IMPACT OF IMPROVED SORGHUM VARIETIES ON POVERTY REDUCTION AMONG RURAL FARMING HOUSEHOLDS IN THARAKA NITHI COUNTY, KENYA

BACKSON MUTONYA MWANGI (MSc)

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A THESIS SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (AGRICULTURAL ECONOMICS) IN THE SCHOOL OF AGRICULTURE AND ENTERPPRISE DEVELOPMENT OF KENYATTA UNIVERSITY

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DECLARATION

I, **Backson Mutonya Mwangi**, declare that this thesis is my original work and has not been presented for the award of a degree in any other university or any other award.

....

Signature Date

Backson Mutonya Mwangi (A99/27899/2014)
Department of Agricultural Economics

SUPERVISORS

We confirm that the work reported in this thesis was carried out by the candidate under our supervision and has been submitted with our approval as University Supervisors.

Dr. **Ibrahim Macharia Ndegwa** (PhD)
Department of Agricultural Economics
Kenyatta University

....

Signature Date

Dr. **Eric Kiprotich Bett** (PhD)
Department of Agricultural Economics
Kenyatta University

....

Signature Date

DEDICATION

To my wife Rebeccah Wairimu and my two sons namely Nethan Mwangi and Osteen Ngugi. Also, to my parents and sister, for your unconditional love, support and patience throughout the study period.

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LIST OF ACRONYMS AND ABBREVIATIONS

ASALs	Arid and Semi-Arid Land Areas
AIC	Akaike Information Criterion
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
BIC	Bayesian Information Criterion
CD	Cobb-Douglas
DFID	Department for International Development
DA	Duration Analysis
DH	Double Hurdle
EABL	East African Breweries Limited
EAML	East African Maltings Limited
ESR	Endogenous Switching Regression
GoK	Government of Kenya
Ha	Hectares
HH	Household Head
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IPWRA	Inverse Probability Weighted Regression Adjustment
ISVs	Improved Sorghum Varieties
KBL	Kenya Breweries Limited
PSM	Propensity Score Matching
USD	United States Dollar

ABSTRACT

Poverty alleviation and attainment of food security are among the major concerns facing majority of households in arid and semi-arid land areas of Kenya. The Government of Kenya in partnership with other sector stakeholders have invested heavily in the development and promotion of suitable high yielding improved sorghum varieties that are less susceptible to climate change, pests and diseases. Over the years, sorghum demand has outstripped supply. The deficit supply gap keeps expanding and this trend is unexpected since farmers have been assured of a market and price through forward delivery contracts. The interventions are intended to reduce poverty among adopting households. However, the impact of the interventions is not clear and has not been empirically established. In response, this study formulated three specific objectives where the first aimed to assess the determinants of adoption, intensity of use and speed of uptake of improved sorghum varieties. The second and third attempted to evaluate the profit efficiency and estimate the impact of improved sorghum varieties on poverty reduction respectively. Cross-sectional research design was used and primary data were collected from a sample size of 452 households using a structured questionnaire. Further, focus group discussions and key informant interviews were also conducted. Data were analyzed using Double Hurdle and Duration Analysis models for the first objective. To answer the second objective, Cobb-Douglas Stochastic Profit Frontier was used. Furthermore, 3 models namely; Propensity Score Matching, Inverse Probability Weighted Regression Adjustment and Endogenous Switching Regression models were used to answer the third objective related to impact of improved sorghum varieties on poverty reduction. Findings generated by Double Hurdle and Duration Analysis models indicated that determinants of the three adoption decisions are not necessarily the same. While many variable coefficients depicted expected *a priori*, distance to the nearest agricultural offices and intensity of use of improved sorghum varieties depicted unexpected positive *a priori* indicating possible use of home saved seeds. Further, access to agricultural credit returned unexpected negative *a priori* for both intensity of use and speed of adopting improved sorghum varieties' decisions. On the other hand, results generated by Cobb-Douglas Stochastic Profit Frontier showed a wide range of profit efficiency from 0.12 to 0.96 for the worst and best sorghum farmer, respectively, with a mean of 0.17. Average treatment effects results generated by the 3 impact models indicated a positive significant difference in daily consumption expenditure per adult equivalent of between USD 0.09 to 0.21. Further, counterfactual results generated by Endogenous Switching Regression model showed that, non-adopters would have increased their consumption expenditure per adult equivalent by on average USD 0.96 daily had they decided to adopt. Therefore, adoption-stimulating policies that target to raise resource endowment of households, improve access to extension service and rural infrastructure need to be implemented. Further, this study advocates for incentive-based policies aimed at widening agro-dealer networks mainly directed to County Government to consider reducing certifications such as trade permits. Additionally, policies targeting to reduce credit providers' cost of doing business and increase their lending appetite such as use of technology, business champions and guarantee schemes should be developed.

CHAPTER ONE

INTRODUCTION

1.1 Background information

1.1.1 Agriculture and poverty alleviation

Poverty is widespread and more prevalent in the rural areas of developing nations, where approximately 75 percent of the poor live and heavily rely on agriculture to support their livelihoods (GoK, 2019a). Over the years, the African continent has lagged behind other developing regions in poverty reduction efforts (Beegle *et al.*, 2016; World Bank, 2016). Estimates indicate that in Africa, on average, 40 percent of the population lives in extreme poverty (United Nations, 2015). This shows that efforts and attention should be directed towards the formulation and implementation of poverty alleviation interventions targeting poor rural households. Improved agricultural productivity presents a good game changer for exiting this situation.

In the wake of the ever-increasing human population, especially in the developing world, appropriate agricultural targeted interventions are needed to mitigate hunger and poverty (Cervantes-Godoy and Dewbre, 2010; United Nations, 2015). In the past decade, Kenya’s population has increased by over 25 percent and estimated at 47.5 million by the year 2019 (GoK, 2019a). The population growth trend is expected to exert more pressure on food production and worsen a current situation where demand outstrips supply. This underpins the need to address agricultural production in the country, which is a net importer of many agricultural products. From the year 2006 – 2016, food imports in the country increased at a rate of 10 percent annually (GoK, 2019b). Population increase and existing land practices, including massive fragmentation into uneconomic units adversely affect food production in the country (GoK, 2019b).

This means that, for Kenya to produce enough for her population, several strategies should be employed, including increasing agricultural productivity by efficiently utilizing limited available resources. According to World Bank (2007), the main pathway to poverty alleviation is through improved productivity and sustainability of smallholder agriculture, especially in many African economies that mainly depend on the sector.

The Kenyan economy is agrarian based practised majorly by smallholder farmers who heavily depend on rain-fed agriculture (D'Alessandro *et al*., 2015). Most of the farmers who practice smallholder farming are resource-constrained especially those that reside in areas experiencing low and unpredictable rainfall patterns (GoK, 2010). Due to changing weather conditions, the households become more vulnerable and therefore, robust strategies on how to reduce poverty levels need to be advocated for including diversification and adoption of high yielding drought-resistant crop varieties.

1.1.2 Poverty profile in Kenya

In Kenya, the first attempt to comprehensively measure both rural and urban poverty using monetary and multi-dimensional metrics for different population groups was carried out using data collected in year 2015/16 for the Kenya integrated household budget survey (GoK, 2020). Approximately, 23.4 million Kenyans accounting for 53 percent were reported as multi-dimensionally poor compared to 15.9 million (36 percent) indicated as monetary poor.

Additionally, 27 percent of total population was reported as being both monetary and multi-dimensionally poor. Approximately 6.4 million (48 percent) of the youth sub-group (aged 18 – 34 years) were reported to be multi-dimensionally poor whereas about 3.8 million (29 percent) were monetary poor. There exists a higher rural incidence of monetary poverty (40 percent) as compared to urban (29 percent). The youth recorded the lowest poverty incidence (29 percent) which was highest among the children aged below 18 years (42 percent). In terms of age group disaggregation, although monetary poverty was highest among children (55 percent), it was lowest among the elderly 60 years and above (6 percent).

The report indicated the monetary poverty line for rural and urban areas to be at Kes. 3,252 and Kes. 5,995 per month respectively expressed in adult equivalent terms. The monetary poverty included minimal provisions for both non-food and food expenditures. Approximately, 36.8 percent of the total population recorded less than USD 1.90 in daily consumption expenditure per adult equivalent (GoK, 2020).

1.1.3 Poverty profile in Tharaka Nithi County

Approximately, 23 percent and 63 percent of the total population in Tharaka Nithi County are reported monetary and multi-dimensionally poor respectively (GoK, 2020) as disaggregated in Table 1.1. Children reported highest monetary metric percentages (26.2), followed by adult population (18 - 35 years) at 24.6 percent and least were the youth (18.8 percent). On the other hand, adult population was the most multi-dimensionally poor (75.1 percent) followed by elderly (60 years and above) at 58.9 percent (Table 1.1).

Table 1.1: Monetary and multi-dimensional poverty in Tharaka Nithi County

Age bracket (years)	Monetary poverty (percent)	Multi-dimensional poverty (percent)	Overlap between Multi-dimensional and Monetary poverty (percent)
Less than 18	26.2	58.4	19.9
35 - 59	24.6	75.1	22.8
60 and above	20.6	58.9	13.6
18 - 34	18.8	58.1	13.3

Source: GoK, 2020

On average, poverty incidence levels in the 15 wards within Tharaka Nithi County was highest in Gatunga ward (between 72 - 85 percent) followed by Mukothima, Chiakariga and Marimanti wards, jointly reported at between 58 - 71 percent. The ward with the lowest poverty incidence levels of less than 15 percent were reported as Ganga, Muthambi and Magumoni (Table 1.2).

Table 1.2: Poverty incidence levels by wards in Tharaka Nithi County

Wards	Poverty incidence (percent)	Poverty gap (percent)
Gatunga	72 - 85	21 - 31
Mukothima	58 - 71	13 - 20
Marimanti	58 - 71	13 - 20
Chiakariga	58 - 71	13 - 20
Nkondi	44 - 57	8 - 12
Igambang'ombe	44 - 57	8 - 12
Mugwe	30 - 43	5 - 7
Mariani	30 - 43	8 - 12
Mitheru	16 - 29	3 - 4
Karingani	16 - 29	8 - 12
Chogoria	16 - 29	5 - 7
Mwimbi	16 - 29	5 - 7
Magumoni	Less than 15	5 - 7
Muthambi	Less than 15	5 - 7
Ganga	Less than 15	3 - 4

Source: Tharaka Nithi County Development Plan, 2018

1.1.4 Poverty reduction and agricultural research

From literature, attempts to link the importance of agricultural research to reduction of poverty among rural household livelihoods have been made contributing to a large body of knowledge (de Janvry and Sadoulet, 2001). Agricultural research plays an important role in increasing productivity through the uptake of improved technologies. There is huge potential of improved agricultural technologies to directly or indirectly reduce poverty levels of rural households (Becerril and Abdulai, 2010). For example, direct effects may arise by smallholder farmers using improved technologies, thereby improving production and subsequently household income, especially when they have access to profitable markets. Additionally, households can benefit directly through reduction of production costs due to technological efficiency. On the other hand, indirectly, poverty could be alleviated by reducing food prices as well as increasing wages in agricultural production (Becerril and Abdulai, 2010).

Further, enhanced agricultural productivity can be achieved if cost-effective varieties aimed at increasing yields are developed and disseminated to the rural poor farming households. This underpins the importance of agricultural research coupled with technological improvements that are crucial factors for increased farm productivity (de Janvry and Sadoulet, 2001).

In Kenya, livelihoods in Arid and Semi-Arid Areas (ASALs) are often characterized by harsh climatic conditions, making them more susceptible to hunger and poverty (GoK, 2010). In an effort to adapt to the ever-changing climatic conditions in those regions, farmers have been advised to embrace sorghum crop as the main source of sustainable livelihood (Nagarajan and Audi, 2007).

To support this course, the Government of Kenya working together with other sector stakeholders have heavily invested towards research, development and promotion of high yielding improved sorghum varieties (ISVs) with desirable agronomic and market traits (GoK, 2010). It is a good option for farmers, especially in ASALs, because of its adaptability and resilience to bio-stress and excessive heat (Orr *et al.,* 2016). By the year 2018, about 43 ISVs had been released (GoK, 2018a). However, despite the varieties being high yielding, the national average yields remain below 1 ton ha^{-1} compared to the potential of 2 - 5tons ha^{-1} (GoK, 2015) as indicated in Table 1.3.

Table 1.3: Sorghum production data year 2010-2014

Year	2010	2011	2012	2013	2014
Area of land harvested `000 (ha)	226	254	224	224	214
Yield (90kg ha^{-1})	8.07	6.99	8.27	8.39	9.24
Yield (tons ha^{-1})	0.72	0.63	0.74	0.76	0.83

Source: GoK, 2015

The eastern region of Kenya is the country's sorghum basket that has continued to benefit from Government's heavy investment in the sector (GoK, 2010). However, despite these investments in the sorghum sector, yields are still low. For example, according to EAML, on average, Tharaka Nithi smallholder sorghum farmers produce 0.6 tons ha^{-1}. Although, low yields can be attributed to several factors some of which are beyond farmers' control such as climate change, high level of inefficiencies is a major contributing factor (Wollie *et al.*, 2018; Chepng'etich *et al.*, 2014; Chimai, 2011).

Sorghum farmers in eastern Kenya have been reported to be technically inefficient with a low mean level of 41 percent (Chepng'etich *et al.*, 2014) despite huge investment in the value chain. This underscores the need for continued research efforts on efficiency, which perhaps should expand the scope to other efficiency aspects beyond technical. This study is not aware of any research, which has attempted to assess profit efficiency levels of sorghum farmers in eastern Kenya. Therefore, this study aimed to bridge the identified knowledge gap by analyzing profit efficiency among sorghum farmers in Tharaka Nithi County using Cobb-Douglas Stochastic Profit Frontier method.

On the other hand, farmers adopting ISVs are still few despite being offered forward supply contracts guaranteeing them a market and price (KBL, 2018). According to EAML, approximately half of the households (26,000) in Tharaka Nithi County located in areas suitable for sorghum production had adopted ISVs compared to the total potential population of more than 50,000 majority residing in Tharaka North and South sub-Counties. This begs the question why? Finding answers to these questions are critical now that, low farm-level productivity coupled with few adopting farmers, among other factors, have created a huge deficit in sorghum produce supply. This deficit continues to destabilize the sorghum market especially for brewers whose annual demand is twice the supply and expected to increase following decision by Keroche Breweries Limited to start beer brewing using sorghum (Keroche, 2019). Further, market actors continue to invest in the value chain with East Africa Breweries Limited (EABL) opening a new processing plant located in Kisumu County and expected to serve west Kenya region. The move has been necessitated by shortage of sorghum supply from eastern Kenya. The opening of the new brewery has pushed the EABL's annual demand of sorghum to 60,000 tons. However, the supply is barely less than half of the targeted amount (KBL, 2018).

The promotion of ISVs as a major source of livelihood in the ASALs is a government strategy aimed to have a positive impact on household's food security, increase income and reduction in poverty levels (Ochieng *et al.*, 2011). This contributes to the food security pillar of the Government's big four agenda on sustainable development (GoK, 2018b).

In Africa, many impact assessment studies have been conducted majorly on maize, cassava, mango among other crops (Biru *et al.,* 2019; Marechera *et al.,* 2019; Midingoyi *et al.,* 2019; Agunbiade and Oke *et al.,* 2019; Ahmed *et al.,* 2017; Feleke et *al.,* 2016; Khonje *et al.,* 2015; Afolami *et al.,* 2015). However, few studies have attempted to understand whether, how, and to what extent ISVs impact on poverty reduction among rural farming households. This study aimed to address this paucity of information by estimating the impacts of ISVs on poverty reduction in Tharaka Nithi County. Consumption expenditure adjusted in adult equivalence terms was used as the outcome variable since it is a more reliable indicator and accounts for differences in household size, demographic structure and economies of scale in consumption (Haughton and Khandker, 2009).

1.2 Statement of the research problem

Government of Kenya and other stakeholders have prioritized interventions targeting reducing food insecurity and poverty levels among the rural farming population, especially in ASALs. This has led to heavy resource investments directed towards the development and promotion of ISVs that are high yielding, drought tolerant and have suitable traits that make them appropriate for commercial use especially in the brewing industry. Despite the varieties being high yielding and with a potential of producing on average 2 - 5 tons ha^{-1}, the recorded yields in the study area are low (0.6 tons ha^{-1}). Over the years, EABL's sorghum demand has not been fulfilled, and the deficit gap is bound to increase with the entrant of Keroche Breweries Limited in beer brewing using cereals particularly sorghum. For example, EABL's annual demand of sorghum is 60,000 tons but the supply is barely less than half of the targeted amount.

Additionally, approximately 26,000 out of a possible 50,000 households located in areas suitable for sorghum production have adopted ISVs. Therefore, finding out why nearly half of the target population have not adopted ISVs is crucial since the price and market for these commercial varieties is consistent and guaranteed through contractual farming. Furthermore, farmers are assumed to make rational investment decisions, and thus, they often prioritize most profitable farm enterprises. In Kenya, although several studies have been conducted on sorghum, very few have attempted to assess whether smallholder farmers are profit efficient. This study, therefore, attempted to address this dearth of information by assessing the profit efficiency of smallholder sorghum farmers.

The main intention and aim of developing and promoting ISVs is to increase income and consumption expenditure levels hence reducing poverty among the adopting households. It is important to note that, about 63 percent and 23 percent of population in Tharaka Nithi County is reported as multi-dimensionally and monetary poor, respectively. The poverty incidence levels across the 15 wards within the County are highest (ranging between 58 – 85 percent) in sorghum producing areas particularly those located in Tharaka South sub-County namely; Gatunga, Marimanti and Chiakariga. Mukothima ward which is the study area located in Tharaka North sub-County also reported poverty incidence levels of between 58 – 71 percent and a high poverty gap of 13 – 20 percent. Owing to the fact that ISVs are intended to contribute to the reduction of poverty levels of adopting households, the high poverty incidence levels are unexpected. Further, since the impact of ISVs towards poverty reduction is not clear and has not been empirically established, this study was conceptualized to fill this knowledge gap. Therefore, this study attempted to find out, whether and to what extent, ISVs influences poverty reduction among smallholder farmers in Tharaka Nithi County.

1.3 Objectives of the study

The overall study objective was to evaluate the contribution of improved sorghum varieties towards poverty reduction and efficient attainment of sustainable livelihoods among smallholder farmers in Tharaka Nithi County, Kenya. The specific objectives were:

1. To assess the determinants of adoption, intensity of use and speed of uptake of ISVs.
2. To evaluate the profit efficiency of smallholder sorghum farmers.
3. To estimate the impact of ISVs on poverty reduction among smallholder farmers.

1.4 Research questions

1. What are the determinants of adoption, intensity of use and speed of uptake of ISVs?
2. Are smallholder sorghum farmers in Tharaka Nithi County profit efficient?
3. What is the impact of ISVs on poverty reduction among smallholder farmers?

1.5 Justification of the study

In Kenyan ASALs, researchers have identified sorghum as an important crop capable of supporting livelihoods of farming households. Through collaborations involving the Government, researchers and other relevant stakeholders, ISVs have been developed, disseminated and widely promoted to increase yields and household incomes, thereby reducing poverty. Although most ISVs are grown for commercial purposes with an assured price and market, the volumes produced and marketed do not meet the ever-increasing demand. For example, EABL's annual demand for sorghum is pegged at 60,000 tons but the brewer never gets half of the requirement. The demand is expected to keep growing as EAML's capacity continue increasing, while other companies such as Keroche Breweries Limited have started using sorghum as a raw material for brewing (Keroche, 2019). The failure of EAML to get enough sorghum supplies from eastern Kenya pushed the brewer to recently open a new processing plant in Kisumu County targeting to serve and tap west Kenya's region potential. This study is therefore crucial in understanding why the production of sorghum in the study area does not match the demand. Further, the results of this study will be important to EABL for scale purposes in west Kenya as well as other brewing entrants.

The estimated number of households in the study producing sorghum is half (26,000) compared to potential of more than 50,000. Understanding why the farmers are not yet incentivized enough to produce in large numbers and satisfy the consistent and guarantee market is crucial. This study therefore is important in that it adds to the body of knowledge on why the adopting farmers are low and captures the aspect of profitability.

On the Government policy front, sorghum continues to be a key crop in increasing resilience of ASAL households as well as contributing towards poverty reduction. For example, in the Kenya's Vision 2030, sorghum contributes to its realization under the economic pillar through science, technology and innovations foundation hinged on research and development (GoK, 2007). It is also a key component in realization of Big '4' Agenda particularly the one relating on food and nutrition security, which builds into the Vision 2030. Further, under Agricultural Sector Transformation and Growth Strategy (ASTGS), sorghum contributes through 3rd pillar of increasing household food resilience with an attempt to reduce food insecure Kenyans in ASALs from 2.4 million to zero (GoK, 2019b). Furthermore, sorghum is an integral crop in supporting the achievement of United Nations Sustainable Development Goals particularly 1 and 2 of eradicating poverty and erasing hunger respectively.

On impact assessment, no reviewed study has been commissioned to evaluate the impact of ISVs on poverty reduction, thus the importance of filling this knowledge gap. This is because, with the high poverty incidence levels in the study area, it is critical that we understand the contribution of ISVs in reducing poverty. It is worth noting that, impact assessment studies are very critical in informing technology developers and policy-makers about the contribution of the interventions to the target beneficiaries. They assist policymakers in making decisions on whether programs are generating intended impacts on the targeted beneficiaries.

Additionally, impact studies assess how the effects of one intervention can guide co-existing and future evaluations of related interventions (Khandker *et al.,* 2010). It is critical to understand what works, what does not, and how changes in the livelihoods of beneficiaries can be attributed to poverty reducing interventions targeting ISVs and gives insights of how to scale within Tharaka Nithi County and beyond. Furthermore, the impact assessment also ensures that public resources are allocated accountably. It is against this backdrop that, this study attempted to estimate the poverty-reducing impact of ISVs among sorghum farming households in Tharaka Nithi County. This study was relevant since results highlighted the impact of adopting ISVs and enumerated specific recommendations that sorghum stakeholders particularly EABL, Tharaka Nithi County Government and credit providers could consider to implement and increase the number of farmers adopting the improved sorghum varieties as well as how to scale within the County and to other similar areas.

1.6 Limitations and scope of the study

Although ISVs have been promoted in many counties in eastern Kenya, this study focused on Tharaka Nithi County and cross-sectional data was limited to year 2017/2018 cropping season. Despite the fact that, there are many sorghum varieties promoted and adopted by farmers in the county, including traditional ones, this study only assessed the impact of improved sorghum varieties on poverty reduction. On the other hand, there exists several ways of measuring poverty majorly through use of either monetary or multi-dimensional metrics. However, this study limited itself to monetary measurement of poverty. Despite the fact that monetary measurement can be undertaken using income or consumption expenditure approach (Haughton and Khandker, 2009), this study used the latter and adjusted it into adult equivalent terms. This was in order to take into account differences in household size, demographic structure and economies of scale in consumption.

1.7 Operational definitions of terms

1. **Technology adoption:** Refers to a mental process through which a farmer is exposed (becomes aware) to a particular technology (ISVs) and decides to practise (plant the varieties). In this study, an adopter was regarded as any farmer who cultivated any of the ISVs during year 2017/2018 cropping season.
2. **Intensity of use:** This is the proportion of the area of land under ISVs to the total cultivated land of a household.
3. **Speed of uptake:** Refers to the length of time (years) a farmer waits from the time of becoming aware about existence of ISVs to the actual time of deciding to adopt (adoption spell).
4. **Impact assessment:** This is an evaluation geared to understand the effects of a particular intervention (ISVs) on the target beneficiaries (Khandker *et al.*, 2010).
5. **Monetary poverty:** This is a poverty measure by use of money metric terms mostly income or consumption expenditure and indicates the proportion of the population, which fall below an identified poverty line.

6. **Multi-dimensional poverty**: This measures poverty in non-monetary terms to provide a more comprehensive assessment of the extent of poverty and deprivation by including several aspects such as health, education and standard of living.
7. **Poverty incidence:** Refers to the proportion of people/households who are under the identified poverty line.
8. **Povery gap:** Refers to the extent to which on average households fall below the identified poverty line as a proportion of the poverty line.
9. **Consumption expenditure per adult equivalent:** Refers to an index computed from information related to purchases and consumption of food, non-food items and services in a given household adjusted in adult equivalent terms[1].
10. **Improved sorghum varieties:** Means any sorghum variety that had been bred using formal breeding methods. It also included any formally bred cultivars that was recycled but still maintained some of the inherent characteristic attributes.

[1] Adult equivalent scale used is presented in appendix 9.

1.8 Theoretical framework

This sub-section provides an overview of the theory that supports this study. It also presents a sustainable livelihoods approach which has largely been used by many development partners in explaining poverty. In literature, there are many economic theories of poverty presented and supported by several different schools of thought. These theories include; Classical theory, New-classical theory, Marxist/radical theory, Keynesian theory/Neoliberal and social exclusion and social capital theory among others. Due to the complex nature and dynamics of poverty and although different theories contribute something to the understanding of poverty, none is in itself sufficient (Davis and Sanchez-Martinez, 2015; Agola and Awange, 2014).

Whereas Classical theory explain that, individuals are ultimately responsible for poverty and thus provides a foundation for *laissez-faire* policies, Neoclassical school of thought is more diverse and presents other factors which are responsible for poverty such as market failures which are beyond individuals' control. The converging aspect of Classical and Neo-classical theories is the fact that they over-emphasize the monetary aspects, limited role of government in poverty eradication and focusses on individuals rather than the groups. One distinguishing factor of Neo-classical school of thought is the fact that, it focuses on individual choices in relation to education, training and mobility to explain differences in incomes and pays little attention or emphasis on the role played by other factors such as economic institutions and social norms.

Neo-classical theory further explains that, income inequality is necessary for growth and efficiency of an economy and that, existence of different and varying initial endowments is the basis for specialization and exchange. The theory argues that the differences in incomes is a reflection of the variations in physical and human assets base. It also finds that, savings rate and investment levels are bound to increase following income inequality. Additonally, Neo-classical economists argue that, a decrease in income inequality is likely where exchange and growth exists (Davis and Sanchez-Martinez, 2015). It is also worth noting that, the Neo-classical economic theory of poverty is premised on the marginal productivity of labour concept. The main advantages of both Classical and Neo-classical theories is the fact that, they advocate for use of monetary units to measure poverty and also highlight the influence of incentives on individual behavior. They also share the same school of throught on the relationship between productivity and income.

On the other hand, Keynesian/Neo-liberal school of thought focus mainly on the aspects of macroeconomic forces and role of government in providing economic stability and public goods. They argue that poverty is involuntary and caused by unemployment. Marxian/radical argues that, class and group discrimination is central to poverty and therefore amplify the role of the state regulation of markets. Finally, social exclusion and social capital theories argue that, the role of social as well as economic factors is crucial when addressing poverty related matters. Based on the above review, this study sits well and is explained better by the New-Classical theory of poverty.

To further deepen the understanding of poverty, this study presents sustainable livelihoods approach first introduced by the Brundtland Commission on Environment and Development. United Nations Conference later expanded the concept of Environment and Development in 1992, which advocated for the inclusion of sustainable livelihoods as a broad goal for poverty eradication. It has widely been used by several organizations such as the British Department for International Development (DFID) in their developmental works as well as other researchers (Chambers and Conway, 1992; Ellis, 2000).

Several definitions have been suggested that generally seek to emphasize the capabilities of people to shape their lives using the asset base at their disposal to make a living. Ellis (2000) defines livelihood as “the capabilities, assets (including both material and social resources) and activities required for a means of living”. On the other hand, Chambers and Conway (1992) define livelihood as comprising of “the capabilities, assets (stores, resources, claims and access) and activities required for a means of living”. They continue to describe a livelihood sustainable when it “can cope with and recover from stress and shocks, maintain or enhance its capabilities and assets, and provide sustainable livelihood opportunities for the next generation; and which contributes net benefits to other livelihoods at the local and global levels and in the short and long-term”.

The sustainable livelihoods approach is comprised of five major components. Component one addresses the vulnerability context, which describes externalities facing the households, e.g. shocks (environmental, conflict-related etc.), seasonalities and emerging critical trends. The second component relates to livelihood assets, which are a fundamental input for households to realize a positive outcome that is varied in nature. Human, social, natural, physical and financial capitals are some of the most common assets owned by many households (Scoones, 1998) and are presented in Figure 1.1 .

