IMPACT OF CLUSTER FARMING ON THE TECHNICAL EFFICIENCY OF MAIZE PRODUCERS IN SILTI DISTRICT, SILTIE ZONE, CENTRAL ETHIOPIA REGION

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DEDICATION

I dedicate this thesis work to the memory of my father, for his support, prayer and devotion until his death, who passed away while I was elementary school. Let God save his soul in heaven.

STATEMENT OF THE AUTHOR

By my signature below, I declare and confirm that this thesis is my own work. I have followed all ethical and technical principles in data collection, data analysis, and compilation of this thesis. Each and every source of materials used for this thesis work has been given recognition through citation.

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BIOGRAPHICAL SKETCH

The author was born on July 18, 1997, in Yefekterek Kebele, Cheha District of Gurage Zone in Central Ethiopia Region, Ethiopia from his father Mr. Abdo Nurye, and his mother Mrs. Senya Sedo. He attended his elementary school in Megenase Primary School, and secondary and preparatory school in Emdibr. After the successful completion of secondary school, he joined Jimma University in 2014 and graduated with a BSc in Agricultural Economics in 2017. After graduation, he began to work in the Southern Agricultural Research Institute at the currently Central Ethiopia region, Worabe agricultural research center in 2018 as a junior agricultural-economics researcher. After two years of service, he was promoted to the position of Assistant researcher-I. And after that, he worked for four years and half, and get promoted to the position of Assistant-II. During his working time, he published four paper and one proceeding until he joined Haramaya University to pursue his MSc study in Agricultural and Applied Economics in 2022.

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ACRONYMS AND ABBREVIATIONS

ACC	Agricultural Commercial Clusters
ADB	African Development Bank
ATA	Agricultural Transformation Agency
ATT	Average Treatment Effect on Treated
ATU	Average Treatment Effect on Untreated
CSA	Central statistical Agency
CF	Cluster Farming
DEA	Data Envelopment Analysis
ESR	Endogenous Switching Regressions
FAO	Food and Agricultural Organization
GTP	Growth and Transformation Plan
GDP	Growth Domestic Product
IV	Instrumental Variable
LPM	Linear Probability Model
MOA	Ministry of Agriculture
OLS	Ordinary least square
PSM	Propensity Score Matching
SNNP	South Nation Nationality and People
SPFA	Stochastic Production Frontier Approach
SSA	Sub-Saharan Africa
TE	Technical Efficiency
TLU	Total Livestock Holdings

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Impact of Cluster Farming on the Technical Efficiency of Maize Producers in Silti district, Siltie Zone, Central Ethiopia Region

ABSTRACT

Ethiopian agriculture is largely characterized by small-scale subsistence farming. Maize is one of the main crops in Ethiopia. However, the average yield in Ethiopia is much lower than the global average. To improve this, cluster farming has introduced to transition of farmers from subsistence to marker oriented. Even through various cluster farming schemes are growing the study that shown, the effects of cluster farming on maize technical efficiency are still limited. Therefore, this study was conducted to determine the technical efficiency level of sample households, identify factors affecting farmers' participation in maize cluster farming and its impact on maize technical efficiency in the Silti district, Central Ethiopia. The study was based on primary data collected from 304 respondents selected through multistage sampling procedure, of which 153 were cluster participants and 151 were non-participants. Additionally, secondary data was obtained from various sources. For analysis, both descriptive statistics and econometric models such as Cobb-Douglas stochastic frontier and endogenous switching regressions were employed. The cobb-Douglas stochastic frontier model result showed that labor, fertilizers, chemicals, land size, and oxen-power were significant factors that determine the efficiency level of maize production. The average TE of the sample households was 74.2% and cluster participants had higher mean technical efficiency (82%) than non-participants (66%). The first stage ESR model results show that age, sex, educational level, land size, extension contact, access of information and access of training positively affected the probability of participation while distance from the nearest market was negatively affected. The results from the average treatment effect on the treated indicate that farmers who participated in maize cluster farming had 34.4% more TE compared with counterfactual. For non-participants, the treatment effect would increase by 19.7% if they had chosen to participate in maize cluster farming. The findings suggest that promoting cluster farming can be effective strategy to enhance the TE of smallholder maize producers. Thus, government and NGOs should focus on addressing the factors that influence participation in cluster farming.

Keywords: Cluster farming, Endogenous Switching Regressions, Maize, Technical efficiency, . Silti district, Ethiopia

1. **INTRODUCTION**

1.1. Background of the Study

Majority of African's depends on agriculture for their livelihood and, it plays significant role in sub-Saharan Africa (SSA), which provide great proportion of GDP and job opportunities (FAO, 2022). Agricultural sector is the major contributor to Ethiopian economy and the focus of government's growth and development plan. It accounts about 32.4% of the country's gross domestic product (GDP) (NBE, 2022) and 85% of export earnings (UNDP, 2021). Provides employment opportunities about 65.5% of the total population (ILO, 2021) and Supply 90% of the raw materials manufacturing industries (NBE, 2020).

However, Ethiopia's, agriculture is largely characterized by small-scale subsistence farming. The sector account 96% of the total area of cultivated land and generate around 95% of the major crops such as oilseed, vegetable, root crops, fruit and cash crops (CSA, 2022). Small-scale farming challenges by financial problems, limited land size, declining soil fertility status, insufficient irrigation, and low productivity due to limited access to modern technology and improved seed (FAO, 2022; Gebreselassie *et al.*, 2017; Gebeyanesh *et al*., 2021). In order to increase the productivity of agriculture and transform subsistence farming to market oriented it necessary to smallholder farmers require to better technology to improve the technical efficiency and productivity (ATA, 2022).

The main cereal crops grown in Ethiopia are *teff*, wheat, maize and sorghum (NBE, 2020). Out of the total area covered by grain crop cereals such as *teff*, maize, sorghum, barley and wheat account for 24%, 16.98%, 14.97%, 6.97% and 13.49% respectively. However, the production and productivity of cereal are still unsatisfactory and below the standard levels (CSA, 2016). In the past two decades, Ethiopian agricultural policies and investments have focused on developing and intensifying cereal crops (Birhanu *et al.,* 2022). Which is an important driver of income for a significant population. Moreover, in 2021, cereal production level in Ethiopia, reached out to 29,080,826.3 tons, again, these crops represent about 95% of agricultural production in terms of area coverage (CSA, 2021).

As globally maize ranked the second most produced grain in terms production volume following rice and also second most widely grown crop in terms of area coverage following wheat and in terms of production, the world top three maize producing countries are USA, China and Brazil, which produce 347,048,000, 260,958,000 and 101,139,000 tons respectively of the 1.1 billion tons of maize produced in the world (FAO, 2021). Maize is the main cereal crops that support the livelihood of millions of smallholder farmers in Africa. When it comes to Ethiopia, it has achieved tenth in terms of average maize yield in SSA in 2021 production season, moreover, the maize production level was 9,636, 000 tons in 2019 (FAO, 2021) and 10,200,000 metric tons in 2022 (FAOSTAT, 2024). According to World data atlas report in Ethiopia 2021, maize gives the highest yield per unit area at 4 tons per ha followed by rice, wheat, sorghum, barley and *teff* but the production level is still lower than the rest of the world (5.78 ton/ha). In Ethiopia, maize is one of the main crops ranking first in production and productivity and second in area coverage (FAO, 2017) this makes the highest proportion of annual grain production of the country accounting for 27.02% followed by *teff* 17.29% of the total produce.

Agriculture is the backbone of the regional economy (Central Ethiopia region) and in 2021, cereal production level in Siltie zone about 347,572.954 metric tons (CSA, 2021). In addition, maize production level in Siltie zone in 2022 was about 98,880.454 metric ton produce in 32,425.56 hectares of land (CSA, 2022). This crop in terms of both area coverage and volume of production obtained the major staple food in 2016/17 production season were high. Moreover, from in this zone the total area of cereals allocated for maize covered 20.89%, with the yield of 36.74 quintals per ha (CSA, 2017). However, the production landscape is not uniform across all regions (Ndoye *et al.,* 2023) this shows maize production are fluctuate in the country and in the region over time. To solve such kinds of problems cluster farming were a liable solution.

Agricultural cluster farming is one of the Ethiopia's government strategies supporting smallholder farmers to market oriented, increase crop productivity and maximize their income (ATA, 2017). It has been designed and planned closely link the smallholder farmers with the development of the integrated agro-industrial parks in Ethiopia; (Louhichi *et al*., 2019). In order to ensure commercialization, specialization, sustained supply of raw materials and to generate income, the link could increase the participation of smallholder farmers' priority agricultural commodity cluster farming with an ultimate emphasis on processing and value addition

(Timothy and Randall, 2016). In framework of the growth and transformation plan (GTP-I) the concept of agricultural cluster was introduced as a means of integrating intervention in the transformation agenda in specific geographical areas targeting a limited number of high value commodities, such as wheat, barely, *teff* and maize (ATA, 2017). Moreover, up to 2019, 31 agricultural crop cluster have been set up in the four-major agricultural region of Amhara, Oromia, SNNPR and Tigray with 3.7 million farmers in 300 selected districts, allowing for enhanced benefits in terms of production, marketing and value addition (Louhichi *et al*., 2019).

Furthermore, Siltie Zone, located in the Central Ethiopia Region, which is one of the areas where commodity cluster farming has been implemented. Maize production plays a vital role in the livelihoods of smallholder farmers in this zone. In terms of both area coverage and production volume, maize became a significant staple crop during the 2020–21 production season. Within the zone, maize accounted for 44.11% of the total cereal-cultivated area, achieving an average yield of 43.7 quintals per hectare (CSA, 2021). Despite the fact that various cluster farming schemes are growing in the country in general and in the study area in particular, the studies that have explored the effects of cluster farming on maize technical efficiency is still limited. Therefore, this study assessed the factors affecting farmers' participation in maize cluster farming and its impact on maize technical efficiency in the study area. It can provide information to different stakeholders that can used to develop better strategies to contribute to scaling up cluster farming.

1.2. Statement of the Problem

The primary issue facing Ethiopian agricultural economy is low production due to financial constraint, limited land size, declining soil fertility status, insufficient irrigation, and low productivity due to limited access to modern technology and improved seed which in turn to poverty and food insecurity (Danso-abbeam *et al.*, 2018; FAO, 2022; Gebreselassie *et al.,* 2017; Gebeyanesh *et al*., 2021). The average maize yield in Ethiopia was 4.19 tons/ha (CSA, 2022). Regionally, the yields were as follows: Amhara region - 4.286 tons/ha, Oromia region - 2.58 tons/ha, Benishangul-Gumuz region - 4.302 tons/ha, Sidama region - 4.4 tons/ha, Gambella region - 4.53 tons/ha, and SNNP region - 3.99 tons/ha. Specifically, in the Siltie zone, the yield was 3.05 tons/ha (CSA, 2022). Those statistical data showed that despite the maize as a main food crop, the production level is still lower than the world average (5.78 tons/ha in 2022). According to studied by(Mengistu *et.al,* 2024), there is still a significant gap between the actual and potential yield in smallholder maize farmers in Ethiopia due to biotic and abiotic stresses such as diseases, insect pest, drought, flood, land fragmentation account for a large part of the yield difference. According to this study the actual average maize production in the Ethiopia was 3.24 ton/ha with the technical efficiency of 0.86 in which the farmers are potential to increase the production level by 14.4% if the resource use efficiently (Mengistu *et.al,* 2024).

The concept of cluster farming explains as the concentration of agricultural activity that generate income and employment opportunities in and around a specific area (Galves-Nogales & Webber, 2017). In cluster farming, groups of smallholders usually pool their resource together for agricultural production, coordinate and market their product jointly and consequently reduce transaction cost, lower information asymmetries and improve bargaining power (Fischer & Qaim, 2012; Liverpool-Tasie, 2014). It can serve as an efficient mechanism for extension service and private business company to reach and interact with multiple farmers and share agricultural related information (Joffre *et al.,* 2019). It is also a coordination effort of government and development actors in reaching out to farmers, especially for targeted input provision like fertilizers, improved seed, and mechanization and so on. Moreover, support service such as extension, training and capacity building (Louhichi *et al.,* 2019). In cluster farming groups the farmers are expected to adopt the current full package of the farm recommendation including the use of input like improved seed, fertilizers, and other improved agricultural practice which in turn to improve their technical efficiency (ATA, 2021).

In Ethiopia, the studies conducted on technical efficiency of many potential crops revealed that, there are significant agricultural production problems in which, producing crops less than the frontier level of production. For instance, in the case of production it has produce 44% (Banchayehu, 2023); 29.97% (Aschalew, 2020) and 18% (Getahun *et al.*, 2020) less than efficiency levels. Therefore, cluster farming could be a strong option in order to help smallholder farmers to overcome these constraints and produce at efficient level. Due to fact that cluster farming is one of easy way of distribution of improved technologies when farmer has organized in-group in cluster. Even if cluster farming has given those huge important to the farmers, in the study area farmers have not fully participated in cluster farming, why? These shows there are existence of factors that directly or indirectly hindering farmers' participation in cluster farming and efficiency of production in the study area. Therefore, this study attempted to identify those factors.

In addition, various empirical studies undertaken in the area of examined the impact of agricultural technology adoption on the smallholders welfare, productivity and income (Bedada *et al*., 2015; Tesfaye *et al.*, 2016; Negese and Jemal, 2020; Zewdie *et al.,* 2020; Bedilu *et al.,* 2021), and the effect of adopting improved varieties of maize on food security and poverty (Geffersa *et.al,* 2022). However, no more attention was given to study the production of maize in cluster farming. Beyond that, the existing studies that are concerned with technical efficiency of maize did not well interconnect with clustering farming practice. Such studies did not show how much technical efficiency were generated by the implementation of such improved farming practice (cluster farming practice) of the smallholder producers specifically in maize production. There is also scarcity of empirical study in Central Ethiopia region regarding the effect of cluster farming participation on household technical efficiency. Limitation of such empirical investigations has created a knowledge gap on the performance and effect of such better practices in the region. Therefore, due to this case it is uncertain to know the extent at which the households participating in maize cluster farming are more efficient than their counterparts. Besides, the factors hinder the smallholder farmers not to produce their potential output and participate in cluster farming. Moreover, no effort has been made by the researchers similar to the current study to identify the determinants of participation in maize cluster farming and its impact on technical efficiency of maize farmers.

Furthermore, most existing impact studies on productivity, commercialization, efficiency and food security those by Adekunle (2018), Tsion *et al*., (2023), Abdul-Rahaman and Abdulai (2018), and Solomon and Belayneh (2021), rely on simple regression and Propensity Score Matching (PSM) methods. While these approaches are useful, while, they fail to account for unobservable factors and often require extensive datasets to ensure matching quality. This limitation can lead to biased results if unobserved variables influencing the effects of cluster farming are not adequately addressed. To fill this methodological gap, this study employs the endogenous switching regression model, which simultaneously estimates participation decisions and their impacts while correcting for selection bias.

Understanding the impact of maize cluster farming on technical efficiency and the factors influencing participation is crucial for providing policymakers and stakeholders with robust empirical evidence. This study aims to generate actionable insights that can support the effective implementation of cluster farming initiatives, addressing the need for reliable and relevant information in this area.

1.3. Research Questions

1. How much the level of technical efficiency of maize producers in the study area?
2. What are the determinant factors that influence cluster farming participation?
3. What is the impact of cluster farming on maize technical efficiency?

1.4. Objective of the Study

1.4.1. General Objective

The general objective is to evaluate the impact of cluster farming on technical efficiency of smallholder maize farmers in Silti district, Siltie Zone, Central Ethiopia region.

1.4.2. Specific Objectives

1. To determine the technical efficiency level of maize on the sample households
2. To identify factors affecting farmers participation in maize cluster farming in the study area
3. To evaluate the impact of cluster farming on the technical efficiency of maize production.

1.5. Significance of the Study

This study helps to generate empirical evidence on whether the smallholders maize producers participating in maize cluster farming improve their maize technical efficiency or not in the study area. Relevant information about cluster farming involvement and its effects on the technical efficiency level of maize growers in the study area was generate and provided by this research. Additionally, identifying the various factors that limit the farmers participation in cluster farming and its effect on farmer’s technical efficiency in the country have numerous benefit for different agent such as government body, policy makers and other stakeholders. Hence, the groups of stakeholders, maize producers, policy makers, agricultural extension agents, and other governmental and non-governmental organizations is benefit that take evidence-based decisions on efficient resource use, promotion and scaling-up of yield improving technologies. It’s also helps to make judgement on program impacts, contributes to awareness on the available cluster farming in the local context and evaluate them related to cluster farming on technical efficiency. It has also provide future research directions for those who might be interested in carrying out additional research in related fields. On the other hands it may encourage other researcher to carry out similar studies on the effect of cluster farming on maize producers’ technical efficiency in the country. Additionally, it may lead to further inquiries on theoretical and empirical argument among the researchers toward a valid understanding of the impact of cluster farming on maize technical efficiency.

1.6. Scope and Limitation of the Study

The study was conduct in Silti district, Central Ethiopia region. The objective of the study is limited to identify technical efficiency level of maize farmers, to determine major factors affecting the decision in cluster farming participation and evaluating the impact of cluster farming on technical efficiency. Due to the time limit allotted for the study and the expensive nature of other data sets like panel data, this study was use cross-sectional data gained from 304 sampled households from four representative Kebeles considering only 2023/24 production year this can cause unable to hold the production trend that produce over time. In addition, the study was focus on maize crop due to its importance for food consumption, increasing market demand, agro-ecological suitability and it’s important of the study area. This study was focus on household farm input and production in one district of Siltie zone, Ethiopia. The finding may not apply to the other year or region. The other limitation of the study finding may not apply to other crops commodity unless there is a similar condition. In addition, cluster farming is introduce recently in Ethiopia; it may be difficult to get relevant reading materials for deeper insights. This constraint is alleviate with a consultation of different actors in this program.

