Environmental Heterogeneity and Technical Efficiency in Malaysian Oil Palm Smallholder Production

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Abstract: Independent smallholders are crucial to Malaysia's oil palm sector, yet their productivity remains below potential due to technical inefficiency and diverse production environments. This study examines the technical efficiency and production determinants of independent oil palm smallholders using a stochastic frontier analysis (SFA) framework. Primary survey data were analysed with a Cobb-Douglas stochastic frontier production function estimated under half-normal and truncated-normal distributions, with models specified both with and without environmental variables. The truncated-normal model provided the best fit, and the mean technical efficiency was about 0.63, indicating that smallholders produce only 63% of their potential output, with substantial variation across farms. Including environmental variables – such as rainfall, temperature, soil type, land type, humidity, sunlight and climate-related shocks – improved model fit and altered several input elasticities. Fertiliser use showed a negative association with output, while irrigation, labour, pest control, sunlight and temperature contributed positively to productivity. Accounting for environmental heterogeneity reduced unexplained variance, revealing that part of the observed inefficiency reflects environmental constraints rather than managerial shortcomings. These findings highlight the need for site-specific strategies tailored to local agroecological conditions to enhance smallholder productivity.

Keywords: Environmental production conditions, Malaysia, oil palm smallholders, productivity, stochastic frontier analysis, technical efficiency
JEL classification: C13, Q12, Q18

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1. Introduction

Palm oil is Malaysia's leading agricultural commodity, and the country is among the world's largest producers. However, in recent years the industry has faced declining demand due to global economic uncertainties, environmental concerns, and product boycotts by the European Union and other Western countries. The COVID-19 pandemic further disrupted productivity, with the Malaysian Palm Oil Board (MPOB) reporting a 5.8% production drop in the first half of 2020 and a 7.5% decline in average fresh fruit bunch (FFB) yield in 2021 (MPOB, 2022). In light of these challenges, enhancing efficiency in resource use is crucial to maintaining competitiveness.

Malaysia's oil palm industry comprises large private estates, state schemes and smallholders. Smallholders, who own less than 40.46 ha, account for 40% of production and contribute about 18 million tonnes annually. They are classified as organised (e.g., Federal Land Development Authority (FELDA), Federal Land Consolidation and Rehabilitation Authority (FELCRA), Rubber Industry Smallholders Development Authority (RISDA) or independent. Organised smallholders receive technical and financial support from government agencies, while independent smallholders obtain limited assistance from MPOB's TUNAS centres. Independent smallholders manage about 0.99 million ha (16.7% of total planted area) and number around 260,353 farmers, mainly in Johor (Arshad et al., 2020; MPOB, 2018). Many are family-run farms relying on family and migrant labour, often with limited capital, land tenure and market access (Aznie et al., 2018; Vermeulen & Goad, 2006).

Efficiency is vital for improving agricultural productivity, and numerous studies in developing countries highlight its importance. Palm oil yields depend on inputs such as fertilisers, pesticides, labour, capital and land, while factors like plant age and land class also influence output. Achieving economic efficiency requires both technical efficiency (maximising output from given inputs) and allocative efficiency (using input combinations optimally based on prices). The decline in oil palm output has been linked to the technical inefficiency of farmers, especially independent smallholders.

Technical inefficiency has long been recognised as a central constraint on agricultural productivity in developing countries, particularly among smallholder producers who operate under resource, information and environmental limitations. In production economics, technical inefficiency refers to the inability of a producer to attain the maximum feasible output from a given set of inputs and technology (Farrell, 1957). Within the stochastic frontier framework, inefficiency is distinguished from random shocks such as weather variability and measurement error, allowing observed output gaps to be decomposed into managerial inefficiency and uncontrollable noise (Aigner et al., 1977; Meeusen & van den Broeck, 1977). This distinction is especially important in agriculture, where production outcomes are highly sensitive to natural conditions.

In Malaysia's oil palm sector, independent smallholders play a crucial role in national output but consistently record yields below potential. Unlike organised smallholders operating under schemes such as FELDA or FELCRA, independent smallholders receive limited technical support, rely heavily on family or informal labour, and often manage heterogeneous plots with varying soil quality and exposure to climatic risks. Empirical evidence indicates that these farmers operate substantially below the production frontier, with average technical efficiency commonly reported between 0.60 and

0.70, implying sizeable output losses without any increase in input use (Hasnah et al., 2004; Welda et al., 2020). This study similarly finds a mean technical efficiency of approximately 0.63, suggesting that independent smallholders produce only about 63% of their potential output under existing technology.

However, a growing body of literature argues that measured technical inefficiency may be overstated when environmental production conditions are ignored. Schultz's (1964) seminal hypothesis proposed that traditional farmers are "efficient but poor," rationally allocating scarce resources within severe constraints. Subsequent stochastic frontier studies reporting low efficiency levels among smallholders appear to contradict this view. Researchers have reconciled this contradiction by demonstrating that omission of environmental variables – such as soil quality, rainfall, temperature and topography – biases production function estimates and incorrectly attributes environmentally induced yield variation to managerial inefficiency (Kalirajan & Shand, 1985; Rahman & Hasan, 2008; Sherlund et al., 2002).