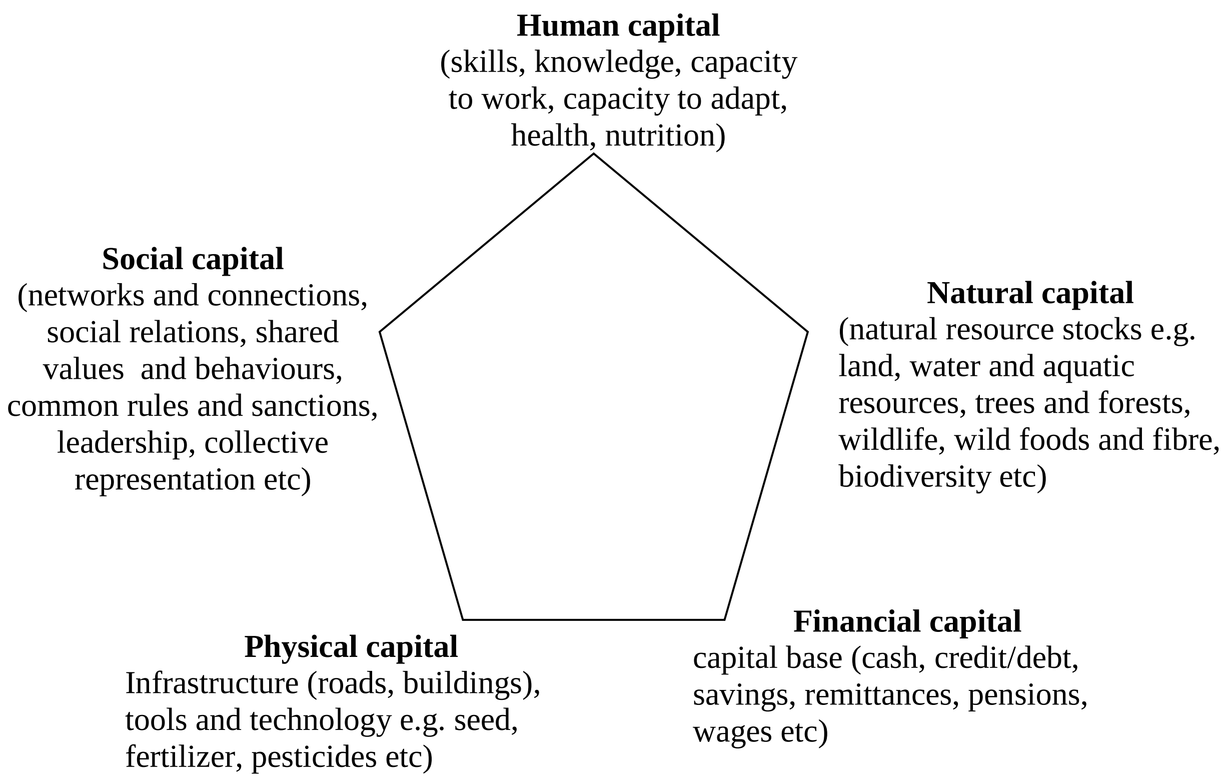

Figure 1.1: The capitals of a sustainable livelihood

The third component indicates the transforming structure and process that includes institutions, organizations and policies which affect livelihoods of the population's poor section. They determine different kinds of assets accessible to the poor household. For the rights of the individuals to be secured, several processes such as ownership rights and laws as well as international agreements, must be in place.

The fourth component shows the livelihood strategies that refer to a dynamic process where households combine interventions and choices in order to facilitate the achievement of their desired outcomes. They are directly dependent on asset base, policy framework, institutions and processes in a given set-up. Households employ different strategies depending on the assets that they can access as well as the structures and processes available in a given society. The fifth and last component shows the livelihood outcomes, which refer to the achievements, made by households after embracing life-changing strategies such as increased income and well-being etc. It is important to understand the goals of particular groups and monitor the level of their progressive achievement.

1.9 Conceptual framework

The conceptual framework used in this study (Figure 1.2) builds into Neo-Classical theory and on the sustainable livelihoods approach. According to Chambers (1983), sustainable livelihoods approach is used since it examines where households are located, what they have at their disposal as well as their needs and interests. The approach distinguishes itself from other frameworks, which normally regard a farmer as a passive beneficiary of a certain technology. On the contrary, it recognizes a farmer as an actor in the process who has assets and capabilities which, when combined effectively, will enable him/her to pursue and achieve desired livelihood goals. The approach focuses on indicating variant poverty contributing factors that determine access to different kinds of assets by farming households and thus their livelihoods.

It shows the interactions between the livelihood components in a smallholder farmer context and how they relate for a household to achieve the desired outcome, i.e. poverty reduction. The livelihood outcome can produce feedback effects on the household asset base. For example; after a household realizes its desired outcome for example of increased income levels, they can reinvest part of that income into physical capital with a view of making them more resilient and thus improve future livelihood outcomes. This might be a catalyst that positively contributes to poverty reduction.

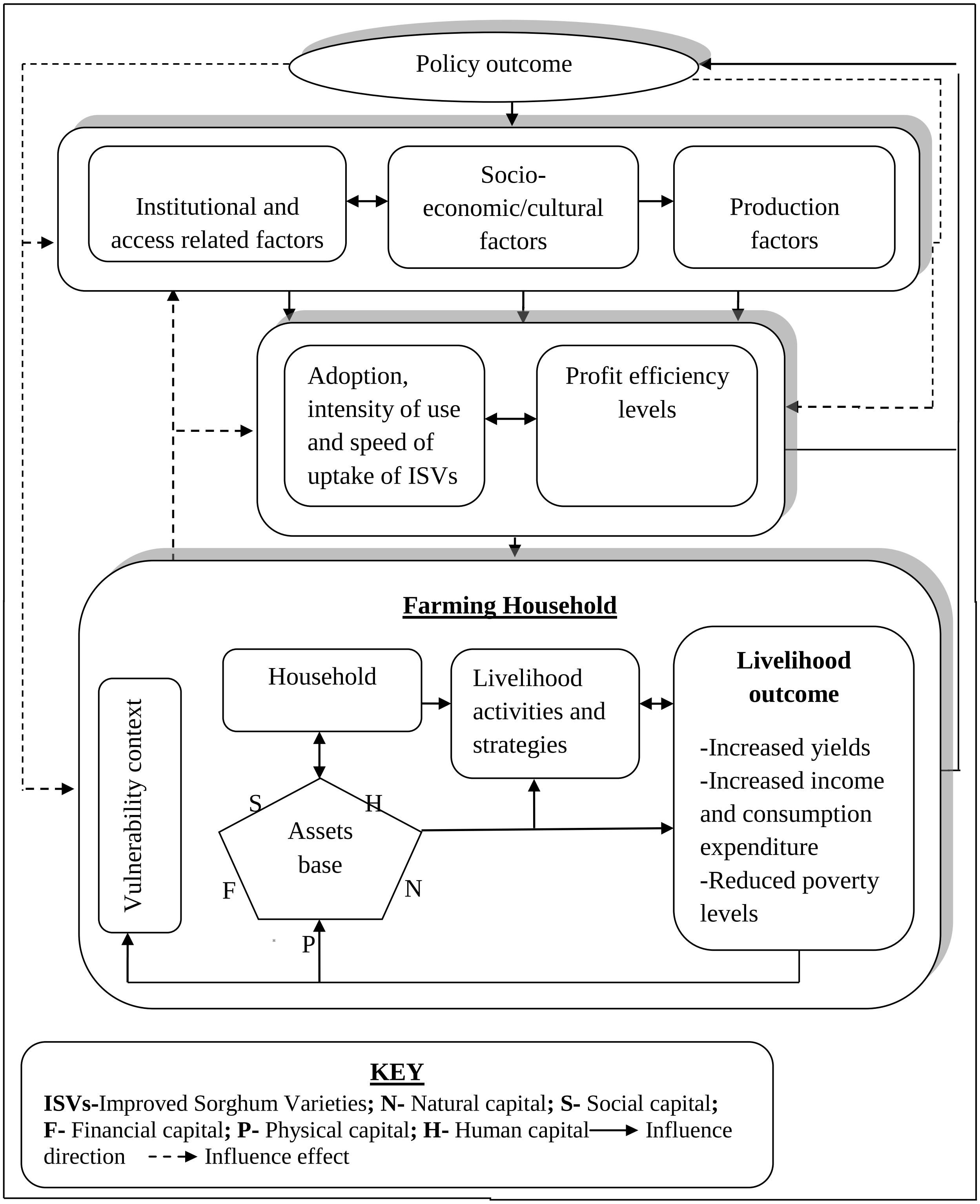

Figure 1.2: Conceptual Framework

Source: Author's modification, adopted from DFID (2001)

On the other hand, a livelihood outcome might combine with assets negatively through unsound agricultural practices and affect natural capital (natural resource base). As a result, a household's vulnerability levels might increase thus subjecting them into further poverty. Agricultural research on new technologies is crucial in shaping the asset base of farming households. Introduction of new agricultural technologies can have varied influences on the vulnerability of a household. For instance, the introduction of high yielding varieties, which are drought and pest resistant, may contribute to declining poverty levels through reduction of the vulnerability of resource-poor farmers. However, in some cases, new technologies might increase the vulnerability of the farming households and reduce their resilience thereby increasing poverty levels. For example, the introduction of inappropriate agricultural technologies, which negatively affect some resources (natural capital) as well as when human capital (measured in terms of the households' skills, expertise and knowledge base) needed to exploit the different components of agricultural research to maximize the benefits is missing.

Decisions to adopt, intensity of use and speed of uptake of ISVs as well as profit efficiency levels among smallholder sorghum farmers were expected to be influenced by production, socio-economic as well as institutional and access related factors. The farmers that had adopted ISVs were expected to increase income levels in turn anticipated to have a feedback effect on socio-economic factors, institutional and access related factors. The farmers were expected to use the income to acquire high-quality inputs such as certified seeds etc hence leading to increased uptake levels.

Consequently, they were also expected to use the increased incomes to access institutionalized services.

Policies and institutions play a vital role in influencing access to agricultural research products and how the targeted clientele uses them. For example; private and public extension service agents coupled with other effective dissemination pathways are important in passing the technology information from researchers to the farming households. Additionally, both profit efficiency and adoption levels were expected to influence policy that would impact positively on consumption expenditure, thereby reducing poverty levels of adopting households.

1.10 Organization of the thesis

This thesis is organized into five chapters. Chapter one gives the background information, highlights statement of the research problem, study objectives and presents theoretical and conceptual frameworks. Chapter two gives a detailed review of recent literature related to adoption, efficiency and impact of adopting of agricultural technology. Further, chapter two provides a summary of the identified knowledge research gaps. Chapter three illustrates the methodology used detailing study area, sampling determination and procedure. Besides, data collection, analysis, model specifications and description of variables used are also described in chapter three. The results and discussions from descriptive statistics and econometric findings used in achieving the three study objectives are presented in chapter four. Finally, chapter five presents study conclusions, recommendations and policy implications.

CHAPTER TWO

LITERATURE REVIEW

This chapter presents recent studies which have researched aspects of agricultural technology adoption, efficiency in resource allocation and impact evaluation of such innovations with a bias to improved crop varieties. The chapter also provides insights on overview of empirical methods for the different objectives and provides justification for the models chosen. Furthermore, the chapter highlights the identified research gaps, which this study aimed to fill.

2.1 Agricultural technology adoption, intensity of use and speed of uptake

Globally, agricultural technology uptake remains as one of the heavily researched areas. Depending on the context, adoption can have several definitions and in this study, adopt means to bring a given technology such as ISVs under use with a view of increasing household income thereby contributing to poverty reduction. Technology adoption can be measured through three unique dimensions namely: (i) the level of adoption which indicates the proportion of farmers that take up a given technology. When farmers become aware of ISVs, they decide whether to adopt or not; (ii) the adoption intensity which shows the level of uptake of a particular technology (proportion of land put into ISVs compared to the total cultivated land); and (iii) the rate of uptake that refers to the speed (adoption spell/duration) which an agricultural technology (ISVs) is taken up by segments of the population (Rogers, 2003).

More recently, the speed of adoption has gained immense importance to researchers. This is by the introduction of a time element that takes into consideration the population's dynamic aspects of the agricultural technology uptake process (Rodgers, 2003). Speed of uptake refers to the time taken to adopt the varieties from the time a household became aware of the existence of the ISVs. The three adoption measures are usually governed by a set of complex factors such as farm and farmer specific, institutional and technological. Understanding the adoption process and pattern in the context of these complex factors is important, and failure to do so often leads to low uptake levels of new disseminated agricultural technologies (Feder *et al.,* 1985). Researchers have conducted many studies to understand the underlying reasons for low adoption rates despite the obvious benefits. The resulting body of literature is so huge that sometimes it becomes difficult to summarize.

Table 2.1 summarizes recent studies conducted on themes related to adoption, the intensity of use and speed of adoption of agricultural technology. Further, the table indicates the objectives, analytical methods used and summarize the identified knowledge research gaps from the respective studies. The studies reviewed were conducted between year 2011 – 2019 and covered different countries and crop varieties many of which are improved. Out of the 12 studies reviewed, only two conducted in Zimbabwe and Tanzania focused on sorghum crop. For example, none of the reviewed five studies conducted in Kenya namely Ochieng *et al.,* (2019); Kinuthia *et al.,* (2019); Njuguna *et al.,* (2015); Ogada *et al.,* (2014); Murage *et al.,* (2011) focused on sorghum. They researched on other crops such as potato, tomato, amaranth and maize.

Table 2.1: Summarized recent studies on technology adoption, intensity of use and speed of uptake

Author(s)	**Objective(s)**	**Analytical methods**	**Focus crop(s) and country**	**Results and policy implications**	**Critique (research gaps)**
Ochieng *et al.*, 2019	-To quantify the adoption of improved amaranth varieties in Kenya and Tanzania	-Means and percentages	-Improved amaranth varieties, Kenya and Tanzania	-Results showed that improved amaranth varieties were planted on 51 percent of the planted area in Kenya and 70 percent in Tanzania. -Further, 12 percent of farmers used certified amaranth seed (37 percent in Kenya; 10 percent in Tanzania).	-Apart from finding out the percent of adopters, the study failed to evaluate the factors that influenced adoption. -The study also failed to evaluate factors influencing intensity and speed of uptake.
Ashoori *et al.*, (2019)	-Studied the factors that influenced the adoption of Modern Rice Cultivars in Northern Iran	-Logistic regression	-Improved rice varieties; Iran	-The positive influence of perceived profitability and importance of modern varieties, experience in rice farming, and size of livestock holdings on the adoption of improved cultivars were reported. - The study recommended that information flow on improved cultivars be done from experienced farmers to other farmers.	-Determinants of intensity and speed of adoption were not investigated.
Musara *et al.*, (2019)	-Evaluated factors affecting sorghum adoption and allocating differential land proportions towards the crop	-Double hurdle model	-Sorghum; Zimbabwe	-Different set of variables influenced the two decisions with information flow from networks and conditions of market platforms remaining important in both decisions. There is also a need to decentralize sorghum markets, strengthen local networks and increase the efficiency of formal extension delivery systems.	-Speed of adoption was omitted from the analysis.

Kinuthia *et al.*, (2019)	-Investigated determinants of the intensity of uptake of alternative pest control methods	-Multi-variate Tobit	-Tomato; Kenya	-Group membership, age, education and number of training increased the intensity of uptake of alternative methods while farm size had decreasing effects. -Policies to be centred on awareness creation and comprehensive training programs.	-Other facets of adoption, namely; decision for uptake and speed of adoption were not taken into consideration.
Theophilus *et al.*, (2019)	-Identified factors that influence the intensity of adoption of improved maize production technologies	-Tobit	-Improved maize; Ghana	-Several factors influence the intensity of adoption including; education, farming experience, extension contact, access to credit, and group membership. -Recommended policies related to the introduction and dissemination of improved maize production technologies	-Determinants of adoption and speed of uptake were not evaluated.
Teshome *et al.*, (2019)	-Analyzed determinants of adoption of improved Jalenea potato variety	- Binary logistic regression	-Improved potato variety; Ethiopia	-Apart from age, sex, extension access, attending training and field day, membership of seed multiplication cooperative, non-farm activity, and farm income had a positive influence on adoption. -Emphasized the need for institutional support in extension, training and farmer cooperatives.	The study failed to include the evaluation of factors that influenced speed of adoption.
Yigezu *et al.*, (2018)	-Investigated the effect of awareness and exposure to new agricultural technologies on adoption	-Double hurdle and Duration analysis models	-Wheat and barley; Syria	-Propensity, speed, and intensity of adoption increases as farmers attend field days and demonstration trials and emphasized the need for awareness enhancing policies. -The increase is complemented by providing free access to costly zero-tillage seeders for first-time users.	Although, the study studied the 3 adoption facets, the focus crops were wheat and barley and not sorghum

Kaliba *et al.*, (2018)	-Determined the factors that affected the adoption of improved sorghum varieties in Tanzania under information and capital constraints	-Multiple-hurdle Tobit	-Improved sorghum varieties; Tanzania	-Awareness creation methods, eg. Radio and other mass media outlets will increase adoption among farmers who do not face capital constraint. -Field days, on-farm trials, and demonstration plots are important considerations coupled with pluralistic research and extension.	-Study overlooked the effect on adoption intensity and how fast farmers could adopt improved sorghum varieties.
Njuguna *et al.*, (2015)	-Assessed influence of demographic characteristics on adoption of improved potato varieties	- Ordinal logit regression	-Improved potato varieties, Kenya	- Important factors that influenced decision to adopt improved potato varieties were namely; perception , family size, access to credit as well as extension services	-Study failed to determine further the factors which influenced decision to intensify the use of improved potato varieties and speed of uptake.
Abebe and Bekele (2015)	-Analysed adoption spell of improved common bean varieties in the central rift valley of Ethiopia	-Duration model approach	-Improved common bean varieties; Ethiopia	-Non-parametric results showed that speed of adoption of beans was rapid in the early years and declines eventually. - Parametric results show that the size of cultivated land, proximity to extension office and remoteness to fertilizer market hastened adoption. -On the other hand, dependency ration and livestock ownership contributed to increase in the adoption spell.	-Study focused on speed only and overlooked other facets of adoption.

Ogada *et al.*, (2014)	-Simultaneously assess adoption of inorganic fertilizer and improved maize variety decisions	- Bivariate probit model	-Improved maize varieties; Kenya	-Results indicated that, the adoption of the two technologies were influenced by farmer characteristics, plot-level factors and market imperfections such as limited access to credit and input markets, and production risks	-Study did not explore the determinants of intensity of use and speed of adopting improved maize varieties
Murage *et al.*, (2011)	-Evaluated duration to adoption of Push –pull technology using several dissemination pathways	-Duration analysis	-Push-pull technology Kenya	-Results indicated several variables which accelerated adoption namely; education, household size and high-income level. -However some variables such as gender, Tropical Livestock Units (TLUs) and group membership had delaying effects on the adoption of push-pull technology.	-Although the study researched on speed of adoption, it failed to find out the effect on adoption and intensity of use decisions

Source: Author’s compilation, 2018

Although, many research have extensively focussed on agricultural technology adoption, few such as Yigezu *et al.,* (2018) have attempted to assess the three facets in one ago that is determinants of adoption, speed of uptake and intensity of use of ISVs. Many of the studies investigate either one or at best two adoption aspects (Ochieng *et al.,* 2019; Ashoori *et al.,* 2019; Musara *et al.,* 2019; Kaliba *et al.,* 2018; Njuguna *et al.,* 2015; Abebe and Bekele, 2015; Ogada *et al.,* 2014). Investigating the three facets is important in understanding adoption pattterns and behaviour of smallholder farmers, which informs interventions geared towards increasing the uptake levels. Therefore, this study investigates all the three adoption facets by use of a multi-dimensional approach to fill that knowledge gap. The information generated is important for guiding policymakers in the formulation of strategies in light of the different determinants to address the adoption, intensity of use and speed of uptake of ISVs.

On the analytical methods front, studies that attempted to investigate the determinants of adoption and intensity of use employed different approaches. For example, while Musara *et al.*, (2019) and Yigezu *et al.*, (2018) used Double Hurdle model, the rest either used Tobit or Logistic regressions. Whereas Tobit model assumes that the determinants influencing decision to adopt a technology and intensity of its use are the same, Double Hurdle model contradicts by assuming that they are not. Further, whereas Double Hurdle model assumes a household makes decisions to adopt and intensify the use independently and sequentially, Tobit assumes the decisions are made simultaneously and jointly (Cragg, 1971).

Following the above mentioned strengths, this study used Double Hurdle model to evaluate the determinants of adopting and intensifying the use of ISVs. On the other hand, all the three reviewed studies on speed of uptake (Yigezu *et al.*, 2018; Abebe and Bekele, 2015; Murage *et al.*, 2011) used Duration Analysis model which this study opted to employ.

2.2 Assessment of efficiency levels among smallholder farmers

In developing nations such as Kenya, measurement of efficiency among smallholder farmers remains an important research area of study that needs special emphasis. It is normally computed through three approaches, namely: technical, allocative and economic efficiency metrics. Research indicates that, if a farmer is technically and allocatively efficient in resource use, then he/she is regarded as being profit efficient. Economic efficiency is referred to as the ability and capacity of a farm to achieve/realize the highest possible profit margin, given its fixed factors' levels and pricing (Ali and Flinn, 1989).

Table 2.2 presents a summary of efficiency-related studies by providing information on the objectives, results, policy implications and the identified knowledge gaps. The table shows that efficiency-related studies have been conducted in Africa with a bias to technical efficiency. Out of the eight studies reviewed, only one conducted by Aka *et al.,* (2019) assessed profit efficiency, whereas all the rest focused on technical and allocative efficiencies.

Further, most of the studies concentrated on other crops apart from sorghum such as maize, rice (Konja *et al.*, 2019; Aka et *al.*, 2019). However, very few have concentrated on sorghum. The case is no different in Kenya where several efficiency studies have been carried, but few such as Chepng'etich *et al.,* (2014) attempted to evaluate the profit efficient levels of sorghum farmers. It is important to understand profit efficiency among sorghum producers and the relationship with several farm-level factors. This is because it equips and guides policymakers in formulating efficiency-enhancing policies.

Table 2.2: Summarized recent studies on efficient allocation and utilization of resources

Author(s)	**Objective(s)**	**Analytical methods**	**Focus crop(s) and country**	**Results and policy implications**	**Critique (research gaps)**
Mehta (2019)	-Estimated changes in average technical efficiency in herbicide-tolerant Cotton compared to conventional Bt cotton crops	-Cobb-Douglas frontier production function	-Cotton; India	-Herbicide-tolerant technology was technically more efficient due to the reduction in wastage of farm inputs. -The policy need to focus on technological innovations and dissemination of scientific knowledge to enhance the efficiency levels in agriculture.	-The study investigated only technical efficiency aspect and failed to expound to profit efficiency
Dessale (2019)	-Assessed technical efficiency of small-holder wheat farmers	-Cobb-Douglas stochastic production frontier	-Wheat; Ethiopia	-The estimated mean technical efficiency level was about 82 percent. -The inefficiency was affected negatively by age, education, improved seed, training and credit and positively by farm size.	-There was no assessment of profit efficient levels
Kassa *et al.*, (2019)	-Estimated technical efficiency levels of teff production	-Translog stochastic frontier analysis	-Teff; Ethiopia	-The average estimated technical efficiency of smallholder farmers ranges from 0.13 to 0.92 percent, with a mean efficiency of 73 percent. -Age, extension, seed type, were major socio-economic factors that influenced efficiency.	-The study failed to estimate profit efficiency levels of Teff producers

Okello *et al.*, (2019)	-Assessed allocative efficiency of rice production in Gulu and Amuru districts, Northern Uganda	- Stochastic frontier approach	-Rice; Uganda	-Mean allocative efficiency was 75 percent. -Some factors had significant effects on allocative efficiency, namely distance to trading centre, farm and household sizes number of crop enterprises, use of hired labour, and access to credit. Study recommended reallocation of farm resources, particularly labour and adoption of technologies, e.g. ox-ploughs.	-The study failed to determine whether the farmers were profit efficiency.
Aka *et al.*, (2019)	-Investigated profit efficiency of maize production among smallholder famers and their determinants	- Translog stochastic frontier profit function model	-Maize; Ethiopia	-Average profit efficiencies was 78.4 percent -Education, experience, extension, soil conservation practice, credit service, non-farm employment and access to markets significantly influenced profit efficiency.	-The study was focused on maize and not on sorghum
Konja *et al.*, (2019)	-Estimated technical and resource-use efficiency	- Stochastic frontier profit function model	-Rice; Ghana	-Study reported a wide technical efficiency range (11 percent to 98 percent) with a mean of 75 percent. -Some factors influence the inefficiency namely age, extension, household size, years of education, and credit. -The study recommends that a farm-level policy directed towards the stimulation of extension work through motivation to give the rural farm households raining on farm management.	-Study failed to assess the profit efficient levels of the rice farmers

Salat and Swallow (2018)	-Evaluate resource use efficiency of smallholder maize farmers in Nyando, Kenya	- Stochastic frontier analysis	-Maize, Kenya	-Results showed that, maize production in Nyando is associated with mean technical efficiency of 45 percent. -Further, soil conservation practices such as residue management, legume intercropping, and improved varieties significantly increase farmers' technical efficiency.	-Study failed to assess the profit efficiency of maize farmers
Kamau *et al.*, (2017)	-Assessed technical efficiency of smallholder enterprises in Murang'a	-Data envelopment analysis	-Coffee; Kenya	-Mean technical efficiency levels reported was 54 percent. -Access to credit, farm size, variety of coffee, household size and age the house head significantly influenced technical efficiency.	-Study failed to assess the levels of profit efficiency
Chepng'etich *et al.*, (2014)	-Analysis of technical efficiency of sorghum production in Lower Eastern Kenya	-Data envelopment analysis	Sorghum; Kenya	- A low average technical efficiency level (41 percent) was reported. - Study suggested policies be pegged on innovative arrangements geared towards increasing farmers' capacity to efficiently use the available resources in sorghum production.	-The study constrained itself to technical efficiency and failed to expand the estimation of efficiency to profit levels.
Mburu *et al.*, (2014)	- Study attempted to estimate the levels of technical, allocative, and economic efficiencies	- Stochastic frontier analysis	-Wheat, Kenya	- Results showed that, on average technical, allocative, and economic efficiency of small scale wheat farmers were 85%, 96%, and 84%, respectively. -On the other hand, efficiency levels for large scale farmers were 91%, 94%, and 88%, respectively. - Several factors influenced efficiency namely; distance to extension advice, number of formal schooling years and the size of the farm.	-Although, the study analyzed the 3 aspects of efficiencies, the focus was on wheat and not sorghum which is not practised by a mix of small and large scale farmers in the study area

Source: Author's compilation, 2018.

Although, many methods used in estimating efficiency are available in literature, Coelli *et al.,* (1998) outlines four major (commonly used) approaches namely: non-parametric programming, parametric programming, deterministic statistical and the stochastic frontier. The studies captured in Table 2.2 show that, majority of studies used stochastic frontier analysis method namely Mehta (2019); Dessale (2019); Kassa *et al.*, (2019); Okello *et al.*, (2019); Aka *et al.,* (2019); Konja *et al.,* (2019); Salat and Swallow (2018). On the other hand, some studies used Data envelop analysis methodology such as Kamau *et al.*, (2017) and Chepng'etich *et al.*, (2014). As pointed out by Coelli (1994), most agricultural researchers in assessing efficiency prefer using stochastic frontier approach due to its inherent stochasticity nature. Based on this, this study attempted to evaluate the profit efficiency of smallholder sorghum farmers using stochastic frontier approach.

2.3 Ex-post impact evaluation studies on agricultural technology measuring welfare and poverty reduction

In Africa and globally, researchers have conducted several studies aimed at evaluating the ex-post technology impact of agricultural interventions targeting to improve welfare and reduce poverty levels of the farming population using different methodologies. Table 2.3 summarizes selected recent impact assessment studies conducted with a bias on poverty reduction of smallholder farmers. Further, Table 2.3 presents a summary of the study objectives, impact evaluation methodologies used, results coupled with suggested policy implications. Finally, the table highlights the identified knowledge research gaps for each study.

Out of the 11 studies reviewed, almost half (5) namely Marechera *et al.,* (2019); Ahmed *et al.,* (2017); Khonje *et al.,* (2015); Zeng *et al.,* (2015); Becerril and Abdulai (2010) evaluated impact of improved maize varieties on wellbeing and poverty reduction. The rest of the studies concentrated on other crops such as improved cassava varieties and mango (Manda *et al.,* 2019; Midingoyi *et al.,* 2019; Agunbiade and Oke *et al.,* 2019; Feleke *et al.,* 2016 and Afolami *et al.,* 2015). This study therefore purposed to contribute to the body of knowledge by estimating the impact of ISVs on poverty reduction among smallholder farmers in Tharaka Nithi County, Kenya.