1.7. Organization of the Thesis

The thesis was organized into five chapters. The first chapter introduces the background information, the statement of the problem, the objectives, limitations, and significance of the study. The second chapter presents a review of literature where relevant materials related to the present study. The third chapter deals with the research methodology, where all the statistical ways of undertaking the study were outlined and justified as well. The fourth chapter was about the results and discussion of the study, the descriptive and econometric analysis results of the study were presented and discussed in this section. Summary, conclusion, and recommendations were presented in the chapter five.

2. LITERATURE REVIEW

This chapter reviews the key concepts, theoretical frameworks, analytical frameworks, and empirical studies on smallholder farmers' technology adoption and the impact of maize cluster farming on technical efficiency. The theoretical framework contextualizes the study and explains its rationale, while the analytical framework specifies methods and procedures. The empirical literature offers evidence from past studies and identifying the gaps the existing researches were the aim of this research.

2.1. Definition and Concepts of Key Terms

2.1.1. Cluster Farming

The concept of clustering originated from the work of the economist Marshall (1890) referred to a phenomenon as "the concentration of specialized industries in particular localities" and noted that these groups of small businesses benefited from economies of scale comparable to those of large firms.

Cluster farming refers to a group of farmers who corporate in the same location to produce the same crops, collaborate on groups buying for input requirements, sell jointly to the same buyers and engage in joint negotiation and sharing of implements (Timothy and Randall, 2016).

Cluster farming define as a concentration of agricultural activity in and around a certain location that provide for income and employment opportunity (Porter, 1998; Galves-Nogales & Webber, 2017). It refers to a group of producers, agribusinesses, and enterprises working in the same agricultural or agro-industrial subsector that creates valuable networks by collaborating to solve the problems and gain opportunities (Galvez-Nogales, 2010).

Ethiopian government has been using cluster farming since 2018 to alleviate poverty and promote rural development (Louhichi *et al.*, 2019). The goal of cluster farming initiative in Ethiopia focuses on facilitating smallholder farmer's transition from subsistence to semi-commercial farming. This achieve through stronger market connection, faster dissemination of the best practice, bargaining power, and affordability of modern technology (ATA, 2019a).

Cluster farming believe that cluster households can benefit from economies of scale including more affordable modern technology, more negotiating power, and improve market connections provided to large-scale producers (Louhichi *et al.*, 2019; ATA, 2019b).

Cluster farming is a modern agricultural production strategy that uses spatially interconnected farms for the selected crops with the goal of commercialization (Dejene, 2019) where farmers in the groups recommended to adopt full package of extension service such as fertilizer, chemical, and seed (ATA, 2021).

2.1.2. Concept of Technical Efficiency

Efficiency is defined as performance of farm production capacity to attain optimum output gain from a given set of input factors (Farrell, 1957). According to Farrell and Lovell (1978) the means of measuring the production technology is a production function where the scalar output case specifies the maximum amount of output that can obtain from the input vector. Technical efficiency is defined as the performance of the given firm to obtain maximum output from a given combination of input used with the given level of technology. Moreover, the given firm is technically efficient, when the combination input give rise to maximum possible outcome and has no room for further improvement of the output of the firm; it can be express as the physical relation between input and the final output (Farrel, 1957).

The capacity of an organization to produce potential output from a bundle of inputs, given the most efficient technology available, is measured by its technical efficiency. Means, technical efficiency of output is obtained; the ratio of actual output to potential output conditioned to the amount of input used by firm. This concept differs from productivity, which is the amount of output gain per unit of input factors (Beatrice *et al.*, 2011). Technical efficiency can take output or input-oriented terms. An output-based technical efficiency happens when the higher quantity of yield is obtained for a particular set of inputs while an input-based technical efficiency deals when a minimum quantity of inputs that are needed to produce a given yield (Farrell, 1957). The fundamental intension under this study is to estimate the technical efficiency level of maize production and explain its response to maize yield to multiple inputs in cluster and non-cluster farming. Efficiency is generated through reducing resources needed to produce an output or maximizing outputs from a set of inputs (Varian, 1992; Cochrane and Bekele, 2018). In this study an output-based technical efficiency estimation method was used.

2.1.3. Concept of Impact Evaluation

According to the European commission, the term impact refer to all expected changes resulting from the implementation and use of a certain policy choice or intervention. These effects might be important at various sizes (local, regional, national), occur over various periods, and influence various players. Impact in the context of evaluation refers to the long-term changes brought about by a specific intervention. broadly define as the influence of academic research beyond the academic sphere including area such as business, education, public health, policy, public debate, culture etc., has been progressively implemented in various system of science evaluation and trend observable worldwide (Donovan, 2011; Grant *et al.,* 2009; European Science Foundation, 2012).

Impact evaluation is a systematic and rigorous approach to assessing the change that can be attribute to a particular intervention or program (Gertler *et al.,* 2016). Its aim is to determine whether the intervention had the intended effect on the target population and to quantify the magnitude of that effect. According to Gertler *et al. (*2016) impact evaluation involve the following key elements first establishing the counterfactual this refers to the situation that would have occurred in the absence of the intervention, against which the observed outcome can be compared. The other one is measuring changes means impact evaluation measure the changes in outcomes that can be directly attribute to the intervention rather than changes that would have occurred anyway. Moreover, establishing causality means impact evaluation seek to establish a causal relationship between the intervention and the observed changes ruling out alternative explanation for the observed outcomes.

2.2. Cluster Farming in Ethiopia

According to ATA (2019) Agricultural Commercial Clusters (ACC) and cluster maize production introduced in Ethiopian. The productivity of maize has increased by 50% due it but still the production level is not reach at the required optimum level. These clusters are intended to be converted into commercial farms controlled by the farmers themselves through the ACC initiative, which seeks to unite farmers who own small plots of land to farm together while utilizing all available resources to increase production. Farmers through agricultural commercialization cluster established the farmer production cluster project, where 30–200 farmers join on contiguous property to cultivate as one. Cluster households are expect to benefit from economies of scale such as greater affordability of modern technology such as sharing overhead cost of tractors, strong bargaining power, strong market linkage to serve bulk buyers or a large-scale buyer like contract farming with large processes in Ethiopia (Louhichi *et al.*, 2019; ATA, 2019b).

cxThe ACC is being implemented in 300 districts, which are organized into 31 crop clusters in four key areas, including Amhara, Oromia, SNNPR, and Tigray, during the five-year plan between 2019/2020 to 2023/24. Concentrating on 11 main grains: *teff*, sesame, wheat, maize, and malt barley Approximately 30,000 of the 76,000 commodity clusters that have been established nationwide are focused on the production of maize, and they are located in the Amhara, Oromia, and SNNPR areas. From those, 3,300 are in the Amhara, 2,500 are in SNNPR, and 24,000 are in the Oromia region. The productivity of maize has increased from 40 quintals/ha to 60 quintals/ha by using clustering. Being the second most populated country in Africa, the country is still classified as food insecure, which is an uncomfortable condition. Therefore, it is the responsibility of the current generation to turn things around. (Abebe, 2021). (Addisu *et al.*, 2019) reported that there were 1,208 maize clusters, and 72,695 participant farmers in maize clusters, and 48,707 ha of land were allocated for maize production in SNNP.

2.3. Theoretical Framework

This section explains the theoretical basis for impact analysis of cluster farming and provides the way that this study was follow by using various theories. In addition, the methodology and research questions were connected to the content of the theories used in this study.

2.3.1. Network Governance Theory

Network governance theory highlights the importance of flexible, decentralized decision-making processes and the establishment of trust-based relationships among stakeholders in complex and interdependent systems like cluster farming. By adopting network governance approaches, cluster-farming initiatives can leverage the expertise and resources of multiple actors while maintaining adaptability and responsiveness to changing conditions. The concept of network governance provides insights into how diverse actors within a networked system collaborate, negotiate, and make decisions to achieve collective objectives (Oh and Bush, 2016).

Network governance in cluster farming has its own strengths and limitations that influence its effectiveness in promoting collaboration, and sustainable development within agricultural clusters. One of the strengths of network governance in cluster farming is to promote collaboration and sustainable development by fostering shared decision-making among stakeholders like farmers, producers, policymakers, researchers, and consumers (Mayer, 2012). However, it also has limitations, such as power imbalances, where powerful actors may dominate, marginalizing weaker farmers and limiting their participation in governance processes (Sørensen and Torfing, 2007).

2.3.2. Transaction Cost Theory

Transaction cost theory, derived from the "new institutional economics" school of thought, which is widely used to study agricultural markets and farmers group/collective action in developing countries (Okello and Swinton, 2007). It emphasizes the role of institutions in managing transactions and explains the benefits of joint action through economies of scale and bargaining power. Transaction costs are the observable and hidden expenses incurred during the exchange of products and services (Williamson, 2000). Smallholders often face high transaction costs in accessing markets for inputs, credit, information, etc. Cluster farming can be a viable option for smallholders as it lowers their production's transaction costs compared to other options. This theory can be useful in analyzing the impact of cluster farming in Ethiopia.

Transaction cost theory offers insights into cluster farming, where multiple farms or enterprises co-locate in close proximity. It emphasizes efficiency in coordination, reducing coordination costs and promoting resource allocation and production processes (Williamson, 1975). However, they are its own limitations which include dependency on external factors like government policies, infrastructure development, market conditions, and socio-economic dynamics. Changes in these factors can significantly influence the viability of cluster arrangements (Klein *et al.,* 2010).

2.3.3. Social Capital Theory

Social capital theory, widely applied to agricultural innovation and farm practices, emphasizes the role of social organization features like trust, norms, and networks that enhancing societal efficiency through coordinated action. Farming is view as a social network involving various actors connected to individual farmers rather than a solitary activity. The creation of "value networks," incorporating vertical relationships among suppliers, horizontal relationships among producers, and support relationships between producers and facilitating organizations, is see as a key strategy to address challenges faced by smallholder farmers and enhance long-term competitiveness in the agricultural sector (Gálvez-Nogales, 2010).

Mutual trust is crucial in collaborative activities as it reduces transaction costs and eliminates the need for monitoring others (Vanni, 2014). Reciprocity plays a key role in establishing long-term trust between individuals and organizations. Rules and sanctions that protect the interests of groups and individuals are important for successful collective action. Social capital, including networks, trust, and norms, can lower barriers and enhance the efficiency of collaborative governance. These attributes of social capital are highly relevant to cluster farming, which relies on information flows and networks for decision-making (King *et al*., 2019). As a result, these attributes of social capital are highly relevant to cluster farming, because CF depends on information flows and networks between participants to enable them for decision-making.

Social capital theory offers valuable insights into the social dynamics of cluster farming, emphasizing the importance of social relationships, trust, and cooperation. However, issues of exclusivity, cooperation scope, and dependency within the cluster context may limit its applicability (Portes, 1998).

2.3.4. Classical and Neo-classical Theory of Production

According to the classical theory of production, it is assumed that the farm /firm operate efficiently and any deviation from the frontier output results from external factors that are entirely out of the decision-makers control. Whereas, the neo-classical production theory assumes that producers in the economy operate at different levels of output even if they use the same level of inputs and technology. The difference in observed output from the frontier among producers can be explained by unforeseen external factors outside the producers control and through difference in the efficiency of using existing resources (Korres, 2007). This theory prefers for measuring technical efficiency level for the production process.

Classical and neoclassical theories of production offer insights into the economic aspects of cluster farming, focusing on factors such as inputs, outputs, and production efficiency, market integration, and technological innovation. However, their applicability maybe limited by assumptions of homogeneity, overlooking externalities, and neglecting market imperfections within the cluster context (Stiglitz, 1976).

2.2.5. Utility Maximization Theory

Cluster farming benefits smallholder farmers by maximizing their utility. Farmers adopt improved agricultural technologies and practices if the net benefit is higher than the benefit from non-adopting. Various studies that used this method (Khonje *et al*., 2015; Abdulai and Huffman, 2014). Because utility maximization theory helps understand farmers' decisions regarding the adoption of specific technologies and practice, considering factors such as input prices, output prices, and technological efficiency (Jensen, 2007). The theoretical framework for practicing new technology is the random utility model, where farmers choose a strategy that provides the highest utility among the given alternatives.

This study uses a random utility framework to describe a household's decision to join cluster farming. In modeling the satisfaction result using maize cluster farming practice, the benefits related to the use of maize cluster farming over non-cluster farming need to be consider. Therefore, the farmers who participate in cluster farming if the utility from participation of cluster (U_A) is higher than the utility from non-participants (U_N) which means $U_A > U_N$ or $U_A - U_N > 0$, even if those utility are unobservable they can be stated as a function of observable aspect in the latent variable model and show below.

$$Y_i^* = \alpha Z_i + \eta_i, \qquad Y_i^* = \begin{cases} 1 \; if \; Yi > 0 \\ 0 \; otherwise \end{cases} \qquad (1)$$

Where Y_i^* is binary where the decision to adopt cluster farming that equal to one if the household i^{th} is a cluster farming participant and zero otherwise. α represent a vector of the parameters that need to be estimate and Z_i is represent the factors such as demographics, socio-economics, household level characteristics and η_i, represent random error terms of the normal distribution.

The probability that the households was practice CF conditional on Z could be define as:

$$P = p(Y{=}1|Z) = P\,(U_A > U_N) \qquad (2)$$

$$= P\,(\alpha_A Zi + \eta_A - \alpha_N Zi + \eta_N > 0|Z)$$

$$= P\,(\alpha_A Zi - \alpha_N Zi + \eta_{A} - \eta_N > 0|Z)$$

$= P (\alpha^{*} Z_i + \eta^{*} > 0|Z) = F (\alpha^{*} Z_i)$ (3)

Where P is a probability function, $\eta^{*} = \eta_{A} - \eta_{N}$ is a random disturbance term $\alpha^{*} = \alpha_A - \alpha_N$ which is unknown parameters it can be interpreted as the net influence of the vector of independent variables influencing adoption. F ($\alpha^{*} Z_i$) is the cumulative distribution function of η^{*} estimated at $\alpha^{*} Z_i$ and the real distribution of F depends on the distribution of the random disturbance terms. In theory, the optimal level of new technology use increases with a higher output price if the elasticity of the risk response to modern input is lower compared to the elasticity of the average yield response to the modern input use. Therefore, in this study more focus on random utility theory.

2.4. Analytical Framework

2.4.1. Models for Technical Efficiency Estimation

The parametric and non-parametric techniques are the two types approaches that are frequently employ to measure the technical efficiency of the production process (Coelli, 1998) for the detailed explanations on these methods the two frontier estimation techniques are further described below.

Non-parametric frontier estimation model

To measure technical efficiency, various approaches have been addressed in the literature, one of the methods is data envelopment analysis (DEA); which is a mathematical programming model employed for the observed data that brings the building of production possibility frontiers and for the derivation of efficiency scores provide from constructed frontiers. The characteristic group of the non-parametric method of the frontier the so-called data envelopment analysis (DEA). Which is a classic example that can easily handle multiple input and output relations. Moreover, in DEA, application inputs and output can have very different units of measurement without requiring any a priori trade-off or any input and output prices. DEA does not impose any assumptions about functional form; hence, it is less prone to misspecification.

Further, the DEA does not take into account random errors. It is not subject to the problems of assuming an underlying distribution about the error term. However, since DEA cannot take account of such statistical noise, the efficiency estimates may be bias if the production process is largely characterized by stochastic elements. Another limitation of DEA is the problems of the model performance hypothesis testing since estimation of the model parameters is not possible. In addition, DEA assume all deviation from the frontier are due to inefficiency. Due to this, non-parametric frontier approach may overstate inefficiency and outlier may exist on the magnitude of inefficiency (Coelli *et al*., 2005).

Parametric frontier model estimation

Deterministic and stochastic production frontiers are further classifications for parametric frontier model estimation. According to the deterministic model, inefficiency is the reason for any deviation from the frontier. The stochastic function, however, permits statistical noises (such as measurement error, weather, natural disaster, industrial action, etc.) which are natural circumstances and not under the control of households or firms.

The deterministic frontier model: which measuring the difference between the estimated frontier values and the actual production values, one could predict the technical efficiency of specific firms within the context of the deterministic frontier production function. It was initially determined by Aigner and Chu (1968) using a function that provided an appropriate possible output as a conditional function of the inputs that were provided. They take into consideration of the following parametric of frontier production function estimate using a Cobb-Douglas production function. (Coelli *et al.*, 1998) discussed common functional forms namely Cobb-Douglas, and translog production function. Each functional form has its own strength and weakness. The Cobb-Douglas functional form has been commonly used in the empirical estimation of frontier model. Its simplicity has very attractive feature. However, this simplicity is associated with a number of restriction features such as constant elasticity, constant return to scale for all firms. On the other hand, the translog functional forms impose no restriction however, translog functional form is susceptible to multicollinearty and degree of freedom problems (Coelli *et al.*, 1998).

The stochastic production frontier approach (SPFA): which was independently applied and developed by Aigne *et al*. (1977), is an alternative and the extended estimation method that is use in the context of estimating technical efficiency. It declares the problems associated with the random disturbance term in the deterministic approach. The stochastic production frontier was developed by adding a symmetric error term (vi) to the non-negative error term (u_i) and which is associated with random factors (e.g., measurement errors in production, weather, disease effect, etc.) that are not under the control of the farmers. However, since data envelopment analysis cannot take account of such statistical noise, the efficiency estimates may be bias if the production process is largely characterized by stochastic elements. Moreover, it is necessary to estimate the efficiency score using the sample data. Therefore, in this study used a parametric stochastic frontier model (i.e., dividing the stochastic term into error and inefficiency).

