) arguments as educated household heads with at least a primary education are more likely to adopt CSA technologies, due to the fact that education has the power to change the knowledge, skill and attitude of farmers. Aryal, Rahut, et al. (2018) and D’souza et al. (1993) studies have shown that households with higher level of education may have greater access to off-farm income to purchase inputs, thus being more capable to implementing CSA methods. Farmers’ off-farm income can supplement household income and give farmers financial flexibility to switch to sustainable practices compared to farmers who are economically unfortunate, and thereby influence households’ adoption decision. However, a significant negative effect was found on the access to number of CSAPs adopted by farmers as far as off-farm income. As a result, farmers engaging in non-farm activities are less likely to accept CSA package such as organic fertilizer only (IoF1Po), a combination of organic fertilizer with biological pest management (IoF1P1), or with improved seeds (IIF1Po), a combination of improved seeds with biological pest management (IIFoP1), and as well as full packages (IIF1P1). This may be because a farmer’s off-farm job is likely to be negatively associated to his or her decision to adopt CSA, since this additional income also derived from reduced farm hours as well as diminished mental and physical capacities (Tey, 2013). This contrasting association suggests a trade-off between on-farm efforts and off-farm incomes, contradicting the view of Mutyasira et al. (2018) and Fazio et

al. (2014) has results. But the analysis shows that household family size does not affect the adoption of any combination of CSA practices.

The results also reveal that the size of the farmers' land has a positive and strong influence on adoption actions. There is a significant and a positive association with the adoption of biological pest management (IoFoP1) implementation. Therefore, farmers with large plots are highly likely to apply only pest management practices than households with less farm land. On the other hand, total livestock unit (TLU) can also negatively affect adoption behavior. Consequently, the results show that farmers with a large livestock holding are less likely to accept the package in combination and separately. This revealed that the larger the livestock population, the fewer farmers used organic fertilizers (IoF1Po), a combination of organic fertilizers with pest control (IoF1P1), and a combination of organic fertilizer with improved seeds and biological pest control (IIF1P1). This result contradicts Aryal, Rahut, et al. (2018; Mutyasira et al. (2018) and Teklewold et al. (2016) findings on households with a higher proportion of livestock ownership are more probable to adopt CSA practices. This may be due to the reason that farmers with large livestock size are more reluctant to manage their farmland, as they have engaged in action of carrying and spending more time on managing livestock and are less likely to increase agricultural production through adoption of climate-friendly agricultural practices.

Agricultural information and extension service variables also have a positively correlation with the adoption of climate- friendly agricultural practices. For instance, farmers who have sufficient information about climate friendly agricultural are more exposed to adopt improved crop varieties in combination with organic fertilizers (IIF1Po) and adopt all packages at the same time. The results also show that farmers are more expected to adopt a combination of organic fertilizer and biological pest control than other farmers when agricultural extension service are provided. Moreover, the results reveal that the effect of agricultural credit on adoption of a combination of climate-smart practices has increased significantly. Therefore, access to credit should have a positive impact on adoption decision. Thus, Table 8 demonstrates that when combining credit avail households are more probable to adopt of packages with only organic fertilizer (IoF1Po), when push-pull pest management combined with organic fertilizer (IoF1P1), improved crop seeds with push-pull pest management (IIFoP1), and IIF1P1 (all packages are adopted). Feder et al. (1985) suggest that credit-constrained households (those who need credit but cannot afford it) are less

likely to adopt practices that require cash outlay. The results support the importance of credit constraints in impeding the adoption of CSA practices (Lipper et al., 2018). This indicates that resource-poor farmers are not adopting externally purchased inputs, improved seeds and organic fertilizer. This may be due to the fact that wealthy farmers have both the ability to buy external inputs and take risks than poor farmers. This result is inconsistent with a significant negative impact on CSA practices that use credit access (Aryal, Jat, et al., 2018). Since credit taken for agricultural purposes is often used for other social purposes, such as to cover marriage, dowry and medical expenses. However, Mutyasira et al. (2018) found that there is a variation of 20% in the adopting SAPs by farmers with access to agricultural credit. This shows the influence of the decisions to implement SAPs on the farm.

The result of environmental factors also reveal that the presence of high temperature reduces the probability of adopting a combination high-yield species with pest control (IIFoP1), biological pest control (IoFoP1), improved seeds (IIFoPo), as well as complete packages (IIF1P1). In contrast, the decrease and irregularity rain encourage farmers to adopt organic fertilizer (IoF1Po) and to adopt organic fertilizer with improve seeds (IIF1Po). By adopting organic fertilizer or improved seeds together with organic fertilizer, farmers can reduce crop failure during inconsistent rainfall, which can offset shortage of rainfall and upsurge agricultural production in shorter term. At the same time, the appearance of extremely high temperature lessens agricultural yields with a significant adoption of combined improved seeds and pest management (IIFoP1) as well as full packages. This shows farmers prefer the traditional (native seeds) and are unlikely to adopt organic pest management and fertilizer because they need precipitation (adequate rain fall). Furthermore, the existence of pests and diseases is positively correlated with the adoption of the IoF1P1 and IIF1Po packages. This suggest that under the presence of pests and diseases, farmers are more likely to embrace the possibility of adopting organic fertilizers in conjunction with pp pest management and improved crop varieties highly. We can infer that adoption of pp pest management can help to halt pest and disease incidence biologically.

