Soil Properties and the Technical Efficiency of Paddy Production in Malaysia: An Application of Stochastic Frontier Analysis

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Abstract: This study investigates the impact of soil properties on technical efficiency in paddy production, focusing on Malaysia's two main paddy granaries: KADA and IADA BLS. These granaries play a significant role in Malaysia's paddy production. The research employed three different models, with productivity as the dependent variable. In models 1 and 2, standard physical inputs were used as independent variables. Model 3, however, augmented the inputs with the addition of soil property variables. The stochastic frontier model was analysed using the maximum likelihood estimation method. The empirical results revealed significant impacts from fertiliser, pesticide and land inputs, with the exception of land in model 1, where its coefficient was not statistically significant. Additionally, soil pH and the calcium+magnesium/potassium ratio emerged as crucial factors affecting paddy productivity. Importantly, incorporating soil property variables into the analysis resulted in a relatively lower technical inefficiency estimate. These insights are invaluable for policy formulation, highlighting key inputs that can optimise paddy production. The study's findings regarding soil properties are particularly relevant for refining strategies in national paddy development programs, emphasising the importance of sustainable soil management. Looking ahead, the study advocates for comprehensive technical efficiency estimations that account for all forms of heterogeneity, including weather conditions, to ensure more accurate and insightful assessments.

Keywords: Maximum likelihood estimation, paddy production, Cobb-Douglas, translog, soil properties
JEL classification: O130, Q180, Q120

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1. Introduction

Agricultural practice encompasses a set of principles adopted by farmers throughout the production process to achieve two primary objectives: high yield and profit. In paddy production, key agricultural practices include land preparation, sowing, water management, fertiliser application, pest and disease management and harvesting. Various agencies, with the Ministry of Agriculture and Food Industries (MAFI) of Malaysia being a primary source, have published standard guidelines for proper agricultural practices. However, agricultural practices adopted by farmers vary across granaries and fields, influenced by local culture, socioeconomic factors, production goals and individual perceptions. This variation is a major factor contributing to disparities in yield production. Beyond selecting specific production techniques, each farmer makes distinct decisions regarding the types and quantities of inputs, as well as the frequency and timing of their application. The observable differences in agricultural practices among farmers are numerous, and with countless agronomic managements being applied, there is a continual process of development. These practices ultimately determine the extent to which inputs affect yield levels and the observed yield gap.

According to economic theory, decisions regarding alternative production processes, especially input allocation, are pivotal in determining output. In paddy production, a farmer's proficiency in making sound decisions about the use of available technology is crucial for performance, and this proficiency is closely associated with their level of technical efficiency. Production theory posits that for a given technology, observations of the input-output relationship in the production process should lie on a single production function. However, in practice, this theory is not perfectly realised due to firm-specific factors, leading to variations in resource utilisation efficiency. This variation underscores the differing efficiencies with which firms utilise technology, with some being more efficient than others. Consequently, the technical efficiency of agricultural production has been a subject of extensive research.

However, the majority of frontier efficiency studies often overlook soil properties factors, which are prominently emphasised in the agronomy and production ecology studies of the crop growth models (De Koeijer et al., 1999; Hoang, 2013; Van Dijk et al., 2017). In many cases, the direct consequence of this oversight is an increase in estimates of technical inefficiency, as any heterogeneity not accounted for by input factors, mainly soil properties, is attributed to technical inefficiency (Greene, 2017; Karagiannis & Kellermann, 2019; Sherlund et al., 2002).

Thus, the main objective of this study is to evaluate the influence of soil properties factors on the technical efficiency of paddy production in the main granary areas of Malaysia. The study extends the framework of existing frontier methodology for estimating efficiency by incorporating soil properties components into the stochastic frontier analysis (SFA) model.

The study places significant emphasis on soil properties, acknowledging that the input-output interaction in agricultural production, particularly in the paddy sector, is highly dependent on location. This refers to the environmental characteristics, namely the chemical and physical aspects of the production environment, where crop production occurs. It is suggested that when particular production practices are implemented in different biophysical environments, the yield may vary due to the crop's response to each environment. Both the chemical and physical aspects of the environment can influence potential crop yield or the level of optimal input required to attain a specific crop yield. On the contrary, agricultural activities may also impact the biophysical environment, although such effects are not immediate, given the smaller time coefficient of agricultural practices compared to that of the production environment (Van Ittersum & Rabbinge, 1997). The biophysical environment encompasses factors such as soil chemistry, physical properties, nutrient pools and abiotic factors in the soil and atmosphere like temperature and rainfall that affect crop activity (Al-Kaisi et al., 2017; Silva et al., 2017; Van Ittersum & Rabbinge, 1997). Biophysical environment factors, particularly soil properties, differ from field to field, influencing resource utilisation efficiency and, ultimately crop yield (Rabbinge, 1993; Van Ittersum & Rabbinge, 1997; Yanai et al., 2001). Consequently, overlooking any existing heterogeneity in these models could result in less accurate efficiency estimates.

The technical efficiency of paddy production has been extensively studied in developing countries, especially in Asia, where disparities in technical efficiency are a primary contributor to low paddy productivity levels. Efficiency research is vital for identifying methods to enhance paddy productivity without increasing resource use or relying on new technologies, which are often limited in these economies (Dam et al., 2019). As such, efficiency is a key driver of productivity growth. Improving farmers' technical efficiency is paramount to addressing the rising demand for rice. In the context of Malaysia, where resources and new technologies are limited, arable land is diminishing, and the population is growing, improving efficiency becomes increasingly critical in paddy production. Enhancing efficiency is not only pivotal for increasing crop yields but also ensuring Malaysia's food security.

Many efficiency studies focus on agricultural production, with paddy crops being a significant global subject. Similar research has also been conducted in Malaysia. However, none of the efficiency studies conducted in Malaysia take into account the variations in soil properties of the paddy fields. This oversight has led to a notable knowledge gap regarding the impact of soil properties on technical efficiency and productivity in Malaysian paddy fields. Furthermore, the potential influence of soil properties on paddy productivity may be underrepresented in the development of paddy cultivation strategies.

Thus, the novelty of this study lies in its extension of the framework established by previous researchers, by incorporating new variables of soil properties into the SFA models. This research aims to shed light on at least two aspects: firstly it examines the impact of soil property components such as pH, nitrogen, phosphorus, potassium, Ca:Mg, and (Ca+Mg)/K ratio on paddy productivity; secondly, it seeks to provide more precise estimates of technical efficiency and to discern the disparities in inefficiency estimates between the full model (which includes soil properties) and the more simplified model.

This paper is organised into five main sections. The first section provides an introduction, delineating the study's background, research objectives and its significance. The subsequent section offers a literature review, focusing on soil properties and the estimation of technical efficiency. The third section details the data and methodology employed in the study. This is followed by the fourth section, which discusses the results and includes a comprehensive discussion. Finally, the fifth section presents the study's conclusions.

2. Literature Review

This section presents an extensive review of the literature, encompassing the theory, methodology, and empirical findings related to the effects of soil properties on the technical efficiency of paddy production. It begins by establishing foundational theories and definitions of technical efficiency. The section then progresses to explore heterogeneity in paddy production, primarily attributed to biophysical environmental factors, with a particular emphasis on soil properties. It further elucidates various aspects of soil properties, including soil pH, nitrogen (N), phosphorus (P), potassium (K), and soil cation ratios. Additionally, this section reviews empirical studies that analyse the impact of soil property components on the estimation of technical efficiency. Finally, it identifies and highlights gaps in existing studies, setting the stage for further discussion and analysis in subsequent sections.

The neoclassical theory of production presupposes full technical efficiency for all firms, positing that they operate at the production frontier and utilise best practices for their given technology level. According to this theory, any observed inefficiency is attributed solely to allocative inefficiency. However, in reality, firms' performances often deviate from this theoretical ideal of complete technical efficiency. While some firms are relatively efficient and operate at the potential frontier, others operate below this potential frontier (Kalirajan & Shand, 1999). Technical efficiency is defined as a firm's ability either to produce the maximum output from a given set of inputs and technology (output maximisation) or to minimise inputs for producing a unit of output (input minimisation) (De Koeijer et al., 2002; Thiam et al., 2001; Van Dijk et al., 2017). It is quantified by measuring the observed firm's distance from the production frontier, indicative of best-practice performance. Importantly, technical efficiency is distinct from technical change (TC), which is characterised by an outward shift of the frontier due to technological advancements (Bravo-Ureta et al., 2007; Fare et al., 1994; Van Dijk et al., 2017).

