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POST GRADUATE STUDIES

IMPACT OF *TEFF* CLUSTER FARMING ON RURAL HOUSEHOLD INCOME: THE CASE OF HIDABU ABOTE DISTRICT, NORTH SHEWA ZONE, OROMIA NATIONAL REGIONAL STATE, ETHIOPIA

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Impact of *Teff* Cluster Farming on Rural Household Income: The Case of Hidabu Abote District, North Shewa Zone, Oromia National Regional State, Ethiopia

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APPROVAL SHEET

I hereby certify that I have read and evaluated this Thesis entitled "**Impact of *Teff* Cluster Farming on Rural Household Income: The Case of Hidabu Abote District, North Shewa Zone, Oromia National Regional State, Ethiopia**" prepared under my guidance by **Solomon Legesse**. I recommend that it be submitted as fulfilling the thesis requirement.

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DEDICATION

I dedicated this thesis manuscript to my mother Mrs.Aberash Hunde for her dedicated encouragement in my academic achievement and life.

STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this thesis is my own work and all sources of materials used for it have been duly acknowledged. The thesis has been submitted in partial fulfillment of the requirements for Master of Science in **Agricultural Economics** degree at Salale University and is deposited at the University's Library to be made available to borrowers under rules of the library. I solemnly declare that this thesis is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

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BIOGRAPHICAL SKETCH

The author, Solomon Legesse, was born at Debela Bokolo *Kebele*, Hidabu Abote district, North Shewa zone. Oromia National Regional State, Ethiopia on 29 July 1976. He attended elementary education at Debela Kontere Primary School from 1983 to 1988. After that, he joined Gebre Guracha Secondary School starting from 1989 to 1994. Then, he joined Bako TVET College starting from 1996 to 1998 to pursue his diploma in the field of Natural Resource.Then starting from 1999 to 2002 he joined Haramaya University to pursue his BSc degree in Agricultural Economics. After his graduation, he employed in Hidabu Abote district Agricultural Office, Hidabu Abote TVET College office and other office related to my profession. Finally, in October 2021, he joined Salale University to pursue his MSc degree in Agricultural Economics.

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ABBREVATION AND ACRONOYMS

AGRA	Alliance Green Revolution in Africa
ATA	Agricultural Transformation Agency
ATT	Average Treatment Effect on the Treated
CIA	Central Intelligence Authority
CIA	Conditional Independence Assumption
CSR	Common Support Region
CSA	Central Statistical Agency
FAO	Food and Agricultural Organization
FGD	Focus Group Discussion
GDP	Gross Domestic Product
HADANRO	Hidabu Abote District Agriculture and Natural Resource Office
KII	Key Informant Interview
KM	Kernel Matching
LR	Likelihood Ratio
MoA	Ministry of Agriculture
NBE	National Bank of Ethiopia
NGO	Non-Governmental Organization
NNM	Nearest Neighbor Matching
PSM	Propensity Score Matching
RM	Radius Matching
SM	Stratification Matching
SSA	Sub- Sahara Africa
TLU	Tropical Livestock Unit

TABLE OF CONTENTS

Page

APPROVAL SHEET	iii
DEDICATION	iv
STATEMENT OF THE AUTHOR	v
BIOGRAPHICAL SKETCH	vi
ACKNOWLEDGEMENTS	vii
ABBREVATION AND ACRONOYMS	viii
TABLE OF CONTENTS	x
LIST OF TABLES	xiii
LIST OF FIGURES	xiv
ABSTRACT	xv
1.INTRODUCTION	1
1.1. Background of the Study	1
1.2. Statement of the Problem	4
1.3. Research Questions	6
1.4. Objectives of the Study	6
1.4.1. General objective	6
1.4.2. Specific objectives	6
1.5. Significance of the Study	6
1.6. Scope and Limitation of the Study	7
1.7. Organization of the Thesis	7
2. LITERATURE REVIEW	8
2.1. Theoretical Review	8
2.1.1. Basic concepts and definition	8
2.1.2. Agricultural technology adoption	9
2.1.3. Determinants of agricultural technology adoption	10
2.1.4. Theories of decision making	10
2.1.5. Cluster farming	11
2.1.6. Why cluster farming is needed in Ethiopia?	12

2.1.7. Impacts of adoption of modern agricultural technologies 14
2.1.8. Methodological and analaytical review 14
2.2. Empirical Review 16
2.3. Conceptual Framework of the Study 21
3. RESEARCH METHODOLOGY 24
3.1. Description of Study Area 24
3.2. Sampling Frame and Sample Size Determination 25
3.3. Research Design 26
3.4. Data Sources and Tools 26
3.5. Method of Data Analysis 28
3.5.1. Descriptive and inferential analysis 28
3.5.2. Econometric analysis 28
3.5.2.1. The propensity score matching (PSM) model 28
3.5.2.2. Mathematical specifications of PSM method 31
3.5.2.3. Implementation of the PSM 33
3.6. Variable Definition and Hypothesis 38
3.6.1. Dependent variable 38
3.6.2. Explanatory variables 38
4. RESULTS AND DISCUSSIONS 42
4.1.Descriptive Statistics 42
4.1.1. Characteristics of sample households in terms of categorical variables 42
4.1.2. Characteristics of sample households in terms of continuous variables 44
4.1.3. Adoption decision of teff cluster farming 46
4.2.Econometric Results 47
4.2.1. Factors Affecting adoption of teff cluster farming 47
4.2.2. Impact of Teff Cluster Farming on Income of the Household 49
4.2.2.1. Results of Propensity Scores Matching 49
4.2.2.2. Common Support Region 49
4.2.2.3. Matching Quality Test 50
4.2.2.4. Results of Average Treatment Effect for the Treated 51
4.2.3. Sensitivity Analysis 52

5. SUMMARY, CONCLUSION AND RECOMMENDATION 53
5.1. Summary and Conclusion 53
5.2. Recommendation 53
6. REFERENCES 55
7. APPENDICES 62

LIST OF TABLES

Table	Page
1:Summary of variable definition	42
2: Results of infrential analysis (Chi-square test for categorial variables)	44
3: Results of inferential analysis (t- test for continuous variables)	46
4. Adoption decision of cluster farming	46
5: Binary logistic regression model output	48
6: The distribution of propensity scores	49
7: Matching Quality Test among Treated and Control group	51
8: The average treatment effect of matched adopter and non-adopter households	52
9: Sensitivity Analyis	52

LIST OF FIGURES

Figure	Page
1: Conceptual framework	23
2: Map of the study area	24
3:The Distribution of propenstity scores for treated and untreated groups	50

ABSTRACT

Hidabu Abote is one of the potential districts in teff production. To enhance this potential production, cluster farming technology was introduced for smallholder farmers. However, household adoption level and its impact on household income have not been evaluated. Thus, this study aimed to measure the households adoption decision of teff cluster farming technology and evaluate its impact on household income. Multi stage sampling technique was used to select 196 sample households. Moreover, the study used a logistic regression model to identify the factors affecting the adoption decision of cluster farming technology while propensity score matching used to evaluate the impact of cluster farming technology adoption on household income. The result of the logistic regression model shows that the education level of the household head, frequency of extension contact, access to credit services, cooperative membership and market information had positive and significant effect on the household adoption decision of teff cluster farming technology. The result of the average treatment effect for treated shows that adopters of cluster farming technology earned ETB 5,482.789 more than non-adopter farmers. The difference in household income between the two groups shows that there is considerable room for improvement of household income through increasing the number of adopter of cluster farming technology in the study area. Based on these findings, it is recommended that provision of education, expanding of credit services, better extension service, giving awareness for farmers to be a cooperative member and increasing market information may have the potential to attract the farmers in to cluster farming in the study area.

Keywords: Adoption, Cluster Farming, Logit, Propensity Score Matching

1.INTRODUCTION

1.1. Background of the Study

Sub-Saharan Africa (SSA) is one of the regions in the world that is mainly characterized by smallholder farm households whose livelihood depends primarily on agriculture. The majority of the poor in developing countries particularly Sub-Sahara African countries heavily depend on agriculture for survival, as a result, agriculture is considered as a key fundamental for stimulating income, overcoming poverty, and enhancing food security. Productivity increases in agriculture can reduce poverty by increasing farmers' income, reducing food prices and thereby enhancing increments in consumption. Yet, still Africa is producing too little food and low value- added products, and productivity has been broadly stagnant since the 1980s (AGRA, 2018). Most of the hungry live in low-income countries, and many of them make the necessary headway towards the structural transformation of their economies. Such successful transformation is driven by agricultural productivity growth which enable the people to shift from agriculture towards manufacturing, industry, increase in per capita income and reduction in poverty and hunger (FAO, 2017).

Agriculture is the main economic activity in Ethiopia, which provides employment opportunities to 83% of the labour force. The sector contributed 37.57% to the country's GDP and around 79% of the national export earnings was obtained from this sector (CSA, 2021). This indicates that the performance of the entire economy of the country largely depends on the performance of agricultural growth and there is no a mere solution than modernizing the agriculture sector. However, Ethiopia's macroeconomic performance saw mixed results in 2021/22.The Ethiopian economy continued to grow in 2021/22 withstanding both domestic and external challenges. Real GDP grew 6.4% slightly higher than 6.3% growth in the previous year. This growth was attributed to 7.6% growth in service sector, 6.1% increase in agriculture and 4.9% expansion in industry sector. As a result, the share of services in GDP rose to 40% from 39.6% a year ago while that of agriculture dropped to 32.4% that of industry to 28.9% (NBE, 2022).

One of the main characteristics of the Ethiopian agricultural sub sector is dominated by cereal crop production constituting a significant proportion of the sub-sector. Despite the substantial contribution of the sector, the level of productivity is at lower stage due to several factors. Accordingly, several socio-economic factors are accounted for as the factors for a lower levels of productivity. These include patterns of various input use such as size and quality of cultivated land, labor size, numbers of oxen and hoes, market failure, use of improved agricultural technologies and climate types are among the variables (Nisrane *et al*., 2011).

Cereals are the major food crops in Ethiopia, both in terms of the area they are planted and the volume of production obtained. They are produced in larger volume compared with other crops because they are the principal staple crops. Cereals are grown in all regions with varying quantities. Out of the total grain crop area, 81.19% were under cereals. *Teff*, maize, sorghum, and wheat took up 22.56%, 19.46%, 12.94% and 14.62% of the grain crop area, respectively and this makes *teff* the first among cereals in the country in area coverage. Concerning production, cereals contributed 88.36% of the grain production. Maize, *teff*, sorghum, and wheat made up 30.88%, 16.12%, 16.91% and 13.22% of the grain production respectively and this implies teff is the third among cereals in production. The national productivity of major cereals during crop season in 2020/21 reported as teff is 18.88 quintals per hectare; maize 41.79 quintals per hectare; wheat 30.46 quintals per hectare; and sorghum 26.9 quintals per hectare (CSA, 2021). It indicated that the *teff* productivity is very low as compared with other cereals crop. This low productivity of *teff* is due to low utilization of improved technologies and traditionally accustomed ways of teff production (Nisrane *et al*., 2011).

Therefore, sustaining the growth of the agricultural sector should be one of the central agenda in the developmental policy of Ethiopia and in order to ensure the fruits of development to be percolated to the grass root levels, a pronounced priority must be given to the development of the agricultural sector. However, agricultural development should involve a process of transformation from traditionally oriented agricultural activities towards an acceptance and reliance on science and technology mainly through the adoption of improved, scale-appropriate and ecofriendly technologies (Mottaleb, 2018).

Moreover, to bring transformation to the nation's economy, improving the quality of the small scale farming should be a priority agenda and so far various measures have been taken to improve the productivity and income due to subsistence, rain dependent, low input use and fragmented land tenure system as well as low adoption of improved agricultural technologies. Capitalizing on the agriculture sector through the adoption of new agricultural technology to drive development is both critically important and urgent for enhancing aggregate economic growth and improving the income of millions of extremely poor (Dejene, 2019).

Cluster farming development programs have helped small-scale farmers to increase the productivity of teff, wheat, barley and other types of food of crops on top of boosting food security. Ethiopia's labor intensive subsistence farming coupled with a rain fed agricultural system remained unproductive for centuries, which needs to transform the archaic approach into a modern one (ENA, 2019; Biniam, 2019). Cluster farming offers some pathways to improving farm production and productivity with ensuing impacts on smallholder income. It has been highlighted as improving smallholder economic integration and commercialization in many developing countries through its role as a suitable avenue for implementing development projects, disseminating extension services, connecting farmers to input and output markets and providing farmers with access to capacity building and innovations (Montiflor *et al*., 2015).

Teff which is one of the staple food crops of Ethiopians is believed to have originated, domesticated and diversified in the country. It is a hugely important crop to Ethiopia, both in terms of production, consumption and serves as a source of income at the household level and a contributor to the country's foreign currency earnings. It is a multipurpose crop, being utilized in different forms where the grain is used to make the Ethiopian staple food and an important source of cash for the farmers because of the higher prices of both its grains and straw than those of the other cereals. *Teff* is used to produce a daily staple food *injera* consumed by the Ethiopian population and the crop is also gaining popularity in the Western world as a source of food; because of its health advantage for people having celiac disease (Dekking and Koning, 2005).

