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Research Article

Analysis of Economic Efficiency in Rice Production Among Smallholder Farmers in Shabe Sombo District, Oromia Regional State, Ethiopia

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Abstract

Ethiopia faces persistent food security challenges owing to rapid population growth and low agricultural productivity. This study examines the technical, allocative, and economic efficiency of smallholder rice producers in Shabe Sombo District, Oromia Region, and identifies factors influencing efficiency. A two-stage sampling technique was used to select 255 farmers; primary data were collected for the 2022/23 production year. A stochastic frontier approach with a Cobb–Douglas production function was applied to estimate efficiency levels, while a two-limit Tobit model was used to identify determinants of efficiency. Land, chemical inputs, oxen power, and seed positively and significantly influence rice output, with estimated returns to scale of 0.96 indicating decreasing returns. Mean technical, allocative, and economic efficiency stood at 94%, 75%, and 70% respectively, indicating that allocative inefficiency is the dominant source of overall efficiency loss. Tobit results show that farm distance from homestead, household size, and market distance negatively affect technical efficiency, while sex of household head, farm size, and extension contact frequency have positive effects. Age, education level, and livestock ownership negatively influence allocative and economic efficiency; training participation has a positive effect. Policy interventions should focus on strengthening extension services, expanding access to training and education, improving rural infrastructure and access to credit.

Keywords

Technical Efficiency, Allocative Efficiency, Economic Efficiency, Rice Production, Stochastic Frontier Analysis

1. Introduction

Agriculture remains the central economic sector of Ethiopia, accounting for more than 40% of GDP, 80% of exports, and the majority of employment [29, 32]. Agricultural productivity remains low despite recent economic growth, with significant negative consequences for food security and poverty reduction [10, 18]. Cereals dominate Ethiopia's agricultural production, accounting for the majority of cultivated land and total agricultural output [9].

Rice has become a major staple crop driven by population growth, urbanization, and changing food habits. Domestic production has not matched rising demand, resulting in increased dependence on imports and pressure on foreign currency reserves [19]. Although research efforts and improved varieties introduced in the mid-1990s have expanded rice production, productivity levels remain low [23] and a substantial gap between domestic supply and demand persists [9].

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Shabe Sombo District in Oromia Region is an emerging rice-producing area with favorable agro-ecological conditions. However, smallholder farmers face multiple constraints including limited access to modern inputs, inadequate infrastructure, weak market linkages, and socio-economic challenges [3, 28], resulting in inefficiencies, low yields, and reduced farm income.

While several studies have examined agricultural efficiency in Ethiopia, findings are largely generalized with little locality-specific reference [18, 30]. Empirical evidence on rice production efficiency in Shabe Sombo District is absent. This study therefore assesses the technical, allocative, and economic efficiency of smallholder rice producers in the district, identifies key socio-economic and institutional factors influencing efficiency, and examines the constraints facing rice producers.

2. Literature Review

2.1. Concept of Efficiency

In agricultural economics, efficiency refers to producers' ability to maximize output from given inputs or minimize the cost of a given output. Technical efficiency (TE) denotes a farm's ability to produce maximum output from its inputs; allocative efficiency (AE) denotes the ability to use inputs in optimal proportions given their prices; and economic efficiency (EE) combines both [13-15].

Efficiency is commonly measured using frontier approaches that compare observed output with the maximum feasible output [11]. The stochastic frontier analysis (SFA) approach is widely used in agricultural studies because it separates inefficiency from random shocks such as weather and measurement error [2, 17]. The Cobb–Douglas function is the most commonly adopted functional form because of its simplicity and ease of interpretation [6, 8]. Efficiency determinants are typically identified using a two-stage approach in which efficiency scores are regressed on explanatory variables using OLS or Tobit models [7].

2.2. Empirical Literature

Empirical studies consistently show smallholder farmers operating below potential efficiency levels. [16] Found small-scale wheat farmers in Kenya to be on average 85%, 96%, and 84% technically, allocative, and economically efficient respectively, with education and farm size positively influencing efficiency. In Ethiopia, [24] reported high TE but low AE and EE among rice farmers in Fogera District, indicating problems in cost management and resource allocation. Studies on maize farmers show similar patterns, with EE far below TE; education, extension services, credit, and farm size boost efficiency while market distance and infrastructure constrain it [26].

Despite these contributions, context-specific evidence on rice production efficiency in Shabe Sombo District is absent. This study fills that gap, providing location-specific empirical evidence using the stochastic frontier approach.