The estimation of technical efficiency hinges on two primary components: physical inputs and output. Common physical inputs include land, labour, fertiliser, pesticide, seed and equipment, while the output is generally measured as crop yield. Agriculture production is significantly influenced by the locally specific biophysical environmental factors, varying from field to field, playing a critical role in affecting resource utilisation efficiency and crop yield (Rabbinge, 1993; Van Ittersum & Rabbinge, 1997; Yanai et al., 2001). However, most frontier efficiency studies often overlook these biophysical environmental factors, despite their prominent emphasis in the agronomy and production ecology of crop growth models (De Koeijer et al., 1999; Hoang, 2013; Van Dijk et al., 2017). The consequence of this oversight, which leads to the neglect of potential heterogeneity, may result in significantly biased parameter estimates and an overestimation of technical inefficiency (Karagiannis & Kellermann, 2019; Mar et al., 2018; Rahman & Hasan, 2008; Sherlund et al., 2002).

Two main biophysical environmental factors impacting agricultural production are weather and soil properties (Silva et al., 2017). Weather variables, such as rainfall and temperature, are considered truly exogenous, while soil properties are seen as quasi-fixed elements (Rahman & Hasan, 2008; Sherlund et al., 2002). Soil properties hold particular relevance for farmers as they can be moderately improved through the application of suitable inputs and effective agricultural practices. Specifically, soil properties have a direct influence on both the input and output of agricultural production. Therefore, including soil properties in the estimation of technical efficiency is crucial, as they impact the availability of inputs, thereby affecting plant yield and overall productivity (Van Dijk et al., 2017, 2020). Indeed, soil properties are integral to growth-limiting factors in the yield response function, with the plant's response being influenced by the availability and concentration of soil property components and their interaction with applied inputs (Dobermann et al., 1996b; Van Ittersum & Rabbinge, 1997). Suboptimal environmental conditions can hinder plant growth and yield, preventing them from reaching their potential (Silva et al., 2017).

The plant depends on soil for support, with the soil providing an optimal environment for the plant to take root. Soil primary functions to store and supply water and nutrients to plants. However, soil characteristics vary significantly across different locations, largely due to its inherent properties. These properties influence a plant's capability to absorb water and extract specific nutrients. Fertile soil is essential for promoting optimal plant growth and enabling plants to achieve their maximum yield potential. One of the most critical factors in this context is the soil's pH level, which determines the plant's access to soil nutrients by influencing chemical reactions and regulating the chemical forms of certain minerals. An imbalance in soil pH can contribute to either an excess or a deficiency of specific nutrients, significantly impacting nutrient uptake (Fernández & Hoeft, 2009). Generally, the ideal soil pH range for effective nutrient uptake lies between 5.5 and 8 (Husson, 2013).

Yield variability is influenced not only by soil pH but also by other soil properties, including total Nitrogen (N), available phosphorus (P) and iron (Fe), exchangeable potassium (K), magnesium (Mg) and calcium (Ca) (Trangmar et al., 1987). These elements, essential for plant growth, are absorbed from the soil or supplemented through fertilisers. Typically, these minerals are categorised into primary and secondary macronutrients. Nitrogen, phosphorus and potassium are the primary macronutrients, while calcium, magnesium, iron and sulphur are secondary macronutrients. These macronutrients are vital for plant metabolism and provide resilience against various abiotic stresses (Tripathi et al., 2014). Furthermore, soil science recognizes an important classification known as soil cation saturation, which includes certain elements from both primary and secondary macronutrients, such as Mg, K, Na, Ca and Al.

Cationic nutrients are essential for plant growth. Beyond their individual roles, the interaction among these nutrients significantly influences their availability to plants and other nutrients. Potassium, magnesium and calcium can interfere with each other during plant absorption, where an excess of one may lead to a depletion of the others (Voogt, 1985). The basic cation saturation ratio philosophy posits that 6.5 is the ideal Ca:Mg ratio (Hodges, 2010). However, Phillips (2015) contends that this ideal ratio varies with texture, suggesting a 3:1 ratio in sandy soil and a 7:1 ratio in clay soil, especially considering Ca's role in loosening heavy soil. A low exchangeable Ca to Mg ratio, below the ideal, impedes Ca uptake and leads to excessive Mg consumption (Jones, 1999; Nguyen et al., 2016, 2017). Conversely, a high ratio of Ca and Mg to K (Ca+Mg/K) can limit K uptake, hindering the plant's ability to extract K from the soil, even when it is present in abundance (Biswas et al., 2019; Dobermann et al., 1996a; Nguyen et al., 2017). High levels of Ca and Mg can originate from water sources, particularly groundwater, and become concentrated in the soil system. Owing to their higher positive charges, Ca and Mg are less prone to leaching compared to K (Hodges, 2010).

Relatively few studies have incorporated soil variability into the estimation of technical efficiency. These studies have integrated various soil property variables into their models, including soil available nitrogen (N,) phosphorus (P), and potassium (K), as well as soil organic carbon in paddy production (Rahman, 2009), and soil type, soil organic carbon and soil pH in maize crop analysis (Van Dijk et al., 2017). Most of these variables were found to significantly impact crop yield. These findings underscore the critical role of soil properties in agricultural production. They highlight how soil properties influence the relationship between the inputs supplied and the resultant output performance, thereby affecting farmers' efficiency.

In a distinct study, Rahman and Hasan (2008) estimated the technical efficiency of wheat production, considering both models with and without environmental variables. Their findings revealed that factors such as soil fertility, late sowing and land type significantly affect crop yield. Notably, the mean efficiency of the full model with environmental controls was four percentage points higher, suggesting that neglecting environmental variables can lead to a higher estimation of inefficiency. This conclusion aligns with the previous study by Sherlund et al. (2002), who found that omitting environmental variables increases estimates of farm technical inefficiency. In their study, the environmental variables included rainfall, number of rainy days, soil erosivity, soil fertility, plot slope, and pest and disease infestation, with most of these variables significantly impacting paddy production. Similarly, Silva et al. (2017) incorporated various soil propertiy variables such as clay and sand content, soil organic carbon, available phosphorus, and exchangeable potassium in a full model, while omitting these variables in a more simplified model. Their results indicated that technical efficiency estimates were 1.5 percentage points higher in the full model that included soil properties.

This study introduces a novel approach by extending the framework established by prior researchers, incorporating new variables of soil properties into the SFA models. The findings of this study are anticipated to illuminate two key aspects. Firstly, it aims to examine the impact of soil property components such as pH, nitrogen, phosphorus, potassium, Ca:Mg and (Ca+Mg)/K on paddy productivity. Secondly, the study seeks to provide more accurate estimates of technical efficiency, and to identify the differences in inefficiency estimates between the full model (which includes soil properties) and the simplified model.

Generally, soil properties are incorporated into the SFA model to enhance the precision of technical efficiency estimation. While some soil property components have been examined, the impact of soil cation ratios of K, Ca and Mg on technical efficiency remains relatively unexplored, despite their known influence on plant nutrient absorption. Furthermore, to the best of the authors' knowledge, no efficiency studies conducted in Malaysia have considered the impact of soil properties on agricultural production. Therefore, this study seeks to evaluate the influence of soil properties, with a particular focus on the newly introduced variable of soil cation ratios, on paddy yield and technical efficiency. The findings are expected to significantly contribute to the existing body of knowledge regarding the effects of soil properties on paddy production, especially concerning the Ca:Mg and (Ca+Mg)/K ratios. This study also aims to elucidate the effects of controlling soil property components on technical efficiency estimates, potentially leading to more accurate estimations of technical efficiency. Additionally, the study intends to explore the optimal quantification of physical inputs, primarily labour and pesticide variables, as these are essential for an improved estimation of technical efficiency.

3. Methodology

The analysis primarily utilised primary data, complemented by secondary data, including soil property factors. Primary data collection occurred from January to March 2022. Due to the model's requirement for both secondary data on soil properties and primary data on paddy production inputs, outputs and agricultural practices, respondents were selected from sub-units of granaries that had undergone soil profiling. The study focused on KADA's[1] Jajahan Pasir Putih and IADA BLS's[2] Bagan Terap and Pancang Bendena. These locations were chosen as they represent sub-units of granaries where soil profiling had been completed, and data were available at the time of primary data collection. The samples comprised randomly selected farmers from these granary sub-units. Data collection involved individual or small-group interviews with these farmers at their respective locations. Soil property data, including coordinates for each paddy field plot, were obtained from the respective granaries. The plot coordinates, sourced from i-plan Malaysia based on the plot numbers provided by respondents, were then matched with the soil properties data using *Google Earth Pro* software.

