International Journal of Sustainable Development and Planning
Vol. 21, No. 5, May, 2026, pp. 2189-2196
Journal homepage: http://iieta.org/journals/ijsdp

Sustainable Resource Planning in Palm Sugar Agroindustry on Lombok Island: A Two-Stage DEA-Tobit Approach

Anna Apriana Hidayanti[1,2*], Nuhfil Hanani[3], Fitria Dina Riana[3], Rosihan Asmara[3]

[1] Doctoral Program in Agriculture, Brawijaya University, Malang 65145, Indonesia
[2] Agribusiness Study Program, Faculty of Agriculture, University of Mataram, Mataram 83125, Indonesia
[3] Faculty of Agriculture, Agribusiness, Brawijaya University, Malang 65145, Indonesia

Corresponding Author Email: anna_apriana@unram.ac.id

https://doi.org/10.18280/ijsdp.210522

Received: 9 March 2026
Revised: 12 May 2026
Accepted: 21 May 2026
Available online: 31 May 2026

Keywords:
RStudio, palm sugar, Agroindustries, Lombok Island, technical efficiency, Tobit model, sustainable

ABSTRACT

The palm sugar agroindustry on Lombok Island plays an important role in the local economy. The appropriate utilization of natural resources is a key factor in ensuring industrial sustainability and achieving optimal technical efficiency. This study aims to analyze the technical efficiency of 150 palm sugar agroindustries on Lombok Island and examine the socioeconomic factors affecting inefficiency levels. A two-stage approach was employed using RStudio. In the first stage, technical efficiency was estimated using the input-oriented Banker, Charnes, and Cooper (BCC) model of Data Envelopment Analysis (DEA). In the second stage, Tobit regression analysis was applied to identify the determinants of inefficiency. The results show that the average overall technical efficiency under constant returns to scale (TE-CRS) was 0.7094, the average pure technical efficiency score under variable returns to scale (TE-VRS) was 0.9034, and the average scale efficiency (SE) was 0.772. Based on the TE-VRS measurement, 60% of the agroindustries reached the efficiency frontier. The evaluation of returns to scale indicated that 60% of the agroindustries operated under increasing returns to scale (IRS), 37% operated under constant returns to scale (CRS), and the remaining 3% operated under decreasing returns to scale (DRS). Furthermore, the Tobit regression results indicate that age had a negative and significant effect on inefficiency, thereby reducing the level of inefficiency (p-value = 0.0547). In contrast, institutional participation had a positive and significant effect on inefficiency (p-value = 0.0369). Education, experience, and technology showed negative but statistically insignificant relationships with inefficiency. The findings highlight the importance of developing the palm sugar agroindustry through improvements in business scale.

1. INTRODUCTION

Indonesia is a country endowed with rich plant biodiversity. One of its native plant species, characterized by a unique and natural distribution, is Arenga pinnata (sugar palm) [1]. Arenga pinnata belongs to the Palmae family [2], and has been widely utilized by local communities for generations due to its diverse benefits and uses. Various processed products are derived from this species [3]. with palm sugar produced from its sap (nira) being the most prominent [4].

According to the official report of the Directorate General of Estate Crops, Ministry of Agriculture of the Republic of Indonesia, the Province of West Nusa Tenggara (NTB) is one of the regions with significant potential for sugar palm development. Data indicate that the cultivated area of Arenga pinnata in NTB has shown an increasing trend from 2021 to 2023, covering 993 hectares, 984 hectares, 1,031 hectares, and reaching 1,062 hectares [5]. This expansion reflects the strong potential for palm sugar production. Data from the Central Bureau of Statistics (2019-2024) further show that West Lombok and East Lombok Regencies, located on Lombok Island, have relatively high levels of sugar palm harvest [6] The development of the food processing industry is also closely associated with geographic clustering as a key indicator [7].

The role of government is essential in strengthening the agricultural sector as a foundation for industrial development [8]. The increase in palm sugar production represents a form of agricultural commodity diversification into value-added processed products. This transformation contributes to local economic development and supports agricultural sustainability [9], including job creation for local communities and increased regional income [10].

Adequate land availability for sugar palm cultivation is a crucial prerequisite for enhancing productivity and ensuring production sustainability [11], particularly in West Lombok and East Lombok Regencies. Despite the abundance of raw materials, palm sugar production has not yet reached its optimal economic potential. This is mainly because most processing activities remain categorized as small-scale household industries, often operated through traditional, hereditary practices. Limited skills and uneven capacity development over time have resulted in both technical and non-technical constraints in business operations [12].

In developing palm sugar agroindustry, strategic approaches should not only focus on expanding cultivated areas but also emphasize the efficient utilization of production inputs, including land, labor, capital, and raw materials. Achieving maximum output from a given set of inputs can be assessed through technical efficiency measurement [13]. This measurement is particularly important, as small-scale agroindustries are often prone to inefficiencies due to the prevailing perception among producers that maintaining business continuity is more important than optimizing profits [14]. Technical efficiency can be analyzed using a non-parametric method, namely Data Envelopment Analysis (DEA), which measures relative efficiency by comparing decision-making units (DMUs) through linear programming techniques [15].