Other explanatory variables, such as perceived economic, psychological, and technological variables were simulated in the MNL model to affect their decision to adopt using their average values. Consequently, farmers are more likely to choose organic pest system to prevent pests and diseases if they expect the usefulness of adopting climate smart farming practices are perceived to

be beneficial. Likewise, farmers' expectations toward perceived usefulness increase the possibility of adopting non-chemical pest management with organic fertilization (IoF1P1) with improved seed varieties (I1FoP1) and full adoption (I1F1P1). The perceived usefulness of adopting CSA practice can be measured by a variety of parameters. As shown from Table 8, this result is in line with data on off-farm, credit service, lesser livestock unit and information regarding CSA practice. Large land size, with non-farm activities, substantial expansion and loan servicing, and having highly educated household are useful for adopting CSA practices. The result revealed that the larger the size of land, the greater the perceived usefulness of up taking the IoFoP1 package. Furthermore, households with non-farm income, lesser total livestock unit, climate-friendly farm information and credit, and apparent benefit from pests and diseases would have higher perceived benefits, resulting in a greater likelihood of adopting organic fertilization and planting biological pest control. Since, farmers have access to credit services and income outside of agricultural activities, it is also beneficial to adopt biological pest control in combination with improved seeds (I1FoP1). The perceived usefulness encourages the likelihood of applying the comprehensive technologies (I1F1P1) to farmers who attains higher level of education, exposed to up-to-date climate-friendly agricultural information, have a lower total livestock unit, and have access to credit services. The application of these technologies in separation or combination has the power to improve production and the environment by interrupting pest outbreaks, improving soil fertility, and controlling striga and stem borer weeds, as well as improving fodder are better than the advantage of conventional practices. This result revealed that the economic viability (cost effectiveness) of adopting CSA practices affect their broader adoption decision and had a similar result with Kassie & Zikhali (2009).

On the other hand, the perceived costs have a mixed effect on the introduction of different technologies. The finding shows that adopting only improve crop varieties only (I1FoPo) indicates a positive correlation with adoption behavior. This implies that even if the cost of the associated inputs (for example, improved seeds) is greater than that of the local seeds, there is still a great probability to take over the package, i.e., I1FoPo (improve crop varieties). This suggests that despite high input costs, farmers prioritize the improved over conventional inputs (local seeds) due to their excessive advantage. However, it is expected to become less affordable as the costs increases, which shows the presence of negative connotation between accepting packages combined with the associated cost of the packages. The higher the perceived input costs, the less

it is possible to use improved seeds in combination with an organic fertilizer (IIF1Po) or complete technologies (IIF1P1). This is due to the sensitivity of farmers to the monetary cost of purchase of rodus grass and labor for the preparation of organic fertilizer or to manage pest control as well as a combination of all costs. The result of the associated risk shows a strong positive effect, which plays an important role in reducing health risk and crop failure on household's adaptive behavior. As shown in Table 8, the associated risk has a positive and significant correlation when only PP pest management (IoFoP1) is used. This finding suggests that farmers are more likely to adopt pest control (IoFoP1) measures, as the health risks and crop failure are obvious. The introduction of biological pest mechanism reduces the risks associated with crop failure (for instance, by preventing pest outbreaks and controlling strigas) than the traditional practice. The result is supported by the fact that Jirata et al. (2016) have reported that it is effective in controlling weed parasitic in maize and sorghum fields, and efforts are underway to adapt and implement this push-pull technique.

Many researchers seek to explain the acceptance of a particular behaviors in terms of common psychological factors such as farmers' attitudes, social norms, and behavioral control. As the results show, farmers who have the best attitude towards adopting certain CSA practices have a strong and positive impact on the decision to implement one or more technologies. Proactive follow-up of these farmers could adopt one technology, such as IIFoPo (improved seeds), a combination of improved seeds and organic fertilizers (IIF1Po), or a combination of three technologies (IIF1P1). However, there is a negative correlation between the farmer's recommendation for his or her decision to apply the CSA approach and the approval of the farmer's friends, family, and neighbors. This may be related to the household's ability and confidence to make adoption decisions and reject the recommendations of others. Similarly, Teklewold et al. (2013) stated that it is not the extension contact that influence adoption, but rather the quality of the extension services. The behavioral control variable explained in Table 8 shows a mixed effect. Farmers are less likely to use improved seeds with biological pest techniques (IIFoP1) when households acquire the skills and knowledge, the decision-making and take the responsibility up on him as well as have necessary resource allows adoption decision. While the probability of accepting complete packages (IIF1P1) requires skills and knowledge, decision and responsibility along with necessary resource required to make a decision about acceptance.

Technological characteristics like compatibility, complexity, trialability and attributes also effect farmers' adoption decision. When CSA practices are compatible with all aspect of household's farming experience and societal value the likelihood of adopting packages separately (I1FoPo, IoF1Po and IoFoP1) and jointly (I1F1Po, I1FoP1 and I1F1P1) are greater. Similarly, if technologies are being trialability that can be straightforwardly do-able without changing farmers' farm operation or if he/ she has a great opportunity to try so far increases the possibility of adopting a combination of packages (like, IoF1P1, I1F1Po and I1F1P1). On the other hand, technical complexity in particular and attributes of technologies in general are perhaps strongly and negatively correlated with the choices of different adoption packages. Technological complexity was measured by whether farmers could adopt CSA practices without external help, or requires mental and physical effort to make adoption technically difficult. Consequently, the attributes of technologies were found to be more complex, so it was possible to adopt I1FoPo (improved seeds), organic fertilizer (IoF1Po) plus organic fertilizer with push-pull (IoF1P1) and with improved seeds (I1F1Po), and or adoption of improved seeds with push-pull practice (I1FoP1), and I1F1P1 (full packages) make it more difficult for farmers to apply on their plot. The attribute also shows that if CSA innovations consume much time while farmers carried out at their farm land, the probability of adopting packages of technologies separately (I1FoPo) and (IoFoP1) or jointly (I1F1Po, I1FoP1, and I1F1P1) were very limited.