3. Methodology

3.1. Study Area and Sampling

The study was conducted in Shabe Sombo District, Jimma Zone, south-western Ethiopia, 395 km south-west of Addis Ababa. The district covers 1,191 km^2 with 20 rural and 2 urban kebeles, an estimated population of 163,276 [9], and agro-ecological zones ranging from 1,300 to 3,000 meters above sea level with mean annual rainfall of 1,420–2,200 mm.

A cross-sectional design was used with primary data collected for the 2022/23 production season through structured household interviews. A two-stage sampling method was employed: three rice-producing kebeles were selected randomly in the first stage; 255 sample households were then selected using probability proportional to size (Table 1), with sample size determined using [33] formula at 6% precision.

Table 1. *Number of sampled rice producer households.*

Kebele	Population	Sampling proportion (%)	Sample size
Kishe	1,300	8.31	108
Machi	960	8.23	79
Gasara	823	8.26	68
Total	3,083	8.27	255

Source: Agricultural Bureau of Shabe Sombo; own sampling design (2023).

3.2. Data Collection

Primary data were collected through structured questionnaires administered via face-to-face interviews by trained enumerators. Focus group discussions and key informant interviews with woreda agricultural experts and development agents supplemented the household survey. Secondary data were obtained from published sources, MoA reports, and woreda annual reports.

3.3. Econometric Models

Following [2, 17] the stochastic frontier production function with a Cobb–Douglas specification is expressed in log-linear form as:

$$\ln Y_i = \beta_o + \Sigma \beta_j \ln X_{ij} + \varepsilon_i \tag{1}$$

Where Y_i is rice output (quintals) for farmer i; X_{ij} are the j farm inputs; β_o and β_j are parameters to be estimated; and $\varepsilon_i = V_i - U_i$ is the composed error term. V_i is iid N $(0, \sigma^2_v)$, capturing statistical noise; U_i is non-negative half-normal, representing technical inefficiency. Following [5], the variance ratio $\gamma = \sigma^2_u/(\sigma^2_v + \sigma^2_u)$ is used since it is bounded between 0 and 1 and directly measures the share of output variation attributable to inefficiency. The dual cost function derived analytically from the production function provides the basis for computing AE and EE.

The likelihood ratio (LR) test, $\lambda = -2\{\ln[L(H_o)] - \ln[L(H_1)]\}$, following a chi-square distribution, was used to select the appropriate functional form and test for the presence of inefficiency.

A two-limit Tobit model was used to identify efficiency determinants, since efficiency scores are bounded between 0 and 1. The model is specified as:

$$y_i^*(TE, AE, EE) = \beta_o + \Sigma\, \beta_j Z_{ij} + \mu_i \tag{2}$$

Where y_i^* is the latent efficiency score; Z_{ij} are socio-economic, institutional, farm-related, and demographic explanatory variables; and $\mu_i \sim N(0, \sigma^2)$.

4. Results and Discussion

4.1. Descriptive Statistics

The average age of respondents was 47 years (SD = 11.14), ranging from 26 to 75. Average household size was 7.20 (SD = 3.10); 73.33% of household heads were male. Average education was 3.97 years of schooling (SD = 2.65), indicating generally low formal education. Average livestock holding was 11.14 TLU (range 3–20). Institutional characteristics are summarized in Table 2.

Table 2. *Institutional characteristics of sampled households.*

Variable	Mean	Min	Max	SD
Extension contact frequency (visits/season)	8.03	1	15	2.89
Distance to nearest market (hours)	0.95	0	3	0.81
Credit utilization — user (%)	54.90	—	—	—
Training participation (%)	76.08	—	—	—
Cooperative membership (%)	87.84	—	—	—
Perception of weather hazard — yes (%)	67.06	—	—	—

Source: own computation (2024).

Extension contact averaged 8.03 visits per season but ranged widely (1–15), indicating highly uneven advisory support. Market access was similarly varied (mean: 0.95 hours; range: 0–3 hours), implying that a subset of farmers faces substantially higher transaction costs. Cooperative membership was high (87.84%) and most farmers had received training (76.08%), suggesting strong collective institutional support. Credit access was more mixed, with 54.9% of farmers having used credit.

Table 3. *Descriptive statistics of production function variables.*

Variable	Unit	Mean	SD	Min	Max
Output	Quintal	78.69	27.47	35	180
Labour	Man-days	5.69	2.06	2	12
DAP	Kilogram	111.45	31.55	50	200
Urea	Kilogram	108.50	29.24	45	250
Seed	Kilogram	130.01	38.40	45	260
Chemical	Litter	2.98	0.77	1.5	4.5

Variable	Unit	Mean	SD	Min	Max
Oxen	Pair-days	3.13	1.05	2	7
Land	Hectare	1.14	0.36	0.5	2.5

Source: own computation (2024).