In the Oromia region, teff is the major cereal crop with its coverage of large area but the productivity is comparably low. For instance, in the production year, 2020/21 out of the total land area in the region, about 1.39 million hectares are covered by teff. In this region, around 26.9 million quintals of teff are produced by the farmers. In line with this, the productivity of teff in this region is 19.31 quintals per hectare. In North Shewa Zone around 153666 ha of land was covered by teff and its productivity was 20.05 quintal per hectare which is relatively very low compared with other zones of Oromia like East Shewa(21.10 qt/ha) (CSA, 2021).

In Hidabu Abote District, the national agricultural research system has generated a number of improved technologies and recommendations such as crop variety, agronomic practices, crop protection measures as well as other technical advise and practices. Moreover, cluster farming is also one of the technologies that Ethiopia; specifically in the study area is applying to increase the productivity and income of the smallholder farmer. From the total agricultural land of the district (32767ha), around 13676 ha (41.73%) is covered by teff and from this, 9384 ha is covered by cluster farming. However, this technology is not fully used by all farmers and varies from farmer to farmer (HADANRO, 2022). So, this study was aimed to know the impact of *teff* cluster farming technology adoption on rural household income in the case of Hidabu Abote District, North Shewa Zone, Oromia National Regional State, Ethiopia**.**

1.2. Statement of the Problem

The adoption of agricultural practices by farmers is a complex human domain that includes how new practices are communicated and the channels of dissemination. Farmers' decisions to adopt agricultural technologies and practices are predicated upon two primary layers of agents: the decision-makers and agricultural extension level support. However, the final adoption or non-adoption decision ultimately relies on a farmer's attitude towards the new innovation. While the social sciences provide a clear human-driven pattern explaining the process of choices and behaviors regarding technology use, there is still less clarity on what really influences the choice of technologies among smallholder communities and what supports or impedes farmers' adoption decisions (Ferroni& Castle, 2011).

A number of studies reported that the decision to adopt a certain agricultural technology is highly likely among male-headed rural households as compared to their female counterpart (Amare & Simane, 2017; Launio *et al*., 2018). On the contrary, the study by Simtowe *et al*. (2016) showed the likelihood of adopting at least one variety of diminishes with being a male farmer. On the other hand, other group of studies found that sex of the household head was not statistically significant in influencing the decision to adopt agricultural technology (Chala &Tilahun, 2014; Feyisa, 2020).

Many research articles were conducted so far about the impact of technology adoption in different parts of Ethiopia. But, the majority of these studies focused on the impact of adoption of improved seed, row planting of different crops like teff and wheat (Dawit *et al*., 2019; Solomon *et al*., 2021). But, to my best of knowledge there is no study regarding to the impact of cluster farming on the household income in Ethiopia and specifically in the study area.

The same is true for other determinants of agricultural technology adoption.So, this may not provide plenty of information for decision-makers and policy intervention. Therefore, existence of inconsistent results on the determinants of agricultural technology adoption among rural households calls the need for further study on the issue in order to come up with a better policy option targeting to improve the decision to adopt cluster farming among rural households. Moreover, in the study area around 9384ha of land is cultivated by teff cluster farming technology. But, all farmers are not participating on this technology. These initiate the researcher to conduct a study on this issue to get recent scientific results and bridge the prevailing information gap by providing empirical evidence on the impact of cluster farming technology. Thus, this study is targeted to evaluate the impact of *teff* cluster farming technology adoption on household income in Hidabu Abote District, North Shewa Zone, Oromia Regional state, Ethiopia.

1.3. Research Questions

- What are the factors affecting the adoption decision of smallholder farmers towards teff cluster farming?
- Does participation in *teff* cluster farming improve the household income in the study area?

1.4. Objectives of the Study

1.4.1. General objective

The overall objective of this study is to examine the impact of *teff* cluster farming technology adoption on the income of the household the case of Hidabu Abote District, North Shewa Zone, Oromia National Regional State, Ethiopia.

1.4.2. Specific objectives

- To identify factors affecting the adoption decision of *teff* cluster farming in the study area.
- To analyze the impact of *teff* cluster farming on income of the household in the study area.

1.5. Significance of the Study

Knowledge generated from this study is useful in location-specific capacity building programs in the adoption of *teff* cluster farming for similar contexts. Researchers who want to conduct similar and related studies can refer to the findings and can conduct their research on the identified gaps as well. This study will help to identify and analyze the problem oriented and context specific situation with regard to the study topic. The end result is to enhance the effective; evidence based decision making process by all concerned stakeholders (primarily the smallholder farmers) and then by increasing the cluster farming and income of the household. The output of this research is also essential for agriculture professionals, socio-economic development planners, policymakers, environmentalists and development agents in order to have appropriate measures in the effort of planning, implementing and controlling the context specific thematic interventions.

1.6. Scope and Limitation of the Study

The scope of the study can be described in terms of methods, area of study, thematic and time dimensions. The study was limited to identifying only the impact of teff cluster farming technology adoption on the income of the household. The spatial scope is limited to the Hidabu Abote District due to the existing crop production potential and the research interest to make a comprehensive investigation on the selected title.

The data for this study was collected at one point at a time (cross-sectional data). Cross-sectional data reflects farmers' circumstances in a given year; the specific climate of the year may affect the result, as agriculture is weather dependent. Moreover, the result of cross-sectional data does not show inter-temporal differences in the income levels of households.

1.7. Organization of the Thesis

The thesis was organized into 5 chapters. It started with the introduction, which includes background, statement of the problem, objectives, significance, scope and limitations of the study. The second chapter reviews literature that deals with past studies and information pertinent to the study. The third chapter explains research methodology including the description of the study area, sampling techniques, sources, types, methods of data collection and tools for data analysis. In the fourth chapter, the main findings of the study are presented and discussed. Finally, summary, conclusions and recommendations are provided in chapter five.

2. LITERATURE REVIEW

2.1. Theoretical Review

2.1.1. Basic concepts and definition

Adoption: The adoption of an innovation within a social system takes place through its adoption by individuals or groups. Feder *et al*. (1985) classified adoption as an individual (farm level) adoption and aggregate adoption. Adoption at the individual farmers' level is defined as the degree of use of new technology in long run equilibrium when the farmer has full information about the new technology and its potential. In the context of aggregate adoption behavior they defined the diffusion process as the spread of new technology within a region. This implies that aggregate adoption is measured by the aggregate level of specific new technology within a given geographical area or within a given population.

Adoption Process: Rogers (1983) defines the adoption process as the mental process through which an individual passes from first hearing about an innovation or technology to final adoption. This indicates that adoption is not a sudden event but a process. Farmers do not accept innovations immediately; they need time to think over things before reaching a decision.

Rate of adoption: The rate of adoption is defined as the percentage of farmers who have adopted a given technology. The intensity of adoption is defined as the level of adoption of a given technology. The number of hectares planted with improved seed (also tested as the percentage of each farm planted with improved seed) or the amount of input applied per hectare will be referred to as the intensity of adoption of the respective technologies (Nkonya *et al.,* 1997).

Technology: refers to the application of knowledge to the practical aims of human life or changing and manipulating the human environment. It is an idea, object, or practice that is perceived as new by the members of the social system (Mahajan and Peterson, 1985). It includes the use of materials, tools, techniques, and sources of power to make life easier or more pleasant and work more productive. It is a systematic application and collective human rationality to the solution of the problems through the assertion of control over nature and all kinds of human processes. It is understood as a new; scientifically derived; input introduced to farmers by an organization with deep technical expertise. On the other hand, technology is the application of knowledge for practical purposes. It is used to improve the human condition, the natural environment, or to carry out other socio-economic activities (Swanson *et al*., 1997). Technology is also defined as an idea, practice, or object that is perceived as new by the farmers' Rogers (1983).

Agricultural Technology: includes both the components and process of agricultural production process like production of plants, animal breeding (including biotechnology), and introduction of new crop varieties, mechanization services, infrastructural development and other inputs. Farming technologies are new farming solutions that enable farmers to take more output than the previous by increasing quality, quantity and cost effectiveness. Successful farming technology has been largely attributed to improved farming technologies such as fertilizer, improved seed and soil and water conservation (Gebremedhin and Johnston, 2002).

Cluster farming: It is defined as a new agricultural production approach using geographically interconnected farms or plots of land for selected crops with the objective of commercialization. It is a joint agricultural production where subsistent farmers who lack sufficient investment for modern production technologies individually are able to use large mechanization and other farm inputs in geographically grouped farming. It is simply a concentration of producers, agribusiness and institutions that are engaged in the same agriculture and interconnect and build value networks when addressing common challenges and pursuing common opportunities (Dejene, 2019).

2.1.2. Agricultural technology adoption

The decision of whether to adopt a given agricultural technology is not an overnight phenomenon. The adoption process of the new agricultural technology starts with the awareness of the adopter about the existence of the specific technology. In the next phase, the potential adopter analyzes the information about the new technology and the potential adopter gets to understand the attributes of a technology further. In the third place, the potential adopter will make a trial or experimentation before adopting the technology. Based on the perceived benefits of the technology, the individual goes through the fourth stage, which involves the actual technology adoption. Once the technology is adopted, the adopter may decide to continue using it or discontinue depending on the experience and benefits after adoption (Simtowe *et al*., 2016).

2.1.3. Determinants of agricultural technology adoption

A number of studies have been carried out on the determinants of agricultural technology adoption. Understanding the factors affecting the decision to adopt explicitly is vital to bringing a profound change in the development of the agricultural sector and the livelihood of the farm household. Additionally, understanding of the factors affecting a range of agricultural technologies is crucial for development practitioners working on developing the agricultural sector and producers entangled in the production of agricultural technologies (Hall and Khan, 2003). In this study, following (Mwangi&Kariuki, 2015) the literature on the determinants of agricultural technology will be reviewed using the household-specific factors, socio-economic factors, technology factors and institutional factors as categories.

2.1.4. Theories of decision making

In the literature, the characteristics of the innovation, particularly the cost of the innovation and its economic benefits, are important attributes to its sustainable diffusion (Fliegel&Kivlin, 1966). Actual perceptions of the cost of the innovations, especially in the context of the potential returns of that innovation is an important attribute that determines how individuals are likely to perceive a particular innovation. In essence, potential users of technology evaluate how they might be better off by applying a particular innovation. Studies have also suggested that differential perceptions of innovations and adoption rates can be a result of innovation attributes, convenience, risk, and uncertainty of the innovation (Kivlin & Fliegel, 1967).

Some decision-making theories highlight the role of extrinsic factors such as the characteristics of the technology and the attributes of the external environment. The characteristics of the users of these technologies are an integral part of the technology adoption literature (Kivlin & Fliegel, 1967). A potential consumer's ability to afford a particular technology, depending on its cost attribute, can determine the pace of adoption of an innovation. However, the recent literature emphasizes the internal decision-making characteristics of users, psychological factors, and their motivational considerations. This process also considers the design of a technology message and how individual farmers or households may perceive it. The key characteristics that are embedded in these studies include knowledge, attitudes, diffusion, policy, and farmer practices (Röling & Jiggins, 1994). In the Röling &Jiggins (1994) study, the authors used an example of Dutch farmers, who by far have the most intensive forms of land use in the adoption of technologies, to illustrate how desirable farming practices use science-based component technologies in the adoption and delivery of innovations.

2.1.5. Cluster farming

The word cluster differ by sectors (industry cluster, agriculture cluster and specific enterprise or crop cluster such as coffee farming cluster, flower farming cluster, agro processing industries cluster textile industries cluster), involvement of different actors and geographical demarcation size (large clusters like zonal or regional level cluster and small village based cluster like banana village or cluster and fruit or vegetable village or cluster). Michael Porter was the first to use the term cluster in an economic context. He introduced the term in the competitive advantage of nations in 1990. The term cluster is also known as business cluster, industry cluster, competitive cluster or Porterian cluster. A cluster is a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities. Clusters take varying forms depending on their depth and sophistication, but most include end-product or service companies; suppliers of specialized inputs, components, machinery, and services; financial institutions, and firms in related industries (Porter, 1990). Clustering is a tool used in many countries to group producers with similar interests and/or commonalities to benefit from positive outcomes associated with group marketing, access to finance, and economies of scale. Therefore, it is a tool that can aid smallholder farmers to reducing the risks associated with agribusiness development while allowing policy makers to focus resources and policies toward focal points.

According to the Philippines Department of Agriculture a typical farm cluster involves smallholder farmers and cooperatives within at least 400 ha of contiguous lands with a cropping intensity of 200%. This strategy was originally developed by the corn industry to access government funding. In the vegetable industry, the cluster farming concept was adopted by farmer groups in Southern and Northern Mindanao. It also involves smallholder farmers, but not necessarily in contiguous farms. The main objectives of cluster farming are to plant similar crops, to produce good uniform quality, to consolidate the produce to obtain a higher volume, deliver in bulk to save on transportation costs, and increase income. This paper aims to examine the socio-economic impact of cluster farming in the Philippines since there has been no evaluation of the benefits for smallholder farmers in Northern and Southern Mindanao (Montiflor *et al*., 2009).

