IOP Conference Series: Earth and Environmental Science

PAPER • OPEN ACCESS

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To cite this article: J Duasa *et al* 2025 *IOP Conf. Ser.: Earth Environ. Sci.* **1535** 012016

Assessing the drivers of palm oil production in Malaysia: A quantile regression approach with environmental considerations

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Abstract. This study examines the factors influencing palm oil production in Malaysia across different points of the output distribution, with a particular focus on environmental factors. Employing quantile regression, which provides a more comprehensive analysis than Ordinary Least Squares (OLS) by capturing heterogeneous effects across quantiles, we analyze time series data spanning from 1991 to 2022. The findings reveal that CO_2 emissions significantly and positively contribute to palm oil production at lower quantile but become insignificant at higher quantiles. Pesticide use positively affects production at middle quantile, while labor has a consistently negative and significant impact across all quantiles. The results highlight the need for sustainable production practices, particularly for small-scale producers reliant on emissions-intensive methods. Stricter pesticide regulations and eco-friendly alternatives should be promoted to mitigate environmental risks. Additionally, addressing labor shortages through mechanization and workforce training is crucial for industry sustainability.

1. Introduction

Malaysia is one of the world's largest producers and exporters of palm oil, contributing significantly to the global vegetable oil market. The country's palm oil industry began in the early 20th century, but large-scale commercial production expanded in the 1960s as part of Malaysia's agricultural diversification strategy [1]. Today, palm oil plantations cover approximately 5.67 million hectares, mainly in Sabah, Sarawak, and Peninsular Malaysia [2]. The industry plays a vital role in Malaysia's economy, accounting for over 4% of GDP and employing more than 600,000 workers [3]. However, environmental concerns, including deforestation, biodiversity loss, and greenhouse gas emissions, have led to increasing scrutiny and calls for sustainable production practices [4]. In response, Malaysia has implemented certification schemes such as the Malaysian Sustainable Palm Oil (MSPO) standard to promote sustainable production [2]. Despite its economic benefits, palm oil production faces challenges such as climate change, labor shortages, and fluctuating global demand [5] which requires a balance between economic growth, environmental sustainability, and social well-being.

Quantile regression is increasingly used in agricultural research to analyze crop yields and production efficiency across different points in the distribution, especially when data exhibit heteroscedasticity or non-normality. Unlike OLS, it captures heterogeneous effects, which is crucial in industries like palm oil, where environmental and economic factors influence plantations differently.

Nurhayati et al. [6] used the Quantile Autoregressive Distributed Lag (QARDL) model to examine palm oil production's impact on CO_2 emissions in Indonesia (1990–2020). They found that palm oil production significantly contributed to emissions in lower to middle quantiles (0.05th–0.7th) in the long term and across all quantiles in the short term, emphasizing the need for sustainable practices. Wong and Pinjaman [7] applied quantile regression to analyze stock prices in Malaysia's plantation sector (2008–2023), finding that earnings per share, business condition index, and inflation positively influenced stock prices across all quantiles, while consumer sentiment and exchange rates had a negative impact.

Past studies on Malaysian palm oil production relied on OLS or panel data models, assuming homogeneous relationships. Alias and Tang [8] found land expansion had the greatest impact on yield but did not account for variations across high- and low-yield plantations. Rahman et al. [9] assessed climate change's role but did not explore its differential impact by production level. Similarly, research on CO_2 emissions in agriculture [10, 11] focused on sustainability and policy impacts rather than yield variations across quantiles. Temperature fluctuations affect palm oil growth differently by location and soil quality. Hasan et al. [12] used average temperature data but did not capture land-specific variability. This study addresses that gap by examining differential effects across low-, medium-, and high-yield plantations. Prior studies analyzed economic and environmental factors separately [13, 14] but did not integrate CO_2 emissions or temperature changes. This study combines labor, land, emissions, and climate variables in a single quantile regression framework for a more holistic analysis.

Climate adaptation strategies remain understudied in their effectiveness across production levels. Most research [15] discusses general mitigation strategies without differentiating their impact on smallholders versus large estates. By using quantile regression, this study identifies the most vulnerable farms and provides targeted adaptation recommendations.

