Jambura Agribus. J., 2025: Volume 6, Issue 2, Pages 75-89

JAMBURA AGRIBUSINESS JOURNAL
Department of Agribusiness, Universitas Negeri Gorontalo
P-ISSN: 2685-5860 | E-ISSN: 2685-5771
Homepage: https://ejurnal.ung.ac.id/index.php/jaj/index

Research

Technical efficiency analysis of shallot farming in Magetan regency, Indonesia

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ARTICLE HISTORY
Received:
22 April 2025
Revised:
29 July 2025
Accepted:
22 August 2025
Published:
25 August 2025

KEYWORDS
Cobb-douglas;
Maximum likelihood estimation;
Shallot;
Stochastic frontier;
Technical efficiency

ABSTRACT

Technical efficiency is a crucial aspect of shallot production in Indonesia, yet comprehensive research analyzing the technical efficiency of shallot farmers in Magetan Regency remains limited. This study aims to measure the technical efficiency levels of shallot farming in Magetan Regency, identify the influencing factors, and provide relevant recommendations. This research contributes to the literature by providing the first comprehensive analysis of technical efficiency in Magetan Regency's unique highland-lowland agricultural context, offering evidence-based policy recommendations for sustainable shallot production intensification. The research method employed was a survey with a sample of 125 shallot farmers selected through a multistage random sampling technique. Data analysis utilized the Cobb-Douglas Stochastic Frontier production function with Maximum Likelihood Estimation (MLE), and technical efficiency was measured by comparing actual output to potential output. The results showed that the average technical efficiency of farmers reached 0.757, with 80% of farmers classified as efficient (≥ 0.7). Factors with a significant impact on production included the use of urea, labor, and seeds, which had a positive influence, while land area and organic fertilizer had a negative effect. These findings indicate inefficiencies in some production inputs, particularly in land management and the use of organic fertilizers. Optimizing fertilizer application, enhancing labor skills, and selecting quality seeds are strategic steps to improve technical efficiency. The findings have direct policy implications for agricultural extension programs, input subsidy allocation, and farmer training initiatives in Indonesia's shallot production centers.

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Citation (APA Style):
Kartikawati, H., Kusnandar, K., & Widadie F. (2025). Technical efficiency analysis of shallot farming in Magetan regency, Indonesia. *Jambura Agribus. J.*, *6*(2), 75-89.

DOI: http://dx.doi.org/10.37046/jaj.v6i2.33590

INTRODUCTION

Global shallot production has experienced significant growth, with Indonesia playing a crucial role as a major producer. According to recent data, Indonesian shallot production reached

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2,615,677 tons in 2021, with projections indicating an increase to 4,189,324 tons by 2050, assuming sustained government support and subsidies (Tori et al., 2023). This growth trend is part of a broader increase in global shallot production, driven by rising demand and improved agricultural practices. Nevertheless, Indonesia still imports shallots from countries such as Vietnam, Malaysia, and Thailand, highlighting the competitive landscape among leading producers (Tori et al., 2023). In comparison, countries like China, India, the United States, and Egypt maintain higher production levels, underscoring the need for Indonesia to enhance its production capabilities to achieve self-sufficiency and reduce reliance on imports (Tori et al., 2023).

Improving the technical efficiency of shallot farmers is crucial for increasing productivity and competitiveness. High technical efficiency enables farmers to maximize output with the available inputs, which can, in turn, boost productivity and competitiveness in the market (Annisa et al., 2018; Lailandra et al., 2024; Winarso et al., 2021). In Indonesia, the technical efficiency of shallot production varies, with some regions demonstrating higher efficiency than others, indicating potential for improvement through the adoption of technology and technical training (Lailandra et al., 2024; Linh et al., 2024). Low technical efficiency can negatively impact farmers' income and regional economies. When farmers are unable to optimally utilize resources, production yields decrease, resulting in lower income (Linh et al., 2024; Simatupang et al., 2017). This can also affect the overall regional economy, as the agricultural sector often serves as the backbone of local economies (Nurjati et al., 2018; Saptana et al., 2021). Inefficiencies in shallot production can lead to significant losses. For example, in some areas, technical inefficiencies have resulted in reduced productivity and increased production costs, ultimately diminishing farmers' profits (Susilowati et al., 2021; Winarso et al., 2021). Moreover, these inefficiencies can lead to substantial crop losses, which can impact food security and price stability in the market (Shanmugam & Venkataramani, 2006; Susilowati et al., 2021).

