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Measuring Technical Efficiency of Thai Oil Palm Production Using the Three-Stage Data Envelopment Analysis

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ABSTRACT
This study analyzes the efficiency of oil palm production in Thailand, identifying factors contributing to technical inefficiency and examining production trends in the oil palm sector. Secondary data were collected from four regions in Thailand over the 2018/19 to 2022/23 planting seasons and analyzed using the Three-Stage Data Envelopment Analysis (DEA) model. DEA was employed to evaluate technical efficiency levels and mitigate the impact of unfavorable environmental effects. Additionally, the Malmquist Productivity Index was used to measure changes in oil palm production efficiency and estimate productivity trends. The findings indicate that the technical efficiency score in Stage 3 of the Three-Stage DEA is higher than in Stage 1 due to adjustments in input variables and the exclusion of environmental factors from the model, with scores of 0.823 and 0.864, respectively. Furthermore, results show that the northern region has lower technical efficiency scores compared to other regions, while the Northeast recorded the largest decline in productivity among the four regions. Despite demonstrating favorable performance and positive productivity trends, farmers and government agencies must prioritize production management, as it plays a crucial role in enhancing efficiency and reducing production costs to compete in a high-demand market.

Keywords: Oil Palm Production, Three-stage DEA, Malmquist Productivity Index, Technical Efficiency.

INTRODUCTION

Oil palm is one of Thailand's primary economic crops, making Thailand the world’s third-largest oil palm producer, with production in the 2023/24 season reaching 3.6 million metric tons, following Indonesia and Malaysia (Foreign Agricultural Service, 2024). Oil palm plays a significant role in the food, energy, and cosmetics industries. Most of Thailand's oil palm cultivation and crude palm oil extraction facilities are concentrated in the southern region, accounting for 85.9% of the total harvested area nationwide, especially in Surat Thani, Krabi, and Chumphon provinces (collectively around 57.3%). The remainder is cultivated in the central, northeastern, and northern regions (Sowcharoensuk, 2023). The popularity of oil palm cultivation is due to its high yield and low production costs (Zamri et al., 2018). The Office of Agricultural Economics (2024) forecasts an increase in the total productive area nationwide in 2024, particularly in key southern production zones, due to favorable oil palm prices since 2021 and government support to boost oil palm productivity under the comprehensive oil palm and palm oil reform plan in Thailand, spanning 2017-2036. This plan aims to achieve fresh fruit bunch yields of 3.50 tons per rai per year and a 23% oil extraction rate (Office of Agricultural Economics, 2024). Consequently, farmers have expanded oil palm cultivation areas, replacing rubber plantations in 2021, with some areas converting rice paddies and idle lands to oil palm. Despite increased support and demand, the oil palm industry still faces declining production efficiency due to various external factors, particularly the impact of El Niño and drought periods in 2023-2024. Insufficient rainfall has affected oil palm growth, causing incomplete fruit bunches or partial dryness, reducing the weight per bunch. Additionally, extreme heat has led to a “sunburned palm” condition, reducing oil extraction rates (Office of Agricultural Economics, 2024). Aside from weather-related factors, other factors impacting production volume remain unclear, highlighting the need to study technical efficiency in oil palm production to assess production capabilities and identify factors influencing efficiency to enhance productivity quality.

Therefore, this research focuses on analyzing oil palm production efficiency in Thailand, identifying factors affecting technical inefficiency, and examining production trends using the Three-Stage Data Envelopment Analysis (DEA) model. This approach allows for comparing production efficiency across regions and separating uncontrollable factors, such as weather, from controllable factors. This method provides an overview of factors impacting production efficiency and can inform policy development, production planning, or management of production inputs to strengthen Thailand's oil palm industry.