Many of the reviewed literature used either income (Manda *et al.,* 2019; Midingoyi *et al.,* 2019 and Marechera *et al.,* 2019) or consumption expenditure (Biru *et al.,* 2019; Ahmed *et al.,* 2017; Khonje *et al.,* 2015; Becerril and Abdulai, 2010) as poverty indicator. Consumption expenditure is arguably a better indicator for poverty since its less prone to under or over-estimations (Khandker *et al.,* 2010; Haughton and Khandker, 2009). However, literature further argues that, consumption expenditure adjusted per adult equivalent is a superior indicator compared to per capita consumption expenditure since it takes into account differences in household size, demographic structure and economies of scale in consumption (Haughton and Khandker, 2009). Therefore, due to its superiority, this study used consumption expenditure per adult equivalent as the poverty indicator.

Table 2.3: Summarized recent impact studies related to poverty alleviation

Author(s)	**Objective(s)**	**Analytical methods**	**Focus crop(s) and country**	**Results and policy implications**	**Critique (research gaps)**
Manda *et al.*, (2019)	-Evaluated the impacts of adoption of improved cowpea varieties on income and asset poverty reduction	-Endogenous switching regression model	-Improved cowpea varieties, Nigeria	-Results indicated an increase in per capita household income and asset ownership by 24 and 17 percent, through adoption of improved cowpea varieties. -Conterfactual results showed that, adoption of improved cowpea varieties reduced both income poverty and asset poverty by 5 percent.	-The study failed to complement results of Endogenous switching regression with another method for robustness of results. -Further, the study failed to use consumption expenditure which is argued as a better indicator of poverty than income.
Biru *et al.*, (2019)	-Evaluated impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia	-Two stages multinomial endogenous switching regression model	-Not crop-specific; Ethiopia	-Study finds that the adoption of improved technologies increases consumption expenditure. -Combining adoption with multiple complementary technologies has the greatest impact.	-The study did not use consumption expenditure per adult equivalent. -The study is not crop-specific
Marechera *et al.*, (2019)	-Analyzed the impact of DroughtTEGO® hybrid maize variety on agricultural productivity and poverty alleviation	-Propensity score matching	-Improved maize variety; Kenya	-Adoption led to an increase in total and maize incomes by 75 percent and 82 percent respectively. Depth of poverty reduced by 46-point margins. -Policies targeting adoption of DroughtTEGO® hybrid maize varieties be implemented.	-The study failed to use consumption expenditure per adult equivalent as an outcome variable -Failed to check the robustness of the results by another complementary model

Midingoyi *et al.*, (2019)	-Estimated the impacts of a bundle of integrated pest management practices on mango yield and net income	-Multinomial endogenous switching treatment regression model -Ordered probit	-Mango; Kenya	-Results indicate that IPM-adopting farmers have higher mango yields and mango net income. -Intensification of IPM-adoption efforts and encouragement of the use of multiple IPM practices.	-The study failed to use consumption expenditure per adult equivalent as an outcome variable
Agunbiade and Oke *et al.*, (2019)	-Analyzed poverty estimates among cassava farming households in Osun State	-Foster-Greer Thorbecke index -Tobit regression	-Cassava; Nigeria	- Poverty incidence and depth were 28.9 percent and 5.3 percent respectively, while poverty severity was about 1.5 percent. - The study indicated that, by controlling the number of childbirths, increasing revenue generated from cassava farm households could study area could reduce their poverty depth.	-The study computed poverty indices and failed to use consumption expenditure per adult equivalent as an outcome variable.
Ahmed *et al.*, (2017)	-Investigated the impact of improved maize varieties on-farm productivity and smallholders' wellbeing	-Propensity score matching -Endogenous switching regression	-Improved maize varieties; Ethiopia	-Findings showed significant improvement of wellbeing and farm productivity through adoption of improved maize varieties. -There was reported gains in consumption expenditure per adult equivalent of the adopting households	-The focus crop was maize and not sorghum
Feleke *et al.*, (2016)	-Evaluated impacts of cassava technology on poverty reduction in Africa	-Endogenous switching regression	-Cassava; Tanzania, Democratic Republic Of Congo, Sierra Leone and Zambia	-Cassava adoption reduced the poverty rate by about 10 percent. -The study suggested that regional and global development organizations support the existing cassava improvement programme to sustain the technology development efforts in the continent.	-The study failed adjust daily per capita consumption expenditure in adult equivalent terms -Failed to check the robustness of the results by another complementary model

Khonje *et al.*, (2015)	-Analyzed adoption and impacts of improved maize varieties	-Propensity score matching -Endogenous switching regression	-Improved maize varieties; Zambia	-Adoption of improved maize varieties (IMVs) leads to significant gains in crop incomes, consumption expenditure, and food security. -IMVs have significant poverty-reducing impacts in eastern Zambia	-The study failed to use consumption expenditure per adult equivalent as an outcome variable
Afolami *et al.*, (2015)	-Evaluated the welfare impact of farm households adoption of improved cassava varieties in Southwestern (SW) Nigeria using poverty as an indicator	-Foster-Greer Thorbecke index -Tobit regression	-Improved cassava varieties; Nigeria	-Uptake of improved cassava varieties increases the annual income consumption expenditure of producing households' thus increasing welfare in the SW Nigeria. - Concluded that, efforts in making sure that farmers have access to adequate improved cassava cuttings at the right time and place be intensified.	-The study failed to use consumption expenditure per adult equivalent as an outcome variable. -Used only one econometric model to measure poverty i.e failed to check for robustness of results
Zeng *et al.*, (2015)	-Evaluated ex-post impacts of improved maize varieties on poverty in rural Ethiopia	-Foster–Greer–Thorbecke (FGT) poverty indices -Propensity score matching	-Improved maize varieties, Ethiopia	- Results showed that, improved maize varieties led to a drop in poverty head count ratio by 0.8 – 1.3 percent. -Further, the study concluded that the due to the small sizes of land of poor producers, they benefit the least from adoption of improved maize varieties.	-The study failed to use consumption expenditure per adult equivalent as an outcome variable which is considered as superior
Becerril and Abdulai (2010)	-Assessed the impact of the adoption of improved maize varieties on household income and poverty reduction	-Propensity score matching	-Improved maize varieties, Mexico	- Results indicated that, adoption of improved maize varieties resulted in an increase of household per capita expenditure by an average of 136–173 Mexican pesos thus contributing to a reduction of their probability of falling below the poverty line by about 19–31%.	-The study failed to use consumption expenditure per adult equivalent. -Study did not complement propensity score matching with another model for robustness of results.

Source: Author's compilation, 2018

In impact evaluation, several techniques are available such as simple regressions, matching methods, double-difference estimation method, instrumental variable methods, regression discontinuity design and pipeline methods among others (Khandker *et al*., 2010). This is confirmed by the various methodologies used and summarized in Table 2.3. For example, Marechera *et al.,* (2019); Zeng *et al.,* (2015); Becerril and Abdulai (2010) used Propensity Score Matching (PSM) while several studies namely Biru *et al.,* (2019); Manda *et al.,* (2019) and Feleke *et al.,* (2016) employed Endogenous Switching Regression (ESR) to measure impact.

The disadvantage of using one econometric model and not complemented by another approach is that resultant estimates are sometimes not robust enough (Ahmed *et al.,* 2017; Khonje *et al.,* 2015; Di Falco *et al.,* 2011). This is because each of the models has its own limitations that are not possible to be corrected individually. For instance, a methodology using an instrumental variable, there is a requirement to include at least one variable in the selection model (i.e. instrument) during the specification of the outcome model. This specific requirement has proven to be a major setback in empirical studies (Jalan and Ravallion, 2003). Furthermore, the standard instrumental variable approach often ignores the variations of variable interactions arising between agricultural technology adoption and other influencing factors.

Further, PSM being one of the extensively used impact evaluation methodology has its advantages and disadvantages. First, the methodology is advantageous since it allows the researchers to define causal effects without making functional forms and does not necessarily need to make distributional assumptions. In addition, it does not need baseline data so works well with cross-sectional research data similar to this study. It does so even with probabilistic properties' specification of the outcomes or assignment as put forward by the researcher. The model uses observable characteristics assuming conditional independence and the common support condition. It also allows a sensitivity test of the treatment effect to hidden bias to support the inference to be drawn from the analysis results (Imbens and Woolridge, 2009).

Despite its numerous advantages, PSM has its shortcomings. Firstly, the methodology requires heavy data requirements for covariates matching purposes. Secondly, applying matching methods sometimes is difficult because of a variety of algorithms available in literature. Thirdly, whereas PSM does not take care of unobservable factors that affect the uptake process, it also assumes that coefficient to characteristics of both adopting and non-adopting households are quite similar. However, several studies have proved this not to be necessarily the case (Asfaw *et al*., 2012). Due to the above mentioned considerations, this study used PSM and Inverse Probability Weighted Regression Adjustment (IPWRA). The IPWRA method is also a matching methodology that uses all the cases to construct comparison groups and does not require a bandwidth like PSM. This study complemented the two matching methods and ensured robustness of results by using ESR model in evaluating the impact of ISVs on poverty reduction among smallholder farmers in Tharaka Nithi County.

CHAPTER THREE

METHODOLOGY

This chapter describes the study area, research design and sampling procedure. Further, the methods used to collect both primary and secondary data that included administration of structured questionnaire and conducting focus group discussions as well as key informant interviews are presented. Lastly, this chapter presents a summary of the variables and data analysis models used.

3.1 Study area

This study was carried out in Tharaka Nithi County that is among the major sorghum producing counties in eastern Kenya. Furthermore, it is one of the leading sorghum-producing counties in upper eastern Kenya. Majority of the livelihoods in Tharaka Nithi County depend on sorghum most of it being grown in Tharaka North sub-County, which was the focus of this study (KBL, 2018). Tharaka Nithi County borders the counties of Embu to the South and South West, Meru to the North and North East, Kitui to the East and South East. It shares Mount Kenya with Kirinyaga County and Nyeri County to the West. The County lies between latitude 000 07’ and 000 26’ South and between longitudes 370 19’ and 370 46’ East. The total area of the County is 2,662.1 Km^2 including 360Km^2 of Mt. Kenya forest.

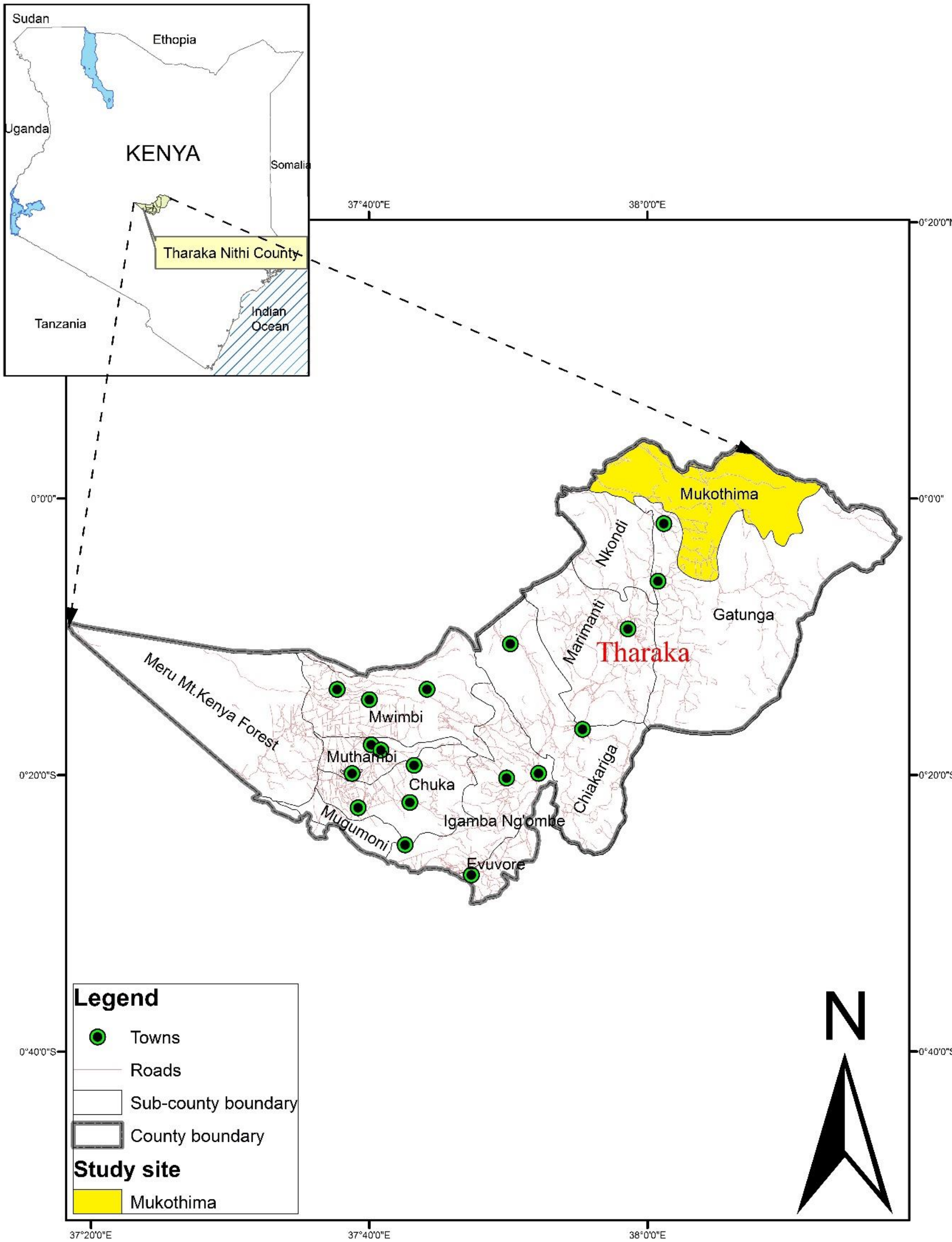

Figure 3.1: Map of the study area

Source: Generated from ArcGIS using georeferenced survey data (2018)

Administratively, the County is divided into 5 sub-Counties namely; Tharaka North, Tharaka South, Maara, Chuka and Igambang'ombe. The sub-Counties in order of size are as follows; Tharaka North sub-County (803.4 Km^2), Tharaka South (746.1 Km^2), Maara (465.3Km^2), Chuka (316Km^2) and the smallest is Igambang'ombe (308Km^2). The County has two main ecological zones namely the highlands (upper zone) comprising of Maara and Chuka that receive fairly adequate rainfall compared to the semi-arid (lower zone) covering Tharaka North and South sub-Counties. The County has a bi-modal rainfall pattern with the long rains falling during the months of April to June and the short rains which are the most reliable and considered as the main season in October to December. Rainfall ranges from 2,200mm in Chogoria forest areas to 500mm in Tharaka which is mostly unreliable and poorly distributed. Temperatures range between 14^0C to 30^0C in the upper zone and 22^0C to 36^0C in the lowland areas with Tharaka constituency recording temperatures of up to 40^oC at certain periods (Tharaka Nithi County Development Plan, 2018).

3.2 Research design and sampling

This study used cross-sectional research design which is a type of observational study design. This is because a researcher is able to measure the outcome and the exposures in the study participants at the same time. The selection of participants in a cross-sectional study is based on the inclusion and exclusion criteria set by the researcher. Further, cross-sectional research design is a one-time measurement of exposure and outcome.

On the sampling technique, this study used a multi-stage stratified sampling approach. The first stage involved purposive sampling of Tharaka Nithi County, which is one of the leading sorghum producing county in upper eastern Kenya. The second and third stages involved a purposive selection of Tharaka North sub-County and Mukothima ward due to their high ISVs production levels, respectively (Figure 3.1). The fourth stage was the selection of sample villages and was not entirely random since it purposively included villages where on-farm trials and demonstrations on ISVs had been conducted. In selecting the treated sample villages, a list of all villages where ISVs (called '*improved sorghum villages'*) had been introduced was constituted first. All the 9 *improved sorghum villages* were sampled. Then, for each sample *'improved sorghum village'*, a list of neighbouring villages within 5 - 15 kilometres (*km)* where any research activity on ISVs had not been introduced (called '*non-improved sorghum villages'*) was constituted and sample villages randomly selected from that list.

A total of 27 *non-improved sorghum villages* were randomly selected. The fifth stage involved compiling a sample frame comprising of all households in the sampled villages. The sampling of households was random and proportionate to the size of the population apportioned to each village. The sampled households for both *improved* and *non-improved* sorghum villages ranged from 6 to 25.

Using an approximate 1,500 households with a characteristic of interest (sorghum farming) and assuming acceptable error of 4 percent, the total sample comprised of 441 households as indicated by Yamane (1967) formula (equation 1).

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

where *n* = sample size, *N* = size of the target population (sorghum farming households), *e* = margin of error (4 percent) chosen after budget availability and data requirement considerations for matching methodologies.

The sample size was calculated as follows:

$$n = \frac{1{,}500}{1 + 1{,}500(0.04 * 0.04)} = 441 \dots\dots\dots 2$$

However, this study collected data from more households (an extra 4 percent of the sample size) to cover for any incomplete data which could have occurred. As a result, complete data for 452 households were collected and analyzed.

3.3 Data collection and analysis

This study collected both primary and secondary data. A structured questionnaire (Appendix 1) was used to collect primary quantitative data. Socio-cultural, economic, institutional, expenditure and access related data for households covering year 2017/2018 season were collected by trained enumerators. The data collected for the household which was the unit of analysis in this study was done through interviewing the respective heads. Qualitative data were collected from farmer groups and key informants using focus group discussions and key informant interviews. The guides used to facilitate focus group discussion and key informant interview are attached in Appendix 2 and 3 respectively. This study carried out a pilot before commencing the actual data collection exercise where trained enumerators administered the research instruments to a section of the target sample. This was important inorder to affirm the validity of the sample participants and that of the questions where logic and sequencing was tested. On the other hand, secondary data and information was collected from published and/or unpublished work. Data collected were analyzed using both descriptive and econometric techniques. Several data analysis softwares including Microsoft Excel, Statistical Package for Social Sciences, STATA and FRONTIER 4.1 were used.

3.4 Model specifications

This sub-section presents various econometric models that were used to answer the study objectives, respectively. Firstly, it presents Double Hurdle (DH) and Duration Analysis (DA) models used to analyze the first objective of this study which sought to understand the determinants of adoption, intensity of use and speed of uptake of ISVs detailed in sub-sections 3.4.1 and 3.4.2 respectively. Secondly, to achieve the second objective which attempted to analyze the profit efficiency of smallholder sorghum farmers, this sub-section presents two methods used namely sorghum profitability analysis and Cobb-Douglas stochastic profit frontier detailed in sub-sections 3.4.3 and 3.4.4 respectively. Lastly, the three methodologies employed to answer the third objective of assessing the impact of ISVs on poverty reduction among smallholder farmers namely ESR, PSM and IPWRA are presented under sub-section 3.4.5.

3.4.1 Double Hurdle (DH) model

To evaluate the determinants of a technology adoption, several methods can be used where many studies use Heckit, Logit and Tobit models. Whereas the Tobit model assumes that the determinants influencing the decision to adopt technology and intensity of its use are the same, the DH model contradicts by assuming that they are not. This model considers only the dependent variable to be censored at zero and ignores the source of zero observations (Martinez-Espineira, 2006). To choose the most suitable model for the analysis, this study compared the DH model with standard Tobit and Heckit models. Likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) tests were run, and DH model proved to be superior (Appendix 4). This confirms the fact that sampled households make the two adoption decisions independently and sequentially.

Originally proposed by Cragg (1971), the DH model has been extensively used by many authors due to its superiority over other similar methods (e.g. Burke, 2009). In order for households to be considered as adopters, they must cross the two hurdles. The first hurdle is for the household to decide whether to adopt ISVs or not. The second hurdle is for the households to decide on how much of the ISVs to put into use (intensity of use). The following equations express decisions made by a household:

$$y_i = 1 \; if \; y_i^* > 0 \; and \; 0 \; if \, y_i^* \leq 0 \; \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 3$$

$$y_i = X_i \propto + \varepsilon_i \; \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 4$$

where:

y^* is latent adoption variable that takes the value of 1 if a household planted any of the ISVs and 0 otherwise,

X is a vector of explanatory variables capturing institutional, farm and farmer characteristics, and α is a vector of parameters.

In the first hurdle, a positive significant coefficient result indicates that the corresponding regressor increases the likelihood of a positive observation in the adoption process.

The second hurdle closely resembles the Tobit model and is expressed as follows:

$$t_i = t_i^* \; if \; t_i^* > 0 \; and \; 0 \; if t_i^* \leq 0 \ldots \ldots \ldots \ldots 5$$

$$t_i = 0 \quad otherwise$$

$$t_i^* = \; Z_i\beta + V_i \ldots \ldots \ldots \ldots 6$$

where:

t_i is the observed response on the proportion of land allocated to ISV expressed as a ratio of the household's total cultivated land,

Z is a vector of the explanatory variables capturing institutional, farm and farmer characteristics, and β is a vector of parameters.

A positive coefficient results in the second hurdle conditional on a positive count; the corresponding variable increases the value of the count (Burke, 2009). Theoretically, Cragg (1971) never guided on how to choose explanatory variables for each hurdle. Therefore, the choice of the variables is somewhat complex and arbitrary. Therefore, this study run Probit and Tobit models to ascertain the explanatory power of the different variable combinations. The variable combination that recorded the highest explanatory power was chosen.

3.4.2 Duration Analysis (DA) model

To investigate the speed of adoption of ISVs, this study used the DA model by employing both non-parametric and parametric models. Kaplan-Meier survival function was used to present non-parametric results. Adoption spell (duration of time taken by a farmer from the time he is exposed on ISVs to the actual date of adopting the technology) was considered as a dependent variable. The probability that a household adopts ISVs (if he/she had not adopted before), at time t, is defined by a conditional distribution function $F(t)$ as:

$$F(t) = \Pr(T \leq t) \ldots \ldots \ldots 7$$

Let T be a non-negative continuous random variable representing the duration of stay in the non-adoption state. The variable t is the actual time a farmer takes from deciding to adopt ISV and ceasing being a non-adopter. However, at the time of conducting the survey, it is expected that not all farmers will have adopted ISVs. Therefore, in such a scenario, the probability of not adopting the ISV at time t is defined as a survival function, $S(t)$ as:

$$S(t) = 1 - F(t) = \Pr(T \geq t) \ldots \ldots \ldots 8$$

Hazard rate $h(t)$ was specified to show the relationship between explanatory variables to the timing of adopting ISVs.

The hazard function is the probability that the failure event (adoption of ISVs) occurs in the period t and Δt, conditional on the fact that adoption of the improved varieties has not occurred by t:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta | T \geq t)}{\Delta t} \quad \ldots \quad 9$$

There are many parametric forms for duration analysis model such as Weibull, Exponential, Log-logistic, Gamma probability, among others. However, the most commonly used parametric methods are Weibull and Exponential models. This study used both models and tested which of the two fit the data best by using AIC and BIC. Results indicated that the Exponential model recorded the lowest AIC and BIC (Appendix 5) and was therefore used in this study. The hazard rate was regarded as the likelihood that households adopt ISVs at time t given that they were yet to adopt until that specific time. Right censoring of data observations was done for households who had not adopted any of the ISV by the end of the year 2018 when the study commenced.

3.4.3 Sorghum profitability analysis

This study used several approaches to conduct profitability analysis, which aided the generation of data used to estimate profit efficiency levels and their determinants using Cobb-Douglas Profit Frontier model. First, data on costs, which included depreciation costs for fixed capital and revenue accrued after selling sorghum, were compiled. The basis of analysis for profitability was on per unit of land measured in hectares (Ha). Dependent variable net profit was derived by subtracting the total cost from total revenue.

The total variable cost included costs of inputs (seed, fertilizer, labour and insecticides). Cost of inputs was used as opposed to their respective prices due to their similarity; thus, no difference would be evident. Since farmers would buy different quantities of inputs, then the cost would vary. Labour costs were captured and quantified as per activities executed during sorghum production such as land preparation, planting, fertilizer application, weeding, spraying, birds scaring, harvesting, transport to homestead, threshing, transport to a collection centre and loading to buyer's vehicle. Labour was categorized as hired or from family members. Family labour segment captured the ages and gender of the member and subsequently male equivalent opportunity cost was calculated using the wage rate for the study area as the base using [2]the formula suggested Kerr (1967).

The total cost included the value of fixed capital assets such as farming implements, buildings, machinery and land. Farmers in the study area were customary

[2]I man-equivalent day (8 hours)= 1.25 woman days = 2 child days (Kerr 1967; FAO, 2005)

owners of land and hence not paying taxes. Sometimes, the farmers would leave land fallow for a certain period and as such, during the fallow period; the land had no economically valuable output. Several studies have argued that fixed cost has a negligible contribution to the farming enterprise, especially in smallholder subsistence farming (Ohen and Ajah, 2015; Abdullahi, 2012). With this in mind, the cost of land was not included in the analysis. However, this study included the depreciation cost for fixed capital. Generally, although, no buildings and machinery were used for sorghum production, farmers used farm implements such as hoes, sickles, knapsack sprayers etc on all crops thus no specific implements was designated for sorghum. They were used until completely worn out, and thus their residual value was equated to zero.

Depreciation for farm implements used for the production of ISVs was carried out using the straight-line method as follows.

$$d = \frac{Iv - Rv}{n}\left(\frac{LdISV}{TotLD}\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots 10$$

where:

d = annual depreciation

IV = initial value of the tool

RV = residual implement value

n = economic life span of the implement in years

LdISV = area of land under ISV

TotLD = total area of land under crops

3.4.4 Cobb-Douglas Stochastic Profit Frontier model

Several profit efficiency models exist in the literature, including Data Envelop Analysis. However, Stochastic Profit Frontier is considered as superior due to its ability to give way for the sensitivity of data to random shocks that include a conventional random disturbance term in the estimation of the profit frontier. This enables the researcher to attribute only deviations influenced by controllable decisions to inefficiency (Joforullah and Premachandra, 2003).

The choice of functional form is important because results significantly differ according to the functional form applied. In profit function literature, many functional forms are available and have been used extensively. However, the two most popular functional forms are Translog and Cobb-Douglas (Battese and Coelli, 1995). To choose the functional form, which best fitted the data, likelihood ratio (LR) test was conducted using the following formula (Greene, 2012).

$$LR_{\lambda} = -2\left\{ln\frac{L(H_0)}{L(H_1)}\right\} = -2\{[ln(L(H_0)] - \ln[L(H_1)]\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .11$$

where:

$L(H_0)$ and $L(H_1)$ represent the values of the log-likelihood under null and alternative hypothesis, respectively. LR_{λ} has approximately a Chi-square distribution with the number of degrees of freedom equal to the number of restrictions, assumed to be zero in the null hypothesis. Null hypothesis fails to be rejected when LR_{λ} is lower than the correspondent critical value for a given significance level (Abu and Kirsten, 2009).

The null hypothesis stated that coefficients of the second-order variables in the Translog model are zero; implying that the Cobb-Douglas function is best fit for the model. The result from this study $[\chi^2(21) = 23]$ was not significant with a *P*-value = 0.34. Further, AIC and BIC values support the results in that, the Cobb-Douglas model reported smaller values (943.48 and 968.38) compared to those of Translog function form (962.48 and 1,062.07) respectively. This means that the Translog model reduced to the Cobb-Douglas profit function. Therefore, results generated from the Cobb-Douglas model were more accurate and thus was the functional form which best fit the data.

This study, therefore, used a Cobb-Douglas Stochastic Profit Frontier model whose functional form was specified as follows:

$$ln\pi_i = \beta_0 + \beta_1 lnP_{1i} + \beta_2 lnP_{2i} + \beta_3 lnP_{3i} + \beta_4 lnP_{4i} + \beta_5 lnP_{5i} + \beta_6 lnP_{6i} + (V_i - U_i) \ldots \ldots \ldots 12$$

where:

the subscript "*i*" represents the i_{th} farmer in the sample

π_i = Normalized profit per Ha in USD computed as profit divided by output price.

P_{1i} = Normalized cost of seed per Ha

P_{2i} = Normalized cost of insecticides per Ha

P_{3i} = Normalized cost of family labour per Ha

P_{4i} = Normalized cost of hired labour per Ha

P_{5i} = Normalized cost of fixed capital base per household

P_{6i} = Area of land under ISVs in Ha

β_k = Parameters to be estimated

V_i = Random error assumed to be independently and identically distributed.