The previously estimated coefficients earlier in the MNL model shown in Table 8 reflects only the direction of the effect of the explanatory variables on the outcome / choice variable. Therefore, the estimated coefficients do not represent the actual amount of change or the probability of each change in the unit in the independent variable. However, the marginal effects reflect the predicted change in probability of a particular choice will be made in relation to a unit change in the independent variable. As a result, Table 9 depicts the marginal effects of various combinations of packages and was evaluated at each value for continuous variables and for a discrete change from 0 to 1 for dummy variables (represented by asterisks).

Table 9: Marginal effect for various combinations of packages of explanatory variables

Variables	IoFoPo		IIFoPo		IoFIPo		IoFoP1		IoFIP1		IIFIPo		IIFoP1		IIFIP1	
	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE
Household Characteristics																
Gender*	0.001	0.008	-0.058	0.052	0.007	0.027	0.005	0.020	0.003	0.004	-0.034	0.072	0.074	0.072	0.003	0.047
Age	0.000	0.000	0.006	0.003**	-0.001	0.002	-0.001	0.001	0.000	0.000	0.003	0.004	-0.004	0.004	-0.002	0.003
Edu*	-0.014	0.017	-0.069	0.053	0.032	0.029	-0.036	0.029	-0.003	0.005	0.040	0.080	0.006	0.077	0.044	0.039
HHfamsize	0.005	0.005	0.006	0.021	-0.002	0.013	0.004	0.008	0.001	0.001	-0.011	0.030	-0.002	0.032	0.000	0.023
Household farm Characteristics																
Lsize	-0.006	0.007	0.022	0.052	-0.067	0.032**	0.041	0.028	-0.007	0.005	0.076	0.071	0.018	0.077	-0.077	0.041*
TLS	0.005	0.005	0.044	0.019**	-0.021	0.012*	0.014	0.010	-0.001	0.001	0.037	0.031	0.055	0.030*	-0.134	0.028***
offarm*	0.037	0.042	0.238	0.106**	-0.013	0.026	0.003	0.035	-0.004	0.003	-0.053	0.084	-0.115	0.081	-0.092	0.039**
Agricultural information and extension service																
CSAinfo*	-0.012	0.014	-0.091	0.060	-0.064	0.042	-0.015	0.016	-0.004	0.005	0.185	0.075**	-0.037	0.074	0.039	0.043
Aagriex*	-0.007	0.010	-0.212	0.088**	0.007	0.032	0.021	0.020	0.009	0.007	0.031	0.092	0.043	0.095	0.108	0.041***
Acredit*	-0.022	0.020	-0.206	0.101**	0.015	0.038	-0.018	0.027	0.004	0.003	-0.143	0.096	0.323	0.068***	0.046	0.048
Agro-ecological factors																
Temp*	0.010	0.011	-0.094	0.066	0.076	0.034**	-0.045	0.052	0.000	0.004	0.163	0.077**	-0.055	0.087	-0.055	0.061
Rain*	-0.008	0.018	-0.473	0.161***	0.048	0.023**	0.014	0.016	-0.024	0.022	0.386	0.053***	0.055	0.140	0.003	0.061
Pestdes*	-0.006	0.020	-0.388	0.153***	0.022	0.056	-0.152	0.129	0.008	0.006	0.343	0.052***	0.159	0.123	0.015	0.100
Perceived Economic Utility																
Use	-0.004	0.010	-0.171	0.049***	-0.028	0.030	0.056	0.026**	0.015	0.010	-0.434	0.076***	0.371	0.073***	0.196	0.053***
Cost	0.001	0.005	0.288	0.076***	0.003	0.024	0.021	0.014	0.000	0.002	-0.291	0.067***	0.129	0.074*	-0.150	0.044***
Risk	-0.004	0.010	-0.093	0.053**	0.002	0.032	0.057	0.023**	-0.005	0.005	0.020	0.068	-0.027	0.065	0.049	0.046
Psychological Factors																
ATT	-0.016	0.016	0.160	0.051***	-0.023	0.023	-0.050	0.026*	-0.004	0.004	0.061	0.083	-0.060	0.068	-0.069	0.046
SN	0.003	0.009	0.068	0.044	-0.039	0.028	-0.059	0.029**	-0.009	0.006	0.084	0.064	0.057	0.068	-0.105	0.046**
PBC	0.008	0.010	0.018	0.044	0.001	0.034	-0.006	0.019	0.002	0.004	0.021	0.066	-0.296	0.064***	0.251	0.064***

Variables	IoFoPo		IIFoPo		IoF1Po		IoFoP1		IoF1P1		IIF1Po		IIFoP1		IIF1P1	
	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE
<i>Technological Attributes</i>																
Comptbl	-0.013	0.015	0.144	0.042***	0.029	0.024	0.016	0.025	-0.007	0.006	-0.077	0.066	-0.067	0.062	-0.025	0.039
Complx	0.026	0.025	-0.076	0.048	0.011	0.035	0.013	0.026	-0.005	0.005	-0.023	0.073	0.035	0.072	0.019	0.044
Tria	-0.014	0.015	-0.038	0.037	-0.040	0.022*	-0.024	0.016	0.002	0.003	0.131	0.055**	-0.052	0.050	0.035	0.033
Attri	0.015	0.015	-0.033	0.033	0.100	0.034***	-0.009	0.012	-0.003	0.002	-0.034	0.047	0.025	0.046	-0.061	0.029**

Note: *, **, and *** The null-hypothesis is rejected at a level of significance of P = 0.10, 0.05, and 0.01.

