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QUANTILE INSIGHTS INTO THE ROLE OF FERTILISER, HARVESTERS AND ESTATE SIZE IN SHAPING OIL PALM FRESH FRUIT BUNCHES (FFB) YIELD

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ABSTRACT

This study investigates the impact of fertiliser application, harvester availability and estate size on oil palm fresh fruit bunches (FFB) yield using quantile regression for Malaysian estates. Unlike traditional mean-based approaches, quantile regression allows for a deeper understanding of how these factors influence estates at different yield levels. The results reveal that fertiliser has a strong, positive effect across all yield quantiles, with diminishing returns at higher yield levels. Harvester availability plays a significant role, particularly for medium-yield estates. Estate size exhibits varying effects whereby small and medium-small estates underperform at lower quantiles and show modest improvements at higher quantiles. However, these upward shifts are only weakly significant and have limited effect sizes. These insights suggest while smaller estates may benefit from targeted support, the magnitude of their advantage at higher yield levels is modest. The findings contribute to optimising resource allocation and enhancing sustainability in Malaysia's palm oil industry.

Keywords: estate size, FFB productivity, quantile regression, yield determinants.

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INTRODUCTION

Palm oil stands as a cornerstone of the global vegetable oil market, accounting for 36% of global consumption and reaching over 75 million tonnes consumed in 2023 (Parveez et al., 2024). Malaysia plays a pivotal role in this industry, ranking as one of the leading producers alongside Indonesia and contributing over 25% of global palm oil production (Minal, 2025). However, the Malaysian oil palm sector faces a critical challenge which is the stagnation of fresh fruit bunches (FFB) yields. Despite advancements in planting materials and agronomic practices, national average yields have plateaued at 15–19 t ha^{-1}, falling significantly short of the potential 30–35 t ha^{-1} (Henson, 2003; Parveez, 2024). This yield gap raises concerns about the industry's future growth and sustainability, especially given the limited opportunities for plantation expansion due to land constraints and environmental regulations.

Previous study has explored various factors influencing FFB yield, including agronomic practices, environmental conditions and socio-economic constraints. Studies have highlighted the importance of fertiliser application, harvest intervals and nutrient management, but often with limitations. Brunelle et al. (2015) demonstrated the risk of diminishing returns and potential productivity losses from inefficient fertiliser use. De Vos et al. (2021) and Monzon et al. (2023) pointed to suboptimal yields among smallholders due to poor input management and harvest practices. However, existing studies often rely on mean-based models that assume uniform impacts across estates, overlooking the potential for differential responses based on yield levels (Kamil et al., 2024; Wing et al., 2021). Furthermore, the interaction between estate size and other factors,

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such as input effectiveness and socio-economic constraints, remains underexplored (Brandão & Schoneveld, 2021; Hadi et al., 2025; Webb et al., 2011).

This study aims to address these gaps by employing panel quantile regression to investigate the determinants of FFB yield across Malaysian oil palm estates. This approach provides a more differentiated understanding of the constraints and opportunities at varying yield levels. The goal is to inform more targeted productivity strategies and support evidence-based interventions in Malaysia's plantation sector. This article focuses specifically on estates reporting to Malaysian Palm Oil Board (MPOB) eCOST and e-submission systems between 2016 and 2021. While this allows for a robust, estate-level panel analysis, the study does not include smallholders or account for some agronomic and environmental variables, such as tree age profile, standing per hectare, rainfall and other related variables due to data limitations. Nonetheless, the findings offer timely insights into operational control that could help close the yield gap in this resource-constrained industry.

MATERIALS AND METHODS

Data on fertiliser expenses and estate size were obtained from the MPOB eCOST database, while yield data were sourced from the MPOB e-submission database. The data cover the period 2016-2021 and were aggregated annually for analysis. The MPOB eCOST is an online system that requires all MPOB licensees at the estate and mill levels to annually declare their cost of producing FFB and crude palm oil (CPO), ensuring high data coverage and reliability due to required reporting. Similarly, the MPOB e-submission mandates that all MPOB-licensed estates declare their operational data such as area, FFB yield and number of harvesters, on a monthly basis for monitoring purposes. These reporting requirements, with penalties for non-compliance, contribute to the high data quality and reliability of the MPOB eCOST and e-submission portals.