A structured questionnaire was developed as the primary tool for data collection. This questionnaire comprised three major sections: socio-economic and demographic information of farmers, paddy planting information and institutional data. The first section delved into various socio-economic and demographic aspects of the farmers, including age, gender, education and income. The second section, focusing on paddy planting information, encompassed questions about all inputs used, yield produced and agricultural practices. The final section gathered data on development programs for farmers offered by various institutions. To ensure comprehensive data collection, the questionnaire underwent a series of cross-validations with experts from both granaries.

[1] The Kemubu Agricultural Development Authority (KADA) is one of the main paddy granaries in Malaysia, situated in the state of Kelantan on the East Coast of Peninsular Malaysia.

[2] The Integrated Agriculture Development Area Barat Laut Selangor (IADA BLS) is one of the IADA granaries, located in the West Coast of Peninsular Malaysia.

The study involved a total of 80 respondents,[3] a sample size deemed sufficient to achieve the objectives, as supported by the arguments in relevant literature (Andor & Hesse, 2011; Coelli, 1993; Thiam et al., 2001).

3.1 Research Framework

The foundational concepts of this research are grounded in production theory and the yield response function. Production theory primarily elucidates the transformation of physical inputs into outputs, with its function illustrating the technical relationship between these inputs and the resultant output. A central tenet of production theory is that an increase in input quantities generally leads to an increase in output, adhering to a specific production function. However, this proportionate increase in output corresponding to input increases assumes that observations are perfectly efficient and located at the production frontier. In practice, though, a multitude of firms exhibit varying degrees of inefficiency.

From an agronomic perspective, the relationship between inputs and outputs in agriculture is often characterised as a yield response function. The output in this function is determined by three major components: growth-defining, growth-limiting and growth-reducing factors (Rabbinge, 1993; Van Dijk et al., 2017). This concept parallels agricultural economics, where most inputs are similarly considered. However, agricultural economics studies frequently overlook certain key elements of the yield response function, notably soil properties. These properties are crucial as they interact with the supplied inputs, influencing efficiency. Effective utilisation of inputs is more likely in superior soil conditions, and less so in inferior ones. In this study, a variety of soil property variables are analysed.

Figure 1 presents the analytical framework of SFA, focusing on three distinct models that were central to this study. These models, with varying specifications, were employed to estimate technical efficiency. Models 1 and 2 represent the standard stochastic frontier model, where technical efficiency estimation is based solely on physical inputs such as land, labour, fertiliser, pesticide and seed. These models do not account for potential heterogeneity that might affect the accuracy of the estimation. Models 1 and 2 differ in their functional forms, with Model 1 employing the translog and Model 2 the Cobb-Douglas functional form. Log-likelihood ratio (LR) statistics were used to evaluate these two standard models and determine which functional form more accurately represented the data. In contrast, Model 3 incorporates soil heterogeneity into the stochastic frontier model. This includes factors such as soil fertility components, soil nutrients and soil cation ratios, alongside the standard physical inputs. The technical efficiency of all three models was estimated using maximum likelihood estimation (MLE), incorporating regression analysis to examine factors influencing paddy output.

[3] According to Thiam et al. (2001), sample size may not significantly impact the estimates of technical efficiency. Their analysis revealed that a substantial number of studies utilised sample sizes smaller than 80. Concurrently, Andor and Hesse (2011) observed that with a minimum sample size of 50, the SFA method demonstrated significantly improved performance.

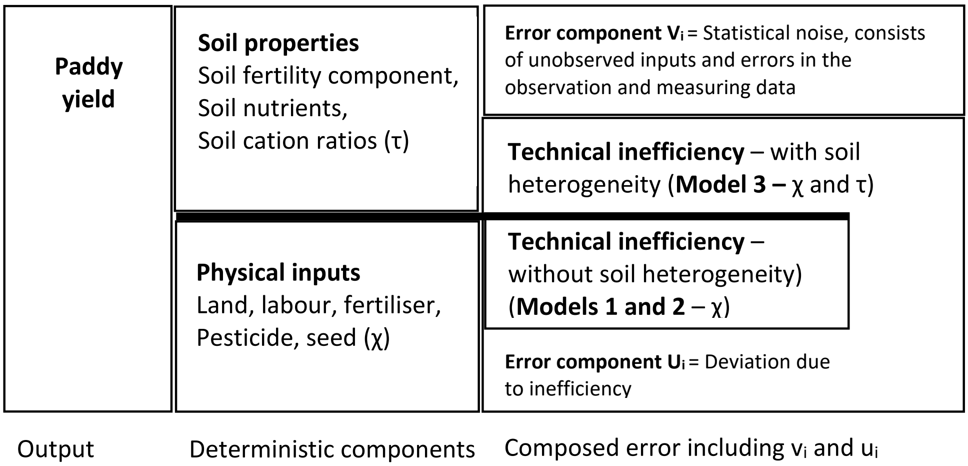

Figure 1. Analytical framework of stochastic frontier analysis

3.2 Model Specification

This study primarily employed stochastic frontier analysis (SFA) as its analytical approach, with multiple model specifications established. SFA operates on the premise that deviations from the production frontier are composed of two elements: random error (statistical noise) and inefficiency. The random error component is designed to capture all events beyond the control of the Decision Making Unit (DMU), including econometric inaccuracies such as measurement errors and production function mis-specification (Worthington, 2004). The portion of deviation from the frontier that accounts for inefficiency is typically bounded between 0 and 1 (Nguyen et al., 2019).

The general model of stochastic frontier production functions can be expressed as follows:

$$y_i = f(x_i, \beta) + \varepsilon_i = f(x_i, \beta) + v_i - u_i, i = 1,2,\ldots N \qquad (1)$$

y_i = output of i-th paddy farm
x_i = vector of production input of i-th paddy farm
β = vector of unknown parameters to be estimated
ε_i = composed error including v_i and u_i.
$v_i \sim iidN(0, \sigma_v^2)$ = random variable is independently and identically distributed $N(0, \sigma_v^2)$ and independent of the u_i
$u_i \sim iidN(\mu, \sigma_v^2)$ = non-negative random variable associated with the technical inefficiency in production and are assumed to be independently distributed as truncations at zero of the $N(\mu, \sigma_v^2)$ distribution

The fully efficient plot for a given input vector x_i is on the production frontier and can be expressed as follows:

$$yte_i = \exp(x_i\, \beta + v_i) \qquad (2)$$

The technical efficiency for the i-th farm is defined as the ratio of the observed paddy yield to the paddy yield of a fully efficient farm, given the same input and technology. Mathematically, this ratio can be expressed as follows:

$$TE_i = \frac{y_i}{yte_i} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i) \tag{3}$$

3.3 Functional Form of SFA analysis

In the SFA methodology, it is crucial to specify the production function. Among various functional forms, the Cobb-Douglas function stands out as a prominent and widely used model. The translog function, noted for its flexibility and minimal constraints, is another frequently employed form (Berndt & Christensen, 1973). While both the Cobb-Douglas and translog functions are inherently non-linear, they can be linearised through logarithmic transformation of variables (Coelli et al., 2005). The study examines both these functional forms: Model 1 is formulated using the translog functional form, whereas Models 2 and 3 employ the Cobb-Douglass functional form.

Models 1 and 2

For Models 1 and 2, the translog and Cobb-Douglas functions are used, respectively, with all variables expressed in logarithmic form. These models represent 'short model' specifications that exclude soil heterogeneity components in estimating technical efficiency. The respective equations for Models 1 and 2 are as follows:

$$\begin{aligned}\ln y_i = {} & \alpha_0 + \sum_{j=1}^{5}\alpha_j \ln x_{ij} + \sum_{j=1}^{5}\beta_j (\ln x_{ij})^2 + \sum_{j=1}^{5}\sum_{l>j}^{5}\delta_{jl}(\ln x_{ij})(\ln x_{il}) + \\ & v_i - u_i \text{ (Translog)}\end{aligned} \tag{4}$$

$$\ln y_i = \alpha_0 + \sum_{j=1}^{5}\alpha_j \ln x_{ij} + v_i - u_i \text{ (Cobb} - \text{Douglas)} \tag{5}$$

where y_i is the paddy yield per hectare for the i-th farm, and X_{ij} denotes the j-th input for the i-th farm. The parameters α_j, β_j and δ_{jl} are associated with the linear, quadratic and interaction components, respectively. ln denotes the natural logarithm, while v_i and u_i are the random variables as previously defined.