Marginal effects (dy/dx) are calculated at the mean for continuous variables and for a discrete change from 0 to 1 for dummy variables.

Household characteristics include variables such as gender, age, level of education and family size in a particular household. The result shows that, though the coefficient of adaptation options is positive for most adaptation options, the marginal effects of being male or literate and family size are insignificant. However, the age of the head of household, which represents farm experience, has affected adaptation to climate change. For instance, an additional year in the age of the head of household results in a 0.6% increase in the probability of adopting improved crop varieties.

In addition to household characteristics, farm features such as land size and total livestock unit have a significant impact on the selection model. An extra hectare of land reduces the likelihood of only application of organic fertilizer and or with a combination of biological pest control for climate smart adaptation choice by 6.7 and 4.1%, respectively. This may be due to labour shortage and health risks from the adopting organic fertilizers, as well as input cost, improved seeds and PP pest management. The marginal effect of the total livestock unit indicates a mixed effect. In some cases, farmers support the acceptance of only improved seeds or in combined with biological pest mechanisms for additional livestock unit. Thus, an additional unit (equivalent to 500kg) of total livestock will increase the likelihood of adopting improved seeds or when it is adapted to eliminate pests by 1.9 and 5.5%, respectively. Simultaneously, an increment in the unit of total livestock unit reduces the likelihood of adopting of organic fertilizers or when it is combined improved seeds with pp pest practices by 2.1 and 13.4%, respectively. This result is contradicted with Teklewold et al. (2013), as they noted that livestock ownership also positively influences the adoption of manure farming, because livestock waste is the single most important source of organic fertilizer for small farms in most parts of Ethiopia. However, this may be the nature of the trade-off between farming and raising livestock methods, where traditional lifestyle of most rural farmers is tied with their perception of livestock. Similarly, someone participated in non-farm income, increasing the probability of adopting improved crop varieties by 10.6%. Since off-farm activities can cover input costs. However, the decline in farmers implementing all packages as adaptation strategies by 9.2%. This indicates that when farmers have nonfarm incomes options, farmers may shift to climate-friendly agricultural related practices such as adopting (IIF1P1) relative to on-farm income generating activities.

According to Teklewold et al. (2013) access to CSA information increases the probability of applying improved seeds with organic fertilizer mitigating climate change. For instance, with

additional pieces of information on climate change for farmers, the chances of using seeds with organic fertilizer would result to increase by 18.5%. Agricultural extension and credit services shown in Table 3 have a mixed effect. The availability of these services represents a slight reduce in the probability of using improved seeds. In addition, farmers using extension services, the chance of a complete package (IIF1P1) increased by 10.8%, and also the availability of credit improves the implementation of improved seeds with biological pest control by 32.3%. This plays an important role in covering the input costs of rodus grass and striga weed and fodder inputs, which are necessary inputs for farmer's with large livestock unit.

The existence of high temperature in the study area increase the probability of adopting organic fertilizer and a combination of organic fertilizer with improved seeds by 7.6 and 16.3% respectively. These results indicate that as temperature rise, farmers use organic fertilizers and drought-resistant varieties to cope with rising temperatures to maintain soil fertility and water content (Teklewold et al., 2016; Teklewold et al., 2013). The marginal effect of erratic rainfall and pest and diseases goes with same sign. The marginal values of inconsistent rainfall and occurrence of pest and disease are negative. That is, these dummy variables reduce the use of improved seeds by 47.3 and 38.8% because adaptation options have a negative relationship with adaptation to climate change. However, inconsistency of rainfall promotes the adoption of organic fertilizer and when jointly applied with improved seeds by 4.8 and 38.6% respectively. While incidence of pests and diseases in the area increases adoption of IIF1Po (improved seeds with fertilizer) by only 34.3%. This suggests that the same variables may have different influences on the decision to adopt CSA practices and may have a partial / marginal effect on the behavior adopted (Teklewold et al., 2013).

The perceived economic values, such as usefulness, cost, and risk of adaptation, indicated in table 9 show a mixed effect on adoption selection decision. The marginal effect shows that the likelihood of using improved seeds alone and in combination with organic fertilizer will decreased by 17.1 and 43.4%, respectively when farmers having fully understand the economic viability of sustainable agriculture. This result implies the trivial role of improved seeds among households that have experienced unstable rainfall, and pest and disease. As a result, this adaptation option does not support the use of adaptation to reduce the adverse impact of climate change. On the other hand, the specific benefits of sustainable agriculture lead to the possibility of adopting biological

pest control alone and also in combination with improved crop varieties at 5.6 and 37.1%, respectively. This implies that the perceived profitability of these adaptive options affect their broader diffusion (Kassie, Zikhali, Pender, et al., 2009). Besides, if the labor and other input costs of non-climate-smart agricultural system are relatively higher than the CSA method, the option to adapt improved seeds and improved seeds jointly with push-pull technology were increased by 28.8, and 12.9%. While improved seeds with organic fertilizer and full adaptation options were reduced by 29.1 and 15%, respectively. In accordance with Nowak (1991) and (Fazio et al., 2014), if the prices for conventional commodities are good, the incentive to accept sustainable practices is diminishes, since financial risk reduces with the increasing potential profit. The perceived risk, that is the reduction of health risk and the failure of the harvest, also significantly influence the choice of adjustment options. Consequently, if farmers believed that adaptation options could reduce their health and crop failure risks, the adoption of push-pull technology would increase marginally by 5.7%, while adoption of improved crops would decline by 9.3%.

