

Effect of Cluster Farming on Barley Productivity and Technical Efficiency: The Case of Gumer and Alichu Districts

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<p>Abstract: Cluster farming serves as an emerging government strategy designed to transition subsistence based smallholder production toward a market oriented production system. However, there is restricted evidence regarding cluster farming effects on barley productivity and technical efficiency. So, this study evaluates how cluster farming adoption affects the productivity and technical efficiency of barley production. For that, 154 sampled respondents were selected through systematic random sampling. To analyses the efficiency and the impacts of cluster farming, this study employed a one - stage Cobb-Douglas stochastic frontier estimation approach and endogenous switching regression (ESR) models, respectively. The stochastic frontier model result shows that barley output is most responsive to land for barley production, NPS fertilizer and labour inputs. The estimated mean technical efficiency of smallholder barley producers was 79.6%. Education status, frequency of extension contact and agricultural mechanization are significantly associated with technical efficiency. Cluster farming adoption is significantly influenced by education status, farm size, agricultural mechanization, frequency of extension and livestock holding. The result of ESR model depicts that cluster farming adopters would have lost 26.46% and 11.91% in barley productivity and technical efficiency, respectively if they had not adopted cluster farming, while if non-adopter farmers participated in cluster farming they would have gained additional 23.18% and 16.16% in barley productivity and technical efficiency. Consequently, development strategies should accelerate adoption of cluster farming through enhancing extension services, promoting agricultural mechanization, and investing in adult education.</p> <p>Keywords: Cluster Farming, Stochastic Frontier, Technical Efficiency, Barley, Endogenous Switching Regression.</p>	<p style="text-align: center;">Research Paper</p> <p>*Corresponding Author: <i>Destaw Muluye</i> Agricultural Economics Researcher, Worabe Agricultural Research Center, Central Ethiopia Agricultural Research Institute, Worabe, Ethiopia</p>
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INTRODUCTION

Agriculture is a pillar to Ethiopia’s economy, accounting nearly 50% to the country GDP, 80% to export revenues and employing more than 80% of the labour force. Also the sector plays a vital role to address poverty and food insecurity [1, 2].

Cereal crop production accounts for the bulk of the country’s volume of production and food supply. Which is the primarily grown by smallholder farmers. Barley ranks among the leading cereal crops in Ethiopia, contributing for 20,718,071.07 quintals of the total production [3]. Whereas barley is an economically importance cereal crop with high yield potential, the adoption of improved barley technologies remains low. This leads to stagnant yields, and a production gap that fails to fill the country’s rapidly increasing demand[4, 5].

In response to these challenges, the Ethiopian government has implemented cluster farming as a strategic development plan across the country including the study areas. Cluster farming is the way of consolidating adjacent farmland plots owned by individual farmers to produce uniform crop [2–8]. The Agricultural Transformation Agency (ATA) launched cluster farming as a development intervention to transition smallholder farmers from subsistence level production to a market oriented production [9]. Cluster farming helps smallholder farmers supply collectively their goods to market, obtain agricultural inputs timely, adopt uniform crop varieties and management practices, share information frequently, and create opportunities to interact with and help respective actors [9–14].

Cluster farming has a positive effect on household food security, productivity, consumption and poverty reduction. By commercializing their farming, the

revenue from surplus production enables smallholder farmers to enhance their purchasing power to meet basic needs through the market, while simultaneously retaining a surplus for home consumption [14–16]. Although the adoption of cluster farming has shown promising results in crop farming, empirical evidence regarding cluster farming effects on barley yield and technical efficiency in the study area was not studied. Specifically, what factors influence barley cluster farming adoption by smallholder farmers and does cluster farming adoption has a positive effect on barley yield and technical efficiency. Consequently, this study has been conducted to address the above research gaps by utilizing primary data obtained from the two key districts in the Central Ethiopia region, where characterized by the active implementation and adoption of cluster farming.

RESEARCH METHODOLOGY

Description of the Study Area

The study was conducted in Central Ethiopia region in six selected barley growing kebeles of two districts (Gumer and Alichu).

Gumer district is one of the districts in Gurage zone with an area of 234.04km² and is located 8° 5' 59" N & 38° 12' 0" E. The district characterised by high Altitude range between 2540 and 3178 m.a.s.l. Gumer districts is bordered on the southeast by the Silt'e Zone, on the southwest by Geta, on the northwest by Cheha, and on the north by Ezha. The capital city of the Gumer district is Arekit, which is 65 km far away from Wolkite the capital city of Gurage Zone. The average temperature is 18.5°C with minimum and maximum temperature of 16°C and 21°C, respectively. Annual average rainfall of the district is 1600mm with three distinct seasons, locally known as *Belg*, *Kiremt*, and *Bega*. The *Belg* (small rain) extends from February to May; the *Kiremt season* (the main rain) mostly occurs from June to September and is crucial for *Meher* livelihood type, and the *Bega* (dry) season extends from October to January. Mixed crop-livestock farming is the dominant livelihood activity in the district. The major crops grown in the district include enset barley, faba bean, wheat, field pea, potato, and kale [17].