2.1.6. Why cluster farming is needed in Ethiopia?

Agricultural cluster initiatives are starting to be seen as a key approach to help promote the agricultural sector of developing countries. The promotion or inducement of such clusters has various advantages relative to other approaches. In particular, cluster approaches recognize that all the actors in the agricultural value chain are often more innovative and successful when they interact with supporting institutions and other actors in the supply chain. By promoting vertical and horizontal links between local agricultural enterprises, as well as supporting relationships between them and facilitating organizations (e.g. local governments, research institutes and NGOs), cluster policies promote the diffusion of innovation, as well as the use and generation of important local externalities. Agricultural clusters can also enhance access to markets and information. Cluster policies are argued to be crucial, especially for smallscale farmers and agribusiness, as they enable them to engage in higher productivity, more market oriented and higher value-added production. Accordingly, central and local governments have discovered that cluster promotion is a valuable tool to support agricultural enterprises in their territory and help them link to global agricultural value chains in a more efficient and sustainable manner (Dejene, 2019).

In Ethiopia, cluster farming involves about 30–200 smallholder farmers with adjacent farm plots who voluntarily pool a portion of their land to benefit from targeted government support and cluster economic agglomeration (ATA, 2019a; Tabe-Ojong & Dureti, 2023). Farm households participating in the clusters are required to contribute at least 0.25 ha of land, and the cumulative land per cluster must be at least 15 ha to harness the full benefits of participation. In these clusters, farmers commit to cultivating cluster priority crops and adhere to the best farm agronomic recommendations. Beyond farmers, this approach involves many stakeholders directly or indirectly at each stage along the cluster crop value chain (research, inputs, production, transportation, storage, marketing, and consumption) and fosters backward and forward-linkages (ATA, 2019b). Cluster households are expected to benefit from economies of scale such as greater affordability of modern technology (e.g., sharing the overhead costs of purchasing tractors), stronger bargaining power (e.g., negotiating favorable prices for their products), and stronger market linkages to serve bulk buyers or a large-scale buyer (e.g., contract farming with large processors) (Louhichi *et al*., 2019; ATA, 2019b).

The cluster farming approach differs from previous cooperatives and contract farming in three main ways. First, the approach fosters government alignment of development policies and strategies with agro-climatic and ecological conditions, which aims to encourage specialization and economies of scale at the local level and production diversification at the national level based on comparative advantage (MoFED, 2010; Louhichi *et al*., 2019; ATA, 2019b). Second, although it promotes market orientation like cooperatives and contract farming, cluster farming takes a broader approach that aims to integrate efforts that benefit smallholder farmers as well as other value chain actors through a market-driven and geographically-based approach (Louhichi *et al*., 2019). The cluster approach also entails both horizontal and vertical integration by encouraging the marriage of cooperative and contract farming initiatives. For instance, one of the program's primary goals is to vertically connect clusters to Integrated Agro-Industrial Parks (IAIP) and agribusiness firms (large traders, processors, and exporters) (ATA, 2019b). This link can boost private sector participation in cluster priority crops, with an ultimate focus on processing and value addition to ensure specialization, diversification, continuous raw material supply, and rural development.

2.1.7. Impacts of adoption of modern agricultural technologies

Agricultural products are very crucial products that generate significant amount of foreign exchange and contributes to the GDP of the country enhancing the development of the country. It is very important employer of manpower in the country. As such it is very important to produce it in a sufficient amount at a very desirable productivity level. Based on this fact, it is not to be delayed to find factors that determine significant agricultural production at the required efficiency level and to implement the information thus obtained to get high yield per hectare of existing farmlands to overcome the upcoming future limits of resource and the wastage of today"s resource (Merga, 2013).

2.1.8. Methodological and analaytical review

Different methods have been developed and used in the literature to assess the impact of programs, policies and adoption of improved agricultural technologies on poverty reduction or welfare however, the results have been mixed. For instance Mendola (2007) adopted the Propensity Score Matching (PSM) methods to assess the impact of agricultural technology adoption on poverty in Bangladesh and observes that the adoption of high yielding improved varieties has a positive effect on household wellbeing in Bangladesh.

One method of analyzing the impact of modern agricultural technologies adoption is by considering the income differentials between adopters and non-adopters. Estimation of the impact of technology adoption on household welfare outcome variables (i.e., income and consumption per capita, based on non-experimental observations), is not trivial. What we cannot observe is the outcome variables for adopters, in case they did not adopt (their incomes had they not adopted the modern technology). That is, we do not observe the outcome variables of households that adopt had they not had adopted it (or the converse). In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of the households (as adopters and no adopters), but rather the household itself deciding to adopt given the information it has. Therefore, adopters and non-adopters may be systematically not similar as desired (Austin, 2015).

Unlike the parametric methods mentioned above, propensity score matching requires no assumption about the functional form in specifying the relationship between outcomes and predictors of outcomes. The drawback of the approach is the strong assumption of unconfoundedness. As argued by Smith and Todd (2005), there may be systematic differences between adopters and non-adopters outcomes even after conditioning because the selection is based on unmeasured characteristics. However, Jalan and Ravallion (2003) point out that the assumption is no more restrictive than those of the IV approach employed in cross-sectional data analysis.

In a study by Michalopoulos *et al*. (2004) to assess which non-experimental method provides the most accurate estimates in the absence of random assignment, they concluded that propensity score methods provided a specification check that tended to eliminate biases that were larger than average. On the other hand, the fixed effects model did not consistently improve the results. Therefore, in this study propensity score matching model was used to measure the impacts of teff cluster farming technology adoption on income of the smallholder farming households.

In order to analyze the adoption of the technology the logit and probit models are the convenient functional forms for models with binary dependent variables (Dinardo, and Johnston, 1997). These two models are commonly used in studies involving qualitative choices. The logit model uses the cumulative logistic function. However, this is not the only cumulative distribution function that one can use. In some applications, the normal cumulative distribution function has been found useful. The estimating model that emerges from a normal cumulative distribution function is popularly known as the probit model. The chief difference is that the logistic function has slightly flatter tails that is the normal curve approaches the axes more quickly than the logistic curve (Gujarati, 2004).

Feder *et al*. (1985) showed that many models used in adoption studies fail to meet the statistical assumptions necessary to validate the conclusion based on the hypothesis tested, and the advocated the use of qualitative response models. The advantage of logit or probit models is that the probabilities are bounded between 0 and 1. Moreover, they compel the disturbance terms to be homoscedasticity because the forms of probability functions depend on the distribution of the differences between error terms associated with one particular choice and the other.

2.2. Empirical Review

Gadisa and Addisu (2022) conducted a study on the Impact of Technology Adoption on Household Income, the Case of Teff in Dendi District, Ethiopia. The study was intended to assess the impacts of the adoption of improved and high-yielding tef varieties on the improvement of household income in Dendi District. The study used 210 sample households from five peasant associations in the Dendi District. Descriptive and econometric data analyses were done. The propensity score matching method and logistic regression model were used for econometric data analysis. The result revealed that household heads who are using improved and high yielding teff technologies on average get more income of 7943 birrs compared to household heads that are non-users of teff technologies. Conclusion: Based on the result of this research, improving the awareness of teff farmers towards adoption of high yielding improved teff technologies will contribute more to improving the household income and their livelihood specifically and also contribute to improving national income generally.

Nigusu *et al*. (2022) study on factors affecting adoption level and intensity use of *Teff* row planting technology in the selected districts of North Shewa Zone, Ethiopia. Multi-stage random sampling techniques were used to select 400 respondents. Adoption index, independent sample mean t-test, chi-square test and double hurdle model were used for data analysis. The results of adoption index reveals that among 400 sample households, 79.8% was non-adopter while 20.2% were adopter of Teff row planting technology. A total of 10 variables were hypothesized to affect the adoption level and intensity use of Teff row planting technology in the study area. Among these, 6 variables had significant effect on adoption level of teff row planting technology while 4 variables had significant effect on the intensity use of Teff row planting technology. Accordingly, the experience of household in teff production, education level of household head, family size, extension contact, credit utilization and demonstration site visit had positive and significant effect on the adoption level of Teff row planting technology adoption at 1, 1, 5, 1, 1 and 1% significance level respectively. Moreover, family size, education level of household head, frequency of extension contacts and demonstration site visit had positive and significant effect on the intensity use of Teff row planting technology at 10, 1, 1 and 1% significant level respectively.

Solomon *et al*. (2021) study aimed to assess the perception and determinants of agricultural technology adoption in North Shoa zone, Amhara regional state, Ethiopia. Data were collected from 796 farming households from four districts namely, AngolelaTera, Menz Gera, Minijar Shenkora and Moretna Jiru. For analysis purpose, t-test and binomial logistic model was employed. The result indicates that the likelihood of adopting improved seed, chemical fertilizer and irrigation is higher among households with higher age, greater years of schooling, large farm size, large livestock ownership and many extension contacts. Additionally, the likelihood of adopting these agricultural technologies is higher for household participating in non-farm income generating activities, having membership status in various social group and having access to credit. The likelihood of adopting the prevailing agricultural technologies also found higher for male- headed households as compared to female-headed ones. Distance to the nearest market also negatively and significantly affects the decision to adopt various agricultural technologies. The study suggested that the awareness of farmers concerning the available agricultural technologies should be raised through membership of different social group and frequent extension contact. On the other, promoting farmers to participate in offfarm income generation activities and creating access to credit service can reduce the financial constraint in purchasing and possessing new agricultural technologies.

Wordofa *et al*. (2021) study on Adoption of improved agricultural technology and its impact on household income: a propensity score matching estimation in eastern Ethiopia. Primary data for the study was obtained from a random sample of 248 rural households, 119 of which are improved technology users and the rest are non-users. The research employed PSM procedure to establish the causal relationship between adoption of improved crop and livestock technologies and changes in farm income. Results from the econometric analysis show that households using improved agricultural technologies had, on average, 23,031.28 Birr (Birr is the official currency of Ethiopia. The exchange rate according to the National Bank of Ethiopia was 1 USD = 27.6017 Birr on 04 October 2018) higher annual farm income compared to those households not using such technologies. Their findings highlight the importance of promoting multiple and complementary agricultural technologies among rural smallholders. They suggest that rural technology generation, dissemination and adoption interventions be strengthened. Moreover, the linkage among research, extension, universities and farmers needs to be enhanced through facilitating a multi stakeholder's innovation platform.

Joffre *et al*. (2020) conducted a research on why are cluster farmers adopting more aquaculture technologies and practices? The role of trust and interaction within shrimp farmers' networks in the Mekong Delta, Vietnam. The paper examines the role that farmer clusters play in the adoption of practices and technologies by shrimp farmers in Vietnam. Understanding the decisions that lead to adoption is important because these have a key impact on sustainable land use in aquaculture. They report on two complementary studies that test the role of farmer clusters in accessing different sources of knowledge and the trust associated with each of the knowledge sources. First, a survey (N = 193) tested the relationship between cluster membership and adoption, and showed that shrimp farmers who are members of farmer clusters are more likely to adopt three types of pond management practices (i.e. water quality management, feed input, and disease control practices). Furthermore, frequency of interaction with, and trust related to, key stakeholder actors could partly explain this relationship. Second, focus group discussions further zoomed into the dynamics that underlie the adoption of technologies and practices by cluster farmers and non-cluster farmers, respectively. They found that input retailers, buyers and hatcheries were only valued for their input on specific products and issues, but not trusted, as the information always needed being verified through testing by, amongst others, neighbors. Consequently, trust relations with these actors can be described as strongly calculative. Farmer clusters increase trust and tighten relationships between members. As a result, members trust each other when verifying information or sharing knowledge acquired from less trusted sources. On the basis of these results, they argue that reliance on existing farmer networks (i.e. clusters) is a viable tool to improve adoption of sustainable technologies and achieve land use planning objectives.

Yonas (2019) study the impact of row planting of teff crop on rural Household income: A case of TahtayMaychewwereda, Tigrai, Ethiopia. This paper assesses the impact of the row planting technology specifically *teff* crop on farm household income in TahtayMaychewweredaTigrai regional state. Both descriptive and econometric data analysis techniques were applied. The analysis was based on primary household level cross sectional data collected from 300 randomly selected rural households of which 120 of them were participants and the remaining 180 were nonparticipants and secondary data were employed. They applied the propensity score matching (PSM) and Heckman two stage selection models. The results of a propensity score matching show that the adoption of row planting had increased the teff crop income by about 1062.667 Birr per year for NNM, which is significant at 5% probability level, 1077.854 birr per year for SM which is significant at 1% probability level, 1004.172 birr per year for KM which is significant at 1% probability level and 1959.602 birr per year for RM which is significant at 1% probability level, on average compared to the non-adopters. In the first stage of the Heckman two-step procedure six variables were found to determine participation in row planting technology. After the selectivity bias is controlled by the model in the second stage the inverse Mills ratio (LAMBDA) variables and other three variables were found to have significantly determined household teff crop income.

Regasa *et al*.(2018) conducted a study on determinants of improved *teff* Varieties Adoption and Its Impact on Productivity: The Case of Non-Traditional *Teff* Growing Areas of Western Ethiopia. The main objective of the current study was to examine factors affecting adoption of improved *teff* varieties at farm level in non-traditional *teff* growing areas of Benishangul-

Gumuz Region of Western Ethiopia, by using random sampling technique and the data were collected from 249 smallholder Teff growing farmers using face to face interview. Descriptive statistics, Tobit estimation model and propensity score matching (PSM) were employed to analyze the data. The empirical evidence showed that dependent members of the households, land allocated to cereal and horticultural crops had negative and significance effect on area under improved Teff varieties, while livestock ownership (heifer and poultry), access to training and information on Teff, being progressive farmer and social networks have contributed positively and significantly to Teff adoption. The PSM results indicated that adoption of improved Teff varieties had significant impact on Teff productivity of adopters as compared to the non-adopters with increased Teff productivity over 276.6 kg/ha. Moreover, the average treatment effect on the treated (ATT) on productivity of Teff is 656.43 kg while the controls groups harvested around 379.82 kg. The average treatment effect on the treated (ATT) of Teff productivity is greater compared to the non-adopters that has brought about 42.14%, indicating change for being participated on improved teff production compared to non-users.