2.4.2. Factors Affecting Farmer's Participation in Cluster Farming

Research scholars used a different model to represent the factors that hinder the participation decisions in way of both qualitative and quantitative studies. Among those model, Probit model (Liao, 1994; Maddala, 1983), Logit models (Aldrich, 1984 and Nelson), and Tobit model (Leamer, 2010) were some of the desired models.

Logit model: Logit model is a model that is use to regress a binary dependent variable from different covariates, permitting the estimation of the possibility for event to occur or not. The characteristics problem to this model is it does not make any assumptions about normality, homogeneity of variance, or linearity for the logistic independent variables (Aldrich and Nelson, 1984).

Tobit model: Tobit model also referred to as a censored regression model is intended to determine linear correlations between variables in situations where the dependent variable has either left- or right-censoring and also termed censoring from above and below, respectively. The tobit model useful to learn about the conditional distribution of a variable, dependent given a vector of regressed when the dependent variable is observed only if it is above or below some known threshold (censoring). In the case of censoring from below, values that fall at or below some thresholds are censored (Leamer, 2010).

Multinomial logit or probit model: Multinomial outcomes occur when there are more than two categorical outcomes. The outcomes of these models are usually unordered, such as in choice of transit mode to work. Models are reduced to a series of pairwise choices that do not depend on the other choices available. They are usually the generalizations and extensions of binary models (Katchova, 2013). These models overcome the problem of LPM and the predicted probabilities of these models are between 0 and 1.

Probit Model: it is non-linear probabilistic model in nature, used to solve the limitations made from the LPM's, and applies cumulative normal probability distribution in its analysis. This model usually uses to infer the latent variables from the observed variables by using its mathematical methods. The dependent variable in the probit model takes a discrete (binary) variables, there takes the values of one and zero (Liao, 1994). Therefore, this study was likely to employ the probit model. Due to it fulfil different econometric assumption as compare to the above model to analysis the binary dependent variable and it works, as use of cluster participation is a binary choice, where a farmer decides to cluster participation when there is a positive effect between the marginal net benefits of using cluster participation and not using the cluster participation.

2.4.3. Impact of Maize Cluster Farming on Technical Efficiency

The economic analysis of technological impact on agricultural productivity at farm level is hinder by the lack of observation of before and after activities (Bosch *et al.*, 2017). However, the problem of endogeneity (Hausman, 1978) where technology use is self-interest or targeted to specific groups. Estimating cluster farming participation's impact on the on technical efficiency outcomes is challenging due to non-experimental observations, as participants cannot observe outcomes if they did not participate. Experimental studies address this issue by randomly assigning participants to treatment and control statues, ensuring that observed outcomes are statistically representative of control households without participation. However, participation is not randomly distributed to the two groups of households (as participant and non- participant), but rather to the household itself deciding to participate given the information it has, therefore participants and non- participants may be systematically different (Khonje *et al.,* 2015). In this case, self-selection into intervention leads into endogeneity, and failing to take care for this is challenge the real impact of the technology. In the case of targeted technology intervention, there perhaps farmers those participating the clusters are likely less productive and less efficient, and failure to account for this is understate the true impact of the cluster. Because natural abilities and other issues are responsible for differing initial situations of participant and non- participant for understanding only to the farm households and not to the scientists, these cannot be directly protected to single out the pure effect of cluster participation on productivity, income, or other outcome variables.

Experimental method: Experimental design methods are commonly received a wide consideration, the most accepted and strong ways of impact evaluation systems (Baker, 2000) it also known as randomization. Randomized program intervention allocation involves randomly assigning beneficiaries and non-beneficiaries to target groups, creating statistically equal treatment and management groups. This process avoids selection bias and allows researchers to determine project impact by comparing outcomes for both groups, resulting in independent estimates of impact (Essama, 2006).

Quasi-experimental design: Quasi-experimental design refers to evaluations without the rigor of random assignment in experimental design. Due to viable variations among the groups compared and unobserved forces beyond the test, quasi-experimental designs can be restricted because of their capability to draw causal inferences. But, in some situations, the best controls might built, and quasi-experimental designs perhaps be very useful in answering outcome-associated study questions for residents and neighborhood conditions, given that they consist of environmental controls, identifying treatment and evaluation groups and gathering thorough data for each group. Similar to experimental designs, quasi-experimental designs are costly, complicated, and challenging to execute.

Instrumental variable: When used with cross-section or panel data, an instrumental variables (IV) allows selection bias based on unobserved features to change over time. By identifying a variable (or instrument) that is correlated with the explanatory variable but not with unobserved characteristics influencing the outcome, the instrumental variable approach corrects the program selection bias on unobserved characteristics. This instrument is use to predict program participation (Newey, 2003). However, it is difficult to find strong and valid instrumental variable that affect participation in treatment but do not have a direct effect on the outcome. In this study source of information from (government extension (yes =1) and research center (yes =1) used as instrumental variable. Also source of information used as instrumental variable by Million *et al.* (2019) and Khonje *et al.* (2015) to assess impact evaluation.

Difference-in-Difference (DiD): This method is used to determine the impacts of various policy choices and modifications that are unlikely to have an identical impact on all groups. DiD is a crucial technique when pre-treatment data is available and design is used to fully control for confounding variables or when employing instrumental variables is still not feasible. The DiD design is primarily defined by contrasting four distinct categories of items de facto. The therapy does not affect three of these groups. Time is a critical variable used in many systems to distinguish between groups. Aside from the group that has previously received treatment (post-treatment treated), other groups are handled before receiving treatment (pre-treatment treated), and the non-treated group. The non-treated within the period before the treatment occurs to the handled (pre-treatment non-treated), and the non-treated within the current period. However, to use the method both baseline data and a non-intervention group are needed (Lechner, 2011). It is well applied mainly on panel type of data.

Regression discontinuity design (RDD): Thistle Waite and Campbell (2017) provide a quasi-experimental pretest-posttest design in which the goal is to determine the causal effects of a targeted program by designating a cutoff or threshold, above or below which an intervention is allocate. Additionally, it could depend largely on administrative statistics which would reduce the requirement for data collection though it might still be necessary to compile the results for the individuals who were turn down. The way cut-off point evaluated is through an analysis of the distribution of scores on the scale. Conceptually there could be nearly equal numbers of objects above and below the cut-off point. However, they are significantly affected by resources or implementation concerns. The drawbacks of this method are mainly, there is a desire to be clean assignment criteria and enough samples for the evaluation. The impact is used to predict the population along the edge, which presents a problem for RDD. As opposed to an average treatment effect for the entire treated population, this expected impact is typically referred to as a local average treatment effect (White and Raitzer, 2017).

Propensity score matching method: Propensity-score matching is mainly apply for estimating the average effect of programs intervention and is categorize as non-experimental (Rosenbaum and Rubin, 1985; Heckman *et al*., 1998). It works in such manner that the control villages are match on observed characteristics but may differ on unobserved and assumes that these unobserved characteristics could not affect the outcome of interest. It also tries to match with technology and without technology groups based on observed characteristics or via a propensity score; the closer this score, the better the fit. PSM is an extension of matching technique to efficiently match on multiple variables. A good control group that is likely to be compare is that share identical economic environment and is introduce into the same tests through similar interviewers as the treatment group. In recent years, there have been vast advances in PSM technique applications (Rosenbaum and Rubin, 1985).

A conditional chance is what the propensity score is. More precisely, it is the probability that an individual or groups are participated in the intervention given their observable traits. This likelihood comes from the participation equation, which is a probit or logit regression with a dichotomous dependent variable that takes the value of zero if participants did not take part in the intervention and one if they did. All observable characteristics that potentially affect participation but are unaffected by the spread of technology are included in the explanatory variables, which include person, family or firm, community, and market variables. Having baseline data makes it easier to get a stronger fit since baseline values of all variables, including outcomes, cannot be change by the intervention. The covariate balancing propensity score is a recent innovation that uses weighting to ensure covariates are balance before applying propensity scores in matching. (Imai and Ratkovic, 2014). Due to its inability to control unobservable characteristics, PSM often needs a large data set to identify appropriate comparisons and to be comfortable with its assumption.

Endogenous switching regressions (ESR): Endogenous switching regressions are a methods that help test assumptions about the exogeneity of treatment effects from survey data (Powers DA, 1993). The fundamental strategy has been to employ switching regression model variations, wherein distinct outcome regimes are assigned to the treatment and control groups. Regression-based methods are also used, where two regimes of model outcomes one for the treatment group and the other for the competing/control group allow for the endogeneity of choice into treatment (Maddala and Nelson, 1975). With this approach, the Heckman model's second level (outcome) equation is a switching regression, which is a key example. The endogenous switching regression (ESR) is a model that accurately measures the impact of cluster farming on technical efficiency, addressing the selection bias and heterogeneity of cluster farming impact (Geleta *et al*., 2017; Eshetu *et al*., 2022).

This motivates an endogenous switching regression model considers endogeneity, sample selection and complete interactions between participation and conventional and non-conventional inputs in the production function one production function for participant and another for non- participant (Fuglie and Bosch, 1995). In the endogenous switching regression approach, the participation decision is modeled by standard limited (i.e., binary) dependent variable methods. The formulas for other decision variables are then estimated differently for each group subjective to the participation decision. Particularly, the two-stage switching regression model uses a probit model in the first stage to determine the relationship between participation of cluster farming and a number of households, farm, and technology characteristics. In the second stage, separate regressions are used to model agricultural production conditional on a specified criterion function.

2.5. Empirical literature

The empirical review part discusses the previous research work related to the impact of cluster farming practice on maize technical efficiency. In addition, it discusses studies related to factor that affect cluster farming participation, and level of technical efficiency.

2.5.1. Empirical Studies of Technical Efficiency

The research study by Aynalem (2006) undertook a study on maize production TE in Mecha district of west Gojam zone of Amhara regional state was analyze by a single stage estimation technique for the parameters of the SPF and the technical inefficiency function. Estimate together with the Cobb-Douglas type production function where cross-sectional data was used in analysis. The result showed that technical efficiency score differentials among the sample farmers vary from 33% to 95%, where the mean efficiency levels was 78% implying there was a potential to improve productivity in maize production by 22% at the existing technology and input level in the area. Among the farm specific socio-economics and institutional factors hypothesized to affect the level of efficiency were sex, livestock holding, farm size and educational level were found to important determinates of TE. Farm size has negative effect of the TE of maize farm.

Tolessa (2022) investigate the TE of maize producers in the Gudeya bila district of western Ethiopia. The study SFP function to estimate the TE score. The study indicated that the mean TE of maize producers was 36% with minimum and maximum efficiency score was 1.78% 79.7% respectively. The study employed the Tobit model in order to identify the factor affecting the production efficiency. In addition, farm experience, land conservation practice, on-farm income and mobile use were the factor affecting maize producers.

A study by Anbes (2020) identified factor affecting the TE of smallholder farmers. The study used one-step maximum likelihood estimation result of the Cobb-Douglas SFP function. The model result showed that the mean value of the TE of the household was 0.59. The result showed that smallholders' farmers in Ethiopia can reduce the input requirement for producing the average output by 41% if the action became technically efficient. In addition, study showed that family size, educational level, farm size, land fragmentation, credit use, extension contact, off-farm activity, land quality and crop share were the factor that affect positively and significantly on the TE of smallholders crop production.

Aschalew (2020) investigate the TE of smallholder's farmers and identify the factor affecting maize production. The researcher applied one-step stochastic frontier truncated-normal models to estimate the farmers TE and identify the determinant of maize yield per hectare. The result indicated that the TE of maize producing farmers were 69.03%, which indicate 31.07% of the result was producing less than the potential maize production. The result of the inefficacy model indicated that age, gender, farm income, access of credit, row planting, number of active laborers, farm size, access to improved seed, and number of livestock were the factors that significantly affected maize producers technical efficiency.

Study by Kuse *et al.* (2018) analyzed the TE of sorghum producers in konso district of southern Ethiopia. The study employed the Cobb-Douglas SFP function for which TE was estimated. The result of the model reveled that estimated the mean TE of the sample household at 69%, which illustrate the existence of a possibility to increase the amount of sorghum output by 31% through efficiency use of the existing resource. The study also showed that land size, urea, DAP, oxen power, labor and chemical such as herbicide and pesticide were input variables positively and significantly affect the output.

2.5.2. Empirical Studies on Factor Affecting the Cluster Farming Participation

Chala and Fikru (2021) identified factor affecting smallholder farmer's participation in cluster crop production in west showa zone, Oromia region, Ethiopia. The study employing two-stage sampling technique and the data was collected from 160-farm households and the study apply probit regression model. The study finding revealed that factor like dependency ratio, farm experience, marketable surplus supply, acquisition awareness, frequency of extension contacts and sex of the household (being male) were positively affected the probability of cluster farming participation decisions. However, factor like owning a larger number of livestock negatively affected of cluster farming participation decision.

A study by Gemechis *et al.* (2023) identified the factors influencing the household adoption of improved maize variety in Amuru district of horo Guduu wollega, Ethiopia. They used cross-sectional data to collect randomly selected sample household. Probit model was used to identify the factors affecting the household adoption to improve maize variety technology. The model result showed that educational level, number livestock owned, farm size, access to credit, access to training, access extension service and access to information were affect positively and significantly, family size and distance to the market affect negatively.

Solomon and Belayneh (2021) assessed the factors determining cluster farming participation in Dera woreda, South Gondar, Amhara Regional State. The study was used logit model to analyze the data. The model result indicated that education level, farming experience, training access, cooperative membership, and off-farm engagement are the variables that positively and significantly influenced farmers' decision to join agricultural cluster farming, whereas the age of the household head and the distance of the extension office from the household home had a negative impact on the decision.

Degefu *et al*. (2017), in their study in Gurawa Meta and Habro districts of eastern Ethiopia analysed the factors affecting adoption of wheat technology package by smallholder farmers. The study used 136 randomly selected households and applied two-limit tobit model to analyse the affecting adoption of technology package measured based on an index derived from five components of wheat technology package which include row planting, pesticide application, use of improved varieties and application of DAP and Urea. Among the variable included in the model variation in district, sex of the household head, age, distance to the market are negatively and significantly affected the adoption of wheat technology package and educational level, farm size, cooperative membership, dependency ratio and annual income of the household head were positively and significantly affected the adoption of wheat technology package.

Menasbo (2020) analysed the adoption of fertilizer application on smallholder commercialization. The study utilize cross-sectional farm household data collected randomly selected from 626 farm households in rural Tigrai northern Ethiopia. To analysis factor affecting the probability and extent of inorganic fertilizer adoption were used double-hurdle model hurdle one for probability of adoption and hurdle 2 for the extent of the adoption. The result showed that family size, higher number of male and female adults affect positively and significantly adoption of probability of inorganic fertilizer, while long plot distance and illiterate were key constraint that negatively affected the adoption inorganic fertilizer.

A study by Zakari *et al.* (2021) analyze factors influencing farmers' participation to group membership in Sahel, Niger. In the study, the probit model was used to analyze those factors. The model result showed that factors such as the family size, the number of livestock owner, the size of the farmland, contact with extension agent, ownership of irrigated land, and market access have a positive and significant effect on a farmer's decision to join a group. Thus, the household with irrigated land, larger the household size, high extension contacts, larger number of animals and better access to markets such as roads are more likely to join group membership.

2.5.3. Impact of Cluster Farming on the Technical Efficiency

Solomon (2021) analyzed the impact of cluster farming on farmer's productivity and commercialization in Dera of south Gonder zone of Amhara region, Ethiopia. The data collected from 203 households using multistage sampling technique. The data analyzed using descriptive and econometrics model. The logit model, PSM and IPWRA estimation methods are used to analyze impact of cluster on maize productivity and commercialization. The result showed that educational level, farming experience, training access, cooperative membership, and off-farm engagement are positively and significantly influence farmer's decision to join agricultural cluster farming, while age and distance to extension office affected negatively. The study finding also indicated that cluster farming increased maize yield by up to 8.46 qt/ha (21.34%

change) using PSM and 6.59qt/ha(15.83%) using IPWRA. In addition, the study showed that scaling-up the cluster farming have significant role toward improving maize productivity and commercialization.

Mekdelawit *et al.* (2020) investigated the impact of contract farming on smallholders farmers TE of sesame producers in Ethiopia. The study used DEA to estimate sesame production efficiency. The study investigated the impact of contracting farming of TE by applying PSM. Based on the DEA result shows study contract-farming participants had an average TE score of 0.68 and non-contract farming participants had a 0.56 TE score under constant returns scale. The result indicated that to increase TE, participant and non-participant can reduce the amount of input used by 32% and 44% respectively. Farmers increase TE under variable returns to scale by decreasing input level on average by 23% and 32% for participation and non-participants respectively. In addition, the PSM result indicated that contract farming increase TE by 11%.

Wogderes (2020) evaluated the contribution of cluster farming to the livelihood of farmers in Siyadebrina Wayu district of north Shewa, Ethiopia. The study used descriptive statistics to analyze the quantitative data. The study showed that cluster farm participants increase wheat productivity relative to business as usually farmers. Furthermore, the study identified cluster farming participants had better improvement in asset building capacity in terms of depositing money and purchasing physical asset that helps them to change life style as relative to non-cluster participants. The research further revealed as the market linkage created among the cluster participant farmers and the farmer union of the *kebele* with the aim of creating better opportunities for cluster participants, was not as such strong due to the overall limited capacity of the farmer union.