Farmers' psychological perceptions (attitudes, norms and behavioral controls) also make a significance differences in adoption decision-making behavior. According to Shea et al. (2018), most empirical evidence shows that attitudes have a significant influence on a farmers' adoption decisions when included as an explanatory variables in adoption studies. Good attitudes lead choice of adaptive mechanism such as better seeds and increased the chances of adoption by 16%, but push-pull options are decreased by 5%. Moreover, Rose et al. (2018) noted that behavioral decisions are not just affected by individual traits, but rather is also heavily influenced by family, peer, and advisor networks. Conversely, the result shows that farmers' with a plenty of family, friends, neighbors, and extension advisors were decreased farmer's adoption decision-making of push-pull (IoFoP1) and full package (IIF1P1) by 5.9 and 10.5%, respectively. Farmers having skills and knowledge, control over decisions (responsibility) and resource control increased the likelihood of adopting all packages (IIF1P1) at the same time, but decreased the adoption of improved seeds with PP technology (IIFoP1), respectively by 25.1 and 29.6%.

As expected, when technological attributes are compatible with farming experience of households and the value of communities, the option for adaptation to climate change with improved seeds increased significantly by 14.4%. In addition, the technological characteristics of trialability that can be do-able under farmer's current and previous farming condition will decrease the separate adoption of organic fertilizer by 4% and increase by 13.1% when it was adopted with improved crop varieties.

CHAPTER FIVE: CONCLUSIONS AND POLICY IMPLICATIONS

To reduce the social and economic consequences of climate change, the need for climate-smart farming practices to improve agricultural sustainability is one of Ethiopian's most important goals. And any attempt to transform agriculture into a more sustainable system may require the adoption of CSA practices. Yet the predictability and determinants of adopting CSA practices at the farmer level using an integrative approach are unclear. The study considers social, economic, and psychological issues to understand the adoption of certain CSA practices in the four kebele's of Raya Kobo woreda. The study uses the PLS-SEM to predict non-socioeconomic factors, and multinomial logit (MNL) model were applied to investigate how a mix of non-socioeconomic and socioeconomic variables determine the adoption of CSA packages. In the first stage of the prediction method, the PLS-SEM result showed that both economic and non-economic factors were significant predictors of the number of CSAPs adopted by farmers. The complexity of technology negatively and significantly predicts attributes of technologies. Similarly, farmers' attitude followed by behavioral control and subjective norm were an important predictor of farmer's intention. Among the direct predictors of adopting CSA practices, perceived usefulness was highly and positively, whereas, attributes followed by the perceived cost predict the mechanism of adopting CSA inversely. In addition, intention and risk factors positively and significantly predict farmer's adoption behavior, respectively.

In the second stage, the MNL model was used to analyze determinants of adoption decision. Dependent variables include eight mutually exclusive adaptation choices and the explanatory variables include non-socioeconomic variables measured at their mean combined with other dummy and continuous socio-economic factors. Key social drivers for adoption were education level, off-farm participation, farm size, access to CSA information, agricultural loans, extension services, and agro-ecological factors (existence of high temperature, inconsistent rainfall and presence of pests and diseases). Coinciding with other studies, this study also found that farmers' attitudes, norms and personal controls strongly influence the uptake of CSA packages to mitigate the negative effects of climate change. Furthermore, technological attributes such as the compatibility and trialability of selected adoption method with farming system are positively and significantly increased the probability of two or more CSA practices. However, the particular

complexity in particular and attributes of the technology in general re make it less likely to make a decision.

Generally, these findings are important to promote the practice of CSA and address current interventions for the specific needs of farmers. Multidisciplinary and holistic approach focuses on both technology characteristics, perceived economic, and psycho- social factors as part of effective strategies for encouraging uptakes of CSAPs among farmers. Policies and strategies to improve adoption behaviors could include improving farmers education, providing information regarding climate-smart agriculture, providing outreach services, and addressing liquidity constraints through promotion of adoption of sustainable agricultural practices. These can help to minimize the risk of crop failure and increase the perceived use for agricultural production. Furthermore, policies aiming at building positive attitude and skillful and knowledge can increase the possibility of diffusing sustainable climate change adaptation strategies among farmers. Apart from this result, technological characteristics should appear to be more compatible with farming practice, and technically simple and easily understood, and triable under current farming condition. Finally, this study may help young researchers who are interested in adoption decision using technological attributes and psychological factors besides to socioeconomic variables in determining farmers' decision-making.

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Appendix:

Tables 5: Fornell–Larcker Criterion analysis for checking discriminant validity

Variables	ATT	Attribute	Compatibility	Complexity	Cost	INT	PBC	Risk	SN	Trialability	Usefulness
ATT	0.796										
Attribute	-0.214	0.659									
Compatibility	0.507	-0.153	0.856								
Complexity	0.25	-0.416	0.34	0.844							
Cost	-0.249	0.315	-0.172	-0.286	0.738						
Risk	0.426	-0.125	0.386	0.275	-0.21	0.343	0.287	0.763			
SN	0.33	-0.083	0.343	0.176	-0.091	0.246	0.114	0.3	0.629		
Trialability	0.311	-0.179	0.141	0.093	-0.194	0.24	0.184	0.209	0.08	0.713	
Usefulness	0.562	-0.318	0.464	0.408	-0.367	0.511	0.398	0.457	0.303	0.289	0.774

Source: Own Calculation

Figure 4: Bootstrap Partial Least Square T-statistics and R-square with relative results