LITERATURE REVIEW

Research on oil palm productivity often employs non-parametric methods alongside relevant indicators. This method is widely used in evaluating the technical efficiency (TE) of agricultural production, specifically through Data Envelopment Analysis (DEA). DEA does not require a specific functional form for the efficient frontier; rather, the efficiency frontier is calculated using a mathematical technique called linear programming. This application of linear programming makes DEA a suitable tool for measuring the relative efficiency of decision-making units (DMUs). DEA's advantage lies in its ability to compute specific efficiency scores for each DMU, even when the characteristics of these units are defined by varied types or quantities of inputs and outputs. Additionally, as DEA is a nonparametric method, there are no constraints on the functional form for production functions suitable for the data (Suebpongsakorn, 2012). DEA can also consider multiple inputs and outputs simultaneously (Waduge et al., 2015). Reig-Martínez and Picazo-Tadeo (2004) noted DEA's advantage over stochastic frontier analysis (SFA), as DEA can establish a technological frontier without needing a parametric form for the function. However, DEA has limitations, such as the inability to separate the impact of uncontrollable environmental variables from differences in farm management in single-stage analysis (Silva et al., 2013). Despite these limitations, DEA remains a popular method for assessing DMU efficiency across various fields (Assaf et al., 2011; Chung, 2011). In Thai agriculture, evaluating regional technical efficiency (TE) and its components is crucial, as it supports strategies to enhance productivity with constant returns to scale (CRS) in response to increasing competition. Subsequently, Banker and Morey (1986) adapted the DEA model to include inputs and outputs that are determined externally and non-determined, taking environmental factors into account. Several methods exist for considering environmental factors, with the three-stage method (Three-Stage DEA) being particularly popular. This method, developed by Charnes et al. (1981), Ferrier & Lovell (1990), incorporates environmental factors directly into the linear programming model. The approach has become widely used in research for improving the accuracy of technical efficiency measurement by separating the effects of external or environmental factors from those of management or production unit efficiency.

Numerous researchers have applied the Three-Stage Data Envelopment Analysis (DEA) method in their studies. For instance, Feng & Li (2020) evaluated the environmental regulatory efficiency of industries in China using the Three-Stage DEA, finding a low efficiency score for China's IERE due to external environmental factors. Hu et al. (2021) assessed cereal grain production efficiency using the Three-Stage DEA, emphasizing the importance of environmental variables in determining grain productivity. Pan et al. (2022) analyzed agricultural productivity in the Yangtze River Economic Zone using Three-Stage DEA and the Malmquist model, observing improvements in technical efficiency, technological progress, and adjusted total factor productivity of -0.1%, 0.24%, and 0.22%, respectively, after adjustment. The findings suggested that environmental variables impact production efficiency scores. Recently, Alorzuke et al. (2024) assessed the technical efficiency of maize production in Ghana across 48 cities in six regions using the Three-Stage DEA method, showing a significant influence of environmental factors on production efficiency.

After accounting for environmental factors, efficiency scores increased from 0.752 to 0.853.

This literature review highlights the appropriateness and utility of using the three-stage DEA as a research method to remove environmental impacts in Thai oil palm production. This approach effectively eliminates environmental disturbances that may affect efficiency scores, thereby enhancing measurement accuracy. Research focusing on oil palm production efficiency or management remains limited due to data constraints and challenges in identifying clear input and output factors.

RESEARCH METHODOLOGY

Data and Variables

This study analyzed data from four regions of Thailand—north, northeast, central, and south-covering 77 provinces. It focused on oil palm production during the 2018/19 to 2022/23 planting seasons, evaluating technical efficiency (TE) for rubber production across 77 decision-making units (DMUs) in these regions. Secondary data were collected from various government surveys in Thailand, including those by the Ministry of Agriculture and Cooperatives, the Office of Agricultural Economics, the Department of Agricultural Extension, the Meteorological Department, and the Ministry of Labor. This study identified a suitable combination of input factors based on the characteristics of oil palm production and environmental conditions.

The analysis involved five input factors: Planted Area (X1), Herbicides Quantity (X2), Fertilizer Quantity (X3), Number of Farm Machinery Used (X4), and Labour Force (X5), along with two outputs: Oil Palm Quantity (Y1) and Selling Price (Y2). Additionally, two environmental factors were considered: Temperature (B1) and Amount of Rainfall (B2), which farmers cannot control. DEAP 2.1, EViews 8.0, and SPSS 23 were used for data analysis, with variable details provided in Table 1.