Alichu Werero district is one of the ten districts in Silte zone and is located between 7°58'41"N latitudes and 38°09'53.9"E longitudes. Alichu Werero district is bordered on the south by Wulbareg, on the southwest by Misraq Azernet, on the west and north by the Gurage Zone, and on the east by Silti district. The capital city of Alichu Werero district is Kawaqoto, which is 28 km far away from Worabe the capital city of Silte zone. The district has a total of 29 kebele administrations, 25 rural kebeles and 4 urban kebeles. The district covers 26,318.359 hectares of land. The altitude of the district ranges between 1200 m.a.s.l and 3250m.a.s.l. The district has a rainfall pattern of bimodal type, Belg from

February to April and Meher from Jun to October. The mean annual rainfall ranges between 1000 -1600 mm. The mean annual temperature lies between 9.1⁰c to 18⁰. The dominant crops producing in the district include enset, barley, faba bean, wheat, field pea, vegetables and potato [18].

Data Types, Sources and Methods of Data Collection

In this study both qualitative and quantitative data types were obtained using primary and secondary data sources. To supplement the primary data, secondary data were collected from respective district and kebele office of agriculture, and published and unpublished documents. For this study, cross-sectional household data of 2024/2025 main cropping season was used. Primary data was collected from sampled smallholder barley producer farmers' through household survey, key informant interview and focus group discussion.

Sampling Procedure and Sample Size Determination

To select sample households, a three - stage sampling procedure was followed. In the first stage, study districts were selected purposively based on the potentiality of barley production and cluster farming practices. In the second stage, six barley growing and cluster farming adopter kebeles were identified in collaboration with the district agricultural offices. Finally, from the list of sampling frame (barley growers and cluster farming adopters) obtained from each kebele extension office, 154 sample households were selected randomly based on probability of proportionate to size of the number of barley growers and cluster farming adopters in the kebele. The number of sample households was determined by adopting a sample size determination formula provided by [19].

$$n = \frac{N}{1 + N(e^2)} = \frac{13465}{1 + 13465(0.08)^2} = 154$$

Where, n is the sample size for finite population, N is a number of barley growers and e is level of precision (error), e = 0.08 was assumed.

Methods of Data Analysis

To analyze the study objectives, both descriptive and econometric methods were employed. Such as means, percentages, standard deviations and frequency were applied for the descriptive statistics, while the Cobb-Douglas stochastic frontier production function and an endogenous switching regression models were used.

Econometric Model Specification

Parametric Stochastic Frontier Model

This study used the stochastic frontier model (SFM) to estimate the efficiency of barley producers in the study area. The SFM predicts inefficiencies and random errors that cause variations from the frontier. Parametric SFM is a commonly employed approach for measuring production efficiency and identifying the determinants technical efficiency. The SFM accounts

random and inefficiency error, it is viewed as a more accurate approach for measuring efficiency.

The general SFM is specified as follows:

$$Y_i = f((X_i, \beta_i) + (V_i - U_i))$$

Where Y_i is the barley output of the i^{th} farmer, X_i is a vector of farming inputs, and β_i is a vector of parameters to be estimated. Whereas V_i estimates the random variation in output (Y_i) due to factors beyond the control of the farmers, U_i measures inefficiency.

The functional forms that are commonly employed in SFM are Translog and Cobb-Douglas (CD). To choose the best fit functional form for the data at hand, the null hypothesis was tested using the generalized likelihood ratio (GLR)

Accordingly, the null hypothesis test is conducted using log-likelihood ratio (LR) statistics

$$LR(\lambda) = -2\ln[L(H_0) - L(H_1)]$$

Where λ is the likelihood ratio, $L(H_0)$ is the log likelihood value of restricted (null) hypothesis, and $L(H_1)$ is the likelihood value from unrestricted (alternative) hypothesis.

The λ value computed by the above formula was compared with the upper 5% critical value of the χ^2 at the degree of freedom equals to the difference between the number of independent variables used in both functional forms (in this case degree of freedom = 28).

Accordingly, Cobb-Douglas stochastic frontier production function employed for this study is specified as follows:

$$\ln y_i = \beta_0 + \sum_{j=1}^7 \beta_j \ln X_{ij} + (V_i - U_i)$$

Where \ln represents the natural logarithm; y_i is the barley output in kilograms; X_1 is the land allocated for barley (hectares); X_2 is the seed (kg); X_3 is the NPS fertilizer (kg); X_4 is the Urea fertilizer (kg); X_5 is the labour (man-days); X_6 is the herbicide (litters); X_7 is the oxen power (oxen-days); β_0 represents the intercept; β_i represents the vector of unknown parameters to be estimated in the model; V_i is a random error that is assumed to be independently and identically distributed; U_i represents farmers technical inefficiency, which reflects how far the observed output deviated from the potential yield in a given level of technology.