Mulat (2016) study the impact of technology adoption on agricultural productivity and production risk in Ethiopia; evidence from rural Amhara household survey. The paper investigates the effects of modern farm technology adoption such as improved seed, fertilizer, pesticide and herbicide on both crop yield and downside risk exposure in Ethiopia. The study employed a two-stage approach to estimate a production function, and computed the mean and the production risk factors (both variance and skewness) from a production function using Antle’s moment-based approach. The empirical results indicated that adoption of improved seed, family labor, agriculture capital and manure had a positive and significant effect on crop yield. On another hand, parcel size and chemical inputs (pesticide and herbicide) have negative and significant effect on crop yield. All these factors of production affect the crop yield variation and downside risk exposures (skewness of output) in differently ways: for instance, improved seed and chemical inputs positively and significantly affect the downside risk exposure (risk increasing), and fertilizer and parcel size significantly affect downside risk exposure but negatively (risk decreasing).

Montiflor *et al*. (2009) study socio-economic impact of cluster farming for smallholder farmers in Southern Philippines. Cluster farming is an alternative farming strategy for smallholder vegetable farmers in Mindanao, an island in the Southern Philippines. Two cluster farming approaches were identified: an area based and a commodity based approach. In the area based approach, farmers came together based on the proximity of farms and trading posts, while in the commodity based approach, farmers planted the same type of vegetable and combined their produce to achieve a higher volume. The main objectives of cluster farming are to consolidate smallholder farmers' produce, to deliver in bulk to save on transport and transaction costs, and to increase income. The paper examines the socio-economic impact of cluster farming on smallholder vegetable farmers. A total of 84 smallholder farmers from three cluster groups were interviewed using a structured survey questionnaire. Results show that only one cluster group improved their average monthly income. However, 91% of the respondents believed that they were financially better off after joining the cluster. Participating farmers received other mostly non-monetary benefits such as improved access to wet and institutional markets, market information, market and production linkages, technical and financial support, and production inputs.

2.3. Conceptual Framework of the Study

Figure 1 below indicates the diagram of the conceptual framework for this study. This framework provides a visual view of interactions between socio- economic factors, demographic factors, institutional factors, farm characteristics and other factors affect the adoption decision of households towards *teff* cluster farming technology.

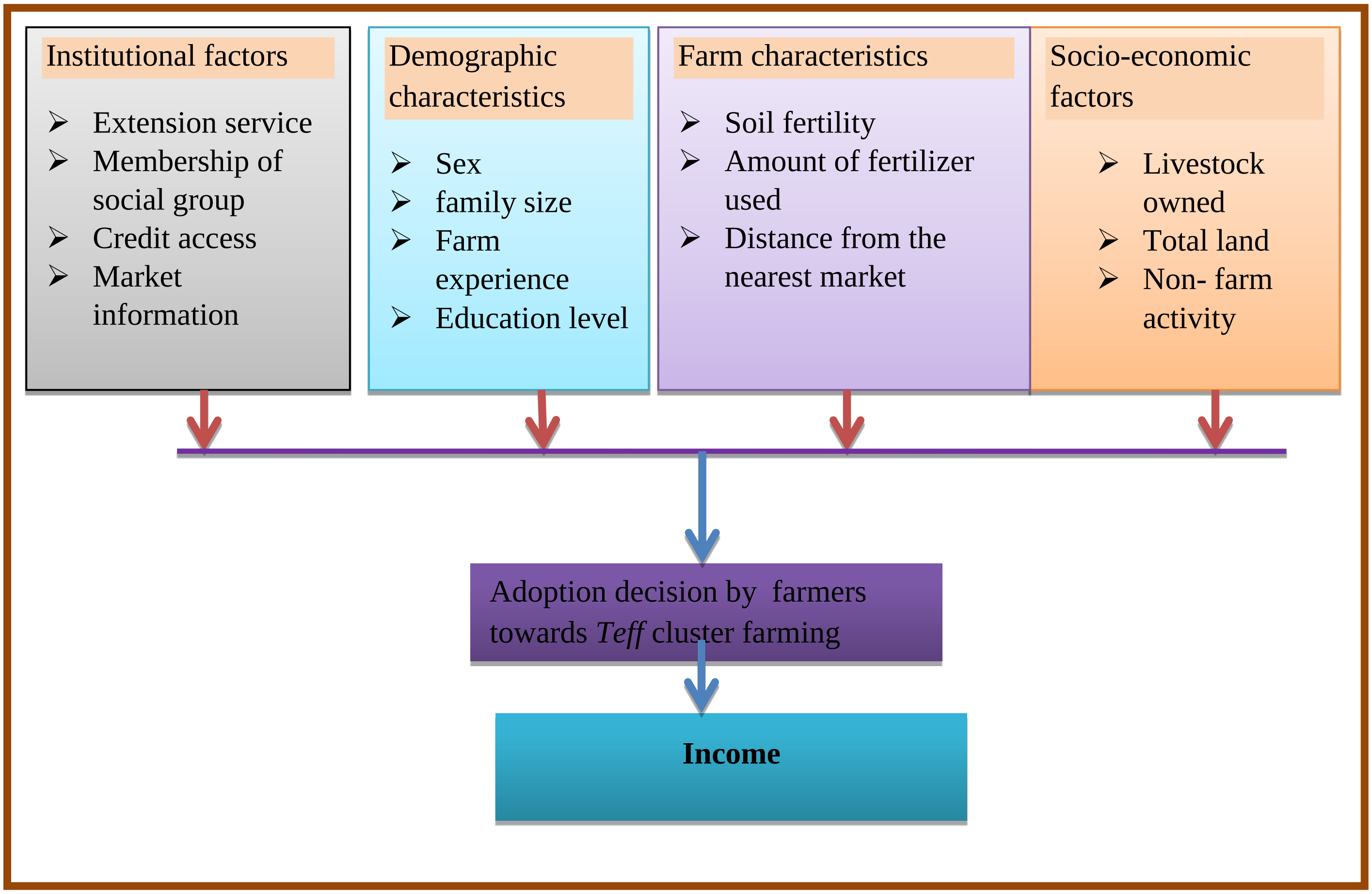

Figure 1: Conceptual framework

Source: Developed by the author based on literature (2023)

3. RESEARCH METHODOLOGY

3.1. Description of Study Area

Hidabu Abote district is located in North Shoa Zone, Oromia Regional State, Ethiopia. There are 19 *kebeles* and 1 urban *kebele* in the district. The district capital town, Ejere, is located 42 km from the town of North Shoa (Fitche) and 147 km from Addis Ababa. It is bordered by Dera district in North, Degem district in South and East, and WeraJarso district in West. Altitude in Hidabu Abote ranges from 1160m to 3000m meters above sea level (masl). Most parts of the district lay between 1387 and 1543; and 1849 and 2067m a.sl. Astronomically, Hidabu Abote district extends from $9^{0}47'15''$- $10^{0}\ 0'45''$north latitudes and $38^{0}26'\ 15''$- $38^{0}38'45''$ east longitudes. The minimum temperature is 13^{0}c and the maximum temperature is 20^{0}c. Soil types are; sandy soil 14%, clay soil 51% and silt soil 35%. The pH of the soils in Hidabu Abote ranges between 4.5 and 6.8. However, the commonly observed problem related to aluminium and magnesium toxicity as a result of low pH is minimal. The average annual rainfall of the district is 800 -1200mm with low variability. It is bimodal distributed in which the small rains are from March to April and the main rainy season is from July to September (HADANRO, 2023).

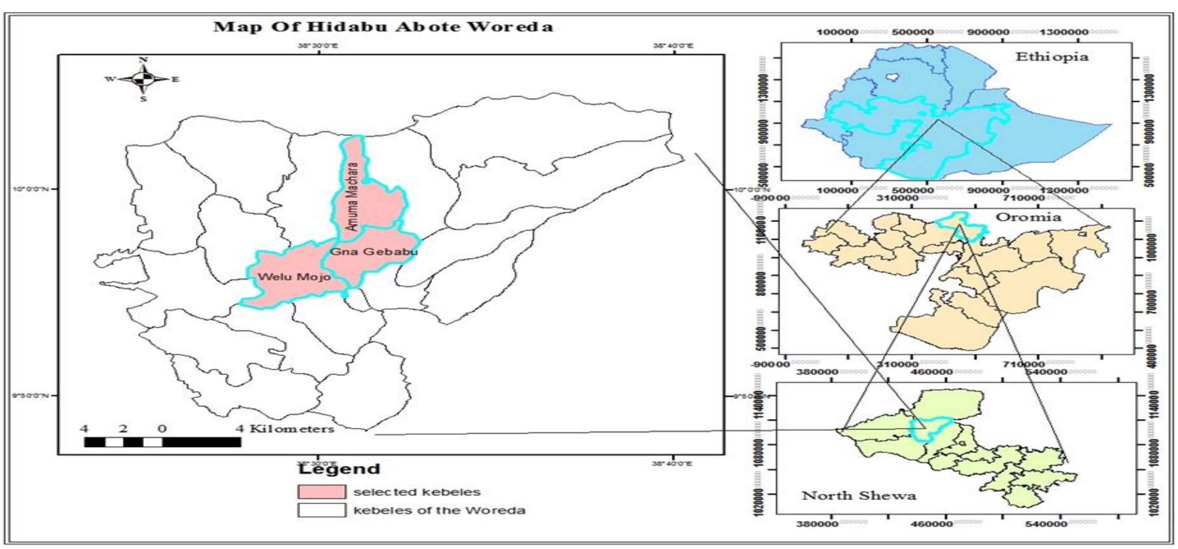

Figure 2: Map of the study area

Source of data : GIS (2023)

The total population of the district was 104,442 from which 51,030 (48.8%) were males and 53,412(51.2%) were females and the number of agricultural households wase 15,086 from which 13,396 (88.8%) were male headed and 1690 (11.2%) were female headed. The total area of the district is 50870.39 ha. From the total area, 32,767(64.41%) ha is used for agricultural land. In the study area, agriculture contributes much to meeing the t major objectives of farmers such as food supplies and cash needs. The sector is characterized by its rain-fed and subsistence nature with traditional farming techniques. It is the mixed farming type where crop and livestock production are undertaken side by side. The dominant crops grown in the study district are *teff*, sorghum, wheat, chickpea, faba bean and lentils. *Teff* is one of the staple food crops, which is mostly used as food and a source of income in the district (HADANRO, 2022). The number of livestock resources in the study area were; cattle (81156), sheep (23899), goats (47596), horses (439), donkeys (12528), mules (173), poultry (43814) and honeybee colonies (15648) (HALFRDO, 2023).

3.2. Sampling Frame and Sample Size Determination

This study follows a multi-staged sampling technique, where a combination of sampling techniques was used to select the study site and participants. In the first stage, the purposive sampling method was employed to select Hidabu Abote District, due to the high potential in teff production. In the second stage, three (3) *kebeles* namely; Machera,Gnea gebabu,wayilu mojo from fifteen (15) potential kebeles were randomly selected. In the third stage, 196 sample farmers in each randomly selected kebeles were stratified into adopter and non-adopter categories giving the relative homogeneity of sample respondents‟ adoption status. Hence, in this study, those farmers who cultivated *teff* cluster farming technology during the 2022/23 production season are considered adopters and those who did not cultivate *teff* cluster farming in the same year as non-adopters. Due to the heterogeneity of the population (adopters and non-adopters), the sample size was determined using the formula developed by Cochran‟s (1997). The key informants (five members in each *kebeles*) and focus group participants (six up to seven members in each *kebeles*) was also selected purposively due to their skill and knowledge to explain the, perceptions of farmers towards *teff* cluster farming technology adoption, challenges and opportunities related with cluster farming in the study area. Accordingly, the sample size for the study is determined based on the following formula:

$$n = \frac{pq(z)^2)}{(e)^2} = \frac{0.5 * 0.5\ (1.96)^2}{(0.07)^2} = 196 \qquad (1)$$

Where, n = sample size, P= sample proportion is 0.5, q=1-p=0.5, e = Level of precisionconsidered(7%) due to limitation of time and resources.

3.3. Research Design

Descriptive research design was appropriately applied in this research. Descriptive research sets out to describe and interpret the questions and looks at the study units with the aim to describe, compare, contrast, classify, analyze and interpret the entities, and the events that constitute the study. Different socio-economic, institutional and demographic situations were described at first. Household surveys and field observations as methods enabled the researcher to describe the phenomena.

In this study, both qualitative and quantitative data collection and analysis approaches were followed to triangulate the interpretation of data and results to enhance the reliability and validity of findings. In the qualitative approach in-depth key informants interviews (KIIs), Focus Group Discussions, and field observations are techniques for data collection.

In the quantitative research method household survey on the basis of a structured questionnaire interview was conducted by the researcher and enumerators. This mixed approach research design is thought to be appropriate to answer the research questions and then meet the objectives, because it helps to identify and analyze the existing physical and non-physical.

