Analysis of technical efficiency and socio-economic factors influencing the development of smallholder oil palm plantations in Batanghari Regency, Indonesia

Yanuar Fitri *; Saidin Nainggolan

Department of Agribusiness, Faculty of Agribusiness, Jambi University, Indonesia

**To whom correspondence should be addressed: email: yanuar_fitri@unja.ac.id*

DOI: 10.22437/ppd.v10i6.38755	Received: 26.12.2022	Revised: 18.01.2023	Accepted: 20.02.2023	Published: 28.02.2023

Abstract

This study aims to analyze technical efficiency and the influence of socio-economic factors on the development of smallholder oil palm plantations. Data were collected using the Simple Random Sampling method, utilizing both primary and secondary data. The analytical methods employed include descriptive analysis and the Stochastic Frontier Production Function with the Maximum Likelihood Estimation (MLE) method. The results reveal that the average size of oil palm plantations is 3.9 hectares per farmer, with a productivity rate of 13,853 kg/ha. Production factors such as land area, NPK fertilizer, urea, and dolomite fertilizer significantly influence production, whereas labor and herbicides show no significant effects. The technical efficiency levels range from 0.81 to 0.95, with an average of 0.86, which is greater than the threshold of 0.62, indicating that oil palm plantations operate at a technically efficient level. Socio-economic factors, including land area and plantation distance, potentially increase technical inefficiency but have no statistically significant effect. Conversely, variables such as farming experience, access to technology, and active participation in farmer groups help reduce technical inefficiency. To promote the development of smallholder oil palm plantations, it is crucial to focus on enhancing technical efficiency, as it directly impacts productivity. Additionally, consideration of farmers' socio-economic conditions and external factors such as market prices and environmental conditions is essential.

Keywords: *Production input, Production response, Socioeconomic, Technical inefficiency*

JEL Classification: O21, Q14, Q17, Q20

INTRODUCTION

The export value of plantation commodities in 2022 reached USD 28.24 billion, equivalent to IDR 410.76 trillion (assuming an exchange rate of USD 1 = IDR 14,582). The significant contribution of the plantation sector to state revenue has positively impacted the Indonesian economy (Directorate General of Plantations, 2023).

During its initial stages of development, smallholder plantations were established under the smallholder core plantation scheme, known as the *perkebunan inti rakyat* (PIR) model. In this model, both private and government plantations served as the core (*inti*), while smallholder plantations functioned as participants (*plasma*). Over time, smallholder plantations have expanded beyond the PIR framework, utilizing funds from commercial credit (provided by cooperatives and banks) as well as personal resources, thereby forming independent plantations. However, oil palm plantations managed independently face several challenges, including low productivity levels.

In 2020, large private plantations (*perkebunan besar swasta* or PBS) dominated the oil palm plantation sector in Indonesia, accounting for 54.69% of the total area, equivalent to 7,977,298 hectares. Smallholder plantations (*perkebunan rakyat* or PR) ranked second, covering 41.44% of the area, or 6,044,058 hectares. Meanwhile, large state plantations (*perkebunan besar negara* or PBN) represented only 5.05% of the total area, with 565,241 hectares (Directorate General of Plantations, 2023).

Data from the Directorate General of Plantations, Ministry of Agriculture of the Republic of Indonesia (2021), indicates that the productivity of smallholder oil palm plantations in Indonesia ranges from 15.2 to 21.6 tons per hectare per year. In Jambi province, however, productivity is even lower, ranging from 9.5 to 20 tons per hectare per year. In comparison, private and state plantations achieve much higher productivity levels, ranging from 28.5 to 45 tons per hectare per year. These figures are still significantly lower than the productivity of oil palm plantations in Malaysia and Thailand, where yields range from 36.3 to 58 tons per hectare per year. This indicates a substantial opportunity to enhance productivity, which could be realized through improved plantation management practices and the application of recommended cultivation technologies.

Jambi Province is among the ten largest oil palm producers in Indonesia in terms of both land area and production levels. In 2020, the province had 1,083,746 hectares of oil palm plantations, producing 2,639,894 tons. It ranked sixth nationally, following Riau Province, West Kalimantan, Central Kalimantan, East Kalimantan, and North Sumatra (Directorate General of Plantations, 2020). According to data from the Jambi Provincial Plantation Office in 2020, approximately 71.23% of oil palm plantations in Jambi were smallholder plantations (*perkebunan rakyat* or PR), while large state plantations (*perkebunan besar negara* or PBN) accounted for 1.88% and large private plantations (*perkebunan besar swasta* or PBS) made up 26.88%. This dominance of smallholder plantations underscores the vital role of oil palm as a leading commodity in supporting Jambi's regional economy.

Oil palm plantations are considered technically efficient when production factors are utilized to achieve maximum output. Allocative efficiency is achieved when minimum production costs result in optimal output, leading to higher profits for farmers. Economic efficiency combines these factors, ensuring that the additional returns from production equal the marginal cost of inputs (Susanto, 2021).

By 2022, Jambi Province remained a key center for oil palm cultivation, ranking seventh nationally with a total plantation area of 1,034,804 hectares and production reaching 2,884,406 tons (Ditjenbun, 2021). Data from the Jambi Provincial Plantation Service (2022) indicates that 62.98% of the plantations were smallholder-managed, while PBN and PBS accounted for 1.97% and 35.05%, respectively.

Within Jambi Province, Batanghari Regency is a significant hub for oil palm cultivation, with 119,672 hectares of smallholder plantations, constituting 17.28% of the province's total smallholder plantation area. It also ranks second in producing plantations (*Tanaman Menghasilkan* or TM), with 89,882 hectares. The regency has the highest number of oil palm farming households in Jambi, totaling 49,582 families.