The estimation of maximum likelihood of the above equation yields estimators for λ and γ :

$$\lambda = \sigma_u / \sigma_v$$

$$\gamma = \sigma_u^2 / \sigma_u^2 + \sigma_v^2 \text{ or } \gamma = \lambda^2 / 1 + \lambda^2$$

Where γ is the parameter that have a value

between 0 and 1, when the value of γ is zero depicts the variation from the frontier is entirely due to random error, whereas a value of one depicts that all variations from the frontier is due to technical inefficiency. σ_u^2 is the variance parameter that indicates variation from the frontier due to inefficiency; σ_v^2 is the variance parameter that indicates variation from the frontier due to random error. To estimate the technical efficiency of barley producer farmers using the Cobb-Douglas production function, the ratio of the actual obtained output value (Y_i) to the corresponding estimated frontier output value (Y_i^*) was used. The technical efficiency score lies between 0 and 1.

$$TE = Y_i / Y_i^* = f(X_i; \beta_i) \exp(V_i - U_i) / f(X_i; \beta_i) \exp(V_i) = \exp(-U_i)$$

The Inefficiency Model

This study employed a one-step stochastic frontier estimation approach to analysis the determinants of technical inefficiency. The stochastic frontier production function and the inefficiency model were estimated simultaneously with the maximum likelihood method.

One-step Cobb-Douglas stochastic frontier production function is given as follow:

$$\ln Y_i = \beta_0 + \beta_i \ln X_i + V_i - (\delta_0 + \delta_i Z_i)$$

Where β_i are the estimated coefficients of input variables; X_i are production inputs expected to affect barley output; δ_i is the estimated parameter coefficients of technical inefficiency explanatory variables; V_i are random error and Z_i are explanatory variables expected to influence technical inefficiency.

Impact Analysis Model Specification

This study employed endogenous switching regression (ESR) to avoid selection bias as compared to PSM approach. The effect of cluster farming participation on productivity and technical efficiency under ESR is estimated in two stages. In the first stage, the binary probit model as the selection equation is employed to estimate participation in cluster based farming. In the second stage, to evaluate the association between the outcome variable and cluster farming, both linear regression and the binary probit model are used.

$$C_i^* = \omega_i X_i + v_i \text{ Where } C_i = \begin{cases} 1 & \text{if } C_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

Where C_i^* is the latent variable, X_i is a matrix of explanatory variables, ω_i is a vector of parameters to be estimated, and v_i denotes the disturbance terms. C_i is an observed binary indicator variable the equals one if the farmer participated on cluster farming and zero otherwise.

The outcome variables for both clusters (Regime 1) and non-clusters (Regime 0) can be explained as the ESR model.

Regime 1 (Adopters): $y_{1i} = \omega_1 x_{1i} + \varepsilon_{1i}$ if $i = 1$
 Regime 0 (Non-adopters): $y_{0i} = \omega_0 x_{0i} + \varepsilon_{0i}$ if $i = 0$

Where y_i indicates the outcome variables (productivity and technical efficiency) of smallholder farmers i for each regime (1= cluster farming participants and 0= non-cluster farming participants), x_i is a vector of explanatory variables that influence productivity and technical efficiency, ω_i is a vector of parameters to be estimated, and ε_i represents the error terms.

Accordingly, the expected outcomes for cluster farming participants, the average treatment effect on the treated (ATT) is obtained by comparing the actual and counterfactual scenarios. Similarly, by comparing the expected values for non-cluster participants in real and counterfactual scenarios the average treatment effect on the untreated (ATU) is obtained.

So, the estimated value of the outcomes for both cluster participants and non-participants in both the actual and counterfactual scenarios is specified as:
 Participants with adoption of cluster farming (actual)

$E(y_{1i}|x = 1) = \omega_1 x_{1i} + \sigma_{1v} \lambda_{1i}$
 Non-participants without adoption of cluster farming (actual)

$E(y_{0i}|x = 0) = \omega_0 x_{0i} + \sigma_{0v} \lambda_{0i}$
 If participants had not decided to participate in cluster farming (counterfactual)

$E(y_{0i}|x = 1) = \omega_0 x_{1i} + \sigma_{0v} \lambda_{1i}$
 If non-participants had decided to participate in cluster farming (counterfactual)

$E(y_{1i}|x = 0) = \omega_1 x_{0i} + \sigma_{1v} \lambda_{0i}$
 ATT of the cluster farming participants is computed as follows

$$ATT = E(y_{1i}|x = 1) - E(y_{0i}|x = 1) = (\omega_1 - \omega_0)x_{1i} + (\sigma_{1v} - \sigma_{0v})\lambda_{1i}$$

ATU of non-participants is computed as follows

$$ATU = E(y_{1i}|x = 0) - E(y_{0i}|x = 0) = (\omega_1 - \omega_0)x_{0i} + (\sigma_{1v} - \sigma_{0v})\lambda_{0i}$$

RESULTS AND DISCUSSION

Hypothesis Testing

As indicated in (Table 1) production functional for selection, inefficiency component and coefficient of the inefficiency effect were tested using the generalized likelihood ratio test (LRT) of the hypothesis.

