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Measurement of Efficiency and Productivity Change of Durian in Thailand

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Abstract

Thailand is the number one country in crop production and durian exports, with the highest recorded export value of nearly 2,816.9 million USD in 2020. Based on a literature review, this study used the Data Envelopment Analysis (DEA) method to measure the production and scale efficiency in Thailand's durian orchards. The Malmquist index was used to analyze durian productivity in different regions of Thailand. The analysis was based on secondary data on essential factors used in durian production in Thailand collected between 2011 and 2020. The findings indicate that the average index of production efficiency changes, in terms of technology change, real technical performance changes, efficiency changes per size, and productivity changes in durian production, were found to be 1.113, 1.040, 0.988, 1.128, and 1.158, respectively. The technology change index and the change in productivity of the central region scored higher than other areas, corresponding to farmland, yield area, and durian yield.

Keywords: Technical Efficiency, Productivity, Durian, DEA, Malmquist index

Introduction

Durian is a unique fruit with a thick peel; it has spikes and a distinctive smell, has a delicious taste, and is commonly consumed; it is known as the “KING OF FRUIT.” At the source of durian plantation, it was found that in the early stages, it was propagated by seeds and later developed into planting with grafted branches from 3 suitable varieties, such as Bat Thongkam, Thongsuk, and Karaket, which resulted in various hybrid durians. The list of durian varieties that can be gathered from documents is up to 227 varieties of durian; at present, there are only a few varieties of durian that are popular in the market, such as Mon Thong, Chani, Kratomthong, and there are also durian varieties that are known as (Geographical Indication: GI) namely Nonthaburi durian, Pala-U Durian, Prachuap Khiri Khan Province, Prachin Durian, Prachinburi Province, Long-Lae Durian, Uttaradit Province, Lin Laplae Durian, Uttaradit Province, Volcano Durian, Sisaket Province, Durian Wong in Ranong Province, Salika Durian, Phang Nga Province and includes many other varieties of folk durian, which are mainly found in the lower area, or the three border provinces in Pattani, Yala, and Narathiwat. At present, durian farmers have cut down other varieties of durian in their gardens and planted only Mon Thong, Kanyao, and Chani varieties. According to the Office of Agricultural Economics, the Ministry of Agriculture and Cooperatives has found that the durian growing areas in Thailand have expanded a lot in all regions, such as the northern region, Lublae district, and Uttaradit province. The northeast region is at Nakhon Phanom, Sisaket, and Nong Khai. The central region is at Ayutthaya, Lopburi, and Saraburi. The southern region is at Chumphon, Yala, Nakhon Si Thammarat, Surat Thani,

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Narathiwat, and Trang, and the eastern region is at Chanthaburi, Rayong, Prachinburi, and Trat, etc. (Office of Agricultural Economics, 2022).

Thailand is the world's number one in the cultivation and export of durian. According to durian production data from 2016 to 2020, Thailand's durian plantation area in 2016 was approximately 120,583.04 hectares, which is already a fruitful planting area of about 96,881.92 hectares. Which was found to be planted in different regions of the country, with durian planting areas in the south at 61,756.96 hectares, the central region at 50,447.2 hectares, the northern region at 7,847.52 hectares, and the northeastern region at 531.36 hectares, respectively. The provinces with the most cultivation of durian were Chanthaburi 32,507.2 hectares, Chumphon 26,536.48 hectares, Rayong 10,681.76 hectares, Yala 8,050.08 hectares, Nakhon Si Thammarat 7,495.2 hectares and Surat Thani 5,524.16 hectare, respectively. When comparing by region, it was found that the southern region's cultivation area and durian production had the highest number (Department of Agricultural Extension, 2016).

