UNDERSTANDING INTENSIFICATION PRACTICES AND PRODUCTION RISK AMONG INDEPENDENT SMALLHOLDER OIL PALM FARMERS: INSIGHT FROM RIAU PROVINCE, INDONESIA

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(Received: April 22, 2025; Accepted: September 15, 2025)

ABSTRACT

Independent smallholder oil palm farmers play a crucial role in Indonesia's palm oil sector, yet their productivity remains significantly below the national averages due to production risks and management constraints. This study examined the factors influencing the productivity of independent smallholders in Riau Province, Indonesia. A structured survey of 256 independent farmers was conducted between August to December 2024, and the data were analyzed using regression models to identify key determinants of yield variations. The results showed that smallholder productivity averages 11,289 kg of fresh fruit bunches (FFB) per hectare, which was notably lower than the national average. Variation in productivity was largely explained by differences in farm management practices, input use, and tree conditions. Most respondents were risk-averse, influencing their decision-making on farm investments, particularly input use. The estimation results revealed that plant age negatively affects productivity, emphasizing the urgency of replanting. Fertilizer applications (urea, TSP, KCl, and NPK) and labor input had strong positive effects on yield, highlighting the importance of proper input management. However, NPK fertilizer increased production risk, whereas the adoption of certified seedlings decreased production risk. Low adoption of certified seedlings and inconsistent input use hindered optimal productivity. These findings highlighted the need for policy interventions that address production risks and improve smallholders' capacity for sustainable oil palm cultivation, particularly by improving access to quality seedlings, credit, and extension services to accelerate the replanting process.

Key words: independent smallholders, risk preference, replanting

INTRODUCTION

Smallholder farmers are significant contributors to the global palm oil industry, producing a substantial portion of the world's palm oil supply (de Vos et al. 2023a). In Indonesia, smallholders managed approximately 40% of the country's 16.8 million ha of oil palm plantations (BPS 2024). Among these, independent smallholders constitute the majority, overseeing more than 3.5 million hectares (Raharja et al. 2020). This places independent smallholder oil palm farmers as key actors in ensuring both national and international food and energy security. They manage a significant share of the country's oil palm plantations and contribute substantially to regional and national economies (Ditjenbun 2023). Unlike smallholders integrated into corporate-supported plasma schemes, independent smallholders manage their oil palm plantations without direct assistance from plantation companies, making them more vulnerable to production risks and economic uncertainties (Petri et al. 2023). These risks pose significant challenges to their productivity, profitability, and long-term sustainability.

One of the key challenges faced by independent farmers is limited access to essential resources, such as capital, technology, and agricultural information. While plantation companies and plasma farmers benefit from corporate investment and technical guidance, independent farmers often operate with constrained financial resources and limited technological adoption (Jelsma et al. 2017; Raharja et al. 2020). For example, many smallholders use uncertified seeds due to cost constraints and lack of knowledge, leading to lower yields and suboptimal productivity (Ardana et al. 2024; Maskromo et al. 2025; Susanti and Ariyanto 2023). Research indicates that low yields among independent smallholders are not solely due to seed quality, but also result from inadequate implementation of Good Agricultural Practices (GAP), such as proper pruning and weeding practices, harvesting cycle, and adequate nutrient application (Jelsma et al. 2019; Lim et al. 2023; Monzon et al. 2023; Sugianto et al. 2023; Woittiez et al. 2018). Consequently, these farmers often rely on low-input, low-output farming systems, which hinder improvements in productivity and sustainability. In 2023, for example, the average crude palm oil (CPO) yield among smallholders' plantations was only 3.26 ton/ha, much lower compared to private estates (3.82 ton/ha) and government estates (4.44 ton/ha) (BPS 2024).

Riau province plays a pivotal role in Indonesia's palm oil sector, producing approximately 9.22 million tons of crude palm oil (CPO) in 2023 from a total planted area of 3.4 million ha, making it the largest oil palm-producing region in the country and contributing nearly 20% of national CPO output. It has the highest concentration of smallholder plantations, covering about 2.29 million ha or 34% of the national smallholder area, supported by a well-established palm oil industry (BPS 2024; Ditjenbun 2023). However, smallholder productivity in Riau averages only 3.18 t CPO/ha, below the national average of 3.62 t/ha, and the province contains around 100,616 ha of old, damaged, and unproductive trees in urgent need of replanting. The remaining plantation area consists of 730,082 ha of immature palms and 2,570,909 ha of mature palms. Limited access to superior seedlings and replanting resources further constrains productivity, making Riau both a critical contributor to and a focal point for interventions in Indonesia's palm oil sector. Therefore, addressing productivity issues requires more than just financial support or access to better planting materials. It necessitates a comprehensive approach that includes technical training, knowledge transfer and improved agricultural extension services (Hendrawan et al. 2024; Jelsma et al. 2024).