U_i = Non-negative profit inefficiency effects which are assumed to be half normal and independently distributed.

It worth noting that, all variables labelled as normalized means that, each of their totals was divided by the output price respectively. Equation 12 was estimated using FRONTIER version 4.1, where several parameters were estimated and reported, such as profit efficiency levels, the value of gamma and determinants of inefficiency in the sorghum production.

To estimate the inefficiency model, the following empirical expression was used:

$$U_i = \delta_0 + \delta_1 W_1 + \delta_2 W_2 + \delta_3 W_3 + \delta_4 W_4 + \delta_5 W_5 + \delta_6 W_6 + \delta_7 W_7 + \delta_8 W_8 + \delta_9 W_9 \ldots \ldots \ldots 13$$

where:

W_1, W_2, W_3, W_4, W_5, W_6, W_7, W_8 and W_9 represents *extension frequency, experience in sorghum farming, group membership, education level, adult equivalent, agricultural credit, age, training and distance to the nearest agro-dealer* respectively.

$\delta_0 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \delta_9$, represented parameters to be estimated.

The fact that the dependent variable is the inefficiency component of the total error term estimated in combination with the profit frontier, the coefficients are interpreted in reference to inefficiency instead of efficiency. It is worth to note that a coefficient sign is very important in result interpretation. A negative sign implies that the variable has a reducing effect on profit inefficiency and vice versa (Galawat and Yabe, 2012; Abu and Kirsten, 2009). Assa *et al.,* (2012) suggests that one can interpret the coefficients in reference to profit efficiency instead of inefficiency by taking the opposite sign of the reported results.

3.4.5 Impact evaluation of improved sorghum varieties on poverty reduction

Literature presents numerous impact assessment econometric methodologies depending on the nature and objectives of the study. In theory, several methods often used to evaluate impact of agricultural technologies include randomization/pure experimental design; non-experimental design and quasi-experimental design (Khandker *et al.,* 2010; Jalan and Ravallion 2003). Non-experimental approach is mostly suitable in situations where the researcher deliberately/intentionally locates a program placement. Quasi-experimental design is similar to randomization design although, it does not need to take place before the intervention (pre-intervention). It is regarded as the only alternative in situations where baseline survey and randomizations are considered not feasible options. In impact assessment, the idea is to estimate the effect of any program on the participants (treated) by finding out the outcome of an individual had he/she not participated in the program referred to as the counterfactual (Jalan and Ravallion 2003).

Many impact studies have been carried out on household welfare using either or a combination of income and consumption expenditure as outcome variables. Since we cannot see what the outcome would have been if a household had not adopted ISVs, in experimental studies, this challenge is addressed by randomly assigning adoption to treatment and control groups. By so doing, the outcome variables observed on the control households without adoption are ensured to be statistically representative of what would have happened without adoption.

However, adoption of ISVs is not randomly distributed to the adopters and non-adopters groups. This is because technology developers purposively decide which villages to disseminate the technology first to through holding of demonstrations. The decision to adopt or not is voluntary for farmers and maybe based on self-selection. The decision to adopt ISVs could also be infuenced by the information that the household has in its possession. Farmers who adopt ISVs may have systematically different characteristics from those who do not based on the expected benefts. The adopters and non-adopters could have different observable characteristics or there could be self-selection bias in the adoption of ISVs. Therefore using simple econometric models to measure the impact of ISVs could yield biased estimates.

Further, literature argues that, use of one econometric model and not complemented by another approach for example, OLS, Tobit or Double Hurdle is disadvantageous in that, the resultant estimates are likely not to be robust enough (Di Falco *et al.*, 2011). This is because, each of the individual models has its own limitations that are not possible to be corrected individually. For a methodology using instrumental variable, there is a requirement to include at least one variable in the selection model (i.e. instrument) during specification of the outcome model. This specific requirement has proven to be a major setback in empirical studies (Jalan and Ravallion, 2003). Furthermore, the standard instrumental variable approach often ignores the variations of variable interactions arising between agricultural technology adoption and other influencing factors.

It is against this background that this study proposed to overcome the challenge by using Propensity Score Matching (PSM) and Inverse Probability Weighted Regression Adjustment (IPWRA) that are matching methods complemented by Endogenous Switching Regression model (ESR). This is important because the results are more robust since ESR controls for unobservable characteristics unlike matching methods such as PSM and takes care of possibilities of unobserved heterogeneities, which might emanate from using cross-sectional data (Di Falco *et al.*, 2011).

3.4.5.1 Endogenous Switching Regression (ESR) model

This study used the ESR model to evaluate the impact of ISVs on poverty reduction among smallholder farmers in Tharaka Nithi County. This model is gaining popularity with several recent impact studies using the model (Kassie *et al.,* 2014; Asfaw *et al.,* 2012; among others). The ESR model corrects bias that emanates from both observable and unobservable factors and takes care of the heterogeneity problem. Standard econometric techniques have been reported to be inappropriate under such conditions due to their assumption of the same impact on adopters and non-adopters from the set of regressors (Khandker *et al*., 2010). The model accounts for unobservable factors that affect both adoption and outcome variables.

The model assumes that, in addition to the observed variables that influence a household's decision to adopt ISVs and reduce poverty levels, there might be unobservable farm/farmer specific characteristics that could have a potential influence on both decisions. Sometimes farmers self-select themselves to adopt technologies due to observable and unobservable variables. In such circumstances, ESR is better suited as it does not suffer from potential endogeneity bias that could arise. The bias might under or over-estimate the impacts of adopting ISVs and poverty reduction among smallholder farmers in the study area.

One of ESR's requirements is the identification of selection instruments that affect the adoption decision but not the outcome variable (Shiferaw *et al.,* 2014). This study, therefore, included farming experience and distance to agricultural office as selection instruments after conducting falsification test suggested by Khonje *et al.,* (2015) and Di Falco *et al.,* (2011).

The approach uses a probit model at the first stage to determine the relationship between the decision of adoption of ISVs and possible determinants of consumption expenditure per adult equivalent referred to in selection equation 14 modelled as follows:

$$S_i^* = \beta X_i + u_i \; with \; S_i = \begin{Bmatrix} 1 \; if S_i^* > 1 \\ 0 \; otherwise \end{Bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 14$$

where:

S_i^* represents the unobservable or latent variable for ISVs adoption

S_i is the observable counterpart representing dependent variable of ISVs adoption equaling 1 for an adopter and 0 otherwise)

X_i accounts for non-stochastic vectors that determine the adoption of ISVs

u_i represents random disturbances (error term).

The second stage regression estimates the determinants of consumption expenditure per adult equivalent conditional on specific criterion the function of adoption decision. Farmers usually face two decisions (a) whether to adopt (referred to as regime 1) and (b) not to adopt (regime 2) modelled as follows:

$$Regime\ 1: Y_{1i} = \alpha_1 J_{1i} + e_{1i} if S_i = 1\ (ISV\ adopters) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots 15$$

$$Regime\ 2: Y_{2i} = \alpha_2 J_{2i} + e_{2i} if S_i = 0\ (ISV\ non - adopters) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots 16$$

where:

Y_i represents consumption expenditure per adult equivalent in regime i

J_i is a vector of exogenous variables with potential expected influence on consumption expenditure per adult

e_i represents error terms

The error terms assumed to be at zero mean follows a trivariate normal distribution and can be expressed in a non-singular covariance matrix as follows:

$$cov(e_{1i}, e_{2i}, u_i) = \begin{pmatrix} \sigma_{e1}^2 & . & \sigma_{e1u} \\ . & \sigma_{e2}^2 & \sigma_{e2u} \\ . & . & \sigma_u^2 \end{pmatrix} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 17$$

where:

σ_u^2 represents the variance of the error term in the selection equation 14

σ_{e1}^2 and σ_{e2}^2 are the variances of the error terms in the outcome equations (15) and (16)

σ_{e1u} and σ_{e2u} represent the covariance of u_i, e_{1i} and e_{2i}.

An important implication of the error structure is that because the error term of the selection equation 14 u_i is correlated with error terms of the outcome equations (15) and (16) (e_{1i} and e_{2i}), the expected values of e_{1i} and e_{2i} conditional on sample selection are non-zero and expressed as below:

$$E[e_{1i}/S_i = 1] = \sigma_{e1u}\frac{\varphi\beta X_i}{\Phi\beta X_i} = \sigma_{e1u}\lambda_{1i} \ldots\ldots\ldots\ldots 18$$

and

$$E[e_{2i}/S_i = 0] = -\sigma_{e2u}\frac{\varphi\beta X_i}{1-\Phi\beta X_i} = \sigma_{e2u}\lambda_{2i} \ldots\ldots\ldots\ldots 19$$

where:

$\varphi(.)$ is the standard normal probability density function

$\Phi(.)$ represents normal cumulative density function

$\lambda_{1i} = \frac{\varphi\beta X_i}{\Phi\beta X_i}$ and $\lambda_{2i} = \frac{\varphi\beta X_i}{1-\Phi\beta X_i}$ where λ_{1i} and λ_{2i} represent the inverse mills ratio calculated from the selection equation (14). If the estimated covariances σ_{e1u} and σ_{e2u} are statistically significant, the decision to adopt ISVs and the welfare outcome variables are correlated. This would mean that there is evidence of endogenous switching.

Given the assumption of a trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of equations (15) and (16) can be modelled as follows:

$$LnL_i = \sum_{i=1}^{n} S_i \left[ln\emptyset \left\langle\frac{e_{1i}}{\sigma_{e1}}\right\rangle - ln\sigma_{e1} + ln\Phi(\varphi_{1i}\right]]$$
$$+ (1 - S_i)\left[ln\emptyset \left\langle\frac{e_{2i}}{\sigma_{21}}\right\rangle - ln\sigma_{e2} + \ln(1 - \Phi(\varphi_{2i}))\right] \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .20$$

where:

$\varphi_{ji} = \frac{(\beta X_i + \gamma_j e_{ji}/\sigma_j)}{\sqrt{1-\gamma_j^2}}$, $j_i = 1{,}2$ with σ_j representing a correlation coefficient between the error term u_i of the selection equation (14) and the error term e_{ji} of equations (15) and (16).

Conditional expectations, treatment and heterogeneity effects

This study used full information maximum likelihood (FIML) estimation employing the *movestay* command in STATA software suggested by Lokshin and Sajaia (2004). The ESR model was used to compare the expected consumption expenditure per adult equivalent of the farmers who had adopted in relation to (i) farmers who had not adopted and (ii) sought out to find out expected consumption expenditure per adult equivalent for their counterfactuals, i.e. (iii) what could have been the consumption expenditure per adult equivalent had the farmers not adopted and (iv) had the non-adopters adopted ISVs. The results obtained are referred to as the average treatment effect of the treated (ATT), and the untreated (ATU).

According to Di Falco *et al.*, (2011), the ATT and ATU are estimated as follows:

1. Adopters with the adoption of ISVs is modelled as follows:

$$E(Y_{1i}|S_i = 1; X) = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} \quad \ldots 21$$

2. Non-adopters without adoption

$$E(Y_{2i}|S_i = 0; X) = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} \quad \ldots 22$$

Counterfactual scenarios:

3. Adopters if they had not adopted ISVs

$$E(Y_{2i}|S_i = 1; X) = X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i} \quad \ldots 23$$

4. Non-adopters if they had adopted ISVs

$$E(Y_{1i}|S_i = 0; X) = X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i} \quad \ldots 24$$

Then expected impact of adopting ISVs on poverty reduction (proxied by consumption expenditure per adult equivalent) for the adopters (ATT) was calculated as the difference between equations (21) and (23).

$$E(Y_{1i}|S_i = 1; X) - E(Y_{2i}|S_i = 1; X) = (X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i}) - (X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i}) \quad \ldots 25$$

On the other hand, the impact on poverty reduction for farmers who had not adopted ISVs had they adopted (ATU) was calculated as the difference between equation (24) and (22) as shown:

$$E(Y_{1i}|S_i = 0; X) - E(Y_{2i}|S_i = 0; X) = (X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i}) - (X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots 26$$

where:

X_1 and X_2 represent explanatory variables affecting sorghum productivity in regime 1 and 2, respectively.

β_1 and β_2 represented parameters which were estimated.

This study also calculated heterogeneity effects. The 'effect of base heterogeneity' for the adopters as the difference between (a) and (d),

$$E(Y_{1i}|S_i = 1) - E(Y_{1i}|S_i = 0) = (X_{1i} - X_{2i})\beta_1 + \sigma_{1\varepsilon}(\lambda_{1i} - \lambda_{2i}) = BH_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 27$$

On the other hand, for non-adopters, the "the effect of base heterogeneity" was calculated as the difference between (c) and (b) as expressed below:

$$E(Y_{2i}|S_i = 1) - E(Y_{2i}|S_i = 0) = (X_{1i} - X_{2i})\beta_2 + \sigma_{2\varepsilon}(\lambda_{1i} - \lambda_{2i}) = BH_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 28$$

This study also computed "transitional heterogeneity" (TH) which indicates whether the effect of adopting ISVs is larger or smaller for adopting households or non-adopters in the counterfactual case that they did adopt expressed as the difference between equation (25) and (26) representing ATT and ATU respectively.

3.4.5.2 Propensity Score Matching (PSM) model

This study used PSM model to ensure consistency and robustness of impact results generated by the ESR model. The model, which is one of the non-parametric estimation techniques that do not depend on the functional form and distributional assumptions, matches observations of adopters and non-adopters of ISVs through predicted propensity of adopting a superior technology (Smith and Todd, 2005; Heckman *et al.*, 1998; Rosenbaum and Rubin, 1983). The model uses observable characteristics assuming conditional independence and the common support condition. It also allows a sensitivity test of the treatment effect to hidden bias to support the inference to be drawn from the analysis results (Imbens and Woolridge, 2009). It also helps to evaluate programs that require longitudinal datasets using a single cross-sectional dataset where the former does not exist. This is done using a matching procedure that creates conditions of a randomized experiment in order to evaluate a causal effect as in a controlled experiment.

Despite its numerous advantages, PSM has its shortcomings. Firstly, the methodology requires heavy data requirements for covariates matching purposes. Secondly, applying matching methods sometimes is difficult due to a variety of algorithms available in the literature. Thirdly, whereas PSM does not take care of unobservable factors that affect the uptake process, it also assumes that coefficient to characteristics of both adopting and non-adoption households are quite similar. However, some studies have proved this not to be necessarily the case (Asfaw *et al*., 2012).

Let G_i denote a dummy variable such that $G_i = 1$ if the i^{th} individual adopts ISVs and $G_i = 0$ if otherwise. Similarly, let Y_{1i} and Y_{2i} denote potential observed poverty-reducing outcomes for the adopter and non-adopter units, respectively. Then $\Delta = Y_{1i} - Y_{2i}$ is the impact of ISV on the i^{th} individual, usually called treatment effect. As we observe, $Y_i = G_i Y_{1i} + (1 - G_i) Y_{2i}$ rather than Y_{1i} and Y_{2i} for the same individual, we are unable to compute the treatment effect for every unit. The primary treatment effect of interest that can be estimated is, therefore, the Average Impact of Treatment on the Treated (ATT) given by:

$$\tau = E(Y_{1i} - Y_{2i} / G_i = 1) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots 29$$

Following Rosenbaum and Rubin (1983), the propensity score can be estimated as follows:

$$P(X) = P\left(G_i = \frac{1}{X}\right) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots 30$$

Given the assumptions that:

(a) $Y_{1i}, Y_{2i} \perp G/X$ i.e., the potential outcomes are independent of ISV adoption given *X*; this implies that:

$$E(Y_{2i}/G_i = 1, P(X) = E(Y_{2i}/G_i = 0, P(X))) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 31$$

and

(b) $0 \prec P(X) \prec 1$, i.e., for all X there is a positive probability of either adopting $(G_i = 1)$ or not adopting $(G_i = 0)$, and this guarantees every adopter a counterpart in the non-adopter population.

Therefore, ATT can be estimated as expressed in equation (32) as follows:

$$\tau = E(Y_{1i} - Y_{2i}/G_i = 1)$$

$$= E[E(Y_{1i} - Y_{2i}/G_i = 1, P(X))]$$

$$= E\left[E(Y_{1i}/G_i = 1, P(X)\right) - E(Y_{2i}/G_i = 0, P(X))] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 32$$

The propensity score generated by PSM is a continuous variable. Adopters and non-adopters (counterfactual) cannot have the same score. The model (PSM) uses various matching algorithms namely nearest-neighbour matching (NNM), kernel-based matching (KBM), stratification based matching (SBM) and radius calliper matching (RCM).

3.4.5.3 Inverse Probability Weighted Regression Adjustment (IPWRA)

To compare the results obtained from PSM and ESR models, this study estimated ATE using IPWRA model. This estimation approach is based on matching and uses the inverse of the estimated treatment-probability weights to estimate missing data corrected regression coefficients subsequently used to construct robust estimates of ATT (Wooldridge, 2010). The Inverse Probability Weights (IPW) is recognized for having less varying results compared to the different forms of matching such as RCM, KBM, and NNM, among others and does not require a bandwidth choice (Wooldridge, 2010). The IPW is calculated by weighting the observations based on the inverse probability of being treated.

According to Rosenbaum and Rubin (1983), estimation of propensity score is expressed as follows:

$$p(X) = \Pr(T_i = 1|X) = F\{h(X)\} = E(T_i|X) \ldots \ldots \ldots \ldots \ldots 33$$

where:

X is the multi-dimensional vector of pre-treatment covariates based on observed characteristics $F\{.\}$ is a cumulative distribution function.

The estimated propensity scores are used to create an artificial sample in which the distribution of calculated baseline covariates is independent of treatment assignment. According to Hirano and Imbens (2001), using simple inverse weights equal to 1 for the treated and $\frac{\hat{p}(X)}{[1-\hat{p}(X)]}$ for the non-treated, the weights can be defined in a combined way as:

$$W_i = T_i + (1 - T_i)\frac{\hat{p}(X)}{[1 - \hat{p}(X)]} \quad \text{...34}$$

where $\hat{p}$ are the estimated propensity scores.

On the other hand, regression adjustment (RA) uses a linear regression model for treated and non-treated groups. It computes averages of the predicted outcome (daily consumption expenditure per adult equivalent) to estimate treatment effects. In estimations of treatment effects, RA concentrates on outcomes while IPW focuses on the treatment. Following Wooldridge (2010), the ATT for the regression adjustment (RA) model can be expressed as:

$$ATT_{RA} = n_A^{-1}\sum_{i=1}^{n} T_i[r_A(X, \delta_A) - r_N(X, \delta_N)] \quad \text{...35}$$

where:

n_A represents adopters of ISVs

$r_i(X)$ refers to the postulated regression model for the adopters and non-adopters (N) based on observed covariates X and parameters $\delta_i = (\alpha_i, \beta_i)$.

The estimation of IPWRA estimator follows a combination of the regression adjustment with the weighting as described in equation (35) and (34), respectively. According to Wooldridge (ibid), a researcher only needs to correctly specify either IPW or RA model to estimate reliable treatment effect, conditional to the given covariates. The ATT for the IPWRA estimator can be expressed as follows:

$$ATT_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^*(X, \delta_A^*) - r_N^*(X, \delta_N^*)] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 36$$

where:

$\delta_A^* = (\alpha_A^*, \beta_A^*)$ is estimated from a weighted regression formula described in equation (36) as follows:

$$\min_{\alpha_A^*, \beta_A^*} \sum_{i=1}^{n} T_i (y_i - \alpha_A^* - X\beta_A^*)^2 / \hat{p}(X, \hat{\gamma}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 37$$

$\delta_N^* = (\alpha_N^*, \beta_N^*)$ is estimated from a weighted regression formula expressed as follows:

$$\min_{\alpha_N^*, \beta_N^*} \sum_{i=1}^{n} 1 - T_i (y_i - \alpha_N^* - X\beta_N^*)^2 / (1 - \hat{p}(X, \hat{\gamma})) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 38$$

Woodridge (2010) concludes that ATT for IPWRA has a similar expression only that, different weighted estimates are used for the regression parameters compared to ATT based on RA. To test for multicollinearity, this study used variance inflation factor. Results indicated acceptable values of less than 10 (Maddala, 2001) as indicated in appendix 6.

3.4.6 Description of variables used in the various econometric models

This sub-section presents the variables used in various econometric models and their description. The variables presented include the dependent and independent variables for the six econometric models used in the respective study objective application, namely PSM, ESR, IPWRA, DH, DA and CD (Table 3.1). Additionally, treatment and outcome variables particularly used in impact assessment methodologies (PSM, ESR and IPWRA) are also presented and described. Further, the unit of measurement for all variables and the respective models where each variable was used is also presented.

Daily consumption expenditure per adult equivalent was measured in USD and used as the outcome variable in PSM, IPWRA and ESR. However, the variable was used for objective 1 in DH and DA models as an independent variable. Binary adoption variable was used as the treatment variable in impact assessment models (PSM, IPWRA and ESR). However, in DH model, it was used as the dependent variable in the first hurdle estimation. In all related monetary variables namely; *consumption expenditure*, *profit*, *per capita income* and a*sset value*, this study used USD conversion equivalent (1 USD = Kes. 101.81) as the standard unit of measurement.

Table 3.1: Description of variables used in this study

Variable	**Description**	**Unit of measure**	**Model where the variable was applied**
	Outcome variable		
Consumption expenditure	daily household's consumption expenditure per adult equivalent	USD[3]	PSM,ESR,IPWRA,DH,DA
	Treatment/Dependent variable		
Adoption	whether a household head had adopted ISVs	1=yes; 0=no	DH,PSM,ESR,IPWRA
Intensity	proportion of the area under ISVs to the total household's cultivated land	ratio	DH
Speed	length of time a farmer waits to adopt ISV (adoption spell)	years	DA
Profit	net profit accrued after deducting total costs from total revenue	USD	CD
	Independent variables		
Age	age of a household head (HH)	years	DH,CD,DA
Education level	years spent in school by a HH	years	DH,CD,DA,ESR,PSM, IPWRA
Experience level	farming experience	years	CD,DA,ESR,PSM,IPWRA
Adult equivalent[4]	household's adult equivalent	number	DH,CD,ESR,PSM,IPWRA
Workforce	household members between 18 and 65 years	number	DH
Tlu[5]	tropical livestock unit per adult equivalent	units	DH,DA
Per capita income	household's total income	USD	DH,DA,ESR,PSM,IPWRA
Extension frequency	average times a household sought extension advice during year 2017/2018 cropping season	number	DH,CD,ESR,PSM,IPWRA
Gender	gender of a household head	I=Male; 0=Female	DH,PSM,IPWRA

[3] I USD was equivalent to 101.81 Kenya Shillings at the time of study

[4] Adult equivalent was computed as **<10 years** = 0.6 for both Male and Female; [**11-13 years** _0.9 = Male; 0.8 = Female]; [**14-16 years**_1 = Male; 0.75 = Female]; [**17-50 years**_1 = Male; 0.75 = Female]; >**50 years**_1 =Male; 0.7 = Female] Source: Storck et al. (1991).

[5] Total livestock unit computed as (0.7 for cow + 0.5 for Heifer + 0.3 for calf +0.1 for goat + 0.1 for sheep + 0.01 for chicken + 0.2 for Pigs) FAO (1986)

Distance to agricultural office	distance to the nearest agricultural office often located at chief's area offices	kilometre	DH,DA,PSM,IPWRA
Nearest town	distance to the nearest town	kilometre	DH,DA
Group membership	whether a HH is a member of any farming group	1=yes; 0=no	DH,CD,DA,ESR,PSM,IPWRA
Agricultural credit	agricultural credit access	1=yes; 0=no	DH,CD,DA
Asset value	household's asset value	USD	DH,DA,ESR,PSM,IPWRA
Cultivable land	average cultivable land	Ha	DH,ESR,PSM,IPWRA
Crop ratio	the ratio of land under crops	ratio	DH
Agrodealer distance	distance to the nearest agro-dealer	kilometre	DH,CD,ESR,PSM,IPWRA
Experience ratio	the ratio of farming and sorghum experience years	ratio	DH,ESR,PSM,IPWRA
Extension access	whether a household head accessed extension services	1=yes; 0=no	DH,DA,ESR PSM,IPWRA
Radio	ownership of a radio	1=yes; 0=no	DH
Training	whether a household head had been trained on any aspect in sorghum production or marketing	1=yes; 0=no	CD

Source: Author's compilation, 2018
Note:
CD = Cobb-Douglas Stochastic Profit Frontier
DH = Double Hurdle model
DA = Duration Analysis model
PSM = Propensity Score Matching model
ESR = Endogenous Switching Regression model
IPWRA = Inverse Probability Weighted Regression Adjustment

CHAPTER FOUR

RESULTS AND DISCUSSIONS

This chapter presents the results and discussions for the sampled farmers in the study area starting with a summary statistics for selected farm and farmer characteristics. Further, DH and DA econometric model results and discussions for the first objective are reported. Additionally, results and discussions generated from CD Stochastic frontier results addressing the second objective are discussed. Lastly, impact related results for the third objective generated by IPWRA, PSM and ESR models are presented and discussed.

4.1 Sample summary statistics

Table 4.1 presents the summary statistics of selected socio-demographic characteristics of sampled households. Several variables such as age, education level, experience level showed significant mean differences between ISV adopters and non-adopters.

4.1.1 Household socio-demographic characteristics

The average age of a household head (HH) was 45.3 years. The mean age difference between ISVs' adopters and non-adopters was significant at 10 percent level. This shows that, on average, adopters of ISVs were older compared to the non-adopters. Majority of the sampled households were male headed (81 percent). On average, heads of adopting households had completed more years in school (7.7) compared to non-adopters (6.2) and mean difference was significant at 1 percent.

Table 4.1: Selected household socio-demographic descriptive statistics

Variable	Pooled data N=452	ISV			
		Adopters N=259	Non-adopters N=193	t-value	χ^2
	Mean/ percent	Mean/ percent	Mean/ Percent		
Age	45.3 (14.1)	45.4 (13.6)	45.2 (14.9)	0.13*	
Education level	7.1 (4.4)	7.7 (4.2)	6.2 (4.5)	3.8***	
Experience	19.2 (12.4)	20.3 (12.8)	17.6 (11.7)	2.3*	
Workforce	2.4 (1.2)	2.3 (1.1)	2.4 (1.3)	-4.3	
Adult equivalent	2.3 (0.6)	2.3 (0.6)	2.4 (0.6)	-1.2	
HH members	4.5 (1.7)	4.4 (1.7)	4.6 (1.7)	-1.6*	
Education					
None	13.1	5.8	7.3		9.7
Primary	59.5	33.4	26.1		
Secondary	18.8	13.1	5.8		
Tertiary	7.7	4.6	3.1		
Adult literacy	0.9	0.4	0.5		
Gender					
1=Male	81.2	46.7	34.5		0.03

Note: Figures in parentheses represent respective standard deviations
***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively
Source: Survey data, 2018

This indicated that, adopters of ISVs were more educated than non-adopters. Majority of the HHs (60 percent) had attained primary school education followed by secondary school level and above (27 percent). Approximately 13.1 percent of the sampled HHs had no formal education. These findings compare closely to Kenya

National Bureau of Statistics (2013)[6] report derived from 2009 census data which reported that, on average, 21 percent of the population in Tharaka Nithi County had attained secondary school education and above. The report also indicated that, in Tharaka Nithi County, more than 62 percent of the population had attained primary school education and 17 percent had no formal education.

On farming experience, the average number of years in farming for the sampled HHs was 19.2. Besides, it was apparent that ISV's adopters were more experienced in farming (20.3) than non-adopters (17.6). The average number of members in the sampled households was 4.5. Non-adopting households reported a higher number of members than the adopters and mean difference significant at 10 percent level. The adult equivalent and labour/workforce within a household was on average calculated at 2.3 and 2.4, respectively. The proportion of workforce was more than 50 percent of the total members in the sampled households. This compares fairly well to the KNBS (2013) report which indicated workforce category to represent 55 percent of the total population in Tharaka Nithi County.