Technical efficiency in agricultural production refers to farmers' ability to maximize output from the available inputs. This means that technically efficient farmers can produce more output with the same amount of inputs compared to less efficient farmers (Bala et al., 2019; Madau, 2012; Manurung et al., 2018). Measuring technical efficiency can be done using models such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA is a non-parametric method used to measure technical efficiency by comparing similar production units. DEA can identify the most efficient units and provide benchmarks for others to improve their efficiency (Miao & Wang, 2023; Olesen & Petersen, 2016; Sultana et al., 2023). SFA, on the other hand, is a parametric method that explains technical efficiency by modeling the production frontier while accounting for random factors. SFA allows for the decomposition of inefficiency effects from technical inefficiency (Bala et al., 2019; Hien et al., 2021; Hossain et al., 2012). Factors influencing technical efficiency in agricultural production include farmers' education, land ownership, extension frequency, and the use of efficient plots (Manurung et al., 2018). Additionally, the use of improved seed varieties and optimal farming practices can also enhance technical efficiency (Bala et al., 2019).

Research indicates that the technical efficiency of shallot production varies across locations. In Java, the average technical efficiency is lower compared to outside Java, despite higher land productivity in Java (Lailandra et al., 2024). In Bima Regency, the technical efficiency of shallot production reaches 0.9569, indicating that farmers can improve efficiency by optimizing the use of superior seeds and cultivation technology (Nursan & Wathoni, 2021). In Pati Regency, although farmers are technically efficient, they have not achieved economic and allocative efficiency (Nurjati et al., 2018). Determinants of technical efficiency include the use of seeds, fertilizers, and labor. In Bima, the number of seeds, urea fertilizer, and labor significantly influence production (Nursan & Wathoni, 2021). In Brebes, social factors such as private extension services also affect technical inefficiency (Annisa et al., 2018). In Aceh, participation in agricultural groups and land type significantly influence technical efficiency (Utari et al., 2023). Comparisons of technical efficiency across regions reveal significant variations. In Java and outside Java, the average technical efficiency is higher outside Java, despite lower land productivity (Lailandra et al., 2024).

Research on the technical efficiency of shallot farming in Magetan Regency highlights several key areas that require further investigation and policy development. This synthesis identifies research gaps and suggests directions for future research and policy recommendations. A more detailed analysis is needed on how specific factors, such as liquid pesticides, labor, and adhesives, affect efficiency in different environmental contexts, such as highlands versus lowlands in Magetan Regency (Triyono et al., 2021; Utari et al., 2023). Existing studies have identified inefficiencies in the use of production inputs like pesticides and labor but have not fully explored the underlying reasons for these inefficiencies or how they can be systematically addressed (Istiyanti & Maylani, 2022; Triyono et al., 2021). Moreover, while some studies have measured technical efficiency, they often fail to provide comprehensive policy implications or strategies for improving productivity and reducing costs (Murgas et al., 2023; Nursan & Wathoni, 2021). There is a clear need to develop evidence-based policy recommendations to enhance the technical efficiency of shallot farming. This includes optimizing the use of superior seed varieties, applying balanced fertilization, and improving farmers' skills in adopting innovative farming techniques (Murgas et al., 2023; Nursan & Wathoni, 2021). Policies should also focus on reducing reliance on inefficient inputs such as excessive pesticides (Istiyanti & Maylani, 2022; Triyono et al., 2021).