Table 1 summarises the key variables for the study which include FFB yield (t ha^{-1}) as the dependent variable, with estate size (area in ha), harvesters per hectare and fertiliser expenses per hectare as the independent variables. Estate size was categorised into four groups, namely small estate (< 200 ha), medium-small estate (200 to < 500 ha), medium-large estate (500 to < 1,500 ha), and large estate (> 1,500 ha). Fertiliser expenses were measured on a per-hectare basis and later log-transformed to address skewness in the distribution.

To further explore the distributional characteristics of the dependent variable (FFB yield), a kernel density plot was generated (*Figure 1*). The horizontal axis represents FFB yield, while the vertical axis represents probability density that indicates the relative concentration of estates around specific yield values. Higher density values reflect a greater number of estates clustered near that yield. The figure highlights three key percentiles, the 25th percentile marks the threshold for low-yielding estates; the 50th percentile or median divides the sample in half; and the 75th percentile identifies the high-yielding group. Most estates yield around 18–22 t ha^{-1} where the density curve peaks, while a smaller number achieve yields above 30 t ha^{-1}, resulting in a right-skewed distribution. This distributional pattern justifies the use of quantile regression, which enables the investigation of how explanatory variables affect yield differently across low-, medium- and high-performing estates.

TABLE 1. SUMMARY OF VARIABLES AND THEIR OPERATIONAL DEFINITIONS

Variable	Operational definition	Unit/scale	Source
FFB yield	Annual FFB output per hectare of planted area for each estate. **Additional note:** Estates at τ = 0.25 (low), 0.50 (medium) and 0.75 (high) yield quantiles.	t ha^{-1} yr^{-1}	MPOB e-submission
Estate size	Estate size is treated as a categorical variable, derived from continuous hectare values and then converted into dummy variables for regression analysis. **Category of estate size:** - Small: < 200 ha - Medium-small: 200 to < 500 ha - Medium-large: 500 to < 1,500 ha - Large: ≥ 1,500 ha	Dummy variables (Large is the reference group)	MPOB e-submission
Harvester availability	Average number of harvesters in a year reported by the estate divided by planted hectares	Workers per hectare	MPOB e-submission
Fertiliser expenses (LFERT)	Natural-log of fertiliser cost per planted hectare	Ln (RM ha^{-1})	MPOB eCOST

Prior to the analysis, the dataset was reviewed for completeness and consistency. Missing values in key variables were imputed using median substitution in EViews to preserve the sample size and minimise potential bias. A small number of extreme and implausible values were also removed based on visual inspection and domain knowledge to improve the reliability of the estimates. Log-transformation was applied to fertiliser expenditure, as a result, some small positive values (e.g., RM0.05 ha^{-1}) appear as negative values in the descriptive statistics (e.g., log (0.05) ≈ –3.0). These do not indicate negative inputs but are a result of the transformation. This transformation allows coefficients to be interpreted in percentage terms, providing insights into relative changes. *Table 2* below shows the data description before and after treatment, highlighting the improvements in data consistency following these adjustments.

Following these adjustments, a correlation analysis was conducted to assess the association between the variables and to ensure there were no multicollinearity issues that could influence the results. The analysis revealed a moderate positive correlation between yield and fertiliser expenses, suggesting that higher fertiliser usage is associated with increased yields. However, the results demonstrated a weak correlation between yield and the number of harvesters, while the correlation between yield and area is nearly zero, showing no linear relationship.

Model Specification and Estimation

This study employs panel quantile regression (PQR) to investigate the factors influencing FFB yield across Malaysian oil palm estates. Unlike ordinary least squares (OLS), which estimates the

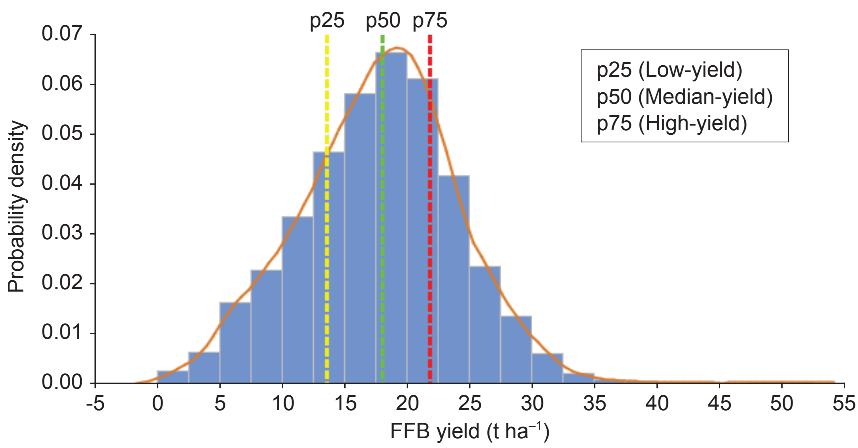

Figure 1. Kernel density distribution of FFB yield across estates.