Despite its scale, Batanghari's productivity remains low, averaging only 2,852 kg/ha, with Mersam District—one of the regency's largest production areas—recording similar productivity at 2,843 kg/ha.

Low productivity in oil palm plantations is often attributed to inefficient allocation of production inputs (Hardiyanti, 2017). Inputs such as land, seeds, NPK fertilizer, urea fertilizer, dolomite, and labor must be managed effectively to achieve higher yields. High productivity is achieved when maximum output is produced with minimal input combinations, as technical efficiency is closely linked to optimal input usage (Tajerin et al., 2005). Consequently, studying technical efficiency is integral to understanding and enhancing productivity.

Technical efficiency is also influenced by socio-economic factors, which can lead to inefficiencies. For example, factors such as farmer education, resource access, and managerial skills can impact the effective utilization of inputs. Susanto (2021) highlights the importance of analyzing technical efficiency to address these managerial and socio-economic challenges, which directly affect the productivity of smallholder farmers. Yahyawi et al. (2022) further emphasize that technical inefficiency stems from socio-economic constraints, representing the inverse of technical efficiency.

Given the importance of smallholder oil palm plantations, it is essential to analyze the socio-economic factors contributing to technical inefficiencies. These insights can guide strategies to improve productivity, optimize technical efficiency, and support the sustainable development of smallholder plantations.

Sustainability in smallholder oil palm plantations depends on three key aspects: economic, social, and environmental. Among these, environmental factors play a pivotal role in determining productivity, technical efficiency, and future development opportunities. The findings of studies on technical efficiency and socio-economic factors can serve as a foundation for developing policies and practices to enhance the sustainability and productivity of smallholder oil palm plantations.

METHODS

This research was conducted in Mersam District, Batanghari Regency, specifically in the villages of Sengkati Mudo, Sengkati Baru, and Simpang Rantau Gedang. The location was selected purposively, as oil palm plantations serve as a primary source of family income in the area. These villages were chosen due to their extensive plantation areas but low palm oil production levels. This research locus was determined to analyze variations in oil palm productivity based on age group differences, aligning with the requirements of the Cobb-Douglas production function model (both OLS and MLE). These models necessitate clear demonstrations of independent and dependent variables, including production inputs and socio-economic factors affecting productivity.

The study focused on smallholder oil palm farmers, with a sample size of 60 farmers categorized into different oil palm age groups. The categorization was based on the classification by Fauzi (2012), dividing plant ages into four groups: 3–8 years, 9–13 years, 14–20 years, and 21–25 years. The Cobb-Douglas production function model using MLE requires homogeneity within the population; this research ensured homogeneity and confirmed data normality with the 60 respondents. However, the sample size and data collection were constrained by factors such as the wide distance between respondents, limited availability for interviews (conducted only in the afternoon and evening), and some farmers’ challenges in comprehending the interview process.

The sampling method employed was Simple Random Sampling, as a sampling frame was available, ensuring each respondent had an equal probability of being selected. This approach met the randomness requirements essential for OLS and MLE model applications. Primary data were collected directly from farmers through interviews using structured questionnaires (Rahim et al., 2012).

Technical efficiency was measured using the stochastic frontier method, conducted in two stages: (1) analysis of the actual production function and (2) analysis of the frontier production function. The ratio of actual production to frontier production represents technical efficiency, expressed as 0<ET<1, where values closer to 1 indicate higher efficiency. This methodology provided a robust framework to evaluate the efficiency levels of smallholder oil palm farmers in the study area.

The first stage involves estimating the actual production function using the Ordinary Least Squares (OLS) method. This step provides an overview of the average performance of oil palm plantation production under current technological conditions. The mathematical form of the actual production function is as follows:

$$Ln\,Y = \beta_0 + \beta_1 lnX_1 + \beta_2 lnX_2 + \beta_3 lnX_3 + \beta_4 lnX_4 + \beta_5 lnX_5 + e^u$$

Where:

- Y: Oil palm production (kg)
- β_0: Constant or intercept
- X_1: Area of land planted with oil palm (ha)
- X_2: Number of workers used (HOK)
- X_3: Amount of NPK fertilizer used (kg/year)
- X_4: Amount of urea fertilizer used (kg/year)
- X_5: Amount of dolomite fertilizer used (kg/year)
- e^u: Error term

This OLS-based estimation evaluates the general performance of production at the existing technology level.

The second stage involves analyzing the frontier production function using the Maximum Likelihood Estimation (MLE) method. This method estimates the parameters for all production factors (β_m), the intercept (β_0), and the variances of the two error components, v_i and u_i . The MLE approach is used to represent the optimal performance of farming under current technological constraints.