Table 1: Generalized likelihood ratio tests

Hypothesis	df	Calculated LR-value	Critical value $\chi^2(0.05)$	Decision
H_0 : No inefficiency component ($\gamma = 0$)	1	62.36	3.84	Reject H_0
H_0 : Production function is SFP Cobb-Douglas ($H_0: \beta_8 = \beta_9 = \dots \beta_{35} = 0$)	28	37.41	41.34	Accept H_0
$H_0: \delta_1 = \delta_2 = \dots \delta_7 = 0$	7	58.78	14.07	Reject H_0

Source: Survey data, 2024

The first hypothesis was to test the existence of an inefficiency component in the stochastic frontier production function. The null hypothesis (H_0) indicates that the inefficiency component (γ) equals zero, showing that there is no technical inefficiency. The alternative hypothesis (H_1) depicts that γ is greater than zero, indicating that technical inefficiency exists. The test result depicts the calculated LR value (62.36) exceeds the critical value (3.84) at 1 degree of freedom for a 5% significance level, so that the study reject the null hypothesis (H_0) and the stochastic frontier production function is an appropriate functional form for the dataset.

The second hypothesis to determine the appropriate functional form for the dataset employed the likelihood ratio test. The null hypothesis (H_0) indicates that the Cobb–Douglas production function and the alternative hypothesis (H_1) depicts that the Translog function. Accordingly, the log likelihood functional values of both Cobb-Douglas and Translog production functions were -8.5031 and 10.2022, respectively. The test result indicates that the calculated LR value (37.4106) is lower than the critical value (41.34) at 28 degree of freedom and 5% significant level so that we accept the null hypothesis that the Cobb–Douglas functional form adequately fits the data.

The third hypothesis test was done to check whether all coefficients of the inefficiency effect model are equal to zero or not. The null hypothesis (H_0) depicts that the coefficients ($\delta_1, \delta_2, \dots, \delta_7$) are zero, showing that independent variables do not affect technical inefficiency. Conversely, the alternative hypothesis (H_1) indicates that at least one coefficient differs from zero. The hypothesis result depicts that the calculated value (58.78) exceeds the critical value (14.07) at 7 degree of freedom for a 5% significance level, so that we reject the null hypothesis (H_0).

Maximum Likelihood Estimation of the SFP Model

Table 2 shows one-step maximum likelihood estimation (MLE) of frontier production function and inefficiency effect model. After testing the above hypothesis the maximum likelihood of one-step Cobb-Douglas stochastic frontier production function was estimated and the model specification result is significant (Wald chi2 (7) = 662.33, Prob> chi2 = 0.0000), suggesting that at the 1% level of significant, the null hypothesis indicates that all slope coefficients are zero was rejected. Furthermore, lambda ($\lambda = 2.14$), which is a diagnostic measure of the inefficiency component that confirms the quality of model estimation and the validity of the distributional form assumed for the composite

error term, is found to be significant in barley production. This shows the presence of technical inefficiency of farmers in the production of barley. The Gamma($\gamma = \lambda^2 / 1 + \lambda^2$) is 0.82, indicates that technical inefficiency

accounts for 82% of the barley yield gap at the frontier, whereas 18% yield gap is due to the factors beyond farmers' control (Table 2).

Table 2: Maximum likelihood estimates of cobb-Douglas SFP function

Variables	Coefficient	Std.err	z
LnLand	0.654***	0.099	6.60
LnSeed	0.029	0.078	0.37
LnNPS	0.165***	0.054	3.02
LnUrea	0.029	0.042	0.68
LnLabor	0.271**	0.121	2.25
LnOxen	-0.120	0.114	-1.06
LnHerbicide	-0.009	0.053	-0.17
Constant	6.095***	0.527	11.56
Mechanization	-0.893**	0.384	-2.32
Farm size	-0.191	0.393	-0.49
Education status	-0.249**	0.120	-2.07
Training	-0.213	0.363	-0.59
Off-farm income	0.031	0.367	0.09
Frequency of extension contact	-0.312**	0.142	-2.19
Livestock holding	0.030	0.120	0.25
Constant	-0.904	0.644	-1.40
Lambda (λ) = 2.14 Gamma(γ) = 0.82 Wald chi2(7) = 662.33 Prob> chi2 = 0.0000 Log likelihood = 20.8854 Mean TE = 79.6 RTS = 1.02			