This study enhances the literature by providing a policy-relevant analysis of the factors influencing palm oil production in Malaysia, emphasizing the varying impacts of environmental and economic factors across production levels. Unlike past research relying on OLS or panel data, this study applies quantile regression to examine the effects of CO_2 emissions, temperature changes, and other determinants on low-, medium-, and high-yield plantations. By capturing these heterogeneous effects, it offers a more understanding of palm oil production dynamics.

2. Methodology

The production function is a fundamental economic concept that relates input use to output production. In agriculture, it explains how factors such as land, labor, capital, and technology determine crop yields [16]. For palm oil, key inputs include fertilizers, pesticides, labor for harvesting, land availability, and mechanization. A commonly used specification in agricultural studies is the Cobb-Douglas production function [17]:

$$Y=A\cdot L^{\alpha}\cdot K^{\beta} \tag{1}$$

where Y represents palm oil output, L is labor, K is capital, A represents total factor productivity (TFP), and α, β are input elasticities. This model assumes constant returns to scale but can be modified to account for technological changes and environmental constraints [18]. Environmental factors, particularly CO_2 emissions and temperature variability, have a growing influence on agricultural productivity. While traditional models often assume exogenous technological progress, recent studies

IOP Conf. Series: Earth and Environmental Science **1535** (2025) 012016 doi:10.1088/1755-1315/1535/1/012016

suggest that climate-related factors directly impact palm oil yields [19]. Furthermore, temperature fluctuations affect palm oil growth differently depending on soil conditions and geographical regions [20]. Labor availability and cost significantly influence palm oil productivity. While many studies analyze economic and environmental factors separately, there is limited research integrating these factors within a unified quantile regression framework. This study fills this gap by examining how CO_2 emissions, temperature changes, labor costs, pesticide use, and other inputs influence palm oil production at different quantiles.

This study utilizes the quantile regression framework to capture distributional effects on palm oil production. Introduced by Koenker and Bassett [21], quantile regression accounts for non-linear and asymmetric relationships, unlike ordinary least squares (OLS), which focuses only on the conditional mean [22]. Unlike OLS, which assumes homogeneity, quantile regression estimates variable effects at different points in the distribution [23, 24, 25]. It is particularly useful for skewed or heavy-tailed distributions [26] and is robust against outliers by minimizing absolute residuals instead of squared residuals. Additionally, its linear programming approach enhances interpretation and robustness [26]. In contrast to piecewise regression, which divides the dependent variable into segments before applying OLS—leading to sample selection biases—quantile regression directly models conditional quantiles, making it more reliable [27]. Given these advantages, this study adopts quantile regression to examine the heterogeneous effects of key factors influencing palm oil production across different levels of output distribution. The basic quantile regression model specifies the conditional quantile as a linear function of explanatory variables. This can be written as following:

$$y_i = x_i'\beta_\theta + u_{\theta i}, 0 < \theta < 1 \tag{2}$$
$$Quant_\theta\,(y_i|x_i) = x_i\beta_\theta$$

where y is the dependent variable, x is a matrix of explanatory variables, u is an error term whose conditional quantile distribution equals zero, and $Quant_\theta$ $(yi|xi)$ denotes the θth quantile of y conditional on x. The distribution of the error term u is left unspecified. An individual coefficient $\beta_{\theta j}$ associated with the jth independent variable in the vector x_i, called x_{ij}, could be interpreted as 'how y_i in its θth conditional quantile reacts to a (ceteris paribus) marginal change in x_{ij}'. The method allows us to identify the effects of the covariates at different locations in the conditional distribution of the dependent variable. The θth regression quantile estimate, $\widehat{\beta_\theta}$, is from the following minimization problem which is solved via linear programming:

$$\min_\beta \sum_{y_i \geq x_i'\beta} \theta|y_i - x_i'\beta| + \sum_{y_i \geq x_i'\beta} (1-\theta)|y_i - x_i'\beta|$$