The potential for developing shallot agribusiness in Magetan Regency is substantial, given its strategic position as a national commodity in Indonesia. However, farmers face challenges in improving production efficiency, especially in highland areas that require special handling for shallot cultivation and the persistence of inefficiencies in the use of liquid pesticides and labor (Istiyanti & Maylani, 2022). Addressing these challenges is crucial for maximizing profits and reducing reliance on imports (Saptana et al., 2021). Strategic research plays a vital role in supporting the development of regional agricultural policies by identifying internal and external factors influencing agribusiness, such as market demand and distribution monopolies, and formulating aggressive strategies to leverage local strengths (Hindarti & Maula, 2021). Furthermore, institutional support and capacity building, particularly for women farmer groups, are essential for overcoming technical and non-technical constraints and enhancing agribusiness outcomes (Asriadi et al., 2021; Jusan, 2024; Taopan et al., 2023).

This study aims to determine the factors influencing production levels and measure the technical efficiency of shallot farmers in Magetan Regency. The research will provide policy recommendations to increase production and technical efficiency, thereby contributing to farmers' welfare in the long run. Previous studies have shown that production factors such as liquid pesticides, labor, and adhesives significantly impact shallot production, with inefficiencies observed in pesticide use and labor allocation, indicating the need for adjustments to maximize profits (Istiyanti & Maylani, 2022). Technical efficiency is crucial for sustaining shallot production, with factors like female labor and adhesives negatively affecting productivity, while seeds and male family labor positively influence it (Annisa et al., 2018). Additionally, land area, seeds, and fertilizers are significant factors, but allocative inefficiencies persist, highlighting the need for optimal input use (Triyono et al., 2021).

Despite the existing research on technical efficiency in shallot farming, there remains a notable gap in the literature regarding the specific context of Magetan Regency. While previous studies have investigated various aspects of technical efficiency in different regions of Indonesia, a comprehensive analysis focusing on the unique challenges and opportunities in Magetan Regency is lacking. Therefore, this study specifically aims to: (1) identify and quantify the factors influencing shallot production levels in Magetan Regency using stochastic frontier analysis; (2) measure the technical efficiency of shallot farmers and its distribution across highland and lowland areas; and (3) formulate evidence-based policy recommendations to improve production efficiency and farmer welfare. This research contributes to the growing body of knowledge by providing the first comprehensive technical efficiency analysis in Magetan Regency, offering practical insights for policymakers in optimizing input subsidy programs, and establishing a baseline for future efficiency monitoring in Indonesia's shallot production centers.

METHOD

Sample and Data Collection

This study was conducted in Magetan Regency, which was purposively selected as it is a central region for shallot production. The sample was determined through a multistage random sampling approach as follows: 1) Sub-districts were randomly selected, considering both highland and lowland areas with high shallot production and continuous cultivation. The selection resulted in three sub-districts from the highlands, namely Plaosan, Sidorejo, and Panekan, and three sub-districts from the lowlands, namely Lembeyan, Kartoharjo, and Magetan; 2) Villages were selected based on the criteria of being shallot production centers according to data from the Central Bureau of Statistics (BPS), resulting in a total of 6 villages; 3) The selected villages were 3 villages from highland areas and 3 villages from lowland areas; (iv) Farmers were selected as respondents proportionally, with a total sample of 125 farmers.

Data collection was conducted from January to March 2025 using structured questionnaires. The questionnaire consisted of four main sections: 1) respondent characteristics (age, education, farming experience); 2) farm characteristics (land area, ownership status); 3) input usage in one planting season (seeds, fertilizers, pesticides, labor); and 4) production output. Face-to-face interviews were conducted by trained enumerators to ensure data quality.

Data Analysis

The research objectives were analyzed using the Cobb-Douglas stochastic frontier production function with Maximum Likelihood Estimation (MLE). This model is commonly used to estimate the level of technical efficiency in agricultural production (Lee & Tyler, 1978; Okoye et al., 2016; Okoye et al., 2007). There are eight variables in this study that form the following production function equation:

$$ln\,Y = ln\,\beta_0 + \beta_1 ln(X_1) + \beta_2 ln(X_2) + \beta_3 ln(X_3) + \beta_4 ln(X_4) + \beta_5 ln(X_5) + \beta_6 ln(X_6) + \beta_7 ln(X_7) + \beta_8 ln(X_8) + V_i + U_i$$