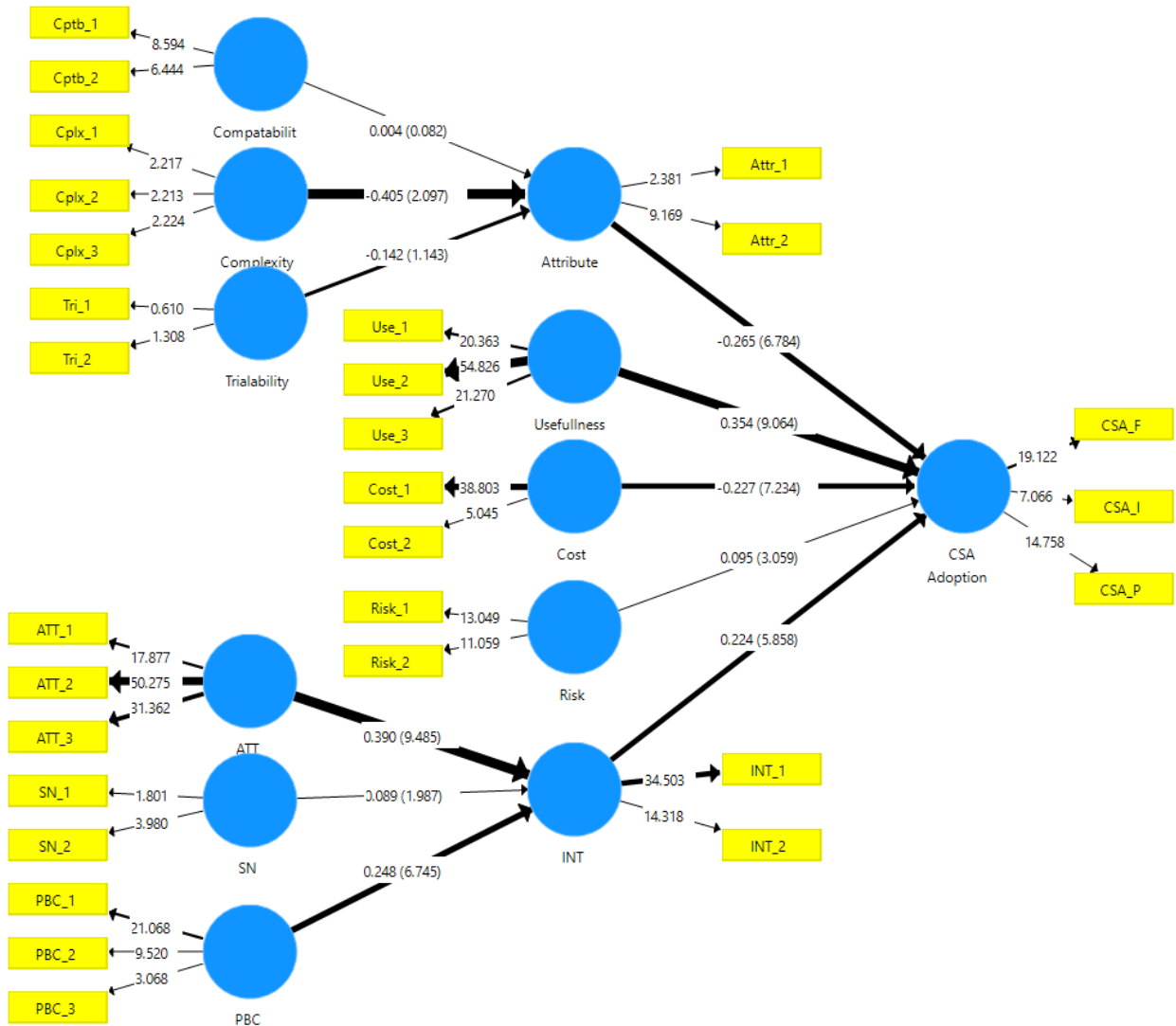
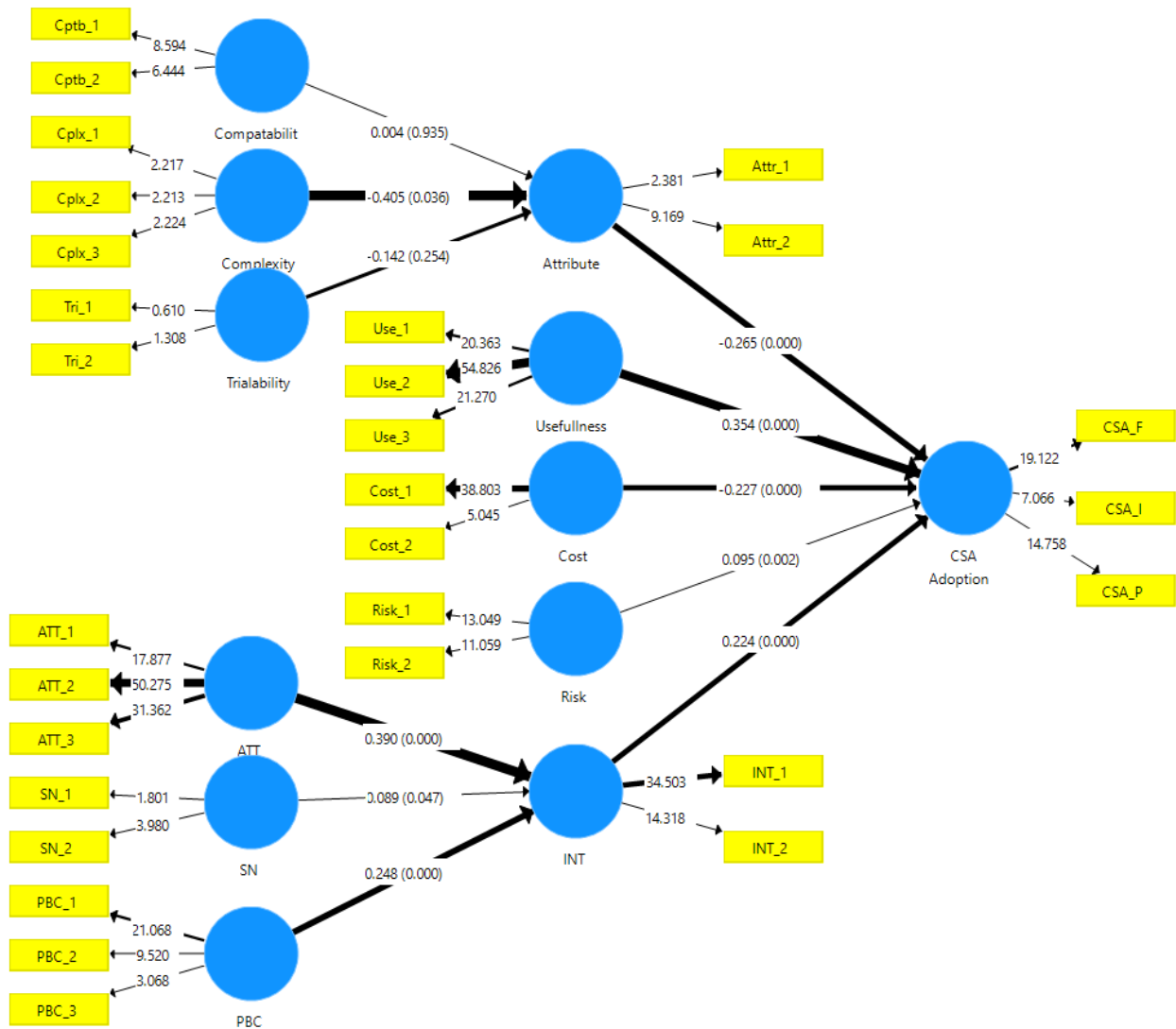