From the statistics of cutting ripe durian from 2015 to 2022, it was found that the average price of durian producers in Thailand has increased yearly. It was found that from 2015 to 2019, the average price was 1.4259 USD, 1.9091 USD, 2.1767 USD, 2.3715 USD, 3.0271 USD, 3.05 USD, 3.40 USD, and 3.08 USD per Kilogram, respectively. (Office of Agricultural Economics, 2019) The data found that in 2019, the average durian price was the highest since durian cultivation in Thailand and also found that from 2018 to 2020, the volume of Thai durian production increased from 759,828 metric tons to 1,017,097 metric tons and 1,111,928 metric tons, respectively (Office of the Agricultural Economics, 2021). as the results from expanding arable land, more care and maintenance, and a favorable climate, resulting in increased productivity (Ministry of Commerce, 2023). According to data on durian production in Thailand in 2020, it was found that the highest durian production in the country was the Central and Eastern region (558,890 metric tons), the Southern region (522,101 metric tons), the Northern region (25,881 metric tons), the Northeastern region (5,056 metric tons) accounted for 51.5, 45.7, 2.3 and 0.5 percent, respectively. Significant problems of durian production include agricultural problems such as diseases, insects, natural disasters, weather conditions, and maintenance of durian trees; these are problems that affect the value of durians, such as product quality and price; durian yields each year vary significantly due to environmental influences, especially climatic conditions that affect the maturity of durian trees and the flowering and fruiting yields of durian in the past five years, from the statistics of the quantity and average value of durian as mentioned above. The growth rate is increasing yearly, which can be explained by economic theory related to the demand and supply of the durian market. Durian farmers in Thailand will experience both the pros and cons of the growing durian market. In the short term, durian farmers will earn income from selling durian produce. It can often generate profits from durian cultivation from the costs paid for the inputs. On the other hand, in the long run, durian farmers will sell durian at a lower price. Durian production technology will be developed, which will help increase the amount of durian production. In contrast, the quality of durian will decrease. The cause is that durian is oversupplied; durian farmers cannot control the taste and size of the durian.

Therefore, there is a great need to accelerate study research on the measurement of efficiency and productivity change of durian in Thailand to find the essential production factors that help increase the ability to compete in durian production and reduce the risk of falling durian prices that will occur in the future for durian farmers in Thailan

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Materials and Methods

Efficiency Measurement

Production efficiency is the ability of a production unit to increase productivity with constant production factors or reduce the production factors without reducing the output. Farrell (1957) concept of classifying the economic efficiency of a unit of production into two types, namely, Allocative Efficiency refers to the ability of a production unit to select the appropriate proportion of inputs under constraints, The price of inputs, and technical efficiency refers to the ability of a production unit to increase the amount of output under the number of inputs available. (Output-Oriented Measure) or can be determined by the ability of the production unit to reduce the number of inputs, where the amount of output remains the same.

A unit's Technical efficiency requires producing output at minimal cost or achieving maximum profit. Therefore, to comply with the meaning of the word production efficiency. Technical efficiency can be measured in 2 methods: The technical efficiency of inputs and the technical efficiency in productivity. According to Farrell's concept, production efficiency measurement can be measured using two statistical methods: parametric and non-parametric. Parametric approach applied to information that can be measured quantitatively, such as average, standard deviation, and regression correlation analysis. Such analysis wants to know the distribution pattern of the population to use econometric tools, then to calculate parameters to measure production efficiency in a form known as Stochastic. Such calculations must be able to identify the type of production function, such as Cobb-Douglas or Translog Function, and for measuring efficiency by using non-parametric statistics that do not need to know the distribution pattern of the population and do not need to Know the production function model. However, suitable mathematical tools for calculating parameters to measure production efficiency will be Non-Stochastic, which is Linear Programming. Nowadays, the most popular tool to measure production efficiency in this approach is Data Envelopment Analysis (DEA), which is a method that uses Linear Programming to calculate the boundaries (Frontier) of the production unit to determine the most efficient use of resources or Proportion of production of goods to achieve maximum production volume under limited resources (Charnes et al., 1978).