Table 1 Table caption

Variables		Unit	Source
Output variables	Oil Palm Quantity (Y1)	kg/ha	Abdul et al. (2022)
	Selling Price (Y2)	Baht/kg	Suebpongsakorn (2020);
Input variables	Planted Area (X1)	ha	Ruenggate et al. (2022)
	Herbicides quantity (X2)	liters/ha	Damayanti et al. (2023)
	Fertilizer Quantity (X3)	kg/ha	Puruhito et al. (2019);
	Machinery Used (X4)	per area per number of tractors	Abdul et al. (2022)
	Labour Force (X5)	persons/hr.	Chaira et al. (2024)
Environmenta factors	Temperature (E1)	Degree Celsius	Azwan et al. (2016);
	Amount of Rainfall (E2)	Millimeter	Varina et al. (2020)

Data Analysis

Technical efficiency (TE) in oil palm production in Thailand was analyzed using the Three-Stage DEA model and the Malmquist Productivity Index (MPI). The three-stage analysis begins with estimating the efficiency frontier using a simple DEA model that excludes environmental variables, focusing on either input-oriented (reducing inputs to maintain output levels) or output-oriented (maximizing outputs with observed input levels). This study used an input-oriented model to analyze oil palm production efficiency in Thailand.

In the second stage, ordinary least squares (OLS) regression was applied to control the effects of uncontrollable environmental factors, re-evaluating efficiency with the adjusted model after removing the influence of unnecessary input use. The final stage measures efficiency under ideal conditions. Efficiency scores range from 0 (minimum) to 1 (maximum), with the improved model explained as follows:

Data Analysis using Three-Stage DEA

Step 1: Standard DEA Analysis

The first step of data analysis begins with using the CCR model developed by Charnes et al. (1978), which assumes that increased output results from proportionate increases in inputs. The CCR model can be divided into two forms: input-oriented and output-oriented. In this study, the input-oriented form is used to assess management efficiency, which can be modeled as follows (Charnes et al., 1978).

$$min\theta - \varepsilon \left(\sum_{t=1}^{m} s_t^- + \sum_{r=1}^{s} s_r^+\right) \qquad (1)$$

Subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ijo} \quad i = 1,2,\dots,m$$

$$\sum_{j=1}^{n} y_{ij}\lambda_j - s_i^+ = y_{rjo} \quad r = 1,2,\dots,s$$

$$\lambda_i, s_i^-, s_r^+ \geq 0 \qquad j = 1,2,\dots,n$$

In equation (1) s_i^- and s_r^+ = slack variables Input and Output, m and s represent the variables indexes.

x_{ijo} and y_{rjo} = observed values of inputs and outputs for DMUo

θ = The efficiency score for each DMU ranges between 0 and 1

(θ=1 indicating technical efficiency and, θ<1 indicating technical inefficiency.)

At this initial stage, it is not possible to separate the impact of external environmental factors and internal management factors on production efficiency. Therefore, the efficiency score of each DMU does not fully reflect the root causes of inefficiency. To achieve a more detailed assessment of DMUs' efficiency, external factors should be removed in the second step.

Step 2: OLS Model

In the first stage of data analysis, the impact on efficiency scores is influenced by environmental factors, statistical noise, and management inefficiencies, but clear efficiency scores for each region cannot be determined. To address this, ordinary least squares (OLS) regression is used in this step to examine factors influencing the slack values of each input and to separate the effects on efficiency scores as outlined by Aigner et al. (1977), using a linear programming model.

$$min \sum_{j=1}^{n} \varepsilon_j \quad (2)$$

Subject to

$$ln\beta_0 + \sum_{i=1}^{m} \beta_i lnx_{ij} - lny_i = \varepsilon_j \qquad j = 1, 2, \dots, n \quad (3)$$

$$\varepsilon_j, \beta_i \geq 0 \quad \forall i, j$$

In equation (3) j = 1, 2,..., n refers to the observations. The OLS (Ordinary Least Squares) The OLS method minimizes the sum of squared residuals, providing closed-form expressions for estimates of unknown parameters β (Aigner et al. 1977)

Step 3: DEA Model with Adjusted Inputs

The final stage of data analysis involves using the original output from Step 1 and the adjusted inputs from Step 2 to measure the efficiency of each DMU. This stage separates the influence of environmental variables and statistical noise, yielding a true efficiency score.