Production risk is a major concern for smallholders and significantly influences their livelihoods (Salman et al. 2010; Alam et al. 2024). Production risk encompasses uncertainties that adversely impact harvest, such as extreme weather events (e.g., droughts, floods, or erratic rainfall), pest and disease outbreaks, fluctuating market prices, and the availability of production inputs like fertilizers and pesticides. These risks directly affect smallholders' income and overall well-being (Haile et al. 2017; Sundström et al. 2014). Crop failure or yield reductions result in financial loses, making it difficult for farmers to recover their investment in production costs (Coulibaly et al. 2015; Mishra et al. 2018). Given these uncertainties, many farmers are hesitant to allocate significant resources for intensification practices, fearing that their investment may not yield sufficient returns (Kurkalova et al. 2006).

Farmers' risk preferences play a crucial role in their willingness to adopt (Lien et al. 2023; Patil and Veettil 2024), which affects their adoption of intensification practices such as fertilizer application, pesticide/herbicide use, and the selection of certified seedlings. For example, farmers who perceive high risks in fertilizer application, such as uncertainty in price fluctuations or unpredictable returns on investment, may underuse or entirely forgo fertilizers, leading to suboptimal yields (Adnan et al. 2020; Bozzola and Finger 2021; Hasibuan et al. 2022). Similarly, the adoption of certified seedlings is influenced by risk attitudes, where many farmers hesitate to purchase high-quality seedlings due to concerns over delayed financial returns, despite the long-term benefits for productivity and sustainability (Hasibuan et al. 2021; Ponce-Pacheco et al. 2025). Given that much of the existing research has focused on large-scale plantations and plasma smallholders, there remains a critical gap in understanding how independent smallholders assess and respond to production risks.

A comprehensive understanding of smallholders' risk behavior is essential for enhancing productivity and sustainability in the independent oil palm sector. By identifying the key factors influencing farmers' decisions and their risk-related constraints, policymakers and stakeholders can design targeted interventions to improve adoption rates of Good Agricultural Practices (GAP). Moreover, insights into risk behavior can guide government agencies, research institutions, and development organizations in formulating policies that provide effective risk management solutions, such as crop insurance schemes, input subsidies, and targeted agricultural extension services.

This study sought to bridge this knowledge gap by analyzing the relationship between production factors, risk behavior, and adoption of intensification practices among independent smallholder oil palm farmers. It employed the Just and Pope production function model, which allowed for the examination of two critical aspects: (1) the average productivity function, which explains how production inputs—such as superior seeds, fertilizers, pesticides, and labor—affect productivity; and (2) the productivity variance function, which assesses the impact of these inputs on output variability, serving as an indicator of production risk. This study will provide valuable insights into the nature of production risk and risk behavior in independent smallholder oil palm farming. The findings are expected to contribute to policy discussions on sustainable palm oil production by identifying key behavioral and risk-related constraints and proposing strategies to enhance the adoption of intensification practices. A deeper understanding of smallholders' risk behavior can help design more effective policies and interventions, ultimately improving productivity, sustainability, and the long-term welfare of independent smallholders.

METHODOLOGY

Study area and data collection. This study was conducted in Riau Province, Indonesia, from August to December 2024. A multi-stage sampling technique was employed to capture the diversity of independent smallholder oil palm farming systems. Four regencies, i.e. Rokan Hilir, Rokan Hulu, Kampar, and Siak, were selected based on the extensive presence of independent smallholder oil palm plantations. Data collection included structured surveys of smallholder oil palm households and in-depth interviews with key decision-makers to assess production risks and input utilization. In addition, independent smallholders refer to the oil palm farmers who operate independently without the support of large companies or government programs.

Sampling and survey design. A multi-stage sampling technique was employed for data collection, targeting four regencies: Rokan Hilir, Rokan Hulu, Kampar, and Siak. These regencies were chosen due to their extensive oil palm plantations and the prevalence of old and damaged oil palm trees. Multi-stage sampling was used for data collection across four regencies. Within each of these four regencies, three sub-districts were selected. A total sample of 64 individuals was obtained from each district. This resulted in a total sample size of 256 (64 samples/district x 4 districts). The study collected quantitative data through household surveys and interviews with 256 heads of households, identified as the key decision-makers. Households were selected as the primary focus for this study since risk management approaches are developed at the individual farm and household level (Kimura et al. 2010).