CCR Model

The proposed the first model of the DEA method to measure the performance of DMUk; k = 1, 2, ..., n, (Charnes et al., 1978). The Input-Orientated Perspective of the DEA model has a linear programming model as follows:

Objective functions

$$Max \quad £_k = \sum_{r=1}^{s} u_r y_{rk} \qquad (1)$$

Constraint Conditions

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad (j = 1, 2, 3, \dots, n)$$

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$$u_r, v_i > 0 \quad (r = 1, 2, \ldots s\,; i = 1, 2, \ldots, m)$$

when £ serves as, efficiency score

xij represents the input at i of the DMU at j.
yrj represents the yield factor at r of the DMU at j.
vi represents the weighted value of the inputs at i.
ur represents the weighted value of the yield factor at r.
m represents the number of inputs.
s represents the number of yield factors.
n represents the number of units produced (DMU).

This model is called the CCR model, after the first name of the co-developers. Under the assumptions, the CCR model aims to determine the maximum value of the Overall Technical Efficiency (TECRS) score (1). Constant Returns to Scale (CRS) is sometimes referred to as the CRS model. The overall efficiency score can range from 0 to 1. If the overall efficiency score is 1, the DMU is efficient. However, the DMU could be more inefficient if the overall efficiency score is closer to 0. In other words, the model creates a hyperplane called the efficiency region, where any DMU is on the boundary line, indicating that the DMU is efficient. However, if any DMU is within the efficiency range, then it is not efficient. The DMU's efficiency rating will decrease according to the distance between the DMU and the scope.

In the practical aspect, a dual model is commonly used, that is, £ , , λ_1,... $\lambda_2 \lambda_n$ are coupled variables associated with conditions 1 , 2 , ... , n + 1 , thus obtaining the coupled model of the CCR model in the Input-Orientated view as follows:

Objective function Min $£_k$ (2)

Constraint Conditions

$$£_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \qquad (i = 1, 2, \ldots, n)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{rk} \geq 0 \qquad (r = 1, 2, 3, \ldots, s)$$

$$\lambda_j > 0 \qquad (j = 1, 2, \ldots, n)$$

In addition, the CCR model can be written in output-orientated view as follows:

Objective Function Maxα_K (3)

Constraint Conditions

$$x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - \alpha_k y_{rk} \geq 0$$

$$\lambda_j > 0$$

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BCC Model

The CCR model, subject to the fixed return assumption, is appropriate when the DMU is operating at a reasonable level but when incomplete competition occurs or financial constraints arise, which is one of the causes that prevent the DMU from operating at the proper level. Banker et al., (1984) developed a new model to solve that problem: the BCC model was intended to determine the value of efficiency scores. Under the assumption, returns can change. The efficiency score derived from this model is called Pure Technical Efficiency: TEVRS.

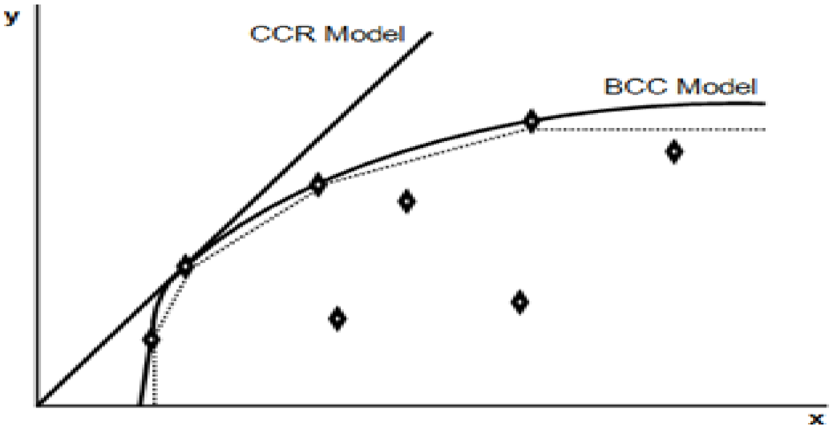

Figure 1. comparing CCR models and BCC models
Source: Banker Charnes and Cooper (1984)