Oil palm production is particularly sensitive to environmental conditions. Yield performance depends not only on conventional inputs such as fertiliser, labour and capital, but also on agroecological conditions including soil type, land elevation, rainfall patterns, temperature, sunlight and exposure to floods or droughts. Excessive rainfall can cause waterlogging, nutrient leaching and disease outbreaks, while prolonged dry spells reduce bunch formation and oil extraction rates (Filho et al., 2021; Norizan et al., 2021). Soil constraints – especially in peat, mixed or poorly drained soils – further limit the productivity of chemical inputs and mechanisation (Behera et al., 2021). When such factors are excluded from efficiency models, farmers operating under unfavourable conditions are systematically misclassified as inefficient. Nevertheless, these factors are often neglected in efficiency studies in Malaysia resulting in biased estimates (Kalirajan & Shand, 1985; Radam & Shamsudin, 2001). Only a few studies have examined how production conditions and physical inputs jointly affect efficiency (Kellermann, 2015; Njuki et al., 2019; Rahman & Hasan, 2008) or how environmental inputs (weedicide, pesticide, herbicide, fertiliser) influence both efficiency and environmental outcomes (Bayard & Jolly, 2007; Reinhard et al., 1999; Zhang & Xue, 2005).

Recent methodological advances therefore emphasise the integration of environmental production conditions directly into stochastic frontier models. Studies incorporating environmental variables show that accounting for heterogeneity improves model fit, alters input elasticities and reduces unexplained variance attributed to inefficiency (Njuki et al., 2019; Sherlund et al., 2002). This study adopts this approach by explicitly modelling rainfall, temperature, sunlight, soil type, land type, humidity and climate-related shocks alongside conventional inputs. The results demonstrate that once environmental factors are controlled for, part of the observed inefficiency reflects structural and ecological constraints rather than poor farm management alone.

In general, the persistence of technical inefficiency among Malaysia's independent oil palm smallholders reflects the combined influence of managerial limitations and environmental constraints, rather than irrational behaviour or systematic misallocation of resources alone. Limited access to site-specific agronomic knowledge, heterogeneous soil and land conditions, and exposure to climatic variability reduce the effectiveness of inputs and lead to lower observed productivity. However, much of the existing oil palm efficiency literature, particularly in the Malaysian context, either ignores environmental production conditions or treats them as random noise, thereby overstating managerial inefficiency and obscuring the true sources of productivity gaps.

This study therefore focuses exclusively on technical efficiency, which measures the ability of smallholders to maximise output from given inputs and technology under prevailing environmental conditions. Technical efficiency is the most appropriate concept in this context because independent smallholders often face imperfect or distorted input and output markets, limited access to reliable price information, and constrained input choices. Under such conditions, assumptions required for measuring allocative efficiency – notably profit maximisation and price-taking behaviour – are unlikely to hold, rendering allocative efficiency estimates unreliable and potentially misleading.

Moreover, analysing allocative efficiency without first accounting for environmental heterogeneity risks confounding price-related inefficiencies with biophysical constraints beyond farmers' control. By integrating environmental variation directly into a stochastic frontier framework, this study addresses a key gap in the literature and provides a more accurate diagnosis of productivity shortfalls among independent smallholders. The findings offer policy-relevant insights by distinguishing inefficiency arising from management practices from that driven by environmental constraints, thereby supporting more targeted interventions that combine efficiency-enhancing farm management with investments in environmental infrastructure such as drainage, irrigation and soil rehabilitation.

The remainder of this paper is structured as follows. Section 2 reviews the related literature, Section 3 explains the data and methodology, Section 4 presents and discusses the findings, and Section 5 concludes the paper with policy implications and recommendations for future research.

2. Literature Review

Agricultural production outcomes are shaped by the interaction of environmental, behavioural, and policy dimensions (Clapham, 1980). While much of the literature attributes declining productivity to agricultural intensification and the excessive use of chemical fertilisers and pesticides – leading to soil degradation, biodiversity loss and water contamination (Pretty, 1995) – environmental constraints in resource-poor settings can independently disrupt production. These include declining soil fertility, pest resistance, irregular rainfall, floods, droughts and temperature stress, all of which directly affect crop performance regardless of farmers' managerial effort (Clapham, 1980; Hoang & Yabe, 2011). As a result, farm productivity depends not only on access to physical inputs and technology but also on environmental production conditions that shape the effectiveness of those inputs.

Empirical studies using frontier approaches consistently report technical efficiency levels ranging between 60% and 82% across developing countries, suggesting substantial output gaps (Ali & Flinn, 1989; Battese & Coelli, 1995; Coelli et al., 2002; Khanal et al., 2018; Rahman, 2003; Wang et al., 1996). These estimates are drawn from diverse developing-country contexts, including rice farms in Bangladesh and Pakistan, mixed cropping systems in China, dairy and grain farms in South and Southeast

Asia, and smallholder systems in Africa and Latin America. The wide range reflects heterogeneity in agroecological conditions, institutional settings, market access and exposure to climatic risks. In tropical and subtropical regions, where agriculture is heavily rain-fed and climate-sensitive, production variability due to excess rainfall, drought, or soil constraints often translates into lower measured efficiency (Larson & Plessmann, 2002; Nguyen & Kondo, 2018; Villano et al., 2005).

Geographic and climatic conditions play a critical role in explaining these relatively low efficiency levels. Smallholders operating in flood-prone lowlands, marginal soils, or ecologically fragile zones often face biophysical constraints that reduce yields independently of managerial skill. When such environmental heterogeneity is ignored in efficiency models, yield losses caused by weather shocks, soil limitations, or pest pressure are incorrectly attributed to farmer inefficiency (Njuki et al., 2025; Rahman & Hasan, 2008; Sherlund et al., 2002). This methodological omission partly explains why efficiency estimates in developing countries cluster well below the frontier even when farmers behave rationally.

This issue is closely related to Schultz's (1964) hypothesis, which argued that traditional small farmers are "efficient but poor," meaning that they allocate resources rationally given their limited technology and harsh production environments. Schultz contended that low productivity does not necessarily indicate inefficiency, but rather reflects binding constraints such as limited capital, weak infrastructure and unfavourable natural conditions. However, subsequent stochastic frontier studies appeared to contradict this view by reporting widespread inefficiency among smallholders. The apparent contradiction has been reconciled by later studies showing that the failure to control for environmental production conditions biases inefficiency estimates upward, thereby creating an artificial gap between Schultz's theoretical argument and empirical findings (Abedullah & Mushtaq, 2010; Kellermann, 2015; Rahman & Hasan, 2008; Sherlund et al., 2002). When environmental variables are explicitly incorporated, measured inefficiency declines and becomes more consistent with Schultz's hypothesis.