TABLE 2. DATA DESCRIPTION BEFORE AND AFTER TREATMENT

Item	Raw data				Cleaned data			
	FFB yield	Fertiliser expenses	Harvester	Area	FFB yield	Fertiliser expenses	Harvester	Area
Mean	17.787	1,128.257	0.047	1,039.528	17.788	6.796	0.047	1,039.528
Median	18.093	1,023.610	0.041	389.000	18.093	6.931	0.041	389.000
Maximum	52.031	7,257.451	3.000	24,955.530	52.031	8.890	3.000	24,955.530
Minimum	0.527	0.035	0.017	0.000	0.527	-3.362	0.017	0.000
Std. Dev.	6.253	718.821	0.048	1,699.030	6.246	0.847	0.048	1,699.030
Skewness	-0.027	1.732	38.195	4.979	-0.027	-3.499	38.233	4.979
Kurtosis	3.090	9.571	2,204.431	46.100	3.096	27.427	2,208.898	46.100
Jarque-Bera	3.0766	1.31E+04	1.36E+09	5.50E+05	3.438	1.81E+05	1.37E+09	5.50E+05
Probability	0.215	0.000	0.000	0.000	0.179	0.000	0.000	0.000
Sum	1.20E+05	6.42E+06	317.468	7.01E+06	1.20E+05	4.58E+04	318.040	7.01E+06
Sum Sq. Dev.	2.63E+05	2.94E+09	15.453	1.95E+10	2.63E+05	4.84E+03	15.454	1.95E+10
Obs	**6,730**	**5,688**	**6,730**	**6,744**	**6,744**	**6,744**	**6,744**	**6,744**

average effect of explanatory variables, quantile regression allows the analysis of effects at different points in the yield distribution (i.e., low-, medium- and high-yield estates) (Koenker & Bassett, 1978; Kumar & Khanna, 2023). This is particularly valuable in the oil palm sector, where estates differ in land quality, management practices and other local factors that affect yield. PQR is well-suited for this analysis because it is more robust to outliers and heteroscedasticity in the dependent variable than OLS. It enables us to assess whether variables like fertiliser and labour have different levels of impact on lower- versus higher-yielding estates, which is an important insight for designing more targeted and efficient interventions.

By including estate size categories as dummy variables, the model captures how small, medium-small and medium-large estates compare to large estates across the conditional distribution of yield. The dependent variable in the model is FFB yield (YIELD), measured in t ha^{-1} and further stratified into low-, median- and high-yield groups based on the 25th, 50th and 75th percentiles of the distribution, representing estate productivity. The key independent variables include fertiliser expenses (LFERT), representing nutrient application intensity. Harvesters per hectare (HARVESTER) proxy labour availability and operational efficiency. It is calculated as the total number of harvesters reported by each estate divided by its planted area. This metric reflects not only the supply of labour but also the estate's operational capacity to harvest FFB efficiently. A higher value indicates greater harvester presence relative to estate size, which can influence yield performance. Estate size is represented by dummy variables, with large estates serving as the reference category.

The general quantile regression model is specified as Equation (1):

$$\text{YIELD}_\tau = \beta0_\tau + \beta1_\tau\,\text{LFERT} + \beta2_\tau\,\text{HARVESTER} + \beta3_\tau\,\text{SMALL\_ESTATE} + \beta4_\tau\,\text{MEDIUM\_SMALL\_ESTATE} + \beta5_\tau\,\text{MEDIUM\_LARGE\_ESTATE} + \epsilon_\tau \quad (1)$$

where, τ represents the quantiles of interest (e.g., 25th, 50th and 75th percentiles), β_τ denotes the quantile-specific coefficients, and ϵ_τ is the quantile-specific error term.