The differences between the concepts of the CCR model and the BCC model are shown in Figure 1, with the beginning to develop the BCC model for use in evaluating the efficiency of incomplete competition, with the addition of conditions to the CCR model in the Input- Orientated view, which is a limitation of convexity constraint, (Banker et al., 1984) The Convexity Constraint results in the following BCC models:

Objective function Min $£_k$ (4)

Constraint Conditions

$$£_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{rk} \geq 0$$

$$\lambda_j > 0$$

For the BCC model in Output-Orientated view, the display can be written as follows:

Objective Function Max α (5)

Constraint Conditions

$$x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$$

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$$\sum_{j=1}^{n} \lambda_j y_{rj} - \alpha_k y_{rk} \geq 0$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0$$

Pure Technical Efficiency and Scale Efficiency

Efficiency scores from the CCR model, called overall efficiency, instead of TE_{CRS}, consist of two efficiency scores (Charnes and Cooper, 1984).

1. Pure Technical Efficiency is aa efficiency score from the BCC model instead of TE_{VRS} if $TE_{VRS} = 1$ means that the DMU is technically efficient, i.e. the DMU is an operational technique to allocate existing inputs to be more productive than other DMU's, but if $TE_{VRS} < 1$, it means that the DMU is not technically efficient. Output is less or equal to other DMU's.

2. Scale Efficiency (SE), where SE = $\frac{TE_{CRS}}{TE_{VRS}}$ i.e., if a DMU has a $TE_{CRS} = TE_{VRS}$ value, It represents scale efficiency, i.e., DMU can increase productivity by simply changing the size of the business by increasing or decreasing the use of import factors to be appropriate. Without any technical changes, any DMU with $TE_{CRS} = TE_{VRS}$ values indicates scale efficiency, i.e., DMU can increase productivity only by increasing or decreasing the size of the use of import factors accordingly.

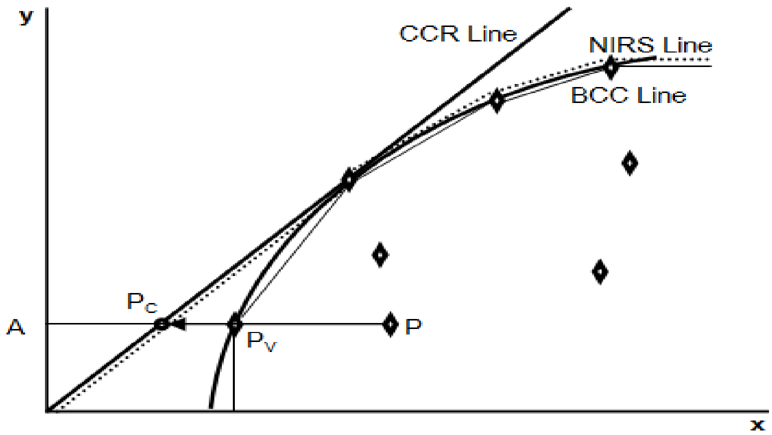

Figure 2. Size Efficiency (SE) and Efficiency of Non-Increasing Return to Scale
Source: Charnes and Cooper, (1984)

Figure 2 is an idea for calculating the SE efficiency score. When considering the DMU at point P, it can be seen that

$TE_{CRS} = \frac{AP_C}{AP}$ and $TE_{VRS} = \frac{AP_v}{AP}$ where SE $= \frac{AP_C}{AP_v}$ so SE $= \frac{TE_{CRS}}{TE_{VRS}}$ the values of TE_{CRS} TE_{VRS} and SE have a value from 0 to 1, if SE = 1, then the DMU has a reasonable size efficiency, but if SE < 1, then the DMU has improper size efficiency. Size efficiency is achieved by appropriately increasing or decreasing the size of inputs, such as determining the right proportion of investment or having the correct number of employees. For size efficiency, there are three types: 1) organizations of reasonable size (CRS), 2) organizations that should be scaled down (DRS), and 3) organizations that should increase (IRS) (Banker, R.D. et al. 1984).