This study employs the DEA-Banker, Charnes, and Cooper (BCC) model, which evaluates relative efficiency based on input and output values in palm sugar production [16]. Furthermore, a Tobit regression model is applied to analyze censored dependent variables [17]. Socio-economic factors are expected to influence the level of technical efficiency in palm sugar production, including age, experience, and education level [18], as well as business capital, training [19], institutional support, and technology adoption [20].

2. RESEARCH METHOD

2.1 Research sites

This study was conducted in Sikur District, East Lombok Regency, as well as in Batu Layar, Gunung Sari, and Lingsar Districts in West Lombok Regency. These locations were purposively selected due to their relatively high concentration of palm sugar agroindustries [21].

2.2 Sampling unit and unit of analysis

The sampling units in this study were household-scale palm sugar agroindustries. Samples were drawn from both West Lombok and East Lombok Regencies using a multi-stage random sampling technique [22]. Specifically, respondents were selected from four sub-districts, covering seven villages and twelve hamlets. A total of 150 respondents were obtained, all of whom met the predefined sampling criteria.

2.3 Data collection techniques

Data collection was conducted through several stages. Primary data were obtained through field observations, structured interviews, and in-depth interviews. Field observations involved direct visits to production sites, discussions with village officials, and examination of production activities, including equipment, raw materials, labor utilization, and output levels. Structured interviews were conducted using semi-closed questionnaires to capture respondents' characteristics and socio-economic variables. In-depth interviews were carried out to explore detailed aspects of the production process, including equipment depreciation costs and initial capital investment.

Secondary data were collected from relevant institutions, including NTB Satu Data, the Central Bureau of Statistics (BPS), the NTB Provincial Industry Office, and other relevant sources.

2.4 Data processing

The collected data were processed and analyzed using Microsoft Excel. Data from each respondent were tabulated, classified, and adjusted according to respondent characteristics.

In the analysis of technical efficiency, the focus was on the use of inputs to generate optimal output [2]. The output variable used in this study was the quantity of palm sugar produced (kg) [23]. Input variables included the volume of palm sap (liters), labor input, fuel costs, packaging costs, and supporting material costs used in the production process [24].

Furthermore, in the Tobit regression analysis, socio-economic factors influencing inefficiency included age, education, experience, participation in training, and institutional involvement [18, 19].

2.5 Data analysis

Technical efficiency was measured using the BCC-DEA model. This model is widely applied in efficiency analysis across various sectors, including agroindustry with heterogeneous scales of operation [25] under the assumption of variable returns to scale (VRS) [26]. The BCC-DEA model enables the identification of inefficient production units, whether due to managerial inefficiencies, scale inefficiencies, or socio-economic factors affecting production performance [27].

The mathematical formulation of the input-oriented BCC model under the assumption of VRS is presented as follows:

$$\begin{gathered}
\text{Minimize} \quad \theta_k \\
\mathit{Subject\ To:} \\
\sum_{j=1}^{n} \lambda_j \mathcal{X}_{ij} \leq \theta_k \mathcal{X}_{ik}, \mathrm{i} = 1,\dots,m, \\
\sum_{j=1}^{n} \lambda_j \mathcal{Y}_{rj} \geq \mathcal{Y}_{rk}, \mathrm{r} = 1,\dots,s, \\
\sum_{j=1}^{n} \lambda_j = 1, \\
\lambda_j \geq 0, j = 1,\dots,n\dots.
\end{gathered} \tag{1}$$

It can be observed that θ_k denotes the efficiency value or score, $\mathcal{X}_{ij}$ represents the (i)-th input of the (j)-th agroindustry, and λ_j denotes the intensity variable or intensity weight, which links the agroindustry being evaluated with other agroindustries used as benchmarks, namely efficiency reference units.

Eq. (1) above indicates that θ_k is the technical efficiency score of the (k)-th agroindustry being evaluated. If θ_k = 1, the agroindustry has achieved full efficiency, implying that its input combination, is the most optimal compared with other agroindustries. Conversely, if the efficiency score is mathematically expressed as ($0 < \theta_k < 1$), the agroindustry is considered technically inefficient [28].

To establish the relationship between socio-economic factors and inefficiency scores derived from the technical efficiency analysis, a Tobit regression model was employed. The Tobit model addresses the limitations of DEA in capturing the influence of exogenous factors [29]. Incorporating socio-economic variables is essential, as production performance and inefficiency are strongly influenced by individual characteristics and managerial capacity [30].