In the Malaysian context, studies on oil palm smallholders highlight a similar pattern. Independent smallholders in Johor, for instance, have been found to experience relatively low yields despite lower production costs and higher household incomes (Ismail et al., 2003). This apparent paradox can be explained by several structural and environmental factors. First, many Johor smallholders cultivate oil palm on heterogeneous land parcels, including marginal or flood-prone areas, where yields are inherently constrained. Second, lower costs may reflect underinvestment in yield-enhancing inputs such as quality fertilisers, soil diagnostics, drainage systems, or mechanisation, which reduces output even if net income remains relatively high due to favourable palm oil prices or diversified income sources. Third, income levels may be supported by off-farm activities, masking underlying inefficiencies in on-farm production.

Beyond yield performance, oil palm cultivation among smallholders has broader social and ecological implications. Empirical studies document changes in soil microbial diversity and soil health associated with monoculture oil palm systems (Ayob & Kusai, 2021; Uke et al., 2021; Wong et al., 2021), which can reduce long-term soil productivity and input responsiveness. At the landscape level, oil palm expansion affects ecosystem services, carbon stocks and local livelihoods, generating both positive income effects and negative environmental externalities (Ayompe et al., 2021; Jaroenkietkajorn et al., 2021; Krishna et al., 2017). Water use studies further show that oil palm is sensitive to both water deficits and excess rainfall, with irrigation needs and drainage conditions playing a critical role in determining yields (Filho et al., 2021; Norizan et al., 2021).

Other strands of the literature highlight how soil nutrient imbalances, inappropriate fertiliser use and limited adoption of biofertilisers constrain productivity (Behera et al., 2021; Mahmud et al., 2021), while climate-related impacts – such as greenhouse gas emissions and carbon losses, particularly on peat soils – raise sustainability concerns (Kusumawati et al., 2021; Manning et al., 2019; Melling et al., 2021). Pest and disease pressures, including basal stem rot and bunch moth infestations, further exacerbate yield variability and increase production risk, especially where integrated pest management practices are weak (Kamu et al., 2021; Siddiqui et al., 2021; Su et al., 2021).

Methodologically, agricultural efficiency has been analysed using both non-parametric approaches such as data envelopment analysis (DEA) and parametric methods such as stochastic frontier analysis (SFA). SFA is particularly suitable for agricultural settings because it explicitly separates inefficiency from random shocks, including weather and measurement errors (Alemdar & Oren, 2006; Coelli et al., 1998; Kedebe, 2001). While many studies link efficiency outcomes to farmers' demographic, socio-economic and institutional characteristics (Obwona, 2000; Olukosi & Erhabor, 2005), relatively few explicitly integrate environmental production conditions into the frontier itself.

Most oil palm efficiency studies focus on Indonesia, reporting technical efficiency levels ranging from 0.59 to 0.86 depending on region, production system and methodology (Abdul et al., 2023; Alwarritzi et al., 2015; Fitri & Nainggolan, 2023; Hasnah et al., 2004; Welda et al., 2020). In contrast, Malaysian evidence remains limited and fragmented, with environmental heterogeneity rarely incorporated into efficiency estimation. This gap is particularly salient for independent smallholders, who are more exposed to environmental risks and receive less institutional support than organised schemes.

In sum, the literature suggests that observed inefficiency among smallholders is often the result of unmodelled environmental heterogeneity rather than pure managerial failure. Despite extensive research on oil palm production and sustainability, there is limited empirical work that integrates environmental production conditions directly into stochastic frontier models for Malaysian independent smallholders. This study addresses this gap by introducing an environmental variation model within the SFA framework, enabling a more accurate diagnosis of technical inefficiency and providing stronger evidence for site-specific, environmentally informed productivity interventions.

3. Data and Methodology

This study develops an alternative model to assess how physical inputs, environmental variability and management practices affect production efficiency among independent oil palm smallholders in Malaysia, using a Cobb–Douglas stochastic production frontier.

Frontier techniques for measuring productive efficiency were first proposed by Farrell (1957) and have since been widely applied in developing-country agriculture. Technical efficiency (TE) is estimated by constructing a production frontier representing the maximum possible output for a given set of inputs, with efficiency measured as the deviation of observed output from this frontier.

Two main approaches are commonly used: the stochastic frontier production function (SFPF) and data envelopment analysis (DEA). DEA, introduced by Charnes et al. (1978), applies linear programming to estimate an empirical frontier, while the SFPF, developed by Aigner et al. (1976, 1977) and Meeusen and van den Broeck (1977), uses econometric methods to estimate parametric functions and distinguish inefficiency from random noise.

Building on this, stochastic production frontiers incorporating variables that capture environmental production conditions alongside physical inputs have been used to explain productivity performance, as discussed by Rahman and Hassan (2008) and Sherlund et al. (2002). Specifically, the stochastic production frontier for the *i*th farmer is expressed as:

$$Y_i = (X_i, W_i) - U_i + V_i \tag{1}$$

where Y_i is output, X_i is physical input and W_i is the vector of environmental variables which control the production conditions existing in the palm oil plantation, V_i is assumed to be independently distributed N(0, $\sigma^2{}_v$) two sided random error, independent of the U_i which is a non-negative random variable ($U_i > 0$) associated with inefficiency in production and is assumed to be independently distributed as truncation at zero of the normal distribution with mean $-Z_i\delta$ and variance $\sigma_u^2, U_i \sim N^+(-Z_i\delta, \sigma_u^2)$, where Z_i denotes the set of farm-specific variables that explain inefficiency for farmer *i*. In this specification, output is assumed to be strictly monotonically increasing with respect to both physical inputs and environmental conditions. In line with the existing literature, most empirical studies typically estimate the following functional form:

$$y_i = g\left(X_i, W_i^*\right) - u_i^* + v_i^* \tag{2}$$

where $W_i^* \subseteq W_i$ which omits some or all of the elements of W_i, and therefore, results in biased estimates of the parameters of the production function, overstatement of technical inefficiency, as well as biased correlates of inefficiency (Sherlund et al., 2002).