Analytical framework and model specification. A multiple linear regression analysis examined the impact of input utilization on agricultural output and production risk. Production risk was assessed based on the variance of output. The study employed the Just and Pope model (Robinson and Barry 1987), incorporating a Cobb-Douglas production function in natural logarithmic form. The production function is formulated as follows:

$$Ln(PROD) = a_0 + a_1Ln(UT)_i + a_2Ln(LHKS)_i + a_3Ln(UREA)_i + a_4Ln(TSP)_i + a_5Ln(KCL)_i + a_6Ln\,(NPK)_i + a_7Ln(TTK)_i + a_8Ln(PEST)_i + a_9Ln(HERB)_i + a_{10}D1_i + \varepsilon \tag{1}$$

While the production variance is:

$$\sigma^2Y_i = (Y_i - \hat{Y}_i)^2 \tag{2}$$

Hence, the formulation of production variance function (risk) is formulated as follows:

$$Ln(\sigma^2Y_i) = \theta_0 + \theta_1Ln(UT)_i + \theta_2Ln(LHKS)_i + \theta_3Ln(UREA)_i + \theta_4Ln(TSP)_i + \theta_5Ln(KCl)_i + \theta_6Ln(NPK)_i + \theta_7Ln(TTK)_i + \theta_8Ln(PEST)_i + \theta_9Ln(HERB)_i + \theta_{10}D1_i + \in \tag{3}$$

where PROD is fresh fruit bunch production (kg), UT is oil palm age (years), LHKS is land area (ha), UREA is the use of urea fertilizer (kg), TSP is the use of phosphate fertilizer (kg), KCl is the use of potassium fertilizer (kg), TTK is total labor usage (man-days), PEST is pesticide usage (liters), HERB is herbicide usage (liters), D1 is dummy variable for seedling usage (certified = 1, uncertified = 0), ε is error term, and I is farmer household (1 = 1... 256)

The analysis employed the Ordinary Least Squares (OLS) method. Before analysis, classical assumptions are tested to ensure model validity. These tests include normality, multicollinearity, and heteroscedasticity. Normality is assessed using the Kolmogorov-Smirnov test. Multicollinearity is checked through Variance Inflation Factors (VIF), with values below 10 indicating no issues. Heteroscedasticity is evaluated using the Glejser test. To ensure unbiased results, the model must pass all classical assumption tests. Subsequently, statistical tests are conducted, including R-squared, F-test, and t-tests. R-squared measures the model's overall fit, with higher values indicating better performance. The F-test assesses the joint significance of all independent variables, while the t-test evaluates the individual significance of each predictor.

Risk preference analysis. Risk preferences were analyzed using the Arrow -Pratt Risk Aversion Measure Approach (Arrow 1965). This method determines the degree of risk aversion based on the shape of a farmer's utility function (Keenan and Snow 2022). This approach allows for the characterization of several decision models through a set of intuitive consistency requirements (Baillon and L'Haridon 2021). The following steps were undertaken:

1. Determining the utility function (U(W)). The utility function represents how an individual evaluates wealth (W)—commonly used general forms of utility functions:

   U(W) = ln(W) (logarithmic utility function, for risk-averse individuals) or

   $U\,(W) = \frac{W^{1-r}}{1-r}$ (CRRA function - Constant Relative Risk Aversion).

2. Calculating the Absolute Risk Aversion Coefficient (ARA, RA). The ARA coefficient is calculated as

$$r_A\ (\mathrm{W}) = \frac{U''(W)}{U'(W)},$$

where: $U'(W)$ is the first derivative of the utility function (marginal utility) and $U''(W)$is the second derivative of the utility function. The value of r_A (W) > 0 indicates a risk-averse individual, r_A (W) = 0 indicates risk-neutral, and r_A (W) < 0 indicates risk-seeking.

3. Calculating the Relative Risk Aversion Coefficient (RRA, r) (if needed). It is defined as:

$$r_R\ (\mathrm{W}) = \mathrm{W}\ .\ r_A\ (\mathrm{W})$$

This coefficient indicates a level of relative risk aversion to changes in the scale of wealth.