The short model incorporates five independent variables developed to measure efficiency levels in KADA and IADA BLS. The equation for the short model specification is as follows:

$$\ln y_i = \alpha_0 + \alpha_1 \ln Ld_i + \alpha_2 \ln Lab_i + \alpha_3 \ln Fer_i + \alpha_4 \ln Pd_i + \alpha_5 \ln S_i + v_i - u_i \tag{6}$$

where y_i is the paddy yield and the five independent variables are land (Ld), labour (Lab), fertiliser (Fer), pesticide (PD) and seed (S).

Model 3

Model 3 represents the full model specification, utilising the Cobb-Douglas function. This model expands upon the short model by including variables representing soil properties. The full model is formulated as follows:

$$\ln y_i = \alpha_0 + \sum_{j=1}^{5} \alpha_j \ln x_{ij} + \sum_{k=1}^{6} \tau_k \ln s_{ik} + v_i - u_i \tag{7}$$

where s_{ik} denotes the variable that represents soil properties, and τ_k is the corresponding parameter to be estimated. All other variables are as previously defined. The full model incorporates a total of 11 variables.

The equation representing the full model specification is as follows:

$$\begin{aligned} \ln y_i = {} & \alpha_0 + \alpha_1 \ln Ld_i + \alpha_2 \ln Lab_i + \alpha_3 \ln Fer_i + \alpha_4 \ln Pd_i + \alpha_5 \ln S_i + \tau_1 \ln pH_i + \\ & \tau_2 \ln SN_i + \tau_3 \ln SP_i + \tau_4 \ln SK_i + \tau_5 \ln CaMg_i + \tau_6 \ln CaMgK_i + v_i - u_i \end{aligned} \tag{8}$$

where y_i is the paddy yield. The five independent variables remain the same as in the short model – land (Ld), labour (Lab), fertiliser (Fer), pesticide (PD) and seed (S) – and are complemented by six soil property variables: soil pH (pH), soil total nitrogen (SN), soil available phosphorus (SP), soil exchangeable potassium (SK), the soil Ca:Mg ratio (CaMg) and the soil (Ca+Mg)/K ratio (CaMgK). All other variables are as previously defined.

3.4 Inferential Analysis

The study's inferential analysis began with the estimation of technical efficiency using stochastic frontier analysis. However, prior to estimating the models, several pre-estimation tests were conducted to validate the fitness of the data for the stochastic production frontier model.

The first test aimed to identify any multicollinearity issues among the explanatory variables using the variance inflation factor (VIF). According to Gujarati (2006), a VIF value higher than 10 suggests a strong relationship between variables, indicating a potential multicollinearity problem.

Secondly, the study assessed whether the production functions of the sampled farmers exhibited any technical inefficiencies. This involved determining whether the traditional average production function using ordinary least squares (OLS) or the stochastic frontier model (SFM) provided a better fit for the data.

The generalised log-likelihood ratio (LR) statistics were employed, defined by the following equation:

$$LR = -2\{\ln[L(H_0 - L(H_1)]\} \tag{9}$$

If the LR test value exceeds the chi-square (x^2) tabulated value at two degrees of freedom for a significance level of 5%, then the null hypothesis H_0: $y = \delta_0 = \delta_1 = \delta_2 = 0$ is rejected in favour of the alternative hypothesis H_1: $y = \delta_0 = \delta_1 = \delta_2 \neq 0$, indicating that the SFM model is a better fit for the data and suggesting inefficiency in paddy production. Conversely, if the null hypothesis is not rejected, it implies that deviations in the observed output from the maximum attainable output are due to statistical noise rather than specific factors.

The third test was to identify the most appropriate functional form for the paddy production data. This involved comparing the log-likelihood ratios of the Cobb-Douglas and translog functional forms. The null hypothesis posited that the Cobb-Douglas form is appropriate, while the alternative hypothesis suggested the translog form. If the LR test value is greater than the chi-square (x^2) tabulated value at 15 degrees of freedom for a 5% significance level, then the null hypothesis $H_0 : \beta_6 = \beta_7 = \cdots\beta_{20} = 0$ is rejected in favour of the alternative hypothesis $H_1 : \beta_6 = \beta_7 = \cdots\beta_{20} \neq 0$. This result would indicate that the translog form is more suitable for the data. Conversely, if the null hypothesis is not rejected, it implies that the Cobb-Douglas form adequately represents the data.

4. Results and Discussions

4.1 Descriptive Statistics

The top panel of Table 1 presents the descriptive statistics for the five physical inputs and one output utilised in the technical efficiency estimation. The average land size was 3.59 hectares, with labour costs amounting to RM723.27. The mean quantities of fertiliser, pesticides and seeds were 211.87 kilograms, RM665.66 and 162.07 kilograms, respectively. The mean paddy yield among the farmers was four tonnes per hectare. It is important to note that all physical inputs and outputs, except for land, were measured on a per-hectare basis. Land measurement considered the total operational land, encompassing both owned and rented areas. Labour costs encompassed the monetary value of labour for tasks including land preparation, sowing, and application of fertilisers and pesticides, covering both self and hired labour. Pesticide costs,

Table 1. Summary of inputs and output

Variable	Unit	Notation	Mean	Std. dev.	Min	Max
Yield	tonne ha^{-1}	Y	4	1.51	0.66	8.64
Physical inputs						
Land	ha	Ld	3.59	2.93	0.4	12.14
Labour	rm ha^{-1}*	Lab	723.27	263.49	290.53	1349
Fertiliser	kg ha^{-1}	Fer	211.87	35.62	53.75	291.88
Pesticide	rm ha^{-1}*	PD	665.66	242.92	237.60	1241
Seed	kg ha^{-1}	S	162.07	34.5	83.33	288.06
Soil properties						
pH	pH level	pH	4.99	0.46	4	5.94
Total nitrogen	percentage	SN	0.24	0.12	0.03	0.5
Available phosphorus	mg/kg	SP	22.93	19.10	0.65	142.5
Exchangeable potassium	cmol (+)/kg	SK	0.63	0.40	0.11	1.66
Ca:Mg	ratio	CaMg	2.69	1.59	0.71	5.94
(Ca+Mg)/K	ratio	CaMgK	13.87	5.76	0.66	26.04

Note: * Exchange rate of USD1.00 = RM4.15 in 2021 (Bank Negara Malaysia, n.d.).

acconting for weed, insect and disease management, were also quantified in monetary terms. On the other hand, seed and fertiliser inputs were measured in physical units.

The bottom panel of Table 1 presents the descriptive statistics for six soil property variables included in the full model. The mean values for these variables were as follows: 4.99 for pH level, 0.24% for total nitrogen, 22.93 mg/kg for available phosphorus, 0.63 cmol (+)/kg for exchageable potassium, 2.69 for the Ca:Mg ratio, and 13.87 for the (Ca+Mg)/K ratio.

The labour variable in this study is quantified in monetary terms, reflecting a prevalent trend among Malaysian farmers to outsource their field operations to service providers. Table 2 illustrates that the majority of the main field operations, including sowing, pesticide spraying and fertiliser application are outsourced for over 50% of the paddy fields. Notably, pesticide spraying is the most outsourced activity, with 81% of rice fields utilising service providers. This shift towards outsourcing is significantly influenced by the development of drone technology, which is often charged on a per-hectare basis. Consequently, paddy farming, especially in the context of pesticide spraying, has transitioned from being labour-intensive to capital-intensive, with increased adoption of machinery, technology and equipment.