Two main approaches are commonly identified in the literature for analysing the determinants of technical efficiency (or inefficiency). The first, adopted by several authors (Hallam & Machado, 1996; Parikh & Shah, 1994; Tadesse & Krishnamoorthy, 1997), involves a two-stage procedure. In this approach, stochastic frontiers are first estimated using the maximum likelihood method to predict farm-level efficiencies, which are then regressed on farm-specific variables such as managerial experience, ownership characteristics and production conditions to explain variation in output across farms. This procedure assumes that inefficiency effects are identically distributed.

However, this assumption has been widely criticised (Battese & Coelli, 1995; Battese et al., 1989; Kumbhakar et al., 1991; Reifschneider & Stevenson, 1991), as socioeconomic variables may have a direct influence on production efficiency and should therefore be incorporated directly into the frontier estimation. To address this issue, Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) proposed a single-stage stochastic frontier model, in which the inefficiency effects (u_i) are explicitly modelled as a function of a vector of farm-specific variables and a random error term.

Following this line of work, the present study applies the single-stage approach of Battese and Coelli (1995), in which the technical inefficiency parameter is related to a set of farm-level managerial and household characteristics, while also accounting for statistical error, such that:

$$u_i = Z_i\delta + \zeta_i \geq 0 \tag{3}$$

where Z_i are the farm specific managerial and households' characteristics, δ is a vector of parameters to be estimated and the error ζ_i is distributed as $\zeta_i \sim N(0,\sigma_v^2)$. Since $u_i \geq 0$, $\zeta_i \geq -Z_i\delta$, so that the distribution of ζ_i is truncated point, $-Z_i\delta$. The production efficiency of farm *i* in the context of the stochastic frontier production function is defined as:

$$EEF_i = E(\exp(-u_i) \mid \zeta_i) = E(\exp(-\delta_0 - \sum Z_i\delta \mid \zeta_i)) \tag{4}$$

where *E* is the expectation operator. This is achieved by obtaining the expressions for the conditional expectation u_i upon the observed value of ζ_i where $\zeta_i = v_i - u_i$. The estimation of the stochastic frontier model and the inefficiency effects function is carried out simultaneously using the maximum likelihood (ML) method. In this framework, the likelihood function is parameterised in terms of the variance components of the error structure. Specifically, the total variance of the composed error term is defined as:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2$$

where σ_v^2 represents the variance of the random noise and σ_u^2 denotes the variance of the inefficiency component. In addition, the parameter

$$\gamma = \frac{\sigma_u^2}{\sigma^2}$$

is estimated to indicate the proportion of the total variance attributable to inefficiency rather than random noise. A higher γ value implies that deviations from the production frontier are largely due to inefficiency effects rather than statistical noise.

3.1 Empirical Model

Two common production function forms are the Cobb–Douglas (C–D) and the transcendental logarithmic (translog). The C–D form is popular for its simplicity and ease of estimation but assumes constant returns to scale, fixed output elasticities, and a unitary elasticity of substitution. The translog is more flexible, approximating any function locally, though it requires more parameters and may face multicollinearity issues (Irz & McKenzie, 2003).

This study applies a Cobb–Douglas stochastic production frontier for its interpretability. To evaluate environmental effects, the model is estimated with and without environmental variables, with the conventional form excluding the W_i variables:

$$\ln Y_i = \alpha_0 + \sum_{j=1}^{p}\alpha_j \ln X_{ij} + \sum_{j=1}^{p}\beta_j D_{ij} + v_i - u_i \tag{5}$$

and

$$u_i = \delta_0 + \sum_{d=1}^{p}\delta_d Z_{id} + \zeta_i \tag{6}$$

where Y_i is the production of palm oil, X_{ij} is the jth input for the ith farmer, D_{ij} could be the dummy variables used to account for the zero values of input use and have the value of 1 if the jth input used is positive and zero otherwise, p is the total number of variables of each category, v_i is the two sided random error, u_i is the one sided half-normal error, ln is the natural logarithm, Z_{id} are the variables representing managerial and socio-economic characteristics of the farm to explain inefficiency, Z_i is the truncated random variable, and αs, βs and δs are the parameters to be estimated.

Similarly, the full specification includes variables which will represent environmental production conditions in equation 5 and can be written as:

$$\ln Y_i = \alpha_0 + \sum_{j=1}^{p} \alpha_j \ln X_{ij} + \sum_{j=1}^{p} \beta_j D_{ij} + \sum_{k=1}^{p} \varphi_k E_{ik} + v_i - u_i \quad (7)$$

and

$$u_i = \delta_0 + \sum_{d=1}^{p} \delta_d Z_{id} + \zeta_i \quad (8)$$

where E_{ik} are the environmental production condition variables and φ_k is the parameter to be estimated. The production inputs (X), environmental production condition variables (E), and variables representing managerial and socioeconomic characteristics of the farmer (Z) are considered to be included in the inefficiency effects model as predictors of technical inefficiency in both short and full specifications. Table 1 presents the variables and their units of measurement.