The inefficiency value is obtained by transforming the DEA efficiency score using the formula ((1 - θ_k) [31]. Through this transformation, an agroindustry with full efficiency θ_k= 1, has an inefficiency value of 0. In contrast, an agroindustry with an efficiency score below 1 has an inefficiency value greater than 0 and approaching 1. Tobit regression analysis, is used when the dependent variable is censored. In this study, the inefficiency score, which serves as the dependent variable, ranges from 0 to 1. This indicates that the data are continuous but truncated or bounded, with a concentration at the lower limit of 0. Therefore, the data are censored. If the ordinary least squares (OLS) method is applied to such data, the resulting regression estimates may deviate from the true values and become biased [16, 31]. The distribution of censored data follows a censored normal distribution, with the assumption N (μ, σ^2).

The latent variable model is specified as:

$$yi^* = x_i\beta + \varepsilon_i \tag{2}$$

where, $\varepsilon_i \sim N(0, \sigma^2)$. In this specification, x refers to the observed explanatory variable, whereas y^* denotes the latent outcome variable. The latent variable is observed only when its value exceeds the censoring threshold τ., and is censored when its value is less than or equal to τ. Accordingly, the measurement equation for the observed outcome yyy can be expressed as follows.

$$yi = \begin{cases} yi*, if\ yi* > \tau \\ \tau i\ , if\ y* \leq \tau \end{cases} \tag{3}$$

Combining Eqs. (2) and (3), the observed model becomes:

$$yi = \begin{cases} yi* = xi\beta\ +\ \varepsilon i, if\ yi* > \tau \\ \qquad \tau i \qquad , if\ y* \leq \tau \end{cases} \tag{4}$$

The variables hypothesized to influence technical efficiency were selected based on previous studies and adjusted to the specific context of the study area. These variables include age, education, experience, extension services, technology, and institutional participation [19, 29, 31]. The Tobit model used in this study is specified as follows:

$$IT = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + e \tag{5}$$

where,

IT = Technical inefficiency of the palm sugar agroindustry based on the BCC model;

X_1 = age of the palm sugar agroindustry owner (years);

X_2 = years of formal education completed by the palm sugar agroindustry owner;

X_3 = years of experience in operating the palm sugar agroindustry;

X_4 = participation of the palm sugar agroindustry owner in palm sugar production training activities, measured as a dummy variable: 0 = never participated, 1 = participated;

X_5 = type of equipment or technology used in the palm sugar production process, measured based on predefined criteria: 0 = traditional, 1 = modern;

X_6 = active participation in institutional activities related to the development of palm sugar production, measured as a dummy variable: 0 = inactive, 1 = active;

eee = error term.

3. RESULTS AND DISCUSSION

3.1 Data analysis results

Section 3.1 presents the general and specific results of the data analysis used in this study.

3.1.1 The implementation of RStudio for two-stage efficiency analysis utilizing the input-oriented BCC-DEA model and Tobit regression

The analysis used in this study consisted of two stages. The first stage involved efficiency analysis, followed by Tobit regression analysis. The analyses were conducted using R software with the benchmarking and censReg packages.

3.1.2 Results of technical efficiency analysis using Data Envelopment Analysis

The results generated using RStudio indicate that palm sugar agroindustries in West Lombok and East Lombok Regencies exhibit substantial variation in production scale. This is reflected in the minimum, maximum, range, and mean values of production and income across the 150 DMUs.

The minimum production level was 12 kg, while the maximum reached 600 kg, with an average production of 138.438 kg.

In terms of income, the minimum value was IDR 300.000, while the maximum reached IDR 25.000.000, with an average income of IDR 2.874.213,33. These findings indicate a considerable disparity in income among agroindustries, suggesting heterogeneity in production performance and input utilization [32].

Table 1. Distribution of technical efficiency under variable returns to scale assumption (TE-VRS)

VRS Efficiency		
Efficiency Score	**Frequency**	**Persentage (%)**
< 0.400	1	0.667
0.400 - 0.599	3	2
0.600 - 0.749	18	12
0.750 - 0.898	33	22
0.899 - 0.999	5	3.333
1	90	60
Total	150	100
Mean		0.9034
Minimum		0.346
Maximum		1.000
Range		0.654
Standard Deviation		0.1397

The efficiency analysis shows that the average overall technical efficiency score under constant returns to scale (CRS-TE) was 0.3733, while the average pure technical efficiency score under variable returns to scale (TE-VRS) was 0.6000. This implies that palm sugar agroindustries in West Lombok and East Lombok could potentially reduce input usage by approximately 40% while maintaining the same level of output. Economically, this suggests that inputs such as palm sap, labor, fuel costs, packaging, and supporting materials are being used inefficiently, resulting in excessive input use relative to output levels [33]. The distribution of technical efficiency scores under the VRS assumption is presented in Table 1.

The results indicate that 60% of agroindustries are fully efficient under the VRS assumption, with an average efficiency score of 0.9034. The minimum efficiency score is 0.346, and the relatively moderate range (0.654) suggests a fairly even distribution of efficiency levels across agroindustries.

The average overall technical efficiency score under constant returns to scale is presented in Table 2.