4. Determining farmers' risk preferences. By calculating the value of r_A (W), farmers can be classified into three categories: Risk Averse: If r_A (W) > 0, farmers prefer making decisions that minimize risk. Risk Neutral: If r_A (W) = 0, farmers are indifferent to risk. Risk Seeking: If r_A (W) < 0, farmers tend to make riskier decisions.

5. Analysis of results and implications. A high ARA or RRA value indicates that farmers are highly risk-averse, so they prefer safer production techniques. A low ARA value indicates that farmers are more willing to take risks, for example, by adopting innovations or investing in more varied production inputs.

RESULTS AND DISCUSSION

Respondents profile. This study focused on independent oil palm farming households, defined as those operated autonomously by farmers who, through their own initiative and financial investment, established and managed their oil palm plantations without any affiliation with a specific company. Table 1 presents the demographic and socioeconomic characteristics of respondents. The average age of respondents was 49.03 years, with a standard deviation of 11.38 years, indicating a moderately diverse age distribution ranging from 25 to 76 years. The level of formal education varied significantly, with an average of 8 years and a standard deviation of 4.25 years. Some respondents had no formal education, while others had up to 18 years or hold a master's degree, reflecting varying access to education among independent smallholders.

Table 1. Respondent characteristics

Variable	Mean	Std. Dev.	Minimum	Maximum
Age (years)	49	11.38	25	76
Education (years)	8	4.25	0	18
Farming experience (years)	20	7.48	3	35
Number of family members	4	1.47	1	10

Source: primary data

Farming experience was a crucial factor in shaping farmers' decision-making and risk management practices. Respondents had an average of 20 years of farming experience, ranging from 3 to 35 years, demonstrating a mix of seasoned and relatively new farmers in the sector. Household size was also an important factor, with an average of 4 members per household and a standard deviation of 1.47, ranging from single-person households to families with up to 10 members. These characteristics provide a fundamental understanding of the respondent population, which was essential for contextualizing the findings on production risk and replanting decisions.

Input use, production and productivity of independent smallholders. Input use among smallholders reflected the level of intensification in their oil palm plantations, which directly influenced production and productivity. This study did not differentiate input application between wet and dry seasons; the data represented annual averages. Table 2 summarizes key variables related to farm production, productivity, input use, and management practices among independent oil palm smallholders in Riau Province.

Table 2. FFB Production, productivity, input use, and management practices among independent oil palm smallholders in Riau Province, 2024.

Variable	Mean	Std. Dev.	Minimum	Maximum
Production (kg FFB)	41736.73	30163.34	8820	212480
Productivity (kg FFB/ha)	11288.99	2625.53	3528	21248
Tree age (years)	17.56	4.68	3	28
Area (Ha)	3.74	2.57	1	21
NPK fertilizer (kg)	144.31	280.38	0	1608
Urea fertilizer (kg)	391.37	373.20	0	3000
TSP fertilizer (kg)	229.13	352.64	0	3000
KCl fertilizer (kg)	180.12	302.87	0	3000
Pesticides (liter)	9.28	31.97	0	500
Herbicides (liter)	9.51	10.86	0	75
Labor (man days)	58.36	142.93	7.19	2287.82
Certified seeds (1 if yes)	0.04	0.20	0	1

Source: primary data

The productivity of independent oil palm farmers, measured in fresh fruit bunch (FFB) yield per hectare, averaged 11,289 kg/ha, with a standard deviation of 2,625 kg/ha. This productivity was relatively lower than the national levels for smallholders, which reach 15.3 ton/ha (Monzon et al. 2021). The productivity varied widely, ranging from 3,528 to 21,248 kg/ha, reflecting differences in farm management practices, input use, and tree age and conditions. The productivity levels in smallholder oil palm plantations in Indonesia were influenced by the tree age, nutrient management, harvesting, weed control, and pruning (Monzon et al. 2023) . The average age of oil palm trees was 17.56 years, with a range from 3 to 28 years. This suggested that many plantations were approaching or exceeding their optimal production phase, highlighting the urgency of replanting efforts (Hendrawan and Musshoff 2024; Petri et al. 2023). Farm size also varied significantly, with an average landholding of 3.74 hectares, but with a large standard deviation (2.57 ha), indicating considerable heterogeneity in farm sizes. Some smallholders managed as little as 1 hectare, while others cultivate up to 21 hectares. This variation influences input use intensity and production efficiency.