Several statistical tests were conducted to identify the most appropriate specification of the stochastic frontier model. Among these, the likelihood ratio (LR) test was employed to compare alternative model formulations. Four specifications were developed: Models 1 and 3 excluded environmental variables, while Models 2 and 4 incorporated environmental variables to account for their potential influence on production efficiency.

3.2 Data

Cross-sectional data were collected through structured face-to-face interviews to ensure reliable responses. This approach is well suited to rural settings, where literacy and familiarity with self-administered questionnaires may vary, and direct interaction enhances data quality (Opdenakker, 2006). The study focused on key independent smallholder states in Peninsular Malaysia – Johor, Perak and Pahang (see Figure 1). Johor, Perak and Pahang were selected because they are among the major oil palm-producing states in Peninsular Malaysia and host a large concentration of independent smallholders, which aligns with the focus of this study. These states also exhibit substantial agroecological heterogeneity in terms of land type, soil characteristics, rainfall patterns and exposure to environmental risks, allowing for meaningful analysis of environmental effects on technical efficiency. Moreover, their policy relevance under national smallholder development and sustainability programmes enhances the applicability of the study's findings.

This study adopted a stratified proportional-to-size (PPS) sampling design by first stratifying independent oil palm smallholders by state (Johor, Perak and Pahang) and allocating the target sample according to each state's share of the total smallholder

Table 1. Variables in the stochastic frontier and technical inefficiency model

Variables	Measurement
Input and Output	
Palm oil output	tonnes per year
Land size	acre
Seed	MYR per year
Mechanical power (capital)	MYR per year
Fertilizer	MYR per year
Pesticide and herbicide	MYR per year
Irrigation	MYR per year
Labour	MYR per year
Environmental variables	
Land type	Dummy (1 = low level; 0 = medium and high levels)
Soil type	Dummy (1 = mix soil; 0 = loamy/peat or organic/ clay loam)
Rainfall	mm per year
Average temperature	degree celsius
Humidity	Dummy (1 = medium; 0 = low/high)
Sunlight	hours
Flood	% of crop yield affected
Drought	% of crop yield affected
Managerial & demographic variables	
Age	years old
Gender	Dummy (1 = male; 0 = female)
Marital status	Dummy (1 = married; 0 = single/widow/widower)
Education	Dummy (1 = no education; 0 = primary/secondary/ diploma/bachelor/postgraduate)
Household size	unit
Experience	years
Household income	MYR per month
State	Dummy (1= Johor; 0 = others)
Training	Dummy (1= received training in the last few years; 0 = No training)
Source of procuring seed	Dummy (1 = received from government; 0 = own expenses)
Sources of agricultural information	Dummy (1 = Internet; 0 = other sources)

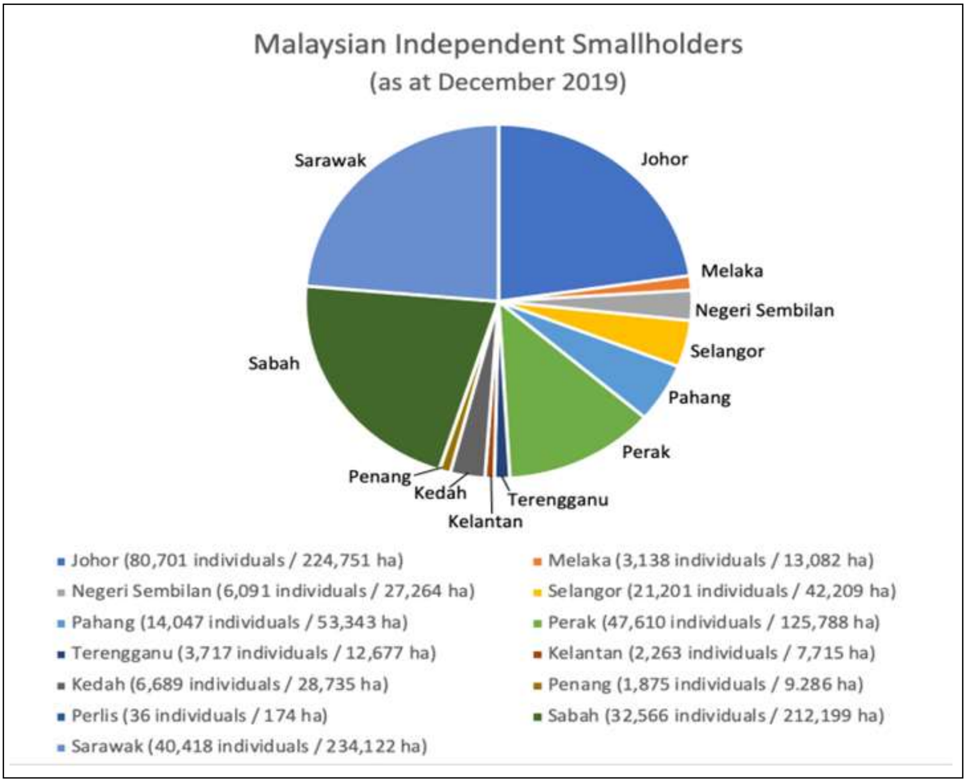

Figure 1. Malaysian independent smallholders
Source: MPOB (2020).

population based on MPOB records. A total sample of 180 smallholders was determined using Cochran's formula at a 95% confidence level and ±7.5% margin of error, with 5% added for non-response. Stratified proportional-to-size sampling based on MPOB records yielded about 80 respondents from Johor, 56 from Pahang, and 44 from Perak. Respondents were randomly selected from MPOB's registry, with replacements pre-listed. The pooled margin of error was ±7.5% and state-level margins ranged from ±11% to ±15%.