Table 2. Distribution of technical efficiency under constant returns to scale assumption (TE-CRS)

	CRS Efficiency	
Efficiency Score	**Frequency**	**Percentage (%)**
< 0.400	12	8
0.400 - 0.599	61	40.67
0.600 - 0.749	12	8
0.750 - 0.898	5	3.333
0.899 - 0.999	4	2.667
1	56	37.33
Total	150	100
Mean		0,7094
Minimum		0.1429
Maximum		1.0000
Range		0.8571
Standard Deviation		0.2606

The results show that only 37.33% of agroindustries are fully efficient under the constant returns to scale (CRS) assumption, with an average efficiency score of 0.7094. The minimum efficiency score is 0.1429. This indicates the presence of scale inefficiency among many production units.

3.1.3 Normality test using RStudio

Prior to conducting the Tobit regression analysis, a normality test was performed to assess the distribution of residuals (Figure 1) with the distribution measurement results (Table 3). Given that the sample size exceeds 50 observations (N = 150), the Kolmogorov-Smirnov test was employed [34].

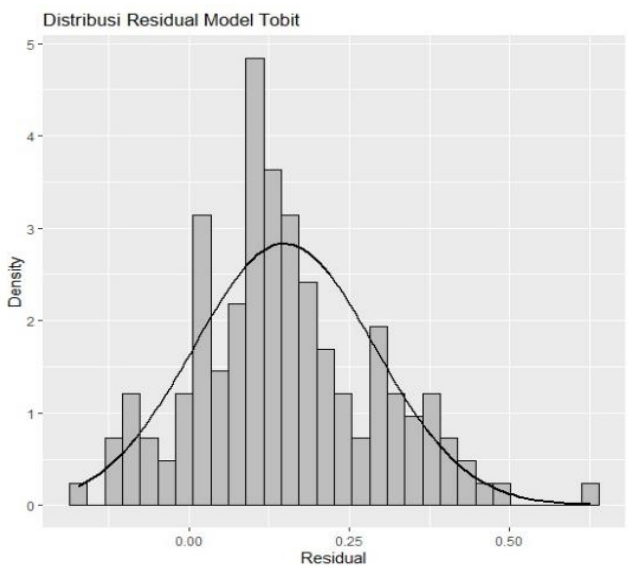

Figure 1. Residual distribution of the Tobit model

Table 3. Distribution measurement results

Indicator	**Value**
P-value	0.2552
Kurtosis	3.207
Skewness	0.430
N	150

The results indicate that the p-value (0.2552) is greater than the significance level of 0.05, suggesting that there is no significant difference between the sample distribution and the theoretical normal distribution. The kurtosis value of 3.207 indicates a distribution close to normal peak characteristics, while the skewness value of 0.430 suggests a slight positive skewness. Overall, these results confirm that the residuals are approximately normally distributed [35].

3.2 Discussion

A further analysis of technical efficiency involves examining the distribution of scale efficiency (SE) values across the 150 sampled palm sugar agroindustries.

3.2.1 Analysis of technical efficiency based on scale efficiency

Table 4 presents the efficiency scale values obtained using the following formula:

$$SE = \frac{\theta CRS}{\theta VRS} \tag{6}$$

Table 4. Distribution of Scale Efficiency (SE) values

	SE	
Efficiency Score	**Frequency**	**Percentage (%)**
< 0.400	2	1.333
0.400 - 0.599	48	32
0.600 - 0.749	14	9.333
0.750 - 0.898	18	12
0.899 - 0.999	12	8
1	56	37.33
Total	150	100
Mean		0.7721
Minimum		0.2859
Maximum		1.000
Range		0.7141
Standard Deviation		0.2305

Production scale conditions of palm sugar agroindustries on Lombok Island (Figure 2)

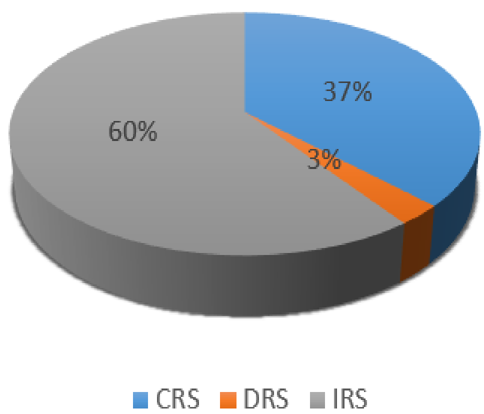

Figure 2. Production scale conditions

SE is calculated as the ratio between overall technical efficiency under constant returns to scale (TE-CRS) and pure technical efficiency under variable returns to scale. The results of Table 4, indicate that 37.33% of agroindustries operate at the optimal production frontier, achieving full SE. However, a gap of approximately 23 percentage points is observed when compared to pure technical efficiency, where 60% of agroindustries are efficient under the VRS assumption. This disparity suggests that although most palm sugar agroindustries are relatively efficient in managing inputs internally, many have not yet reached optimal production scale. In other words, inefficiency is largely driven by external or scale-related constraints, rather than purely managerial inefficiency [36].