Source: Own computation based on 2024 field survey

Table 2 shows the maximum likelihood parameter estimates of the Cobb-Douglas stochastic frontier production function, and the results confirm that allocated land for barley production, NPS fertilizer and labour were found to positively and significantly affect barley output. The coefficients of land and NPS fertilizer were significant at 1% level of significance, and the coefficient of labor was significant at 5% level of significance. On average, as the farmer increases land allocated to barley, amount of NPS fertilizer application and labor for the production of barley by 1% each, the farmer can increase the level of barley output by 0.654, 0.165 and 0.271, respectively, while all other factors keep constant. The coefficients of inputs depict the elasticity of output, which is summed to be 1.02, this means that a 1% increase in all inputs would increase the overall barley yield greater than 1% (Table 2) and depicts that there was potential for barley producers to increase their production or they are not efficient in allocation of resource and there is a room to increase barley production at an increasing rate [1–22].

Determinants of Technical Inefficiency

The focus of this analysis was to offer empirical evidence of the determinants of inefficiency gaps among smallholder barley farmers in the study area. Because having knowledge that farmers are technically efficient might not be important without the causes of the

efficiency being identified. Out of the seven variables used in the model, three variables were found to influence significantly the inefficiency of smallholder barley farmers. Accordingly, the negative and significant coefficients of education status, mechanization and frequency of extension contact depict that enhancing these factors contributes to increase technical efficiency.

Education Status

The statistical result reveals that education has influenced technical inefficiency negatively at 5% significance level. This implies that smallholder farmers with more education achieve higher efficiency levels as compared to less educated farmers. Education enables smallholder farmers to access and apply technical knowledge on agricultural input optimization. This result is in line with the study by [1-20].

Frequency of Extension Contact

Extension services serve as a critical mechanism in strengthening smallholder farmers' decision making capacity and efficiency. The coefficient frequency of extension contact in the inefficiency model is negative and statistically significant at 5% as was expected. This suggests that technical inefficiency decreases as farmers receive more frequent extension support explicitly on barley production related activities. This result is in line with the finding of [1-20].

Uses of Mechanization

As presented in Table 2, use of agricultural mechanization negatively and significantly influenced farmers' technical inefficiency in barley production at 5% significance level. The result indicates that smallholder farmers who produced barley using mechanization achieved higher efficiency levels compared to non-mechanized production. This is because mechanization enhances farmers' efficiency by reducing labor costs, time, length of plowing and harvesting, and postharvest losses. This result is in line with the study by [23–26].

Barley Producers' Technical Efficiency Scores

Table 3 shows that the average technical efficiency (TE) of barley producers is 79.6%. This result

suggests that barley output could be increased by 20.4% on average using their current levels of inputs or without utilizing more inputs. Minimum technical efficiency (TE) for barley cluster farming participants (CLFP) and non-cluster participants (NCLFP) is 61.7% and 38.7%, respectively. These results indicate that the least efficient barley producers among the adopters and non-adopters of cluster farming are operating 38.3% and 61.3% below the production frontier, respectively. Maximum technical efficiency (TE) for barley cluster farming participants and non-participants is 98.3% and 96.7%, respectively. These figures show that the best efficient barley producers among the adopters and non-adopters of barley cluster farming are producing below the frontier possibility curve by 1.7% and 3.3%, respectively.

Table 3: Technical efficiency scores

Category	Mean	Std. dev	Minimum	Maximum
CLFP (75)	0.893	0.076	0.617	0.983
NCLFP (79)	0.704	0.137	0.387	0.967
Combined (154)	0.796	0.146	0.387	0.983

Source: Own computation based on field survey, 2024

Determinants of Barley Cluster Farming Participation

Probit model was employed to identify the determinants of barley cluster farming participation decision. As presented in Table 4, the model estimation result depicted that the barley cluster farming

participation decision is positively and significantly affected by the education, mechanization, frequency of extension contact and farm size, whereas livestock holding have negative and significant influence on the adoption of barley cluster farming.