Fertilizer application rates showed substantial variability among independent smallholders. The average NPK application was 144 kg per year, with some farmers not using it at all, while others applied as much as 1,608 kg. Urea fertilizer was used more extensively, with an average of 391 kg per year but high variability (0–3,000 kg). The same trend was observed for TSP and KCl fertilizers, with mean application rates of 229 kg and 180 kg, respectively. The wide variation suggested differences in affordability, access to inputs, and agronomic knowledge. Numerous studies indicated that fertilizer application in smallholder plantations was relatively low, leading to lower fresh fruit bunch yields compared to large plantations. For example, there was a need to increase potassium (K) fertilization to improve the oil palm yield (Thoumazeau et al. 2024) . Additionally, widespread nutrient deficiencies (potassium (K), nitrogen (N), boron (B), phosphorus (P), and magnesium (Mg)), have constrained productivity in smallholder plantations (Lim et al. 2023; Sugianto et al. 2023). This issue of nutrient deficiency was also raised in other studies (Agus et al. 2024; Monzon et al. 2021, 2023).

The use of pesticides and herbicides was relatively low on average but varied significantly. Pesticide use averaged 9.28 liters per year, with a standard deviation of 31.97 liters, indicating that some farmers relied heavily on chemical pest control while others used none. Herbicide application averaged 9.51 liters per year, with a maximum of 75 liters, demonstrating differing weed management strategies. Labor inputs, measured in man-days per year, average 58.36 but exhibit extreme variation, ranging from 7.19 to 2,287.82 man-days. This discrepancy likely reflects differences in farm size, reliance on hired labor, or variations in farm mechanization. Only 4% of respondents reported using certified seeds, highlighting a potential challenge in achieving high and stable yields. The low adoption of certified seeds suggested financial constraints or a lack of awareness about their benefits, which may contribute to increased production risks and lower farm productivity (Hutabarat et al. 2019; Jelsma et al. 2019; Maskromo et al. 2024; Schoneveld et al. 2019).

The findings highlighted the diverse conditions among independent smallholders, particularly in productivity, input use, and farm management practices. The significant variation in tree age suggested that many farmers were at a critical juncture for replanting. However, the relatively low use of certified seeds and uneven fertilizer application indicated potential barriers to effective replanting and yield optimization. The substantial variation in labor input suggested differences in farming intensity, potentially linked to household labor availability or financial constraints in hiring external workers. Additionally, the high standard deviations in input use emphasized the need for targeted interventions, such as improved access to fertilizers, pest management training, and financial support for replanting efforts. These results underscore the necessity of tailored policies that address production risks while enhancing smallholders' ability to engage in sustainable oil palm cultivation. Providing support mechanisms, such as subsidized certified seeds, training programs, and improved credit access, could mitigate risks and accelerate replanting efforts among independent smallholders in Riau Province.

Diagnostic testing for classical assumptions. To ensure the validity and reliability of the estimated model, a series of diagnostic tests were conducted to assess compliance with classical linear regression assumptions. The results indicated no evidence of multicollinearity, as all variance inflation factor (VIF) values were below the critical threshold of 10. The Jarque-Bera test confirmed that the residuals followed a normal distribution ($p > 0.05$ supporting the assumption of normality. Tests for heteroscedasticity yielded mixed outcomes, while the White test suggested potential heteroscedasticity. Both the Breusch-Pagan-Godfrey and Glejser tests were statistically non-significant. These results indicated that any heteroscedasticity present was likely minor and did not materially compromise the robustness of the model.

Factors affecting oil palm productivity. The factors influencing oil palm productivity were estimated using Eq. 1, with the results presented in Table 3. The model demonstrates robust explanatory power, evidenced by an adjusted R-squared value of 0.919, indicating that the independent variables accounted for a substantial proportion of the variance in palm oil production. The overall model significance was confirmed by the F-test ($p < 0.01$). Plant age (UT) exhibited a statistically significant negative relationship with production, whereas land area (LHKS), fertilizers (urea, TSP, KCl, NPK), and labor (TK) demonstrated statistically significant positive effects. In contrast, pesticides (PEST) and herbicides (HERB) did not have a significant impact on production.

Table 3. The estimation results of oil palm production function

Variable	Coefficient	
Constant	9.221	***
	(0.248)	
Plant age (years)	-0.172	***
	(0.051)	
Land area (Ha)	0.769	***
	(0.045)	
Urea fertilizer (Kg/ha)	0.038	***
	(0.004)	
TSP fertilizer (Kg/ha)	0.009	***
	(0.003)	
KCl fertilizer (Kg/ha)	0.014	***
	(0.003)	
NPK fertilizer (Kg/ha)	0.016	***
	(0.003)	
Labor (man-days/ha)	0.152	***
	(0.053)	
Pesticides (l/ha)	0.007	
	(0.010)	
Herbicides (l/ha)	0.005	
	(0.009)	
Dummy seedlings (1 if certified)	0.030	
	(0.026)	
Number of observations	256.000	
R-squared	0.919	
Adjusted R-squared	0.916	

Note: Standard errors are in parentheses. *, **, *** is significant at 0.5, 0.1 and 0.01 percent levels.