The results further reveal the distribution of returns to scale among the sampled agroindustries (Figure 2): 60% (90 agroindustries) operate under Increasing Returns to Scale (IRS), indicating that increasing inputs would lead to a proportionally greater increase in output. This suggests that most agroindustries are still operating below optimal scale and have strong potential for expansion. 37% (56 agroindustries) operate under CRS, representing the most efficient and optimal production condition, where proportional increases in inputs result in proportional increases in output. 3% (4 agroindustries) operate under decreasing returns to scale (DRS), indicating that these agroindustries have exceeded their optimal scale, where additional inputs may lead to a decline in output.

3.2.2 Individual parameter significance test in Tobit regression

The Tobit regression model was estimated for socio-economic factors on the censored dependent variable (inefficiency score) in Table 5 [37].

Table 5. Parameter estimation results of factors affecting technical inefficiency in palm sugar agroindustry

Variable	Coefficient (Estimate)	Std, Error	*t*-value	*p*-value	Remark
Intercept	0.3041	0.1462	2.079	0.0376	**
Age	-0.0065	0.0034	-1.921	0.0547	*
Education	-0.0096	0.008	-1.196	0.2317	Not significant
Experience	-0.0012	0.003	-0.382	0.7023	Not significant
Training	0.0595	0.0832	0.715	0.4744	Not significant
Technology	-01186	0.138	-0.859	0.3903	Not significant
Institutional Participation	0.249	0.1193	2.087	0.0369	**
logSigma	-1.2996	0.1057	-12.297	0.000	***
Model Summary Statistics					
Number of observations	150				
Left-censored	90				
Uncensored	60				
Log-likelihood	-60.7214				
Pseudo R^2	0.0909				
AIC	137.4427				

Notes: *) Significant at α 10%, **) Significant at α 5%, ***) Significant at α 1%, AIC = Akaike Information Criterion

Based on the model summary statistics, the Tobit model was estimated using data from 150 palm sugar agroindustries on Lombok Island. The results show that 90 agroindustries, or observations, were left-censored at the lower limit of 0. This indicates that 60% of the total agroindustries operated at full efficiency. Meanwhile, the remaining 40%, equivalent to 60 agroindustries, were classified as uncensored observations, representing agroindustries experiencing technical inefficiency, with inefficiency values greater than 0. The log-likelihood value of −60.7214 indicates the degree of model fit to the data

The estimation results indicate that age and institutional participation significantly influence inefficiency scores. Age is significant at the 10% level, while institutional participation is significant at the 5% level. In contrast, education, experience, training, and technology do not exhibit statistically significant effects. The estimated Tobit model can be expressed as follows:

$$\begin{aligned} &IT^* \\ &= 0.3041 - 0.0065\,Age - 0.0096\,Education \\ &- 0.0012\,Experience + 0.0595\,Training \\ &- 0.1186\,Technology \\ &+ 0{,}249\,Institutional\ Participation + \varepsilon_i \end{aligned}$$

The age variable has a negative and statistically significant coefficient (p-value = 0.0547), indicating that an increase in age reduces inefficiency. Specifically, a one-year increase in age decreases inefficiency by 0.0065 units. This suggests that older agroindustry operators tend to be more efficient, likely due to stronger psychological attachment to their business and greater focus on production activities [38].

The education variable also shows a negative coefficient (-0.0096), implying that higher education levels may reduce inefficiency. Although not statistically significant, this result aligns with the notion that education enhances adaptability, innovation, and openness to new production practices [39]. The experience variable has a negative but insignificant effect, indicating that longer business experience slightly reduces inefficiency; however, the impact is minimal. This suggests that experience alone does not necessarily lead to significant improvements in production efficiency [40].

The training variable is not statistically significant, indicating that participation in training programs does not necessarily translate into improved efficiency. Field observations suggest that training programs are not evenly distributed and that their effectiveness depends more on quality and relevance rather than frequency [41, 42].

The technology variable has a negative coefficient (-0.1186), indicating that the adoption of modern technology tends to reduce inefficiency compared to traditional methods. Although not statistically significant, this finding highlights the potential of technological adoption to enhance production efficiency and productivity [43].

The institutional variable had a significant effect on efficiency (p-value = 0.0369 < α = 0.05), with a coefficient of

0.249. This indicates that business actors who were actively involved in institutional activities tended to have an inefficiency score 0.249 points higher than those who were not institutionally active. This finding suggests that the role of institutions in supporting improvements in business efficiency has not yet functioned optimally. The results further indicate that the participation of palm sugar agroindustry owners in institutional arrangements or farmer/business groups established to support palm sugar production and regional production development remains very limited. This is reflected in the fact that, among respondents with an inefficiency score of 0, approximately 98% were not actively involved in village-level institutions. Therefore, although institutional participation was statistically significant, its current implementation appears to be insufficiently effective in enhancing production efficiency.