Tesfaye *et al.* (2016) studied the impact of improved wheat technology adoption on productivity and income in Ethiopia. The study employed the propensity score matching methods to carry out the impact study. The probit model show that sex of the household head and livestock ownership increase the adoption of improved variety. Moreover, the result of propensity score matching improve variety adoption on average increased wheat productivity of adopter by about 1 to 1.1 ton/ha than non-adopter. Similarly, the result of PSM showed that the average income of adopter was 35 to 50% greater than the non-adopter household.

Abdul-Rahaman and Abdulai (2018) used PSM method to examine the impact of membership in rice group farming on farm yield and efficiency of smallholder farmers in northern Ghana. The findings showed that, in comparison to farmers who produce individually, participation in farmer groups is related with increased yield and technical efficiency. Additionally, land, fertilizer, chemicals, rice variety, soil quality, and access to irrigation have significant impact on rice yield for both members and non-members of farmer groups.

Study by Solomon and Belayneh (2021) have evaluated the impact of cluster farming on maize productivity and commercialization in Dera district of south Gondar zone of Amhara national regional state by using logit model, PSM and IPWRA estimation methods. According to the findings, cluster farm participants generate more yields. These results suggest that cluster farming improves productivity.

As previously mentioned, several studies have used various approaches to examine the variables that affect farmers' decisions to engage in-group or cluster farming and how that decision affects agricultural production in many developing nations. However, research on farmers' decisions to participate in cluster farming and how those decisions affect the yield of certain crops, like maize, still needs to be available in Ethiopia and the study area. This suggests that further research is required to close this knowledge gap and add to the body of literature.

2.6. Conceptual Framework of the Study

Agro-clusters, contracts farming, groups, cooperatives, organizations, and other closely related producer organization ideas are prevalent in many farming systems (Dubbert, 2019). As a result, framework in figure 1 illustrates the concept and interrelationship among different variables and CF interventions in the context of this study. Factors such as household characteristics (sex, age, educational status, household size, off-farm income, and family size), asset ownership (farmland and livestock holdings), and institutional characteristics (access to credit, cooperative membership, training, extension service, information source and distance from market) are factor affecting farmers decision to participate in cluster farming and maize technical efficiency directly or indirectly. The improved agricultural policy clustering are crucial for agricultural sector by improving the production and productivity, income source and modifying livelihoods of farming households and reducing poverty. This is mainly state that farmers which only participate in cluster if it contributes more to profit than cost, given productive resources. The variable that determine the technical efficiency like seed, fertilizers, labor, ox-power and chemicals were considered. Thus, participate in cluster implies if the net benefit (i.e. in this case Technical efficiency) is higher than the benefit from non-participate in cluster. The linkage among components showed general relationship that exist and investigation of all connection. In addition, factors that hypothesized are associated with participation in cluster farming.

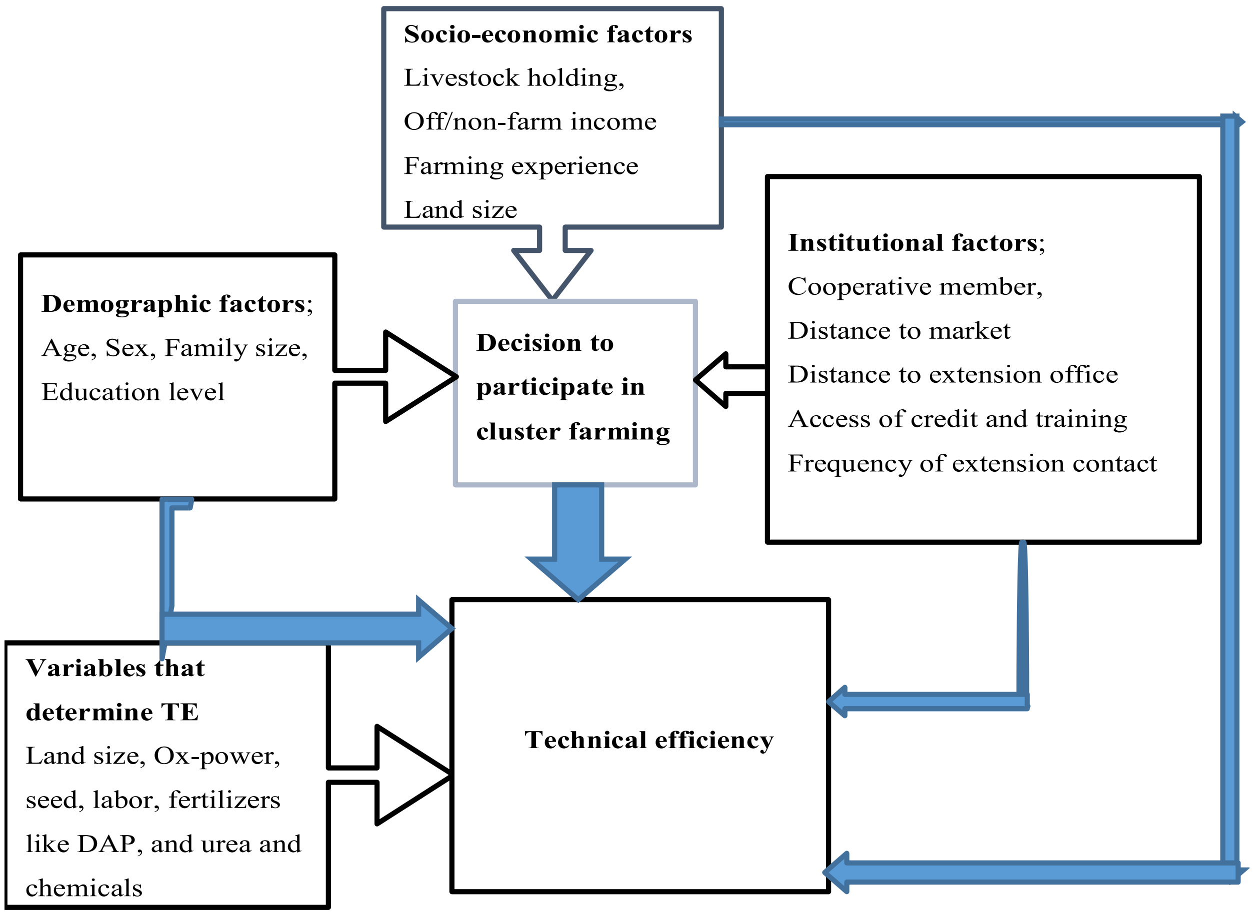

Figure 1 Conceptual Framework

Source: Constructed by researcher based on different literatures review (2024)

3. RESEARCH METHODOLOGY

3.1. Description of Study Area

This study was conducted in Siltie zone silti district, Siltie is one of the zones of Central Ethiopia region. The capital of this zone is worabe, which is around 172 kilometers from Addis Ababa along the main road that connects to Hossana. It's structured in to ten district and one urban town. The features of Siltie zone has plains, hilly areas, and plateaus. This zone contains own distinct agro-climatic conditions, including 37% highland and 63% mid-land, regards to climate. The rainfall is between 700 and 1818 mm. In addition, 95.5 % of people are engaged in agriculture which indicate agriculture is the main economic activity in this zone and district. Nonetheless, there are not many variations between seasons in the normally high temperatures. According to the 2019 meteorological data, the mean annual temperature in this zone is 12 - 26°C. The zone can be classified into three major climatic zones on the basis of altitude, rainfall and temperature: 20.6% Dega, 74.4% Woina-Dega and 5% Kolla from the total area of the region which shows the study area have varied ecological zones that range from lowland to highland, which makes possible the cultivation of various crop.

Silti district is border on the east from Oromia region, on the west from Alicho wurero, on the north from Gurage zone and Lanfuro and Dalocha on the south. Approximately 207,151 people (101,460 men and 105,691 women) live in this district, of whom 19,211 are urban and 187,940 are rural. About 53,112 hectares of land make up the entire districts of that, 25,635 hectares are annual agricultural land, 11,221 hectares are perennial, 6,365 hectares are grazing pasture, forests, and 6,904 hectares are bush land (SZBoA, 2019; Derebe *et al.,* 2020). Among ten districts, five of them are involving in cluster farming of the major crops such as wheat, maize, barley and *teff*. These districts are Silti, Snkura, Mirab azernet, Hullbareg and Alicho. From those districts, one of the major one that appear maize cluster farming is Silti district. Cluster farming is being initiated to increase the quality and amount of maize output Silti district. The major cereal crops grown in cluster farming in the study area are wheat, maize and *teff*. The farm households in the study area participating in the cluster farming required to contribute at least 0.2 ha of land to participation in cluster farming. In those cluster farmers implement the most effective farm agronomic recommendations and undertake to grow cluster priority crops.

The area of this district has been bound by the community is around 13,500 hectares of land. In addition, In Silti district, 4494 hectares of land are cover by maize seeds of which 3958 hectares of are cultivated in clusters and totally in 91 clusters are appear in 10 *kebele* (SZBoA, 2024; ATA, 2019b). In this district widely adopted cluster farming initiative which optimizing use of full package of agricultural input.

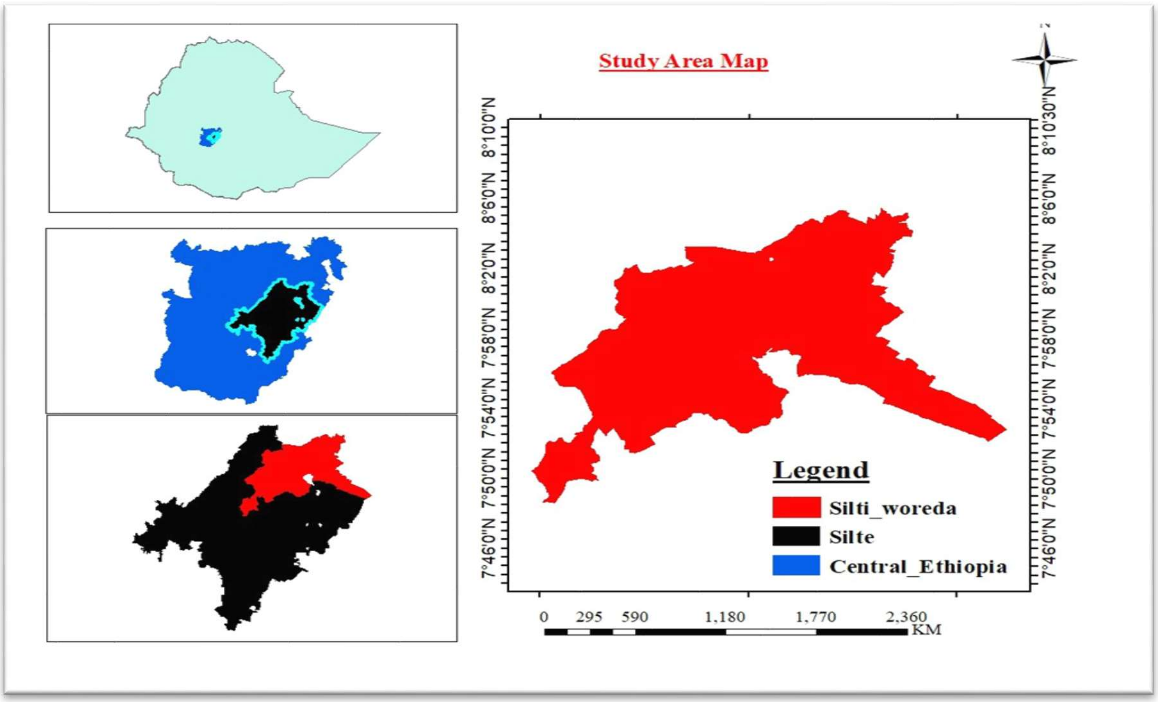

Figure 2 Map of the Study area

Source: Own design with the support of GIS expert, (2024)

3.2. Data type, Sources and Collection Methods

Both primary and secondary data were used for the study. The primary data collected from smallholder maize producers achieved through interview. The questioners were pre-tested on the sample households from sample households from participates and non-participants in maize cluster farming before conducting the actual field survey to check its relevance. Enumerators having experience in data collection was recruit and train as well as follow with close supervision in order to minimize errors in data collection and correct them. Finally, survey questionnaire was translated into local language. Secondary data was collected from the cooperative union, district and *kebele* level agricultural office, journal papers and books.

3.3. Sampling Technique and Sample Size

Multistage sample procedure was used to select the sample households. In the first stage, Silti district purposefully selected from Siltie zone based on maize production level and the current potential to undertake maize cluster farming from the existing districts. There are 24 *kebeles* in the districts and among those *kebeles* 10 of them were practicing maize cluster farming. In the second stage, from the existing *kebeles* that undertake cluster farming, four *kebeles* were selected randomly. Finally, the households were stratified into two strata which is cluster farming and non- participants and the total respondents were selected using simple random sampling from the two groups with respect to proportional size of the two groups in respective kebele. Yamane's (1967) formula was used to determine the total sample size of smallholder farmers in the study area.

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

Where, n = sample size, N = population size of maize producers in the district (according to the districts agriculture office total maize producers in the district is 18,402), e = level of precision which is 6% was used due to homogeneous characteristics of the population and consideration of budget constraint because the reduction of budget by the fund supporting organization. Hence, according to Yamane's formula, the intended sample size was 274 farmers. However, for this study, 304 farmers were surveyed to accommodate potential inaccuracies.

Table 1 Sample district and *kebeles* households with respect to their participation

District	Kebele	Total household	Non-participant Sampled	Participant Sampled	Total sampled	Proportion
Silti	Dubena bate	961	41	59	100	32.9
	Shelewasho	953	42	45	87	28.6
	Dubo sabola	854	32	22	54	17.76
	Dubena enseno	883	36	27	63	20.74
Total		**3,651**	**151**	**153**	**304**	**100**

Source: The districts agriculture office, *kebeles* office and own computation, 2024

3.4. Method of Data Analysis

3.4.1. Descriptive Statistics

The descriptive statistics analysis such as maximum, minimum, mean, standard deviation, percentages, and frequency was used to analyze the demographic and socio-economics characteristics of the maize producers' households. In addition, test statistics such as t-test was applied for continuous variables, chi-square ($\chi 2$) test was used for dummy variables to check the significance different and associations of variables between cluster participants and non-participants of maize producers, respectively.

3.4.2. Econometric Methods

For this study, stochastic frontier production function and endogenous switching regression (ESR) models was used for measuring the technical efficiency and the impact of cluster farming on TE respectively. Factors that affect the cluster farming participations was captured using the first stage ESR (probit model).

The stochastic production frontier approach (SPFA): The stochastic frontier production model was used to estimate the technical efficiency level. It is used due case that, it has potential of capturing the random effects like weather, measurement error, which leads inefficiency among smallholder farmers. Stochastic frontier analysis was based on a specific functional form which was introduce by (Aigner *et al*., 1977) and Meeusen, (1977) and were independently proposed to indicate those firms/farmers usually do not achieve their full potential output due to the existence of inefficiencies. The stochastic production frontier was developed by adding a symmetric error term (vi) to the non-negative error term and in general is given by;

$$Y_i = f(X_i ; \beta)\exp(V_i - U_i) \qquad (4)$$

Where, Yi is output of maize, $f(X_i ; \beta)$ and $\exp(V_i - U_i)$ represents both the deterministic and stochastic part of the production frontier function respectively. V_i is a random error having zero mean, which is associated with random factor. The above equation written as

$$\ln(yi) = \beta 0 + \beta 1 \ln(area) + \beta 2 \ln(seed) + \beta 3 \ln(fertilizer) + \beta 4 \ln(chemical) + \beta 5 \ln(labor) + \beta 6 \ln(oxen) + \mathcal{E}i(vi - ui) \qquad (4a)$$

Where: *ln* natural logarithms, yi represents the maize output of sample farmer, area represents the land allocated for maize production per hectares, labor is the numbers of both hired and family labor used by the farmer in man-days. Oxen is the numbers of oxen power used for operation by the farm household in oxen-day, fertilizers is the quantity of NPS and urea fertilizers applied by farmer in maize and measured in kilogram. In addition, maize seed represents the quantity of maize seed used in kilogram; β is production coefficient or unknown parameters to estimate. ε_i is an error term made up of two components; v_i is random error having zero mean, N (0, δ2v) which is associated with random factors. Error such as measurement error in production and weather effect, which are out of the control of the farmers and assumed to be independently and identically distributed as N (0, δ2v) with a random error. u_i is the non-negative efficiency measured relative to the stochastic frontier that is firm not attaining maximum efficiency of production and ranges between 0 and 1, which is also assumed to be independently and identically distributed as half-normal at zero mean or truncated half-normal at mean μ, N [μ, δ2u].

Given the assumptions of the stochastic frontier model (1), inference about the parameters of the model can be based on the maximum-likelihood estimators due to the standard regularity conditions hold. Aigner *et al.* (1977) suggested that the maximum-likelihood estimates of the parameters of the model obtained in terms of parameterization, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $(\lambda) = \sigma_u / \sigma_v$ under the work of (Coelli and Battese, 1995), the technical efficiency function is give as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i\beta_i)\, e^{v_i - u_i}}{f(X_i\beta_i)\, e^{v_i}} = e^{-u_i} \qquad (5)$$

Where Y_i is the actual yield obtained by farm household, Y_i^* is the maximum potential yield from cluster maize, u_i represents the technical inefficiency of i^{th} farmer, β_i is a vector of unknown parameters to be measured, and v_i are unobserved random terms that are independently distributed with zero mean and variance of δ^2 .