Table 2. Distribution of labour input

Activities	Self-labour (%)	Hired labour (%)
Seeding	34	66
Pesticide spraying	19	81
Fertiliser applications	35	65

The extensive use of drones in paddy farming is attributed to several factors. First, the cost of drone services is competitive compared to hired manual labour, offering quicker completion of tasks with fewer workers than traditonal methods. Second, the availability of hired manual labour is somewhat limited, as many workers are also farmers and age-related issues reduce their capacity for heavy labour in daily farming operations. According to Dilipkumar et al. (2021), 64.5% of farmers in KADA and 75.1% of farmers in IADA BLS are aged 41 or older, predominantly in the 51–60 age group. Third, drones offer practical advantages over manual labour, particularly in accessing grown paddy fields for spraying operations. Fourth, drone technology has demonstrated greater productivity in the field compared to manual labour (Rosedi & Shamsi, 2022; Shahibi et al., 2023). These practices are becoming widespread in the country and are expected to gain more significance in the future. Therefore, these findings highlight that conventional methods of measuring labour variables, such as person-hours or number of workers, do not adequately capture the quality of unit labour or reflect the actual labour setting in Malaysian paddy farming.

Table 3 presents detailed information on the pesticide inputs used by paddy farmers, highlighting that the majority employed all three types of pesticides: herbicide, insecticide and fungicide. The study found that the usage of herbicide, at 4.06 litres per hectare, was twice that of insecticide (2.5 litres per hectare), and 3.1 times that of

Table 3. Quantity and value of pesticides input

Pesticides	Quantity ($l\ ha^{-1}$)	Value ($RM\ ha^{-1}$)
Herbicide	4.06	280.43
Insecticide	2.05	251.23
Fungicide	1.3	154.37

Table 4. Pesticide price per unit

Pesticide price ($RM\ litre^{-1}$)	Mean	Std. deviation	Minimum	Maximum
Herbicide	91.37	69.9	20.44	292
Insecticide	140.96	60.64	12.52	282.67
Fungicide	155.4	88.95	30	310

fungicide. However, the cost disparity was not as pronounced as the quantity difference, with the value of herbicide being only 1.1 times higher than insecticide and 1.8 times higher than fungicide. This varation can be attributed to differences in pesticide prices. The average price per unit litre or kilogram was RM91.37 for herbicides, RM140.96 for insecticides and RM155.4 for fungicides. Additionally, there is considerable variation in price within each pesticide type, dependent on the product or active component, which reflects differences in concentration and quality. As indicated in Table 4, the price range per unit litre or kilogram for herbicides varied from RM20.44 to RM293, for insecticides from RM12.52 to RM282.67, and for fungicide from RM30 to RM310.

The quantity of pesticides used represents the physical amount, while the value reflects both the quantity and quality of the pesticides. It is crucial to carefully consider the unit of measurement in the analysis, as an incorrect choice may impact the results. For instance, a farmer using a larger quantity of herbicide or a cheaper type of pesticide (which may require higher quantities due to lower quality and concentration) could result in a higher total pesticide volume than a farmer using less herbicide or more expensive pesticide. The implication is that a high volume of lower-quality pesticide might not be as effective, potentially leading to similar or lower crop outputs compared to using smaller quantities of higher-quality pesticide. This discrepancy could lead to inaccurate estimations of the input-output relationship, failing to accurately capture the plant's response to the applied inputs.

4.2 Stochastic frontier production function

Before the main analysis, several pre-estimations tests were undertaken to evaluate the data's suitability for the stochastic frontier model. The first test evaluated multi-collinearity among the explanatory variables using the VIF. With a VIF below 10, the test indicated no significant multicollinearity issue. The results of the second and third tests

Table 5. Hypothesis testing

Null hypothesis	Degree of freedom	LR	Critical value*	Decision
No technical inefficiency in the model H_0: $y = 0$	2	27.33	5.13	Reject H_0
Cobb Douglas production function is appropriate H_0: $\beta_6 \cdots = \beta_{20} = 0$	15	9.48	24.38	Fail to reject H_0

Note: *Critical value (χ^2 0.05) obtained from Kodde and Palm (1986).

are presented in Table 5. These tests examined the presence of technical inefficiency and the appropriate functional form for the data. The test for technical inefficiency yielded a LR value of 27.33, significantly exceeding the critical chi-square (x^2) value of 5.13 at two degrees of freedom and a 5% significance level. This result led to the rejection of the null hypothesis, suggesting that the stochastic frontier model is the best fit for the data and indicates a problem of inefficiency in paddy production. The third test compared the translog and Cobb-Douglas functional forms (Model 1 and Model 2, respectively) to identify the better fit. The LR value for this test was 9.48, while the critical chi-square (x^2) value at two degrees of freedom and a 5% significance level is 24.38. The failure to exceed this critical value resulted in the non-rejection of the null hypothesis, indicating that the Cobb-Douglas functional form is more suitable for the paddy production data.

In summary, these tests confirm the absence of multicollinearity, the presence of technical inefficiency in paddy production, and the appropriateness of the Cobb-Douglas functional form for this study. Therefore, the stochastic frontier model with the Cobb-Douglas functional form is established as a robust framework for the subsequent analysis.

Table 6 presents the results from the analyses of all three models. The short models (Models 1 and 2) consist of main physical inputs excluding soil variables, with Model 1 employing a translog functional form and Model 2 using a Cobb-Douglas form. The regression analysis, conducted through maximum likelihood estimation, revealed that most physical input variables significantly influenced yield per hectare. In Model 1, all variables except land, and in Model 2, all except seed, were significant.

Model 3, incorporating soil properties alongside standard physical inputs, was specified using the Cobb-Douglas functional form, as it best suited the sample farmers' data. This analysis indicated that, apart from seed and labour, all other physical input variables were significant determinants of yield. Fertiliser and pesticide exhibited a positive relationship with paddy yield, suggesting that an increase in their per-hectare usage would enhance paddy productivity. This aligns with the findings of Biswas et al. (2021) and Sun and Li (2021) for fertiliser, and Abiola et al. (2016) and Dam et al. (2019) for pesticide. On the other hand, the land variable exhibited a negative relationship with yield, echoing findings by Solís et al. (2007) and Van Dijk et al. (2020), who observed that larger land areas could reduce yield due to limited scale capacity and timing issues in field operations. A larger land area might lead to delays in critical farming activities, thereby impacting overall productivity.

Focusing on soil properties as detailed in Table 6, two variables – soil pH and the (Ca+Mg)/k ratio – exhibited significant relationships with paddy yield. Soil pH was positively associated with paddy production, indicating that an increased in pH level leads to higher paddy yields. This outcome aligns with the study area's average pH of 4.99, which is below the optimal range of 5.5 to 8 (Husson, 2013). Given that many fields in the area have pH levels below this optimal range, increasing the soil pH is likely to enhance paddy yields. Soil pH plays a critical role in influencing chemical reactions

Table 6. Maximum likelihood estimates of the production frontier

Variables	Model 1	Model 2	Model 3
Production function			
Constant	257.92***	-1.85*	-4.96***
lnFertiliser	39.14***	0.47***	0.52***
lnFertiliser^2	-0.23		
lnPesticide	16.48***	0.23**	0.24**
lnPesticide^2	-0.46**		
lnSeed	21.73***	0.20	0.25
lnSeed^2	0.95*		
lnLabour	14.04***	-0.21**	0.06
lnLabour^2	-0.49*		
lnLand	2.33	-0.10**	-0.10**
lnLand^2	0.12		
pH			0.20**
Nitrogen			0.75
Phosphorus			-0.00
Potassium			-0.30
Ca:Mg			-0.00
(Ca+Mg)/K			-0.02**
lnFertiliser x lnPesticide	-0.02		
lnFertiliser x lnSeed	-5.25***		
lnFertiliser x lnLabour	-1.50***		
lnFertiliser x lnLand	0.31		
lnPesticide x lnSeed	-1.25***		
lnPesticide x lnLabour	-0.60**		
lnPesticide x lnLand	0.19		
lnSeed x lnLabour	0.84*		
lnSeed x lnLand	-0.17		
lnLabour x lnLand	-0.00		
TE Score (%)	69.03	70.00	70.23

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels.
Models 1 and 2 are the standard frontier models with translog and Cobb-Douglas functional forms, respectively.
Model 3 is an extended model that incorporates soil properties with the Cobb-Douglas functional form.

and regulating the chemical forms of certain minerals, thereby affecting the plant's access to soil's nutrients (Fernández & Hoeft, 2009). Van Dijk et al. (2017) also noted improved yields with the maintenance of optimal pH levels.