The negative and statistically significant relationship between plant age and production suggested that most oil palm plantations in the study area surpassed their peak productive phase and were entering a period of decline. This finding was consistent with prior research on the oil palm yield cycle. A typical yield curve shows productivity peaks between 7 and 15 years before gradually declining (Corley and Tinker 2021) . Older palm trees exhibited lower productivity due to physiological aging, reduced nutrient uptake efficiency, and an increase in trunk height, which made harvesting more difficult (Woittiez et al. 2017). This finding underscored the necessity for timely replanting strategies to sustain long-term productivity in oil palm plantations.

In addition to plant age, land area also exhibited a statistically significant and positive effect on oil palm production. This supported the principle of scale efficiency where larger plantations benefited from more efficient use of resources, greater opportunities for mechanization, and optimized input allocation (Barrett et al. 2010). Furthermore, larger farm sizes were often associated with wealthier farmers who were more capable of investing in good agricultural practices, leading to superior yields (Jelsma et al. 2019). However, scale alone was not sufficient, realizing the full productivity potential also depended on the effective and balanced use of key inputs.

Among these inputs, fertilizer application played a critical role. The significant positive relationships observed between production and the application of urea, TSP, KCl, and NPK fertilizers were consistent with prior studies emphasizing the importance of nutrient balance in achieving optimal yields (Goh et al. 2003; Lim et al. 2023; Sugianto et al. 2023; Woittiez et al. 2018). Proper fertilizer management not only enhances productivity but also minimize risks associated with over- or under-application, which could have led to soil degradation, nutrient leaching, and yield instability. Thus, access to training on nutrient management and soil health was essential for improving smallholder performance.

While inputs like fertilizer were crucial, labor remained a key determinant of productivity, especially among smallholder farmers who typically lacked access to mechanization (Bou Dib et al. 2018). The positive andsignificant impact of labor use was in line with the findings of Euler et al. (2016) and Kubitza et al. (2023), which emphasized the labor-intensive nature of smallholder oil palm farming. Effective oil palm maintenance required substantial human input for activities such as harvesting, fertilization, weeding, pruning, and pest management, all of which significantly influenced yields (Jelsma et al. 2017; Monzon et al. 2023). Efficient labor utilization directly influenced fresh fruit bunch (FFB) harvesting frequency, which in turn impacted overall productivity. Labor shortages, particularly in rural areas, could have been a limiting factor in achieving optimal yields (de Vos et al. 2023b; Habibi 2023), making mechanization and improved workforce management critical for sustainability.

Oil palm production risk. To complement the analysis of productivity, this study also investigated the factors contributing to production risk, using the estimated production variance function. This function modeled the variance in oil palm output as a function of various production inputs, providing insight into the factors that introduced volatility or uncertainty in yields. The dependent variable was the variance of oil palm production, and the explanatory variables include plant age, land area, usage of urea, TSP, and KCl fertilizers, type of seedlings used (certified = 1, uncertified = 0), total labor usage, as well as pesticides and herbicides. The results estimation offers a basis for understanding how different inputs influenced productivity (Table 4).

Table 4. The estimation results of oil palm risk function.

Variable	Coefficient
Constant	-0.002
	(0.055)
Plant age (year)	-0.006
	(0.011)
Land area (Ha)	-0.009
	(0.010)
Urea fertilizer (Kg)	-0.001
	(0.001)

Variable	Coefficient	
TSP fertilizer (Kg)	0.000	
	(0.001)	
KCl fertilizer (Kg)	0.000	
	(0.001)	
NPK fertilizer (Kg)	0.002	*
	(0.001)	
Labor (man-days)	0.018	
	(0.012)	
Pesticide (l)	0.001	
	(0.002)	
Herbicide (l)	-0.003	
	(0.002)	
Dummy seedling (1 if certified)	-0.017	***
	(0.006)	
Number of observations	256.000	
R-squared	0.096	
Adjusted R-squared	0.059	

Note: Standard errors are in parentheses. *, **, *** is significant at 0.5, 0.1 and 0.01 percent levels

A variance function test employing Ordinary Least Squares (OLS) regression was conducted to investigate factors influencing oil palm production risk. The model exhibited a low coefficient of determination ($R^2 = 0.0955$), indicating that the explanatory variables accounted for a limited proportion of the observed variance in production risk. Despite this low explanatory power, the model achieved statistical significance ($F(df1, df2) = 2.59$, $p = 0.0054$), suggesting that the included variables exert a discernible, albeit small, influence on production risk variability. Further investigation is warranted to identify additional factors contributing to production risk in this context.