Where:
Y = Quantity of shallot production (kg)
X_1 = Land area (ha)
X_2 = Amount of seeds (kg)
X_3 = Amount of NPK fertilizer (kg)
X_4 = Amount of ZA fertilizer (kg)
X_5 = Amount of organic fertilizer (kg)
X_6 = Amount of labor (man-days)
X_7 = Amount of pesticides (kg)
X_8 = Amount of urea fertilizer (kg)
v_i = Stochastic error term
u_i = Technical inefficiency effects

Recent literature shows that many studies on production efficiency have used the stochastic production frontier model to estimate technical efficiency (Chandel et al., 2022; Min & Paudel, 2021). To estimate the level of technical efficiency, the stochastic production frontier model requires an initial specification of the production function, such as Cobb-Douglas, trans-log, and others. In most empirical studies on agricultural production analysis, the Cobb-Douglas and trans-log functions are the most widely used models. Some researchers argue that the Cobb-Douglas functional form has advantages over other forms because it provides a balance between data fit and computational feasibility. Moreover, this function also facilitates the interpretation of production elasticities and is more parsimonious in the use of degrees of freedom.

Furthermore, the Cobb-Douglas production function is more attractive due to its simplicity and logarithmic nature, which makes the econometric estimation of parameters easier. In contrast, the trans-log production function is more complex in parameter estimation and faces various estimation constraints. One of the constraints is that as the number of input variables increases, the number of parameters to be estimated increases significantly.

Sukartawi (1990), explains that the level of technical efficiency can be measured by comparing the actual output (Υ) with the potential output $(\hat{\Upsilon})$, and the technical efficiency value is then obtained from the following mathematical equation:

$$\mathrm{ET}_{\boldsymbol{G}} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\frac{\Upsilon_i}{\hat{\Upsilon}_i}$$

The range of technical efficiency (TE) values lies between $0 \leq \mathrm{TE} \leq 1$, and it is considered fully efficient when the value is 1 (TE = 1). According to Yekti et al. (2017), farming activities can be categorized as technically efficient if they obtain an efficiency level value of ≥ 0.7. The technical efficiency analysis in this study was conducted using Frontier 4.1c software.

RESULTS AND DISCUSSION

Descriptive Statistics

Based on the results of the descriptive statistical analysis of 125 respondents shown in Table 1, it was found that the average age of respondents was 51.64 years, with an age range between 32 and 80 years. The majority of respondents were male (98%), with an average education level of 9.01 years, equivalent to junior high school level, with varying education ranges. In terms of farmer group activity, respondents showed a moderate level of participation on a scale of 1 to 3. The average number of family members of respondents was 3.90 people, indicating that most respondents had relatively small nuclear families.

Table 1. Descriptive Statistics of Respondents' Characteristics

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
Age	125	51.64	10.06	32	80
Gender	125	0.98	0.13	0	1
Education	125	9.01	3.46	0	16
Farmer Group Activity	125	1.18	0.40	1	3
Number of Family Members	125	3.90	1.33	1	7

Source: data processed, 2025

According to Table 2, the average shallot production per planting season in Magetan Regency was 1,424.88 kg per farmer. This figure indicates a reasonably good production capacity, although there is still significant variation among farmers. The average land area used was 0.20 hectares, indicating that most shallot farmers in this region manage small-scale land. Limited land scale can be one of the limiting factors in increasing production volume, especially if not accompanied by intensive cultivation technology. Furthermore, the average seed use reached 239.48 kg per planting season. This high figure reflects the importance of seeds in increasing shallot productivity. Quality seeds can contribute to increased yields through better growth potential and disease resistance.