In contrast, the (Ca+Mg)/K ratio exhibited a negative relationship with yield, indicating that a larger ratio reduces paddy yield. This supports the notion that higher concentrations of Ca+Mg may impede the plant's ability to absorb potassium (K) (Biswas et al., 2019; Dobermann et al., 1996a; Nguyen et al., 2017). Potassium is a crucial macronutrient necessary for various physiological and metabolic processes in plants (Oosterhuis et al., 2014). Inadequate K absorption caused by a higher (Ca+Mg)/K ratio could lead to diminished paddy yields.

Other soil variables, including soil N, P, K and the Ca:Mg ratio, were found to be insignificant. The primary macronutrients N, P and K are predominantly supplied through fertilisers, which plants can directly absorb. Furthermore, the availability of these nutrients to plants is largely influenced by microbial activity, soil colloidal interactions, and soil's chemical and physical properties (Hodges, 2010). Therefore, plant yield may be less sensitive to variations in soil N, P and K. Similarly, the Ca:Mg ratio showed no significant impact, indicating that its interplay has minimal effect on plant productivity.

The technical efficiency score in Model 3 showed an increase of 0.23 points compared to Model 2. This increment highlights that the exclusion of soil variables in the model leads to an overestimation of inefficiency. This finding aligns with the research of Rahman and Hasan (2008) and Silva et al. (2017), where the inclusion of heterogeneity factors in the SFA model led to lower inefficiency scores by approximately 1.4 points. Therefore, although the increase in efficiency is modest, this study corroborates previous findings, underscoring that neglecting to account for any form of heterogeneity, including soil properties, can result in inflated estimates of technical inefficiency.

The mean technical efficiency of farmers was 70.23%, indicating the potential for them to raise their output by approximately 29.77% without additional inputs. Indeed, extensive research on paddy crop efficiency has been conducted in Malaysia. These studies reported mean technical efficiency scores varying from 55.6% to 85.5% (Ghee-Thean & Ismail, 2013; Mailena et al., 2014; Soh et al., 2016). Globally, similar research, employing diverse approaches and methods, has been widespread. Bravo-Ureta et al. (2007) found that the average technical efficiency for paddy production in various countries ranged from 35% to 89.1%.

The categorisation of farmers' technical efficiency results is illustrated in six distinct groups. Figure 2 provides a detailed depiction of the technical efficiency distribution. A predominant segment of farmers achieved efficiencies ranging from 0.81 and 0.90, followed by those within the 0.71 to 0.80 bracket and those below 0.5. For models 2 and 3, the distribution of efficiency scores among the top three categories exhibited remarkable similarity. However, subsequent rankings diverged slightly. In model 2, the fourth-highest efficiency score was 0.91 or higher, contrasting with model 3, where it ranged between 0.61 and 0.70. The least represented group in model 2 fell into the 0.61 to 0.70 effieincy range, while in model 3, the smallest proportions were in the 0.51 to 0.60 range and above 0.91.

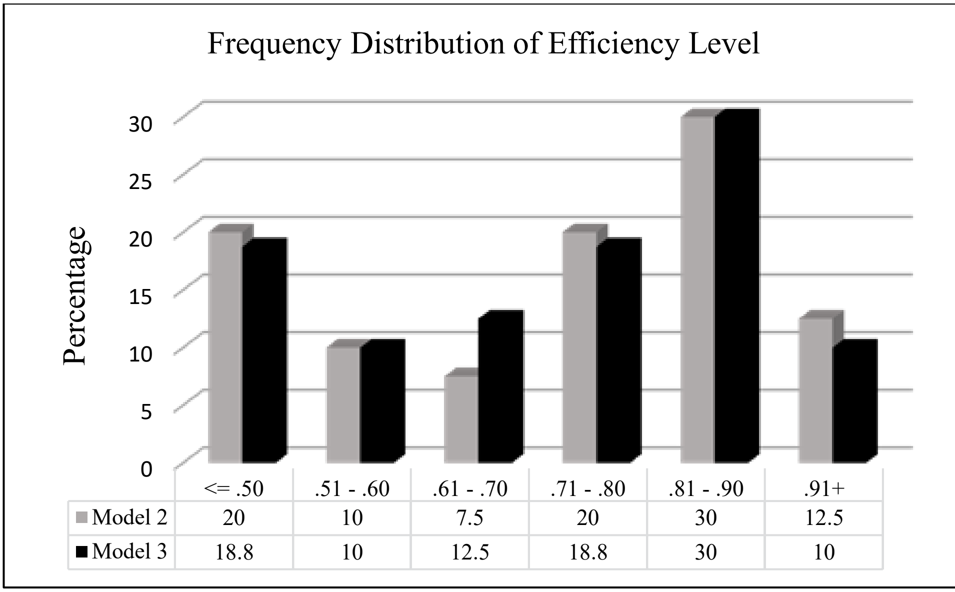

Figure 2. Frequency distribution of efficiency score

In essence, the analysis of technical efficiency focusses on assessing the efficiency of the production process in coverting inputs into outputs. Understanding a production's efficiency is crucial for enhancing output without additional inputs. However, neglecting existing heterogeneity in such estimations often leads to inflated inefficiency results. The stochastic frontier model analysis in this study reveals that accounting for soil properties yields slightly higher technical efficiency estimates for certain farmers as well as the average for all farmers, compared to a standard model. This finding aligns with theoretical expectations and corroborates previous empirical research.

5. Conclusion

The main objective of this study is to evaluate the impact of soil properties on the technical efficiency of paddy production in Malaysia's two main granaries, KADA and IADA BLS. The study advanced the frontier methodology for efficiency estimation by incorporating soil parameters in the stochastic frontier analysis (SFA) model. It brought to light several critical findings that significantly enrich the existing knowledge, particularly regarding methodological approaches and analysis of various crucial aspects of paddy production and technical efficiency. The initial part of the analysis focussed on the practices of paddy farmers in the KADA and IADA granaries. A considerable variation was observed among the farmers in terms of physical inputs, notably land, seed, fertiliser, pesticide and labour.

The second section of the analysis delved into the stochastic frontier production function. Regression analysis indicated that an increase in land size negatively affects paddy productivity, suggesting challenges in managing larger areas effectively. This ineffiency stems from the need for more focussed attention, as varying environmental conditons across different locations necessitate tailored treatments. To enhance outcomes, farmers are recommended either to intensify their field supervision efforts or to operate on a more manageable land size. This consideration becomes increasingly vital in the context of competitive land rental, especially in Malaysia's western region. Regarding seeds, their impact on paddy yield was found to be minimal. This is attributed to the widespread use of modern, high-yielding seed varieties in recommended quantities. The availability of these uniformly high-yielding varieties in Malaysia means a farmer's choice of seed is unlikely to significantly differentiate yield potential. Nonetheless, factors like pest infestation and inadequate fertilisation can hinder plants from achieving their full yield potential.

Fertilisers and pesticides are pivotal in paddy production, with their management significantly influencing overall performance. Fertiliser, being heavily subsidised and generally applied uniformly across farms, presents a less complex scenario. Most farmers utilise the subsidised fertiliser and follow the recommended application schedule, leading to relatively standard practices across farms. Pesticides, comprising various active ingredients, are essential for controlling a spectrum of pests, including weeds, insects and diseases. The efficacy of pest and disease management hinges on selecting the correct active ingredient, dosing accurately, and timely application. However, farmers often encounter difficulties in effective pesticide application due to factors like varying weather conditions, financial limitations in procuring high-quality pesticides, timing considerations in relation to neighbouring fields, and evolving pest and disease resistance.

The study highlights the profound impact of pesticide and fertiliser management on paddy yield. It suggests that relevant authorities should prioritise the development of crop varieties that are more resistant to major pests and diseases. Extension services need to focus more attentively on the management of weeds, pests and deseases. Additionally, enhancing credit accessibility is essential to enable farmers to procure necessary pesticides and additional fertilisers or boosters, supplementing what is already subsidised. In terms of labour, the study found that its influence on paddy yield was negligible. Current labour practices in Malaysian paddy farming are increasingly oriented towards outsourcing, marking a shift from the historical norm where most tasks were undertaken by farmers themselves. This transition has led to more uniform labour practices, predominatly managed by a limited number of firms or individuals.

The study proposes that future research should measure labour variables in terms of the value of self-labour and paid services, rather than relying on operator person-hours or the number of workers. This recommendation stems from the prevalent practice of charging for labour services on a per-hectare basis in recent times. Additionally, with the increasing adoption of drone technology in paddy farming, which offers a faster and less labour-intensive alternative to manual practices, traditional metrics like person-hours or worker count are becoming less relevant and practical.