Average rice output was 78.69 quintals per household, but the wide range (35–180 quintals) a nearly fivefold difference indicates substantial productivity variation among farmers operating on broadly similar land areas (mean: 1.14 ha). This variation motivates the frontier efficiency analysis. Seed use showed the greatest absolute variation (mean: 130.01 kg, SD: 38.40), while chemical application was the most uniform (mean: 2.98 litres, SD: 0.77). DAP and urea applications were nearly equal on average, suggesting similar fertilizer management practices across farms.

Table 4. *Descriptive statistics of cost function variables.*

Variable	Mean (Birr)	SD	Min	Max
Cost of seed	5,884	1,745	2,250	11,700
Cost of DAP	4,083	1,169	1,851	7,404
Cost of urea	4,150	1,166	1,710	9,500
Cost of land rental	2,296	722	1,000	5,000
Cost of labour	570	206	200	1,200
Cost of oxen hire	1,569	525	1,000	3,500

Average household revenue: 273,000 birr (range: 122,500–630,000 birr).
Source: own computation (2024).

Seed was the largest input cost (mean: 5,884 birr), followed by urea (4,150 birr) and DAP (4,083 birr), together accounting for the dominant share of total production costs. Labour costs were low (mean: 570 birr), consistent with heavy reliance on household labour. Wide standard deviations across all cost items indicate significant heterogeneity in input access and farm management practices among rice producers.

4.2. Hypothesis Testing and Production Function Results

The LR test confirmed the Cobb–Douglas specification as the appropriate functional form. The computed LR statistic of 29.76 is less than the critical chi-square value of 41.337 (df = 28, p = 0.05), so the null hypothesis that the Cobb–Douglas form fits the data is accepted. A second LR test confirmed the presence of technical inefficiency (LR = 30.96, df = 15; critical value = 24.996 at 5% level), rejecting the null that all inefficiency coefficients equal zero. Results are summarized in Table 5.

Table 5. *Generalized likelihood ratio tests of hypotheses.*

Null hypothesis	LR statistic	df	Critical χ^2 (5%)	Decision
All interaction terms = 0 (Cobb–Douglas)	29.76	28	41.337	Accept H_o
No inefficiency effects (all $\delta = 0$)	30.96	15	24.996	Reject H_o

Source: own computation (2024).

Table 6. *Cobb–Douglas stochastic frontier production function estimates.*

Variable	Parameter	Coefficient	Std. Error
Constant	β_0	3.2459***	0.2821
Land (ha)	β_1	0.7120***	0.0625
Labour (man-days)	β_2	0.0368	0.0291
DAP (kg)	β_3	0.0276	0.0335
Urea (kg)	β_4	0.0192	0.0318
Seed (kg)	β_5	0.1369***	0.0419
Chemical (litres)	β_6	0.0572**	0.0263
Oxen (pair-days)	β_7	0.0825***	0.0298
Returns to scale ($\Sigma\beta$)	—	0.960	—
Sigma squared (σ^2)	—	0.0279***	—
Gamma (γ)	—	0.598***	—
Log-likelihood	—	156.07	—

***, ** and * denote significance at 1%, 5% and 10% levels respectively. Source: own computation (2024).

Land was the most elastic input ($\beta = 0.712$): a 1% increase in cultivated area raises rice output by approximately 0.71%. Seed ($\beta = 0.137$), oxen ($\beta = 0.083$), and chemicals ($\beta = 0.057$) also had significant positive effects on output. Labour, DAP, and urea were not statistically significant, possibly reflecting substitutability among inputs. The returns-to-scale estimate of 0.96 indicates slightly decreasing returns, suggesting farmers are operating near the technically optimal scale. Gamma ($\gamma = 0.598$) indicates that approximately 60% of total output variation is attributable to farm-specific inefficiency rather than random noise.

4.3. Cost Function Results

Table 7. *Stochastic frontier cost function estimates.*

Variable	Parameter	Coefficient	Std. Error
Ln cost of land	β_1	0.1766*	0.0730
Ln cost of labour	β_2	−0.0056	0.0210
Ln cost of urea	β_3	0.0526	0.0381
Ln cost of DAP	β_4	0.4305***	0.0700
Ln cost of seed	β_5	0.2348***	0.0559
Ln cost of chemical	β_6	−0.0070	0.0337
Ln cost of oxen	β_7	0.1216***	0.0325
Constant	—	−3.2740***	0.6943

***, ** and * denote significance at 1%, 5% and 10% levels respectively.
Source: own computation (2024).

DAP, seed, and oxen are the dominant cost drivers, with statistically significant elasticities of 0.431, 0.235, and 0.122 respectively, meaning a 1% rise in any of these input prices produces the largest increases in total production cost. Land cost was also positive and marginally significant (0.177, $p<0.10$). Labour and chemical cost coefficients were small and statistically insignificant, indicating minimal contribution to cost variation at current usage levels. The high elasticity of DAP and seed costs highlights them as priority targets for input subsidy or procurement support policies.