The stochastic frontier production function is expressed mathematically as:

$$Y = X_i\, \beta + (vi - ui)$$

The transformation form of the Stochastic Frontier production function is expressed as follows:

$$Ln\ Y^* = \beta_0^* + \beta_1^* lnX_1^* + \beta_2^* lnX_2^* + \beta_3^* lnX_3^* + \beta_4^* lnX_4^* + \beta_5^* lnX_5^* + \beta_6^* lnX_6) + (vi-ui)$$

Where:

Y : oil palm production (kg)
β_0 : constant or intercept
X_1 : area of land planted with oil palm (ha)
X_2 : amount of workers used (HOK)
X_3 : amount of NPK fertilizer used (kg/year)
X_4 : amount of urea fertilizer used (kg/year)
X_5 : amount of dolomite fertilizer used (kg/year)
X_6 : amount of herbicide used (liter/year)

vi : random disturbance (disturbance terms)
ui : technical inefficiency effects
i : indicates the i-th farmer

Measuring the technical efficiency of oil palm plantations is estimated by using (Tasman 2008) and Nainggolan, et.al (2024) as follows:

$$ET_i = \frac{Y_i}{Y_i^*} = \exp(-u_i)$$

Where:
ET_i : technical efficiency achieved by farmer i
Y_i : Actual farming production
Y_i* : Potential production
u_i : one-side error term ($u \geq 0$) or random variable

The criteria for farmers who are classified as technically efficient are if the efficiency index value is ≥ 0.62. On the other hand, if the efficiency value is <0.62 then the smallholder oil palm plantation is still not technically efficient. Assumption of 0.62 is said to be technically efficient because there are many constraints of internal and external factors faced by farmers and cannot be controlled. While the value of technical efficiency on state and private plantations > 0.90.

The estimation of the technical inefficiency model for oil palm plantations refers to the equation model developed by (Coelli et al, 2005). The estimating equation model used in this research is as follows:

$$u_i = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 z_{3i} + \delta_4 z_{4i} + \delta_5 z_{5i} + \delta_6 z_{6i}$$

It is suspected that factors that negatively affect technical inefficiency are access to input, access to technology, and activity in farmer groups. Meanwhile, factors that have a positive influence on technical inefficiency are land area and plantation distance.

RESULTS AND DISCUSSION

Characteristics of respondent farmers

Farmer characteristics encompass various factors that influence their farm management practices. In this study, the examined characteristics include the age of the farmers, their farming experience, and the size of the land they cultivate. A summary of these characteristics is presented in Table 1.

Table 1. Characteristics of respondent farmers in the research area in 2023

Farmer Characteristics	Average (person)	Percentage (%)
Farmer Age (Years)	34 – 68	43,6
Experience (Years)	10 - 32	17,6
Number of Dependents (Individuals)	3 – 7	4
Land Area (ha)	1,8 – 7,2	4,36

Table 1 indicates that the age of farmers falls within the productive age group, as the average age of the respondent farmers is 43.6 years. According to Hernanto (2018), the productive age is classified as ranging from 15 to 60 years, confirming that the majority of the farmers are within this category.

The respondents also demonstrate a relatively high level of farming experience, with an average of 17.6 years. Hernanto (2018) highlights that farming experience is a critical factor in achieving success in agriculture. With increased experience over time, farmers are likely to enhance their efficiency and improve their farming practices.

The dependency rate in the respondent households is notably low, with an average of four individuals per family. This reduced dependency level could alleviate economic and labor pressures on the farmers, enabling them to allocate more resources to farming activities.

The land area cultivated by the farmers varies from 1.8 to 7.2 hectares, with an average of 4.36 hectares. This is classified as a moderate landholding size when compared to other regions. For instance, the average land area per farmer in Muaro Jambi Regency is 6.7 hectares, in Tanjabbar Regency, it is 7.1 hectares, and in Tebo Regency, it is 5.7 hectares (Nainggolan et al., 2019).

Use of production factors

Production factors play a crucial role in enhancing farm productivity, and their use should align with recommended standards to achieve optimal results. The production factors employed by oil palm farmers in Gerunggung Village are summarized in Table 2.

Table 2. Use of production factors by respondent farmers in the research area in 2023

Production Factors	Range	Average
NPK Fertilizer (Kg/Ha)	180-240	215,6
Urea Fertilizer (Kg/Ha)	130-200	168,3
Dolomite (Kg/Ha)	600-800	720,5
Herbicide (Kg/Ha)	1200-1700	1450,8
Labor (Hok)	65-80	71,4

Table 2 demonstrates that the use of NPK fertilizer in the research area remains relatively low and does not align with the recommendations provided by Balitbang (2013), which suggest an average application of 350 kg/ha for oil palm plantations. In contrast, the use of urea fertilizer is most prevalent in the range of 267–291 kg/ha, with approximately 36.67% of the sampled farmers falling within this category. The minimum recorded application of urea fertilizer was 167 kg/ha, while the maximum reached 340 kg/ha. On average, sample farmers applied 262 kg/ha of urea fertilizer. This usage level is still below the recommended range of 300–375 kg/ha, as outlined by Balitbang (2013).

The use of dolomite in the research area varied, with the highest application recorded at 563 kg/ha and the lowest at 125 kg/ha. Most farmers (33%) applied dolomite in the range of 440–502 kg/ha. On average, dolomite use in the study area was 405 kg/ha, exceeding the recommended application rate of 375 kg/ha, as per Balitbang (2013).

The discrepancies in fertilizer application—both below and above recommended levels—can be attributed to several factors. The lower-than-recommended use of NPK fertilizer is primarily due to its untimely availability and relatively high cost, which makes it unaffordable for many farmers. Conversely, the excessive use of dolomite likely results from farmers' limited understanding of proper dosage requirements, which may vary depending on the geographical characteristics of the land, such as whether it is flat or undulating.

Farm production function analysis

The analysis of the production function aims to evaluate how various production factor variables influence farm output. Before conducting the analysis, the Ordinary Least Squares (OLS) method was employed for testing. The analysis results yielded an R^2 value of 0.99, indicating that 99% of the variation in production can be explained by the model.

The variables found to have a significant effect on production were land area, NPK fertilizer, urea fertilizer, dolomite, and herbicides. In contrast, the labor variable did not show a significant impact on production.