A special case of the quantile regression is the median regression, which is obtained by setting θ = 0.5. Other variations of θ could be used to obtain other quantiles of the conditional distribution. In this study, the relationships among selected explanatory variables across the conditional distribution of palm oil production using the 25th, 50th, and 75th quantiles are reported. Besides, the bootstrap method is used to obtain estimates of the standard errors for the coefficients in quantile regression, as illustrated in [25]. This is importance as it is a consistent and robust estimation method, particularly when the error term is non-normally distributed and heteroscedastic. The following equation is the model used in the current empirical study:

$$poil_t = \beta_0 + \beta_1 land_t + \beta_2 labour_t + \beta_3 pest_t + \beta_4 fert_t + \beta_5 emi_t + \beta_6 temp_t + \in \tag{3}$$

where *poil* (palm oil) is the Gross Production Value of oil palm fruits (constant 2014-2016 thousand MYR), *land* is the share in agricultural land (%), *labour* is the share of employment in agriculture in total employment (ILO Modelled Estimates) (%), *fert* is fertilizer use per value of agricultural production (g/$), *pest* is pesticide use per area of cropland (kg/ha), *emi* is Emissions Share (CO2) (%), and *temp* is temperature change on land (°c). The analysis was conducted using time series data spanning from 1991 to 2022 that sourced from the statistical database of the Food and Agriculture Organization (FAO) of the United Nations.

3. Findings

Table 1 presents descriptive statistics for the study's variables from 1991 to 2022, highlighting trends in Malaysia's palm oil industry. The gross production value averaged MYR 38.0 million, fluctuating between MYR 16.5 million and MYR 53.3 million, with a high standard deviation of MYR 12.1 million, reflecting market demand, policy shifts, and environmental influences. Agricultural land use remained stable at an average of 84.53%. This stability suggests a long-term commitment to agricultural cultivation, with minimal shifts in land allocation despite fluctuations in production levels. Meanwhile, agricultural employment declined from 18.9% to 10%, with the mean value stood at 14.15%. The decrease in agricultural employment over time could be attributed to structural transformations in the economy, mechanization, and the increasing reliance on foreign labor for plantation work.

Table 1. Descriptive statistics of variables

Variable	N	Mean	Standard deviation	Min.	Max.
poil	32	3.80e+07	1.21e+07	1.65e+07	5.33e+07
land	32	84.53	1.99	82.13	89.2
labor	32	14.15	2.52	10	18.9
fert	32	33.47	8.78	15.78	47.87
pest	32	5.47	1.49	3.09	8.47
emi	32	12.98	7.52	8.26	35.97
temp	32	0.70	0.35	0.16	1.48

Fertilizer use per value of agricultural production varied significantly, with an average of 33.47 grams per dollar. The recorded values ranged from 15.78 grams to 47.87 grams per dollar, with a standard deviation of 8.78 grams. This variation suggests fluctuations in input intensity, which could be due to changing agricultural practices, fertilizer price volatility, or policies aimed at promoting sustainable farming. Similarly, pesticide use per hectare of cropland exhibited notable fluctuations, with an average of 5.47 kg/ha, a minimum of 3.09 kg/ha, and a maximum of 8.47 kg/ha. The relatively high variation could indicate shifts in pest control strategies, changes in pest prevalence, or regulatory measures affecting pesticide application.

Emissions, measured as a share of CO_2 emissions from total emissions, displayed substantial variability. The average emission share was 12.98%, but values ranged from 8.26% to a peak of 35.97%. The high standard deviation of 7.52% suggests that emissions have been influenced by production scale, deforestation rates, and environmental policies over time. The fluctuations in emissions also indicate that while palm oil production remains a major contributor to greenhouse gas emissions, efforts to reduce its carbon footprint may have had varying levels of success.

Finally, temperature change on land, an important environmental indicator, showed a clear warming trend over the study period. The mean temperature change was 0.70°C, with a minimum of 0.16°C and a maximum of 1.48°C. The steady increase in temperature over the years could have significant implications for agricultural productivity, affecting crop yields, water availability, and the incidence of pests and diseases. Climate change remains a crucial factor in shaping the future sustainability of palm oil production. Generally, the findings suggest that while the palm oil industry remains a critical component of Malaysia's economy, ongoing environmental and labor-related challenges must be addressed to ensure its long-term viability.