The study's key discovery concerns the influence of soil properties on paddy yield, revealing that paddy productivity is influenced not only by agricultural practices but also by soil characteristics. Specifically, two soil variables – soil pH and the Ca+Mg/K ratio – were idenfitied as having significant impacts on paddy productivity. Soil pH positively influences yield, while the Ca+Mg/K ratio has a negative effect. Consequently, it is recommended to optimise soil pH levels and adhere to a regular liming schedule, which is crucial for efficient paddy production. Furthermore, the study advises authorities to monitor the cation ratio closely, as it significantly affects paddy yield. Ensuring the ideal cation ratio allows plants to optimally absorb all necessary nutrients. This concept aligns with findings from Musa et al. (2021), who reported that plots employing site-specific nutrient management (SSNM) achieved a 19% higher yield compared to standard practices.

It is important to recognise the potential challenges associated with successfully implementing the recommended soil enhancement practices. The foremost challenge lies in the time requirement and the necessity for sustained commitment from farmers to improve soil properties. Financial commitment presents another hurdle, as achieving optimal results often necessitates regular soil profiling and treatment activities. To mitigate these challenges, it is advisable for farmers to initiate the process on a small scale, using a test plot under expert guidance. Demonstrating positive outcomes on these sample plots can serve as a motivation for farmers to expand the practices to additional plots, while also helping to distribute the financial burden over time as these activities are conducted periodically.

Farmers exhibit considerable variation in their choice of inputs, both in terms of quantity and quality, with some investing heavily to boost production. However, it is important to note that high investment does not inherently assure high returns. The key to achieving high technical efficiency lies in the judicious use of correct inputs coupled with effective agricultural practices. Efficient production means optimising all inputs to achieve the maximum possible paddy yield at the efficiency frontier. While numerous studies have assessed the technical efficiency of paddy farmers, overlooking soil heterogeneity in these estimates can lead to skewed results. The study found that models incorporating soil properties exhibited lower inefficiency scores compared to those excluding these factors. The findings align with previous research, suggesting broader applicability, particularly within the rice production sector in various regions. In conclusion, the study strongly advocates for future research to consider all forms of heterogeneity, including weather factors, to provide more accurate and insightful technical efficiency estimates.

References

Abiola, O.A., Shamsudin, M.N., Radam, A., & Latif, I.A. (2016). Resource-use and allocative efficiency of paddy rice production in MADA, Malaysia. *Journal of Economics and Sustainable Development, 7*(1), 49–55.

Al-Kaisi, M.M., Lal, R., Olson, K.R., & Lowery, B. (2017). Fundamentals and functions of soil environment. In M.M. Al-Kaisi & B. Lowery (Eds.), *Soil health and intensification of agroecosystems* (pp. 1–23). Academic Press. https://doi.org/10.1016/B978-0-12-805317-1.00001-4

Andor, M., & Hesse, F. (2011). *A Monte Carlo simulation comparing DEA, SFA and two simple approaches to combine efficiency estimates* (CAWM Discussion Paper, No. 51), 1–33. https://www.econstor.eu/bitstream/10419/51383/1/672474034.pdf

Bank Negara Malaysia. (n.d.). *Exchange rates*. Retrieved 2 October 2022 from https://www.bnm.gov.my/exchange-rates

Berndt, E.R., & Christensen, L.R. (1973). The translog function and the substitution of equipment, structures, and labor in U.S. manufacturing 1929-68. *Journal of Econometrics, 1*(1), 81–113. https://doi.org/10.1016/0304-4076(73)90007-9

Biswas, B., Mallick, B., Roy, A., & Sultana, Z. (2021). Impact of agriculture extension services on technical efficiency of rural paddy farmers in southwest Bangladesh. *Environmental Challenges, 5*, Article 100261. https://doi.org/10.1016/j.envc.2021.100261

Biswas, J.C., Haque, M.M., & Saha, P.K. (2019). Soil calcium, magnesium and potassium status: Concern for rice production in Bangladesh under unfavorable ecosystems. In A. Oliveira Ferreira (Ed.), *New perspectives in international plant and soil research, vol. 1* (pp. 51–60). B P International. https://doi.org/10.9734/bpi/npipsr/v1

Bravo-Ureta, B.E., Solís, D., Moreira López, V.H., Maripani, J.F., Thiam, A., & Rivas, T. (2007). Technical efficiency in farming: A meta-regression analysis. *Journal of Productivity Analysis, 27*(1), 57–72. https://doi.org/10.1007/s11123-006-0025-3

Coelli, T. (1993). *Finite sample properties of stochastic frontier estimators and associated test statistic, No. 70*, 1–36. https://www.une.edu.au/__data/assets/pdf_file/0019/12646/emetwp70.pdf

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., & Battese, G.E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). Springer. https://doi.org/10.1007/b136381

Dam, T.H.T., Amjath-Babu, T.S., Zander, P., & Müller, K. (2019). Paddy in saline water: Analysing variety-specific effects of saline water intrusion on the technical efficiency of rice production in Vietnam. *Outlook on Agriculture, 48*(3), 237–245. https://doi.org/10.1177/0030727019850841

De Koeijer, T.J., Wossink, G.A.A., Struik, P.C., & Renkema, J.A. (2002). Measuring agricultural sustainability in terms of efficiency: The case of Dutch sugar beet growers. *Journal of Environmental Management, 66*(1), 9–17. https://doi.org/10.1006/jema.2002.0578

De Koeijer, T.J., Wossink, G.A.A., Van Ittersum, M.K., Struik, P.C., & Renkema, J.A. (1999). A conceptual model for analysing input-output coefficients in arable farming systems: From diagnosis towards design. *Agricultural Systems, 61*(1), 33–44. https://doi.org/10.1016/S0308-521X(99)00030-X

Dilipkumar, M., Ahmad-Hamdani, M.S., Rahim, H., Chuah, T.S., & Burgos, N.R. (2021). Survey on weedy rice (*Oryza* spp.) management practice and adoption of Clearfield® rice technology in Peninsular Malaysia. *Weed Science, 69*(5), 558–564. https://doi.org/10.1017/wsc.2021.16

Dobermann, A., Cassman, K.G., Cruz, P.C.S., Adviento, M.A., & Pampolino, M.F. (1996a). Fertilizer inputs, nutrient balance, and soil nutrient-supplying power in intensive, irrigated rice systems. II. Effective soil K-supplying capacity. *Nutrient Cycling in Agroecosystems, 46*(1), 11–21. https://doi.org/10.1007/BF00210220

Dobermann, A., Cassman, K.G., Cruz, P.C.S., Adviento, M.A.A., & Pampolino, M.F. (1996b). Fertilizer inputs, nutrient balance and soil nutrient supplying power in intensive, irrigated rice systems. III. Phosphorus. *Nutrient Cycling in Agroecosystems, 46*(1), 111–125. https://doi.org/10.1007/BF00704311

Färe, B.R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review, 84*(1), 66–83.

Fernández, F.G., & Hoeft, R.G. (2009). Managing soil pH and crop nutrients. In College of Agricultural, Consumer and Environmental Sciences, Illinois Extension, *Illinois Agronomy Handbook: 24th Edition* (pp. 91–112). University of Illinois at Urbana-Champaign. http://extension.cropsciences.illinois.edu/handbook/pdfs/chapter08.pdf

Ghee-Thean, L., & Ismail, M.M. (2013). Efficiency performance of paddy farming in east and west coast of Peninsular Malaysia. *International Journal of Agricultural Research, 8*(1), 42–48. https://doi.org/10.3923/ijar.2013.42.48

Greene, W.H. (2017). *Econometric analysis* (8th ed.). Pearson.

Gujarati, D.N. (2006). *Basic Econometrics* (4th ed.). Tata McGraw-Hill Education.

Hoang, V.N. (2013). Analysis of productive performance of crop production systems: An integrated analytical framework. *Agricultural Systems, 116*, 16–24. https://doi.org/10.1016/j.agsy.2012.12.005

Hodges, S.C. (2010). *Soil fertility basics: NC certified crop advisor training*. North Carolina State University Soil Science Extension.