Endogenous switching-regression model (ESR): To estimate the impact of technology adoption and farm practices, several studies have been used econometric models such as PSM, instrumental variables, and etc. Aside from the selection bias associated with non-randomness in technology adoption (CF in this study), heterogeneity of technology impact is an important econometric aspect. However, the result of the PSM is likely to be biased if there are unobservable variables that might influence adoption decisions and the outcome variable. The instrumental variable capture only unobservable heterogeneity but it assumed that the parallel shift of outcome variable might be consider as treatment effect (Musa *et al*., 2017; Bekele *et al*., 2014). The strength of ESR model is overcome those problems. The estimation framework of the ESR model also satisfy the objective of this study by determine factor affecting smallholder maize producers decision to participate in cluster farming which is first stage ESR using probit model and its subsequent impact on smallholder farmers maize technical efficiency which is second stage of ESR. Therefore, this study applied endogenous switching regression model.

The difference between the utility from participant (U_iA) , and otherwise (U_iO) of cluster maize farming which is unobservable. So that an individual i participate maize cluster for a given survey period on his/her farm plot if expected utility from participation (U_iA) is greater than the expected utility from non-participation (U_iO), $M^* = U_iA$ -$U_iO > 0$. The ESR model is apply to evaluate the impact of cluster farming on the technical efficiency of smallholders maize farmers. The switching regression was modeled in two stage the first stage is estimation of the selection equation that estimate the decision to participate cluster farming. This stage of the ESR framework is estimate using probit model and various studies used this methods (Kirtti and Phandindria, 2018; Gorst *et al*., 2018; Million *et al.,* 2019), this study was adopt random utility framework to describe a household decision to participate cluster farming. As rational farmers would participate in cluster farming if the utility from participation (U_A) is greater than the utility from non-participation (U_N). Even if the two utilities are unobservable, they can be express in the latent variable model specified.

$$M^* = \alpha Z_i + \eta_i, \qquad Y_i^* = \begin{cases} 1\ if\ Yi\ > 0 \\ 0\ otherwise \end{cases} \qquad (6)$$

M^* Represents the latent variable that capturing the unobserved preferences (expected benefits from the participation decision with respect to not participating in CF) associated with the participation of cluster farming is determined by observed institutional, asset ownership and characteristics of the household (Z_i) and (η_i) is error terms.

In this study, participants are define as the farmers practicing maize cluster farming on its farmlands and take the maize production produce from that land. If the selection equation of the first stage is endogenous in the outcome equation (second stage) the result would be biased and inefficient (Moti *et al*., 2018). This is because of variables in the vectors Z and X may overlap. Therefore, the ESM to be identify, it is important to include selection instruments that affect the participation decision but not the technical efficiency of the outcome variable (Bekele *et al*., 2014). Means the instrumental variable should affect the participation decision to cluster farming but not the outcome variable. Moreover, the validity of the instrumental variable was checked using a falsification test. In this study source of information from government extension (yes = 1) and research center (yes = 1) used as instrumental variables.

In the second stage of ESM framework that link between the outcome variable and a group of explanatory variables on the participation decision is identify by using OLS regression with selectivity adjustment. According to Ndeye *et al*. (2018), the second stage of the ESR is the outcome equation that split the endogenous model into two regimes participant (regime 1) and non-participant (regime 2) can be written as an endogenous switching regime model:

$Regime\ 1$: $Y_{1i} = \beta_1 Xi_1 + \epsilon_{1i}$ if $M_i = 1$ (participant) (7)

$Regime\ 1$: $Y_{2i} = \beta_2 Xi + \epsilon_{2i}$ if $M_i = 0$ (non-participant) (8)

Where: Y_1 and Y_2 are the outcome variable in this study maize technical efficiency and X_i is a vector of explanatory variable related to maize production, β_1 and β_2 are vectors of parameters, ϵ_{i1} and ϵ_{i2} are the error terms for participants and non-participants respectively. In the switching regression model, the selection bias would manifest itself in error terms ϵ and μ. As long as the unobserved variables are not capture by the explanatory variables, the error terms of the production and selection equation are correlate with corr $(\epsilon, \mu) \neq 0$. The error terms μ_i, ϵ_{i1} and ϵ_{i2} follow a tri-variate normal distribution with zero mean and the covariance matrix is specify as:

$$\text{Cov}(\mu_i, \epsilon_{i1}\, \epsilon_{i2}) = \begin{bmatrix} \sigma_\mu^2 & \sigma_{1\mu} & \sigma_{2\mu} \\ \sigma_{1\mu} & \sigma_1^2 & . \\ \sigma_{2\mu} & . & \sigma_2^2 \end{bmatrix} \quad (9)$$

Where: $\sigma^2{}_\mu$, $\sigma^2{}_{1\mu}$, $\sigma_2{}^2\mu$, is representing the variance of the error terms in the selection and the two production maize 1 and 2 is respectively. $\sigma^2{}_{1\mu}$ and $_\sigma{}^2{}_{2\mu}$ are the covariance of the selection equation and error term (μ_i) and the maize production regimes 1 (ϵ_{i1}) and 2 (ϵ_{i2}) is respectively. The dot (.) shows that the maize 1 and 2 outcomes cannot be simultaneously observed for a farmers and hence the covariance is not present (Madalla, 1999). Equations (8 -10) should be estimated in a way that account for the correlation between the error terms. A two-stage procedure can be use to estimate the probability of participating in maize cluster farming using the maximum likelihood estimation approach. The estimated probability (cluster participate) are used to estimate selectivity terms that account for the endogeneity of maize cluster farming participation. The selectivity terms denoted by 0 and 1 are express as: λ_1

$$E\ (w1i|M\ =\ 1) = \sigma\mu 1 \frac{\phi(x_i\beta\ \ )}{\Phi(xi\beta)} =\ \sigma\mu 1\lambda 1 \quad (10)$$

$$E\ (w2i|M\ =\ 0) = \sigma\mu 2 \frac{\phi(x_i\beta\ \ )}{1-\Phi(xi\beta)} =\ \sigma\mu 2\lambda 2 \quad (11)$$

Where ϕ is standard normal density function, Φ is the normal cumulative density function $\lambda_1 = \frac{\phi(x_i\beta\ )}{\Phi(xi\beta)}$ and $\lambda_2 = \frac{\phi(x_i\beta\ )}{1-\Phi(xi\beta)}$ are the inverse mills ratio obtained from the selection equation and are incorporated in equation 7 and 8 to correct the biases arising from selection in the stage procedures. Based on Bekele *et al.* (2014), the actual and counterfactuals structure, the average treatment effect on treated (ATT) and untreated (ATU) was estimated using the effects of predicted values of the dependent variables for participants and non- participants, in relation to calculating their correlation coefficients for selection criteria.

$E\ (Y_{1i}|M = 1; z) = Z_{i1}\delta_1 + \sigma\mu_1\lambda_1$ (participant with the participation of cluster farming) (12)

$E\ (Y_{2i}|M = 0; z) = Z_{i2}\delta_2 + \sigma\mu_2\ \lambda_2$ (non-participant without participating cluster farming) (13)

$E\ (Y_{2i}|M = 1; z) = Z_{i1}\delta_2 + \sigma\mu_2\lambda_1$ (participant decided not participate of cluster farming) (14)

$E\ (Y_{1i}|M = 0; z) = Z_{i2}\delta_1 + \sigma\mu_1\lambda_2$ (non-participant decided to participate cluster farming) (15)

Where (14) and (15) are counterfactual statement, which means the ATT effect is compute as the difference between (12) and (14) and that of ATU is calculated as the difference between (13) and (15). In actual and counterfactual context, the (ATT) and (ATU) was estimate using the effects of predicted values of the dependent variables for participations and non-participations, in relation to calculating their correlation coefficients for selection criteria.

$$ATT = E\ (Y_{1i}|M = 1) - E\ (Y_{2i}|M = 1) = (Z_{i1}\delta_1 + \sigma\mu_1\lambda_1) - (Z_{i1}\delta_2 + \sigma\mu_2\lambda_1) \quad (16)$$

$$ATU = E\ (Y_{2i}|M = 0) - E\ (Y_{1i}|M = 0) = (Z_{i2}\delta_2 + \sigma\mu_2\ \lambda_2) - (Z_{i2}\delta_1 + \sigma\mu_1\lambda_2) \quad (17)$$

3.5. Variables Definition and Hypotheses

3.5.1. Outcome Variable for this Study

Maize Technical efficiency: has been determined as an outcome of interest to estimate the impact of maize cluster farming. It is a capacity of farmers that measures the relative ability of farms to get the maximum feasible output from set of inputs used. It was measured by technical efficiency scores after estimation of the stochastic frontier model. To estimate the following variables were used.

3.5.2. Variables to Estimate Technical Efficiency in Stochastic Frontier Model

Dependent variable (Output variable): Output refers to the amount of maize produced by sample households during meher production season (2023/2024), expressed in kilograms (kg). In order to operate efficiently, this is eventually transformed to natural logarithm.

Independent variables (Production inputs): The amount of maize land available, labor (both family and hired), maize seed, fertilizers (NPS, urea), chemicals (pesticides and insecticides), oxen, have an impact on the maize output. Justifications of input variables are present as follows:

Maize seed: the quantity of maize seed planted, used for maize production in the survey period by sample households. It was measured in kilogram (kg).

Inorganic fertilizers: the amount of NPS or Urea added and used for maize production measured in kilogram (kg).

Land size: the area a farm households assigns for maize production measured in hectare.

Oxen: is the numbers of oxen power used by farmers in oxen-day by sample households for tillage and for threshing of maize.

Labor: the number of labor force, hired and family labor power used by the farmer in man-days for maize production.

Chemicals: It refers to the amount of chemicals (pesticides and insecticides) used by the sample maize producers for maize production in the year 2023/24 measured in liters.

3.5.3. Dependent and Independent Variables for Participation in Cluster Farming

Dependent Variable (Treatment Variable):

Cluster farming participation: The dummy dependent variable representing cluster farming participation; taking a value 1 if farmers are participant in maize cluster and 0 otherwise:

Independent variables: Several factors, including resource endowments, institutional support systems, demographic characteristics, as well as the researcher's perspective was influence smallholder farmers' participation in maize cluster farming during the study period. Lists of explanatory variables and their expected signs that was used to determine the factors influencing involvement in maize clusters are provide below. These are the specific hypotheses that is select for the given explanatory variables as follow.

Sex of household head: It is a dummy explanatory variable that takes a value of 1 if the household head is male and 0 otherwise. It is explain that male-headed households are more likely than female-headed households to participate in maize cluster farming (Tesfaye *et al*., 2016). Therefore, female-headed households have unfavorable effect on the participation of maize cluster farming. Due to the fact that, male group expect to obtain more benefits from cooperation while, the female farmers tend to be less likely to work together with other farmers (Wardhana *et al*., 2017). According to Adekunle (2018) male farmers have the capacity to working together in groups as compared to female farmers due to man-power of male farmers and time consumed in group farming.

Educational level of household head: it is a continuous explanatory variable measured in years spent in education by the household head. An educated farmer is better able to gather information, evaluate costs and benefits of new farming practices thereby participating in CF. Formal and informal education significantly and positively affects the probability for a household to be a member of an agricultural collective action group (Adjin *et al*., 2020). Farmers with more education are aware of more sources of information, more efficient in evaluating and interpreting information new programs than those with less education (Omotesho *et al*., 2015). Education not only facilitates participation but also enhances productivity, especially among adopters of improved technology (Nasir, 2022). Studies by Sisay *et al.* (2019) and Anbes (2020) prove and conclude that educational level has a positive effect on the efficiency of crop production. Therefore, the education status of the household head was expected to have a positive effect on maize cluster farming participation.

Total land size: It is a continuous variable measuring the land owned by the household in hectares. The larger the farm, they adopt a new technology as they can afford to devote part of their land to try new technology and land is one of the key factors for agricultural production and study indicate that households who have large cultivated land size are in a better position to participate in group farming (Zakari *et al.*, 2021). Therefore, it was expected that farmers who have larger land size have better possibility of participation in maize cluster farming.

Family size of household head: This is a continuous variable estimate in terms of man equivalent (ME). If there are a large number of family members, the greater availability of the labor force that help for production purposes and the adoption of new technologies, and hence, the better possibility of the family participating in the maize cluster farming (Kindye *et al.,* 2023). Having a large family size may imply that the household has enough labor supply for participation in different income generating activities, such as production cooperatives (Gashaw *et al.,* 2018). Therefore, family size has a positive effect on the participation of households in participation decisions.

Age of the household head: It is a continuous variable estimate as the farm household head's age measured in years. It is expected that older farmers have less accepting of innovations because they have more experience with their traditional farming practices and are typically risk-averse (Tsega *et al.,* 2019). However, according to Leta *et al*. (2018), young farmers tend to be more risk-takers and responsive to new technologies. In addition, older farmers may be averse to new technology, while young farmers may be more disposed to trying out novel technology and accept risk associated with adoption of new technology (Kinuthia and Mabaya, 2017). Thus, age of households is hypothesized to negatively affect to maize cluster farming participation.

Total livestock Holdings (TLU): The total number of animals owned by the household, expressed in tropical livestock units (TLU), it is a continuous variable. Which serve as drought animals and produce manure, which can lead to high crop output, owning livestock can be an input for crop production (Tesfaye *et al.,* 2016). To engage in new agricultural practices that can boost income used for building assets from wheat production, owning more cattle provides an additional source of cash income (Tesfaye *et al.,* 2016; Leta *et al.,* 2018). Thus, it is hypothesized that livestock ownership has a positive effect on maize cluster farming participation.

Access to credit: It is a dummy explanatory variable with a value of 1 in the access of credit and 0 otherwise. It has an impact on a farmer's capacity to get the required inputs in the proper amounts at a right time. Maize growers who have received credit has able to buy the inputs they need to increase maize productivity on time. Anbes (2020) and Aschalew (2020) indicated that access to credit affects economic efficiency positively. Therefore, credit is expected to increase the decision to participate in maize cluster farming.

Off/non-farm participation: This dummy explanatory variable has a value of 1 in the event that the head of the household participates in off/non-farm activity, and 0 otherwise. Participation in off/non-farm activities influence positively and negatively on farmers' performance in agricultural practices. Smallholders earn money from these activities, which can help implement new agricultural practices. However, these activities can also compete for labor and skill, potentially counterbalancing the cash income advantage of off-farm activities (Abdulai and Huffman, 2014; Tesfaye *et al*., 2016). As such, it is difficult to identify the signs of off/non-farm activity on cluster farming participation means it may be affect negatively or positively.

Extension contacts: This is a continuous explanatory variable that represents the frequency of extension contact with maize farmers per year. The stronger the linkage between producers and extension experts, the more information flows and technological knowledge transfers. Those maize producers who have frequent contact with development agents are likely to produce better than the others. Study by Sisay *et al*. (2019) and Anbes (2020) found that extension contact affected TE positively. Thus, it hypothesized that there exists a positive relationship between extension contacts and cluster farming participation in maize production.

Distance to nearest market: This is continuous explanatory variable, expressed in kilometers (km), represents the distance from the homestead to the nearest market. Geographic location of the households like road and infrastructure, also have the effects on the decision of farmers to be members or not. Accordingly, farmers who live closer to all-weather roads are better prone to participate in cluster farming (Adjin, *et al*., 2020). Hence the variable is hypothesized that it is expected negatively influence to the cluster farming participation in maize production.

Membership in Agricultural Cooperative (MCOOP): It is a dummy explanatory variable take value 1 if the head of the household is a member of an agricultural cooperative 0 otherwise. Cluster farming help to farmers to participate in group activities that helps them to share ideas on profitable farming practices and implement it as well as participate in better market of inputs or selling of outputs and thereby improve their income. Group membership allows farmers to discuss their problems and go for alternative solutions (Zakari *et al,* 2021). It is expected that households with group experience (past experience in collective action) to have a higher probability of participating in in cluster farming than those work individually. It expected to play crucial role in adoption of improved agricultural technology. Farmer's membership to cooperative has positive and significant influence on adoption behavior, implying that farmers who are members of farmer cooperative are more likely to adopt improved technologies (Kehinde 2021).

Source of information: (INFOSO): It is dummy variable which take value of 1 if the households have access to information from extension agent and research center and 0 otherwise. The provision of relevant information helps farmers to become aware of and get better understanding about the important of cluster farming. A study found that the provision of information increase the probability of farmers to participate in group farming (Abdul-Rahaman and Abdulai, 2018). Therefore, information access is hypothesized to be positively related with cluster farming participation decision.

Availability of training (AVTRIN): It is a dummy explanatory variable take value 1 if the head of the household is access to training 0 otherwise. Training improves in farmers' managerial and technical skills and hence encourages farmers to participate in CF. Training can be theoretical and practical demonstration, on input use (fertilizer, seed and chemical application), weeding and are found to most important by the farmers. Solomon and Belayneh (2021) showed that those farmers who had access to training have the probability of participating in cluster farming. Training of farmers is expected to positively affect the farmers' participation in cluster farming of maize.

Table 2 Variables specification and hypothesis

Variables	Variables definition	Type of variable	Measurement	Expected sign
EDHH	Educational level	Continuous	Year	+ve
OFFNI	Off/on-farm income	Dummy	1or 0	+ve or -ve
TLU	Total livestock holding	Continuous	TLU	+ve
FAMlS	Family size	Continuous	manequivalent	+ve
HHSEX	Sex of household head	Dummy	1or 0	+ve
HHAGE	Age of household head	Continuous	year	-ve
LNSIZ	Land size	Continuous	ha	+ve
DNM	Distance to nearest market	Continuous	km	-ve
CU	Credit access	Dummy	1 or 0	+ve
EXTC	Extension contacts	Continuous	Per year	+ve
INFOEX	Information from extension agent	Dummy	1/0	+ve
INFORC	Information from research center	Dummy	1/0	+ve
MCOOP	Agricultural Cooperative membership	Dummy	1 or 0	+ve
AVTRIN	Availability of training	Dummy	1 or 0	+ve

4. RESULTS AND DISCUSSION

This chapter discusses the result of descriptive and econometrics analyses. The first section presents the descriptive analyses of the socio-economic, demographic, institutional and other farm characteristics of the sampled maize producer households in line with their participation. The econometric analysis part presents technical efficiency measurement, the determinants of maize cluster farming participation and the impact of maize cluster farming on the technical efficiency of maize producers.