Field findings reveal that although many respondents are formally registered as members of local institutions, they are not actively engaged in meetings or activities. Approximately 60% of respondents with zero inefficiency scores are inactive in institutional participation, indicating that many operators prefer to work independently without institutional interference. This reflects a tendency toward self-reliance in managing production inputs and market relationships.

4. CONCLUSIONS AND RECOMMENDATIONS

The DEA results indicate that a large proportion of palm sugar agroindustries operate under IRS, suggesting that most businesses are still operating below optimal scale.

This condition reflects structural constraints associated with small-scale operations. This finding highlights the opportunity for agroindustry operators to increase input utilization in order to achieve higher output levels. Therefore, institutional actors and supporting organizations should play a more active role in facilitating production scaling, providing targeted assistance, and disseminating knowledge on income improvement strategies.

Policy intervention is required, particularly from local governments at the village level, to strengthen outreach, mentoring, and technical support for palm sugar producers. The current lack of widespread and effective extension services has resulted in uneven capacity development among producers, with only a portion of agroindustry actors demonstrating innovation and sustainability-oriented practices.

Strengthening institutional effectiveness, improving training quality, and promoting technology adoption are essential to enhancing the long-term sustainability and competitiveness of palm sugar agroindustries in Lombok.

ACKNOWLEDGMENT

This research was supported by the Ministry of Higher Education, Science, and Technology through the Doctoral Scholarship Program 2024 (ongoing). The authors would like to express their sincere gratitude to the Promotor and Co-Promotor of this dissertation from the Department of Socio-Economics, Faculty of Agriculture, Universitas Brawijaya, Malang, for their guidance and valuable insights. Finally, the authors would like to express their gratitude to their home institution, the Faculty of Agriculture, University of Mataram, for its institutional support in the preparation of this article.

REFERENCES

[1] Wardani, D.K., Junaedi, A., Yahya, S., Sunarti, T. (2020). Morphological characteristics and productivity of sugar palm saps at several levels of tapping age. IOP Conference Series: Earth and Environmental Science, 418: 012040. https://doi.org/10.1088/1755-1315/418/1/012040

[2] Norfarhana, A.S., Jun, W.Y., Azriena, H.A.A., Ilyas, R.A., et al. (2025). Valorization of sugar palm agro-waste into cellulose biosorbents for highly effective methylene blue remediation. International Journal of Biological Macromolecules, 323: 147262. https://doi.org/10.1016/j.ijbiomac.2025.147262

[3] Norfarhana, A.S., Ilyas, R.A., Ngadi, N., Othman, M.H.D. (2024). Optimization of ionic liquid pretreatment of sugar palm fiber for cellulose extraction. Journal of Molecular Liquids, 398: 124256. https://doi.org/10.1016/j.molliq.2024.124256

[4] Asyraf, M.R.M., Syamsir, A., Supian, A.B.M., Usman, F., et al. (2022). Sugar palm fibre-reinforced polymer composites: Influence of chemical treatments on its mechanical properties. Materials, 15(11): 3852. https://doi.org/10.3390/ma15113852

[5] Perkebunan, D. J. (2021). Statistik Perkebunan Unggulan Nasional 2020-2022. Jakarta: Sekretariat Direktorat Jenderal Perkebunan.

[6] Haryoso, A., Hidayati, S., Kurniawan, S., Al Manar, P., Sandra, E., Zuhud, E.A. (2021). Stakeholders role for developing sustainable utilization of sugar palm in Kekait Village, West Lombok, West Nusa Tenggara. Media Konservasi, 26(3): 208-216. https://doi.org/10.29244/medkon.26.3.208-216

[7] Seluhinga, N.S., Philip, D. (2021). The influence of geographical concentration of firms on performance of small agro food processing enterprises in Tanzania. Journal of Agriculture and Food Research, 6: 100220. https://doi.org/10.1016/j.jafr.2021.100220

[8] Qalati, S.A., Magni, D. (2026). Adapting human resource management to social change: Enhancing employee innovation and sustainability outcomes. European Management Journal, 444(3): 532-544. https://doi.org/10.1016/j.emj.2026.02.003

[9] Syahidah, Lestari, A.S.R.D., Arif, A., Taskirawati, I., et al. (2025). Lignin from the sugar palm's Fiber (Arenga pinnata MERR.) as a potential active compound in packaging. Case Studies in Chemical and Environmental Engineering, 11: 101133. https://doi.org/10.1016/j.cscee.2025.101133

[10] Tajidan, T., Setiawan, R.N.S., Efendy, E., Nabilah, S., Mulyawati, S., Sjah, T., Amirah, S.N. (2025). Design to improve sustainable employee welfare using the R-Studio application: The case of the tofu agro-industry in Central Lombok, Indonesia. International Journal of Sustainable Development and Planning, 20(6): 2597-2605. https://doi.org/10.18280/ijsdp.200627. https://doi.org/10.18280/ijsdp.200627