Malmquist Productivity Index (MPI) Analysis

The Malmquist Productivity Index (MPI), proposed by Caves et al. (1982) and based on Farrell’s (1957) technical efficiency concept, is used in this study. The original output from Step 1 and the adjusted input (x_{ij}^\prime) from Step 2 are employed. The MPI, derived from the DEA model, calculates changes in total factor productivity (TFP), technological change (TC), and efficiency change (EC) using panel data. Additionally, the Malmquist Productivity Index consists of two components: one measures technological progress (TC), and the other measures efficiency gaps (EC) between potential maximum and observed output levels. The Malmquist Productivity Index provides a clear explanation of productivity changes as per Equation (4) (Fare et al., 1994).

$$M(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\left(\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \times \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} = TC \times EC \quad (4)$$

From this equation, three cases may arise for the value of M: M>1 indicates an increase in productivity; M<1 signifies a decrease in productivity; and M=1 suggests no change in productivity between periods t and t+1. For EC values, EC>1 means oil palm production efficiency has increased from period t to t+1; EC<1 implies a decrease; and EC=1 indicates stable efficiency over time. advancement:s, TC>1 indicates technological advancement; TC<1 reflects technological decline; and TC=1 means no technological change (Fare et al., 1994).

RESULTS AND DISCUSSION

First-Stage: Using the Conventional DEA model

Efficiency Level and Returns to Scale Analysis of Oil Palm Production Across Four Regions Based on Geographical Location. According to the analysis results in Table 2, which exclude external environmental variables, the average technical efficiency (TE) of oil palm production in Thailand from the 2018/19 to 2022/23 planting seasons is 0.823, with a standard deviation of 0.094. The highest TE score is 0.934, and the lowest is 0.705, as measured by traditional DEA. It can be observed that the average TE is high, suggesting a potential need to further enhance technical efficiency in oil palm production. When examining TE in each planting season, TE scores were 0.742, 0.821, 0.827, 0.846, and 0.877 for the respective seasons from 2018/19 to 2022/23. The analysis also indicates that the lowest average TE occurred in the 2018/19 season, likely due to decreased global market demand for palm oil. However, as the global economy recovered in subsequent years, demand and oil palm production improved, especially within the ethanol industry.

Regionally, the northern region consistently exhibited lower TE scores than other regions across all planting seasons due to less favorable climatic conditions and less suitable production factors. In contrast, the southern region demonstrated higher technical efficiency than other regions, as its climate and geographic conditions are well-suited for oil palm production, resulting in higher TE scores. This aligns with the findings of Nicolas et al. (2018), who noted that favorable climatic conditions impact crop production and yield enhancement. However, traditional DEA models cannot clearly distinguish between high and low efficiency levels.

Table 2. Efficiency scores in the first stage

Region	years					Average
	2561/62	2562/63	2563/64	2564/65	2565/66	
Northern	0.595	0.732	0.636	0.759	0.801	0.705
North-Eastern	0.765	0.86	0.844	0.78	0.892	0.828
Central	0.696	0.785	0.897	0.879	0.862	0.824
Southern	0.912	0.908	0.931	0.966	0.951	0.934
Total average	0.742	0.821	0.827	0.846	0.877	0.823
SD	0.133	0.078	0.132	0.096	0.062	0.094
Maximum	0.912	0.908	0.931	0.966	0.951	0.934
Minimum	0.595	0.732	0.636	0.759	0.801	0.705

Source: Author's calculations

Second-Stage: OLS model
The second step uses the OLS model to calculate the factor frontier for the input slack of five factors during the 2018/19 to 2022/23 planting seasons, which include cultivated area, pesticide quantity, fertilizer quantity, machinery quantity, and labor. Environmental variables, specifically temperature and rainfall, were used as independent variables in the OLS model. The analysis found that temperature had a statistically significant negative effect on cultivated area at the 0.01 level, while rainfall had a statistically significant positive effect on cultivated area at the 0.01 level, with coefficients of -3.267 and 5.126, respectively.

For pesticide quantity, temperature had a positive effect and rainfall a negative effect on efficiency scores, with significance levels of 0.01 and 0.05 and coefficients of 5.491 and -1.785, respectively. Regarding fertilizer quantity, temperature showed a positive effect, and rainfall showed a negative effect on efficiency scores, with significance levels of 0.01 and 0.05, and coefficients of 4.032 and -2.014, respectively.