Table 3. Estimation of the production function of palm oil plantations in the research area using the OLS Method in 2023

Variabel	Parameter	Coefficient	t-count
Constant	β_0	5,4562	31,4356
NPK Fertilizer	β_1	0,2475	9,3674
Urea Fertilizer	β_2	0,1237	8,2433
Dolomite	β_3	0,0976	2,7667
Herbicide	β_4	0,0854	2,5118
Labor	β_5	0,1133	8,1467
Land area	β_6	0,2024	9,0072
Sigma-squared		0,0008	
Σβi		0.6163	
R^2 = 0,8173			
t-table α (0,01), df : 54 = 2,6700			
t-table α (0,05), df : 54 = 2,0049			
t-table α (0,10), df : 54 = 1,6736			

Information : *** = *significant at α (0.01)*
** = *significant at α (0,05)*
* = *significant at α (0,10)*
ns = *no significant effect*

The estimation results of the oil palm production function using the OLS method are as follows:

$$\text{Ln } Y = 7.0877 \, (X_1^{0.4683} \, X_2^{-0.3071} \, X_3^{0.1621} \, X_4^{0.1776} \, X_5^{0.0892} \, X_6^{0.0260})$$

Table 3 reports an R^2 value of 0.8173, indicating that the independent variables—land area, labor, NPK fertilizer, urea fertilizer, dolomite, and herbicides—together explain 81.73% of the variation in production. The remaining 18.17% is influenced by factors outside the model.

The sum of the coefficients (Σβi=0.71323) is less than 1, suggesting that the use of production factors in the research area is within Region II of the production curve, also known as the Decreasing Return to Scale region. This implies that each additional unit of input yields progressively smaller increases in output.

Among the independent variables, land area, NPK fertilizer, urea fertilizer, and dolomite were found to have a highly significant effect on production at the 1% significance level (α=0.01). Conversely, labor and herbicides were not statistically significant. The labor variable's lack of significance in influencing productivity and technical efficiency can be attributed to the fact that labor intensity is not a direct input in the production process.

Analysis of the productivity function of oil palm plantations

The estimation of the productivity function aims to determine the influence of production factor variables on farm productivity. The analysis was conducted using the Maximum Likelihood Estimation (MLE) method.

The results of the analysis indicate an R^2 value of 0.8366, meaning that the independent variables collectively explain 83.66% of the variation in productivity. The sum of the coefficients (Σβi=0.8366) is less than 1, placing the productivity in the Decreasing Return to Scale region, where additional inputs yield diminishing returns in output. Furthermore, the gamma value (γ=0.8976) suggests that most of the variability in productivity is due to differences in efficiency among farms rather than random factors.

The variables that significantly influence productivity include labor, NPK fertilizer, urea fertilizer, dolomite, and herbicides.

Table 4. Estimation of the productivity function of smallholder oil palm plantations in the research area using the MLE Method in 2023

Variabel	Parameter	Coefficient	t-count
Constant	β_0	5,7144	32,4752
NPK Fertilizer	β_1	0,3753	11,1675
UAE Fertilizer	β_2	0,1872	9,7146
Dolomite	β_3	0,1676	5,3334
Herbicide	β_4	0,1128	4,0871
Labor	β_5	0,1253	4,1765
Sigma-squared		0,0008	3,9758
Gamma		0,8967	51,7049
Σβi		0,8366	
LR test of the one-sided error			21.4476
Log-likelihood function MLE			111.6294
Log-likelihood function OLS			132.0563
R^2	= 0,8755		
t-table α (0,01), df : 55 = 2,6682			
t-table α (0,05), df : 55 = 2,0040			
t-table α (0,10), df : 55 = 1,6730			

Information : *** *= significant at α (0,01)*
** *= significant at α (0,05)*

The estimation of the frontier productivity function is represented by the following equation:

$$\text{Ln Y}= 7{,}1480\ (X_1^{0{,}0201}\ X_2^{0{,}1369}\ X_3^{0{,}1840}\ X_4^{0{,}0834}\ X_5^{0{,}4122})$$

Table 4 indicates an R^2 value of 0.8366, which suggests that the independent variables—labor, NPK fertilizer, urea fertilizer, dolomite, and herbicides—together explain 83.66% of the variation in productivity. The remaining 16.34% of the variation is attributed to factors outside the model. The gamma value (γ=0.8967), being close to 1, indicates that 89.67% of the error term is caused by technical inefficiency, while the remaining 10.33% is due to external factors such as topography and rainfall. Furthermore, the sum of coefficients (Σβi=0.9438) being less than 1 places the productivity function in Region II of the production curve, or the Decreasing Return to Scale region. This implies that proportional increases in input use yield diminishing marginal returns in output.

The labor variable has a coefficient of 0.0201 and a thitt_{hit}thit value of 5.3946, which exceeds the critical value of t $\alpha(0.01)=2.6682$. This indicates that labor has a very significant effect on increasing TBS productivity. These findings align with the research of Thamrin (2016), Puruhito et al. (2019), and Febriyanto (2020), which also found labor to be a key determinant of productivity. However, other studies, including Asmara et al. (2011), Ridho et al. (2014), Sitanggang (2018), and Panjaitan et al. (2020), have reported no significant effect of labor on productivity, suggesting that the impact of labor may vary depending on specific contexts and conditions.

The coefficient of the NPK fertilizer variable is 0.1369, with a thitt_{hit}thit value of 4.4577, also exceeding the critical value of t $\alpha(0.01)=2.6682$. This result confirms that NPK fertilizer has a very significant effect on productivity. The findings are consistent with those of Puruhito et al. (2019), Mansyur (2021), and Syuhada et al. (2022), which emphasize the role of NPK fertilizer in enhancing productivity.