4.1.2 Household's access to information and knowledge

Several dissemination pathways were captured, which explained different channels used by households to access information and knowledge about ISVs. Understanding the pathway through which most adopting households accessed information would be important in order to increase the adoption levels of ISVs. Out of sampled households, only 4 percent were not aware of any ISVs. A list of all ISVs had been constructed, and farmers were asked whether they were aware of any

[6] https://www.knbs.or.ke

of the varieties. Awareness in this context was just the mere fact that a household knew about variety existence and not the corresponding independent varietal attributes. The very first source of information for the 'aware' households was compiled. Majority of households, who were aware (38.7 percent), reported having received first information about the ISVs from aggregator agents (Table 4.2)

Table 4.2: Dissemination pathways

Dissemination pathway	Aggregator agent	Neighbour/ friend	Govt. ext.	NGO ext.	Radio	Field day	Print
percent of sampled households which accessed information as a first choice	38.7	32.5	14.7	8.5	3.5	1.8	0.2

On average, more sampled households (76.1 percent) owned a radio compared to the mobile phone (38.7 percent). Other channels of disseminating information and knowledge, such as farmer groups, were captured. The groups were majorly socio-welfare, producer and marketing oriented. Approximately 65 percent of the sampled households were members of groups, men being the dominant gender (81 percent). Chi-square analysis ($\chi 2$) was computed and show a signification association between group membership and ISV's awareness [$\chi 2$ (1) = 3.5, P< 0.1)]. However, using Cramer's V test, the association was reported as weak (0.1). On training, approximately 61 percent of households reported having received knowledge on management sorghum crop through several practices e.g. spacing, seed rate, timing, and weeding.

4.1.3 Adoption of ISVs

4.1.3.1 Uptake of ISV segregated per season

A household was regarded as an adopter if it planted any of the ISVs in either or both seasons during 2017/2018 cropping calendar (short rain season)/long rains season). Out of the sampled households, the majority (57.3 percent) were adopters. The five ISVs that had been adopted include; *Gadam*, *SC Sila*; *Advanta 23012*, *Serena* and *Kari Mtama 1*. All adopted varieties were white sorghum except *Serena*, which is brown. To check whether there exists season based varietal preference among sampled adopting households, average yield data per ISV was captured (Table 4.3).

Table 4.3: Average yield of adopted ISVs disaggregated per season

ISVs	**Short rainy season**		**Long rainy season**	
	percent of sampled adopting households that had planted the variety (N=244)	Mean yield (tons Ha^{-1})	percent of sampled adopting households that had planted the variety (N=102)	Mean yield (tons Ha^{-1})
Gadam	76.6	1.35	72.5	0.97
SC Sila	35.7	1.96	32.4	0.71
Advanta 23012	<1	2.93	<1	0.64
Serena	<1	1.33	0	0
Kari Mtama 1	0	0	<1	0.84

Source: Survey data, 2018

The findings show that more than double of the sampled households planted ISVs during the short rainy season compared to long rainy season. This is because farmers regard short rainy season as the most dependable season due to reliability and distribution of rainfall. During the short rainy season, 54 percent of the sampled households had adopted ISVs and majority planted *Gadam* variety (76.6 percent) followed by *SC Sila* (35.7 percent). Only a few farmers planted *Advanta 23012* and *Serena* varieties (< 1 percent). During this season, some farmers cited a shortage of *SC Sila* seed variety as a major reason to opt to plant the next preferred variety (*Gadam*). Out of the farmers who had planted the respective ISVs, *Advanta 23012* recorded the highest mean yield measured in tons Ha^{-1} (2.93) followed by *SC Sila* (1.96). *Gadam* and *Serena* varieties closely matched at 1.35 and 1.33 respectively. It is worthy to note that, out of the reported adopted ISVs, *Advanta 23012* is the only hybrid variety while all the others are open-pollinated varieties.

On the contrary, during the long rainy season, the number of farmers who planted ISVs is less than half of the farmers who had planted in the short rainy season. Most of the adopters planted *Gadam* variety (72.5 percent) followed by *SC Sila* (32.4 percent). On average, *Gadam* variety yielded higher tons Ha^{-1} (0.97) followed by *Kari Mtama 1* (0.84), *SC Sila* (0.71) and lastly *Advanta 23012* (0.64). The average yield for both seasons was 1.39 tons Ha^{-1}.

Averagely, more land was allocated to ISVs during the long rainy season (0.65 Ha) as compared to short rainy season (0.53 Ha). This represents 24 percent to 30 percent of the households average total land available and suitable for cultivation. In both seasons, the majority of adopting farmers practised monocrop/pure stand cropping pattern. Averagely, majority of the total quantity of sorghum harvested

(93.5 percent) by adopting households was sold majorly through aggregator agents. Additionally, approximately 5.5 percent and less than 1 percent was lost and stored for home consumption, respectively. This shows that farmers in Tharaka Nithi County cultivate ISVs for commercial purposes.

This study also captured the first ever-adopted variety for the 'aware' households (excluded 4 percent who were not aware of any ISV). This is due to the fact that a household cannot adopt any technology without being aware and exposed to it. A majority (90 percent) indicated to have adopted *Gadam* as their first variety followed by *Seredo* (3.5 percent), *SC Sila* (1.8 percent), *Serena* (0.4 percent) and *Kari Mtama 1* (0.2 percent). Out of 434 households who were aware of ISVs, 80 percent reported having adopted ISVs (*'event happening'*) by the time this study was conducted while 20 percent were right-censored meaning they had not yet adopted (i.e. *had not experienced the event*). On average, households took 2.1 years to adopt ISVs.

The non-adopting households (N=193) indicated several reasons for not planting any ISV during the 2017/2018 cropping season, as indicated in Table 4.4. Majority of the non-adopting households (48.7 percent) cited unreliable weather (low levels of rainfall) as the main reason for not adopting ISVs during the year 2017/2018 cropping calendar. This could be explained by the unusual climate variability within the County due to climate change (Tharaka Nithi County Integrated Development Plan report, 2018).

Table 4.4: Highlighted reasons for not adopting ISVs

Reason for non-adoption	Number of households (N=193)	percent of the sampled non-adopting households
Unreliable weather	94	48.7
Expensive sorghum seed	60	31.1
Low buying produce price/kg	57	29.5
Lack of sorghum seed	44	22.8
Birds menace	36	18.7
Labour intensive	31	16.1
High threshing cost	26	13.5
Not aware of the varieties	18	9.3
Lack of extensive services	18	9.3
High herbicide costs	14	7.3
Crop rotation	10	5.3
Lack of produce market	8	4.1
Low yields	3	1.6

Source: Survey data, 2018

Expensive sorghum seed, low buying produce price/kg and lack of sorghum seed were also cited by more than 20 percent of the non-adopters as key reasons for not planting. Other reasons cited, include; bird's menace (18.7 percent), management of the crop being labour intensive (16.1 percent), high cost of threshing (which ranges from Kes. 200 - 300 per 90kg bag) among others. Understanding and addressing these reasons is critical if the non-adopters are to adopt during the upcoming seasons.

4.1.3.2 Profitability of sorghum production

Table 4.5 presents the cost and profitability estimates for the production of ISVs in the study area. The results show that, on average, adopting farmers earned about USD[7] 165 Ha^{-1}. The average yield Ha^{-1} was low (1.39) compared to the expected potential of 2 - 5 tons Ha^{-1} (GoK, 2015). This shows that the average yield for the sampled farmers was less than half of the expected output.

Table 4.5: Profitability and cost estimates for ISVs' production

Variable	**Unit of measurement**	**Sample size (N)**	**Mean**	**Standard deviation**
Profit	USD Ha^{-1}	259	164.88	155.64
Sorghum yield	tons Ha^{-1}	259	1.39	0.75
Land area under sorghum	Ha	259	1.05	0.86
Fixed capital base cost	USD HH^{-1}	249	6.40	1.73
Seed cost	USD Ha^{-1}	255	18.82	7.10
Labor wage cost				
Hired labour cost	USD Ha^{-1}	253	50.83	8.67
Family labor (opportunity cost	USD Ha^{-1}	227	174.58	78.27
Fertilizer cost	USD Ha^{-1}	11	6.63	3.98
Insecticide cost	USD Ha^{-1}	86	12.69	3.70

Source: Survey data, 2018

On costs, on average, farmers spent about USD 19 Ha^{-1} to buy seed while amount used for family and hired labour was approximately USD 51 Ha^{-1} and USD 175 Ha^{-1} respectively. An estimate of 33 percent of the sampled farmers bought insecticides averaging USD 13 Ha^{-1}. On average, less than 5 percent of sampled

[7] I USD was equivalent to 101.81 Kenya Shillings at the time of study i.e. end year 2018

farmers purchased fertilizer at the cost of USD 7 Ha^{-1}. This is quite low and indicates that majority of the farmers in the study area do not use fertilizer. On variable cost share analysis, family labour was the highest accounting to about 66 percent followed by hired labour (20 percent), seed (7 percent), insecticides (5 percent) and lastly fertilizer (3 percent).

4.1.4 Household land access, use and cropping activities

Land ownership, access and usage data were captured for both cropping seasons and did not differ across seasons (Table 4.6). On average, adopting households owned more size of land (1.98 Ha) compared to their counterparts (1.94 Ha). Additionally, adopting households had more land accessible and available to them (2.39 Ha) out of which, 2.11 Ha was cultivated. This compares fairly closely to the landholding indicated in the KNBS (2013) report for smallholder farmers in Tharaka Nithi County, which stands at 2.9 Ha.

Table 4.6: Land ownership and access

Land variable	**Both seasons (Long and Short rainy)**		
	Adopters (N=259)	**Non-adopters (N=193)**	**Mean difference**
Average owned land (Ha)	1.98	1.94	1.0
Average land available for cultivation (Ha)	2.39	1.86	0.4
Average land cultivated (Ha)	2.11	1.62	1.2^{***}
Average leased in (Ha)	0.45	0.12	0.7^{***}

$^{***}P<0.01$, $^{**}P<0.05$ and $^{*}P<0.10$ mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively

Source: Survey data, 2018

Total available land was computed and captured land owned, other lands accessible and available to the household for use e.g. leased in, communal land etc. On average, non-adopting households cultivated less land in both seasons (1.62 Ha) than the adopters (2.11 Ha) and the mean difference was highly significant at 1 percent level. During both seasons, on average, adopting households leased in more land (0.45 Ha) compared to their non-adopting counterparts (0.12 Ha). The mean difference (0.7) was highly significant at 1 percent level. Further, the average area of land planted sorghum by the adopters was 1.05 Ha.

This study also captured the aspect of land tenure of the main household's farmland. Majority of the households (83.2 percent) owned land without a title deed. Only a few households owned land with title deeds (8.8 percent) while 7.3 percent of the main farmland was leased. According to KNBS (2013) report, most land in Tharaka Nithi County is not titled and this is attributed to the slow land adjudication process. The land accessible and available to the household for use is majorly used for crops (73 percent), pasture (8 percent), woodlots (3 percent), homestead which included animal pen (10 percent).

Household's land allocation to specific crops was also captured (Table 4.7). This was achieved by asking the households the three crops allocated the largest cropland respectively in separate seasons. In the short rainy season, majority of the households allocated the largest cropland to sorghum (55.3 percent), followed by green grams (20.4 percent) and millets (11.5 percent). On the contrary, during the long rainy season, green grams crop was allocated the largest cropland by a majority of the farmers (27.5 percent), followed by millets (26.5 percent) and sorghum (22.3 percent).

Table 4.7: Land allocation among crops in both seasons

Crop Name	**Short rainy season**			**Long rainy season**		
	percent sampled households that allocated respective crop the **largest cropland**	percent sampled households that allocated respective crop the **2nd largest cropland**	percent sampled households that allocated respective crop the **3rd largest cropland**	percent sampled households that allocated respective crop the **largest cropland**	percent sampled households that allocated respective crop the **2nd largest cropland**	percent sampled households that allocated respective crop the **3rd largest cropland**
Green grams	20.4	22.8	10.6	27.4	23	10.2
Millets	11.5	26.3	13.3	26.5	21	9.5
Pigeon peas	0.4	0.7	1.8	1.3	1.1	1.1
Cowpeas	6.2	15	14.8	14.8	19.9	14.6
Sorghum	55.3	8.8	10	22.3	9.3	11.7
Maize	4.9	10.6	4.9	5.1	10.6	6.4
Tobacco	0	0	0	0.2	0	0
Ground nuts	0	1.1	0.7	0	1.1	0.7
Beans	0.4	0.9	1.3	0	0	0.2

Source: Survey data, 2018

This conforms well to findings reported in 2018 Long Rains Food Assessment Report for Tharaka Nithi County[8] which showed that green gram crop was allocated highest total land acreage by farmers (16,150 Ha) followed by millet (13,335 Ha) and sorghum (3,350 Ha). This shows that sorghum and green grams are mostly preferred during the short and long rainy seasons, respectively.

[8]https://www.ndma.go.ke/index.php/resource-center

4.1.5 Household's socio-economic characteristics

Several socio-economic parameters for sampled households were captured, which included income, consumption expenditure and asset base. Majority of sampled households were drawing their income from farming (both crops and livestock) representing 48.5 percent of the total income. This was followed by income earned from casual labour (both on and off-farm) at 28.2 percent, off-farm income (19.7 percent), remittances (2.86 percent) and lastly salaried employment (0.74 percent). These results compare fairly well with KNBS (2013) report which indicated that, out of the total population in Tharaka Nithi County, few persons (about 9,188 = < 1 percent) had formal salaried employment). On average, daily consumption expenditure per adult equivalent was USD 2.02. The adopters reported higher consumption expenditure (USD 2.11) compared to their non-adopting counterparts (1.91). Further, on average, adopting households had a higher asset base USD 7,802 compared to USD 4,922 reported by non-adopters.

Income and consumption expenditure inequality was assessed using the Lorenz curves and Gini coefficient. The Lorenz curve is normally used to assess the proportion of income or consumption expenditure controlled by different proportions of the population, as shown in Figure 4.1. On the other hand, the Gini coefficient calculated from the Lorenz curve measures the intensity of inequality among sampled households and ranges between 0 and 1. A Gini coefficient of 0 and 1 implies perfect equality and perfect inequality, respectively.

This study computed the Gini coefficient of income (0.73), consumption expenditure (0.5) and asset (in/exclusive of land). This shows that income levels among sampled households are almost perfectly unequal. These findings conform to KNBS (2013) that reported a Gini coefficient of 0.4 for consumption expenditure among Tharaka Nithi County population.

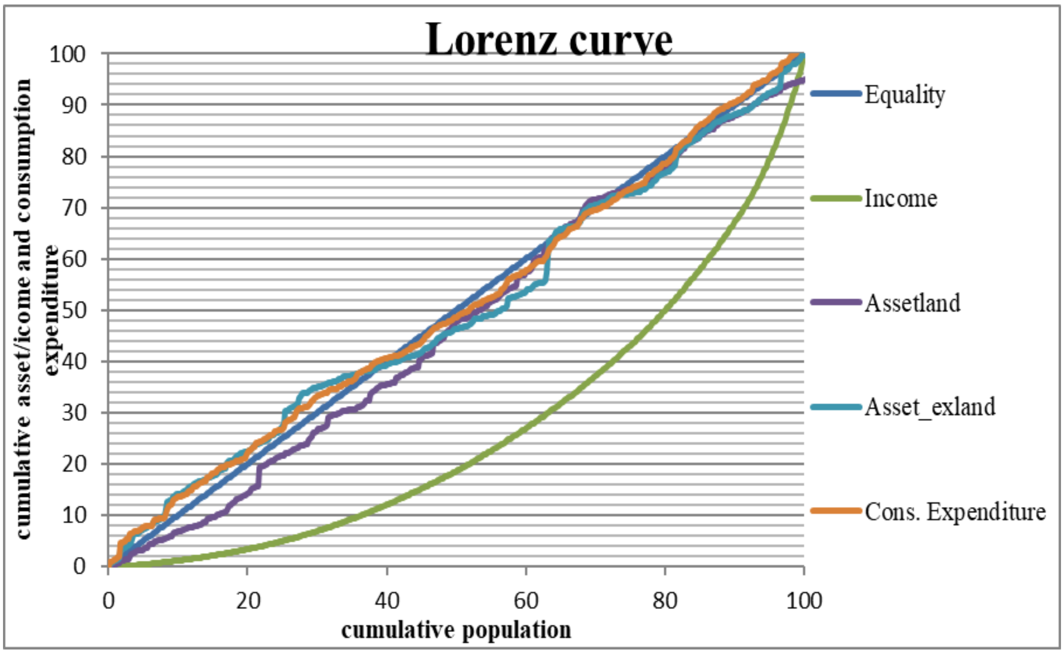

Figure 4.1: Lorenz curve

Source: Survey data, 2018

4.1.6 Household's access to inputs, credit and extension services

4.1.6.1 Access and frequency of seeking extension services

Among the sampled households, approximately 31.6 percent sought extension advice from various sources. Test and strength of association between the adoption of ISVs and extension services' seek was computed. The findings show that there was a significant association between the two categorical variables [$\chi 2$ (1) = 30.6, P< 0.01]. The strength of association was moderate, according to Cramer's V test (0.3). The adopting households indicated their first, second and third extension service source during the year 2017/2018 cropping season as captured in Table 4.8. The extension service sought was generally on how to manage sorghum farm fields. Majority of household's first sought extension advice was from a fellow farmer/neighbor (39.2 percent), followed by government extension agent (22.4 percent) and off-taker/input dealers (14.7 percent).

Table 4.8: Sources of extension services

Extension service source	First source (percent of households; N=143)	Second source (percent of households; N=69)	Third source (percent of households; N=40)
Neighbour/farmer	39.2	37.7	12.5
Government extension agent	22.4	2.9	2.5
Off-taker/input dealers	14.7	21.7	40.0
Family/friend	11.9	17.4	10.0
Private extension agent	5.6	7.2	2.5
NGO agent	3.5	2.9	17.5
Radio/TV	0.7	1.4	5.0
Farmer organizations/coops	0.7	2.9	2.5
Field days/demos	0.7	2.9	7.5
Research organizations	0.7	0.0	0.0
Newspaper/magazines	0.0	1.4	0.0
ASK Shows	0.0	1.4	0.0

Source: Survey data, 2018

On average, a HH visited the first extension source for advice 10 times during both seasons. Those who sought advice from a second extension source (N=69), majority visited neighbour/ fellow farmer (37.7 percent) followed by off-taker/input dealers (21.7 percent). This study collected reasons from farmers for not seeking extension services and summarized them as shown in Table 4.9.

Table 4.9: Summarized reasons for not seeking extension advice

Reasons for not seeking extension advice	**Reason 1**	**Reason 2**
	percent of households (N=309)	**percent of households (N=72)**
Extension agent not showing up	35.3	23.6
Long distance	20.7	1.4
Extension agents not available	16.5	30.6
Time consuming	14.6	41.7
Don't need extension services	12.9	2.8

Source: Survey data, 2018

Most of the households (35.2 percent) cited extension agents not showing up as the main reason why they never sought extension services. This could be as a result of the distance to the households. On average, the distance from the location of sampled households to the nearest agricultural office where extension agents are domiciled was 3.1 *km* with farmers travelling up to a maximum of 15 *km* to seek advice. The terrain is very rough and main mode of transport available was use of a motorcycle commonly referred to as *'boda boda'*. The transport cost goes as high as USD 3.93 for a distance of 15 *km*. According to KNBS (2013) report, only 61 percent of road in Tharaka Nithi County is bitumen standard.

4.1.6.2 Access to ISV seed

For farmers to adopt a certain ISV variety, they need to be exposed (aware of variety existence) and have access to seed. Some farmers cited a shortage of *SC Sila* seed variety as the main reason for planting *Gadam* during the SR season. Approximately, 22.8 percent of non-adopters cited lack of sorghum seed as the major reason for not planting ISVs. Some farmers travelled to as far as Meru town, which is on average, 50-70 *km* from most farm locations within sampled households in search for sorghum seed especially *SC Sila*. Access to seed addresses availability and can viewed from two angles namely (a) either that, the agro-dealers had not stocked enough seed or (b) nearest agro-dealer is far away from a household's location.

4.1.6.3 Access to agricultural credit

Most of the sampled households (94 percent) did not access any form of agricultural credit. For the few who had accessed (N=26), this study captured the credit provider as summarized in Table 4.10. For those who had not accessed credit, attributable reasons were also captured and reported. Majority of households (58.6 percent) had accessed credit from informal sources e.g. Merry-go-rounds and table banking. On the other hand, 39.7 percent and 22.7 percent of the households, who never accessed credit, did not see the need for credit and did not know the credit source, respectively. This could mean that financial literacy is low in the study area and/or farmers are credit constrained.

Table 4.10: Credit service providers and reasons for not accessing agricultural credit

Credit provider	**percent of households which had accessed credit (N=29)**	**Reasons for not accessing credit**	**percent of households which cited the reasons [N=423; 94 percent)**
Merry-go-round / Table banking	58.6	No need	39.7
Bank	27.6	Fear of failing to repay	25.3
Friends and relatives	10.3	Didn't know the source of credit	22.7
Safaricom (*M-Shwari/M-kopa*)	3.4	No collateral	5.4
		Had outstanding loan	4.0
		Didn't have an account	1.7
		Lender lacked cash	1.2

Source: Survey data, 2018

Low financial literacy could be attributed to various factors including and not limited to the high cost of field operations for the credit providers due to bad roads, huge distances from big towns, e.g. Meru, Kathwana, and Mukothima where most of the credit providers are located among others. In most parts of Tharaka North sub-County, agency banking is not available. About 25 percent of households cited fear of failing to pay the loan as a major reason for not accessing credit. This could be attributed to recent unpredicted weather conditions experienced in the region due to climatic change as reported by Tharaka Nithi County Integrated Development Plan report compiled in 2013[9].

[9]www.tharaka nithi county.go.ke

4.2 Determinants of adoption, intensity of use and speed of uptake of ISVs

This section presents results and discussions for the first objective of this study that aimed to analyze the determinants of adoption, intensity of use and speed of uptake of ISVs. Firstly, section 4.2.1 and 4.2.2 presents results and discussions on the determinants of adoption and intensity of use of ISVs, respectively. Marginal effects results and discussions are thereafter presented in sub-section 4.2.3. Secondly, results and discussions on the speed of adoption of ISVs are presented in sub-section 4.2.4.

4.2.1 Determinants of adoption of ISVs

Table 4.11 (column 2) presents the determinants that influence the adoption of ISVs among sampled farmers in the study area. The coefficient for tropical livestock units per adult equivalent (*Tlu*) was positive and significant at 1 percent level. This implies that there exists a significant positive relationship between ownership of livestock and the decision to adopt ISV. Therefore, it means that the probability of adopting ISVs was higher for households that owned livestock compared to their counterparts who did not own. *Tlu* is often regarded as a measure of household wealth. Households which owned livestock were more likely to be wealthier compared to their counterparts and able to afford capital-intensive technologies. Several studies reported similar results e.g. (Asfaw *et al.*, 2016; Mwangi *et al.*, 2014; Murage *et al.*, 2012).

Table 4.11: Determinants of ISV adoption, the intensity of use and marginal effects[10]

Variables	Adoption of ISVs	Intensity of use of ISVs	Marginal effects
	Coefficient	Coefficient	
Extension	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.00)
Tlu	0.48 (0.13)***	-0.02 (0.03)	0.04 (0.02)**
Age	0.01 (0.01)	-0.00 (0.00)	-0.00 (0.00)
Marital	-0.04 (0.06)	-0.01 (0.02)	-0.01 (0.01)
Education level	0.05 (0.02)***	-0.00 (0.01)	0.00 (0.00)
Gender	-0.20 (0.24)	-0.05 (0.06)	-0.04 (0.04)
Distance to agricultural office	-0.09 (0.03)***	0.03 (0.01)**	0.00 (0.01)
Nearest town	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Group	0.03 (0.14)	-0.00 (0.04)	0.00 (0.02)
Extension access	0.68 (0.16)***	0.06 (0.04)	0.08 (0.02)***
Agricultural	0.02 (0.28)	-0.14 (0.08)*	-0.05 (0.04)
Asset value	0.12 (0.16)	0.05 (0.05)	0.03 (0.03)
Cultivable land	0.00 (0.02)	-0.05 (0.01)***	-0.02 (0.01)***
Crop ratio	0.72 (0.37)**	0.35 (0.12)***	0.20 (0.06)***
Agrodealer	-0.02 (0.03)	-0.01 (0.01)	-0.00 (0.01)
Consumption expenditure	0.32 (0.12)***	0.06 (0.04)	0.05 (0.02)***
Radio	0.02 (0.14)	-0.04 (0.04)	-0.01 (0.02)
Per capita income	-0.15 (0.17)	0.11 (0.05)**	0.03 (0.02)
Experience ratio	0.39 (0.26)	-0.01 (0.03)	0.03 (0.04)
Adult equivalent	0.08 (0.17)	-0.09 (0.05)**	-0.03 (0.03)
Workforce	-0.02 (0.09)	-0.00 (0.03)	-0.00 (0.01)
N	452		
Wald Chi^2 (21)	97.53		
Prob > Chi^2	0.000		
Log-likelihood	-125.653		

Note: Figures in the parentheses are the standard errors associated with the coefficients and marginal effects.
***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively.
Source: Survey data, 2018

[10]Average partial effects (APEs) coefficients are presented as marginal effects values

There was a significant positive relationship between the level of education attained by a HH and adoption of ISVs. Education levels are associated with human capital, and educated HHs were more likely to adopt ISVs compared to their counterparts. This is line with findings by several studies (Lunduka *et al.,* 2019; Yigezu *et al.,* 2018; Smale *et al.,* 2018; Danso-Abbeam *et al.,* 2017; Asfaw *et al.,* 2016; Ahmed *et al.,* 2016). Educated farmers are more informed and able to unpack information provided in a technology package. On the other hand, less educated farmers have a low probability of adopting ISVs considering that, they might not be able to understand the information usually presented in the form of print, pamphlets, brochures etc.

Distance to the nearest agricultural office used as a proxy of extension information access in this study, was inversely related to the adoption of ISVs. This shows a significant negative influence implying that households located far away from agricultural offices were less likely to adopt ISVs. This could be because of the fact that, as the distance from a household to the nearest agricultural office increases, transaction and transformation costs are expected to increase. This discourages farmers from seeking information and therefore acts as a disincentive to the adoption of ISVs. This finding supports those of Asfaw *et al.,* (2016) and Mwangi *et al.,* (2014).

Households that had a higher ratio of land under crops (*crop ratio*) were more likely to adopt ISVs. This could be probably because the households had more farming experience and they would plant ISVs as a way of managing risk through diversification. On the other hand, there was a significant positive influence of seeking extension advice and adoption of ISVs. The extension advice equips farmers with the necessary information to profitably grow and manage their sorghum crop. It acts as a catalyst to technology adoption through the provision of necessary extension information to farmers. This finding corroborates that of several studies, Yigezu *et al.,* (2018); Milkias and Abdulahi (2018); Verkaart *et al.,* (2017); Danso-Abbeam *et al.,* (2017) and Ahmed *et al.,* (2016) among others.

Households with higher consumption expenditure were more likely to adopt ISVs compared to their counterparts. This was evident by the positive coefficient for consumption expenditure (0.32) significant at 1 percent level. This could be interpreted that, wealthy households had a higher probability to adopt ISVs compared to their poor counterparts. This finding is in line with Simtowe and Mausch (2019) and Asfaw *et al.,* (2016) who reported that wealthy farmers are more likely to adopt ISVs and modern inputs in Tanzania and Niger respectively. This is probably because the wealthy households can seek information and purchase the required inputs e.g. certified seeds, fertilizers etc. It is also likely that poor households are not connected to information networks like contract farming modalities, aggregation concept, participation in field day events, farmer to farmer linkages and dynamics etc.

4.2.2 Determinants that influence the intensity of use of ISVs

The determinants that influenced adoption intensity of ISVs are presented in Table 4.11 (column 3). The results indicated unexpected positive significant influence between distance to the nearest agricultural office and intensity of use of ISVs. This means that, households far away from the agricultural offices are more likely to expand the area of land under ISV compared to their counterparts in close proximity. The possible explanation to this unexpected *a priori* would be that, the study area is characterized by rugged terrain and the dominant means of transport is motorcycles commonly referred to as *'bodabodas'* which charge exorbitant fares. This act as a disincentive for farmers far away from agricultural office to seek information and opt for other alternative means e.g. fellow farmers, aggregator agents, Non-Governmental Organizations (NGOs) and input company staff among others. In fact, descriptive statistics indicated that 33 percent of sampled farmers sought extension advice from fellow farmers. This result is in agreement with the findings by Simtowe and Mausch (2019), which noted that several neighbours growing sorghum positively influenced farmers in Tanzania to adopt ISVs.

On the other hand, due to high costs incurred to travel a long distance, farmers might grow more sorghum so that they can have enough to sell and save some seed for the following season. This shows that, if certified seeds were not locally available, farmers would not travel long distances to purchase but would rather use their home saved seed that might yield low due to poor quality. It could also imply that farmers far away from agricultural office might be seed sellers due to limited network of agro-dealers. Therefore, it could be that these farmers would expand land under ISVs to produce and sell more grain and make money on seed sales. Although some studies support this finding e.g. Amotide *et al.,* (2016), some such as Murage *et al.,* (2012) contradicts by indicating an inverse relationship.