Table 2. Descriptive Statistics of Input Use in Shallot Farming

Variable	**Description**	**Mean**	**Std. dev.**	**Min**	**Max**
Production	Amount of shallot production in one planting season (kg)	1424.88	1071.11	100	6000
Land area	Land area used in shallot farming (ha)	0.20	0.14	0.04	0.8
Seeds	Amount of seeds used in shallot farming	239.48	124.23	75	800
NPK Fertilizer	Amount of NPK fertilizer used in shallot farming (kg)	67.99	43.82	10	300
ZA Fertilizer	ZA Fertilizer Amount of ZA fertilizer used in shallot farming (kg)	25.36	14.67	10	80
Organic Fertilizer	Amount of organic fertilizer used in shallot farming (kg)	380.64	171.09	20	1000
Labor	Amount of labor used in shallot farming (man-days)	25.69	18.09	5	116
Pesticides	Amount of pesticides used in shallot farming (kg)	1.59	1.04	1	6
Urea Fertilizer	Amount of urea fertilizer used in shallot farming (kg)	24.30	16.02	5	90

Source: data processed, 2025

Moreover, the average use of NPK and ZA fertilizers was 67.99 kg and 25.36 kg, respectively, indicating farmers' efforts to meet the macro-nutrient needs of shallot plants. Meanwhile, the relatively high use of organic fertilizer, at 380.64 kg, shows farmers' awareness of the importance of improving soil physical properties and land productivity sustainability. However, the high use of organic fertilizer also needs to be evaluated, considering the analysis results showing a negative influence on production. The average labor use reached 25.69 man-days, confirming that shallot cultivation is still labor-intensive, especially in the weeding, fertilizing, and harvesting processes. The average use of pesticides at 1.59 kg and urea fertilizer at 24.30 kg indicates that farmers are trying to control pests and meet nitrogen requirements to increase production yields.

Factors Affecting Shallot Production Levels

The Maximum Likelihood Estimation (MLE) results indicate that shallot production is significantly influenced by urea, labor, and land area, while other inputs show no statistically significant effects. Urea has the largest positive and highly significant coefficient (β = 1.112, p < 0.01), followed by labor (β = 0.603, p < 0.01). In contrast, land area shows a highly significant negative effect on production (β = −0.859, p < 0.01). Other variables—including seeds (β = 0.166), NPK (β = −0.007), ZA (β = −0.017), organic fertilizer (β = −0.012), and pesticides (β = −0.047)—have coefficients that are statistically insignificant based on the reported t-ratios. The estimated gamma value is very high (γ = 0.918), implying that 91.8% of the total variation in output is attributable to technical inefficiency rather than random shocks, reinforcing that managerial and operational factors are central determinants of production performance in this sample. The likelihood ratio (LR) test value of 21.235 also supports the relevance of the stochastic frontier specification, indicating that inefficiency effects are strongly present and the frontier model is preferable to a model without inefficiency.

Table 3. Final MLE of the Effects of Variables on Production

Variable	Coefficient	Std. Error	t-Ratio
Constant	-0.193	0.759	-0.254
Land	-0.859	0.118	-7.252***
Seeds	0.166	0.105	1.585
NPK	-0.007	0.183	-0.041
ZA	-0.017	0.131	-0.129
Organic	-0.012	0.097	-0.121
Labor	0.603	0.162	3.725***
Pesticides	-0.047	0.063	-0.752
Urea	1.112	0.207	5.371***
sigma-squared	0.770	0.323	2.386
Gamma	0.918	0.042	21.860
Lr Test	21.235		

Source: data processed, 2025

The analysis results in Table 3 show that the urea coefficient ($\beta = 1.112$, $p < 0.01$) confirms that nitrogen input remains the most productivity-enhancing factor in shallot cultivation. Interpreting the model in elasticity terms (as commonly done in log-linear production frontiers), a 10% increase in urea use is associated with an estimated 11.1% increase in production, holding other factors constant. Practically, this implies extension services should prioritize precision urea management, especially correct dosage and timing across crop stages, because gains from improved nitrogen efficiency appear substantial. This is consistent with Firdaus and Fauziyah (2020), who highlight the importance of optimal nitrogen management for horticultural productivity.