4.1 Descriptive Analysis

4.1.1. Descriptive Statistics of Continuous Variables

This part tries to discuss socio-economic, demographic, institutional and other farm characteristics among participants and non-participants. Table 3 below presents the continuous explanatory variables used in participation decision and its impact on maize cluster farming. Based on the results, there was a statistically significant difference between participants and non-participants in terms of age, education level, family size, livestock owned, total land and frequency of extension contacts.

The mean age of the sample household heads was 42.13 years and the mean age of cluster farming participants' and non-participant households were 48.22 and 35.98 years respectively. The result show that, the average education level in years of schooling of household head was approximately 2 years. Furthermore, it was observed that the average educational level of cluster participants was higher than that of non-participants with a mean schooling of approximately 3 and 2 years, respectively. The t-value results indicate that there was significant difference among participants and non-participants of maize cluster farming with respect to the age and educational of household heads at 1 and 5% significance level, respectively.

The average land size of cluster farming participants was 1.04 ha of land, while 0.76 ha for their counterparts. This indicate that cluster farming participants own greater cultivated land than non-participants. The t-value result of farm size shown that there was existence of statistically significance mean difference between two groups at 1% level. The result also indicated that the maize producers' households in the study area had on average approximately 5 TLU. Comparing the two groups, maize cluster participants had greater average livestock (6 TLU) than non-cluster participants (4 TLU). The t-value results for farm size and livestock ownership indicate that there was significant mean difference between participants and non-participants at 1% level

The results in Table 3 indicated that the average family size (man-equivalent) of the total sampled households was approximate to 4. Which can be consider as a proxy for the labor resource for maize production and the result shows that the mean family size of cluster participants and non-participants were almost approximately equal to 5 and 4 respectively. This is important due to the family size is the main source of labor for developing countries like Ethiopia. The other important variable was frequency of extension contacts with the sampled farm households. According to the study results, cluster participant households get a higher average frequency of contacts (13.96) as compared to the non-participant (2.1). This result indicated cluster participant households had better opportunity to get services of extension contacts related to new agricultural technologies and practices. The t-test result shows that there was significant difference in terms of family size and frequency of extension contacts between cluster participants and non-participants at 1% significance level.

Table 3 Descriptive statistics of continuous variables

Variables	**Non-Participant (N = 151)**		**Participant (N= 153)**		**Total Sample (N=304)**		**T-Value**
	mean	**SD**	**mean**	**SD**	**Mean**	**SD**	
Age	35.98	7.752	48.22	9.37	42.13	10.55	-12.4***
Education level	1.629	2.87	2.86	2.88	2.25	2.9	-3.74**
Family size(man equivalent)	3.5	1.3	4.6	1.7	4.07	1.6	-6.25***
TLU	3.699	2.377	5.43	2.77	4.57	2.72	-5.82***
Total land	0.759	0.283	1.04	0.48	0.7	0.48	-6.16***
Frequency of extension contact	2.1	4.54	13.96	15.23	8.07	12.72	-9.18***
Distance from nearest market	7.65	2.53	6.27	3.06	7.01	2.9	4.65

*** And ** indicate significant probability levels at 1% and 5% respectively.

Source: From own computation (2024)

4.1.2. Descriptive Statistics of Categorical Variables

The descriptive summary of categorical variables used in this study are presented below in Table 4. From those categorical variables, access to training, access to credit, access to information and cooperative membership had shown existence of significant association with maize cluster participants' status, while sex and off/non-farm participation did not show the existence of significant association with maize cluster participants' status.

With regard to the sex of the household heads, about 85.5 % of the total household heads were male and the remaining 14.5% of the respondents were female headed. In addition, for participants and non-participants, the proportion of male headed households were 87.58 and 83.44% respectively.

Another key factor was the accessibility of training, among the respondents 62.17% had access to training concerning maize production and the importance of cluster farming, while 37.83% of the respondents did not receive any training. From cluster farming participants, 89.55% had access to training which was higher as compared to 34.44% of the non-cluster participants. More advanced training helps to enhance access to information about the importance of technological practices, which help farmers to increase their productive capacity. Furthermore, the chi-square results indicated that there was a significant association between training access of the households and their maize cluster participants' status at 1% significant level.

The other variable was participation in off/non-farm activity which was one of the economic characteristics of the sample households and important for income source for farmers of the study area. The statistical result indicted that from the total sampled households, 42.76% of them were engaged in off/non-farm activities. Moreover, 43.14% of cluster participants and 42.38% of non-cluster participants engaged in off/non-farm activities.

Agricultural credit is important resource that could be used to boost agricultural production and productivity as it is expected to enhance farmer's ability to purchase essential agricultural inputs. According to the study result in Table 4, shows that only 21.4% of the sample respondents had credit access. Further, 28.76% of cluster participants and 13.9% of the non-participants had access to credit. The chi-square test result shows that there was a significant association between credit access and maize cluster participants' status at 5% level.

The other institutional variable of interest with cluster farming participations decision was membership in various agricultural association/cooperative, as this helps farmers in accessing essential agricultural inputs timely and at fair price. The chi-square test result shows that there was existence of significant association between cooperative membership and maize cluster participants' status at 1% level. As shown in Table 4, from the total sampled households, 30.3% were member of the agricultural cooperatives in the study area. The result also indicated that from sampled cluster participant households, 42.2% were member of agricultural cooperatives which was higher as compared to 17.88% for non-participants.

The other variable was source of information to the farmers in the study area. Farmers get information from different source, among the sample respondents about 66.12% accessed information from government extension agent and 10.2% from research center. Among the sample of cluster participant and non-participant households 77.78 and 54.3% were access information from government extension agent respectively. This shown the higher proportion of cluster participants access information from extension agent compare to non-participants.

Table 4 Descriptive statistics of discrete variables

Variables	Description	Non-participant (151)		Participant (153)		Total (304)		x^2-value
		Freq.	**%**	**Freq**	**%**	**Freq.**	**%**	
Sex	Female	25	16.56	19	12.42	44	14.5	1.05
	Male	126	83.44	134	87.58	260	85.5	
Off/non-farm income	Yes	64	42.38	66	43.14	130	42.76	0.0176
	No	87	57.62	87	56.86	174	57.24	
Info_ from extension agent	Yes	82	54.3	119	77.78	201	66.12	18.7***
	No	69	45.7	34	22.22	103	33.88	
Info_ from research cent	Yes	1	0.7	30	19.6	31	10.2	29.8***
	No	150	99.3	123	80.4	273	89.8	
Access of credit	Yes	21	13.9	44	28.76	65	21.4	9.97**
	No	130	86.1	109	71.24	239	78.6	
Training access	No	99	65.56	16	10.45	115	37.83	98.12***
	Yes	52	34.44	137	89.55	189	62.17	
Cooperative membership	No	124	82.12	88	57.5	212	69.7	21.8***
	Yes	27	17.88	65	42.5	92	30.3	

***, and ** indicate significant probability levels at 1%, and 5% respectively

Source: Own computation survey (2024).

4.1.3. Descriptive Statistics that Identify Technical Efficiency of Maize Production

The technical efficiency of smallholder maize farmers is determined by many factors. In order to realize the aspects, it is essential to know the descriptive statistics of the input utilization and the maize yield obtained in the study period. The quantity of maize seed for sawing, oxen-power, labor force, chemical and fertilizers (NPS and urea) were the factors that used to identify technical efficiency and quantity of maize production as an output. The result in Table 5, shows that on average the households produced 42.2 qt/ha with standard deviation of 16. 3, and the amount of maize produced by the participants and non-participants were 53.15 and 29.2 qt/ha, respectively. This shows the cluster participants produce more maize output than their counterparts. The average amount of maize seed used for sowing by the households were 11.74 kg with standard deviation of 6.8. Cluster participant households used higher mean quantity of seed (13.2 kg) than non-participants (10.3 kg).

The average land size allocated for maize production by the sample households was 0.5 ha and mean value of land distribution for maize production by cluster participants (0.54 ha) slightly higher than non-participants (0.46 ha). In the study area, all of the respondents used improved maize varieties. The other variables used as input was fertilizers which include NPS and urea. The mean amount of NPS fertilizers used by the total sample households was 49.05 kg. The average amount of NPS fertilizer utilized by participants and non-participants were 54.5 and 43.57 kg, respectively. On the other hand, the mean amount of urea used by the total sample households was 57.87 kg. And the mean amount of urea used during the production season by cluster participants and non-participants were 71.6 and 43.98 kg, respectively.

Maize producers in the study area used daily labor for different farming activity, including for tillage, chemical application, sawing, weeding, harvesting, threshing and other farm activities. The source of labor in the study area are either hired or family labor. The result shows that the average amount of labor in maize producer households was 26.6 man-days with standard deviation of11.2. Further, the average labor utilized by cluster participants and non-participants were found to be 29.2 and 23. 98 man-days, respectively. The other input variable used by maize producers is oxen-power. The result indicates that the average oxen-power utilized by the households was 4.3 oxen-days, and the average number of oxen used by the participants and non-participants were 4.6 and 4 oxen-days per production season, respectively. Another essential variable used by the farmers were chemicals. The survey result shows that the average chemicals utilized by the households for maize production were 0.49 liter. In addition, the average level of chemicals used by cluster participant and non-participant households were 0.54 and 0.44 liters, respectively. Finally, the t-test value indicates that, except chemicals, all the remaining factors of production shows significant mean difference among the groups at 1% and 5% significance levels.

Table 5 Descriptive statistics of variables to identify technical efficiency

Variables	**Non-participants**		**Participant**		**Total**		
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**t-value**
Maize output (qt/ha)	29.2	6.09	53.15	19.4	42.2	16.3	
Land size (ha)	0.46	0.2	0.54	0.32	0.5	0.27	-2.6**
Maize seed (Kg)	10.3	4.97	13.2	7.89	11.74	6.8	-3.92***
NPS (Kg)	43.57	20.1	54.5	32.2	49.05	27.4	-3.5**
Urea (Kg)	43.98	22.3	71.6	45.1	57.87	38.2	-6.75***
Oxen (oxen-day)	4.02	2.3	4.6	2.4	4.3	2.4	-2.3**
Labor (man-days)	23.98	8.4	29.2	12.8	26.6	11.2	-4.24**
Chemical (liter)	0.44	2.7	0.54	0.59	0.49	1.9	-0.45

*** And ** indicate significant probability levels at 1%, and 5% respectively.

Source: Own computation survey (2024).

4.2. Econometric Model Results

Before running the model, the hypothesized independent variables were checked for multicollinearity problem among the variables. To diagnose the multicollinearity problem between the explanatory variables, the variance inflation factor (VIF) for continuous variables and the contingency coefficient for dummy variables were used. As a rule of thumb, if there is multicollinearity problem among explanatory variables then the value of VIF greater than 10 (Gujarati, 2009) and contingency test pair-wise correlation matrix shows very weak collinearity between any two independent variables in which the value is less than 0.7 among the variables. The VIF and contingency test result show that there is no serious multicollinearity problem among explanatory variables (Appendix Tables 3 and 4). In addition, to check for the existence of the heteroscedasticity problem, the Breusch-Pagan test was performed and the test result indicated that there is no heteroscedastic problem (Appendix Table 5). Also, to test the instrumental variables by using falsification test, in this study access to information from extension agent and research center was used as an instrumental variable. This variables were not directly related to the outcome variable (technical efficiency) but found to significantly relate to cluster participation (Appendix Table 6). The falsification test was conducted by using OLS regression on the outcome variable with the selection instrument.

This section has three parts. The first part is the estimation of technical efficiency level by using Cobb-Douglas stochastic frontier model. Next, identified the main factors affecting the decision of cluster farming participation from binary decision model (probit), and at last, applied the ESR model to estimate the treatment effect on the outcome variables of interest (technical efficiency).

4.2.1. Estimation of Technical Efficiency Level

Before the estimation of the SFP for the analysis of the technical efficiency of maize producers' different test were conducted. The decision to choose appropriate functional form for the data, either Cobb-Douglas or Translog production function, depends on the calculated value of likelihood ratio. As indicated by Kodde and Palm (1986), the number of restrictions is taken to be equal to the degree of freedom. If the calculated LR value is less than the critical chi-square value then Cobb-Douglas functional form was used to estimate the technical efficiency. In Table 6, the test results, of the null hypothesis (H0) stating that all elasticities of the interaction terms in Translog function are equal to zero, against the alternative hypothesis (H1) of they are different from zero are presented. The tests were done based on generalized likelihood ratio test, $\mathbf{LR} = -2\ [\log L(H0) - \log L(H1)]$ or $-2\ [\log L(cobb) - \log L(translog)]$ so, $\mathbf{LR}$ = -2(-37.2588 – 6.4553) = 87.428 The calculated log likelihood ratio (LR) was found to be 87.428 and the critical chi-square (χ^2) distribution with the degree of freedom at 21 and a 1% significance level is 88.43. This shows that it is possible to use the Cobb-Douglas production function due to the calculated likelihood ratio is less than the critical value. Therefore, in this study Cobb-Douglas functional form was used to estimate the technical efficiency of the sample households.

Table 6 Likelihood ratio test result of the data

Null hypothesis	LR	Critical $\chi 2$-value	DF	Decision
$\mathbf{Ho}: \boldsymbol{\beta}_7 = --, \boldsymbol{\beta}_{27} = \mathbf{0}$	87.428	88.43	21	Accepted

DF= degree of freedom, LR=likelihood ratio, at 1% significant level.

Source: own survey result, (2024).

As it was explained at the methodology part, SPF model was used to analysis technical efficiency level of maize producers in the study area. Land size, seed, labor, fertilizers (NPS and urea), chemical and oxen power were used in the model. The results in Table7, shows that the (Wald chi2 (6) = 1484.73) was significant for a group of maize producers at 1% significant level indicating that the model as the whole was significant in the study area. Specifically, labor, fertilizer, chemical, maize land size, and oxen power were the significant variables that determine technical efficiency level of maize producers in the study area. The coefficients of explanatory variables are equivalent to sensitivity of the output with respect to each input. For instance, the coefficient of oxen power indicated that a 1% increase in the use oxen power increases the maize output by 0.126% keeping the quantities of other input constant. This result is similar to Bekele and Regasa. (2019) and Missiame *et al*. (2021). Similarly, a 1% increase in the number of labor force increases the amount of maize output by 0.843% *ceteris paribus*. The quantity of chemical utilized affects the amount of maize production positively at 1% significant level, in which a 1% increase in the amount of chemical used increases the maize output by 0.015% when other things are held constant. In addition, fertilizers affect the maize production level positively at1% significant level. This result is consistent with the findings of Milkessa *et al*. (2019) and Anbes (2020).

This result implies that labor, fertilizer, chemical, and oxen power were the main inputs to determine the output level of maize at best practice. Furthermore, the gamma value (γ) is 0.66, which implies 66% of total variation of maize output is due to technical inefficiency. The remained effect of variability on the potential maize yield was due to random shock which accounts 34%. Moreover, the result shows that the return to scale of production process of the data was increasing returns to scale. That is, the sum of the input variables elasticity was 1.29, showing that a unit increase of all inputs would increase the maize output by more than one unit. This result indicates that maize production in the study area is found in the stage-I of production. In this stage as the inputs increase the output increases at an increasing rate due to the more efficient use of the variable input. The result is consistent with the findings of Solomon *et al.* (2020), and Zinabu *et al*. (2021). Land size negatively affected maize output in which 1% increase the maize land size decreases the amount of maize output by 0.22% ceteris paribus. This is due to the fact that, if the land size is too large, it may be difficult to manage and maintain the maize crops effectively. This can lead to inefficiencies in the use of resources, such as water and fertilizers, which can result in a lower maize output.

Table 7 Estimates of the Cobb-Douglas frontier production function

Variables	Coef.	Std. Err.	z	P>z
Lnseed	.105	.09	1.16	0.248
lnoxen	.126**	.05	2.42	0.015
lnlabor	.843***	.103	8.2	0.000
lnchemical	.015***	.003	4.6	0.000
lnland	-.22	.12	-1.92	0.055
lnfert	.42***	.07	6.00	0.000
_cons	-2.053***	.52	-4.01	0.000
sigma_u	.24	.03	8.42	0.000
sigma_v	.17	.02	8.93	0.000
Variance of parameters				
(σ^2) = $\sigma^2_u + \sigma^2_v$	0.0865			
Lambda (λ) = σ_u/σ_v	1.38	.044	31.69	0.000
Gamma (γ) = (1- 1/1+λ^2) or (σ^2_u / σ^2)	0.66***			
Return to scale	1.29			
Log likelihood	-37.2588			
Wald chi2(6)	1484.73***			

***and ** indicate significance levels at 1% and 5% respectively

4.2.2. Technical Efficiency Score among Maize Producers

The results in Table 8 indicated the technical efficiency results among maize cluster participant, non-participant and the total sample households. The estimated technical efficiency of the sample households ranged from 31.5% to 95.7%, with a standard deviation of 0.141. This indicates that the least efficient maize producers achieved an output that was 68.5% below the maximum potential, while the most efficient producers operated at 4.3% below the maximum possible production frontier. The minimum technical efficiency of maize cluster participants in the study area was 52.6%. This shows that the least performing of cluster maize producers in the sample households were 47.4% less than the maximum potential yield. And the minimum technical efficiency of non-cluster participants was 31.5% which means the least performing of non-cluster maize producers in the sample households were 68.5% less than the maximum potential output. The maximum technical efficiency of cluster participants and non-cluster participants were 95.7 and 91.5%, respectively. This means the best performing of maize producers in the study area 4.3 and 8.5% below the maximum potential possibility frontier for cluster participants and non-cluster participants, respectively.