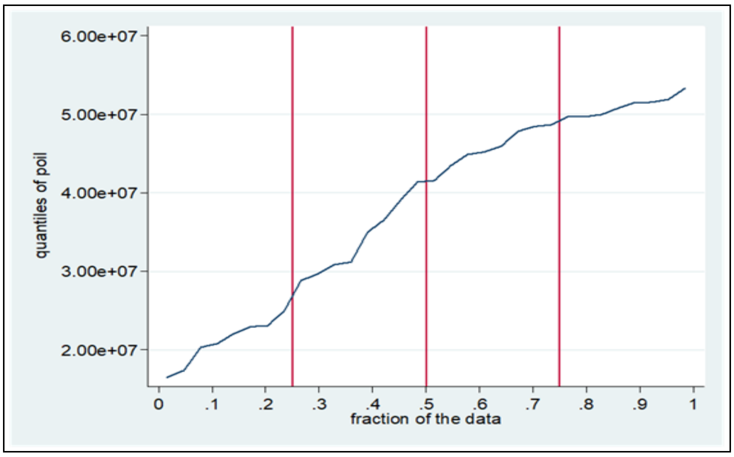

Figure 1. Nick Cox's plot of dependent variable at 25th, 50th, and 75th percentiles.

The plot, following Nick Cox's approach, depicts the cumulative distribution of "quantities of *poil*" with red vertical lines marking key quantiles (25th, 50th, and 75th) as in Figure 1. The non-linear patterns indicate distribution variations, justifying the use of quantile regression. Unlike OLS, which focuses on average effects, quantile regression captures variable relationships across different quantiles, making it useful for addressing heteroskedasticity. This approach provides deeper insights into how factors influence different levels of "quantities of *poil,*" offering valuable implications for policy and decision-making.

The OLS regression results are displayed on Table 2, which show the relationship between the dependent variable *poil* (palm oil production) and several independent variables (*land, labor, fert* (fertilizer), *pest* (pesticides), *emi* (emissions), and *temp* (temperature)). The overall model is highly significant, as indicated by the *F*-statistic of 134.48 with a p-value of 0.0000, suggesting that the independent variables collectively explain a significant portion of the variance in *poil.* The *R*-squared value of 0.9699 indicates that approximately 97% of the variation in *poil* is explained by the model. The adjusted *R*-squared of 0.9627 confirms that the model maintains a strong explanatory power even after accounting for the number of predictors.

Table 2. OLS and quantile regression results

Independent variable	Dependent variable: poil			
	OLS	25th quant	50th quant	75th quant
constant	2.39e+07 (5.10e+07)	-6983500 (1.08e+08))	3.34e+07 (9.66e+07)	5.49e+07 (1.10e+08)
land	765416.8 (565179.4)	1066322 (1211347)	591030.4 (1083638)	337749.1 (1204854)
labor	-4383548*** (381288.4)	-4.68117*** (700395.6)	-4198152*** (610872.1)	-4283607*** (862494.6)
fert	182548.8** (73257)	232723.2 (169461)	124748.6 (139871.3)	197470.6 (132730.8)
pest	1330732*** (411925.8)	830537.1 (939259.2)	2016564** (861720)	1688253* (904560.4)
emi	196395.9*** (70686.4)	230446.9* (117264.7)	189766.3 (167869.8)	153838 (175559.4)
temp	-6461549*** (2243881)	-6141978 (4436425)	-4892487 (4705661)	-2101552 (5288306)

N	32	32	32	32
Adj. R^2	0.9627			
Pseudo R^2		0.8612	0.8588	0.8270
Slope equality test				
	$\tau_{0.25,0.50,0.75}$			
	F-statistic		*p*-value	
land	0.12		0.8837	
labor	0.03		0.9737	
fert	0.45		0.6399	
pest	1.05		0.3637	
emi	0.06		0.9401	
temp	0.36		0.7032	