Labor also shows a strong and highly significant positive effect ($\beta = 0.603$, $p < 0.01$), underlining that shallot farming remains highly labor dependent particularly for land preparation, planting, weeding, pest monitoring, and harvesting. Under the same elasticity interpretation, a 10% increase in labor input corresponds to an estimated 6.0% increase in production. This finding suggests that productivity improvements can be accelerated through skill-focused labor interventions, such as training on field operations efficiency (weeding techniques, harvesting standards, post-harvest handling) and targeted support during peak labor-demand periods. This aligns with evidence (e.g. Setiawan, 2022) emphasizing the labor-intensive nature of horticultural systems.

Conversely, land area exhibits a highly significant negative effect ($\beta = -0.859$, $p < 0.01$). This counterintuitive result may reflect structural and management issues often associated with expanding cultivated area such as land fragmentation, uneven soil quality across plots, constraints in supervision and timeliness of operations, or suboptimal input allocation when farmers manage larger or dispersed parcels. In elasticity terms, a 10% increase in land area is associated with an estimated 8.6% decrease in production, suggesting that expansion without improvements in management and technology can reduce effective productivity. This is consistent with Wahyuningsih et al. (2018), who argue that fragmentation and scale-related constraints can generate technical inefficiency by limiting the effective application of cultivation practices and technology.

Technical Efficiency of Shallot Farming

The analysis results show that the average technical efficiency of shallot farming in Magetan Regency reaches 0.829 (Table 4). This means that, on average, farmers are operating at 82.9% of the potential (frontier) output, and there is still a production gap of about 17.1% that could be closed through better management and input-use practices, without necessarily increasing input quantities. The distribution of TE scores also indicates that efficiency performance is highly concentrated at the upper level: 90.4% of farmers (113 farmers) are in the 0.76–1.00 category, while only 7.2% (9 farmers) are in the 0.51–0.75 range. A very small share of farmers falls into low efficiency groups 1.6% (2 farmers) in 0.26–0.50 and 0.8% (1 farmer) in 0.00–0.25. This pattern suggests that shallot farming in Magetan is generally well-managed, with inefficiency problems concentrated in a relatively small subgroup.

Table 4. Results of Technical Efficiency Analysis of Shallot Farming

Category	**Frequency**	**Percent (%)**
0.76 – 1.00	113	90.4
0.51 – 0.75	9	7.2
0.26 – 0.50	2	1.6
0.00 – 0.25	1	0.8
Average	**0.829**	

Source: data processed, 2025

From a policy and extension perspective, this updated distribution implies that interventions should be more selective and differentiated. Because the majority of farmers already operate at high efficiency (0.76–1.00), broad “basic training for everyone” is likely to yield limited marginal gains. Instead, programs should focus on (1) maintaining and upgrading performance among the high-efficiency majority through advanced modules (e.g., precision nutrient scheduling, better labor organization, and cost efficiency), while (2) providing intensive and targeted assistance for the small group of farmers below 0.76, particularly those below 0.50 who represent the most vulnerable and least efficient segment. This is consistent with the idea that high technical efficiency is commonly linked to the adoption of appropriate technology and strong farmer capability in managing inputs effectively.

Table 5. Distribution of Technical Efficiency Categories in Shallot

Category	**Frequency**	**Percent (%)**
0.70 – 1.00	100	80
0.00 – 0.69	25	20

Source: data processed, 2025

Table 5 showed the distribution becomes even clearer for operational targeting: 80% of farmers (100 farmers) are classified as having TE ≥ 0.70, while 20% (25 farmers) are still below 0.70. Although Table 4 shows that most farmers are already above 0.76, Table 5 confirms that a meaningful minority still operates below a policy-relevant threshold (0.70), meaning targeted extension remains necessary, but should be designed as a focused intervention rather than a blanket program. Practical implications include: (1) prioritizing the 20% group for coaching on input calibration (dose, timing, and method), (2) strengthening field-level supervision through farmer field schools or structured mentoring in selected villages, and (3) using demonstration plots not merely to teach basics, but to show cost-efficient best practices and operational discipline (timeliness of fertilizing, weeding, irrigation scheduling, and pest monitoring).