The urea fertilizer variable has a coefficient of 0.1840 and a thitt_{hit}thit value of 4.8780, further exceeding the critical value of t $\alpha(0.01)=2.6682$. This indicates that urea fertilizer also has a very significant effect on increasing TBS productivity. This result aligns with the research findings of Ridho et al. (2014) and Napitupulu et al. (2020). However, some studies, such as those by Nainggolan et al. (2019) and Puruhito et al. (2019), found no significant effect of urea fertilizer on productivity, highlighting potential differences in outcomes based on regional or methodological variations.

The dolomite variable has a coefficient of 0.0834, with a thitt_{hit}thit value of 3.6781, which again exceeds the critical value of t $\alpha(0.01)=2.6682$. This confirms that dolomite has a significant positive effect on productivity, consistent with the findings of Napitupulu et al. (2020). However, other research, such as Ridho et al. (2014), reported no significant effect of dolomite, suggesting that its influence may depend on specific soil or environmental conditions.

The herbicide variable has a coefficient of 0.4122 and a thitt_{hit}thit value of 2.2209, which is greater than the critical value of t $\alpha(0.05)=2.0040$. This indicates that herbicides have a significant effect on productivity at a 95% confidence level. These findings are in line with Syuhada et al. (2022), which also noted a positive effect of herbicides on productivity. However, other studies, such as those by Ridho et al. (2014) and Puruhito et al. (2019), reported no significant effect of herbicides, suggesting that their influence might vary depending on usage intensity and environmental factors.

In conclusion, the analysis highlights that labor, NPK fertilizer, urea fertilizer, dolomite, and herbicides are key factors that significantly influence TBS productivity. Most variables exhibit very significant effects at the $\alpha=0.01$ level, except for herbicides, which are significant at $\alpha=0.05$. These findings underscore the importance of optimizing the use of these inputs to improve productivity, while acknowledging the potential for variability in outcomes due to external influences and regional differences.

Analysis of technical efficiency of oil palm plantations

The measurement of technical efficiency is conducted to evaluate the level of production by comparing potential production with actual production. The technical efficiency value is determined by dividing actual production by potential production. A farming system is considered technically efficient if the technical efficiency value exceeds 0.62. The distribution of technical efficiency is illustrated in Figure 1, while the specific values are detailed in Table 5.

Table 5. Technical efficiency of smallholder oil palm plantations in the research area in 2023

	Technical Efficiency	Number of Farmers (people)	Percentage (%)
	0,60 – 0,65	5	8,34
	0,66 – 0,71	14	23,34
	0,72 – 0,77	26	43,34
	0,78 – 0,83	12	20
	0,84 – 0,89	3	5
Total	-	60	100,00
Total Lowest Value	0,61		
The highest score	0,85		
Average	0,73	-	-

Figure 1 reveals that the technical efficiency of smallholder oil palm plantations in the research area ranges from 0.61 to 0.85, with an average technical efficiency value of 0.73. This implies that the average productivity achieved by oil palm farmers is approximately 73% of the potential frontier production, leaving room for a 17% increase in productivity.

The average technical efficiency value in the research area, at 0.73, is greater than the threshold of 0.62, indicating that farming is technically efficient. However, there is still room for improvement, as the technical efficiency can potentially be increased by another 27%. Compared to the findings of Harefa (2021), where the average technical efficiency was reported at 0.86 (with a minimum of 0.63 and a maximum of 0.99), the technical efficiency in this study is relatively lower. The opportunity for increasing productivity in the current research area is therefore higher, at 38%, compared to the 14% potential increase identified in Harefa's research.

These findings suggest that while oil palm farming in the research area is operating efficiently by technical standards, significant improvements are still feasible. Enhanced management practices, input optimization, and farmer training could help close the gap between actual and potential production levels.

The influence of socio-economic factors on technical inefficiency of oil palm plantations

An analysis of technical inefficiency was conducted to evaluate the influence of socio-economic factors on the inefficiency of oil palm farming. The analysis employed the Ordinary Least Squares (OLS) method, and the results indicated no violations of classical assumptions based on Adjusted R^2, Prob (F-statistic), and Durbin Watson statistic values.

Table 6. Estimation results of sources of technical inefficiency

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Z1_INPUT ACCESS	-0,00485	+0,00061	7,95081	0,00071
Z2_EXPERIENCE	-0,03614	+0,00874	4,13501	0,00003
Z3_TECHNOLOGY ACCESS	-0,08356	+0,04343	1,92401	0,01256
Z4_DISTANCE	+0,12634	0,04247	2,97480	0,02783
Z5_ACTIVITY	-0,06167	0,11852	3,32991	0,07634
Z6_LAND	+0,13444	0,03941	3,41131	0,00831
C	0,18334	0,06334	2,89453	0,00667

R-squared	0.801999	Mean dependent var	0.191333
Adjusted R-squared	0.779584	S.D. dependent var	0.028372
S.E. of regression	0.013320	Akaike info criterion	-5.689783
Sum squared resid	0.009404	Schwarz criterion	-5.445443
Log likelihood	177.6935	Hannan-Quinn criter.	-5.594208
F-statistic	35.77921	Durbin-Watson stat	1.585674
Prob(F-statistic)	0.000000		

The Prob. (F-statistic) value of 0.000 is less than α=0.05, indicating that the independent variables in the model collectively have a significant effect on technical inefficiency. The Durbin Watson statistic value of 1.585, being less than 2.00, confirms that the model is free from autocorrelation.