The model is specified based on the production theory, which suggests that output, which is the yield, is influenced by the inputs used in the production (fertiliser and labour) and the scale of operations (the area to proxy estate size). Fertiliser is essential in agriculture for replenishing soil nutrients (Barcelos et al., 2015; Henson, 2003), especially in oil palm plantations where it constitutes a major portion of production costs (Goh, 2005). Its pivotal role in achieving optimal yields makes it a crucial variable in any econometric model analysing oil palm production. Ensuring adequate nutrients through fertiliser application supports healthy growth and maximises FFB production (Goh et al., 2003). For labour-intensive sector like oil palm sector, labour availability is a key driver for productivity. Estates with more harvesters per hectare are likely to achieve higher yields due to timely and efficient harvesting practices (Bakri et al., 2021; Parveez et al., 2024). Studies have shown that shorter harvesting intervals (10 days) lead to higher FFB yields compared to longer intervals (15 days) because delaying harvest can result in overripe fruits, increased losses from fruit detachment and lower oil quality (Mohanaraj & Donough, 2016). Meanwhile, for estate size, the existing literature suggests that small and medium-small estates tend to underperform relative to large estates (Zakaria et al., 2024). However, Cornia (1985) found that there is a strong negative correlation between farm size and land yields, with smaller farms generally having higher yields due to higher factor inputs and more intensive land use. Based on literature, the choice of quantile regression is deemed to suit the need to understand how fertiliser, harvesters and estate size impact FFB yields differently across estates performing at the lower (25th percentile), median (50th percentile) and upper (75th percentile) levels of productivity. This approach helps to understand the key productivity drivers across different yield levels, offering targeted recommendations for improving yield in low-performing estates and sustaining productivity in higher-performing ones.

RESULTS AND DISCUSSION

Table 3 summarises the quantile regression analysis for FFB yield determinants across oil palm estates at the 25th, 50th and 75th percentiles. The results indicated that fertiliser usage (LFERT) and harvester availability (HARVESTER_FILLED) are consistently positive and statistically significant across all yield levels, with varying magnitudes. This aligns with previous research highlighting the importance of these inputs in oil palm production (Barcelos et al., 2015; Henson, 2003). Medium-yield estates (τ = 0.50) exhibit the strongest response to both inputs, suggesting that estates in this category are particularly responsive to improvements in fertiliser application and harvester availability. This might be attributed to factors such as better management practices or more favourable site-specific conditions in these estates. Low-yield estates (τ = 0.25) also show substantial benefits from increased fertiliser usage and harvester availability, indicating potential resource constraints in this category. This finding supports previous studies

TABLE 3. QUANTILE REGRESSION RESULT (QRR)

Quantile	τ = 0.25		τ = 0.50		τ = 0.75	
Variable	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
C	-10.5631***	1.1230	-9.6281***	1.0801	-8.4395***	1.1428
LFERT	3.5288***	0.1603	3.7420***	0.1288	3.3752***	0.2177
HARVESTER_FILLED	30.8750***	7.5063	34.5902***	7.2754	28.7170***	5.9287
SMALL_ESTATE	-1.0750***	0.2611	-0.5299**	0.2234	0.4499*	0.2744
MEDIUM_SMALL_ESTATE	-1.0464***	0.2792	-0.4074	0.2568	0.5646**	0.2455
MEDIUM_LARGE_ESTATE	-0.1101	0.2800	0.0543	0.1964	-0.1044	0.2201
Pseudo R-squared	0.1299		0.1166		0.1017	

Note: *** - 1% significant; ** - 5% significant; * - 10% significant.

that have identified resource limitations as a major challenge for smallholder farmers and low-performing estates (De Vos et al., 2021; Monzon et al., 2023).

Estate size dummies reveal that small and medium-small estates underperform in low-yield conditions but exhibit modest improvements at higher yield levels. This suggests that while smaller estates may face disadvantages in resource-limited settings, their performance can improve under more favourable conditions or with appropriate support, although unobserved environmental and managerial factors may also contribute to these outcomes. This finding aligns with the literature on the heterogeneity of oil palm estates and the potential for smaller estates to achieve high productivity with adequate support (Zakaria et al., 2024). Delving into the specifics, fertiliser usage (LFERT) shows robust positive coefficients at all quantiles (τ = 0.25: 3.5288; τ = 0.50: 3.7420; τ = 0.75: 3.3752), affirming its vital role in enhancing yield. The slightly lower impact at the upper quantile suggests diminishing marginal returns in already high-performing estates, which is consistent with previous findings on fertiliser response (Brunelle et al., 2015).