Note: 1. Standard errors are in parentheses; ***statistically significant at the 1% level; **5% level; *10% level.
2. For quantile regressions, standard errors are bootstrap (100) standard errors

Examining the coefficients of individual predictors provides a deeper understanding of their impact on palm oil production. The coefficient for land is 765,416.8, suggesting a positive relationship between *land* allocation and oil production. However, its p-value of 0.188 indicates that this effect is not statistically significant. This finding is consistent with studies by Baffes [29], who noted that land expansion alone may not significantly drive production unless accompanied by improvements in technology and resource management. On the other hand, *labor* exhibits a significant negative impact on oil production, with a coefficient of -4,383,548 and a p-value of 0.000. This suggests that an increase in labor is associated with a reduction in oil output, potentially due to inefficiencies or diminishing returns to labor. Previous research by Aghion et al. [30] highlights similar findings, emphasizing that over-reliance on labor-intensive production may lead to productivity losses in extractive industries.

The role of agricultural inputs, such as fertilizer (*fert)* and pesticides (*pest*), is also notable. The fertilizer coefficient of 182,548.8 is statistically significant (p = 0.020), confirming that increased fertilizer application positively affects oil production. This result is supported by studies like those by Fuglie [31], who found that fertilizers significantly enhance yield in agricultural and extractive sectors. Similarly, the coefficient for pesticides (1,330,732) is positive and statistically significant ($p = 0.003$), reinforcing the argument that improved pest control measures contribute to higher productivity. These findings align with existing literature, which suggests that optimal chemical inputs play a crucial role in maintaining production efficiency [32].

Another important factor influencing oil production is emissions (*emi*), which has a positive coefficient of 196,395.9 and a *p*-value of 0.010. This suggests that increased emissions correlate with higher palm oil output. While this result may indicate a link between industrial activity and production, it also raises concerns about environmental sustainability. Studies by Stern [33] and Acemoglu et al. [34] have documented similar trends, emphasizing the trade-off between production efficiency and environmental degradation. Policymakers may need to balance productivity goals with regulatory frameworks aimed at reducing carbon footprints.

The impact of temperature (*temp*) is particularly striking, as it has a large negative coefficient of -6,461,549 and is statistically significant ($p = 0.008$). This suggests that rising temperatures have a detrimental effect on palm oil production, potentially due to heat stress on crops, increased evaporation rates, or disruption of extraction processes. Previous research by Dell, Jones, and Olken [35] highlights the adverse economic consequences of climate change, noting that temperature fluctuations can significantly hinder agricultural and industrial productivity. This result underscores the urgency of climate adaptation strategies in resource-dependent economies.

Thus, the OLS findings reinforce the importance of efficient resource management and climate resilience in palm oil production. While factors like fertilizers and pesticides positively influence productivity, labor inefficiencies and rising temperatures present challenges that require policy attention. Given the limitations of OLS in capturing distributional heterogeneity, a quantile regression approach may be beneficial in providing deeper insights into the impact of these variables across different levels of production.

The results from the simultaneous quantile regression provide a deeper understanding of the varying impact of independent variables across different points in the conditional distribution of palm oil production. Unlike ordinary least squares (OLS), which estimates the average effect, quantile regression allows for a more nuanced analysis of how predictors influence different levels of production. The pseudo R-squared values for the 25th, 50th, and 75th percentiles (0.8612, 0.8588, and 0.8270, respectively) in Table 2 suggest that the model explains a significant portion of the variation in palm oil production across these quantiles, though slightly less so at the higher quantiles. This aligns with the findings of Koenker and Bassett [21], who emphasized that quantile regression is particularly useful when heteroskedasticity is present in the data.

The effect of land on palm oil production is inconsistent across quantiles. In the lower quartile (q25), the coefficient is 1,066,322, while in the median (q50) and upper quartile (q75), the values drop to 591,030.4 and 337,749.1, respectively. However, none of these effects are statistically significant, suggesting that land allocation alone is not a key determinant of oil production at different levels. This result aligns with Baffes [29], who noted that land expansion without complementary factors such as improved technology or irrigation does not significantly enhance productivity.