The coefficient for cultivable land was negative (-0.05) and significant at 1 percent level. This finding shows that households with less cultivable land were more likely to intensify the use of ISVs. This could mean that, as cultivable land increase, households tend to go into multiple cropping and thus reduce land allocated to ISVs. Therefore, households with less cultivable land tend to have a higher degree of specialization into ISVs. The farmers tend to specialize in crops that have a higher chance of tolerating climatic condition changes thus increasing their resilience. This result conforms to the findings by Awotide *et al.,* (2014).

Access to agricultural credit is an important factor to technology adoption. This is because access to agricultural credit relaxes households' cash constraints, enabling them to acquire inputs easily and other accompanying farming services. Surprisingly, the result shows an unexpected significant *a priori* negative sign (-0.138). This means that households who expand land under ISVs the most are those who lack access to agricultural credit. This result suggests that, by expanding land under ISVs, farmers may become financially stable. Generally, it shows that sampled farmers in the study area are credit constrained.

The following could also be explanations for the negative (inverse) significant relationship between intensity of ISVs' adoption and access to agricultural credit. Firstly, farmers could divert accessed credit to other priorities, e.g. alternative agricultural uses and/or non-agricultural uses e.g. off-farm activities.

Secondly, due to the stringent loan requirement/conditions attached to credit (e.g. use of the certified seed, fertilizer etc), which increase the repayable amount most farmers may opt to grow ISVs in a small area that they can ably manage. This is bound to increase their chances of producing enough to cover the loan amount amidst drastic climate change in the study area. Thirdly, the farmers could be fearing borrowing loans due to uncertain of how to repay. This finding is in line with findings reported by Amotide *et al.,* (2016).

The results reported a significant positive relationship between the ratio of land under crops (*crop ratio*) and intensity of ISV adoption. This shows that households with a higher proportion of land under crops were more likely to intensify the use of ISVs compared to their counterparts. This could be because the households were more experienced in farming and that, and they could easily switch to high-value crops, including ISVs.

The relationship between a household's income level and decision to intensify the use of ISVs was reported as positive and significant at 5 percent level. This means that households with higher income levels have a high probability of putting more of their land under ISVs. This could enable farmers to purchase certified sorghum seed, fertilizer and other inputs. Furthermore, more income, especially which exceeds food expenditure and other social expenditures, would enable farmers to expand investments into more agricultural activities, including such inputs such as top-dressing fertilizer etc. This finding is similar to the results reported by Simtowe and Mausch (2019).

The study established a significant negative relationship between a household's adult equivalent and decision to expand land under ISV. This implies that smaller households were more likely to expand land under ISVs compared to larger households. This was contrary to the *a priori* expectation. This could be interpreted to mean that, as members of a household increase, expenditure on food and other related amenities increase. Thus, this could further depress the resource base of the already constrained households. This lowers the household's income base and their propensity to expand the use of ISVs. This finding is in agreement with Umar *et al.,* (2014). However, it contradicts the results reported by Danso-Abbeam *et al.,* (2017) which indicated a significant positive relationship between household size and intensity of adoption of improved maize variety in Ghana.

4.2.3 Marginal effects (unconditional average partial effects)

The marginal effect for tropical livestock unit *(Tlu)* was positive *(ME= 0.036)* and significant at 5 percent level. This implies that households with more livestock units were more likely to intensify the use of ISV. On average, a unit increase of *Tlu* would increase the land put under ISV by 0.04 Ha. Whilst *Tlu* is regarded as a sign of wealth; the result conformed to that notion suggesting that wealthier households were more likely to expand land under ISV compared to their poor counterparts. This finding is in agreement with that reported by Asfaw *et al.,* (2016); Mwangi *et al.,* (2014) and Murage *et al.,* (2012).

On average, households that sought extension advice were expected to increase land under ISVs by 0.084 Ha. This is because they are expected to acquire necessary required information e.g. agronomic, gross-margins among others. This information is vital in ensuring that the households increase productivity, thus the urge to expand more land under ISVs. This finding corroborates that of the studies by Yigezu *et al.,* (2018); Milkias and Abdulahi (2018); Danso-Abbeam *et al*. (2017); Verkaart *et al.,* (2017) among others.

Households with less cultivable land were more likely to intensify the use of ISVs. This is confirmed by a negative marginal effect *(ME= -0.017)* highly significant at 1 percent level. This shows that, on average, a unit decrease in accessible cultivable land, the area put under ISV is bound to increase by 0.017 Ha. This could be because as cultivable land decrease, farmers tend to specialize and switch to high-value crops. This finding agrees to that reported by Awotide *et al.,* (2014).

The ratio of land put under crops (*crop ratio*) and intensity of ISV adoption depicted a positive significant marginal effect *(ME= 0.196)*. If a household increased the ratio of land put under crops by 1 percent, the propensity to extend land under ISVs would increase by 0.196 Ha. This implies that households switch land from other uses into growing crops and prioritize ISVs.

Relatively wealthy households were more likely to intensify the use of ISVs compared to their poor counterparts. This was confirmed by the positive and significant consumption expenditure marginal effects *(ME= 0.052)*. This could be because, wealthy households are able to cope with risks, shocks and cover related costs. This is because they are more risk-loving than their poorer counterparts. This is in line to the findings by Simtowe and Mausch (2019).

4.2.4 Results and discussions on the speed of adoption of ISVs

This sub-section presents both parametric and non-parametric results and discussions generated from DA model. The aim was to evaluate the determinants that influence the decision on how fast (speed) to adopt ISVs.

4.2.4.1 Non-parametric results

This sub-section presents and discusses results generated by Kaplan-Meier survival function for ISV adoption summarized by Figure 4.2. The graph shows the percentage of farmers who had not adopted ISVs at the time of the survey. The horizontal axis shows the number of years that elapsed from the date of a household becoming aware of ISVs' existence to the year of the first adoption.

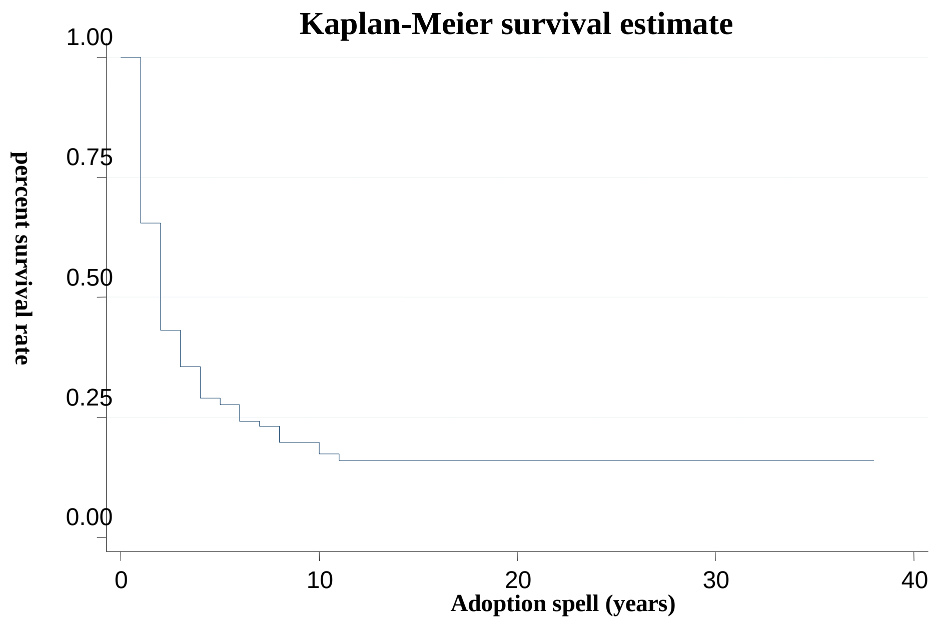

Figure 4.2: Kaplan-Meier survival function

Source: Survey data, 2018

It is worth noting that, at point t = 0, the value of the survivor function is equal to 1. This follows an assumption that all households had initially not adopted ISVs and they enter the function at t = 0 despite the time when they start to be observed. The survival rate falls as the adoption of ISV is reported to occur. It is noted that, during the first five (5) years, the value of the survivor function sharply drops which shows that, during these initial years, majority of the households adopted ISVs after being aware of the existence of ISVs. This is expected since the exponential adoption trend is normally reported during the initial stages of most agricultural technology adoption. The survivor function levels fall between 10^{th} and 38^{th} year, implying few or no new ISV adopters during that time spell.

4.2.4.2 Parametric results and discussions

A hazard ratio greater than one implies that the variable has a positive impact on the likelihood of adoption occurring. This means that the variable hastens ISV adoption process i.e. reduces the time to ISV adoption and vice versa.

The results indicate that it took a longer time for households with less tropical livestock units to adopt ISVs compared to those with high *Tlu* units (Table 4.12). This was indicated by a hazard ratio of more than 1 (1.36) significant at 1 percent. This was expected since more *Tlu* units signify wealth. Therefore, wealthier households were likely to adopt ISVs faster than their poorer counterparts. This finding contradicts that of study by Abebe and Bekele (2015).

Table 4.12: Exponential model coefficients, hazard ratio and percentage change

Variable	**Coefficient**	**Hazard ratio**	**Percent change (percent)**
Extension access	-0.16 (0.17)	0.85 (0.15)	-14.8
Age	-0.00 (0.01)	1.00 (0.01)	-0.3
Education level	-0.00 (0.02)	1.00 (0.02)	-0.1
Agricultural credit	-0.53 (0.32)*	0.59 (0.19)*	-41.1
Nearest town	0.01 (0.02)*	1.01 (0.01)*	0.8
Group membership	-0.05 (0.16)	0.95 (0.15)	-4.7
Asset value	-0.26 (0.21)	0.77 (0.16)	-22.6
Per capita income	0.35 (0.20)*	1.42 (0.29)*	41.5
Tlu	0.31 (0.09)***	1.36 (0.12)***	35.8
Consumption expenditure	-1.32 (1.29)	1.00 (1.29)	0
Distance to agricultural office	-0.06 (0.03)**	0.94 (0.03)**	-5.9
Experience level	0.01 (0.01)	1.01 (0.01)	1.3
constant	-1.76 (1.36)	0.17 (0.23)	-82.8

No. of subjects = 281
No. of failures = 195
Time at risk = 892
LR $Chi^2(12)$ = 27.16
Prob > Chi^2 = 0.01
Log likelihood = -378.90

Note: Figures in the parentheses are the standard errors associated with the coefficients and hazard ratios

***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively.

Source: Survey data, 2018

Households with a higher income level were likely to adopt ISVs faster compared to their counterparts. This is depicted by the positive hazard ratio greater than 1 since households with higher income levels have a higher purchase power for inputs and can cover related costs. This is in line with findings by Murage *et al.,* (2011).

The relationship between distance to the nearest town (proxy to input and output market) and early adoption of ISVs was positive. This means households far away from town are more likely to adopt ISVs faster compared to those nearing towns. This could be that most households located far away from town use saved seed from their previous harvest or from their neighbours. This is in agreement with Ahsanuzzaman (2015).

The findings depicted a negative relation between access to agricultural credit and speed of ISVs' adoption confirmed by 41 percent lower hazard rate (Table 4.12). This result suggests that households that accessed credit were likely to adopt ISVs at a slower rate compared to their counterparts. The *a priori* was unexpected and suggested that, households in the study area are credit constrained or feared borrowing loans.

Households located far away from agricultural offices reported 5.9 percent lower hazard rate. This means that they were likely to adopt at a slower rate compared to those in the near proximity. This could be because of the related transaction and transformation costs incurred while seeking information. The result shows that extension information is paramount for farmers to adopter at a faster rate. This result concurs to those by Abebe and Bekele (2015).

4.3 Results and discussions on profit efficiency among smallholder sorghum farmers

This sub-section presents results and discusses profit efficiency among smallholder farmers and their determinants as generated from the Cobb Douglas Stochastic Profit efficiency model. These results attempted to achieve objective two of this study, which sought to evaluate the profit efficiency of smallholder sorghum farmers in Tharaka Nithi County.

4.3.1 Maximum likelihood parameter estimates of the profit efficiency model

Table 4.13 presents the maximum likelihood estimates of the parameters of the Cobb-Douglas stochastic profit frontier model. The results show statistically significant coefficients for sigma squared (σ^2) and gamma (γ) parameters.

Table 4.13: Maximum likelihood estimates for parameters of the Cobb-Douglas Stochastic Profit Frontier model

Variable Name	**Parameter**	**Coefficient**	**t-ratio**
Constant	β_0	1.49 (0.66)	2.26
$\ln P_{seed\ cost}$	β_1	-0.02 (0.27)	-0.08
$\ln P_{insecticide\ cost}$	β_2	0.08 (0.10)	0.80
$\ln P_{family\ labour\ cost}$	β_3	0.14 (0.07)**	2.11
$\ln P_{hired\ labour\ cost}$	β_4	-0.12 (0.13)	-0.92
$\ln P_{fixed\ capital\ cost}$	β_5	0.20 (0.09)**	2.12
$\ln P_{land\ under\ ISV}$	β_6	0.21 (0.25)	0.85
Diagnostic statistics			
Sigma-squared	σ^2	5.91 (0.73)***	8.05
Gamma	γ	0.95 (0.02)***	39.62
Log likelihood function value	LLF	-461.81	
Sample size	259		

Note: Figures in parentheses represent standard errors
***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively
Source: Survey data, 2018

The estimated gamma or variance ration parameter coefficient (0.95) means that approximately 95 percent of profit variation could be attributed to inefficiencies with one-sided error Rahman (2003). The value of γ which is close to 1 implies that variation in actual profit from the maximum profits for sorghum farmers was due to differences in farming practices and less on exogenous factors outside farmers control. This confirms that there exists a high level of inefficiency among sorghum farmers which is stochastic in nature.

The estimated sigma squared (5.91) is significant at 1 percent confidence level, meaning the model was a good fit (Rahman, 2003). The elasticity findings show that when the cost of family labour and fixed capital increases by 1 percent, profit increases by 0.14 percent and 0.20 percent respectively.

4.3.2 Distribution of profit efficiency scores

Table 4.14 shows that distribution of profit efficiency levels for sampled sorghum farmers. The scores indicate a wide range of profit efficiency from 0.12 to 0.96 for the worst and best sorghum farmer, respectively, with a mean of 0.17.

Table 4.14: Deciles frequency distribution of profit efficiencies

Efficiency level	Frequency	Relative Percentage
< 0.25	185	71.43
0.26 - 0.50	52	20.08
0.51 - 0.60	7	2.70
0.61 - 0.70	9	3.47
0.71 - 0.80	2	0.77
0.81 - 0.90	0	0.00
0.91 - 1.00	4	1.54
Total	259	100
Minimum		0.12
Maximum		0.96
Mean		0.17
Std. Dev.		0.21

This implies that, an average farmer in the study area have the room to increase profits by 83 percent by becoming efficient. Further, results reveal huge profit efficiency variation, with over 70 percent of sampled farmers recording an efficiency score of less than 0.25. The least profit efficient and average farmers need a cost-saving (efficiency gain) of 87.50 percent[11] and 82.3 percent[12] respectively, to attain the profit efficiency level of the best farmer in the study area. On the other hand, the best farmer needs a cost saving of 4 percent[13] to be on the frontier.

[11] [1-(0.12/0.96)]*100
[12] [1-(0.17/0.96)]*100
[13] [1(0.96/1)]*100

Additionally, with mean profit efficiency estimated at 0.17 and actual profit at USD 164.88 ha^{-1}, sampled sorghum farmers incurred profit-loss[14] of approximately USD 804.99 ha^{-1}. Therefore, this implies that sorghum farmers could, on average, attain [15]potential profit of about USD 969.87 ha^{-1} through the improvement of technical, allocative, and scale efficiencies. This is quite a significant amount of income for sorghum farmers in Tharaka Nithi County.

4.3.3 Sources of profit inefficiencies among sorghum farmers

Table 4.15 presents results of the inefficiency model. The results show a negative, highly significant relationship between experience in sorghum farming and inefficiency (-0.006). This implies that experienced farmers are more likely to be profit efficient.

Table 4.15: Determinants of profit inefficiency

Variable Name	Parameter	Coefficient	t-ratio
Constant	δ_0	0.894 (0.054)	16.52
W_1=*Extension frequency*	δ_1	-0.001(0.001)	-0.34
W_2 = *Experience*	δ_2	-0.006 (0.002)***	-2.77
W_3 = *Group membership*	δ_3	-0.001 (0.018)	-0.06
W_4 = *Education level*	δ_4	0.003 (0.002)	1.22
W_5 = *Adult Equivalent*	δ_5	-0.013 (0.0130)	-1.04
W_6 = *Agricultural credit*	δ_6	-0.116 (0.026) ***	-4.38
W_7 = *Age*	δ_7	0.001(0.001)	1.33
W_8 = *Training*	δ_8	-0.046 (0.021)**	2.21
W_9 = *Agrodealer distance*	δ_9	0.010 (0.003) ***	2.76

Note: Figures in parentheses represent standard errors associated with the coefficients

***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively

Source: Survey data, 2018

[14] Profit-loss = Actual profit * (1-Profit efficiency)/Profit efficiency

[15]Potential average profit = actual profit + profit-loss.

The experienced farmers were expected to operate at a higher level of profit efficiency compared to their less experienced counterparts. The results corroborate those of Konja *et al.,* (2019), Saysay *et al.,* (2016), Trong and Napasintuwong (2015), Munir *et al.,* (2015), Sadiq and Singh (2015) but contradict Tanko and Alidu (2017).

Access to agricultural credit and profit efficiency depicted a significant positive relationship denoted by a negative coefficient (-0.116). Sampled farmers were reported to be cash-constrained, and access to credit could push the financial constraint outward enabling farmers to acquire required inputs in sorghum farming particularly fixed capital base and labour reported to be the major contributing cost elements depressing profits. Further, access to credit hands farmers more purchasing power, catalyzes adoption and usage of improved seed as well as fertilizer reported to be crucial in improved productivity and profitability yet used by few sampled farmers. This result is in agreement with Wongnaa *et al.,* (2018), Saysay *et al.,* (2016) and Biam *et al.,* (2015).

As expected, trained farmers were operating on a higher profit efficient level compared to their untrained counterparts. This is evident from the significant negative coefficient (-0.046). Training is crucial in disseminating extension information to farmers, particularly on good agronomic practices, post-harvest handling and market information among other topical subjects. This finding is in agreement with Bocher and Simtowe (2017), Trong and Napasintuwong (2015).

Distance to the nearest agro-dealer depicted a negative relationship with profit efficiency (0.10) as indicated in Table 4.15. This relates to the high transaction and transformation cost associated with an increase in distance, which discourages farmers from accessing inputs and information. The terrain in the study area is rough, and the motorcycles are the most predominant means of transport from the households to the nearest market where agro-dealers are domiciled. Due to a shortage of means of transport options, the motorcycles charge exorbitant prices, therefore, discouraging farmers from visiting the market to purchase input and acquire necessary information. This result concurs to those of Bocher and Simtowe (2017).

4.4 Results and discussions on the impact of adopting ISVs on poverty reduction

This sub-section presents and discusses the results generated from three impact assessment models, namely; PSM, IPRWA and ESR. The results answer the third objective of this study, which attempted to evaluate the impact of adopting ISVs on poverty reduction among rural farming households in Tharaka Nithi County. Daily consumption expenditure expressed in adult equivalent terms was used as the proxy (outcome indicator) for poverty reduction. The determinants of adoption generated from the models are briefly discussed because it was not the main aim of this objective. On average, the findings showed a significant difference in the daily consumption expenditure per adult equivalent between adopters (USD 2.11) and non-adopting counterparts (USD 1.91).

4.4.1 Impact results generated from the PSM model and discussions

This sub-section firstly presents the results and discussions on the impact of adopting ISVs on poverty reduction generated from PSM model. The results showed that, on average, generated propensity score was 0.58 and common support region was between propensity scores 0.19 to 0.99 as indicated in Figure 4.3. The treated and untreated on support shows the farmers in the adopters and non-adopting group, which find a suitable match. On the other hand, treated and untreated off-support indicates the individuals in the adoption and non-adoption classification who fail to find a suitable match with similar characteristics.

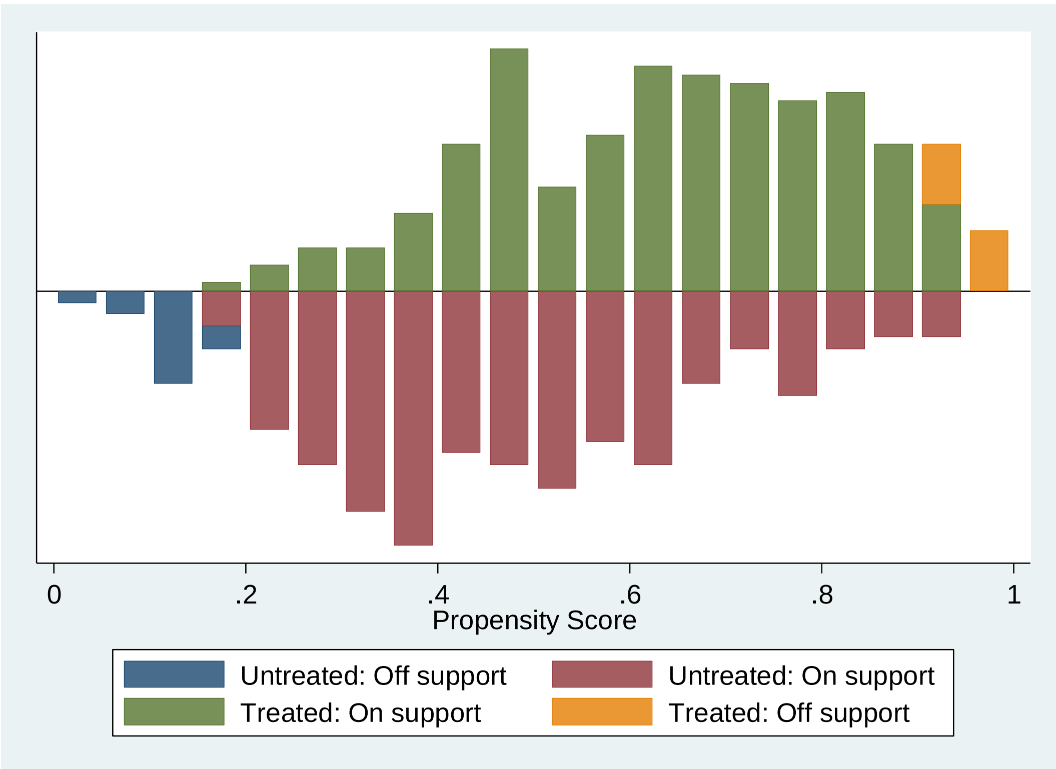

Figure 4.3: Common support region for the predicted propensity score

This study conducted a balancing property test of the generated propensity scores (Table 4.16). This is an important step as it reduces the influence that confounding variables might have on the impact results (Rosenbaum and Rubin, 1983). Different matching methods were used to test for matching quality (Table 4.16). The findings also report insignificant *P*-values after matching. Although, after matching some bias still exist, most indicators show that the matching process was largely successful. The overall bias reduced from 25.9 to a range of 4.4 and 17.0, which indicates a total bias reduction of 23 percent to 72 percent (Table 4.16). The findings of the balancing property test of the generated propensity scores from different matching methods used before matching, values of Pseudo R^2, LR (χ^2) and mean standardized mean bias was high but considerably reduced after matching.

Further, results show that Pseudo R^2 significantly reduced from 0.148 (before matching) to a range of 0.010 and 0.086. This indicates that, after matching, there were no systematic differences in the distribution of covariates between the adopters and non-adopters of ISVs groups. This study proceeded to estimate the average treatment effect of ISVs after making sure that the balancing and matching quality tests for the model were successful. The results are based on the common support area and thus exclude the propensity scores outside this region. This study used three algorithms to estimate the average treatment effects of adopting ISVs on consumption expenditure per adult equivalent (Table 4.16).

Table 4.16: Summary statistics of matching quality indicators

Matching method	Pseudo R^2		LR (χ^2)		Prob $>\chi^2$		Mean standardized bias		Total percent bias reduction
	Before matching	After matching	Before matching	After matching	Before matching	After matching	Before matching	After matching	
NNM	0.148	0.010	91.07	6.83	0.000	0.976	25.90	4.40	23.60
KBM (0.1)	0.148	0.010	91.07	6.50	0.000	0.982	25.90	4.50	23.00
KBM (0.25)	0.148	0.015	91.07	10.13	0.000	0.860	25.90	5.80	28.80
KBM (0.5)	0.148	0.053	91.07	36.12	0.000	0.003	25.90	12.70	55.50
RCM (0.1)	0.148	0.010	91.07	6.80	0.000	0.977	25.90	4.70	23.60
RCM (0.25)	0.148	0.024	91.07	16.43	0.000	0.423	25.90	7.90	36.90
RCM (0.5)	0.148	0.086	91.07	58.64	0.000	0.000	25.90	17.00	72.00

Note: Figures in parentheses indicate the width distance
Source: Survey data, 2018
Key: **NNM** = Nearest Neighbour Matching; **KBM** = Kernel Based Matching; **RCM** = Radius Caliper Matching

However, results from two algorithms; KBM (0.5) and RCM (0.25) and RCM (0.5) best fit the data and were significant. The results from all algorithms are presented in Appendix 7. The results show that, on average, the adoption of ISVs increased daily consumption expenditure per adult equivalent by between USD 0.18 to USD 0.21 (Table 4.17).

Table 4.17: Average treatments effects of adopting ISVs generated by PSM

Matching algorithm		**Treated**	**Controls**	**Difference**
KBM (0.5)	ATT	2.13	1.94	0.19**
	ATU	1.91	2.12	0.21
	ATE			0.20
RCM (0.25)	ATT	2.13	1.96	0.17*
	ATU	1.91	2.10	0.20
	ATE			0.18
RCM (0.5)	ATT	2.13	1.92	0.20**
	ATU	1.91	2.12	0.21
	ATE			0.21

Note: Figures in parentheses indicate the width distance
**P<0.05 and *P<0.10 mean significant at 5 percent and 10 percent probability levels, respectively
Source: Survey data, 2018

This concludes that adoption of ISVs has a positive and significant impact on consumption expenditure per adult equivalent. The impact on daily consumption expenditure per adult equivalent was higher for the non-adopting farmers (untreated group) ranging between USD 0.20 to USD 0.21 across the two algorithms compared to their counterparts (treated group) which ranged between USD 0.17 to USD 0.20. This study used the calculated average adult equivalent of 2.3 to compute the impact of adopting ISVs on poverty reduction at the household level. The results indicate that, on average, sampled households would increase their daily consumption expenditure by between USD 0.41 and USD 0.48.

Several impact studies have used ESR and/or PSM econometric models and reported similar positive impact results on agricultural technology adoption and welfare of smallholder farmers (Biru *et al.,* 2019; Lunduka *et al.,* 2019; Takam-Fongang *et al.,* 2019; Manda *et al.,* 2019; Islam, 2018; Ahmed *et al.,* 2017; Feleke *et al.,* 2016; Khonje *et al.,* 2015; Kassie *et al.,* 2014; Asfaw *et al.,* 2012).

4.4.1.1 Factors influencing adoption of ISVs as generated by PSM model

Table 4.18 presents the factors, which influenced the adoption of ISVs. The findings show that decision to adopt ISVs is determined by six factors, which include; years spent in school, farmer's total experience in general farming and sorghum growing, distance to the nearest agricultural office, household asset endowment and access to extension services.

Table 4.18: Factors influencing the adoption of ISVs

Variable	**Coefficient**	**Std Error**
Gender	-0.34	0.24
Education level	0.03*	0.02
Experience level	0.02*	0.01
Extension seek	0.61***	0.15
Distance to agricultural office	-0.09***	0.03
Marital	-0.05	0.06
Cultivated land	0.02	0.02
Per capita income	-0.13	0.16
Group membership	0.04	0.14
Experience ratio	1.42***	0.43
Extension frequency	-0.002	0.01
Adult equivalent	-0.10	0.10
Sorghum experience	-0.05***	0.02
Agrodealer distance	0.004	0.03
Asset value	0.62***	0.16
Constant	-2.88	1.05
Model diagnostics		
LR (χ^2)	90.54***	
Log likelihood	-263.20	

***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively

Source: Survey data, 2018

Results reveal that propensity to adopt ISVs was positively related to households that had sought extension services and were located close to the agricultural offices. Similarly, higher educated farmers have a higher propensity to adopt compared to their less-educated counterparts. Besides, the findings point out to the importance of asset ownership in influencing adoption of ISVs. This study compares these results with the significant determinants of adopting ISVs generated by DH model in the first objective. The study found out that, three variables were similar which included education level, access to extension and distance to the nearest agricultural office.