Figure 5: Bootstrap Partial Least Square P values and R square with relative results



Questioner

Addis Ababa
University
(Since 1950)



College of Business and Economics Department of Economics

Concentration Area: Natural Resource and Environmental Economics

Adoption of Climate Smart Agricultural practices in Raya Kobo woreda

Name of enumerator: _____

Woreda: _____ Sub-area (Kebele): _____

HH Name: _____ HH Code: _____

Date: _____

The purpose of this study is to understand the adoption of climate smart (friendly) agricultural practices among farmers of Raya Kobo woreda (North Wollo) Amhara Region. Climate friendly (smart) agricultural practices refers to the way of applying agricultural method (system) on your farmland without degrading the environment, harming the society, and reducing farm incomes but which aims enhancing them in sustainable fashion.

Are you the main decision maker of the farm? Yes: No:

This interview will take about half hour to complete. Your participation is absolutely voluntary. During the interview, if you feel uncomfortable, you are free not to answer any of the question and make sure that you are in a good mood. Your valuable input will help us improve the promotion of climate smart agricultural practices.

All your answers will be strictly confidential and anonymous.

Thank you in advance for participating in this interview. If you have any question or comments, please contact us as follows: -

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Block I: Socioeconomic Variables (please put X sign for yes/ no or other dummy variables)

Farmer's Characteristics

1. Gender of HH head. Male: _____ Female: _____
2. HH Head Age (in years): _____
3. HH Education level: Literate: _____ Illiterate: _____
4. HH Family size (in numbers) _____
5. Number of out migrated HH (outside Ethiopia) (in numbers) _____
6. Do you participate in off-farm activities (like petty trade) Yes _____ No. _____?

Farm characteristics

7. Amount of land size (hectares) _____
8. Total Tropical Livestock¹⁵ Unit (TLU) _____

Access to agricultural service

9. Do you have access to information on CSA practices? Yes _____ No. _____
10. Access to agricultural extension service: Yes _____ No. _____
11. Do you have access to credit? Yes _____ No. _____
12. Have you got subsidy when applying CSA practices from 2010 EC? Yes _____ No. _____

Block II: Climate risk experienced by HH over the last 3 years or Agro-ecological factors

13. Have you experienced high temperature? Yes _____ No. _____
14. There is decreasing and erratic rainfall. Yes _____ No. _____
15. There is high soil erosion in the farm. Yes _____ No. _____
16. There is occurrences of pests and diseases. Yes _____ No. _____

Block III: These questions elicit adopt/non-adopt decision of CSA practices from last year harvesting season (1=yes, 0, otherwise).

17. Have you adopted stress tolerated improved crops¹⁶ like teff, maize or sorghum varieties?
Yes _____ No. _____
18. Have you adopted crop rotation system like legumes with staple crops teff, maize or sorghum?
Yes _____ No. _____

¹⁵ Tropical livestock unit (TLU) standardizes the body weight of livestock: one TLU is equivalent to 250 kg of live weight (FAO, 1999).

¹⁶ Improved Teff 1 (Boset, Quncho); Maize (Melkasa2 and 4 and Pioneer) and Sorghum varieties (Girana, EHS 1-4)

19. Have you used organic fertilization on your farm land to increase your staple crops like teff, maize or sorghum production? Yes _____ No. _____
20. Have you adopted push-pull pest and weed management biologically to your farm land? Yes _____ No. _____

Block IV: Expected Economic factors (please rate the perceived usefulness, cost and risk) associated with adoption of climate smart agricultural practices to conventional farming.