For machinery quantity, temperature was not significant, while rainfall had a negative effect at the 0.1 significance level, with a coefficient of -0.873. Finally, for labor, temperature and rainfall both negatively affected efficiency scores, with significance levels of 0.1 and 0.01, and coefficients of -3.014 and -3.912, respectively (Table 3). This is consistent with the study by Yusuf et al. (2023), which stated that external environmental factors, such as rainfall and weather changes, are key determinants of production efficiency.

The above findings indicate that environmental factors significantly impact the efficiency of oil palm production, necessitating the separation and analysis of environmental effects from the model. This aligns with Waduge et al. (2015), who studied agricultural production efficiency by isolating external environmental factors to obtain a true measure of technical efficiency. Upon examining the coefficients shown in Table 3, if the estimated coefficient is negative, it indicates a negative correlation between the environmental variable and the input variable. This means that an increase in the environmental variable leads to a reduction in resource wastage, thereby enhancing oil palm production efficiency. Conversely, a positive estimated coefficient implies that an increase in the environmental variable will increase input variables, resulting in reduced production efficiency.

Table 3 Results in the Second Stage

Dependent variables	Independent variables		
	Constant term (E0)	Temperature (E1)	Amount of Rainfall (E2)
Planted Area (X1)	-1.625	-3.267***	5.126*** (3.214)

	(-0.562)	(-2.893)	
Herbicides Quantity (X2)	1.324	5.491***	-1.785**
	(0.985)	(4.248)	(-2.368)
Fertilizer Quantity (X3)	1.493	4.032***	-2.014**
	(1.218)	(2.985)	(-2.682)
Machinery Used (X4)	-1.103**	8.762	0.873*
	(-2.214)	(1.436)	(-2.016)
Labour Force (X5)	1.985	-3.014*	-3.912***
	(0.732)	(-1.982)	(-2.878)

Note: ns Correlation is not-statistically significant in all levels; ***, **, *correlation is significant at levels 0.01, 0.05 and 0.1, respectively; ethe number shown in parentheses is t-value.

Source: Author’s calculations

Third Stage: Input-Adjusted DEA Model

Based on the analysis in the second step, input variables were adjusted to mitigate the adverse impact of external environmental factors on oil palm production in Thailand. Parameter estimates were applied following the principles proposed by Fried et al. (2002) to isolate the influence of environmental factors on inputs. In this third step, efficiency was measured after adjusting the input variables. The findings showed that, without considering external environmental variables, the average technical efficiency of oil palm production in Thailand from the 2018/19 to 2022/23 planting seasons was 0.864, with a standard deviation of 0.080 and a maximum technical efficiency of 0.967. The minimum technical efficiency was 0.771 according to the third-step DEA. Comparison between Steps 1 and 3 shows that the average technical efficiency in Step 3 is higher than in Step 1, increasing from 0.823 to 0.864 (Table 4). This indicates that oil palm production is transitioning from decreasing returns to scale (DRS) to increasing returns to scale (IRS) through adjustments for environmental impact and efforts in the three-stage DEA model. This suggests that the production scale of decision-making units (DMUs) has been optimized and is now approaching the ideal size, with environmental variables adjusted due to their influence on the technical efficiency of oil palm production in Thailand. The southern region exhibited the highest efficiency scores compared to other regions, as it has the largest cultivated area, favorable topography, and climate conditions for oil palm production, as well as farmers with good skills and experience in oil palm production. The next regions in order of efficiency were the central, northeastern, and northern regions, respectively. efficiency.

Table 4. Efficiency scores in the third stage

Region	years					Average
	2018/19	2019/20	2020/21	2021/22	2022/23	
Northern	0.696	0.751	0.784	0.746	0.876	0.771
North-Eastern	0.791	0.861	0.869	0.868	0.879	0.854
Central	0.796	0.896	0.847	0.899	0.894	0.866
Southern	0.942	0.948	1.000	0.953	0.991	0.967
Total average	0.806	0.864	0.875	0.867	0.910	0.864
SD	0.102	0.083	0.091	0.088	0.055	0.080
Maximum	0.942	0.948	1.000	0.953	0.991	0.967
Minimum	0.696	0.751	0.784	0.746	0.876	0.771

Source: Author’s calculations

Evaluation of Malmquist Productivity Index

This study assesses changes in oil palm production trends in Thailand from the 2018/19 to 2022/23 planting seasons by applying the Malmquist Productivity Index (MPI) within a CCR analysis framework that focuses on input factors. Adjustments were made to input factors, considering the impacts of external factors and any changes that occurred. The analysis separates total factor productivity (TFP) into two main components: Efficiency Change (EC) and Technical Change (TC). The estimates indicate that, during this period, the average rate of technological change in Thailand's oil palm industry was 1.062, the average rate of efficiency change was 0.976, and the average TFP was 1.037, reflecting an overall positive productivity trend from the 2018/19 to 2022/23 seasons. However, it was observed that efficiency (EC) and technological progress (TC) declined during the 2019/20 to 2020/21 seasons (Table 5).