Husson, O. (2013). Redox potential (Eh) and pH as drivers of soil/plant/microorganism systems: A trans-disciplinary overview pointing to integrative opportunities for agronomy. *Plant and Soil, 362*(1–2), 389–417. https://doi.org/10.1007/s11104-012-1429-7

Jones, J.B. (1999). *Tomato plant culture : In the field, greenhouse and home garden*. CRC Press. https://doi.org/10.1201/9781420007398

Kalirajan, K.P., & Shand, R.T. (1999). Frontier production functions and technical efficiency measures. *Journal of Economic Surveys, 13*(2), 149–172. https://doi.org/10.1111/1467-6419.00080

Karagiannis, G., & Kellermann, M. (2019). Stochastic frontier models with correlated effects. *Journal of Productivity Analysis, 51*(2–3), 175–187. https://doi.org/10.1007/s11123-019-00551-y

Kodde, D.A., & Palm, F.C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica, 54*(5), 1243–1248. https://doi.org/10.2307/1912331

Mailena, L., Shamsudin, M.N., Radam, A., & Mohamed, Z. (2014). Efficiency of rice farms and its deter-minants: Application of stochastic frontier analysis. *Trends in Applied Sciences Research, 9*(7), 360–371. https://doi.org/10.3923/tasr.2014.360.371

Mar, S., Nomura, H., Takahashi, Y., Ogata, K., & Yabe, M. (2018). Impact of erratic rainfall from climate change on pulse production efficiency in lower Myanmar. *Sustainability (Switzerland), 10*(2), 1–16. https://doi.org/10.3390/su10020402

Musa, Z., Zain, E.S.M., Choo, L.N.L.K., Jalal, S.K., Haironi, A.S., Sekot, S., Marali, J., & Sedenan, H.A. (2021). Pakej pembajaan spesifik penanaman padi bagi kawasan Skuduk-Chupak di Sarawak. *Buletin Teknologi MARDI, 24*, 145–156.

Nguyen, H.H., Maneepong, S., & Suranilpong, P. (2016). Nutrient uptake and fruit quality of pummelo as influenced by ammonium, potassium, magnesium, zinc application. *Journal of Agricultural Science, 8*(1), 1–10. https://doi.org/10.5539/jas.v8n1p100

Nguyen, H.H., Maneepong, S., & Suraninpong, P. (2017). Effects of potassium, calcium, and magnesium ratios in soil on their uptake and fruit quality of pummelo. *Journal of Agricultural Science, 9*(12), 110–121. https://doi.org/10.5539/jas.v9n12p110

Nguyen, H.-D., Ngo, T., Le, T.D.Q., Ho, H., & Nguyen, H.T.H. (2019). The role of knowledge in sustainable agriculture: Evidence from rice farms' technical efficiency in Hanoi, Vietnam. *Sustainability, 11*(9), Article 2472. https://doi.org/10.3390/su11092472

Oosterhuis, D.M., Loka, D.A., Kawakami, E.M., & Pettigrew, W.T. (2014). The physiology of potassium in crop production. *Advances in Agronomy, 126*, 203–233. https://doi.org/10.1016/B978-0-12-800132-5.00003-1

Phillips, L. (2015, August 8). Managing soil mineral ratios. *Farmer's Weekly*. https://www.farmersweekly.co.za/crops/field-crops/managing-soil-mineral-ratios/

Rabbinge, R. (1993). The ecological background of food production. In D.J. Chadwick & J. Marsh (Eds.), *Crop protection and sustainable agriculture. Ciba Foundation Symposium 177* (pp. 2–29). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470514474.ch2

Rahman, S. (2009). Impact of soil fertility on rice productivity and efficiency: A case study from Bangladesh. In D.P. Lucero & J.E. Boggs (Eds.), *Soil Fertility* (pp. 35–50). Nova Science Publishers Inc.

Rahman, S., & Hasan, M.K. (2008). Impact of environmental production conditions on productivity and efficiency: A case study of wheat farmers in Bangladesh. *Journal of Environmental Management, 88*(4), 1495–1504. https://doi.org/10.1016/j.jenvman.2007.07.019

Rosedi, F.A., & Shamsi, S.M. (2022). Comparative efficacy of drone application in chemical spraying at paddy field MADA Kedah. *IOP Conference Series: Earth and Environmental Science, 1059*(1), 1–5. https://doi.org/10.1088/1755-1315/1059/1/012002

Shahibi, M.S., Hussin, N., Ibrahim, Z., Zainol, A.S., & Zazmi, M.Z.M. (2023). Factors affecting paddy farmers in using drones. *Journal of Theoretical and Applied Information Technology, 101*(8), 3217–3227.

Sherlund, S.M., Barrett, C.B., & Adesina, A.A. (2002). Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics, 69*(1), 85–101. https://doi.org/10.1016/S0304-3878(02)00054-8

Silva, J.V., Reidsma, P., Laborte, A.G., & van Ittersum, M.K. (2017). Explaining rice yields and yield gaps in Central Luzon, Philippines: An application of stochastic frontier analysis and crop modelling. *European Journal of Agronomy, 82*, 223–241. https://doi.org/10.1016/j.eja.2016.06.017

Soh, N.C., Ismail, M.M., & Arshad, A.M. (2016). Technical efficiency of paddy farming in peninsular Malaysia: Applications of data envelopment analysis. *Journal of Biology, Agriculture and Healthcare, 6*(16), 43–47.

Solís, D., Bravo-Ureta, B.E., & Quiroga, R.E. (2007). Soil conservation and technical efficiency among hillside farmers in Central America: A switching regression model. *Australian Journal of Agricultural and Resource Economics, 51*(4), 491–510. https://doi.org/10.1111/j.1467-8489.2007.00394.x

Sun, Z., & Li, X. (2021). Technical efficiency of chemical fertilizer use and its influencing factors in China's rice production. *Sustainability (Switzerland), 13*(3), 1–19. https://doi.org/10.3390/su13031155

Thiam, A., Bravo-Ureta, B.E., & Rivas, T.E. (2001). Technical efficiency in developing country agriculture: A meta-analysis. *Agricultural Economics, 25*(2–3), 235–243. https://doi.org/10.1016/S0169-5150(01) 00081-0

Trangmar, B.B., Yost, R.S., Wade, M.K., Uehara, G., & Sudjadi, M. (1987). Spatial variation of soil properties and rice yield on recently cleared land. *Soil Science Society of America Journal, 51*(3), 668–674. https://doi.org/10.2136/sssaj1987.03615995005100030021x

Tripathi, D.K., Singh, V.P., Chauhan, D.K., Prasad, S.M., & Dubey, N.K. (2014). Role of macronutrients in plant growth and acclimation: Recent advances and future prospective. In P. Ahmad, M.R. Wani, M.M. Azooz, & L.S.P. Tran. (Eds.), *Improvement of crops in the era of climatic changes (Vol. 2)* (pp. 197–216). Springer. https://doi.org/10.1007/978-1-4614-8824-8

Van Dijk, M., Morley, T., Jongeneel, R., van Ittersum, M., Reidsma, P., & Ruben, R. (2017). Disentangling agronomic and economic yield gaps: An integrated framework and application. *Agricultural Systems, 154*, 90–99. https://doi.org/10.1016/j.agsy.2017.03.004

Van Dijk, M., Morley, T., van Loon, M., Reidsma, P., Tesfaye, K., & van Ittersum, M.K. (2020). Reducing the maize yield gap in Ethiopia: Decomposition and policy simulation. *Agricultural Systems, 183*, Article 102828. https://doi.org/10.1016/j.agsy.2020.102828

Van Ittersum, M.K., & Rabbinge, R. (1997). Concepts in production ecology for analysis and quantification of agricultural input-output combinations. *Field Crops Research, 52*(3), 197–208. https://doi.org/10.1016/S0378-4290(97)00037-3

Voogt, W. (1985). The growth of beefsteak tomato as affected by K/CA ratios in the nutrient solution. *Acta Horticulturae, 22*, 155–165. https://doi.org/10.17660/ActaHortic.1988.222.18

Worthington, A.C. (2004). Frontier efficiency measurement in healthcare: A review of empirical techniques and selected applications. *Medical Care Research and Review, 61*(2), 1–36. https://doi.org/10.1177/ 1077558704263796

Yanai, J., Lee, C.K., Kaho, T., Iida, M., Matsui, T., Umeda, M., & Kosaki, T. (2001). Geostatistical analysis of soil chemical properties and rice yield in a paddy field and application to the analysis of yield-determining factors. *Soil Science and Plant Nutrition, 47*(2), 291–301. https://doi.org/10.1080/00380768.2001.10408393