However, the final realised sample distribution differs slightly from the population proportions shown in Figure 1 due to field constraints such as incomplete farmer lists, non-response, accessibility issues and the need to secure a minimum number of observations per state for reliable stochastic frontier estimation. The study obtained the targeted sample of 180 independent smallholders, proportionally distributed across Johor (85), Pahang (65) and Perak (30). These deviations do not compromise the analysis, as stratification ensures representation across key regions and the econometric framework controls for state-level and environmental heterogeneity at the farm level.

The questionnaire comprised three sections: Section A captured socio-economic characteristics (age, gender, ethnicity, religion, education, income, farm size, family size); Section B gathered farm-related data (expenditure, revenue, inputs, outputs and other plantation factors); and Section C focused on environmental conditions (soil and land type). Additional data on temperature and rainfall were obtained from the Malaysian Meteorological Department. Variable details are shown in Table 1.

To ensure reliability and validity, the instrument was reviewed by two experts – academicians and palm oil production specialists – and piloted with a smaller sample to refine wording and remove ambiguities. Ethical approval was not required as only non-sensitive, non-identifiable information was collected. Participation was voluntary, and informed consent was obtained from all respondents prior to interviews.

4. Results and Discussion

4.1 Preliminary Results

The study achieved the targeted sample of 180 independent smallholders, proportionally distributed across Johor (85), Pahang (65) and Perak (30), ensuring representation from the main smallholder-producing states in Peninsular Malaysia. Tables 2 and 3 present the descriptive statistics of the continuous and categorical variables, respectively.

For continuous variables (Table 2), the average annual palm oil output is 91.1 tonnes (range: 30–150; SD = 35.2), indicating wide productivity variation. Land size averages 15.7 acres (range: 2–30), reflecting diverse operational scales. Mean annual expenditures include MYR315 on seeds, MYR4,890 on fertiliser, MYR2,391 on

Table 2. Descriptive statistics

Variable	N	Min	Max	Mean	Std. dev.	Skewness	Kurtosis
Output (tonnes)	180	30	150	91.12	35.23	-0.043	-1.188
Land size (acre)	180	2	30	15.70	8.08	0.044	-1.219
Seed (MYR)	180	103	499	315.02	118.37	-0.210	-1.307
Capital/mechanical power (MYR)	180	5833	32373	19207.19	7319.64	0.035	-1.018
Fertiliser (MYR)	180	2038	7986	4890.16	1736.20	0.127	-1.157
Pesticide and herbicide (MYR)	180	1002	3989	2390.58	867.24	0.156	-1.193
Irrigation (MYR)	180	1213	5355	3426.44	1148.90	-0.197	-1.105
Labour (MYR)	180	1655	19718	9646.99	3544.73	0.187	-0.340
Average temperature (Celsius)	180	26	28	27.02	0.57	-0.045	-1.160
Rainfall (mm)	180	2507	2998	2717.74	112.96	0.344	-0.282
Sunlight (hours)	180	6	10	7.94	1.44	0.008	-1.352
Flood (%)	180	0	30	15.27	9.16	-0.046	-1.279
Drought (%)	180	0	20	10.39	5.86	-0.030	-1.133
Age (year)	180	21	70	45.97	15.27	-0.009	-1.332
Family size (unit)	180	2	8	4.98	1.92	-0.054	-1.172
Experience (years)	180	1	40	21.25	11.78	-0.094	-1.218
Household income	180	2020	6999	4582.01	1474.21	-0.044	-1.205

Note: The statistics are only for continuous variables.

Table 3. Frequency of categorical variables

Variable		Frequency	Percent
State	Pahang	65	36.1
	Johor	85	47.2
	Perak	30	16.7
	Total	180	100.0
Gender	Male	86	47.8
	Female	94	52.2
	Total	180	100.0
Educational level	No formal education	34	18.9
	Primary	39	21.7
	Secondary	35	19.4
	Pre-uni, STPM, diploma	33	18.3
	First degree	39	21.7
	Total	180	100.0
Ethnicity	Malay/Bumiputera	180	100.0
	Non-Malay/Bumiputera	0	0
	Total	180	100.0
Marital status	Married	62	34.4
	Single	59	32.8
	Widower/widow	59	32.8
	Total	180	100.0

pesticides/herbicides, MYR3,426 on irrigation, and MYR9,647 on labour, showing labour and fertiliser as the largest cost components. Skewness and kurtosis values are close to zero, indicating relatively normal distributions.

Environmental data show stable temperatures (27°C), average annual rainfall of 2,718 mm, and about eight daily sunlight hours. Floods and droughts reduce yields by an average of 15% and 10%, respectively, highlighting the impact of climate shocks. Socio-demographically, respondents average 46 years in age (range: 21–70) and 21 years of farming experience, with mean monthly household income at MYR4,582 and family size averaging five.

Overall, these descriptive statistics reveal substantial heterogeneity in farm size, input use, environmental exposure and farmer characteristics, underlining the importance of including environmental variables in the stochastic frontier analysis to avoid biased efficiency estimates.

Table 3 summarises the socio-demographic and regional profiles of the sampled independent smallholders. Most respondents are from Johor (47.2%), followed by Pahang (36.1%) and Perak (16.7%), reflecting the major smallholder regions in Peninsular Malaysia. The sample is fairly gender-balanced (52.2% female, 47.8% male), showing the active role of women in oil palm cultivation. Educational attainment varies:

18.9% have no formal education, while 21.7% hold a degree, indicating a mix of low and high education levels that may influence adoption of better practices.

All respondents are Malay/Bumiputera (100%), consistent with the ethnic composition of smallholders in these states. Marital status is evenly distributed (34.4% married, 32.8% single, 32.8% widowed), suggesting varied household structures that may affect labour use and decision-making. Overall, the sample reflects diversity in education, gender and household structure, while being regionally and ethnically concentrated, providing important context for interpreting the efficiency results.