A key finding of this study was the significant positive relationship between NPK fertilizer use and production risk ($p = 0.0194$). This indicates that using NPK fertilizer increased production instability. This result aligned with previous research. For example, Tchonkouang et al. (2024) highlighted how high-input agricultural technologies, like fertilizers, can lead to greater yield variability, particularly when weather conditions are unpredictable. Some inputs may increase expected output, but they can also elevate production risk due to their interaction with environmental factors, such as soil composition and rainfall patterns (Just and Pope 1979). However, single fertilizer components such as urea, TSP and KCl as well as labor use, were found to be statistically insignificant in relation to production risk. This suggests that while these inputs significantly enhance oil palm yield, they were not associated with variability in production outcomes.

Certified seed (D1) significantly reduced production risk ($p = 0.0024$), suggesting that specific periods or conditions could have mitigated risk. This findings aligned with Dercon and Christiaensen (2011), who highlighted the role of seasonality, climate stability, and adaptive practices in reducing output variability. Improved seed quality, coupled with optimal management, mitigated risk. Feder et al. (1985) linked certified seed adoption to farmers' risk preferences and yield stability expectations. Certified seeds, often bred for resilience, buffer against production shocks. Improved seed varieties in sub-Saharan Africa reduce yield variability, especially with integrated soil fertility management (Kassie et al. 2011).

Timing of input application was also critical. Well-timed interventions, like synchronized fertilizer application, maximize benefits and reduce yield uncertainty (Duflo et al. 2011). This was relevant for oil palm farmers, as strategic input application mitigates risks from aging plantations and declining soil fertility. Certified seed adoption is part of a holistic risk management strategy (Ardana et al. 2024). Smale et al. (2013) suggested that smallholders using improved seeds with diversification and adaptive land management are more resilient. This finding aligns with Just and Pope (1978) risk production function, differentiating inputs that increase expected yield from those reducing variability. These results highlighted the importance of certified seeds for stabilizing productivity, especially with favorable conditions and strategic input application. Future research should explore how seed certification standards interact with other practices to enhance long-term resilience in oil palm cultivation.

Farmers' risk preferences. Farmers' risk preferences play a pivotal role in shaping decision-making related to oil palm intensification. These preferences influence how farmers respond to uncertainty in input use, yield fluctuations, and market volatility. The study results revealed that a majority of farmers in the study area were risk-averse, accounting for 41.4% of the respondents (Table 5). This aligned with earlier research showing that Indonesian farmers generally exhibit risk-averse behavior (Hasibuan et al. 2021, 2023; Miyata 2003). Risk aversion tended to decline with increasing asset wealth, with non-agricultural households being the least risk-averse, followed by part-time and full-time farmers (Wu et al. 2024). Meanwhile, 38.6% were classified as risk-takers, and 19.9% as risk neutral.

Table 5. Oil palm farmers' risk preferences.

Risk Preferences	No. of respondents	Percentage
Risk averse	106	41.4
Risk neutral	51	19.9
Risk takers	99	38.6
Total	256	100

To further assess these preferences, the Arrow-Pratt (AR) Risk Aversion Measure was employed. This approach quantifies risk attitudes by evaluating the variance in production outcomes relative to input use. Inputs such as urea, TSP, KCl, NPK, and pesticides yielded positive AR values, suggesting that farmers were generally risk-averse when applying these inputs (Table 6). Conversely, negative AR values were observed for labor (TK) and herbicide use, indicating a more risk-taking attitude in these categories. On average, the overall AR value across all inputs was positive, confirming a prevailing tendency toward risk aversion among independent smallholders.

Table 6. Preference of oil palm smallholders towards production input.