Table 4: Factors affecting barley cluster farming participation decision

Variables	Coefficients	Robust Std. err.	z	Marginal effect
Education status	0.117**	0.058	2.03	0.047
Family size	-0.038	0.055	-0.70	-0.015
Barley farming experience	0.014	0.016	0.86	0.005
Farm size	0.799**	0.320	2.50	0.319
Number of plots	-0.063	0.190	-0.33	-0.025
Mechanization	0.838***	0.282	2.97	0.324
Access to credit	0.034	0.325	0.11	0.014
Planting method	0.108	0.317	0.34	0.043
Training	0.260	0.300	0.87	0.103
Off-farm income	0.178	0.272	0.65	0.071
Cooperative membership	-0.108	0.327	-0.33	-0.043
Frequency of extension contact	0.276***	0.101	2.73	0.110
Livestock holding	-0.309***	0.111	-2.80	-0.123
Constant	-1.095	0.587	-1.87	

Number of obs = 154; Wald chi2(13) = 64.08; Prob> chi2 = 0.0000; Pseudo R² = 0.4075; Log pseudolikelihood = -63.214225

Source: Own computation based on 2024 field survey

Note: *** and ** indicate significance at 1% and 5% probability levels, respectively.

Frequency of Extension Contact

Extension visits positively and significantly influenced the adoption of barley cluster farming at 1% probability level. The model result indicates that frequent extension visits by extension agents serves as catalyst for cluster farming adoption; barley producers with such access had a higher probability of adopting cluster

farming compared to counterparts. The probability of participating in barley cluster farming increases by 11% with every additional extension contact. This positive correlation stems because frequent interaction with extension agents allows smallholder farmers to better internalize and implement the suggested technical recommendations, thereby increasing their probability to

adopt barley cluster farming. The result is in line with the finding of [14–29].

Education Status

As expected, education status positively and significantly influenced the likelihood of adopting barley cluster farming at 5% significance level. The result indicates that each additional year of schooling increases the probability of barley cluster farming adoption by 4.7%, holding other variables constant. Education serves as promoter for cluster farming adoption by improving farmers' capability to understand new technical information, strategies and technologies. The result is in line with the finding of [30, 31].

Livestock Holding

As expected, livestock holding positively and significantly influenced the likelihood of adopting barley cluster farming at 1% significance level. The marginal effect result indicated that a unit increment in livestock holding decreases the probability of participating in barley cluster farming by 12.3%, keeping other factors constant. This depicts that farmers who have a larger number of livestock were less cluster farming adopters than those who had a small number of livestock. This may be because a larger number of livestock holding can slow agricultural technology adoption by competing resources (land, labor and capital). The result is in line with the finding of [32, 33].

Farm Size

Farm size has significantly and positively influenced the adoption decision of barley cluster farming at the 5% significance level. The result depicted

that farmers with larger farm size pursue to adopt new agricultural practices for efficient reasons than those who have small farm size. As the farm size of households increases by one hectare, the likelihood of cluster farming participation decision increases by 31.9%, keeping other factors constant. The result is consistency with the finding of [33–36].

Uses of Mechanization

The econometric model result also depicts that use of mechanization by smallholder farmers significantly and positively affected the adoption of barley cluster farming at the 1% probability level. Agricultural mechanization serves as a primary influencer of farm productivity by enhancing labour efficiency, land productivity, and minimizing postharvest losses [37]. The empirical result shows that the likelihood of adopting barley cluster farming was 32.4% for barley producer farmers who utilize mechanization compared to counterparts. The result is consistency with the finding of [25-27].

Effects of Cluster Farming Participation on Barley Yield and Technical Efficiency

Endogenous switching regression model has been employed to analyze the impact of cluster farming participation on barley productivity and technical efficiency in the study area. Table 5 presents the conditional average treatment effects of cluster farming participation on barley productivity and technical efficiency by comparing the value of barley productivity and technical efficiency under the actual case that has participated with the counterfactual case that had not participated.

Table 5: Average treatment effects on barley yield (Kg/ha) and technical efficiency

Outcome variables	Category	Smallholder farmers decision		Adoption effect (ATE)	Percent change
		Treated (to adopt)	Control (not to adopt)		
Yield	ATT	2405.16	1901.88	503.28***	26.46%
	ATU	2095.11	1700.81	394.30***	23.18%
TE	ATT	.8934	.7982	.0951***	11.91%
	ATU	.8174	.7037	.1137***	16.16%

Source: Own computation based on 2024 field survey

Note: *** indicates significance at 1% probability levels

As presents in Table 5, the model results depicted that cluster farming participation has enhanced smallholder farmers' barley productivity and level of technical efficiency. The result of ESR model depicted that cluster farming participant farmers would have lost 26.46% and 11.91% in barley productivity and technical efficiency, respectively if they had not engaged in cluster farming, while non-cluster participant farmers would have gained 23.18% and 16.16% in barley productivity and technical efficiency, respectively if they had participated in cluster farming. Therefore, the result confirms that the cluster farming participation significantly increases barley productivity and technical

efficiency in the study area. This result is in line with the findings of [8-38].

Barriers of Barley Cluster Farming Practices and Its Sustainability

As indicates in table 6, the study further points out obstacles to cluster farming scalability and sustainability include fragmented land; having inadequate land; inability to purchase inputs at the right time; existence of adjacent plot disagreements; limited crop diversification; lack of crop insurance; vulnerable to crop risk; lack of competitive market; and insufficient support, which might prevent further adoption and sustainability.