3.4. Data Sources and Tools

The research was accomplished using primary and secondary data sources, which are qualitative and quantitative in nature. The primary data necessary to achieve the designed objectives were obtained from sample households through a semi structured questionnaire for sampled households and a checklist for focus group discussion and key informants interviews. Secondary data was collected from relevant sources such as, articles, proceedings, journals, scientific reports, MoA, CSA, Zonal and district annual reports are vital to the study.

Primary data was focused on household characteristics (demographic, socio-economic, and institutional). In addition, information was collected on the challenges and opportunities of cluster farming with the help of a household survey questionnaire. The primary data was generated from key informant interviews, focus goup discussions, household survey questionnaires and field observations.

This tool helps to generate qualitative and quantitative information at the household level. The household survey was undertaken using structured questionnaire which administered through face-to-face contact and interviewing the household head. The questionnaire was pre tested with 5 non-sampled farmers prior to engagement in the actual interview process in order to check for the design of the questionnaire and whether it is understood as per the intended purpose in mind. The questionnaire was rectified based on the input gained from the pre-test and became ready for actual data collection. Research assistants or enumerators fluent in Afan Oromo were recruited and trained before conducting the survey and supervisers during the data collection to reduce errors. These selected enumerators are supervisor and development agents from the Agriculture and natural resource office working in the sample *kebeles*.

Key informants were selected purposively to enrich the data reliability and interview guides or checklists are tools for orienting the discussions. Five key informants from each sample *kebeles* were selected purposively based on their profession and experience to complement the data collected through the household survey. The key informants were *kebele* administrators, development agents, crop production expert experts and Woreda NGO focal persons who better know the general situation about the study context. Homogenous focus group discussions were used to verify the information given by an individual farmer during the survey and to catch an important issue that is not raised by respondent farmers.

3.5. Method of Data Analysis

To address the objectives of this study, both descriptive statistics and econometric methods of data analysis were employed. After coding and feeding the collected primary data into the computer, STATA version 15 was used for analysis.

3.5.1. Descriptive and inferential analysis

Descriptive statistics such as mean, minimum, maximum, percentages, frequencies and standard deviation were applied to describe demographic, socio-economic, farm characteristics, institutional characteristics in the study area. Furthermore, t-test was used to compare mean differences between the two groups across the study. In addition, chi-square test was used to identify the association between categorical variables and independent variables.

3.5.2. Econometric analysis

After classifying sample farmers into adopters and non- adopters of cluster farming technology, the next step is an estimation of factors affecting the adoption decision of cluster farming technology.

Two econometric models were adapted to analyze the data. These were the logit regression model and the propensity score matching (PSM) models. The logit model was used to identify and analyze the factors that determine household participation in teff cluster farming in the study area. The PSM was applied to estimate the impact of teff cluster farming technology adoption on the income of rural households.

3.5.2.1. The propensity score matching (PSM) model

Impact evaluation is used to determine whether the participation of households in teff cluster farming has an effect on their income. Different methodologies have been proposed by different authors to undertake an impact evaluation (Baker, 2000; Ledgerwood, 1999). In analyzing the impact of teff cluster farming on outcome means, the method of matching based on propensity scores is applied. The propensity score matching method is chosen for this study because, Firstly, the study lacks baseline data or longitudinal data and thus depends on cross-sectional data for which PSM model is more appropriate. Secondly, impact assessment requires that the comparison group is matched to the treated group based on the predicted probability of participation given certain observable characteristics and thus PSM model is relevant as it is based on the matching of propensity scores between both groups.

The PSM model is dependent on the selection of observable characteristics of participants and non-participants. The presence of unobservable characteristics that could potentially affect the outcome of the treated group is not accounted for. This is the disadvantage of matching on the basis of a propensity score and could lead into biased estimates. However, Heckman *et al*., (1998) in their seminal paper concluded that the bias due to unobservable factors is empirically less of a concern and can be eliminated through matching methods.

The PSM model involves three steps. Firstly, the predicted probability of participation, i.e., the propensity score is estimated using a standard logit or probit model for each sample household based on observable characteristics. Secondly, a check for balance between the observed characteristics of the treated and controlled group is required to evaluate the overlap or common support based on the propensity scores. For the PSM to work, the balancing property needs to be satisfied. The similarity in the propensity scores for each group shows that the observed characteristics between the two groups are similar. However, if there is a misspecification of variables that enter into the model, the balancing property fails to hold, and the estimated outcomes would be biased (Khandker *et al.*, 2009). Thirdly, a matching estimator is selected to estimate the average effects of the program on outcome of interest is to identify the impact of the intervention variable. Nowday's PSM is a popular method for program evaluation studies in many applications of interest due to the dimensionality of the observable characteristics is high.

This matching method tries to pick an ideal comparison matching based on propensity score in which the comparison group is matched with the treatment group on the basis of a set of observed characteristics or by using the predicted probability of participation given observed characteristics the closer the propensity score, the better the match (Jalan and Ravallion, 2003). PSM is a non-parametric estimation method that works by re-weighting the comparison sample between adopters and non-adopters. Analyzing the impact of project interventions requires the establishment of the requisite counterfactual that represents what would have been had the project not taken place or what otherwise would have been true (Baker, 2000).

The establishment of this counterfactual often poses problems where before intervention situation remains missing. Under such circumstances appropriate estimation of the counterfactual is established by way of a comparative group that does not participate in the intervention. In projects, where participants are selected purposively rather than at random, the problem of "selection bias" is often encountered in evaluation of impacts. Therefore analysis of the impact based on a "with and without" approach yields inaccurate results (Friedlander & Robins, 1995), and any attempt to net out actual project impact must factor in the underlying selection process (Zaman, 2010).

The assignment to participate in teff cluster farming technology in the study area was purposively done. Owing to this mode of assignment, the PSM framework is adopted for estimating the impact of teff cluster farming on household income. Impact through this outcome variable is obtained by matching an ideal comparative group (non-adopters) to the treatment group (adopters) on the basis of propensity scores (P-scores) of X. X is the set of observable characteristics that determine teff cluster farming technology adoption. By doing so, the selectivity bias is largely eliminated.

3.5.2.2. Mathematical specifications of PSM method

To develop the PSM framework, let Y_i be the outcome variable of household i, such that Y_{1i} and Y_{0i} denote household outcomes with and without access to teff cluster farming respectively. A dummy variable I_i denotes farmers who participate on teff cluster farming by household i, where $I_i = 1$ if the household participate on teff cluster farming and $I_i = 0$, otherwise. The outcome observed for household i, Y_i is defined by the switching regression (Quandt, 1973).

$$Y_i = I_i Y_{1i} + (1 - I_i) Y_{0i} \text{-------------------------------} (3)$$

The impact of teff cluster farming on household *i*'s income is given by;

$$\Delta i Y_i = Y_{1i} - Y_{0i} \text{-------------------------------} (4)$$

Where, $\Delta i\, Y_i$ denotes the change in the outcome variable of household i resulting from teff cluster farmers. A household cannot be both ways, therefore, at any time, either Y_{1i}(adopter) or Y_{0i}(non-adopter) is observed for that household. This gives rise to the selectivity bias problem (Heckman *et al*., 1997). The framework assumes heterogeneity in impacts of outcomes.

The heterogeneity assumption is important because, practically all households with access to teff cluster farming cannot benefit equally as a result of differing characteristics. The most commonly used evaluation parameters are averages (Heckman *et al*., 1997). Two means are common in the impact analysis framework, the average treatment effect, (ATE) and the average treatment effect on the treated (ATT). In the case of teff cluster farming technology adoption, ATE estimates the effect of teff cluster farming on the outcomes of the whole population without regards to teff cluster farming but the ATT estimates teff cluster farming effects conditional on access to teff cluster farming schemes. It is the latter which this study seeks to estimate and it is represented as

$$ATT = [E(\Delta_i | I_i = 1] = E[Y_{1i} - Y_{0i} | I_i = 1] = E[Y_{1i} | I_i = 1] - E[Y_{0i} | I_i = 1] \text{-----} (5)$$

From equation (3), $E[Y_{0i} | I_i = 1]$ is the missing data representing the outcomes of adopters? One way to estimate this missing data is to use outcomes of non-adopters. By using the outcomes of a non-adopters, (equation 5) can be rewritten as;

$$[E(\Delta_i|I_i = 1] = E[Y_{1i}|I_i = 1] - E[Y_{0i}|I_i = 1] -------------------- (6)$$

Without controlling for the unobservable heterogeneity, (6) can be shown to consist of a bias in addition to the impact estimate. Subtracting and adding $E[Y_{0i}|I_i = 1]$ to the right hand side of (6) gives;

$$E[Y_{1i}|I_i = 1] - E[Y_{0i}|I_i = 0] - E[Y_{0i}|I_i = 1] + E[Y_{0i}|I_i = 1] ------------ (7)$$

$$E[Y_{1i} - Y_{0i}|I_i = 1] + E[Y_{0i}|I_i = 1] - E[Y_{0i}|I_i = 0]$$

Rearranging (7) gives,

$$p_i p_i = [E(\Delta_i \,|\, I_i = 1] + \{E[Y_{0i}|I_i = 1] - E[Y_{0i}|I_i = 0]\} ------------- (8)$$

Thus, a bias of the magnitude shown in (8) results when non-adopter farmers are selected for comparison with adopter farmers, without controlling for the non-random variable (Cobb-Clark and Crossley, 2003; Ravallion, 2005).

The PSM method takes care of the bias, so that estimated the use of teff cluster farming impact is largely consistent. The method identifies and matches households within the adopters that are similar in observable characteristics Xi, to those of non-adopter farmers. This is done by deriving propensity scores from a binary logit estimation of farmers who participate on teff cluster farming (Dehejia and Wahba, 2002). A binary logit model can be represented as,

$$Pr = (I_i = 1|X = \frac{1}{1 + e^{-\beta x}} = \Pr(X) ------------------------ (9)$$

Where X is a vector of explanatory variables including household demographic characteristics which are deemed to influence access to teff cluster farming; Pr (X) is the propensity score. Based on the propensity scores of adopters and non-adopters farmers, the nearest neighbour matching, Caliper matching, stratification matching and Kernel matching method are used to select the best non-adopter farmers for the adopter farmers. Rosenbaum and Rubin (1985) opine that, since exact matching is rarely possible, an issue of closeness must be considered. Matching therefore uses the expected outcomes of the adopter farmers (with teff cluster farming access), conditional on the propensity scores to estimate the expected counterfactual of the non-adopter farmers (Cobb-Clark & Crossley, 2003). Thus the relation holds, only when the assumption of closeness of propensity scores is valid (common support assumption).

$$\{E[Y_{0i}], I_i = 1, X_1 = x\} = \{E[Y_{0i}I_i, = 0, X \approx x\} ------------------ (10)$$

The "conditional independence" or "exogeneity" assumption must hold for this relation to be true. Rosenbaum and Rubin (1985) showed that once appropriate common support is established the conditional independence assumption becomes valid. They proved that, if outcomes without teff cluster farming (Y_{0i}) are independent of participation in teff cluster farming (*Ii*) given Xi = x, then participants are also independent of participation (I_i) given their propensity scores [P(X)]. In PSM teff cluster farming participation characteristics are used to estimate a single value (P-score) which serves as the basis of comparison rather than the characteristics themselves. The latter could be very laborious; hence PSM solves the "curse of dimensionality". Once common support is established for the adopter farmers, the heterogeneous impact (ATT) of teff cluster farming on household income can then be estimated using Equation

$$ATT = [E(\Delta_i \mid I_i = 1] = \frac{1}{I_i}\sum(Y_0)I_i = \frac{1}{I_i}\sum \Delta_i I_i ---------------- (11)$$

3.5.2.3. Implementation of the PSM

According to Caliendo and Kopeinig (2008), the following steps are implemented in PSM. These are an estimation of the propensity scores, choosing a matching algorithm, checking on common support condition, testing the matching quality and sensitivity analysis.

Step one: Estimation of the propensity scores

First, the propensity score is obtained using either logit or probit models to predict the probability of participation of households. According to Gujarati (2003), both provide similar results. However, logistic distribution (logit) has an advantage over the others in the analysis of dichotomous outcome variables in that it is an extremely flexible and easily used model from a mathematical point of view and results in a meaningful interpretation.

Thus, for comparative computational simplicity logit model is used to estimate propensity scores using households' pre-intervention characteristics (Rosenbaum and Rubin, 1983) and matching is then performed using propensity scores of each observable characteristic, which must be unaffected by the intervention. These characteristics include covariates variables that influence the participation decisions and the outcome of interest. The coefficients are used to calculate a propensity score, and participants are matched with nonparticipants based on having similar propensity scores. The advantage of this model is that the probabilities are bounded between 0 and 1. The dependent variable is dichotomous, taking two values, 1 if an individual participants in teff cluster farming and 0 otherwise. The outcome variables are the total individuals' annual income. The independent variables are both continuous and categorical. After obtaining the predicted probability values, conditional on the observable covariates (the propensity scores) from the binary estimation, matching was done using a matching algorithm. Hence, the logistic model was selected for this study.