4.4.2 Impact results generated from IPRWA model and discussions

This sub-section presents treatment effects estimation results and briefly discusses parameters that influenced both treatment and outcome models under different treatment groups as generated by IPRWA model. Table 4.19 presents the results of average treatment effects (ATE) estimation and potential outcome means (*POmeans*).

Table 4.19: Treatment effects estimation using IPWRA approach

Outcome variable (Daily consumption expenditure per adult equivalent)			**Coef.**	**Robust Std. Error**
Potential outcome means (*POmeans*)	Decision to adopt ISVs	no	1.93^{***}	0.08
		yes	2.09^{***}	0.05
ATE	Adoption of ISVs	(yes vs no)	0.16^{*}	0.09
Outcome model	Linear			
Treatment model	Logit			
Estimator	IPW regression adjustment			
Number of observations	452			

***P<0.01, and *P<0.10 mean significant at 1 percent, and 10 percent probability levels, respectively

Source: Survey data, 2018

Linear and Logit econometric estimation approaches were used for outcome and treatment models, respectively. The results show that the adoption of ISVs increases consumption expenditure per adult equivalent by an average of USD 0.16 daily. Therefore, using an adult equivalent of 2.3, the mean estimates at a household level show that adoption of ISVs would increase consumption expenditure by USD 0.37. Further, potential daily consumption expenditure per adult equivalent for adopters of ISVs was higher (USD 2.09) compared to that of their non-adopting counterparts (USD 1.93).

4.4.2.1 Parameter estimates for treatment and outcome models

Table 4.20 presents the coefficients of several covariates for the treatment model as well as outcome models for both untreated and treated groups. The results are briefly discussed since the main aim of this analysis was to evaluate the impact.

Table 4.20: Parameter estimates for treatment and outcome models

Variable	Treatment model	Outcome model for untreated group	Outcome model for treated group
	Coefficient	Coefficient	Coefficient
Gender	-0.34 (0.24)	-0.35 (0.25)	0.23 (0.12)*
Education level	0.04 (0.02)**	0.003 (0.02)	0.01 (0.01)
Experience level	0.02 (0.01)**	0.02 (0.01)*	0.04 (0.01)***
Sorghum experience	-0.05 (0.02)***	0.02 (0.02)	0.00002 (0.02)
Extension seek	0.61 (0.15)***	0.14 (0.19)	-0.10 (0.09)
Distance to agricultural office	-0.09 (0.03)***	0.01 (0.03)	-0.004 (0.03)
Group membership	0.04 (0.13)	0.05 (0.16)	-0.12 (0.08)
Asset value	0.62 (0.16)***	-0.12 (0.19)	0.17 (0.11)
Per capita income	-0.13 (0.15)	0.12 (0.20)	0.03 (0.09)
Cultivated land	0.02 (0.02)	-0.003 (0.02)	-0.002 (0.01)
Agrodealer distance	0.004 (0.03)	-0.07 (0.03)***	0.02 (0.02)
Extension frequency	-0.002 (0.01)	0.001 (0.01)	0.01 (0.004)***
Experience ratio	1.42 (0.44)***	-0.40 (0.44)	0.48 (0.35)
Marital	-0.05 (0.06)	0.01 (0.06)	0.03 (0.03)
Adult equivalent	-0.10 (0.10)	-0.11 (0.13)	0.09 (0.08)
Constant	-2.88 (1.09)	2.38 (1.08)	-0.30 (0.79)

Note: Figures in parentheses represent standard errors associated with the coefficients ***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively
Source: Survey data, 2018.

The findings recorded two variables namely sorghum experience and distance to the nearest agricultural office that recorded a negative influence on the treatment model. Further, the model generated parameter estimates for treatment and outcome models and indicated five variables which positively influenced the treatment model, namely; education level, experience, extension seek, asset value and experience ratio. However, consumption expenditure for non-adopting sub-population was negatively influenced by agro-dealers distance (-0.07). On the other hand, the coefficient of experience was positive (0.02) and significant at 10 percent level as reflected in the outcome model for the untreated group.

Further, several factors such as gender, experience level and extension frequency reported a positive influence on consumption expenditure for the adopters of ISVs. This study compared the significant variables generated by IPWRA and DH model which was used in objective 1 to determine the factors influencing adoption of ISVs. Three variables were similar to those reported by PSM and DH models namely distance to the nearest agricultural office, access to extension and education level of a HH.

4.4.3 Impact results generated from ESR model and discussions

This sub-section presents impact and FIML estimates' results as generated from ESR model and presented in Table 4.21 and Table 4.22, respectively. On average, adopting households' daily consumption expenditure per adult equivalent was USD 2.21 (Table 4.21). The adopters of ISVs would have decreased daily consumption expenditure per adult equivalent by USD 0.09 had they decided not to adopt. This study used an estimated adult equivalent of 2.3 to compute the impact at the household level. The findings show that, on average, if a household decided not to adopt ISVs, they would decrease their daily consumption expenditure by USD 0.21.

Table 4.21: Average treatment effects of the adoption of ISVs generated by ESR model

Outcome variable	Decision stage		Treatment effect
	To adopt	Not to adopt	
Daily consumption expenditure per adult equivalent (USD)			
Farmers that had adopted (ATT)	2.21	2.12	0.09^{***}
Farmers that did not adopt (ATU)	1.91	0.95	0.96^{***}

On the other hand, non-adopters would significantly increase their consumption expenditure per adult equivalent had they adopted ISVs by USD 0.96 daily. This indicates that, on average, at the non-adopters' household level, the consumption expenditure would increase by USD 2.21 daily. The average treatment effects results show that adoption of ISVs in Tharaka Nithi County has a significant positive impact on consumption expenditure per adult equivalent.

4.4.3.1 Full information maximum likelihood (FIML) estimates generated by ESR Model

Table 4.22: Estimates (FIML) of ESR model of daily consumption expenditure per adult equivalent

Variable	Selection equation (adoption decision)	Outcome equations (consumption expenditure per adult equivalent)	
	Coefficient	Regime 1 (adoption)	Regime 2 (non-adoption)
Gender	-0.26 (0.23)	0.17 (0.18)	-0.24 (0.26)
Education level	0.04 (0.02)***	0.03 (0.01)**	-0.003 (0.02)
Experience level	0.02 (0.01)**	0.03 (0.004)***	0.02 (0.01)***
Extension seek	0.62 (0.14)***	0.22 (0.11)**	0.38 (0.24)
Distance to agricultural office	-0.08 (0.03)***	-0.03 (0.02)	-0.01(0.03)
Marital	-0.05 (0.06)	0.02 (0.05)	0.01 (0.07)
Cultivated land	0.02 (0.02)	0.02 (0.02)	-0.01 (0.02)
Income	-0.07 (0.15)	0.05 (0.11)	0.13 (0.18)
Group membership	0.08 (0.13)	-0.03 (0.11)	-0.12 (0.16)
Experience ratio	1.11 (0.41)***		
Extension frequency	0.001 (0.01)	0.01 (0.01)**	-0.01 (0.01)
Adult equivalent	-0.07 (0.10)	0.04 (0.08)	-0.17 (0.12)
Sorghum experience	-0.06 (0.02)***		
Agrodealer distance	0.02 (0.03)		
Asset value	0.35 (0.16)***		
Constant	-1.89 (0.96)	0.16 (0.64)	1.70 (1.00)
Sigma		-0.16 (0.06)***	0.01 (0.06)
Rho		1.36 (0.17)***	0.14 (0.36)
Model diagnostics			
Wald (χ^2)	83.87***		
Log likelihood	-795.71		

Note: Figures in parentheses represent standard errors associated with the coefficients ***P<0.01, **P<0.05 and *P<0.10 mean significant at 1 percent, 5 percent and 10 percent probability levels, respectively

Source: Survey data, 2018

Table 4.22 presents FIML estimates' results where the estimated coefficients of selection on adopting ISVs or not are indicated in column two. The correlation coefficients were significant, indicating a problem of self-selection bias. These findings show that the effects of selected covariates across adopters and non-adopters are significantly different. The likelihood ratio test rejects the null hypothesis of joint independence [$\chi2$ (2) =16.26; p=0.000]. Therefore, this study was right to use two distinct regression equations or regimes rather than one (Lokshin and Sajaia, 2004).

The ESR model generated results on the determinants, which influenced consumption expenditure for adopters (third column) and non-adopters (fourth column), respectively (Table 4.22). A positive relationship exists between the HH's education level, extension services access and consumption expenditure for adopters. However, the farming experience had a positive influence on consumption expenditure for both adopters and non-adopters of ISVs.

Furthermore, the model generated results on the adoption of ISVs and showed that, the decision is influenced by a combination of farm-farmer characteristics and institutional factors. More educated and experienced HHs were more likely to adopt ISVs. Besides, farmers in close proximity to agricultural offices and had sought extension services were more likely to adopt.

The findings depicted a positive relationship between adoption of ISVs and household's asset endowment. An inverse relationship between adoption of ISVs and experience in growing sorghum was reported. Some studies have reported such results (Ainembabazi and Mugisha, 2014).

Additionally, this study compared the results of factors influencing adoption of ISVs as reported by ESR and DH model in objective 1 and three variables were similar namely education level of a HH, access to extension and distance to the nearest agricultural office. These three factors that influenced adoption of ISVs were similar across the three impact models (PSM, IPRWA and ESR) and were also significant in the DH model used to answer objective 1 of this study.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents a summary of the study by highlighting the conclusions, recommendations with policy implications suggested from the results discussed. The suggestions are crafted in line with the formulated study objectives. The overall objective of this study attempted to evaluate the contribution of improved sorghum varieties on poverty reduction and the efficient attainment of sustainable livelihoods among smallholder farmers in Tharaka Nithi County, Kenya. To attempt to achieve the broad objective, this study formulated three specific objectives.

Firstly, the study sought to assess the determinants of adoption, intensity of use and speed of uptake of ISVs. Although, DH model was used to primarily assess the determinants of adopting ISVs, other methodologies used in the third objective namely PSM, ESR and IPWRA also provided useful results. Therefore, to enrich the conclusions for determinants of adoption of ISVs, this chapter also summarized and presented significant variables alongside the results presented by DH model. Secondly, this study evaluated the profit efficiency of smallholder sorghum farmers using CD stochastic profit frontier model. Lastly, impact of ISVs on poverty reduction among smallholder farmers was estimated using three methods namely PSM, IPWRA and ESR. This chapter also highlighted on some potential areas for further research.

5.1 Conclusions

Results from the first objective generated by DH model indicated six variables that were important in explaining a household's decision to adopt ISVs. Five variables positively influenced a household's decision to cross the first hurdle namely tropical livestock unit, education level, access to extension services, crop ratio and consumption expenditure. However, an expected inverse relationship between distance to nearest agricultural office and adoption of ISVs was reported.

On the other hand, all seven ISV adoption related variables namely education level, access to extension services, experience level, distance to the nearest agricultural offices, sorghum farming level of experience, asset value and experience ratio were significant and similar across the three impact related methods (i.e PSM, IPWRA and ESR). It is important to note that, all the significant variables except distance to the nearest agricultural office and sorghum experience positively influenced the decision of a household to adopt ISVs. Therefore, this study concluded that, human capital and wealth related variables matter in influencing a household's decision to adopt ISVs and cross the first hurdle. Additionally, proximity to agricultural offices is important in shaping household's decision to adopt ISVs.

The results from DH model's second hurdle showed that, a household's decision to intensify the use of ISVs was influenced by six variables, four of which indicated unexpected *a priori*. These variables were namely adult equivalent, size of the cultivable land, agricultural credit and distance to the nearest agricultural offices.

However, per capita income and crop ratio reported an expected positive influence on the household's decision to intensity the use of ISVs. Therefore, this study concluded that, human capital, financial capital, wealth and access related variables matter in influencing a household's decision to intensify the use of ISVs and cross the second hurdle. On the other hand, the unexpected positive relationship between distance to the nearest agricultural office and intensity of use of ISVs led to this study concluding that, perhaps far away households were seed sellers or used home saved seed. Furthermore, the inverse relationship associated with access to agricultural credit led to the conclusion that, the study area is credit constrained. This perhaps portrayed diversion of accessed credit by households to other non-farm activities. Additonally, it could also mean that smallholder farmers in the study area feared accessing credit. The results from DH model shows that, the decisions to adopt and intensify the use of ISVs are influenced by different factors justifying the use of the model in this study. Further, results confirm that the households make decisions on the two hurdles (adopt and intensity of use) independently and sequentially.

The results generated from DA model showed that, the decision on how fast to (speed) adopt ISVs was influenced by five variables namely distance to the nearest agricultural office, access to agricultural credit, distance to the nearest town (proxy of input and output market), per capita income and tropical livestock unit. Access to agricultural credit and distance to the nearest town indicated unexpected *a priori* indicating a high likelihood of households diverting credit to other uses and using home saved seeds respectively. Therefore, following the results generated by DH and DA models, this study concludes that the three adoption decisions are influenced by different sets of determinant combinations that are not necessarily the same thus justifying the use of a multi-dimensional approach in objective 1.

Findings generated by Cobb-Douglas stochastic profit frontier model that attempted to achieve the second objective revealed existence of a wide variation of efficiency with best and worst farmers operating at 96 percent and 12 percent levels respectively. The reported mean profit efficiency of 0.17 indicated that sorghum farmers have opportunities to increase profit efficiency. Family labour and fixed capital base were reported as the major contributing factors to sorghum profitability. Several socio-economic and institutional determinants influenced profit efficiency, namely farming experience, access to agricultural credit, training and proximity to nearest agricultural office and agro-dealers. Owing to the highlighted results, this study concluded that, sorghum farmers in the study area were not profit efficient.

Impact assessment results from PSM, IPWRA and ESR showed that, a household’s daily consumption expenditure per adult equivalent increased with the decision to adopt ISVs. Counterfactual analysis results indicated that had non-adopters decided to adopt ISVs; they would have significantly increased their daily consumption expenditure. Therefore, following these findings, adopters of ISVs had higher daily consumption expenditure per adult equivalent compared to their non-adopter counterparts. This study concluded that adoption of ISVs increased consumption expenditure per adult equivalent and thus contributed to the reduction of poverty levels within adopting households.

5.2 Recommendations and policy implications

Continuous resource investment in sorghum sub-sector may not yield the desired impact without an understanding of several aspects including determinants of the three adoption decisions (i.e whether or not to adopt, intensity of use and speed of uptake of ISVs), profit efficiency and potential anticipated poverty-reducing effects. This therefore calls for the formulation and implementation of appropriate policies intended to increase adoption of ISVs and enhance profit efficiency that would positively impact on poverty reduction among smallholder sorghum farmers in Tharaka Nithi County, Kenya.

Findings from the first objective, indicated the importance of human and financial capital as well as wealth and access related determinants in influencing decision to adopt, intensify the use and speed of uptake of ISVs. Therefore, in order to ensure households have access to extension information, knowledge and skills thereby expanding their human capital base, this study recommends that Tharaka Nithi County Government facilitates mobility of agricultural officers to ensure efficient delivery of extension services to farmers. Furthermore, due to the fact that, agriculture function in Kenya is devolved and County Governments are mandated to offer extension services to farmers, this study advocates for an approach whereby private sector partners especially the buyers such as EAML complement the established Government's system. Additionally, findings from focus group discussion and key informant interviews indicated that farmer training mostly focus on agronomy and conducted by ministry of agriculture staff. Therefore, this study recommends that the training be partner-led and curriculum expanded to also capture other aspects such as post-harvest, agri-financing, business development and entrepreneurship among others.

Further, to avert the likelihood of farmers using home saved seeds in the interior parts of the Tharaka Nithi County and to increase the availability of quality inputs, this study advocates for deliberate efforts towards incentivizing agro-dealers widen their networks/outreach for existing businesses or trigger start-ups. This could be through County Government considering waiving or reducing some certification requirements e.g. trading permit fees etc. To expand their networks, agro-dealers mentioned need of increasing working capital through access to loans though sometimes they shy away from borrowing since the facilities are sometimes expensive. Therefore, this study recommends that the County Government should consider encouraging participation and capacity building the existing village savings and loan associations. Further, the County Government should consider putting in place guarantee schemes for agro-dealers and smallholder farmers. This would in turn increase risk appetite for credit service providers to lend to agro-dealers and smallholder farmers who might lack required collateral and often considered risky. In addition, Government should consider de-risking smallholder farming by extending the maize insurance subsidy to sorghum. It should also consider supporting partners through crop cuts so as to formulate a superior area yield sorghum insurance product.

To ensure that borrowing households do not divert the use of accessed agricultural credit to other non-farm activities and stick to the intended purpose, financial institutions should explore other cost-effective options, e.g. (i) open up agency banking to take financial services closer to the credit-constrained farmers (ii) intensify follow-ups on farmers who access credit and consider using village-level business champions in order to reduce costs. The business champions need to be incentivized through a sustainable commission structure, which could include loans granted and repaid (iii) use technology to self-onboard and train farmers, e.g. use of Interactive Voice Response (IVR) (iv) integrate and promote contract farming.

Results from the second objective particularly low average sorghum yield among the sampled farmers could be attributed to several factors among them, low usage of fertilizer and technical knowhow on production. The fact that few farmers used fertilizer with an under-dose application rate, which is a key ingredient to increased productivity, leads this study to recommend that stakeholders formulate and adopt sustainable awareness and demand creation activities' models, e.g. partner-led demonstration plots. The demonstration plots managed by a team of lead farmers or business champions, agro-dealers and fertilizer companies would allow farmers to witness and associate themselves with the results.

The impact findings from IPWRA, PSM and ESR methodologies assert the poverty-reducing effects of adopting ISVs. Therefore, this study recommends that adoption-stimulating policies to be formulated and implemented that should target to raise resource endowment of households, improve access to extension service and rural infrastructure.

For scalability, results of this study are replicable to other ASAL areas of the country that generally have similar soil, climatic and cultural aspects. However, due to recurring annual raw material shortages, EAML has started active promotion of white sorghum production in western and nyanza counties by putting up a multi-billion processing plant to serve farmers in the region. The regions have different soil types, climatic conndittions as well as cultural norms and beliefs from ASAL areas. Therefore, due to these differences, this study advocates for a similar research in multiple sites in western and nyanza regions to better inform policy on the impact of adopting ISVs in non-ASAL areas. The research should be undertaken using panel data and an impact assessment methodology, which employs a continuous treatment variable.

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APPENDICES

Appendix 1: Survey Questionnaire

<u>HOUSEHOLD SURVEY 2018 ON IMPACT OF IMPROVED SORGHUM VARIETIES ON POVERTY REDUCTION AMONG SMALLHOLDER FARMERS IN THARAKA NITHI COUNTY</u>

This research study is being carried out by a student pursuing a Doctor of Philosophy Degree in Agricultural Economics from Kenyatta University. The overall study objective was to evaluate the impact and contribution of improved sorghum varieties on the efficient attainment of sustainable livelihoods among smallholder farmers in Tharaka Nithi County, Kenya. The information collected will be treated confidentially for academic purposes, therefore feel free to respond to the questions asked.

Date: (ddmmyy):………………………………………….

Respondent name (Household head):…………………………………………………

Gender of the respondent:……………………………………………

Telephone number:…………………………………………………….

<u>Identifying Variables:</u>

Enumerator:……………………………………………………..

Telephone number :………………………………………………..

County:………………………………………………………………..

Sub-county:……………………………………………………

Ward :…………………………………………………………....

Location:……………………………………………………...

Sub-location:…………………………………………….......

Village:……………………………………………………….

1.0 AWARENESS AND INITIAL ADOPTION INFORMATION

(a) Improved sorghum variety (ISV)	(b)Awareness ***(1=yes; 0=no)*** ****if the farmer is not aware of any ISVs, go to question 2.3***	(c) First time you heard about the variety *(year)*	**(d)** Which was your very first source of information about the improved variety? ***Use the following codes: 1=radio ; 2= Government extension officer ; 3=field day; 4= NGO extension officer ; 5=print (pamphlet, brochures, posters) 6=neighbor/friends 7=agent 00=others (specify)***	(e) First time you adopted the variety (year)***Put N/A if the farmer has never planted to date.*** ****If the farmer has never planted any of the ISVs, go to question 2.2***	(f) The land area initially put under the variety that year *(acres)*	(g) Since you started planting any of the ISVs, have you ever stopped? ***(1=yes; 0=no)***	(h) If yes, give reasons (use unit codes provided below the table) Give as many reasons as possible ***If no, go to question 2.0***
Gadam							
SC Sila							
Seredo							
Serena							
KARI Mtama 1							
KARI Mtama 3							
Advanta 23012							
Others - specify							

unit codes : 1=lack of seed; 2=delayed produce payment; 3=seed was expensive; 4=low buying price/Kg; 5=birds menace ; 6=lack of extension services; 7=high cost of threshing; 8=scarcity of seed at the stockists 00=others (specify)………......................

2.0 IMPROVED SORGHUM VARIETY ADOPTION INFORMATION FOR 2017/2018 CROPPING SEASON

(a) Improved sorghum variety	(b) Did you plant any ISV during **2017/2018** cropping season (Oct or March 2018 planting) (**1=yes;0=no**) ***If yes, fill the rest of the table. If no, go to question 2.1***	(c) Short rain (main) season ***(Sept/Oct. 2017 planting)***				(d) Long rain season ***(Feb/March 2018 planting)***			
		Area planted ***(acres)***	Land tenure status ***(use units codes provided below the table)***	planting pattern ***1=monocrop 0=intercrop***	If intercropped, with which crop? ***(use crop codes provided below the table)***	Area planted ***(acres)***	Land tenure status ***(use units codes provided below the table)***	planting pattern ***1=monocrop 0=intercrop***	If intercropped, with which crop? ***(use crop codes provided below the table)***
Gadam									
SC Sila									
Seredo									
Serena									
KARI Mtama 1									
KARI Mtama 3									
Advanta 23012									
Others - specify									
Others - specify									

unit codes: 1=leased; 2=owned with a title deed; 3=owned without a title deed; 4= gift; 5=communal land; 6=others (specify)…………………

crop codes: 1=maize;2=beans;3=greengrams;4=millet;5=pigeon peas;6=cowpeas;7=local sorghum varieties; 00=others (specify)…………….

2.1 If you did not plant any of the ISVs during 2017/2018 cropping season, indicate why? ***1=lack of seed [ ] 2=birds menace [ ] 3=seed was expensive [ ] 4=low buying price/Kg [ ] 5=unreliable weather [ ] 6=high cost of threshing [ ] 7=not aware of the varieties 8=lack of extension services [ ] 9=labour intensive [ ] 10=high cost of herbicides [ ]11=unreliable rainfall [ ] 00=others (specify) [ ]………………………***

2.2 If you have **never started planting any ISVs at all**, but you have heard about them, give reasons for not planting
1=not interested [ ] 2=information I got was not enough [ ] (specify the source)……………. 3=seed not available [ ] 4=don't know how to grow and take care of the crop [ ] 5=don't perceive the crop to be profitable [ ] 6=heard that it is labour intensive [ ] 00=others (specify) [ ] ....

2.3 TRADITIONAL SORGHUM VARIETY ADOPTION INFORMATION FOR 2017/2018 CROPPING SEASON

Traditional sorghum varieties	Short rain (main) season ***(Sept/Oct. 2017 planting)***			Long rain season ***(Feb/March 2018 planting)***		
	Area planted ***(acres)***	Land tenure status ***(use units codes provided below the table)***	Quantity harvested – ***Dec/Jan/ Feb 2018 (Kgs)***	Area planted ***(acres)***	Land tenure status ***(use units codes provided below the table)***	Quantity harvested – ***June/July/ Aug 2018 (Kgs)***
Mugana						
Mweru/Muchuuri						
Kagiri						
Mukumbu						
Mugeta						
Kaguru						
Others (specify)_1…….						
Others (specify)_2…						

unit codes: 1=leased; 2=owned with a title deed; 3=owned without a title deed; 4= gift; 00=others (specify)……………………………………………………………………………….

2.4 Did you plant both **ISVs** and **traditional varieties** during 2017/2018 season (both short and long)? ***1=yes [ ]; 0=no [ ]. If yes, go to question 2.5; if no, go to question 2.7***

2.5 What was the approximate distance between the fields in short rain season ***(Sept/Oct 2017)***?............M;
-If within the same plot: how many lines of ISV…........by how many lines of local variety…………..

2.6 What was the approximate distance between the fields in long rain season ***(Feb/march 2018)***?.........M
-If within the same plot: how many lines of ISV………..by how many lines of local variety…………..

2.7 What are some of the general challenges you experience in sorghum farming?
1=lack of seed [ ] 2=seed is expensive [ ] 3=high cost of threshing [ ] 4=lack of market [ ] 5=low price of output [ ] 6=lack of extension services [ ] 7=birds menace [ ] 8=lack of aggregation/collection centres [ ] 9=labour intensive [ ] 10=high cost of herbicides [ ] 11=unreliable rainfall [ ] 00=others (specify) [ ]……………………

2.8 What is the average amount paid to lease 1 acre of land in your area?..........................Kes
2.9: Do you use manure in sorghum plots? ***1=yes [ ]; 0=no [ ]***

3.0 Land use

Land sub-divisions/allocations	**Sept/Oct. 2017 season 2018**	**Feb/March 2018 season**
Total land owned (acres)		
Land **leased in** (acres)		
Land **leased out** (acres)		
Other land available and **accessed** (gift/public/communal) acres		
Land under **crops** (acres)		
Land under **pastures** (acres)		
Land under **homestead** (acres)		
Land purely occupied by **trees** (woodlot) (acres)		
Land that is not usable (acres) e.g big rocks etc		
Riparian land (**if farm next to river**) (acres)		

3.1 What is the land tenure status of the main household farmland? **tenure** …………………
unit codes: 1=leased; 2= gift; 3= owned with title deed; 4=owned without title deed;
` 00=others (specify)………………………………………………

3.2: Farmland allocation among crops ***(crop 1=crop allocated largest farmland etc....)***

Season	**Farmland allocation**					
	crop 1 name *(use crop codes provided below the table)*	**acres**	**crop 2 name**	**acres**	**crop 3 name**	**acres**
Short rain (main) season (***Sept/Oct. 2017 planting***						
Long rain season (***Feb/March 2018 planting***						

crop codes: 1=maize;2=beans;3=greengrams;4=millet;5=pigeon peas;6=cowpeas;7=sorghum 00=others (specify)…………………………………………………..

4.0 SORGHUM PRODUCTION AND SALES

Cropping seasons	Variety category **(*ISV or Traditional*)**	Sorghum variety ***(use codes provided at the bottom of this table)***	Qty of sorghum harvested **(threshed)** – ***(Kgs)***	Qty stored for consu-mption ***(Kgs)***	Qty given out to workers and friends ***(Kgs)***	Qty lost after harves-ting ***(Kgs)***	Qty sold ***(Kgs)***	Price per unit/ kg ***(Kes)***	Total amount received ***(Kes)***
Short rain (main) season (Sept/Oct. 2017 planting)	ISV								
	Traditional								
Long rain season (Feb/March 2018 planting)	**ISV**								
	Traditional								

ISV codes: 1=Gadam; 2=SC sila; 3=Advanta 23012; 4=KARI Mtama 1; 5=KARI Mtama 3; 6=Seredo; 7=Serena; 00=others (specify)…….
Traditional variety codes: 1=Mugana; 2=Mweru/Muchuuri; 3=Kagiri; 4=Mukumbu; 5=Mugeta; 6=Kaguru; 00=others (specify)………….

4.1: Who do you sell your ISV sorghum to?..

4.2: Does the buyer (in 4.1) give you/your group a contract to produce? ***1=yes [ ]; 0=no [ ]***

4.3: At what stage did the grain losses occur? Tick appropriately in the table below

Stage	**Tick appropriately**	**Reasons (use unit codes provided)_*Enums to probe***
Harvesting		
Transportation to homestead		
Threshing		
Storage		
Transportation to the collection centre/ market		

unit codes:1=lack of harvesting bags/tarpaulins; 2=harvesting while not dry (weight loss after drying); 3=spillage; 4=grain breakages; 5=theft; 6=pest infestation thus being rejected by buyers; 00=others (specify)…………………………………………

Training section

A. Agronomy

4.4: Have ever been trained on how to grow and take care of your sorghum crop (agronomy) e.g. spacing, seed rate, best time for weeding etc?