Table 6: Barriers of barley cluster farming scalability and sustainability

Barriers	Frequency	Percent	Rank
Having inadequate land (yes)	101	65.6	2
Lack of competitive market	79	51.3	8
Inability to purchase inputs at the right time	100	64.9	3
Fragmented land	107	69.5	1
Vulnerable to crop risk	81	52.6	7
Lack of crop insurance	83	53.9	6
Existence of disagreements (APC)	99	64.3	4
Limited crop diversification	85	55.2	5
Insufficient support	78	50.6	9

Source: Own computation based on field survey

CONCLUSION AND RECOMMENDATIONS

The study has evaluated the impact of the adoption of cluster farming on barley productivity and technical efficiency using 154 randomly selected sample respondents in Gumer and Alichu werero districts of the central Ethiopia region of Ethiopia. To analyse the efficiency and the impacts of cluster farming, this study employed a one - stage Cobb-Douglas stochastic frontier estimation approach and endogenous switching regression (ESR) models, respectively. The one – stage stochastic frontier Cobb-Douglas production model results show that barley output was significantly and positively influenced by allocated land for barley production, NPS fertilizer and labour. The average technical efficiency (TE) of barley producers is 79.6%. This result suggests that barley output could be increased by 20.4% on average using their current levels of inputs or without utilizing more inputs. Education status, frequency of extension contact and agricultural mechanization were significantly associated with technical efficiency. The results of the selected equation depict that the participation of barley cluster farming decision by smallholder farmers was positively and significantly affected by education status, farm size, agricultural mechanization, frequency of extension and negatively influenced by livestock holding. The result of ESR model depicted that cluster farming participant farmers would have lost 26.46% and 11.91% in barley productivity and technical efficiency, respectively if they had not engaged in cluster farming, while non-cluster participant farmers would have gained 23.18% and 16.16% in barley productivity and technical efficiency, respectively if they had participated in cluster farming. These findings underscore policymakers and development practitioners should prioritize the promotion of barley cluster farming as a key driver for augmenting barley yield and technical efficiency. To ensure the success of cluster farming approach, interventions should prioritize on creating an enabling environment through access to land, education, mechanization, extension support and financial services.

REFERENCES

- Lema TZ, Masresha SE, Neway MM, Demeke EM (2022) Analysis of the technical efficiency of barley production in North Shewa Zone of Amhara regional state, Ethiopia. *Cogent Econ Financ* 10:2043509.
- Louhichi K, Temursho U, Colen L, Paloma SG, Batt PJ, Murray-prior R (2019) Upscaling the productivity performance of the Agricultural Commercialization Cluster Initiative in Ethiopia. *JRC Sci. Policy Report*, Publ. Off. Eur. Union, Luxemb.
- ESS (2022) Area and Production of Major Crops. Ethiopian Statistics Service, Agricultural Sample Surver. *Surv Rep I:132*
- Kifle SW (2016) Review on barley production and marketing in Ethiopia. *J Econ Sustain Dev* 7:91–100
- Tadesse D, Derso B (2019) The status and constraints of food barley production in the North Gondar highlands, North Western Ethiopia. *Agric Food Secur* 8:1–7
- Getahun A, Milkias D (2021) Review on agricultural extension systems in Ethiopia: a cluster farming approaches. *J Biol Agric Heal* 11:1–6
- Gálvez Nogales E, Webber M (2017) Territorial tools for agro-industry development: a sourcebook.
- Degefu S, Andualem HM, Sileshi M, Ogeto MA, Bacsı Z (2025) Impact of cluster farming on technical efficiency and food security among smallholder wheat producers in Southeastern Ethiopia. *Discov Food* 5:1–18
- Zeleke AZ, Wordofa MG (2024) Contribution of cluster farming to household economy in Ethiopia: A systematic review. *Agric Syst* 221:104146
- Jr Tabe-Ojong MP, Dureti GG (2023) Are agro-clusters pro-poor? Evidence from Ethiopia. *J Agric Econ* 74:100–115
- ATA (2021) ATA (Agricultural Transformation Agency) 2020–21 Agricultural Transformation Agency Annual Report(2021).
- Dureti GG, Tabe-Ojong MPJ, Owusu-Sekyere E (2023) The new normal? Cluster farming and smallholder commercialization in Ethiopia. *Agric Econ* 54:900–920
- Joffre OM, Poortvliet PM, Klerkx L (2019) To cluster or not to cluster farmers? Influences on network interactions, risk perceptions, and adoption of aquaculture practices. *Agric Syst* 173:151–160
- Fola M, Tsegaye G, Zawde S, Matsalo M (2025)