[11] Parré, J.L., Chagas, A.L.S., Arends-Kuenning, M.P. (2024). The effect of farm size and farmland use on agricultural diversification: A spatial analysis of Brazilian municipalities. Agricultural and Food Economics, 12(1): 27. https://doi.org/10.1186/s40100-024-00323-9

[12] Wijaya, F., Elfriede, D.P. (2023). Improving the quality

and safety of palm sugar in north Lombok. Abdi Dosen: Jurnal Pengabdian Pada Masyarakat, 7(1): 9-20. https://doi.org/10.32832/abdidos.v7i1.1545
[13] Mo, M., Zeng, L. (2025). Analysis of technology innovation efficiency and its impact factors based on DEA-fsQCA method: Evidence from listed seed companies in China. Heliyon, 11(4): e42914. https://doi.org/10.1016/j.heliyon.2025.e42914
[14] Getahun, A., Muleta, G. (2022). Analysis of levels and determinants of technical efficiency of tef producers in Walmara District, Ethiopia. American Journal of Theoretical and Applied Business, 8(3): 43-49. https://doi.org/10.11648/j.ajtab.20220803.12
[15] Kamiyama, R., Miyata, T. (2023). Applicability of data envelopment analysis using vessel-level data to the estimation of technical efficiency and capacity utilization of the small-scale squid angling fishery in Aomori Prefecture, Japan. Fisheries Research, 262: 106664. https://doi.org/10.1016/j.fishres.2023.106664
[16] Sun, L., Zhang, X., Zhao, Z., Zhang, J. (2025). ESG is conducive to improving the operating efficiency of fishery enterprises -- Based on DEA model and Tobit regression analysis. Regional Studies in Marine Science, 85: 104158. https://doi.org/10.1016/j.rsma.2025.104158
[17] Liu, S., Sun, J.X., Lyu, C., Chu, T.J., Zhang, H.X. (2021). Evaluating fishing capacity based on DEA and regression analysis of China's offshore fishery. Journal of Marine Science and Engineering, 9(12): 1402. https://doi.org/10.3390/jmse9121402
[18] Coulibaly, N., Siaka, K., Magloire, Y.Y., Sally, T. (2020). Technical efficiency of farms, and fight against poverty: Case of the cashew sector in Côte d'Ivoire. Journal of Agricultural Science, 12(2): 106. https://doi.org/10.5539/jas.v12n2p106
[19] Winarso, R., Syafrial, S., Widyawati, W. (2021). Multi-stage technical efficiency analysis using data envelopment analysis and Tobit regression on shallot farming, case study of Torongrejo Village, Junrejo Sub-District, Batu City, East Java. Jurnal Ekonomi Pertanian dan Agribisnis, 5(4): 1191-1205. https://doi.org/10.21776/ub.jepa.2021.005.04.21
[20] Ibnu, M., Offermans, A., Glasbergen, P. (2018). Certification and farmer organisation: Indonesian smallholder perceptions of benefits. Bulletin of Indonesian Economic Studies, 54(3): 387-415. https://doi.org/10.1080/00074918.2018.1506093
[21] Sari, N.M.W., Suwarsinah, H.K., Baga, L.M. (2016). The Effect of entrepreneurial characteristics towards the business performance of palm sugar micro. Small and Medium Entreprises in West Lombok Regency, 12(1): 5160. https://doi.org/10.25015/penyuluhan.v12i1.11320
[22] Prihantini, C.I., Hanani, N., Asmara, R., Syafrial, S. (2024). Technology gap ratio decomposition in smallholder solar saltworks in Indonesia using meta-frontier data envelopment analysis (MetaDEA). Decision Science Letters, 13(3): 595-604. https://doi.org/10.5267/j.dsl.2024.5.003
[23] Lemos, S.V., Salgado, A.P., Duarte, A., De Souza, M.A.A., De Almeida Antunes, F. (2019). Agroindustrial best practices that contribute to technical efficiency in Brazilian sugar and ethanol production mills. Energy, 177: 397-411. https://doi.org/10.1016/j.energy.2019.04.053
[24] Puspanantasari, E., Parinov, I.A., Wongloucha, C. (2024). Efficiency evaluation in Indonesia's quarrying industry using variable combinations DEA. Spektrum Industri, 22(2): 90-110. https://doi.org/10.12928/si.v22i2.227
[25] Bobitan, N., Dumitrescu, D., Burca, V. (2023). Agriculture's efficiency in the context of sustainable agriculture—A benchmarking analysis of financial performance with data envelopment analysis and Malmquist index. Sustainability, 15(16): 12169. https://doi.org/10.3390/su151612169
[26] Abbasi, Z., Afzalinejad, M., Foroughi, A.A. (2025). Dynamic evaluation of operational, environmental, and unified efficiencies: A DEA application in agriculture. Socio-Economic Planning Sciences, 104: 102411. https://doi.org/10.1016/j.seps.2025.102411
[27] Liu, H., Zhu, Y. (2026). Input-output efficiency evaluation with undesirable outputs: An approach based on uncertain SBM-DEA model. Computers & Industrial Engineering, 216: 111965. https://doi.org/10.1016/j.cie.2026.111965
[28] Yang, G., Zhan, Z., Shang, F. (2026). A comprehensive review of data envelopment analysis approach in agricultural production efficiency. Socio-Economic Planning Sciences, 105: 102508. https://doi.org/10.1016/j.seps.2026.102508
[29] Xia, R., Lu, S., Zhao, L. (2026). Efficiency and determinants of science and technology investment in Chinese competitive sports: A provincial DEA-Tobit analysis. Frontiers in Sports and Active Living, 8: 1738361. https://doi.org/10.3389/fspor.2026.1738361
[30] Iliyasu, A., Mohamed, Z.A. (2016). Evaluating contextual factors affecting the technical efficiency of freshwater pond culture systems in Peninsular Malaysia: A two-stage DEA approach. Aquaculture Reports, 3: 12-17. https://doi.org/10.1016/j.aqrep.2015.11.002
[31] Hindarti, S., Saputro, A.J., Maula, L.R. (2023). Social economic factors affecting the technical inefficiency of shallots in Malang District. Agrisocionomics: Jurnal Sosial Ekonomi Pertanian, 7(1): 39-47. https://doi.org/10.14710/agrisocionomics.v7i1.15577
[32] Frýd, L., Sokol, O. (2026). Hidden heterogeneity in measuring production factors: Implications for two-stage efficiency analysis. Socio-Economic Planning Sciences, 104: 102418. https://doi.org/10.1016/j.seps.2026.102418
[33] Sultana, S., Hossain, M.M., Haque, M.N. (2023). Estimating the potato farming efficiency: A comparative study between stochastic frontier analysis and data envelopment analysis. PLOS ONE, 18(4): e0284391. https://doi.org/10.1371/journal.pone.0284391
[34] Mishra, P., Pandey, C., Singh, U., Gupta, A., Sahu, C., Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. Annals of Cardiac Anaesthesia, 22(1): 67-72. https://doi.org/10.4103/aca.ACA_157_18
[35] Mboma, A.B., Kilima, F.T.M., Mchopa, A.D., Schäfer, J.G. (2026). Determinants of commercialization among smallholder maize farmers in Tanzania: A Tobit regression analysis. Cogent Food & Agriculture, 12(1): 2612201. https://doi.org/10.1080/23311932.2025.2612201
[36] Camanho, A.S., Silva, M.C., Piran, F.S., Lacerda, D.P. (2024). A literature review of economic efficiency assessments using Data Envelopment Analysis. European Journal of Operational Research, 315(1): 1-18. https://doi.org/10.1016/j.ejor.2023.07.027
[37] Zhu, X., So, A.R., Shin, S. (2026). A study on the