Harvester availability also demonstrates substantial effects, peaking at τ = 0.50 (34.5902), indicating that medium-yield estates benefit most from improved mechanisation. This could be due to these estates having a higher capacity to utilise harvesters effectively compared to low-yield estates, while also not facing the same labour constraints as high-yield estates. The negative coefficients for SMALL_ESTATE (-1.0750) and MEDIUM_SMALL_ESTATE (-1.0464) at τ = 0.25 reflect the challenges small estates face under resource-poor conditions, likely due to limited access to capital and technology (De Vos et al., 2021). In contrast, the positive shifts at τ = 0.75 (0.4499 for SMALL_ESTATE and 0.5646 for MEDIUM_SMALL_ESTATE) imply that well-managed or supported smaller estates can outperform larger counterparts, potentially by leveraging their flexibility and adaptability (Zakaria et al., 2024).

While this study provides valuable insights into the role of fertiliser, harvesters and estate size in influencing FFB yield, it is important to acknowledge that other factors, such as environmental conditions, could also play a significant role (Kamil et al., 2024; Wing et al., 2021). However, due to data unavailability, these factors were not included in the analysis. Future research could explore the impact of environmental factors on FFB yield using more comprehensive datasets and potentially incorporate them into the quantile regression framework to gain a more holistic understanding of yield determinants.

Model Diagnostics and Robustness

In terms of the model fitness, the Pseudo R-squared values are relatively low across all quantiles, as it focuses on conditional quantiles rather than explaining the overall variance. The fit is slightly better for the lower quantile (τ = 0.25), which indicates that the model explains the variation in yield better for low-yield estates compared to average or high-yield estates. Overall, the models provide meaningful insights but explain a limited portion of the variability in yield. The inclusion of additional explanatory variables, such as environmental qualities, may enhance to improve the variation in yield.

To evaluate the robustness of the quantile regression models, heteroscedasticity was first tested using the residuals of the OLS model. A likelihood ratio (LR) test was conducted, and the results confirmed the presence of heteroscedasticity (p-value < 0.05), indicating that the residual variance was not constant across observations. This violation of homoskedasticity can lead to inefficient standard errors and unreliable inference in standard models. To address this, the quantile regression models were re-estimated using bootstrapped standard errors, with 1,000 replications, to provide heteroskedasticity-robust estimates. The results in *Table 4* confirmed that the significance of key coefficients remained largely consistent after the adjustment, reinforcing the robustness of the model.

TABLE 4. BOOTSTRAP RESULT

Quantile	τ = 0.25		τ = 0.50		τ = 0.75	
Variable	Std. error	Bootstrap std. error	Std. error	Bootstrap std. error	Std. error	Bootstrap std. error
C	1.1229	1.0249	1.0801	0.9629	1.1428	1.5809
LFERT	0.1603	0.1422	0.1288	0.1288	0.2177	0.2177
HARVESTER_FILLED	7.5063	10.9592	7.2754	7.2754	5.9286	5.9286
SMALL_ESTATE	0.2611	0.2779	0.2233	0.2233	0.2744	0.2744
MEDIUM_SMALL_ESTATE	0.2791	0.2856	0.2567	0.2567	0.2455	0.2455
MEDIUM_LARGE_ESTATE	0.2800	0.2819	0.1963	0.1963	0.2200	0.2200
Pseudo R-squared	0.1299	0.1299	0.1166	0.1166	0.1017	0.1017

Notably, the fertiliser coefficient remained significant across all quantiles, with slight decreases in standard errors, indicating that the impact of fertiliser on yield is both strong and stable. For harvester, the standard error increased at τ = 0.25 (from 7.5063–10.9592), reflecting variability in its impact on low-yield estates. The significance of estate size categories was also robust, although the bootstrap adjustment slightly reduced their significance at higher quantiles, particularly for τ = 0.75. These findings confirm that heteroscedasticity did not bias the key conclusions and the bootstrap-adjusted models provide more reliable inference for policy recommendations.

Additionally, the Pseudo R-squared values remain the same across the bootstrapped and non-bootstrapped models, suggesting that the model's ability to explain yield variation at different quantiles is unaffected by bootstrapping.