The finding of this study reveals that, the mean technical efficiency level of the sampled maize producer farmers in the study area was 74.2%, implying that the average households were producing below their potential possibility frontier level, such that there is existence of inefficiency in their production of maize. The mean value of technical efficiency shows that the level of maize output of the sample respondents can be increased on average by about 25.8% if appropriate measures are taken to improve the level of technical efficiency of maize growing farmers. In the other word, there is possible to increase yield of maize by 25.8% using the resources at their disposal in an efficient manner with the existing technology and resource. In addition, the mean technical efficiency of maize for cluster farming participants and non-participants were 82 and 66%, respectively. The mean difference among the two groups was statistically significant at 1% probability level. This result indicated that, for maize cluster participants and non-participants, it was possible to increase the maize output by 12 and 34%, respectively without using extra inputs. The result further indicates that there exists a room for improving the existing level of maize production through enhancing the level of farmers' technical efficiency.

Table 8 Technical efficiency score

Group	Obs	Mean	Std. Err.	Std. Dev.	Maximum	Minimum	T-value
Non-participants	151	0.66	0.012	0.143	0.915	0.315	
Participants	153	0.82	0.007	0.085	0.957	0.526	
Total	304	0.742	0.008	0.141	0.957	0.315	-11.74***

*** implies significant at 1% probability level.

Source: own survey (2024)

4.2.3. Distribution of Technical Efficiency Score among Maize Producers

The technical efficiency score distribution of cluster participants and non-participants households is shows in Figure 3 below. The results shows that the majority of farmers (75.65%) fall under the technical efficiency range of (0.31-0.6). This would implies that about 75.65% of the sample households in this groups have a room to enhance their maize production at least by 40%. Furthermore, smallest share of farmers' technical efficiencies group falls under the range of (0.61-0.99) which covers 1.7%. Similarly, the second largest efficiency distribution of sampled farmers attained of technical efficiency score ranged from (0-0.3) which covers 16.11% of the efficiency score.

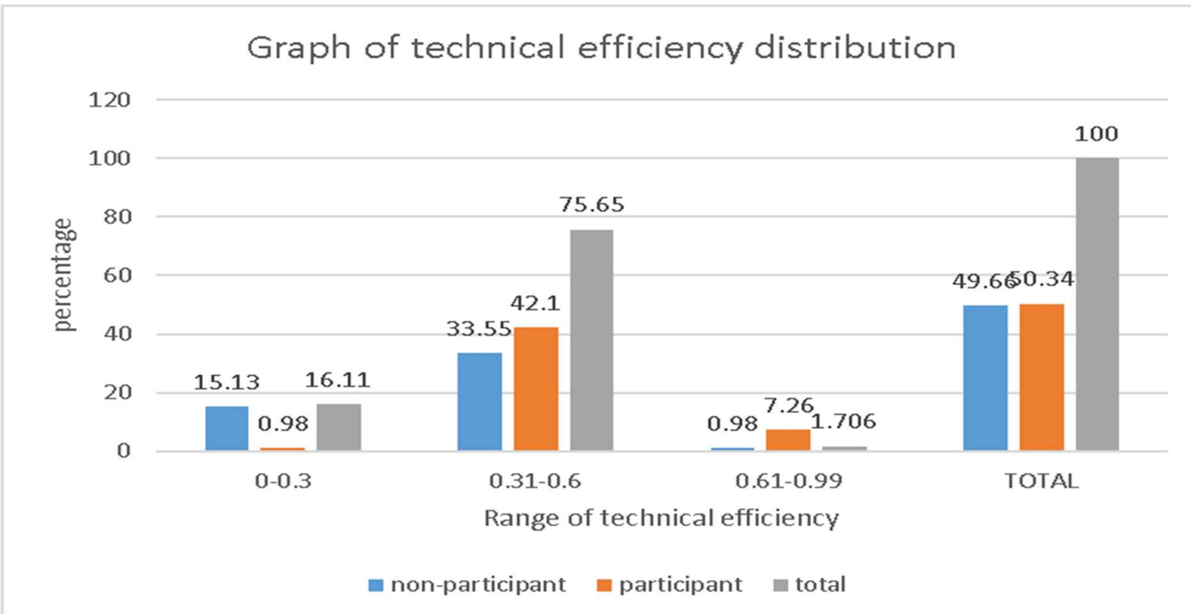

Figure 3 Technical Efficiency distribution

Source: own survey (2024)

4.2.4. Factors Affecting Cluster Farming Participation

The binary probit model was applied as a selection model of ESR in order to identify the determinants of cluster farming participation by farmers in study area. (A Wald chi2 = 296.15, P = 0.000) for the overall fitness of the model was significant at 1% probability level. This means that the overall model result of explanatory variables used in the model had aggregately able to describe farmers' participation in maize cluster farming (Table 9).

The results in Table 9 indicated that out of fourteen independent variables hypothesized to affect the participation decision, nine variables were found to be significantly determine the participation in maize cluster farming at various probability levels. The probit regression results indicated that total cultivated land, education level, age, sex, access of training, frequency of extension contact, source of information from government extension and research center were positively affecting the maize cluster farming participation, while distance to the nearest market was negatively related to the cluster farming participation.

The result of the study indicated that the age of the household heads affected maize cluster participations positively at 1% significance level. The marginal effect result revealed that an increase the age of the household heads by one year increases the likelihood of maize cluster farming participation by 1.8% *ceteris-paribus*. This indicated that the higher the age of the household head, the higher the probability to participate in maize cluster farming. This means, the younger household heads were less likely to participate in maize cluster farming than the older household heads. This due to the fact that mostly age related to experience level old farm households more likely to participate in cluster farming due to their experience and knowledge in farming practice and better understanding of the land, soil and crop management in group, which can beneficial in managing cluster farm as compare to young farmers. In addition, the young farmers mostly focus on other activity to get income and less focus to farm activity. According to Tafesse *et al*. (2023) suggest that mature maize producing farmers can produce a high quantity of product in group and better experience with their farming than young farmers. This study also confirms to the study of Degefu *et al*. (2017) and Negese and Jemal (2020) who found a positive influence of age on agricultural technology adoption. But this result is dissimilar with the study by Leta *et al*. (2018), Tsega *et al.* (2019), and Aklilu *et al*. (2022) that found a negative influence of age on the adoption of new farming technology and confirming the younger age groups are more adopters as compared to the elder.

Sex of the household heads affected the probability of maize cluster farming participation decision positively at 5% significant level. The result of the study reveals that, other things remain constant, being a male head of the family would increase the likelihood of maize cluster farming participation by 10.8%. The positive effect of sex could be due to fact that male headed households have better access to knowledge and information about cluster farming, and better access to social network in the community. This study result coincides with Gebre *et al*. (2021) and Haile *et al*. (2022).

An educated farmer is better able to accumulate information, assess costs and benefits of new farming practices subsequently participating in CF. Educational level of the household heads had significant and positive relation with maize cluster participation at 1% of the probability level. The marginal effects result shows that, when other things remained constant, for additional one year of schooling of the household heads, the probability of participating in maize cluster farming increases by 2.6%. Education equips maize producers with a better understanding of agricultural practices and enhances their ability to make informed decisions, including the adoption of new farming techniques. This finding aligns with the studies by Negese and Jemal (2020) and Aklilu *et al*. (2022), which demonstrated that educational level positively influences the adoption of new farming technologies.

Land is one of the main factors of agricultural production and the households who have large cultivated land size are in a better position to participate in group farming. The model findings also revealed that the total land holding was one of the factors affecting farmers' likelihoods to maize cluster farming participation positively at 10% significant level. The result in Table 9 indicated that 1 ha increase in the cultivated land increases the probability of maize cluster farming participation by 10% *ceteris-paribus*. In fact, large land owners are more likely to participate in cluster farming due to its necessary resource to support the practice and it also have the advantage of economies of scale which make it easier to implement cluster farming. Moreover, it has one of essential resource to invest in the necessary technology to support cluster farming. This finding is consistent with the results of Million *et al*. (2019), Degefu *et al*. (2017) and Aklilu *et al*. (2022), which also showed that farmers with larger land holdings are more likely to adopt improved agricultural technologies.

Frequency of extension contact is one of the main ways that creates stronger linkage between producers and extension experts, and due to this more information flows and technological knowledge transfers to the farmers. As indicated in the results in Table 9, the variable extension contact was positively related to the probability of participating in maize cluster farming at 1% significance level. The marginal effect result shows that, for a unit increase in the frequency of extension contact with farmers per year the probability of cluster participation increases by 0.8% when all other factors are held constant. The result implies that the maize producers with more frequent contact with development agents and other agricultural experts who provide extension services were more likely to be technically efficient due to their higher chance to obtain more technical advice and a better opportunity to receive more agricultural package than those who do not contact them on regular basis. In addition, the provision of better extension service helps to the farmers to become more aware and obtain better understanding about the benefit of cluster participation and acquiring new knowledge regarding the new farming practice. This result is in line with the study of Abdurrahman and Abdulai (2018) who found that the access of information from extension agents enhances the probability of farmers to participate in group farming.

Training improves farmers' skill and awareness in area such as farm practices thereby enhancing their technical efficiency, input use and other practical demonstrations. The probit model result in Table 9 revealed that access to training was positively related to farmers' decision to participate in cluster farming at 1% significance level. The marginal effect results indicated that, keeping other factors constant, farmers who get access to training have 18.5% more probability of participation in cluster farming than those who do not have access to training. This indicates that training related to the managerial and technical abilities help the farmers probably to more participate in maize cluster farming. This study's result is consistent with the study by Solomon and Belayneh (2021) which indicated that farmers who participated in training have more probability to participate in cluster farming.

Another variables that determine cluster farming participation was distance to the existing nearest market in the study area. When the farmers reside close to the market, this facilitates the attainment of input supplies required by farmers easily and with lesser transaction costs allowing them to participate in cluster farming. The result of the study shows that the distance from nearest market influences cluster farming participation negatively at 1% significance level. The marginal effect result indicated that the increase in the distance from the nearest market by one km would decrease the probability of cluster participation by 2.1% other things remaining constant. Farmers who live far from market center expect higher transportation cost as well as loss of information on the availability of production inputs and output price. In addition, this constraint happens due to lack of the infrastructure like well-built road that connect to the existing market. This result is consistent with the findings of Ismail (2023) and Changalima and Ismail (2022) who indicated that the more close the market, the more households are likely to participate in maize market.

The probit model result also shows that access of information from extension agent and research center was positive influence on farmers' decision to participation in cluster farming at 5 and 1% respectively. This revealed that access of information provides more likely to adopt cluster farming. This due to the fact that access of information can help to farmers to connect with other farmers, buyers and suppliers, which can provide for collaboration, more aware and better understand about the advantage of cluster farming. This finding in line with the studies of Million *et al*. (2019), and Abdul-Rahaman and Abdulai (2018) who found that farmers who access to information increase the probability to technology adoption.

Table 9 Factors affecting cluster farming participation

Variables	**Coef.**	**St.Err.**	**Z-value**	**p-value**	**Marginal effect**
Sex	0.944**	0.372	2.68	0.011	0.108
Age	0.16***	0.025	10.58	0.000	0.018
Education level	0.23***	0.053	5.17	0.000	0.026
Man Equivalent	-0.156	0.097	-1.66	0.105	-0.018
TLU	0.079	0.055	1.44	0.155	0.009
Total land	0.88*	0.457	1.96	0.054	0.100
Off/non-farm income	-0.491	0.299	-1.65	0.101	-0.056
Frequency extension contact	0.07***	0.021	3.51	0.001	0.008
Info from DA	1.13**	0.523	2.24	0.031	0.128
Info from research center	2.62***	0.877	3.24	0.003	0.298
Access of training	1.63***	0.417	4.5	0.000	0.185
Credit access	-0.68	0.358	-1.590	0.119	-0.077
Distance to market	-0.18***	0.057	-3.48	0.001	-0.021
Cooperative member	-0.286	0.329	-0.88	0.385	-0.033
Constant	-9.34***	1.404	-6.65	0.000	
Pseudo -R^2	0.703	**Number of obs**		304	
Wald chi2 (13)	296.15***	**Prob > chi2**		0.000	
Log likelihood	-62.64				

***, ** and * indicate significant probability levels at 1%, 5% and 10% respectively

Source: own survey result, (2024)

4.2.5. Impact of Maize Cluster Farming on the Technical Efficiency of Maize Producers

This section elaborates findings arising from the endogenous treatment effect model. The ESR estimates of ATT and ATU account for selection bias arising from the fact that cluster participants and non-participants may be systematically different. The estimation of the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU), along with the heterogeneity effect (HE), demonstrates the impact of cluster farming participation on maize technical efficiency, as presented in Table 10. The result describes the expected value of technical efficiency level with the corresponding actual and counterfactual expectations, which means it predicts maize technical efficiency for participant households compared to what it would have been if they had not been participants. Similarly, non-participant households' maize technical efficiency was compared to the outcome of variables if they had participated in maize cluster farming. The estimate of average treatment effect on the treated (ATT) represents the difference between actual outcome of cluster participants and its counterfactual scenarios. On the other hand, the average treatment effect on the untreated (ATU) means the difference between the real unobserved expected outcomes of non-cluster participants and its counterfactual scenarios.

The predicted technical efficiency level of maize cluster participant was 82% and if those farm households had not participated in cluster farming, their technical efficiency would have become 61%. This finding shows that, for farmers who participated in maize cluster farming, their technical efficiency has improved by a score of about 0.21, which represents about 34.42% increase in the technical efficiency gains from cluster participants (Table 10). And, the causal effect of cluster farming on non-participants is about 0.13 which represents that if they participated in cluster farming their technical efficiency would increase by 19.7%.

The other one is the value of heterogeneity effect (HE) which concerned the phenomenon where the impact of a change or intervention varies across different groups. The value of heterogeneity effect from the findings suggested that there is existence of significant difference between cluster participants and non-participants. It also confirms the presence of unobserved heterogeneities that make cluster participants more technically efficient than non-participants. This finding is consistent with Missiame *et al*. (2021). The base of heterogeneity effect (BH1) for maize producers' technical efficiency revealed that if the current non-cluster participants had participated, they would have gained less technical efficiency (3%) than maize producers that participated. And base heterogeneity effect (BH2) indicated that participants would have a lower technical efficiency (5%) than actual non-participants if they had not participated. The overall transitional heterogeneity (TH), which is the difference between BH1 and BH2 shows the effect is positive 8%, and this implies that the impact of cluster farming participation on the technical efficiency of maize producing households is larger for participants than that of non-participants.

The study finding confirms that participation in maize cluster farming significantly and positively affects the participant farm households than non-participants. This is due to the fact that the farmers participating in the maize cluster farming has common goal and cooperate together by producing the same crop and gain from the economies of scale such as higher affordability of modern technology and input used, faster dissemination of extension service and proper utilization of input, which leads to higher technical efficiency. This finding is consistent with the results of Adane *et al*. (2019), Tezera *et al*. (2020), and Wegayehu and Shery (2021), who found that participation in new farming practice had significant and positive effect on crop productivity.

Table 10 Endogenous switching regression model (Average treatment effect)

Outcome variable	**Treatment effects**	**Decision category**		**Treatment effects**	**Change (%)**
		Participate	**Non-participants**		
Technical efficiency level	**ATT**	(a) 0.82 (0.0024)	(c) 0.61 (0.070)	0.21***	34.42
	ATU	(d) 0.79 (0.003)	(b) 0.66 (0.006)	0.13***	19.7
Heterogeneity effect	**HE**	BH_1= 0.03	BH_2 = -0.05	0.08***	

*** implies significant at 1% probability level,

ATT=Average Treatment effect on Treated; **ATU**= Average Treatment effect on Untreated; **HE**= Heterogeneity effect.

Source: own survey result, (2024).

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary

Agriculture is the backbone of Ethiopian economy and the focus of government growth and development strategy. However, Ethiopia's agriculture is largely characterized by small-scale subsistence farming, means majority of total area of cultivated land occupied by those farmers. Maize is one of the principal crops in Ethiopia, ranking first in production and productivity and second in area coverage. However, the average maize yield in the nation is still lower than the world average. Cluster farming is a strategy used by Ethiopian government to help smallholder farmers' transition from subsistence to commercial farming by improving access to modern technologies and market linkage. Maize production is also an important aspect of smallholder farmers in Siltie zone, Central Ethiopia region which is produced by using cluster as well as non-cluster. Despite the fact that various cluster farming schemes are growing in the country in general and in the study area in particular, the studies that have explored the effects of cluster farming on maize technical efficiency is still limited.

Therefore, this study aimed to evaluate the impact of cluster farming on the technical efficiency of smallholder maize producers in Siltie zone in Silti district, Central Ethiopia region. Specifically, the was done to determine the technical efficiency level of sample households, identify the factors that affecting farmers' participation in maize cluster farming and its impact on maize technical efficiency in the study area. The study is significant as it provides relevant information about cluster farming involvement and its effect on the technical efficiency level of maize growers, which can benefit various stakeholders, including maize producers, policy makers, extension agent and government and non-governmental organization.