The logit models specified as:

$$pi = \frac{e^{zi}}{(1 + e^{zi})} \quad ------------\;---\;\;---\;---------------(12)$$

Where: P the probability of participation for the i household and it ranges from 0-1

z_i is a function of n-explanatory variables which is also expressed as

$Zi = \beta o + \sum \beta_i X_i + U_i$

Where;

i = 1, 2, 3, ⋯, n

β_o = intercept

β_i = regression coefficient to be estimated or logit parameter

U = a disturbance term,

Xi = participant households' characteristics

$Z_i\beta_{1,}\ \beta_2\ldots$ +. B_nX_n = slope of the equation in the model

Z_i=clients' participation

The probability that a household belongs to non-participant is:

$$1 - p = \frac{1}{1 + e^{zi}} \quad ------------------------------(13)$$

Therefore, the odds ratio can be written as:

$$\frac{pi}{1+pi} = \frac{1+e^{zi}}{1+e^{-zi}} -------------------------(14)$$

Now $\frac{pi}{1+pi}$ is simply the odds ratio in favour of participating in teff cluster farming. It is the ratio of the probability that an individual would participate in the teff cluster farming to the probability that he/she would not participate in teff cluster farming. Finally, taking the natural log of equation (12) we obtain:

Hosmer and Lemeshew (1989) pointed out that the logit model could be written in terms of the odds and log of odds, which enables one to understand the interpretation of the coefficients. The odds ratio implies the ratio of the probability (Pi) that an individual would choose an alternative to the probability (1-Pi) that he/she would not choose it. Finally, taking the natural logarithm of the equation (8) and the log of odds ratio can be written as follow.

$$L_i = \ln\left(\frac{p_i}{1-p_i}\right) = Z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_n X_n + u_i Z_i ----------- (15)$$

Where,p_i= is a probability of being participated in the program

Z_i= is a function of n explanatory variables (X_i) which is also expressed as:

$$Z_i = \beta o + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_n ---------------------- (16)$$

Where: β_o , is an intercept, β_1 , β_2 , … , β_n are slopes of the equation in the model

Li =is log of odds ratio, which is not only linear in X_i but also linear in the parameters,

X_i = Pre-intervention characteristics of the an individual in the study area,

If the disturbance term (U_i) is introduced the logit model becomes:

$$Z_i = \beta o + \beta_1 X_1 + \beta_2 \ldots + \beta_n X_n + U_i -------------------------(17)$$

Step two Choice of the matching estimator

The most commonly used matching estimators nearest neighbors matching, radius matching, kernel matching, and caliper matching are discussed below.

Nearest neighbour matching (NNM): it is the most straight forward matching estimator. In the nearest neighbour matching, a household from the comparison group is chosen as a match for a treated household in terms of the closest propensity score or similarity in terms of observed characteristics. Caliendo and Kopeinig (2008) note that the household from the controlled group is chosen as a matching partner for a treated household that is closest in terms of propensity scores. For each treated household i, a control household j that has the closet scores in terms of the observable characteristics is selected.

Caliper or radius matching: it imposes a maximum propensity score distance by which a match can be made. The basic idea of radius matching is that it uses not only the nearest neighbour within each caliper, but all of the comparison group members within the caliper. In radius matching each treated household i, is matched with control household j that falls within a specified radius or caliper. The benefit of this algorithm as indicated by Caliendo and Kopeinig (2008) is that it uses as many comparison units as are available within the caliper, avoids bad matches and improves the quality of matches as it imposes the maximum propensity score range.

Kernel matching: are nonparametric matching estimators that compare the outcome of each treated household to a weighted average of the outcomes of all the untreated households with the highest weight placed on those with scores close to the treated households. Caliendo and Kopeinig (2008) argue that Kernel matching uses a weighted average of all households in a comparison group to construct the counterfactual outcome. The assignment of weights depends on the distance between each household from the comparison group and treated households for which the counterfactual is estimated. Therefore, more weight is assigned to comparison households whose propensity score is closer to that of the treated group. Each household from the treated group is thus matched with several control households with weights inversely proportional to the distance between treated and control households.

Stratification or interval matching: this procedure partitions the common support into different strata (or intervals) and calculates the program's impact within each interval. Specifically, within each interval, the program effect is the mean difference in outcomes between treated and control observations. A weighted average of these interval impact estimates yields the overall program impact, taking the share of participants in each interval as the weights.

The choice of a specific method depends on the data in question, and in particular on the degree of overlap between the treatment and comparison groups in terms of the propensity score. When there is substantial overlap in the distribution of the propensity score between the comparison and treatment groups, most of the matching algorithms yield similar results (Dehejia and Wahba, 2002). A good matching estimator is one that provides a low pseudo R^2 value (Sianesi, 2004) and a statistically insignificant likelihood ratio test of all regresses after matching (a matching estimator that balances all explanatory variables between both groups) (Smith and Todd, 2005).

Step three: Common Support or Overlap Condition: (CS): The common support region is the area that contains the minimum and maximum propensity scores of treatment and control group households, respectively. It requires deleting all observations whose propensity scores are smaller than the minimum and larger than the maximum of treatment and control (Caliendo and Kopeinig, 2008). This assumption requires the existence of a substantial overlap between the propensity scores of treated and untreated groups. Specifically, the common support assumption presupposes that households with the same observable characteristics have a positive probability of being in both the treated and controlled groups (Heckman *et al*., 1999). In other words, for each treated household, there is a matched control household with similar observable characteristics. This requirement can be imposed such that estimation is performed on households that have common support only. The average treatment effect on the treated (ATT) is therefore given by the difference in the mean outcome of matched treated and controlled households that have common support conditional on the propensity scores.

Step four: Balancing test: The main purpose of the PSM is that it serves as a balancing method for covariates between the treatment and control groups. Consequently, the main purpose of balancing tests is to check whether the propensity score is adequately balanced. In other words, a balancing test seeks to examine if at each value of the propensity score, a given characteristic has the same distribution for the treatment and comparison groups. The basic idea of all approaches is to compare the situation before and after matching and check if there remain any differences after conditioning on the propensity score (Caliendo and Kopeinig, 2008). The propensity scores themselves serve only as devices to balance the observed distribution of covariates between the treated and comparison groups. Dehejia and Wahba (2002), emphasized that the crucial issue is to ensure whether the balancing condition is satisfied or not because it reduces the influence of confounding variables.

3.6. Variable Definition and Hypothesis

3.6.1. Dependent variable

Adoption decision:The dependent variable for this study is the adoption decision of farmers towards teff cluster farming technology which takes the value of 1 when the farmers are technology adopters and 0 otherwise.

Outcome variable: The outcome variable of this study was the income of smallholder household which was measured by Ethiopian birr.

3.6.2. Explanatory variables

Sex of household head: It is a dummy variable taking the value 1 if the sex of household head is male and 0, otherwise. This study expected that the sex of the household head may have a positive effect on the adoption decision. Being a female head of household may have negative effects, because in most countries in Africa, men control access to land through customary tenure, and, as a result, are often considered the main decision-makers, pursuing farm inputs, and other major decisions to implement crop production practices. Deressa *et al*. (2008) showed that male headed households could be more likely to have access to technologies than female-headed households. In the study it was hypothesized males are in a better position to adopt cluster farming technology.

Education level of the household: This is a continuous variable that is measured in the school years of the sampled household. Literate household heads are able to acquire and process information easily which may lead to more adoption of crop production practices and technologies and easily understand and analyze the situation better than illiterate farmers. Education level has a significant effect on the adoption of technology, that is, the rate of adoption is supposed to be higher with the increase of level of education (Farid *et al*., 2015). Education is important to engage the income earning potential of a household. The level of education can enable the smallholder farmer to be open to receiving, understanding and implementing the information relevant to the adoption of a new technology (Namara *et al*., 2003). So education of the household head was expected to be related positively with the adoption of teff cluster farming.

Family size: It is a continuous variable and refers to the total number of family members in the household. It is measured in man equivalent and represents the Labour input to the farm. In this study, if the majority of the family members are of active labour force age, the household will have enough labour force and the probability to use different agricultural technology on time (Wordofa *et al*.,2021). In the study area, family size was expected to have a positive effect on the intensity of teff cluster farming adoption in the study area.

Credit access: It is a dummy variable taking the value 1 if the farmers have access to credit and 0, otherwise. Credit can help ease cash constraints and allows farmers to buy purchased inputs such as improved seeds and fertilizers. Thus, this study hypothesized that there is a positive relationship between credit access and adoption of teff cluster farming technology.

Frequency of extension service: This is a continuous variable that is measured in the total times that the sample farmers get extension services related to crop production practices per production year. Extension services are an important source of information on crop production practices. This implies that farmers who had more frequency of extension; could lead them to improvements in resource allocation, facilitate practical use of modern techniques and use inputs in an appropriate way (Getachew*et al*., 2018). Hence, this was hypothesized to affect the adoption of teff cluster farming positively.

Livestock size: It is a continuous variable that refers to the total number of animals possessed by the household measured in tropical livestock units (TLU). Livestock is considered as another asset that is a security against crop failure. It can be also used as draft power which increase the production and productivity of crops. As the total number of animals in the household increases, the farmers are more likely to adopt agricultural technologies. This can be attributed to increased wealth and income based on the farm households which makes more money available in the households (Malefiya, 2017). In the study area, it was hypothesized to affect the adoption of teff cluster farming positively.

Total land size: This variable is a continuous variable measured in terms of the number of hectares that the sample household has in the 2021/22 production season. According to empirical result of Gosa and Jema (2016), farmers with larger area of cultivated land have the capacity to use compatible technologies and increase production. Regarding to the study area it was expected to affect the adoption of teff cluster farming technology positively.

Farm experience: It is a continuous variable and refers to the total years that the household participated in crop production, which is measured in years. The more the farming experience, the higher the likelihood of accumulation of physical and social capital. The accumulation of physical and social capital can offer farmers' better exposure and capacity to adopt new or recommended agricultural technology (Onyeneke *et al*., 2018). In this study, it was hypothesized that households who have more experience are more likely to participate in teff cluster farming technology.

Perception of farmers on fertility status of soil: It is a dummy variable that takes 1 if the land of the sample household is fertile and 0 otherwise. The fertility of land is an important factor in influencing the productivity of crops. This may be associated with those fertile lands have high nutrients which leads to increased crop production and productivity(Getachew *etal*.,2018). In this study, it was hypothesized that fertile soil increases the adoption of teff cluster farming in the study area.

Membership to cooperative: It is a dummy variable that takes 1 if the sample household is a member of social group and 0 otherwise. Being a member can increase the social integration and exchange of different information easily. In this study, it was hypothesized that being a member of social group increases the adoption of teff cluster farming in the study area.

Amount of fertilizer used: It is a continuous variable that is defined as the amount of chemical fertilizer used by the sample farmers in quintal (qt). It is obvious that as fertilizer increases, it will increase the productivity of crops up to the optimum level and the perception of farmers towards agricultural technology. In this study, it was hypothesized that it has had a positive effect on the adoption of teff cluster farming technology adoption.

Market information: it is a dummy variable that takes the value 1 if the sample household has access to market information about the crops and 0 otherwise. Montiflor *et al*. (2009)

found market information benefits households such as improved access to institutional markets, production linkages, and production inputs.In the study area, it had a positive effect on the adoption of teff cluster farming by smallholder farmers in the study area.

Non-farm activity: it is a dummy variable that takes the value of 1 if the sample household participates in non-farm activity and 0 otherwise. Income generated from non-farm activities may be used to acquire purchased inputs (Kusse *etal*., 2018). If farmers have alternative income to farm income they may tend to reduce their participation in cluster farming. Therefore, the sign of this variable was indeterminate (either positive or negative).

Distance to from the nearest market: This is a continuous variable measured in walking minutes. It refers to the distance between the farmers' home and the market. This indicates access to the market present that bought agriculture tools and sold the production of crops. Likewise, if a household is near market access, more has been the chance to participate in the adoption decision of cluster farming. Hence, characteristics of various localities influence the adoption decision (Knowler and Bradshaw, 2006). In the study area, it was hypothesized that distance to market has a positive effect on the adoption decision of teff cluster farming in the study area.

Table 1: Summary of variable definition

Types of variable	Types of variables	Measurement	Expected sign
Adoption decision	dummy	1=adopter and 0 not adopter	
Sex	Dummy	1for male and 0 for female	+
Education	Continuous	School year	+
Family size	Continuous	ME	+
Access to credit	Dummy	1 for who has credit access and 0 if not	+
Livestock owned	Continuous	TLU	+
Total land size	Continuous	Ha	+
Farm experience	Continuous	Years	+
Soil fertility	Dummy	1 for fertile and 0 not fertile	+
Membership to cooperative	Dummy	1 for membership of social group and 0 if not	+
Fertilizer used	Continuous	qt	+
Non- farm activity	Dummy	1 if participate and 0 otherwise	+/-
Distance from market	Continuous	Walking minutes	-
Market information	Dummy	1 if has access and 0 otherwise	+
Extension contact	Continuous	Number	+

Source: Own definition based on previous literature (2023)

4. RESULTS AND DISCUSSIONS

In this chapter, both the results of descriptive, inferential statistics and econometric analysis were discussed briefly.

4.1.Descriptive Statistics

Before discussing results obtained from the econometric models, it is important to briefly present the demographic, socio-economic, farm and institutional characteristics of the sampled farmers in the study area, since they an affect the quality of the management of the farmer directly or indirectly and are believed to have effect on adoption of teff cluster farming. In addition, it would help to draw a general picture of the study area and sampled households.