The influence of labor remains consistently negative across all quantiles, with coefficients of -4,068,117 (q25), -4,198,152 (q50), and -4,283,607 (q75). The statistical significance (p = 0.000 across all quantiles) suggests that increasing labor is associated with lower oil production across all levels. This may indicate inefficiencies due to overemployment or a decline in marginal productivity, as described in the theory of diminishing returns [30]. Similar findings have been reported in labor-intensive industries, where excessive reliance on human capital without mechanization leads to productivity losses [36].

Fertilizer (fert) has a positive but statistically insignificant effect across all quantiles, with coefficients ranging from 124,748.6 (q50) to 232,723.2 (q25) and 197,470.6 (q75). These results suggest that fertilizer usage may contribute to increased oil production, but the effect is not strong enough to be consistently significant. This is in line with Fuglie [31], who noted that while fertilizers enhance productivity, their impact depends on soil quality, application methods, and interaction with other inputs. Pesticide has a significant positive effect at the median quantile (coefficient = 2,016,564, p = 0.028) but is not statistically significant at lower quantile. This suggests medium-scale producers benefit most, as they face higher pest pressure than small farms but lack advanced pest control methods used by large plantations. Smallholders may underuse pesticides due to cost constraints, while overuse at higher production levels can lead to diminishing returns from pest resistance and environmental degradation. Policies should promote integrated pest management (IPM), provide targeted subsidies for smallholders, and regulate pesticide use in mid-scale farms. These findings align with Tilman et al. [32], who noted varying pesticide effects based on cultivation intensity and pest prevalence.

The effect of emissions (*emi*) is inconsistent across quantiles, with a statistically marginal significance in the lower quantile (q25, p = 0.061, coefficient = 230,446.9), but insignificant in the median (q50) and upper quantiles (q75). This may indicate that at lower levels of production, emissions reflect increased industrial activity, but as production scales up, other factors dominate the relationship. This pattern aligns with the Environmental Kuznets Curve (EKC) hypothesis, which suggests that the relationship between emissions and production is non-linear [33].

The temperature (*temp*) variable has a consistently negative effect on oil production across all quantiles, though it is statistically insignificant. The coefficients range from -6,141,978 (q25) to -4,892,487 (q50) and -2,101,552 (q75), indicating that higher temperatures are associated with lower palm oil production. The negative impact of temperature is well-documented in climate change literature, with studies by Dell, Jones, and Olken [35] showing that increased temperatures reduce productivity in agriculture and resource extraction industries. However, the lack of statistical significance in this study suggests that other environmental or technological adaptation mechanisms may mitigate these effects.

IOP Conf. Series: Earth and Environmental Science **1535** (2025) 012016 doi:10.1088/1755-1315/1535/1/012016

Generally, the quantile regression results highlight the heterogeneous effects of explanatory variables on oil production across different production levels. While labor consistently exhibits a strong negative impact, pesticides have a significant effect at the median quantile, and emissions influence production at lower quantiles. These findings emphasize the need for differentiated policy interventions, such as targeted mechanization strategies for labor-intensive firms, optimized pesticide use, and climate adaptation policies.

The slope equality test examines whether the effects of explanatory variables differ across the 25th, 50th, and 75th quantiles. High p-values (0.36–0.97) indicate that all variables—land, labor, fertilizer, pesticide, emissions, and temperature—have consistent effects across quantiles. Low F-statistics further confirm no significant variation in coefficient estimates.

Land's non-significance (F = 0.12, p = 0.8837) aligns with Baffes [29], suggesting that land availability alone does not drive productivity differences. Labor (F = 0.03, p = 0.9737) shows a stable negative impact across quantiles, supporting Krugman's diminishing returns theory. Fertilizer's uniform effect (F = 0.45, p = 0.6399) is consistent with Fuglie [31], indicating that marginal returns remain stable when constraints like soil quality are controlled. Similarly, pesticide use (F = 1.05, p = 0.3637) does not show significant variation, contrasting with Tilman et al. [32], who found diminishing returns at higher production levels. Emissions (F = 0.06, p = 0.9401) have a stable association with production, supporting the Environmental Kuznets Curve hypothesis [33]. Temperature's consistent negative effect (F = 0.36, p = 0.7032) aligns with Dell, Jones and Olken [35], indicating persistent climate impact on agriculture. These findings suggest that production determinants remain stable across different quantiles. Thus, policy interventions—such as labor optimization, mechanization, and input management—are likely to have similar effects across all production levels.