The study employed both primary and secondary data to achieve the study objectives. Primary data was collected from a total of 304 sample respondents out of which 153 were cluster participants and 151 were non- participants. The primary data were obtained by using semi-structured questionnaire and household survey of smallholder maize producers while secondary data were obtained from various sources like journal articles, reports, districts and *kebeles'* offices and other respective stakeholders. A multistage sampling procedures was used to select representative sample households. In the first stage, Silti district was purposefully selected, and in the second stage, four *kebeles* were randomly selected from the existing maize cluster farming *kebeles*. In the third stage, households were stratified into two strata: cluster and non-cluster participants. Then, a total of 304 respondents were selected randomly including both cluster participants and non-participants.

The descriptive statistics and econometrics methods were used to analyze the data. The descriptive statistics were used to analyze the demographics, institutional and socio-economics characteristics of the respondents. From econometrics models, Cobb-Douglas stochastic frontier analysis (SFA) was used to estimate the technical efficiency of maize production, the probit model was used to identify the factor affecting farmers' participation decision in maize cluster farming and the endogenous switching regression model was used to evaluate the impact of cluster farming participation on the technical efficiency.

The results from the descriptive statistics of continuous explanatory variables revealed that, there was significant mean difference between participants and non-participants in terms of age, family size, educational level, livestock ownership, frequency of extension contact and total land. In addition, the chi-square test result of categorical variables indicated that there was a statistically significant association between cluster farming status and access to training, access to credit, access to information and cooperative membership.

The econometric model result shown that labor, fertilizers, chemical, land size and oxen power were significant factors influencing the efficiency level of maize producers. The scale of production was found to be in the increasing return to scale. The average technical efficiency of the sample households was 74.2%, indicating that there is a potential to increase maize output by 25.8% using the existing technology and resource. The mean technical efficiency of cluster participants and non-participants 82 and 66% respectively. The results from binary probit model show that age, sex, educational level, land size, frequency of extension contact, access of information and access to training have positively and significantly affected the probability of participation, while distance from the nearest market had negatively affected the participation decision.

The result of the ESR model revealed that cluster-farming participation had a positive and significant effect on the technical efficiency of maize producers. The average treatment effect on the treated (ATT) shows that cluster farming participants had about 34.42% higher technical efficiency compared to what they would have achieved if they had not participated. In addition, the value of heterogeneity effect (HE) suggested that there are significant differences between cluster participants and non-participants, which can be attributed to unobserved factors that make cluster participants more technically efficient than non-participants.

5.2. Conclusions and Recommendations

As a conclusion the study found that maize cluster farming participants had significantly higher technical efficiency as compared to non-participants. The key factor that influenced the probability of participation in maize cluster farming were identified, including socio-economic, demographic and institutional variables. The finding of this study provides valuable insight for policy maker and agricultural extension service to promote and support the adoption of maize cluster farming practices, which can lead to improved technical efficiency among smallholder maize producers. To enhance the technical efficiency of maize production and promote cluster farming, the study recommends the following to be taken in to account for the upcoming intervention strategies.

Cluster farming has been found to positively and significantly affect maize producers' technical efficiency. Thus, the existing cluster farming initiative should be strengthened by providing comprehensive support, including improved access to inputs, extension services, and training opportunities. This could be done collectively by government, policymakers, agricultural experts, developmental agents and other stakeholders to increase the participation of smallholder farmers.

Educational status and access of training of the household heads were positively and significantly related to the households' decision in joining cluster farming. Therefore, promoting educational and capacity building programs to enhance the technical and managerial skills of smallholder farmers, which can contribute to their effective participation in cluster farming are necessary. In addition, priority should be given by government and other stakeholders investing on education to enhancing, strengthening and encouraging formal and informal education by using training and awareness creation to increase participation in cluster farming.

Frequency of extension contact was positively related to the participation of farmers in maize cluster farming. Therefore, agricultural experts and other concerned bodies should be provide continuous support and technical assistance to maize farmers to effectively use cluster farming practice and to increase their technical efficiency in maize production.

The participation in cluster farming was significantly and negatively affected by distance from the nearest market. The government body should invest in infrastructures development, particularly road network to improve market access and thereby reduce transaction costs for farmers. This encourages households' participation in cluster farming as it is essential for connectivity and extend particular support to those who have lack of essential market access.

Sex of the household heads was significantly and positively affecting the likelihood of the people participate in cluster farming. Thus, policy and development intervention should address the issue of the gaps between male and female headed households in cluster farming and should develop targeted policies and strategies to address the specific needs of female-headed households' to increase their participation in cluster farming.

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7. APPENDICES

7.1. Appendix Tables

Appendix table 1 Conversion factors of tropical livestock unit (TLU)

Livestock Category	**TLU**
Cows	1.000
Oxen	1.000
Heifers	0.750
Calves	0.200
Goats	0.060
Sheep	0.060
Donkey (adult)	0.700
Donkey (young)	0.350
Chicken	0.013
Horses or mules	1.100
Camels	1.250

Source: Storck *et al.* (1991)

Appendix table 2 Conversion factors for man–equivalents

Age group (years)	Male	Female
<10	0	0
10-13	0.2	0.2
14-16	0.5	0.4
17-50	1.0	0.8
>50	0.7	0.5

Source: Storck *et al.* (1991) as cited by Arega and Rashid, 2005)

Appendix table 3 Multicollinearity test for continuous variables in the decision model

	VIF	1/VIF
TLU	1.56	.641
Age	1.51	.66
Total land	1.45	.688
Man Equivalent	1.31	.766
Frequency of extension contact	1.22	.817
Distance from market	1.10	.912
Education	1.06	.944
Mean VIF	1.32	.

Source: Own computation from survey, (2024) Appendix table 4 contingency coefficient test of multicollinearity for dummy variable

Variables	sex	Off/non -farm	Credit access	Train access	Info_ source	Cooperative member	Info_ DA
Sex	1.000						
Off/non-farm income	0.051	1.000					
Credit access	0.146	-0.107	1.000				
Training access	-0.051	0.093	0.175	1.000			
Info_ from research	-0.016	0.107	0.089	0.240	1.000		
Cooperative member	0.149	-0.044	0.285	0.219	0.275	1.000	
Info_ from DA	0.002	-0.089	0.17	0.33	-0.45	-0.023	1.000

Source: Own computation from survey, (2024)

Appendix table 5 Heteroscedasticity test for variables in the decision model

hettest
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of maizefarmingtype
chi2(1) = 2. 5
Prob > chi2 = 0.114

Source: Own computation from survey, (2024)

Appendix table 6 falsification test for instrumental variable

Variable	**Decision stage to participant**	**Technical efficiency**	
	Coef.	**Participants**	**Non-participants**
Info from extension agent	0.021***	0.006	-0.04
	(0.02)	(.0165)	(0.023)
Info from research center	3.32***	-0.012	-0.066
	(0.494)	(0.02)	(0 .143)
_cons	-1.487***	0.822***	0.663***
	(0.224)	(0.008)	(0.018)
$\chi 2$	105.45		
p-value	0.000	0.499	0.645
Pseudo R2	0.25		
R-squared		0.003	0.0014
F-test		0.46	0.214
Prob > F		0.499	0.645
Root MSE		0.085	0.143
Log likelihood	-157.99		
Number of obs	304	153	151

Appendix table 7 Second stage ESR estimation of technical efficiency

		Technical efficiency				
	Participants			Non- participants		
Variables	**Coef.**	**St. Err.**	**p-value**	**Coef**	**St. Err**	**p-value**
sex	.03	.022	.178	.014	.037	.698
Age	-.001	.001	.593	-.005**	.002	.027
Education	-.004	.003	.171	.002	.005	.762
Man equivalent	.006	.004	.148	.018*	.009	.051
TLU	.001	.003	.775	-.001	.006	.848
Total land	.003	.018	.846	-.171***	.045	0.000
Off/non-farm inco	.016	.015	.302	-.028	.024	.24
Extension contact	-.001**	0.0005	.029	-.001	.003	.583
Access of training	.024	.023	.299	-.113***	.031	0.000
Credit access	-.007	.018	.695	.033	.035	.349
Distance to market	.004	.003	.133	-.015**	.006	.023
Cooperative member	.019	.015	.232	.003	.032	.916
mills1	-.02	.02	.327	-.01	.049	.84
Constant	.752***	.057	0.000	1.058***	.107	0.000
Prob > F	0.134			0.000		
R-squared	0.121			0.3		
F-test	1.48			3.9		
Root MSE	.08319			0.123		
Number of observation	153			151		

Source: Own computation from survey, (2024)

7.2. Household Survey Questionnaire

Dear respondent,

Your response to this questionnaire is serve as source of information to my thesis research work entitled with **'Impact of Cluster Farming on the Technical efficiency of Maize Producers in Siltie zone, Silti District Central Ethiopia Region.'** Any response you provide here is strictly confidential and will used only for the research purpose.

PART I: General Information

Date ____________ District ______________________ Kebele ____________________

Name of the enumerator: ___________________ Signature: ______________________

Maize farming type (specify) __________ 1. Cluster farming 0. Non-cluster farming

Part II. Demographic and Socioeconomic Characteristics of the Household

1. Sex of the household head 1. Male 0. Female
2. Age of household head …………………..Years
3. Marital status A. Single B. Married C. Divorced D. Widow
4. Education level of the household head?

A. Illiterate B. Read and write C. Formal education (______Grade)

5. Total family size ________________

Age category	**Sex**		**Total Number**
	Male	**Female**	
<10			
10-13			
14-16			
17-50			
>50			

6. What is your livelihood source of the household head?

A. Crop production B. Livestock rearing C. Both

7. If your livelihood source is crop production, then list the major crops produced and their annual income in 2023/24 production season.

Crop type	**Land (ha)**	**Amount (qt)**	**Quantity sold (qt)**	**Unit Price (ETB)**	**Total Value (ETB**
Maize					

8. If your livelihood source is rearing of livestock, list Livestock resources and income from the sale of livestock by household in 2023/24 production season

No.	Type of livestock	Number owned	Number of Livestock sold	Total income (ETB)
1	Oxen			
2	Cow			
3	Heifer			
4	Calve			
5	Horse			
5	Sheep /goat			
6	Donkey			
7	Chicken			
9	Others			

9. Do you have own land? A. Yes B. No

10. If yes for ***Q 9*, answer the following information of land holding size in the 2023/24.

Land type	Size (ha)	Rental value of land in ETB /Season
Own land		
Rented in land		
Rented out land		
Family land		
Others (specify)		
Total land		

Part III. Access to off/non-farm income

11. did you or any of your family participates in off/non-farm activities in the 2023/24 production season? A. Yes B. No

12. If you yes for ***Q 11***, what are the sources of off/non-farm income?

No.	Source	No. of days worked/ month	Income per working day (ETB)	Total income (ETB) per month
1	Daily labor			
2	Sell local drink			
3	Selling fire wood			
4	House servant			
5	Pension payments			
6	Carpenter			
7	Trading			
8	Clothes making			
9	Government work			
10	Hand craft			
11	Others (specify)			

13. How long your maize farming experience of the household head_________ in years?

14. How far is your maize plot from your home___________minutes or_ _______ km?

IV. Access to Institutional services

15. Do you have contact with extension agent in the 2023/24? A. Yes B. No

16. If you yes for ***Q 15***. How often you contact the extension agents in the 2023/24?

A. Weekly B. Monthly C. Quarterly D. Other (specify) ---------

17. If yes for ***Q 15***, what are the sources of extension services? (*Multiple answer possible*)

A. Development agents' B. NGO C. Research Institutes D. Others________

17. How far your home from Development agent office ____________ km

18. Do you have access to credit in 2023/24 production season in your area?

A. Yes B. No

19. If yes for ***Q 18***, for what kind of production purposes did you borrow money in 2023/24.

No.	**Purpose of credit to buy**	**Amount**	**Source**
1	Seed		
2	NPS fertilizer		
3	Urea fertilizer		
4	Farm land rent		
5	Chemical		
6	Other (specify)		
	Total credit (ETB)		

19. Do you have access to market information? 1. Yes 0. No

20. If you yes for ***Q 19*****,** who are the main sources of market information (multiple answers possible). A. Development agent B. Farmer association/cooperative C. NGO D. Research Center E. Others (specify) ___________

21. If you yes for ***Q 19***, how far the distance from the nearest market (km) ___________

22. Have you access to training related to maize production 1. Yes 0. No

22. Have you participated in any agricultural cooperative (association) in your village?

1. Yes 0. No

23. If you yes for ***Q 21*****,** what kinds of benefit you are getting being a member of agricultural association? (multiple answers possible). A. Access to seed B. Information exchange C. Training opportunity D. Discounted price E. Others specify ___________________

V. Maize production and Cluster farming practice

1. Have you participate in maize cluster farming A. Yes B. No

1. If you yes for ***Q 1,*** for how long have you participate it. ________________ Years.

2. If you are using maize cluster farming how did you join to it?

A. Self-decision B. Advised by DA C. Advised by other farmers

D. Because my land is found near to the cluster E. Forced by government officials

F. Others (specify) ------

3. If you were using maize cluster farming, what kind of production inputs did you get due to joining cluster farming? (Multiple choice possible) A. Fertilizer B. Seed C. Tractor D. combiner E. Chemicals F. Others _______________

4. If you are using maize cluster farming, what kind of services did you get due to joining maize cluster farming? A. Credit service B. Better extension C. Contract marketing arrangement E. Others (specify) ________________

5. How do you perceive the benefit you have generated from cluster farming participation?

1. Low 2. Medium 3. High

6. Which type of maize sawing method did you use in the production season?

A. Broadcast method B. Raw method C. Both

7. If you were using raw planting/sawing method in ***Q 6*** what kind of material did you use?

A. Raw planter B. Own hand C. Local materials D. Others (specify) ---------------

8. Did you use any weed control method to removed weed from your maize farm in the production season? A. Yes B. No

9. If yes for ***Q 11***, what kind of weeding method did you used?

A. Chemical methods B. Hand weeding C. Others (specify) ____________

10. If you are not participating maize cluster farming what are the reasons for not participating it. A. Not aware of it B. My farmland is in mountain area C. No cluster in my farmland area D. I do not believe on it E. Others (specify) __________________

VI. Technical efficiency (outcome variable) related terms

1. How much the total amount of maize produce (KG) in last production season in 2023/24 year_______________

No	Variety name of maize	land (ha)	Amount of output in (Qt)	Price per (Qt)
1	Local			
2	Improved			
Total				

2. Inputs utilized for maize production in last production season in 2023/24.

Type of input used	Unit of measure	Quantity used	Area in hectare (timad)	Cost of inputs per unit in ETB
1. **Maize Seed**	Kg			
2. **NPS**	Kg			
3. **UREA**	kg			
4. **Oxen(______pair)**	Oxen-days			
5**. Labor**	Man-days			
1^{st} tillage				
2^{nd} tillage				
3^{rd} tillage				
4^{th} tillage				
Chemical application				
Hand weeding				
Labor for sowing				
Labor for harvest				
Labor for transporting				
Labor for threshing				
6. **Chemical used**	litter			
Herbicides				
Pesticide				

II Key informant interview guide for maize cluster farming

1. What are the major crops produced in your woreda? ____________________________
2. How many kebele are present in your woreda__________
3. How many kebele are participating in maize cluster farming in your worada_________
4. What is the total size of land covered by maize cluster farming in your woreda? ______
5. How many hectare of land covered by maize production in your Woreda? ________
6. How many number of maize cluster are present in your district? _____________
7. What are the total numbers of maize producers in your district? _______________
8. What is the total land covered by production of different crops in cluster in 2023/24?
   Maize (ha) __________*Teff (ha)* _________Wheat (ha) _________ others (ha) ________
9. What is the recommended number of ploughing frequency by the maize package? _______
10. What is the recommended amount of fertilizer, seed type per one hector?
    NPS_________________ Urea____________ amount of seed sowing ___________
11. Why form cluster farms in your area? ____________________________
12. When the cluster formation was began in your woreda? ___________
13. How was the cluster formed and organized? _____________________
14. What is the criteria for the farmers to include in cluster farming?_____________________
15. Who organized these clusters in your woreda__________________?
16. Why some farmers are not participating in cluster farming? _________________
17. What is the benefit of cluster farming? _________________________
18. Who is the primary buyer of maize from the farmers in your area? ________________
19. What would you consider the most essential elements for the success of the CLF? ----------
20. What is your recommendation for the sustainability of the cluster farming? ____
21. Do farmers get enough support from development agents? What type of support? ____ ________________________
22. Do farmers get fertilizer, improved seed and chemicals according to their request? If no discuss why? ____
23. What are the existing good opportunities that encourage maize production and marketing in your area? ____

22\. Any additional suggestion Please forward _______________________________________

III <u>CHECK LIST FOR FOCUS GROUP DISCUSSION FOR MAIZE CLUSTER</u>

1. The adoption of maize cluster participants reached the expected levels. 1. Yes 0. No
2. If not for ***Q 1,*** what is the reason?

----

3. How is the extension services provision regarding to maize cluster farming?

____

4. Have you ever get training with regard to cluster farming 1. Yes 0. No
5. Do you think participating maize cluster farming has advantage on improving your production performance? 1. Yes 0. No
6. If you yes for ***Q 5,*** what is the advantage of cluster farming participation as compare to non-cluster participation.________________________________
7. Is there any disadvantages of cluster farming? ____________________

8. What are the common problems affecting peoples from participating maize cluster in your area? ____
9. What is your suggestion for the sustainability of the cluster farming? ____
10. **Do** farmers get enough support from development agents and other body? What type of support? ______________________________ ______________
11. What are the existing good opportunities that encourage maize production in your area? _____________________________________
12. What are yours general suggestions with regard to maize cluster farming in your area? ____

Thank you very much for taking your time!