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The type of organizational size efficiency can be determined by calculating the model's efficiency score. Non-Increasing Return to Scale (NIRS). which is obtained by substituting $\sum_{j=1}^{n} \lambda_j = 1$ in the BCC model with $\sum_{i=1}^{n} \lambda_i \leq 1$, consider the following:

1. If SE=1 or $TE_{CRS}=TE_{VRS}$, then the DMU is the right size.
2. If $TE_{NIRS} = TE_{VRS}$ or $TE_{NIRS} \neq TE_{CRS}$, then the DMU should be downsized.
3. If $TE_{NIRS} \neq TE_{VRS}$ or $TE_{NIRS} = TE_{CRS}$, then the DMU should be scaled up.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a nonparametric method for measuring the efficiency of a unit of production without defining a particular function model for the efficient frontier.

However, the efficiency frontier is calculated using a mathematical methodology called linear programming. Then, the performance score is calculated relative to the generated efficiency frontier, where the parametric method is defined as an efficient within-frontier function. The concept of measuring efficiency is divided into two parts: 1.) Input orientation controls costs to a minimum by reducing inputs where the amount of output remains 2.) Output Orientation analysis to increase productivity under existing inputs. These two efficiency measurement concepts are used to measure technical efficiency.

The two types of return hypothesis are: 1.) Constant Return to Scale (CRS) measures cases where a return on a fixed scale or when all production units are produced at the appropriate level; 2.) Variable Return to Scale (VRS) measures cases where incomplete competition results in one business unit not performing production at the appropriate level (Banker, R.D., et al. 1984).

From the concept of efficiency measurement and the assumptions for determining the return above, the simulation model can be summarized under the four different assumptions, as shown in Figure 3.

Input orientated	Output orientated
$\mathrm{Min}_{\theta,\lambda}\,\theta$ Subject to $-y_i + y\lambda \geq 0$ $\theta x_i - x\lambda \geq 0$ $\lambda \geq 0$	$\mathrm{Max}_{\phi,\lambda}\,\phi$ Subject to $-\phi y_i + y\lambda \geq 0$ $x_i - x\lambda \geq 0$ $\lambda \geq 0$

Figure 3. modeling by enveloping the data under different assumptions
Source: Banker, R.D., et al., (1984)

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Input orientated		Output orientated	
	$\mathrm{Min}_{\theta,\lambda}\theta$		$\mathrm{Max}_{\phi,\lambda}\phi$
Subject to	$-y_i + y\lambda \geq 0$	Subject to	$-\phi y_i + y\lambda \geq 0$
	$\theta x_i - x\lambda \geq 0$		$x_i - x\lambda \geq 0$
	$N1'\lambda \leq 1$		$N1'\lambda \leq 1$
	$\lambda \geq 0$		$\lambda \geq 0$

Figure 3. modeling by enveloping the data under different assumptions (Cont.)
Source: Banker, R.D., et al., (1984)

When i is the input at i
r is the yield factor at r.
j is the unit of production at j.
k is the unit of production being considered.
x_{ij} is the number of inputs i of the production unit at j.
y_{rj} is the number of yield factors at r of the j production unit.
θ,φ is the performance score of the production unit.
λ is the weight of the factor.

Malmquist Productivity Index

Malmquist (1953) presented a quantitative index, defined as the consumption per given baseline consumption, to establish the same level of existing utility as before. When the utility can be ordinally measurable, it can be used to measure changes in production in terms of consumption. As for the issue of economies of scale, this context is irrelevant. Caves et al. (1982) and Nishimizu and Page (1982) applied the Maslmquist productivity index to measure the change in the production of pictures (Productivity change). Färe et al., (1997) introduced non-parametric linear programming methods and techniques to help calculate Malmquist's quantitative index. It can be concluded that the Maslmquist productivity index is an applied index rather than a theoretical index. It has been developed periodically and, in many contexts, especially for manufacturers' development. The issue of economies of scale is, therefore, becoming more relevant. Economies of scale also play an essential role in the econometric model of change in productivity (Grifell-Tatjé and Lovell, 1995). Therefore, when referring to the theory used in the study, It can be said that the Maslmquist productivity index has been adapted from studies by Färe et al., (1994) and Bradley et al., (2010).