Economic or Business Implications

The results of the quantile regression analysis provide critical insights into the determinants of FFB yield and their varying impacts across the yield distribution. Unlike OLS, which provides a single average effect, quantile regression reveals how these relationships differ for low-yield, medium-yield and high-yield estates, allowing for more targeted interventions and nuanced policy recommendations. In terms of fertiliser management, the study supports that fertiliser consistently has a strong and positive impact on yield across all quantiles, but its effect is slightly weaker at higher quantiles. For low-yield estates, the marginal benefit of increasing fertiliser usage is greater, suggesting that these estates are operating below optimal input levels. In contrast, higher-yield estates exhibit diminishing returns from additional fertiliser usage. This finding suggests that targeted fertiliser subsidies for low- and medium-yield estates can significantly improve their productivity and contribute to a more equitable distribution of resources within the industry. Additionally, educational or training programs on fertiliser application and nutrient management practices could help reduce inefficiencies and encourage more sustainable use, particularly in smaller or less productive estates. These programmes could focus on soil testing, fertiliser recommendations based on site-specific conditions and the use of precision agriculture technologies to optimise fertiliser application.

In terms of harvesting, the number of harvesters per hectare was found to significantly impact yield across all quantiles, with the largest effect observed at the median quantile (τ = 0.50). Low-yield estates also benefit substantially from increased harvester availability, indicating that mechanisation is a critical bottleneck for these estates. For high-yield estates, while the impact of harvesters remains positive, it is slightly diminished, suggesting that these estates may have already addressed labour constraints to a greater extent. To promote mechanisation and address resource constraints in low- and medium-yield estates, several interventions can be considered. These include providing access to affordable financing options for the acquisition of harvesting equipment, such as electronic cutters, which can enable smaller estates to adopt mechanisation and improve their harvesting efficiency. Other than that, the concept of shared harvester schemes can also be applied. Establishing co-operative schemes for the shared use of harvesters can reduce the financial burden on individual estates and promote resource sharing within the industry. In addition, investing in training programs for harvesters can enhance the effective utilisation of harvesting equipment and ensure its proper maintenance.

Estate size influences FFB yield in varying ways across performance levels. Small and medium-small estates generally yield less than large estates, particularly in the lower and middle quantiles. This disparity is likely due to limited access to resources, such as capital, technology and skilled labour, which can hinder the adoption of optimal management practices and the achievement of economies of scale. While smaller estates may face disadvantages compared to larger estates, they have the potential to achieve high yields if they are well-managed, adopt efficient practices and receive appropriate support. This is supported by the positive (albeit modest) coefficients observed for small and medium-small estates at the upper quantile ($\tau = 0.75$), suggesting that with appropriate conditions, these estates can perform competitively. To address the challenges faced by smaller estates and unlock this potential, support programmes could be tailored to address structural constraints such as improving access to credit, high-yielding inputs, infrastructure and training. These efforts can help smaller estates invest in productivity-enhancing technologies and adopt more efficient, sustainable practices, ultimately improving both yield performance and resilience.

By recognising the heterogeneity of estates and tailoring support programs to their specific needs and constraints, policymakers can promote a more productive, equitable and sustainable palm oil sector. This will not only benefit individual estates but also contribute to the long-term economic growth and competitiveness of the Malaysian palm oil industry.

CONCLUSION

This study harnesses the power of quantile regression to unveil the complex, distributional effects of fertiliser usage, harvester availability and estate size on oil palm productivity. Findings demonstrate that while low- and medium-yield estates derive substantial benefits from increased fertiliser input and mechanisation, high-yield estates experience diminishing marginal returns, highlighting the necessity for precision in resource allocation. Notably, the divergent performance across estate sizes reveals that small and medium estates, despite inherent structural constraints, possess untapped potential when supported by targeted interventions. These insights carry profound implications for policymakers and industry stakeholders by suggesting a strategic shift from uniform input subsidies to a more tailored approach that prioritises support for underperforming estates, implements estate-specific policies and fosters collaborative efforts among government agencies, financial institutions and industry players. In essence, this study not only introduces a distribution-sensitive analytical framework but also provides a data-driven foundation for designing policies aimed at reducing yield disparities and improving resource efficiency across estate sizes.

Although certain agronomic variables, such as palm age and stand per hectare (SPH), are important for understanding yield variation, they were not included in this study due to data harmonisation challenges and limited availability across estates. The absence of these variables may introduce omitted variable bias. For example, mature estates tend to apply more fertiliser and simultaneously achieve higher yields, which could partially inflate the observed fertiliser effect. Similarly, some low-yield estates may reflect over-aged stands awaiting replanting, rather than poor management. Future research could expand on this study by stratifying estates by planting age and, where possible, incorporating SPH to enable per-palm productivity analysis. Applying this quantile regression framework to a more agronomically detailed dataset would offer deeper insights into estate-level yield dynamics and policy targeting.

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