Tables 2 and 3 reveal considerable heterogeneity among independent smallholders in output, land size and input use, with labour and fertiliser as major costs. Environmental shocks (floods, droughts) notably reduce yields. Continuous variables are near-normally distributed, supporting robust econometric analysis, while categorical data show most farmers are in Johor and Pahang, with balanced gender, varied education and predominantly Malay/Bumiputera ethnicity. These patterns reflect the diverse socio-economic and environmental factors influencing smallholder efficiency. These descriptive patterns also provide initial insights into the production environment faced by independent smallholders and are further examined through the stochastic frontier results below.

4.2 Stochastic Frontier Estimates (Production Function Results)

To examine factors affecting palm oil yield and assess technical efficiency, this study applies a Cobb–Douglas stochastic frontier production function (SFPF). Likelihood ratio tests guided the selection of the preferred model. Economic efficiency comprises technical and allocative components, with technical efficiency measuring how closely actual output approaches potential output given inputs. Given the small sample, results are interpreted cautiously, however, the variance parameters (λ and σ) are significant at the 1% level (see Table 4), confirming the suitability of the SFPF in capturing inefficiency effects.

The stochastic frontier production function (SFPF) distinguishes random noise (e.g., weather, measurement errors) from production inefficiency, requiring an assumption about the inefficiency distribution. The half-normal (*hnormal*) model assumes inefficiency is always positive and symmetrically centred at zero, while the truncated-normal (*tnormal*) model allows a non-zero mean to capture systematic differences across producers. As the truncated-normal model better accounts for heterogeneity, it is used as the baseline in this study, with the half-normal model applied as a robustness check. The results in Table 4 reveal that the estimated stochastic frontier production function fits the data well and provides meaningful insights into the production structure of independent oil palm smallholders.

Several input elasticities are statistically significant and exhibit expected signs, while others are surprising and warrant further discussion. Labour, irrigation, pesticide and herbicide expenditures, temperature, sunlight and humidity are positively associated with output. This is consistent with agronomic theory and previous empirical findings that better labour input improves crop care and harvesting (Hasnah et al., 2004), that water management and pest control raise yields, and that warm and sunny conditions

Table 4. Maximum likelihood estimates of the stochastic frontier production function

Variable	(1) tnormal distribution	(2) tnormal distribution	(3) hnormal distribution	(4) hnormal distribution
Stochastic frontier (dependent variable = loutput)				
llandsize	-0.0119***	0.0062***	-0.0119***	0.0016***
	(3.48e-06)	(4.21e-06)	(5.49e-09)	(6.32e-06)
lseed	-0.017***	0.0257***	-0.0170***	0.0163***
	(4.53e-06)	(7.45e-06)	(7.08e-06)	(9.69e-06)
lirr	0.0192***	0.8893***	0.0192***	0.0806***
	(8.66e+06)	(0.00001)	(0.00013)	(0.00006)
lcap	-0.0075***	0.0188***	-0.0075***	0.0107***
	(3.15e-06)	(5.71e-06)	(4.90e-06)	(0.00001)
lfert	-0.0744***	-0.0423***	-0.0744***	-0.0529***
	(7.89e-06)	(8.94e-06)	(0.00001)	(0.00002)
lpest	0.0428***	0.0078***	0.0429***	0.0145***
	(5.19e-06)	(7.54e-06)	(9.71e-06)	(0.00002)
llabor	0.02226***	0.0317***	0.02226***	0.01612***
	(2.53e-06)	(6.06e-06)	(4.26e-06)	(9.69e-06)
lrain		-0.6711***		-0.2673***
		(0.00011)		(0.00037)
ltemp		1.1702***		1.1008***
		(0.00021)		(0.0011)
Dummy_land type		0.0254***		0.0262***
		(7.41e-06)		(0.00002)
Dummy_soil type		0.0091***		0.0159***
		(6.13e-06)		(0.00003)
Dummy_humidity		0.0176***		0.0055***
		(8.29e-06)		(0.00002)
Sunlight		0.0571***		0.0282***
		(8.29e-06)		(0.00002)
Flood				-0.0009***
				(1.15e-06)
Drought				-0.00009***
				(3.32e-06)
constant	5.1268***	5.2332***	5.1268***	2.7347**
	(0.00015)	(0.0009)	(0.0002)	(0.0073)
Efficiency model (dependent variable = TE)				
Dummy_state	0.28007	0.4697*		
	(0.2165)	(0.2605)		
Dummy_info internet	0.21017	0.2485		
	(0.2162)	(0.2417)		
constant	-0.3937	-0.6647		
	(0.4136)	(0.5344)		
sigma_u	0.7807***	0.8212***	0.7172***	0.7051***
sigma_v	8.48e-09	1.08e-08	7.71e-09	1.04e-08
lamda	9.21e+07***	7.59e+07***	9.30e-07***	6.79e+07***
Log likelihood	-69.1277	-64.855	-70.8088	-67.7621
Number of observations	180	180	180	180
Wald Chi-square (*prob*)	4.31e+08	5.98e+08	1.49e+08	3.61e+08
	(0.000)	(0.000)	(0.000)	(0.000)

Note: The TE model could only be developed using truncated-normal (*tnormal*) distribution. It could not be developed using half-normal (*hnormal*) distribution.

favour oil palm growth. Irrigation in particular shows a strong positive effect, which becomes much larger in magnitude once environmental variables are included, suggesting that irrigation is especially beneficial in areas where natural rainfall or soil conditions are poor. This confirms earlier evidence that water availability is a key determinant of oil palm productivity (Norizan et al., 2021).