The analysis revealed that the variables land area, experience, access to technology, and activity in farmer groups significantly affect technical inefficiency at α=0.05. Among these, the coefficient for land area has a positive sign, while experience, access to technology, and activity in farmer groups have negative coefficients. This indicates that larger land areas are associated with increased technical inefficiency, whereas greater experience, better access to technology, and higher levels of group activity reduce inefficiency. These findings align with Napitupulu et al. (2020), who reported similar effects of land area and experience on technical inefficiency. However, they contrast with Syuhada et al. (2022), which found no significant effect of land area, experience, or technology access on inefficiency.

In contrast, input access and the distance from plantations to farmers' homes were found to have no significant effect on technical inefficiency. These results support Syuhada et al. (2022), which also reported that input access does not significantly influence technical inefficiency. However, they differ from Napitupulu et al. (2020), which found that distance significantly impacts inefficiency, with greater distances leading to higher inefficiency due to logistical and operational challenges.

Implications for the development of smallholder oil palm plantations

The productivity of smallholder oil palm plantations, currently averaging 12.8 tons/ha/year, is considerably lower than the best management practices, which yield productivity levels of 38.2–43.8 tons/ha/year (Pahan, 2018). Despite this low productivity, smallholder oil palm plantations retain a high level of competitiveness (Napitupulu et al., 2020; Tasman, 2008; Tuwo, 2011). To enhance productivity and ensure sustainability, it is essential to optimize technology adoption, economic factors, and institutional access.

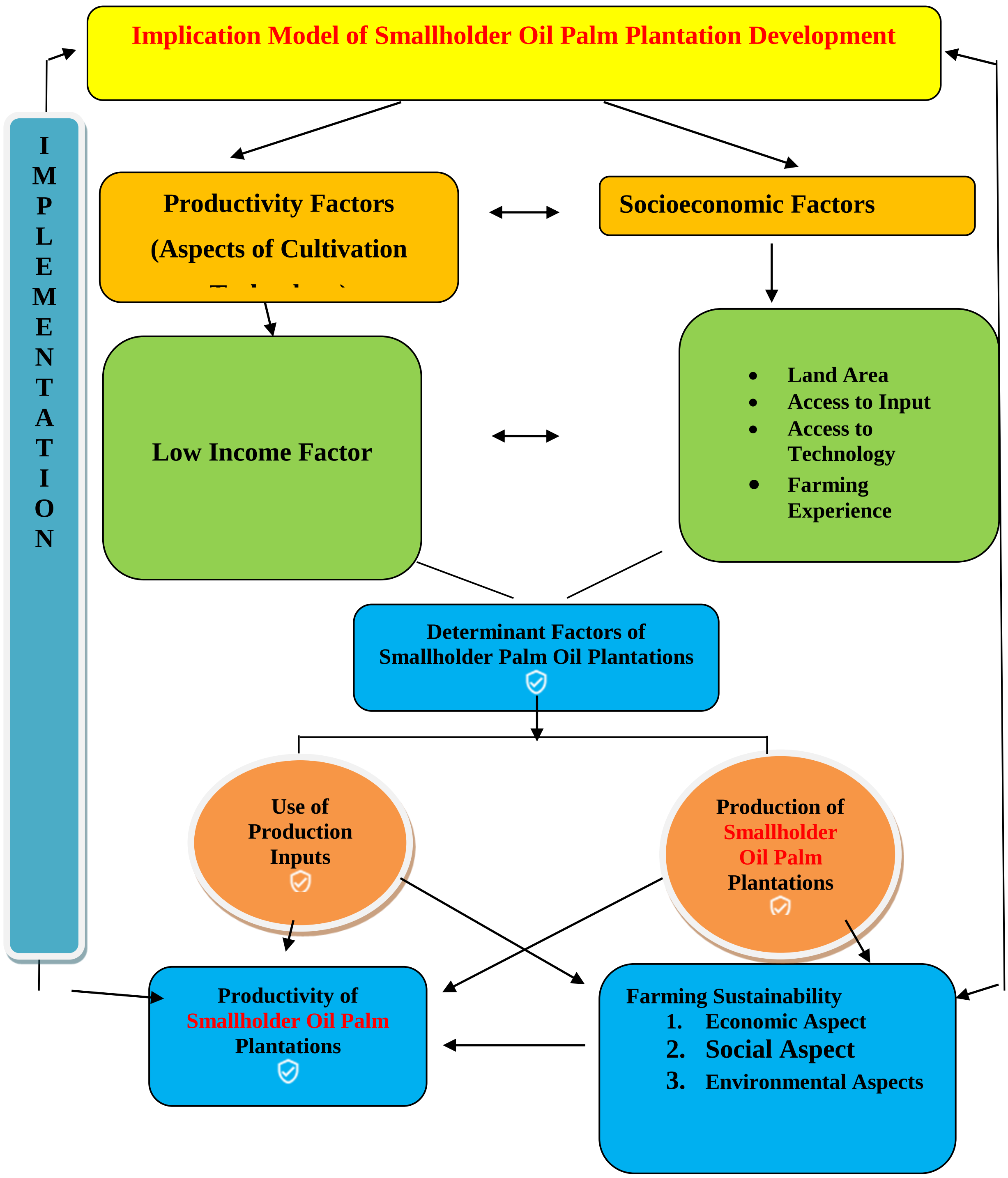
Economic factors such as land area, TBS (fresh fruit bunch) prices, and access to production facilities are pivotal in shaping farmers' economic decisions. These variables collectively influence productivity by determining the resources and investments available for farming activities. Institutional access also plays a critical role by fostering the adoption of innovations and new technologies. Research by Apriliyani and Nasution (2022), Apriyanti (2019), and Bakce (2016) highlights that key institutional factors include access to credit, extension services, and the availability of production facilities. Greater institutional access enhances the ability of farmers to adopt advanced practices, thereby increasing productivity and contributing to the sustainability of smallholder oil palm plantations.