Table 5. Assessment of the Malmquist Productivity Index by period

Year	TC	EC	TFP	The Productivity Trend
2018/19-2019/20	1.079	0.987	1.065	increasing
2019/20-2020/21	0.976	0.994	0.970	decreasing
2020/21-2021/22	1.113	0.954	1.062	increasing
2021/22-2022/23	1.081	0.970	1.049	increasing
Mean	1.062	0.976	1.037	increasing

Source: Author's calculations

Spatial analysis reveals productivity development differences among the four regions, with the central and southern regions showing an upward trend in overall productivity (TFP > 1), indicating improvements in both efficiency and technology. Conversely, the northern and northeastern regions displayed a downward trend in overall productivity (TFP < 1), suggesting the need to enhance both production efficiency and technological development (Table 6).

Table 6. Malmquist Productivity Index by Region

Region	Northern	North-Eastern	Central	Southern	Mean
TC	1.003	0.978	1.115	1.072	1.034
EC	0.994	0.986	0.986	0.998	0.977
TFP	0.997	0.964	1.099	1.070	1.010
The Productivity Trend	decreasing	decreasing	increasing	increasing	increasing

Source: Author's calculations

The application of the Malmquist Productivity Index (MPI) in analyzing the 2018/19 to 2022/23 seasons demonstrates that Thailand's oil palm industry has improved in three main areas: production efficiency, technological progress, and overall productivity growth. The regional productivity differences highlight unique development opportunities and challenges in each area, which should be considered in formulating policies and measures to promote future development in the oil palm industry. Additionally, resource management, mindful of regional environmental conditions, the promotion of new innovations and technologies to mitigate environmental impacts such as implementing appropriate irrigation systems in low-rainfall areas (Chien et al., 2021) and training farmers to enhance input management skills are essential strategies for ensuring sustainable growth in Thailand's oil palm industry.

CONCLUSION

A study on the efficiency of oil palm production in Thailand using the Three-Stage Data Envelopment Analysis (DEA) method revealed that the technical efficiency score in the third stage of the Three-Stage DEA was higher than in the first stage due to adjustments in input variables and the exclusion of environmental factors from the model. This indicates that environmental factors significantly impact the efficiency of oil palm production. Comparing production efficiency across Thailand's four regions, the southern region showed higher technical efficiency than other regions, supported by several factors: the largest cultivation area, suitable geography and climate for oil palm production, and well-skilled, experienced farmers. The evaluation of oil palm production trends in Thailand from the 2018/19 to 2022/23 planting seasons using the Malmquist Productivity Index (MPI) showed an overall increase in production trends. However, spatial analysis across the four regions revealed differences: the central and southern regions exhibited an upward trend in total factor productivity (TFP > 1), while the northern and northeastern regions showed a decline in total factor productivity (TFP < 1), highlighting a need for efficiency improvements and technological advancements in the regions with declining trends.

Although Thailand's efficiency and productivity trends in oil palm production are favorable, farmers and government agencies must prioritize production management, as it plays a crucial role in enhancing efficiency and reducing production costs to remain competitive in high-demand markets. Effective management includes overseeing all planting stages, from selecting suitable cultivation areas (avoiding waterlogged areas or, if unavoidable, elevating ridges and creating drainage ditches to ensure the palm soil level is above flood levels). Fertilizers and chemicals should be applied in appropriate quantities; overuse raises fertilizer concentration in the palms, harming the trunks and unnecessarily increasing production costs, while underuse could lead to poor yields. To manage fertilizer usage accurately, farmers should analyze soil and leaf samples for nutrient levels. Human resource management should include training for laborers on proper harvesting techniques and efficient management of the harvesting process.

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