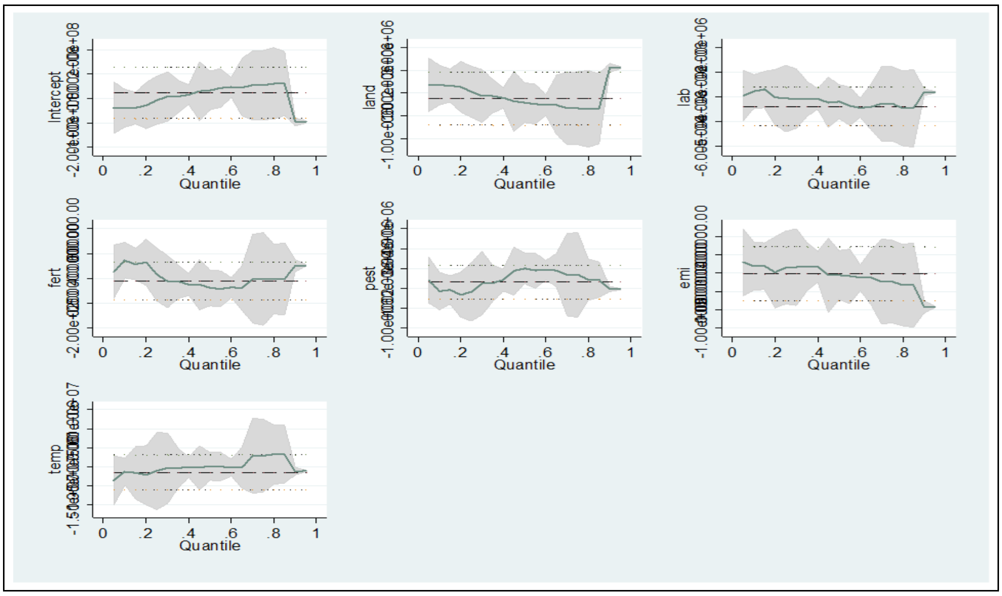

Figure 2. The trend of coefficients of exploratory variables by quantiles.

Figure 2 shows coefficient patterns for each variable, highlighting estimation asymmetries. Pesticide (*pest)* and temperature (*temp)* increase across quantiles, while others decline. Shaded areas represent 90% confidence intervals, with deviations from zero indicating significance. Labor remains significant across all quantiles, emissions (*emi*) at lower and upper quantiles, and temperature (temp) at middle and upper quantiles. Overall, coefficient variations are minimal. The model, based on Pseudo R^2, fits better at lower and middle quantiles, capturing production variations more effectively in these ranges.

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4. Conclusion

This study analyzes palm oil production using OLS and Quantile Regression (QR), revealing varying factor impacts across production levels. OLS results show labor negatively affects output, while pesticide and fertilizer boost productivity. Temperature of land has a negative impact, highlighting climate risks. QR results confirm labor's consistent negative effect, CO_2 emissions significantly affecting small producers, and pesticides benefiting medium-scale producers. The slope equality test indicates stable input-output relationships, with Pseudo R^2 showing better model fit at lower and middle quantiles.

Policy recommendations include improving labor productivity through skill development, mechanization, and automation. Subsidized access to quality fertilizers and pesticides should be balanced with sustainable practices. Climate resilience strategies, such as heat-tolerant crops and precision irrigation, are crucial. Besides, small-scale producers require carbon reduction policies and incentives for green farming. Future research should explore technology adoption, governance, and climate adaptation using advanced models to enhance predictive accuracy and policy effectiveness.

Acknowledgements

We gratefully acknowledge the financial support provided by the MPOB-UKM Endowment Chair Research Grant [MPOB-UKM-2024-013], which made this research possible.

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