Technology adoption is another critical determinant of productivity. According to Suratiyah (2016) and Sujarwo (2019), the ability to procure production inputs and the active participation of farmers in extension activities within farmer groups are key factors driving technology adoption. Ensuring that production inputs are available in the right quantities, at affordable prices, and within farmers' localities is essential for encouraging the use of new technology. Active engagement in farmer groups and participation in extension services expose farmers to profitable ideas and practices, further promoting technology adoption.

To support the development of smallholder oil palm plantations, the government should implement policies that ensure the economical procurement of fertilizers. This includes delivering fertilizers at the right price, time, quantity, and type to meet farmers' specific needs. By facilitating the adoption of more efficient and profitable technologies, productivity will improve, contributing to the sustainability of smallholder plantations across economic, social, and environmental dimensions.

Economic factors such as land area, prices of production inputs, and TBS prices, along with institutional access variables like access to credit, counseling, and input procurement, are critical determinants of productivity. Adoption of new technology, reflected in the procurement and utilization of production inputs and farmer participation in groups, also significantly impacts productivity and sustainability. These exogenous latent variables directly influence the sustainability of farming systems, which can be assessed through their economic, social, and environmental outcomes.

In conclusion, the development of smallholder oil palm plantations hinges on addressing these interconnected factors. Economic improvements, expanded institutional access, and widespread technology adoption are essential for achieving higher productivity and fostering sustainable practices. Such an integrated approach ensures that smallholder plantations remain competitive and viable in the long term, contributing positively to both local livelihoods and broader environmental goals.


Implication Model of Smallholder Oil Palm Plantation Development
IMPLEMENTATION
Productivity Factors
(Aspects of Cultivation
Socioeconomic Factors
Low Income Factor
Land Area
Access to Input
Access to Technology
Farming Experience
Determinant Factors of Smallholder Palm Oil Plantations
Use of Production Inputs
Production of Smallholder Oil Palm Plantations
Productivity of Smallholder Oil Palm Plantations
Farming Sustainability
1. Economic Aspect
2. Social Aspect
3. Environmental Aspects

CONCLUSIONS AND RECOMMENDATION

Conclusion

The management of oil palm plantations in the research area is not fully in accordance with recommended practices, particularly regarding fertilizer use. The application of NPK and urea fertilizers remains below recommended levels, while dolomite usage exceeds the guidelines. As a result, average production remains low compared to the national average and the potential yields achievable with the varieties cultivated.

Key production factors such as land area, NPK fertilizer, urea fertilizer, and dolomite fertilizer significantly contribute to increasing oil palm TBS (fresh fruit bunch) production. Despite being technically efficient, the level of technical efficiency in smallholder oil palm plantations still has room for improvement, as technical inefficiency remains relatively high.

Socio-economic factors, including land area, farming experience, education, and farmer group participation, significantly affect technical inefficiency. On the other hand, factors such as farmers' age and the distance between the plantation and their residence do not have a significant impact on technical inefficiency.

External factors, such as market access and environmental conditions, also play an essential role in determining the competitiveness of smallholder oil palm plantations by influencing their comparative and competitive advantages.

Recommendation

To align plantation management with recommended practices, efforts should focus on optimizing fertilizer use by ensuring that the correct types and quantities of fertilizers are applied according to guidelines. This includes addressing the underuse of NPK and urea fertilizers and monitoring dolomite application to avoid excessive usage.

Enhancing technical efficiency requires targeted interventions aimed at reducing inefficiencies. This can be achieved by strengthening farmer education, fostering participation in farmer groups, and improving access to training and agricultural extension services.

Policies should prioritize socio-economic support for farmers, such as expanding access to credit, providing affordable and timely agricultural inputs, and improving institutional support to enhance technology adoption. These measures will help address the critical factors influencing productivity and technical efficiency.

The development of smallholder oil palm plantations should incorporate initiatives to improve market access and establish closer integration with the palm oil processing industry. Such efforts would provide farmers with economic incentives to boost productivity and efficiency. Furthermore, fostering sustainability through economic, social, and environmental considerations will ensure long-term competitiveness and resilience of smallholder oil palm plantations.

REFERENCES

Apriliyani, K., & Nasution, M. P. (2022). Efisiensi penggunaan faktor-faktor produksi pada usaha tani kelapa sawit rakyat (*Elaeis guineensis Jacq*) (Studi kasus: Desa Tanjung Medan, Kecamatan Kampung Rakyat, Kabupaten Labuhanbatu Selatan). *Jurnal Agriuma*, *4*(1), 31–39. https://doi.org/10.31289/agri.v4i1.7176

Apriyanti, I. (2019). Analisis efesiensi produksi kelapa sawit di kebun PTPN IV Sumatera Utara. *Journal of Agribusiness Sciences, 3*(1), 45–51.

Asmara, R., Hanani, N., & Irawati, N. (2011). The analysis of technical efficiency with frontier approach in business of chips MOCAf (Modified Cassava Flour). *Habitat, 22*(1), 52–59.