4.4. Efficiency Scores

Table 8. Summary statistics of efficiency measures.

Measure	n	Mean	SD	Min	Max
Technical efficiency (TE)	255	0.941	0.015	0.843	0.973
Allocative efficiency (AE)	255	0.752	0.119	0.391	0.942
Economic efficiency (EE)	255	0.708	0.113	0.367	0.903

Mean TE was 94.1% (SD: 0.015), with 98.43% of farmers operating above the 90% threshold, indicating that most farmers are close to the production frontier with current inputs and technology. The narrow TE range (84.3%–97.3%) confirms relatively homogeneous technical performance across the sample.

AE and EE were substantially lower and more dispersed, averaging 75.2% (SD: 0.119) and 70.8% (SD: 0.113) respectively. The wide AE range (39.1%–94.2%) indicates considerable variation in farmers' ability to allocate inputs at cost-minimizing proportions the least efficient farmer could reduce input costs by up to 64.6% if they matched the most efficient. These results suggest that the primary source of overall inefficiency is allocative rather than technical, pointing to resource allocation and input cost management as key areas for intervention.

These findings are broadly consistent with comparable Ethiopian studies. [1] reported TE, AE, and EE of 79%, 86%, and 68% in Fogera District; [18] found 78.5%, 80.6%, and 63.2%; and [20] reported lower values of 73.5%, 54.6%, and 38.0%. The higher TE but lower AE observed in the current study suggests that farmers in Shabe Sombo are technically competent but face greater challenges in optimal input allocation, likely reflecting input market access constraints.

4.5. Determinants of Efficiency

Table 9. Tobit model estimates for determinants of efficiency.

Variable	TE Coeff.	TE SE	AE Coeff.	AE SE	EE Coeff.	EE SE
Constant	0.9414***	0.00974	0.8566***	0.0790	0.8054***	0.0751
Age	−0.0000	0.0000	−0.0012*	0.00066	−0.0012**	0.0006
Sex (1=male)	0.0053**	0.0023	0.0128	0.0189	0.0162	0.0179
Non-farm income	−0.0011	0.00211	−0.0106	0.0171	−0.0103	0.0162
Education (years)	0.00018	0.0003	−0.0065**	0.0028	−0.0059**	0.0026
Extension contact	0.0010***	0.0003	−0.0002	0.0026	0.0004	0.0024
Household size	−0.0008**	0.00041	0.0022	0.0024	0.0021	0.0023
Farm size (ha)	0.0045*	0.0026	−0.0163	0.0197	−0.0123	0.0187
Credit use (1=yes)	0.00754	0.0047	0.0167	0.0382	0.0225	0.0280
Market distance	−0.0049**	0.00248	0.0226	0.0200	0.0176	0.0190
Livestock (TLU)	0.0003	0.00028	−0.0043*	0.0021	−0.0037*	0.0020
Weather perception	0.0002	0.00335	−0.0089	0.0270	0.01765	0.0257
Soil fertility	0.0020	0.00262	−0.0018	0.0212	−0.0016	0.0201

Variable	TE Coeff.	TE SE	AE Coeff.	AE SE	EE Coeff.	EE SE
Training (1=yes)	−0.0014	0.00280	0.0479**	0.0226	0.0439**	0.0215
Plot–home distance	−0.00012***	0.00004	−0.0000	0.0003	−0.0001	0.0003
Cooperative member	−0.0009	0.00360	−0.0477	0.0291	−0.0464*	0.0277

***, ** and * denote significance at 1%, 5% and 10% levels respectively. Marginal effects are available from the author on request. Source: own computation (2024).

Eleven of the fifteen hypothesized variables were statistically significant across the three efficiency measures.

Age had a negative and significant effect on AE ($p<0.10$) and EE ($p<0.05$), indicating that older farmers allocate inputs less efficiently, consistent with [18, 31].

Sex was positive and significant for TE ($p<0.05$), with male-headed households showing higher technical efficiency, reflecting greater engagement in field operations and better access to inputs and technology [1, 28].