Production input	Average AR value	Risk Preference
Urea	6883055.196	*risk-averse*
TSP	14701433.5	*risk-averse*
KCl	11905524.46	*risk-averse*
NPK	13685789.75	*risk-averse*

Production input	Average AR value	Risk Preference
Total labor usage	-41810578.37	*risk taker*
Pesticide	2454127.381	*risk averse*
Herbicide	-232600.4935	*risk taker*
Overall farmer preferences	1083821.632	*risk-averse*

Where:

AR > 0	risk-averse
AR < 0	risk taker
AR = 0	risk-neutral

However, risk preferences can moderate the effect of perceived risk. Higher profits and extensive social networks encouraged adaptive behavior, even among risk-averse farmers. Additionally, more educated, older male farmers with larger landholdings tend to perceive production risks more acutely (Mou and Li 2025). While risk-averse farmers do not entirely avoid risk, they require adequate compensation or incentives to accept it (Robinson and Barry 1987). This highlights the need for agricultural extension programs that emphasize the perceived benefits of technology adoption, farmers' preparedness, and technology-specific features (Owusu-Sekyere et al. 2024).

Production risk analysis indicated that certain inputs, such as NPK fertilizer, can amplify yield volatility, whereas certified seed may have a stabilizing effect. Given the strong risk-averse tendencies among independent smallholder farmers, there was a likelihood that they may reduce NPK fertilizer use to mitigate production risk. Conversely, promoting certified seed adoption presents a promising strategy, as its risk-reducing potential appealed to these farmers. However, the adoption rate of certified seed remained very low, which was likely attributed to a lack of awareness. Survey results indicated that most respondents use well-known oil palm varieties, but due to limited information, they may perceive uncertified varieties as equivalent to certified ones. In reality, numerous studies highlighted that the uncertified seeds used by farmers were often illegitimate, leading to significantly lower productivity (Jelsma et al. 2019; Maskromo et al. 2025).

CONCLUSION AND RECOMMENDATIONS

This study provides an in-depth analysis of the production risk faced by independent smallholder oil palm farmers in Riau Province, Indonesia, and its implications for accelerating the intensification program. The findings reveal substantial variations in demographic and socioeconomic characteristics, input use, and productivity levels among smallholders. The average productivity of 11,289 kg FFB/ha remains below the national benchmark, underscoring significant challenges in farm management and input application. Key factors affecting FFB production include plant age, land area, fertilizer application, and labor input. The study confirms that older plantations exhibit declining yields, emphasizing the urgency of replanting efforts to maintain long-term productivity.

The regression model demonstrates strong explanatory power, confirming the significant impact of land area and fertilizer application on output. The low adoption of certified seeds (4%) highlights a critical gap in achieving higher yields and reducing production risk. Furthermore, substantial variability in fertilizer application suggests disparities in input affordability, knowledge, and accessibility. These findings underscore the importance of targeted interventions to enhance smallholder productivity and mitigate the risks associated with aging plantations. Hence, we recommend several strategies. Firstly, the government and related industries should promote the use of certified seeds through subsidies, training, and awareness campaigns to improve yields and reduce production risks associated with uncertified seedlings. Secondly, given the significant impact of fertilizers on productivity, policies should focus on ensuring affordable access to fertilizers, providing training on optimal nutrient management, and encouraging site-specific fertilization practices to address widespread nutrient deficiencies. Thirdly, since aging plantations significantly reduce productivity, it needs to accelerate the replanting program for smallholders (PSR) that has been launched by the Indonesian government since 2017. Fourthly, labor availability and costs remain constraints for independent smallholders so that training programs on efficient farm management, labor-saving technologies, and small-scale mechanization should be introduced to optimize productivity. Fifthly, many smallholders struggle with the financial burden of replanting and farm investment. Expanding credit access through microfinance institutions, cooperatives, and government-backed loan schemes would enable smallholders to invest in improved farm inputs and replanting initiatives. Lastly, strengthening farmer cooperatives can improve smallholders' bargaining power, facilitate collective input procurement, and enhance knowledge sharing. Government and private sector collaboration should support cooperative development through capacity-building programs. The wide variability in farming practices highlights the need for more effective agricultural extension services. Expanding training programs on good agricultural practices (GAP), sustainable intensification, and yield optimization strategies will help farmers make informed decisions regarding replanting and farm management.

ACKNOWLEDGEMENT

The authors sincerely acknowledge the financial support of the Indonesian Ministry of Agriculture, which enabled the completion of this study. We are also deeply grateful to our colleagues and the anonymous reviewers for their constructive feedback, which has substantially strengthened this manuscript.

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Writing – Review and Editing: RSA, HAR, AIS, TN, AMH. All authors have read and agreed to the published version of the manuscript.