4.1.1. Characteristics of sample households in terms of categorical variables

The chi-square test was used to compare adopters and non-adopters of teff cluster technology in terms of the hypothesized categorical variables included in the study. This is used to indicate an association between various parameters of interest and the adoption decision of sample households. Accordingly, statistically significant association was observed between adopter and non-adopter households in terms of the sex of households head, access to credit and non-farm activities.

Sex of household head

The sex of the household head was hypothesized to affect the adoption of modern beehive technology in the study area. Among 196 sample households about 20.41% and 10.20% were male and female headed adopters while about 51.02% and 18.37% were male and female headed non-adopter of teff cluster farming technology respectively. This implies that the majority of adopter farmers were male than female. Moreover, the Pearson chi-square test result shows that there was a significant relationship between male headed households' and adopters of teff cluster farming technology at 1% significance level with X^2=24.30 (Table 2). This implies being male headed increases the chance of being an adopter of teff cluster farming technology than female headed. This is due to the fact that males have more exposure to external information about new technology which in turn might enhance adoption decisions towards teff cluster farming technology.

Access to credit

Credit is one of the important instruments to enhance agricultural production and productivity. According to the survey results about 32.14% and 5.61% of adopter and non-adopter households obtained credit respectively. This implies that the majority of adopter households used credit from various financial services. The chi-square test result indicates that there was a significant relationship between credit users and adoption of teff cluster farming technology at 1% significance level with X^2=18.78 implying that access to credit enhances the probability of households adopting teff cluster technology than the others (Table 2). This is because credit enhances the probability of households purchasing resources required for teff production.

Non-farm activities

Among the sample respondents about 17.86% and 3.06% participated in non-farm activities. This implies that adopters of cluster farming technology participated in non-farming activities more than non-adopters. The Pearson chi-square test result indicates that there was a statistically significant association between household participation in non-farm activities and adoption decision of cluster farming technology at 1% significance level with chi-square value of 21.46 implying that participation in non-farm activities enhance the chance of households to adopt cluster farming technology than the others (Table 3).

Table 2.Results of infrential analysis (Chi-square test for categorial variables)

Variables Name	Variable Category	Adopters n=60		Non-adopters n=136		Chi^2
		Freq.	%	Freq.	%	
Sex of HHs	Male	40	20.41	100	51.02	
	Female	20	10.20	36	18.37	24.30***
Credit	Yes	50	32.14	80	5.61	
	No	10	7.14	56	55.10	18.78***
Cooperative	Yes	10	5.10	6	3.06	
	No	50	25.51	130	66.33	0.776^{NS}
Soil fertility	Yes	30	15.31	36	18.37	
	No	30	15.31	100	51.02	1.209^{NS}
Non-farm activity	Yes	35	17.86	6	3.06	
	No	25	12.76	130	66.33	21.46***
Market information	Yes	50	25.51	70	35.71	
	No	10	5.10	66	33.67	1.44^{NS}

*** denote significance at the 1% respectively; NS denote non-significant

Source: Survey result (2023)

4.1.2. Characteristics of sample households in terms of continuous variables

A mean difference among continuous variables between adopter and non-adapter households was estimated using an independent sample t-test. Accordingly, a statistically significant mean difference was observed between adopters and non-adopters households in terms of farm experience, family size, extension contact and education level at 1% significance level (Table 3).

Family size

Family size is one of the hypothesized socio-economic factors to affect the adoption of teff cluster farming technology. The availability of an active working labor force in the household is considered as the number of individuals who reside in the respondent's house to perform agricultural activities. The average family size of adopters' and non-adopters' households were 7.55 and 4.60 adult equivalents respectively. The independent sample t-test result also shows that there was a statistically significant mean difference in family size between adopter and non-adopter households' at 1% significance level with t= -24.2 implying that adopter households' was owned a higher family size than non-adopters households (Table 3).

Extension contact

The effort to disseminate new agricultural technologies requires effective communication between the extension workers and farmers at the grassroots level. Frequency of extension contact was hypothesized as the potential force that accelerates the effective dissemination of adequate agricultural information to the farmers thereby enhancing farmers' decision to adopt new technologies. The survey result shows that the average extension contact of the adopter and non-adopter household was 8.02 and 3.70 respectively. This implies that, on average, adopters of cluster farming technology made more extension contact than non-adopter households. The result of an independent sample t-test show that there was a statistically significant mean difference in the number of extension contact between adopter and non-adopter households' 1% significance level with t= -20.9 (Table 3).

Education level

Education is the main instrument to increase agricultural production and productivity through the optimum allocation of necessary resources at the right time. The average education level of adopter and non-adopter households was 0.62 and 0.15 grades respectively implying that adopters of cluster farming technology attended more education than non-adopter. Moreover, the result of the independent sample t-test revealed that there was a statistically significance mean difference in education level between adopter and non-adopter households at 1% significance level with t= -2.60 (Table 3).

Farm experience

Farm experience is hypothesized to positively influence the adoption decision of cluster farming technology. The average farm experience of adopter and non-adopter households were 30.71 and 20.44 years respectively implying that adopter households had more experience than non-adopter. The t-test result also confirms that there was a statistically significance difference in the average experience of households between the two groups with t= -14.9 (Table 3).

Table 3. Results of inferential analysis (t- test for continuous variables)

Variables	Adopters (n=60)		Non-adopters (n=136)		t-test
	Mean	Std. Err.	Mean	Std. Err.	t- value
Farm experience	30.71	0.43	20.44	0.44	-10.9***
Family size	7.55	0.08	4.60	0.10	-24.2***
Livestock size	5.69	0.16	5.87	0.17	0.50^{NS}
Extension contact	8.02	0.18	3.70	0.11	-20.9***
Distance from market	2.05	0.12	2.76	0.09	0.78^{NS}
Education level	0.62	0.07	0.15	0.03	-2.60***
Land size	2.22	0.09	2.31	0.06	0.78^{NS}
Amount of fertilizer	258.75	14.92	241.83	10.02	1.45^{NS}

*** denote significance at the 1%; NS denote non-significant

Source: Survey result (2023)

4.1.3. Adoption decision of teff cluster farming

Among 196 sample farmers, about 30.61% and 69.39% were adopters and non-adopter households of teff cluster farming technology respectively (Table 4). This implies that most of the sample farmers were non-adopters of the technology. This can be attributed to various demographic, socioeconomic, institutional and marketing factors the existed in the study area.

Table 4. Adoption decision of cluster farming

Adoption decision	Frequency	Percent
Adopter	60	30.61
Non-adopter	136	69.39
Total	196	100.00

Source: Survey result (2023)

4.2.Econometric Results

4.2.1. Factors Affecting adoption of teff cluster farming

Binary logistic regression was employed to identify factors affecting teff cluster farming technology adoption in the study area. The logistic regression model output revealed that among 14 hypothesized explanatory variables only 5 namely education level of household head, access to credit, market information, frequency of extension contact and membership to cooperative significantly and positively influenced the adoption of *teff* cluster farming technology. The details are discussed as follows:

Education level: As expected, there was a positive and significant effect of household education on teff cluster technology adoption at 10% significance. The result indicated that as the household education increases by one year, the odd ratio of adopters of the teff cluster technology would increase by 0.115 units. This is because more educated farmers are assumed to have gained knowledge and hence, would be able to accept technology than less educated farmers. The same result was found by the finding of (Mignouna *et al.,* 2011; Kariyasa and Dewi, 2011).

Access to credit: Credit services influenced household adoption of cluster farming technology positively at 1% level of significance. The result revealed that, the odds ratio of being an adopter of the technology was about 1.695 times greater for households with access to credit services than households without such services. This is because farmers who had access to credit would be able to buy the necessary inputs required for the technology than the others. The findings of Sisay et al. (2013) and Workineh (2017) support this finding.

Extension contact: As expected, the frequency of extension contact affected household adoption of cluster farming technology positively at 10% significance level. This revealed that the odds ratio of being an adopter of the technology was about 0.209 times greater for households with higher extension contact than households with lower extension contact. This is because farmers who had more extension contact would be more progressive in the adoption of cluster farming technology. Kassa *et al*. (2018) also found the same result.

Membership to cooperative: This variable influences household adoption of cluster farming technology positively at 10% probability level. The result revealed that, the odds ratio of being adopters of the technology was about 0.846 times greater for households participating in cooperative membership than the others. This is because farmers who join a cooperative would be able to buy the necessary inputs required for the technology than the others. The findings of Sisay *et al*. (2013); Workineh, (2017) support this finding.

Market information: As expected, participation in training affected household adoption of cluster farming technology positively at 1% significance level. The result revealed that the odds ratio of being an adopter of the technology was about 0.904 times greater for households who had market information related to cluster technology than the others. This is because market information enables the farmers to obtain information related to cluster technology than the others. This result is consistent with the empirical findings of Rahman (2007).

Table 5. Binary logistic regression model output

Logistic regression		Number of obs	=	196
		LR $chi^2(14)$	=	44.540
		Prob > chi^2	=	0.0000
Log likelihood = -113.55		Pseudo R^2	=	0.1640
Variables	Odd ratio	Std. Err.	Z	P>z
Sex	0.217	0.806	0.27	0.787
Education	0.115*	0.064	1.81	0.070
Family size	0.120	0.124	0.97	0.334
Access to credit	1.695***	0.339	4.99	0.000
Extension contact	0.209*	0.111	1.88	0.060
Land size	-0.158	0.195	-0.81	0.420
Farm experience	0.028	0.021	1.30	0.192
Soil fertility	-0.398	0.793	-0.50	0.616
Membership to cooperative	0.846*	0.464	1.82	0.068
Amount of fertilizer used	0.003	0.003	0.99	0.324
Non-farm activities	-0.304	0.374	-0.81	0.415
Distance from market	-0.007	0.120	-0.06	0.952
Market information	0.904***	0.341	2.65	0.008
Livestock size	-0.026	0.075	-0.34	0.733
Constant	2.684	1.360	1.97	0.048

*** and * represent significance level at the 1 and 10% respectively
Source: Survey result (2023)

4.2.2. Impact of *Teff* Cluster Farming on Income of the Household

4.2.2.1. Results of Propensity Scores Matching

The propensity score for a given household was estimated using a logit model where the dependent variable is adoption status while different covariates are independent variables. The result in Table 6 revealed that the average propensity score value of adopter and non-adopter farmers was 0.6159 and 0.4001 respectively. Moreover, the average propensity score of the total sample households was 0.5102 with minimum and maximum scores of 0.0735 and 0.9391 respectively. Estimating the propensity score can help us to identify the common support region for both treatment (adopter) and control (non-adopter) groups.

Table 6: The distribution of propensity scores

Adoption decision	N	Mean	Std. Dev.	Min	Max
Adopter	100	0.6159	0.1976	0.0735	0.9391
Non-adopter	96	0.4001	0.2078	0.0881	0.9355
Total sample households	196	0.5102	0.2293	0.0735	0.9391

Source: Survey result (2023)

4.2.2.2. Common Support Region

As suggested by Bernard *et al*. (2007) in order to ensure maximum comparability of the adopter and non-adopter households, the sample used for matching is restricted to those households who are located in the common support region. The common support region is where the values of propensity scores of both adopter and non-adopter groups can be found (Caliendo and Kopeinig, 2008). Based on this, the region of common support is [0.0881, 0.9355] implying that the two groups share the same characteristics in these interval. Based on this criterion, only 5 observations (2 from control and 3 from treatment groups) were discarded from the analysis (Figure 3).

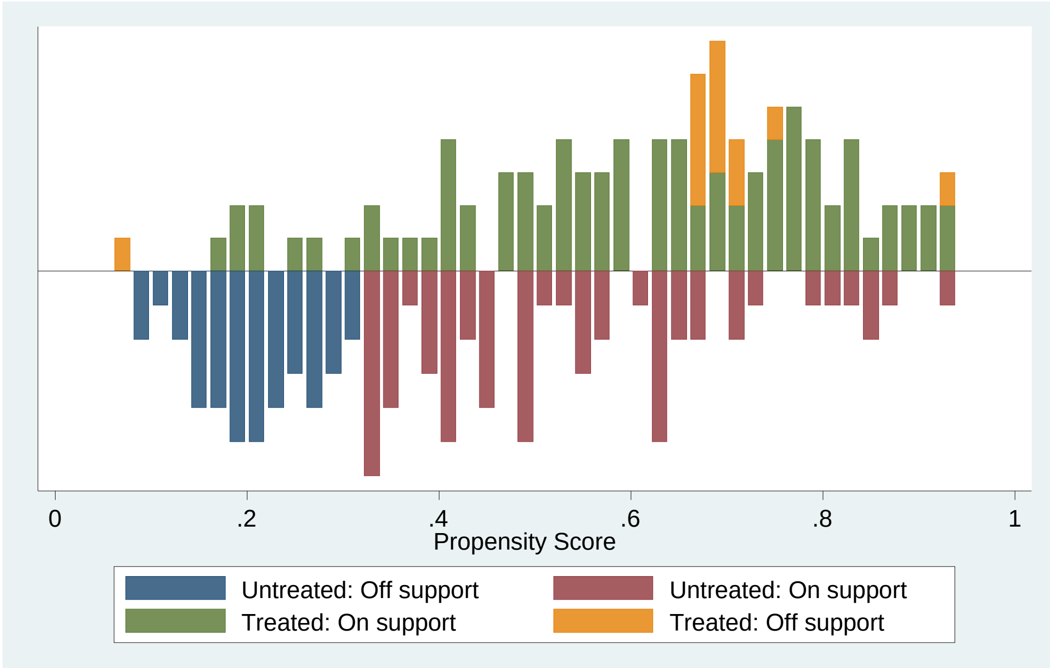

Figure 3:The Distribution of propenstity scores for treated and untreated groups
Source: Survey result (2023)

4.2.2.3. Matching Quality Test

The pseudo R^2, t-test and standard bias are the basic tools for testing the quality of matching between adopter and non-adopter households. Low pseudo R^2, insignificant t-test after matching and standard bias below 20% are the universally accepted criteria to judge the quality of matching between adopter and non-adopter group (Rosenbaum and Rubin, 1983). The result depicted in Table 7 shows that the pseudo R^2 is low (0.041), the t-test value is insignificant and the mean bias is below 20% (11.7%) for all covariates. This implies that the quality of matching was good to balancing the characteristics in the treated and matched comparison group. According to the result, there is no significant difference of the covariates after matching and hence, the balancing property is satisfied. This is estimated using kernel matching bandwidth 0.25.