1=yes [ ]; 0=no [ ] If yes, go to question 4.5; if no, go to question 4.11

4.5: When is the last time you were trained (year)?..........................

4.6: Who offered the training?...............................

1= Government extension officer ; 2=farmer field day; 3= NGO extension officer ; 00=others specify…………………….

4.7: How many days/hours did the training last?....................hours or ………….days

4.8: Where was the trained held?...

4.9: Did you pay any fee to be trained?......................***1=yes [ ]; 0=no [ ]If yes, go to question 4.10; if no, go to question 4.11***

4.10: How much did you pay?.......................................Kes.

B. Post-harvest handling and storage (PHHS)

4.11: Have ever been trained on how to handle your crop after harvest? e.g best time to harvest, best way to transport, best method for threshing so that you can minimize losses?

1=yes [ ]; 0=no [ ] If yes, go to question 4.12; If no, go to question 4.18

4.12: When is the last time you were trained (year)?..........................

4.13: Who offered the training?...............................

1= Government extension officer ; 2=farmer field day; 3= NGO extension officer ;
4= hermetic storage bag company reps; 00=others specify…………………….

4.14: How many days/hours did the training last?.................hours or ……..days

4.15: Where was the trained held?.........................

4.16: Did you pay any fee to be trained?.............***1=yes [ ]; 0=no [ ]***

If yes, go to question 4.17; if no, go to question 4.18

4.17: How much did you pay?....................Kes.

C. Hermetic storage technology

4.18: Do you know about hermetic storage technology? ***1=yes [ ]; 0=no [ ]***

If yes, go to question 4.19; if no go to question 4.24

4.19:Have you used any of the technology?***1=yes [ ]; 0=no [ ]***

If yes, go to question 4.20; if no, go to question 4.24

4.20: Which technology have you used?.................................***1. hermetic bags [ ] 2. hermetic silos [ ] 00=others (specify)………………***

4.21: When did you first use it?............................year

4.22: How did you acquire it?....................

1=bought cash [ ]; 2=was given for free (specify by who) [ ]; 00=others specify………

If bought cash, go to question 4.23; if 2 or 3 go to question 4.24

4.23: If you bought cash, where did you buy from?…………………………….and how much per unit…………………………Kes.

Irrigation

4.24: Do you do irrigation? ***1=yes [ ]; 0=no [ ]. If yes, go to question 4.25; if no, go to question 5.0***

4.25: what type of irrigation do you practice?...........***1=drip[ ]; 2=sprinkler (overhead) [ ]; 3=surface [ ]; 4=manual [ ]; 00=others (specify)…………………………..***

4.26: Do you use solar powered irrigation system? *1=yes [ ]; 0=no [ ]*

5.0: COST OF INPUTS (ISV)– Short rain (main) season***(Sept/Oct. 2017 planting)– (use unit codes provided below the table)***

Input	Name	Qty bought	Unit	Unit price **(Kes)**	Total cost **(Kes)**	Qty used	Unit	Qty given for free	Unit	Given by who? ***(other codes)***	Qty used	Unit	Qty used from farm saved grain/ chemicals	Unit
Sorghum seed_1														
Sorghum seed_2														
Planting fertilizer														
Top-dressing fertilizer														
Top-dressing – *(foliar)*														
Herbicides														
Insecticides/ Pesticides														
Fungicides														

Seed codes: *1= kgs;2=2kg pack;00=others (specify)………………………………………*
Fertilizer codes:*1=kgs; 2=10kg bag; 3=25kg bag; 4=50kg bag; 00=others (specify)………………………………………*
Agrochemical codes: *1=grams;2=5grams; 3=10grams; 4=5mls; 5=10mls; 6=25mls; 7=50mls; 8=100mls; 9=200mls; 10=500mls; 11=1 litre; 00=others (specify)………………………………………*
Other codes: *12=County Govt; 13=NGOs; 14=friend; 00=others (specify)………………………………………*

5.1: COST OF INPUTS (ISV) – Long rain season ***(Feb/March. 2018 planting)– (use unit codes provided below the table)***

Input	Name	Qty bought	Unit	Unit price **(Kes)**	Total cost **(Kes)**	Qty used	Unit	Qty given for free	Unit	Given by who? ***(other codes)***	Qty used	Unit	Qty used from farm saved grain/ chemicals	Unit
Sorghum seed_1														
Sorghum seed_2														
Planting fertilizer														
Top-dressing fertilizer														
Top-dressing –*(foliar)*														
Herbicides														
Insecticides/ Pesticides														
Fungicides														

Seed codes: *1= kgs;2=2kg pack;00=others (specify)……………………………………*
Fertilizer codes:*1=kgs; 2=10kg bag; 3=25kg bag; 4=50kg bag; 00=others (specify)………………………………………*
Agrochemical codes: *1=grams;2=5grams; 3=10grams; 4=5mls; 5=10mls; 6=25mls; 7=50mls; 8=100mls; 9=200mls; 10=500mls; 11=1 litre; 00=others (specify)….*
Other codes: *12=County Govt; 13=NGOs; 14=friend; 00=others (specify)………………………………………*

5.2: What is the distance from your homestead and the **nearest** agrodealer/agrovet shop which stocks seed and fertilizer regularly?.....................................kms

5.3: Are you a beneficiary of ***KCEP/CRAL*** project? **-------------- *1=yes [ ]; 0=no [ ]***

If **yes**, go to question **5.4** and fill the table below in question **5.5**; If **no**, go to question **6.0**

5.4: Which year and season did you start receiving support from ***KCEP/CRAL*** project?..........................year…………………season

5.5:*KCEP/CRAL* project information ***(use codes provided below the table)***

Input acquired	**Name *(Enum try to get the names or packs)***	**Short rain (main) season *(Sept/Oct. 2017 planting)***				**Long rain season *(Feb/March 2018 planting)***			
		Qty received	**Units**	**Qty used**	**Units**	**Qty received**	**Units**	**Qty used**	**Units**
Sorghum seed	Gadam								
	Sc Sila								
Green Grams seed	N26								
Planting fertilizer	23:23:0								
Top-dressing –(foliar)	Omex								
Insecticides	Engeo								
Tarpaulin									
Hermetic bags									

Seed codes: *1= Kgs;2=2kg pack;00=others (specify)……………………………………*

Fertilizer codes:*1=kgs; 2=10kg bag; 3=25kg bag; 4=50kg bag; 00=others (specify)……………………………………*

Agrochemical codes: *1=grams;2=5grams; 3=10grams; 4=5mls; 5=10mls; 6=25mls; 7=50mls; 8=100mls; 9=200mls; 10=500mls; 11=1 litre; 00=others (specify)……………………………………*

Hermetic bag codes: *12=PICS; 13=AgroZ; 14=others (specify)……………………………………*

6.0: Labour use_*Sept/Oct. 2017 planting_Short rains (main)-ISV*

ISV - Short rain (main) season *(Sept/Oct. 2017 planting)*								
Activity	**Description**	**Type**	**Name of the family member**	**Average no. of man hours per day**	**No. of people**	**No. of days/man days/bags**	**Unit cost (Kes)**	**Total cost (Kes)**
Land preparation	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
	tractor/ox-plough	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A				
Planting	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	tractor/anima l power	own	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A				
Weeding	manual (1st)	own/family			N/A		N/A	N/A
					N/A		N/A	N/A

Activity	Description	Type	Name of the family member	Average no. of man hours per day	No. of people	No. of days/man days/bags	Unit cost (Kes)	Total cost (Kes)
Weeding		hired	N/A	N/A				
	manual (2nd)	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	herbicide application	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Top-dressing fertilizer application *(basal and foliar)*	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Spraying *(chemicals)*	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Bird scaring	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				

Activity	Description	Type	Name of the family member	Average no. of man hours per day	No. of people	No. of days/man days/bags	Unit cost (Kes)	Total cost (Kes)
Harvesting	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Transporting harvested sorghum to homestead	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	ox-carts/ motorcycles etc	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A	N/A			
Threshing	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	mechanical thresher		N/A	N/A				
Transporting threshed sorghum from homestead to market/collectio	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	ox-carts/ motorcycles	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A	N/A			
Loading to the buyer's vehicle	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				

6.1: Labour use_*Feb/March 2018 planting_Long rains (main)-ISV*

ISV - Long rain season (Feb/March 2018 planting)								
Activity	**Description**	**Type**	**Name of the family member**	**Average no. of man hours per day**	**No. of people**	**No. of days/man days/bags**	**Unit cost (Kes)**	**Total cost (Kes)**
Land preparation	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
	tractor/ox-plough	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A				
Planting	manual	own/ family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	tractor/animal power	own	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A				
Weeding	manual (1st)	own/ family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A

Activity	Description	Type	Name of the family member	Average no. of man hours per day	No. of people	No. of days/man days/bags	Unit cost (Kes)	Total cost (Kes)
Weeding		hired	N/A	N/A				
	manual (2nd)	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	herbicide application	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Top-dressing fertilizer application (basal and foliar)	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Spraying (chemicals)	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Bird scaring	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				

Activity	Description	Type	Name of the family member	Average no. of man hours per day	No. of people	No. of days/man days/bags	Unit cost (Kes)	Total cost (Kes)
Harvesting	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
Transporting harvested sorghum to homestead	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	ox-carts/ motorcycles etc	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A	N/A			
Threshing	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	mechanical thresher		N/A	N/A				
Transporting threshed sorghum from homestead to	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				
	ox-carts/ motorcycles	own/family	N/A	N/A	N/A		N/A	N/A
		hired	N/A	N/A	N/A			
Loading to the buyer's vehicle	manual	own/family			N/A		N/A	N/A
					N/A		N/A	N/A
		hired	N/A	N/A				

7.0 INDICATE HOUSEHOLD SOURCES OF INCOME IN THE LAST ONE YEAR (2018)

Source	Type of income received	Did you or any household member earn income from this last year ***(1=yes; 0=no)***	Number of units ***(days, weeks, month…) worked per year***	Average income per unit		Total per year **(Kes)**
				Cash **(Kes)**	Payment in kind- cash equivalent **(Kes)**	
Labour	Agricultural labour					
	Non-agricultural labour (shop etc)					
	Salary					
	Pension					
Remittances	Food aid					
	Remittances from relatives, gifts					
Rent	Rent e.g land lease					
Small Business	Carpentry					
	Construction					
	Grain Mill/cereal shop					
	Other…………….					
Sales of forest products	Sales of wood and charcoal					
	Sale of wild nuts/fruits					
Petty trade	Handicrafts					
	Food					
	Beverages, Local brew					
	Sales in normal shop, petty trade					
	Transport (motorcycles, ox-plough)					
Sale of Farm Products	Crop produce					
	Animal Manure					

	Crop residues					
	Hay, grass and fodder					
	Cattle					
	Milk					
	Hides, skins, wool					
	Poultry					
	Eggs					
	Honey					
Shares and savings	Dividend on shares					
	Interest on savings					
	Other specify					

8.0 INDICATE HOUSEHOLD CONSUMPTION EXPENDITURE IN THE LAST ONE YEAR (2018) – outcome variable (impact)

Item name	In the last 7 days, did your household spend money on the listed items? **If 0 go to the next item** ***(1=yes; 0=no)***	Amount spent on the listed items in the last **7 days**? (Kes)
FREQUENT EXPENDITURES		
Cereals (maize, sorghum, millet, wheat)		
Legumes (beans, pigeon pea, cowpeas, green grams)		
Maize flour		
Wheat flour		
Bread		
Root and tubers (potatoes, sweet potatoes/ arrow roots/cassava		
Vegetables		
Meat		
Milk		
Beverages		
Fruits (mangoes, pawpaws, banana, avocadoes)		
Honey		

Sugar		
Salt		
Cooking oil/fat		
Beer and cigarettes		
Fuel (firewood, charcoal, kerosene, gas)		
Transport expenses		
Communication (cell phone, calling, internet)		
Entertainment (cinemas, movies, Tv subscriptions)		
Utilities and taxes (electricity bill and water)		
Other (specify)		
LESS FREQUENT EXPENDITURES		
Item	In the **past 12 months**, did your household spend money on the listed items **If 0 go to the next item** ***(1=yes; 0=no)***	What was your households total expenditure on the items over the last **12 months (Kes)**
Clothes and shoes (including school uniforms)		
School fees and other educational expenses		
Social events (wedding, funeral, harambee etc)		
House improvement (latrine, new roof etc)		
Human health expenses (medication, consultations, hospitalization)		
Electronics (TV, Radio)		
Vacation		
Livestock		
Gas refill		
Other (specify)_1		

9.0: MARKET AND INSTITUTIONAL FACTORS

9.1 Did any household member access any type of credit for farming (agricultural) purposes in year (2018)starting sept 2017?
1=yes [ ]; 0=no [ ]
If **yes,** fill the table below and if **no go to the next question 9.4**

Household Member (name)	Item of credit: ***1 = cash*** ***2 = kind***	*Type of provider:* ***1 = bank*** ***2 = cooperative*** ***3 = trader / shop*** ***4 = money lender*** ***5 = friends and relatives*** ***6 = merry-go-rounds*** ***00= other-specify***	Amount **(Kes)** (if kind estimate value)	Borrowi-ng date ***(month and year)***	Repay-ment period ***(months)***	Borrowing conditions		Have you repayed the loan fully **(1=yes; 0=no)**
						Interest rate in percent	**Per:** ***1=day*** ***2=Week*** ***3=Month*** ***4= Year***	

9.2 If you accessed loan and haven't fully repaid, how much is the balance that you are yet to pay?..**Kes**
9.3 Whyhaven't you paid fully? Tick as many as possible
1=loan has not matured thus still paying [ ]2=lack of cash to pay the premiums [ ]
3=haven't harvested the crop [ ]4=business I started collapsed [ ] 00=others (specify) [ ]

9.4 If you did not seek any form of credit, what was the reason? Tick as many as possible
1=no collateral [ ] 2=had outstanding loan [ ] 3=didn't know the sources of credit [ ] 4=didn't have an account [ ]
5=lender lacked cash [ ] 6=no need [ ] 00=others (specify) [ ]………………………………………………

10.0: ACCESS TO EXTENSION SERVICES

10.1 Did you actively seek advice on crop farming (sorghum) in year 2018? Starting Sept/Oct 2017
1=yes [ ] 0=no [ ]If **yes, go to question 10.2; if no, go to question 10.4**

10.2 Who did you approach for the advice? **Tick first three [Advice 1 ……Advice 2 ……**

Advice 3 ….]

1=Government extension agent [ ] 2=private extension agent [ ] 3=neighbour/farmer [ ] 4=ASK Shows [ ] 5=traders/input dealers [ ] 6=radio /television [ ] 7=family/friend [ ] 8=newspaper/magazines [ ] 9=farmer organizations/cooperatives [ ] 10=NGO agent [ ] 11=field days/demonstrations [ ] 12=research organizations [ ] 00= other (specify) [ ]……………………………………………………………

10.3 How **many times in year 2018** did you contact the extension medium for advice selected answer in question **10.2**? ***[Advice 1 ....; Advice 2……………;Advice 3……………]***

10.4 Why didn't you seek advice? ***(Give up to 2 reasons) [Reason 1 ……….. Reason 2 ………..]***
1=long distance [ ] 2=extension agents not showing up despite contacting them [ ] 3=time consuming [ ] 4=extension agents not available [ ] 5=don't need extension service [ ] 00=other (specify) [ ]……………………………………………….

11.0: TRANSPORT AND COMMUNICATION INFRASTRUCTURES

11.1 What is the distance from you homestead to the nearest market/shopping center ....…..…....(**Km**);

If you were to walk, what time would you take?…………………………………(**minutes/hrs**)

What is the name of market/shopping center?……..…………………………………………….

11.2 Distance from your homestead to the nearest agricultural office …………………. (**Km**);

walking time to the agricultural office?……………………………………….. (**minutes/hrs**)

11.3 Distance from your homestead to the nearest big town …………………………….. (**Km);**

walking time to the big town?………………………………(**minutes/hrs**)

11.4 (a).Type of road to village market: ***1=dirt road [ ] 2=murram road [ ] 3=tarmac road [ ]***
(b). Quality of road: ***1=bad [ ] 2=good [ ] 3=very good [ ]***
11.5 Transport cost (per person) to the nearest market using a bus or a boda boda

………….(**Kes/person**)

11.6 Do you face any problems while marketing your sorghum produce?***1=yes [ ]; 0= no [ ]***

If yes, go to question 11.7, If no, go to part 12.0

11.7 What problems do you face while marketing your sorghum produce? Tick as many as possible

1= lack of market for produce [ ] 2=exploitation by brokers [ ] 3= lack of seed [ ] 4=high transportation cost [ ]5=lack of drying equipment [ ]6=lack of weighing equipment [ ] 7= Low output price [ ] 8= expensive seed [ ] 9=birds menace [ ] 10=high threshing cost [ ] 11=Poor roads [ ] 00= 0thers (specify) [ ]…………………

12.0: MEMBERSHIP TO FARMER GROUPS

Does any member of your family belong to any association?

1=yes [ ]; 0=no [ ] **_ If yes, fill the table and if no go to 12.1**

Member ID	**Name of HH member**	**Type of associat-ion or club you belong to *(Codes A)***	**Functions of the club or association *(Codes B)***	**Role in the organization or club *(Codes C)***

Codes A	**Codes B**	**Codes C**
1. Input supply/service association 2. Producer marketing club 3. Local administration 4. Farmers' club 5. Women's club 6. Youth club 7. Faith-based organization 8. Saving and credit group 9. Welfare/funeral club 10. Government team 11. Water user's club 00. Other, specify..	1. Produce marketing 2. Input access/marketing 3. Seed production 4. Farmer research group 5. Savings and credit 6.Welfare/funeral club 7. Tree planting and nurseries 8. Soil & water conservation 00. Other, specify………	1. Chairperson 2.Vice chairperson 3. Secretary 4. Vice secretary 5. Treasurer 6. Ordinary member 7. Messenger 8. Cashier 9. Coordinator 10. Store keeper 00.Other (specify).…

12.1If household head is not a member, Why**?** (Give reasons) **Tick as many as possible**
1=resigned for personal reasons [ ] 2=resigned since the organization was not useful [ ]
3=finished his/her term [ ] 4=was deposed for some reason [ ] 5= group collapsed [ ]
6=unable to pay annual subscription fee [ ] 7=groups uses a lot of time (time wasting) [ ]
00=others (specify) [ ]……………………………………………………………………

13.0: OBSERVE AND ASK THE FOLLOWING QUESTION

13.1 Does your household own any of the following assets? *1=**yes [ ]; 0=no [ ]***

If yes, fill the following table and if no, go to part 14.0

Asset Name		Total number owned in the household	Total buying price (Kes)	How much would you sell it in its current state? **(Kes)** ***(If>1 Take average)***	Total value **(Kes)**	Expected lifespan (yrs)
Farm Implements	Ox-ploughs					
	Fork jembe					
	Sickle					
	Axe					
	Knapsack					
	Hoes/ijembe					
	Spade or					
	Water pump					
	Panga					
	Mattock					
	Chaff cutter					
	Generator					
	Solar panel					
	Slasher					
Transport	Wheel Barrow					
	Bicycle					
	Tractor					
	Motor cycle					
	Car/taxi/pick					

	Matatu					
Household implements	Posho mill					
	Improved					
	Kerosene					
	Gas					
	Electric stove					
Communication	Radio,					
	Mobile phone					
	TV					
Land	Land owned					

14.0: LIVESTOCK OWNERSHIP

14.1 Does your household own any of the following livestock? *1=**yes [ ]; 0=no [ ]***

If yes, fill the following table and if no, go to part15.0

Livestock name	**Current number owned**	**Current average value (Kes)** ***(If>1 Take average)***	**Total value (Kes)**
Grade cow			
Grade bull			
Grade calves			
Local cow			
Local bull			
Local calves			
Goats			
Sheep			
Chicken-indigenous (both hens and cocks)			
Chicken-improved			
Donkeys			
Others specify			

15.0 HOUSEHOLD SOCIO-ECONOMICS AND DEMOGRAPHY

Member ID	Name of HH member (start with Household head)	Year of Birth	Age (Years)	Gender (Codes A)	Marital status (Code B)	Education level (Code C)	Years of schooling	Relationship to HH (Codes D)	Main Occupation (Codes E)	Farm labour participation (Codes F)
1										
2										
3										
4										
5										
6										
7										

Codes A	*Codes B*	*Codes C*	*Codes D*	*Codes E*	*Codes F*
1. Male *0. Female*	*1. Monogamously married* *2. Polygamously married* *3. Divorced* *4. Widow/widower* *5. Never married(single)* *6. Separated* *00. Other, specify………..*	*1. None* *2. Primary* *3. Secondary* *4. Tertiary* *5. Adult literacy*	*1. Household head* *2. Spouse* *3. Son/daughter* *4. Parent* *5. Son/daughter in-law* *6. Grand child* *7. Other relative* *8. Hired worker* *00. Other, specify………*	*1. Farming (crop + livestock)* *2. Salaried employment* *3. Self-employed off-farm* *4. Casual labourer on/off-farm* *5. School/college child* *6. Herdsboy/girl* *7. Household chores* *8. Non-school child* *00. Other, specify………*	*1. Full time* *2. Part-time* *3. Not a worker*

15.1What is household's head farming experience in years?…………………………………

15.2 What is household head's sorghum farming experience in years?.............................…

15.3: If you have a hired worker, how much do you pay per month?................................kes

Appendix 2: Focus group discussion (FGD) guide

HOUSEHOLD SURVEY 2018 ON IMPACT OF IMPROVED SORGHUM VARIETIES ON POVERTY REDUCTION AMONG SMALLHOLDER FARMERS IN THARAKA NITHI COUNTY, KENYA

This research study is being carried out by a student pursuing a Doctor of Philosophy Degree in Agricultural Economics from Kenyatta University. The overall study objective was to evaluate the impact and contribution of improved sorghum varieties on the efficient attainment of sustainable livelihoods among smallholder farmers in Tharaka Nithi County, Kenya. The information collected will be treated confidentially for academic purposes, therefore feel free to respond to the questions asked.

Date: (ddmmyy):……………………………….

1. What improved sorghum varieties do you and farmers in your villages grow?
2. Tell us about the average sorghum production levels according to the varieties.
3. Which are the existing input delivery channels that exist in your area?
4. Could you tell us about access of inputs particularly seed that you and your farmers need and whether you get them in time?
5. Do you and your farmers need agricultural credit and are there institutions offering the facilities in Tharaka Nithi County?
6. Tell us more about training on sorghum and the different stakeholders offering training to farmers. How important is training in raising productivity levels? Which training medium is effective?
7. Where do you sell the sorghum produce to?
8. What are the challenges that you encounter in sorghum value chain?
9. What would you recommend (and to which stakeholder) on solutions for addressing the challenges?
10. What is your comment on poverty levels in Tharaka Nithi County particularly Tharaka North sub-county?
11. What is your view on the contribution of sorghum in reducing poverty levels in Tharaka Nithi County?
12. Do you have any questions for us?

Appendix 3: Key informant interview (KII) guide

HOUSEHOLD SURVEY 2018 ON IMPACT OF IMPROVED SORGHUM VARIETIES ON POVERTY REDUCTION AMONG SMALLHOLDER FARMERS IN THARAKA NITHI COUNTY, KENYA

This research study is being carried out by a student pursuing a Doctor of Philosophy Degree in Agricultural Economics from Kenyatta University. The overall study objective was to evaluate the impact and contribution of improved sorghum varieties on the efficient attainment of sustainable livelihoods among smallholder farmers in Tharaka Nithi County, Kenya. The information collected will be treated confidentially for academic purposes, therefore feel free to respond to the questions asked.
Date: (ddmmyy):……………………………….
Telephone number:…………………………….
Organization……………………………………
Position………………………………………....

1. Tell us about yourself including the organization you work with and your role?
2. What is the connection of your current role/organization in sorghum value chain?
3. Tell us about general sorghum production levels in Tharaka Nithi County.
4. What is your comment on the current sorghum production levels in Mukothima ward compared to other wards/ sub-counties within Tharaka Nithi County?
5. What improved sorghum varieties do farmers grow in Tharaka Nithi County?
6. What is your comment on input availability and access particularly improved sorghum seed in Tharaka Nithi County?
7. What do you think of the existing input delivery channels including agrodealer network in the county?
8. What do you think of agricultural credit access in Tharaka Nithi County?
9. What do you think about the importance of farmer training and Government extension system?
10. What are the challenges encountered in sorghum value chain in Tharaka Nithi County?
11. What do you recommend (and to which stakeholder) on solutions for addressing the challenges?
12. What are the existing policies/regulations governing sorghum sub-sector in Kenya or in Tharaka Nithi County?
13. What is your comment on poverty levels in Tharaka Nithi County particularly Tharaka North sub-county?
14. What is your view on the contribution of sorghum in reducing poverty levels in Tharaka Nithi County?
15. Do you have any questions for us?

Appendix 4: AIC and BIC values _Tobit vs Craggit

Model	**Akaike's information criterion (AIC)**		**Bayesian information criterion (BIC)**
Tobit (restricted)	884.7647		979.3284
Craggit (full)	341.306		526.322
Likelihood-ratio test	LR chi2(1) =	587.46	
	Prob > chi2 =	0.0000	

Note: Assumption is that restricted model is nested in full model

Appendix 5: AIC and BIC values of Exponential and Weibull functions

Distribution	**Akaike's information criterion (AIC)**	**Bayesian information criterion (BIC)**
Exponential	783.803	831.1016
Weibull	785.6429	836.5798

Appendix 6: Multicollinearity results (Variance Inflation Factor)

Variable	**Variance Inflation Factor (VIF)**	**1/VIF**
Workforce	2.62	0.382409
Adult equivalent	2.57	0.389835
Gender	2.05	0.486696
Education level	2.01	0.498461
Distance to agricultural office	1.54	0.648895
Extension access	1.14	0.880946
Agrodealer distance	1.53	0.652911
Per capita income	1.45	0.688786
Radio ownership	1.06	0.942765
Education level	1.33	0.749802
Asset value	1.31	0.763738
Age	1.27	0.789863
Training	1.26	0.792803
Cultivated land	1.20	0.830707
Tropical livestock unit	1.17	0.858194
Distance to nearest town	1.14	0.879816
Group membership	1.12	0.891427
Crop ratio	1.11	0.901222
Experience ratio	1.06	0.941071
Extension frequency	1.06	0.942900
Agricultural credit	1.05	0.956772
Mean VIF	1.43	

Appendix 7: Matching results from NNM; KBM and RCM algorithms

Matching algorithm		**Treated**	**Controls**	**Difference**
NNM	ATT	2.13	1.97	0.16
	ATU	1.91	2.12	0.21
	ATE			0.18
KBM (0.1)	ATT	2.13	1.97	0.15
	ATU	1.91	2.11	0.20
	ATE			0.17
KBM (0.25)	ATT	2.13	1.97	0.16
	ATU	1.91	2.10	0.19
	ATE			0.17
KBM (0.5)	ATT	2.13	1.94	0.19**
	ATU	1.91	2.12	0.21
	ATE			0.20
RCM (0.1)	ATT	2.13	1.98	0.15
	ATU	1.91	2.10	0.19
	ATE			0.17
RCM (0.25)	ATT	2.13	1.96	0.17*
	ATU	1.91	2.10	0.20
	ATE			0.18
RCM (0.5)	ATT	2.13	1.92	0.20**
	ATU	1.91	2.12	0.21
	ATE			0.21

Note: Figures in parentheses indicate the width distance
**P<0.05 and *P<0.10 mean significant at 5percent and 10percent probability levels, respectively

Source: Survey data

Appendix 8: Tropical livestock unit conversion

Name of the livestock	**Unit**
Cow	0.7
Heifer	0.5
Calf	0.3
Goat	0.1
Sheep	0.1
Chicken	0.01
Pig	0.2

Souce: FAO (1986)

Appendix 9: Adult equivalent computation

Age (Years)	**Male**	**Female**
Less than 10	0.6	0.6
11-13	0.9	0.8
14-16	1	0.75
17-50	1	0.75
More than 50	1	0.7

Source: Storck *et al.*, (1991)

Appendix 10: Publications

Publication 1: A multi-dimensional adoption approach for improved sorghum varieties in eastern Kenya: a climate change adaptation perspective

Publication 2: Analysis of economic efficiency among smallholder sorghum producers in Kenya

Publication 3: Ex-post impact evaluation of improved sorghum varieties on poverty reduction in Kenya: A counterfactual analysis