efficiency and influencing factors of China's four-stage ports using DEA and Tobit two-stage models. Asian Journal of Shipping and Logistics, 42(2): 97-108. https://doi.org/10.1016/j.ajsl.2026.02.001

[38] Cui, G., Kooij, D.D., Zhang, Y., Liu, D., Pan, J. (2025). Building an age-inclusive workplace for older workers: A dual pathway of age-inclusive HR practices to facilitate successful aging at work. Journal of Vocational Behavior, 161: 104148. https://doi.org/10.1016/j.jvb.2025.104148

[39] González-Blanco, J., Rodríguez-Domínguez, M.D.M., Guisado-González, M. (2024). Innovation strategies and technical efficiency. European Research on Management and Business Economics, 30(2): 100243. https://doi.org/10.1016/j.iedeen.2024.100243

[40] Radhi, F., Yuliando, H., Fadhila, A., Faiz, I.A., Zamzami, F. (2025). Technical efficiency analysis using data envelopment analysis (DEA) and Tobit regression on convenience store networks in Indonesia. Cogent Economics & Finance, 13(1): 2539788. https://doi.org/10.1080/23322039.2025.2539788

[41] Ayiko, R., Mujasi, P.N., Abaliwano, J., Turyareeba, D., et al. (2020). Levels, trends and determinants of technical efficiency of general hospitals in Uganda: Data envelopment analysis and Tobit regression analysis. BMC health services research, 20(1): 916. https://doi.org/10.1186/s12913-020-05746-w

[42] Kerorsa, G.M. (2025). Determinants of technical efficiency among smallholder maize producing farmers in Guto Gidda district, Oromia, Ethiopia. Discover Global Society, 3(1): 138. https://doi.org/10.1007/s44282-025-00278-2

[43] Wang, Q., Chang, Z. (2022). Technical efficiency and its influencing factors of the three major urban agglomerations in eastern China—Based on DEA-Tobit model. American Journal of Industrial and Business Management, 12(7): 1222-1237. https://doi.org/10.4236/ajibm.2022.127067