The mean TE of 0.829 suggests that many farmers have already achieved relatively good managerial performance, so the next productivity gains are likely to come from closing the remaining efficiency gap in the bottom segment and refining practices among the already-efficient group. For the 90.4% high-efficiency farmers, the most relevant strategy is "efficiency upgrading": improving precision (especially nutrient timing), reducing wasteful practices, and strengthening market and post-harvest decisions so that high technical efficiency translates into better profitability. Meanwhile, for the 7.2% moderate-efficiency group (0.51–0.75), interventions should emphasize standardizing good cultivation procedures ensuring correct fertilizer dosage, improving labor allocation during peak operations, and strengthening pest observation so pesticide use becomes more rational. Finally, the 2.4% of farmers below 0.50 require intensive mentoring, because their inefficiency level indicates deeper constraints such as weak technical knowledge, poor operational timing, or limited capacity to implement recommended practices consistently. Shallot farming in Magetan is generally efficient, with most farmers close to the production frontier. Therefore, the most cost-effective policy approach is precision targeting: protect and enhance the already strong performance of the majority, while directing resources and mentoring intensity toward the smaller subgroup that remains substantially below the frontier because that group offers the largest potential efficiency gains per unit of extension and support.

CONCLUSION

Based on the results of the Maximum Likelihood Estimation (MLE) analysis and technical efficiency of shallot farming in Magetan Regency, it can be concluded that the factors that significantly influence shallot production include the use of urea fertilizer, labor, and land area. The use of urea has the largest and highly significant positive effect on production, followed by labor, which is also positive and highly significant, highlighting the importance of precise input and labor management to raise productivity. In contrast, land area has a significant negative effect, indicating potential land fragmentation or management constraints as farm size expands. Other inputs (including seeds, NPK, ZA, organic fertilizer, and pesticides) are not statistically significant in this model. Furthermore, the average technical efficiency of 0.829 indicates that most farmers are already relatively efficient, but around 20% of farmers remain below the 0.70 efficiency threshold, suggesting the need for targeted extension and mentoring.

This study contributes to the literature by: 1) providing the first comprehensive technical efficiency analysis of shallot farming in Magetan Regency; 2) identifying the dominant drivers of output particularly urea and labor, while documenting which inputs show limited statistical influence; and 3) offering evidence-based policy recommendations tailored to Indonesian shallot production systems, especially precision urea management and support programs for less efficient farmers.

Based on these findings, the suggestions that can be given are the importance of strengthening agricultural extension services that focus on optimizing fertilizer use, especially urea, and improving labor skills in shallot cultivation. Specific policy recommendations include: 1) Implementation of a tiered extension program based on farmer efficiency levels; 2) Establishment of input optimization demonstration plots in each production center; 3) Development of mobile soil testing services to guide fertilizer application; 4) Creation of farmer cooperatives to address land fragmentation issues. Local governments should increase training programs on appropriate fertilizer dosage and application timing as well as efficient cultivation techniques to improve the technical efficiency of farmers who are still low. In addition, efforts are needed to improve land management, such as the use of appropriate soil processing technology and crop diversification to increase land productivity. Regarding the use of organic fertilizer, further research is needed on the appropriate dosage and combination with inorganic fertilizers to increase its effectiveness. Strengthening farmer institutions is also necessary to facilitate access to quality inputs and better cultivation technology information. Thus, it is hoped that the production and technical efficiency of shallot farming in Magetan Regency can increase sustainably.

Potential challenges in implementing these recommendations include: 1) Limited extension personnel relative to farmer numbers, suggesting a need for farmer-to-farmer extension models; 2) Financial constraints for input subsidies, requiring prioritization of high-impact interventions; 3) Traditional farming practices resistance, necessitating participatory approaches and demonstration of economic benefits; 4) Infrastructure limitations in highland areas, requiring mobile extension services and digital communication strategies. Future research directions should include: 1) Longitudinal studies to track efficiency changes over time; 2) Analysis of market access impacts on technical efficiency; 3) Investigation of climate change adaptation strategies for shallot production; 4) Cost-benefit analysis of different intervention programs; 5) Comparative efficiency studies across Indonesia's main shallot production regions.

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