Table 7: Matching Quality Test among Treated and Control group

Covariates	Mean			t-test	
	Treated	Control	% Bias	t	P>t
Sex	0.805	0.754	12.4	0.71	0.477
Education	5.069	4.544	13.6	0.78	0.439
Family size	4.770	4.790	-1.3	-0.08	0.939
Access to credit	0.621	0.491	27.6	1.54	0.127
Extension	3.621	3.316	18.4	1.04	0.302
Landsize	3.214	3.185	2.2	0.14	0.892
Farm experience	23.230	23.456	-1.9	-0.11	0.91
Soil fertility	0.793	0.737	13.8	0.78	0.436
Membership to cooperative	0.793	0.807	-3.7	-0.20	0.84
Non-farm activity	0.345	0.281	13.7	0.80	0.423
Amount fertilizer used	250.980	254.470	-3.7	-0.21	0.833
Distance from market	4.736	4.544	12.8	0.73	0.464
Market information	0.632	0.579	10.8	0.64	0.525
Livestock size	5.890	5.828	2.7	0.15	0.878

Ps R2	LR chi^2	P>chi^2	Mean Bias	Median Bias
0.041	7.98	0.93	11.7	12.4

Source: Survey result (2023)

4.2.2.4. Results of Average Treatment Effect for the Treated

The average treatment effect on treated should be estimated after the balancing property of the covariates is satisfied. The average treatment effect on treated (ATT) measures the average income difference between the matched adopter and non-adopter households. The income of the households from teff production was estimated by taking the average market price of teff per kilogram (ETB 70) during the survey period, and then multiplying it by the amount of teff produced from non-cluster area per year (control group) and cluster area per year (treatment group). Accordingly, the income sample household obtained from the teff cluster and non-cluster was ETB 171,881.443 and 166,398.655. The income difference due to treatment was ETB 5,482.789 and statistically significant at 1% significance level (Table 8). The variation in income between the treated and control groups was due to disparity in the amount of teff produced from cluster and non-cluster areas. The cluster area produced more teff and hence, generated more income for households than the non-cluster area. This is because cluster areas might get a full package than non-cluster areas.

Table 8: The average treatment effect of matched adopter and non-adopter households

Outcome Variable	Treated	Control	Difference	S.E	t-value
ATT	171,881.443	166,398.655	5,482.789	10,984.698	9.50***

Source: Survey result (2023)

4.2.3. Sensitivity Analysis

In order to overcome the unobserved bias, a Rosenbaum bounds calculation was used (sensitivity test) for the outcome effect on participation of cluster farming, which is positive and significantly different from zero. Results in the Table 9 reveals that the inference for the effect of cluster farming interventions for both the groups remains same and has been allowed to differ in their probability to being treated 1 up to 3 with unobserved covariates. It implies that p-critical values of all the outcome e^{γ} (Gamma) is log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated. Values which is corresponds to each row of the significant outcome variables are p-critical values (or the upper bound of Wilcoxon significance level) at different critical value of variables are found significant which are estimated at various level of critical value of e^{γ}. This further indicated that the study considered important covariates that affected both household participation in cluster farming and outcome variable. On the basis of these results, the study concluded that average treatment on treated (ATT) impact assessment are found insensitive to unobserved selection bias and is an absolute effect of household participation in cluster farming.

Table 9: Sensitivity Analyis

Gamma	$e^{\gamma=1}$	$e^{\gamma=1.25}$	$e^{\gamma=1.5}$	$e^{\gamma=1.75}$	$e^{\gamma=2}$	$e^{\gamma=2.5}$	$e^{\gamma=2.75}$	$e^{\gamma=3}$
Sig+	0.00032	0.00058	0.0011	0.0025	0.0034	0.0062	0.0076	0.0084

Source: Model result (2023)

5. SUMMARY, CONCLUSION AND RECOMMENDATION

5.1. Summary and Conclusion

Cluster farming technology is one of the productivity enhancing technologies introduced for teff production in the study area. The main objective of this study was to measure the adoption of level cluster farming technology in Hidabu Abote district, North Shewa zone, Oromia National Regional State, Ethiopia using cross-sectional data during the 2022 production year.

According to the survey result, among 196 sample households, 60 and 136 were adopters and non-adopters of cluster farming technology respectively. Logistic regression model results indicate that among the 14 hypothesized explanatory variables, only 5 variables namely the education level of household head, access to credit service, frequency of extension contact, cooperative membership, and market information had a positive and significant effect on the adoption decision of cluster farming technology at 10%, 1%, 10%, 10% and 1% significance level respectively. This implies that increasing more educated households, household obtained credit, access to cooperative membership, more extension contact and market information would enhance households' adoption of teff cluster farming technology in the study area. The results of the average treatment effect on treated indicated that households who adopted cluster farming technology earned about ETB 5,482.789 more income than non-adopters of cluster technology for *teff* production.

5.2. Recommendation

Based on the result of the study, the following recommendations are forwarded.

- Since education level of household head had positive and significant effect on adoption of teff cluster farming technology and, income of household; the regional government should have responsibility to keep on the provision of education in this area. This might be through providing adult education in their respective *kebeles*.

- Since access to credit had positive and significant effect on adoption of cluster farming technology and hence, income of household. So, district micro finance institution should give due attention on how to increase credit deployment for smallholder farmers. This might be through establishing and/or strengthening the existing microfinance institutions to deliver the credit for the farmers.
- Cooperative membership was found to be positively and significantly affecting the cluster farming technology and hence, income of household. Therefore, district cooperative office should motivate farmers to join the existed cooperatives. This might be through awareness creation and training for farmers on the advantage cooperatives membership.
- Frequency of extension contact was found to positively and significantly affect cluster farming technology and hence, income of household. So, district and zonal agricultural office should give due attention on how to enhance extension service. This might be through establishing and/or strengthening the existing farmer training center.
- Market information was found to positively and significantly affect cluster farming technology and hence, income of household. So, district and zonal office of commerce should give more ephasis on how to enhance the dissemination of market information. This might be through creating awarenees about the advantage of market information.
- Ther result of average treatment effect indicates that farmers who participated in cluster farming are getting more income than farmers who do not use cluster farming. So, the district and zonal agricultural office should give a great attention to expand this farming sytem.

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7. APPENDICES

Appendix table 1: Conversion factor used to calculate man and adult equivalent.

Age group (years)	Man Equivalent(ME)		Adult Equivalent(AE)	
	Male	female	Male	Female
<10	0	0	0.6	0.6
11-13	0.2	0.2	0.9	0.8
14-16	0.5	0.4	1	0.75
17-50	1	0.8	1	0.75
>50	0.7	0.5	1	0.75

Source: Storck (1991 as cited in Wassie, 2014).

Appendix 2: Conversion factors used to estimate Tropical Livestock Unit equivalents.

Animal category	TLU	Animal category	TLU
Cow and oxen	1	Sheep and goat young	0.06
Bull	1	Horse and mule	1.1
Calf	0.25	Donkey (young)	0.35
Heifer	0.75	Donkey (adult)	0.7
Sheep and goat(adult)	0.13	chicken	0.013

Source: Storck (1991 as cited in Wassie, 2014).

Questionnaire

This interview schedule is developed to gather information from smallholder farmers for the research entitled **": Impact of Teff Cluster Farming Technology Adoption on Rural Household Income: The Case of Hidabu Abote District, North Shewa Zone, and Oromia National Regional State, Ethiopia "in (2014/2015 E.C) production year.** The research is to be submitted to Salale University, Department of Agricultural Economics. So I would like to assure that this questionnaire is used only for research and academic purposes.

Note: Circle the correct letter to choose questions.

Provide your explanation in the space provided for open-ended questions

Woreda______Kebele _______Date of interview --- ----Enumerators name: __________
Village _________________

1. Demographic characteristics

1.1. Household head Id No.___________________

1.2. Family size? A. Male ------------------ B. Female…………… C. Total……………….

1.3. Household family composition in sex, age, educational status, and farm experience

S/N.	Name of the family member	Sex, Male=1 Female=0	Age(years)	Education level(years)	Farm Experience (years)

2. Farm characteristics

2.1. A. Total area of land ……… (ha) B. Cultivated land…… (ha) C. Grazing land…….. (ha) D. Homestead land……… (ha) E. Other land, specify ……… (ha)

2.2. Did you produce teff on 2014/2015 E.C cropping season?
A. Yes B. No

2.3. Did you use cluster farming technology during teff production?
A. Yes B. No

2.4. If you say yes where did you get the information?
A. Extension agents B. Neighbors C. Friends and families
D. Social network source E. *Kebeles* administration F. Others (please specify)

2.5. What is the total number of farmers in one cluster?
A. less than 5 B. 5- 10 C. 10-20 D. Above 20

2.6. If no, what are the reasons for not practicing cluster farming of teff?

A. It requires labor and time B. lack of common understating
C. It is low productive than traditional practices D. Not aware of the benefits
E. Other specifies---------------

2.7. Could you please list all the major crops (under rain fed) that you produced during 2014/15 E.C production year and its income?

Type of crops produced	Area (ha)	Amount of seed(Kg)		Amount of fertilizer(Kg)			Total straw (Qt)	Total crop output(Qt)	Unit price	Total value(birr)
		local	Improved	Organic	NPS/ZNBR	UREA				
Teff(by cluster)										
Teff(not cluster)										

2.8., Could you list all horticultural crops (under irrigation) you produced during 2014/15 E.C production year and income generated from it?

Type of horticultural crops	Area (ha)	Amount of seed(Kg)		Amount of fertilizer(Kg)			Total crop output(Qt)	Unit price	Total value(birr)
		local	Improved	Organic	NPS/ZNBR	UREA			

2.9. Do you use improved seed? A. Yes B. No

2.10. What is the source of improved seed you used for 2014/15 E.C. production year?
A. Owen B. Union C. Cooperative D. Others

2.11. What type of crops you planted last production year (2013/14)? Name of crop____________

2.12. According to your perception what is the fertility status of the land that you planted teff?
A. Fertile B. infertile

2.13. On average, how many times you plow your teff respectively? ------ (in number).

3. Socio Economic and Institutional characteristics

3.1. Frequency of extension contact _______times

3.2. Do you have access to credit? A. Yes B. No
3.3. If yes, how much money did you borrow? --------------------- Birr
3.4. Are you in a cooperative member? A. Yes B. No
3.5. Market distance from the nearest market_____in walking minute
3.6. Do you have market information? A. Yes B. No
3.7. Do you have any income other than farm activity? A. Yes B. No
3.7.1. Mention the off-farm and non-farm activities and estimated income in 2014/2015 E.C .production season?

No.	Types of off-farm and non-farm activity	Participate or not	if the participate amount of income obtained Birr/ year
1	Shopping		
2	Grain trading		
3	Livestock trading		
4	Casual labor		
5	Salary employment		
6	Other, specify		
Total income			

3.8. Do you have livestock? A. Yes B. No
3.9. If yes, type and number of animal owned by household

No.	Type of animal owned		Number owned	Number of sold	Total value in birr
1	Oxen				
2	Sheep (young)				
3	Sheep (adult)				
4	Goats (young)				
5	Goats (adult)				
6	Horse				
7	Donkey (young)				
8	Donkey (adult)				
9	Heifer				
10	Cow				
11	Bull				
12	Mule				
13	Calves				
14	Chickens				
15	Bee colony	Modern			
		Local			
16	Others				

3.10. Livestock product in 2014/2015

No.	Commodity type	Amount	Consumed(liter,	Sold (Birr)/year

		produced (liter, Kg)/year	kg)	
1	Dairy output			
	Milk			
	Butter			
	Honey bee			
	Others			
Total income				

4. Challenges and opportunities of teff cluster farming

No.	Major challenges	Ranks	Major opportunities	Rank
1				
2				
3				
4				
5				
6				
7				
8				

Questions for Key informant interview

1. What are the major crops grown in this woreda and why?
2. What do you think the productivity of teff in your District? Increasing or decreasing? Explain with reasons?
3. What efforts‟ are done to integrate smallholder farmers with new agricultural technology and what are the challenges and opportunities of applying this technology, especially cluster farming?
4. What are the possible solutions to promote cluster farming technology of teff in the woreda?

Thank You for Your Cooperation!!!!!!