Education negatively and significantly influenced AE and EE ($p<0.05$), reducing allocative inefficiency by 0.86% and economic inefficiency by 0.77% per additional year of schooling, consistent with education improving input management decisions [12].

Household size had a significant negative effect on TE ($p<0.05$). Larger households face higher consumption expenditure, constraining timely input acquisition and reducing production efficiency [25].

Extension contact frequency was positively and significantly associated with TE ($p<0.01$), confirming that regular advisory contact improves technical knowledge and on-farm decision-making [21].

Farm size had a positive and significant effect on TE ($p<0.10$), as larger farms offer greater flexibility for crop placement on fertile soils and better scope for technology adoption [27].

Plot distance from homestead negatively and significantly affected TE ($p<0.01$): each additional hour of travel reduces technical efficiency by 0.019 percentage points, reflecting reduced supervision and labour time [20, 22].

Livestock ownership negatively and significantly influenced allocative and economic inefficiency ($p<0.10$), meaning farmers with larger herds were more efficient, reflecting livestock's role in providing draught power and organic inputs [12].

Training was positive and significant for both AE and EE ($p<0.05$), indicating that exposure to production and marketing knowledge improves input allocation and cost management [4].

Cooperative membership showed a significant negative effect on EE ($p<0.10$), contrary to expectations. Membership fees and obligations may impose financial burdens that outweigh collective benefits for some households [28].

Market distance negatively and significantly affected TE ($p<0.05$), as remoteness restricts access to improved inputs and raises transaction costs, reducing production efficiency [27].

4.6. Major Constraints

Table 10. *Major constraints faced by rice producers (% of respondents)****.***

Rank	Constraint	Frequency (%)
1	High input costs (seeds, fertilizer)	23.14
2	Labour shortage	14.12
3	Limited access to modern technology	14.12
4	Inadequate government support	10.98
5	Poor infrastructure	8.24
6	Water scarcity	9.02
7	Market access difficulties	6.67
8	Climate variability	6.27
9	Lack of weather-resistant varieties	4.71

Source: own computation from household survey, FGDs, and KIIs (2024).

High input costs were the most frequently cited constraint (23.14%), followed by labour shortage and limited technology access (14.12% each). These findings corroborate the econometric results: DAP and seed cost elasticities dominate the cost function, and market distance significantly reduces technical efficiency. Weak extension services and poor infrastructure reinforce the efficiency gaps identified in the Tobit analysis.

5. Conclusions and Recommendations

This study analyzed the technical, allocative, and economic efficiency of smallholder rice producers in Shabe Sombo District using a stochastic frontier approach. Rice output significantly and positively responds to land, seed, oxen power, and chemical inputs, with land the most elastic input ($\beta = 0.712$).

Estimated returns to scale of 0.96 indicate slightly decreasing returns, suggesting farmers operate near the technically optimal scale.

Mean TE, AE, and EE were 94%, 75%, and 70% respectively. The high TE relative to AE and EE indicates that inefficiency is predominantly allocative farmers are technically competent but suboptimal in input mix decisions. Using existing resources and technology without increasing inputs, farmers could increase rice output by approximately 6%; improved input allocation could reduce production costs by approximately 25%.

Tobit results indicate that TE is positively influenced by sex of household head, farm size, and extension contact frequency, and negatively affected by household size, plot distance from homestead, and market distance. Age, education, and livestock ownership significantly influence AE and EE, while training participation has a positive effect on both.

The following policy interventions are recommended. First, extension services should be strengthened by increasing the number and quality of development agents, given extension contact's significant positive effect on TE. Second, rural road networks and market infrastructure should be improved to reduce distances to markets and farms plots, which significantly reduce efficiency. Third, education and agricultural training programs should be expanded, particularly for older farmers, to improve allocative and economic efficiency. Fourth, policies to reduce input costs particularly for seeds and DAP fertilizer, which show the highest cost elasticities through subsidies or group procurement schemes should be considered. Fifth, access to affordable agricultural credit should be expanded to enable timely acquisition of inputs, particularly for the 45.1% of farmers currently not accessing credit.

Abbreviations

AE	Allocative Efficiency
DAP	Diammonium Phosphate (fertilizer)
EE	Economic Efficiency
Km	Distance (in kilometers)
LR	Likelihood Ratio
OLS	Ordinary Least Squares
SD	Standard Deviation
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
TLU	Tropical Livestock Unit

Author Contributions

Wasihun Mitiku: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Writing – original draft

Amsalu Mitiku: Supervision, Validation, Writing – review & editing

Ibrahim Aliyi: Supervision, Visualization, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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