Bakce, R. (2016). Efisiensi penggunaan faktor produksi dan pendapatan usahatani kelapa sawit swadaya di kecamatan Kemuning. *Jurnal BiBieT*, *1*(2), 95-107

Balitbang. (2013). *Rekomendasi pemupukan N, P, dan K pada kelapa sawit*. Jakarta: Balitbang

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). Springer Science & Business Media.

Dinas Perkebunan Provinsi Jambi. (2022). *Luas areal, produksi, dan produktivitas kelapa sawit*. Jambi: Dinas Perkebunan Provinsi Jambi

Ditjenbun. (2021). *Statistik perkebunan unggulan nasional 2019–2021*. Direktorat Jenderal Perkebunan Kementerian Pertanian Republik Indonesia. https://ditjenbun.pertanian.go.id/template/uploads/2021/04/BUKU-STATISTIK-PERKEBUNAN-2019-2021-OK.pdf

Fauzi, Y. (2012). *Kelapa sawit*. Penebar Swadaya.

Febriyanto, A. T. (2020). *Analisis efisiensi teknis usahatani bawang merah di Kabupaten Demak.* Universitas Negeri Semarang

Harefa, S. N. (2021). *Analisis pendapatan dan efisiensi teknis usahatani kelapa sawit mandiri di Desa Markanding Kecamatan Bahar Utara Kabupaten Muaro Jambi*. Universitas Batang Hari

Hardiyanti, Si. (2017). Analisis Risiko Usahatani Kelapa Sawit Di Desa Batu Matoru, Kecamatan Lariang Kabupaten Mamuju Utara

Hernanto, F. (2018). *Ilmu usahatani*. Penebar Swadaya.

Mansyur, N. I., Pudjiwati, E. H., & Murtilaksono, A. (2021). *Pupuk dan pemupukan*. Syiah Kuala University Press.

Nainggolan, S., Fitri, Y., & Kurniasih, S. (2019). Study of technical efficiency and farmers' production risk preferences in the context of increasing paddy rice farming productivity in Bungo Regency, Jambi Province - Indonesia. *Journal of Agricultural Science, 2*(1), 13–23.

Napitupulu, D. M. T., Nainggolan, S., & Murdy, S. (2020). Kajian efisiensi teknis, sumber inefisiensi, dan preferensi risiko petani serta implikasinya pada upaya peningkatan produktivitas perkebunan kelapa sawit di Provinsi Jambi. *JALOW: Journal of Agribusiness and Local Wisdom, 3*(2), 2621–1297. https://doi.org/10.22437/jalow.v3i2.11614

Pahan, I. (2018). *Panduan Tekhnis Budidaya Kelapa Sawit untuk Praktisi Perkebunan*. Penebar Swadaya. Jakarta.

Panjaitan, E., Paman, U., & Darus. (2020). Analisis pengaruh faktor produksi terhadap produktivitas usahatani kelapa sawit pola swadaya di Desa Sungai Buluh Kecamatan Kuantan Singingi Hilir, Kabupaten Kuantan Singingi. *Dinamika Pertanian, 36*(1), 61–68. https://doi.org/10.25299/dp.2020.vol36(1).5371

Puruhito, D. D., Jamhari, J., Hartono, S., & Irham, I. (2019). Faktor penentu produksi pada perkebunan rakyat kelapa sawit di Kabupaten Mamuju Utara. *Jurnal Teknosains, 9*(1), 58. https://doi.org/10.22146/teknosains.38914

Rahim, A. S., & Hastuti, D. R. D. (2012). *Model analisis ekonomi pertanian*. Makasar: BP Universitas Negeri Makasar

Ridho, Z., Hadi, S., & Yusri, J. (2014). Efisiensi produksi kelapa sawit pola swadaya di Desa Senama Nenek Kecamatan Tapung Hulu Kabupaten Kampar. *JOM Faperta, 1*(1).

Sitanggang, Y. F. (2018). Analisis efisiensi teknis usahatani cabai merah keriting menggunakan stochastic frontier analysis (SFA) di Desa Mojorejo, Kecamatan Wates, Kabupaten Blitar. *Bitkom Research, 63*(2), 1–3.

Sujarwo, S. (2019). *Ekonomi produksi teori dan aplikasi*. Malang: UB Press

Susanto, A. (2021). Konsep produktivitas dan efisiensi teknis dalam dunia pertanian. *Ekonomi Pertanian*. Surabaya: Global Aksara Pers

Syuhada, F., Hasnah, H., & Khairati, R. (2022). Analisis efisiensi teknis usahatani kelapa sawit: Analisis stochastic frontier. *Jurnal Ekonomi Pertanian dan Agribisnis, 6*(1), 249–255. https://doi.org/10.21776/ub.jepa.2022.006.01.24

Tajerin, T., & Mohammad, N. (2005). Analisis efisiensi teknik usaha budidaya pembesaran ikan kerapu dalam keramba jaring apung di perairan Teluk Lampung. *Economic Journal of Emerging Markets, 10*(1), 95–105.

Tasman, A. (2008). *Analisis efisiensi dan produktivitas*. Jakarta: Penerbit Chandra Pratama.

Thamrin, S. (2016). Efisiensi teknis usahatani kopi arabika di Kabupaten Enrekang. *Ilmu Pertanian (Agricultural Science), 18*(2), 92. https://doi.org/10.22146/ipas.9090

Yahyawi, L., Yurisi, E., & Nthae, S. O. (2022). Efisiensi teknis usahatani kelapa sawit di Kabupaten Sanggau. *Ekonomi Pertanian, 6*, 456–462. https://doi.org/10.1016/j.accinf.2013.02.001