By contrast, fertiliser use shows a consistently negative and significant effect on output, which is counterintuitive. A plausible explanation is that many farmers are applying fertilisers at inappropriate rates, of poor quality, or at the wrong time, resulting in nutrient imbalances, leaching losses, or soil acidification that actually harm plant growth. This could also be linked to soil constraints such as low pH, poor cation balance, or organic matter depletion, which reduce the effectiveness of applied nutrients. Excess rainfall and flooding – both of which show negative effects in the model – may also be leaching nutrients, making fertiliser investments ineffective. This aligns with concerns in the literature that indiscriminate use of chemical fertilisers without soil testing can reduce soil health and yields (Mahmud et al., 2021). The negative fertiliser elasticity thus serves as an important signal that site-specific nutrient management and soil rehabilitation measures are urgently needed.

Land size shows mixed effects: negative in some specifications and positive in others. This pattern suggests that when environmental variables are omitted, larger plots may appear less productive due to lower intensity of management, but once differences in land quality and conditions are controlled for, larger farms show slightly better productivity. This change in sign highlights the importance of including environmental production conditions in the model. A similar pattern is seen for capital (mechanical power) and seed expenditure, which alternate between small positive and negative coefficients depending on specification. These inconsistencies likely reflect heterogeneity in the quality and effective use of these inputs across farmers. Some smallholders may be using low-quality seeds or poorly maintained equipment, which would reduce the expected productivity impact.

Environmental variables such as rainfall, temperature, sunlight, humidity, soil type and land type are also found to have significant effects on production. Rainfall shows a negative and significant effect, possibly indicating that excess rainfall and poor drainage reduce yields through waterlogging, disease and nutrient leaching. Conversely, temperature is positive and significant, which may reflect the beneficial effect of slightly warmer conditions within the narrow tropical temperature range on oil palm growth. Dummy variables for soil type, land type and humidity are also significant, and their inclusion markedly changes the estimated elasticities of other inputs. This finding aligns with the arguments of Rahman and Hasan (2008) and Sherlund et al. (2002) that failing to account for environmental production conditions can bias production function estimates and overstate technical inefficiency. Overall, the results confirm that both managerial and environmental factors play critical roles in explaining oil palm smallholder productivity, with environmental heterogeneity having a particularly large influence.

The average technical efficiency (TE) is estimated at around 0.63, with minimum values as low as 0.20 and some farmers achieving near-perfect efficiency (see Table 5). This indicates that, on average, smallholders are producing only about 63% of their potential output, implying a substantial scope to improve productivity by addressing

Table 5. Descriptive statistics of technical efficiency

Variable	Model	Obs.	Mean	Std. Dev.	Min.	Max.
Technical efficiency	2	180	0.6315	0.2465	0.2022	0.9999
Technical efficiency	4	180	0.6319	0.2455	0.2033	0.9999

Note: Models 2 and 4 are from regressions 2 and 4, respectively, in Table 4.

inefficiency. The large and statistically significant variance parameter (σ_u) and the high lambda (λ) values confirm that most of the deviation from the frontier is due to technical inefficiency rather than random noise. This suggests that management- and practice-related factors, rather than measurement errors or random shocks, are the main causes of the yield gap.

The mean TE estimate of 0.63 is consistent with earlier studies on smallholder oil palm that found TE values in the range of 0.59–0.66 (Hasnah et al., 2004; Abdul et al., 2023), though some other studies in different settings reported higher efficiency (Fitri & Nainggolan, 2023). The lower TE in this study indicates substantial room to raise output without increasing input use, through measures such as improving fertiliser practices, better drainage and irrigation infrastructure, and more targeted pest and disease control. Given the dominance of inefficiency over random shocks in explaining output gaps, such interventions are likely to yield tangible gains. Moreover, because environmental conditions significantly affect productivity, extension and support programs should be tailored to local soil, land type and climatic conditions rather than using one-size-fits-all recommendations.

The stochastic frontier analysis thus shows that environmental conditions strongly influence input elasticities and efficiency estimates among independent oil palm smallholders. Including variables such as rainfall, temperature, soil type and climate shocks significantly altered input coefficients, confirming that environmental heterogeneity is a major determinant of productivity. Ignoring these factors leads to biased estimates, as noted by Rahman and Hasan (2008) and Sherlund et al. (2002), who found that omitting environmental variables overstates inefficiency by attributing environmental yield variation to managerial shortcomings. Incorporating these variables reduced unexplained variance, showing that some farmers deemed inefficient actually face less favourable conditions.

These results imply that productivity strategies should be site-specific, addressing local agroecological constraints, for example, improving drainage in flood-prone areas or tailoring fertiliser use to soil fertility rather than applying generic input-intensive approaches. Improving technical efficiency also requires addressing environmental constraints alongside management training. Methodologically, the study underlines the need to integrate environmental data into frontier models to avoid overstating managerial inefficiency and to produce more accurate, policy-relevant insights.

5. Conclusion and Policy Implications

This study finds that independent oil palm smallholders operate with notable technical inefficiency and that environmental conditions strongly shape productivity outcomes.

Models including factors like rainfall, temperature, soil and land type, and climatic shocks better distinguish between yield gaps from environmental constraints and those from managerial inefficiency, avoiding misdiagnosis that could lead to misguided policies.

Policy implications are clear. Productivity interventions must be site-specific, addressing local agroecological constraints (e.g., soil testing, customised fertiliser, drainage and water management) rather than relying on generic input-intensive strategies. Advisory systems, subsidies and credit schemes should incorporate environmental diagnostics to align support with local conditions and improve input efficiency. Efforts to enhance technical efficiency should also combine managerial training with investments in environmental infrastructure such as drainage, irrigation and soil rehabilitation to enable productivity gains in ecologically disadvantaged areas. Future research should further combine environmental and biophysical data (e.g., soil nutrients, topography, climate patterns) to better understand smallholder productivity.

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