21. Use1. The beneficial of adopting climate smart agricultural practices to my production and to the environment are; Very low: 1 : 2 : 3 : 4 : 5 Very high.
22. Use2. The usefulness of adoption of CSA to disrupts pest outbreak and improves soil fertility than the advantage of conventional practices is;
Very low: 1 : 2 : 3 : 4 : 5 Very high.
23. Use3. The benefit of adopting climate smart agricultural practices on my farming activity in controlling stemborers and striga weed and improves fodder are;
Very unimportant: 1 : 2 : 3 : 4 : 5 Very important.
24. Cost1. The associated labor cost in adopting CSA practices is less than conventional farming. Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
25. Cost2. The associated input costs (eg. improved seeds, inputs used to prepare organic fertilizer and to purchase Rodus grass) of adopting CSA practices are less than conventional farming (e.g. local seeds);
Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
26. Risk1. Adoption of CSA practices (e.g. food produced by organic farming) reduces my associated health risk than non-CSA farming (or using chemical pesticides);
Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
27. Risk2. The reduction of risks arises from crop failure (by tolerating stress, fix nitrogen, and controls pests and disease) from adoption of CSA practices are;
Very low: 1 : 2 : 3 : 4 : 5 Very high.

Block V: Psychosocial Factors (this rate is based on attitude (behavioral beliefs), SN (normative beliefs) and PBC (control beliefs) towards adopting CSA practices).

28. ATT1. My adoption of climate smart agricultural practices for my agricultural system are; very inconvenience: 1 : 2 : 3 : 4 : 5 very convenience .

29. ATT2. My practical adoption of CSA practices can enhance my agricultural production over time; Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
30. ATT3. The effectiveness of my adoption of climate smart agricultural practices in my farming system are; Very unrealistic: 1 : 2 : 3 : 4 : 5 Very realistic.
31. SN1. Most of my friends, families and neighbor's approval (recommendation) my decision to adopt CSA practices are; very low: 1 : 2 : 3 : 4 : 5 very high.
32. SN2. Agricultural agents' recommendation on my decision to adopt CSA practices are; very low: 1 : 2 : 3 : 4 : 5 very high.
33. PBC1. My skill and knowledge to adopt CSA practices in my farm land are; very low: 1 : 2 : 3 : 4 : 5 very high.
34. PBC2. The decision and responsibility to adopt CSA practices is entirely depending on me; Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
35. PBC3. I have the necessary resource which allows me to adopt CSA practices are; very low: 1 : 2 : 3 : 4 : 5 very high.
36. INT1. My regular use of CSA practice so far are; very low: 1 : 2 : 3 : 4 : 5 very high.
37. INT2. My intention to use CSA practices in the future are; very low: 1 : 2 : 3 : 4 : 5 very high.

Block VI: Perceived Attribute of innovations (attributes beliefs)

38. Cptb1. The compatibility of climate smart agricultural practices with all aspect of my farming experience are; very bad: 1 : 2 : 3 : 4 : 5 very excellent.
39. Cptb2. The appropriateness of adopting CSA practices with my farming communities' value are; very low: 1 : 2 : 3 : 4 : 5 very high.
40. Cplx1. Adopting CSA practices can be easily understood without external help needed; Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
41. Cplx2. CSA practices are complex and requires a lot of mental and physical effort, which makes adoption cumbersome are; Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.
42. Cplx3. CSA practices can easily be carried out, which makes adopting relatively technically simple; Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.

43. Tri1. The trialed of CSA practices can be straightforwardly do-able under my current farm condition without modifying my farm operation is;

very challenging: 1 : 2 : 3 : 4 : 5 very practical.

44. Tri2. I have had a great deal of opportunity to try CSA practices in my farm land so far;

Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.

45. Attr1. The attributes of these agricultural innovations can consume much time when adopting in farm land than conventional;

Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.

46. Attr2. The attributes of CSA innovations seem they can't be carried out at farm level.

Strongly disagree: 1 : 2 : 3 : 4 : 5 Strongly agree.

Block VII: Please rate the contribution of adoption of CSA practices for your farm

47. My adoption of improved crop varieties such as teff, sorghum and maize are effective for me in increasing production and productivity in short months by preventing severe heat and precipitation; Very low: 1 : 2 : 3 : 4 : 5 : 6 : 7 : Very High

48. Applying climate-friendly farming practices such as natural fertilizer to reduce the negative impacts (example soil salinity and human health) of chemical fertilizers and soil pesticides; Very unsatisfactory: 1 : 2 : 3 : 4 : 5 : 6 : 7 : Very satisfactory.

49. My adoption of push-pull strategy (using for example roodus grass) reduce the negative impact of artificial chemicals on human and crops which control pest and weeds biological will also serves as animal fodder are; Very unrealistic: 1 : 2 : 3 : 4 : 5 : 6 : 7 : very realistic.

Thank you for your cooperation.

Declaration

I declared this thesis is my original work and it was done in collaboration with my advisors.

Data is collected on the ground and all sources of materials that used for this thesis have been dully acknowledged.

Declared by:

Name: Iyasu Hailu

Signature: _____

Date: _____

As thesis advisor, I hereby confirm that this thesis is the output of research undertaken by Mr. Iyasu Hailu under my supervision and that it be submitted for the M.Sc. degree award.

Confirmed by (Advisor): **Assefa Admassie (PhD)**

Signature: _____

Date: _____

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