- Effect of maize cluster farming on smallholder farmers' technical efficiency: evidence from Southern Ethiopia. *BMC Agric* 1:1–11
15. Nasir IM, Mulugeta W, Kassa B (2017) Impact of Commercialization on rural households' food security in major coffee growing areas of south west Ethiopia: the case of Jimma zone. *Internatinal J Econ Manag Sci* 6:437
 16. Abate S, Kassa B (2021) Impact of cluster farming on farmer's productivity and commercialization: the case of dera woreda. *South Gondar Zo.*
 17. GWAO (2019) Gumer Woreda Agriculture Office.2019. Socioeconomic and demographic characteristics of Gumer Woreda, Arekit.
 18. AWAO (2021) Alichu Wuriro Woreda Agriculture Office.2021. Socioeconomic and demographic characteristics of Alichu Wuriro Woreda, Alichu.
 19. Yamane T (1967) *Statistics: An Introductory Analysis*, 2nd Edition, New York: Harper and Row.. *Ciência Rural* 48:20180342
 20. Yadeta B, Guta R (2019) Technical efficiency of smallholder malt barley producers in Tiyo district (Ethiopia). *Вестник Российского университета дружбы народов Серия: Экономика* 27:525–535
 21. Wollie G (2018) Technical efficiency of Barley production: the case of Smallholde farmers in Meket district, Amhara national regional state, Ethiopia. Preprints
 22. Moges E, Geta E, Mekonnen T, Abate D (2023) Technical efficiency of smallholder producers in barley production in Northern Ethiopia. *Cogent Soc Sci* 9:2269723
 23. Hormozi MA, Asoodar MA, Abdeshahi A (2012) Impact of mechanization on technical efficiency: A case study of rice farmers in Iran. *Procedia Econ Financ* 1:176–185
 24. Min SHI, Paudel KP (2021) Mechanization and efficiency in rice production in China. *J Integr Agric* 20:1996–2008
 25. Abebe GM, Demissie WM, Zewdie MC (2025) Does the adoption of agricultural machinery improve smallholder farmers food security? Evidence from Arsi Zone, Oromia Region, Ethiopia. *Discov Sustain* 6:1–21
 26. Liu X, Li X (2023) The influence of agricultural production mechanization on grain production capacity and efficiency. *Processes* 11:487
 27. Zeleke BD, Geleto AK, Komicha HH, Asefa S (2021) Determinants of adopting improved bread wheat varieties in Arsi Highland A double-hurdle approach Oromia Region Ethiopia. *Cogent Econ. Financ.*
 28. Panta HK, Poudel S, Thapa S, Dahal S, Dhakal C, Regmi K, Basnet M (2023) Determinants of Agricultural Technology Adoption among Commercial Vegetable Growers in Bagamati Province, Nepal. *J Glob Agric Ecol* 15:37–45
 29. Hailu M, Tolossa D, Girma A, Kassa B (2021) The impact of improved agricultural technologies on household food security of smallholders in Central Ethiopia: An endogenous switching estimation. *World Food Policy* 7:111–127
 30. Feyisa BW (2020) Determinants of agricultural technology adoption in Ethiopia: A meta-analysis. *Cogent food Agric* 6:1855817
 31. Adams A, Jumpah ET (2021) Agricultural technologies adoption and smallholder farmers' welfare: Evidence from Northern Ghana. *Cogent Econ Financ* 9:2006905
 32. Ullah A, Khan D, Zheng S, Ali U (2018) Factors influencing the adoption of improved cultivars: a case of peach farmers in Pakistan. *Ciência Rural* 48:20180342
 33. Belay M (2021) Estimating the Impact of Agricultural Technology Adoption on Teff Productivity: Evidence from North Shewa Zone of Amhara Region, Ethiopia. *Ethiop J Econ* 30:77–102
 34. Udimal TB, Jincai Z, Mensah OS, Caesar AE (2017) Factors influencing the agricultural technology adoption: The case of improved rice varieties (Nerica) in the Northern Region, Ghana.
 35. Mponji RF, Cao X, Wang J, Jia X (2024) Meta-Analysis on Farmers' Adoption of Agricultural Technologies in East Africa: Evidence from Chinese Agricultural Technology Demonstration Centers. *Agriculture* 14:2003
 36. Getnet E, Debebe S (2023) Adoption of Agricultural Technology Packages in Barley Based Farming System of Ethiopia.
 37. Gebiso T, Ketema M, Shumetie A, Feye GL (2024) Impact of farm mechanization on crop productivity and economic efficiency in central and southern Oromia, Ethiopia. *Front Sustain Food Syst* 8:1414912
 38. Cheffo A, Ketema M, Mehare A, Shumeta Z, Habte E (2023) Impact of Malt-Barley commercialization clusters on productivity at household level: the case of selected districts of Oromia region, Ethiopia. *Ethiop J Agric Sci* 33:35–48.