Thus, the Malmquist Productivity Index can define conditions based on previous studies by Wilmsmeier et al., (2013) defining the Malmquist productivity index and distance function based on two different intervals.

Let's assume that $x^t = (x_1^t, \dots, x_n^t)$ denotes a vector of "n". Input factor and $y^t = (y_1^t, \dots, y_m^t)$ means Vector of "m" Yield at time t, t,...,T from t to t+1. The term function of the input at time t is defined as follows:

$$D_i^t(y^t, x^t) = \sup\{\lambda: (x^t/\lambda, y^t) \epsilon\, S^t\} \qquad (6)$$

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Define the Malmquist index, the input distance function at time t+1 is defined as follows:

$$D_i^t(y^{t+1}, x^{t+1}) = \sup\{\lambda: (x^{t+1}/\lambda, y^{t+1}) \epsilon\, S^t\} \quad (7)$$

Each distance function can measure the change in the highest proportion in terms of inputs and is a complete feature of T technology.

According to the concept of the input phase function, at time t, the Malmquist yield index is defined by the function as follows:

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \quad (8)$$

Similarly, The input distance function at the time t+1 can be defined by applying the technology as follows:

$$M_i^{t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^t, x^t)} \quad (9)$$

By expressing equations (3) and (4), the technology is assumed to remain the same at time t and t+1 in this context. The technology change can be determined by calculating the geometric mean, so the Malmquist productivity change index based on inputs can be represented as follows:

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = \left[\frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \; \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^t, x^t)}\right]^{1/2} \quad (10)$$

Based on the change in production between the periods t and t+1, an important indicator can be identified by malmquist's productivity index $M_i^t > 1$. If $M_i^t < 1$ productivity is reduced and if productivity is stable $M_i^t = 1$(Lovell, 2003)

An equivalent way to write Malmquist efficiency change index is:

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \left[\frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^{t+1}, x^{t+1})} \; \frac{D_i^t(y^t, x^t)}{D_i^{t+1}(y^t, x^t)}\right]^{1/2} \quad (11)$$

From equation (6), Malmquist productivity changes can be classified into two categories: the first element on the left-hand side measures the efficiency change between the intervals t and t+1, and the second element on the right-hand side measures the technical change by capturing the technological change of the borderline between the intervals t and t+1 (Song and Cui, 2014).

According to the efficiency analysis, there are six steps to the conducted analysis. Step 1: Define Inputs and Outputs. Step 2: Create a Data Matrix. Step 3: Normalize the data. Step 4: Formulate the DEA Linear Programming Model. Step 5: Solve the Linear Programming Model. Step 6: Interpret the Results. DMUs with an efficiency score of 1 are considered efficient, while those with less than 1 are relatively inefficient. Moreover, productivity changes analysis has five steps to the conducted analysis. The analysis is divided into steps: 1. Define the input-output variables, data used, and specify the periods t and t+1 to be analyzed. 2. Create an efficiency curve and calculate the efficiency value. 3. Calculate the Malmquist Productivity Index. 4. Calculate Efficiency Changes (EC),

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Technological Changes (TC), Pure Technical Efficiency Changes (PTEC), and Scale Efficiency Changes (SEC). 5. Summarize the results of the data analysis.

Related Research

Toma, E., et al., (2015) uses Data Envelopment Analysis (DEA) at the regional level to examine agricultural performance in three geographical areas: plain, hill, and mountain. The study divides 36 counties into three categories based on geographical factors and computes technical ratings and scale efficiencies. The study concludes that there are significant disparities in performance between places with comparable geographical features in terms of production element allocation (labor, land, and mechanization) and outputs. Only 14 counties (5 in plains, 5 in hills, and 4 in mountains) attain 100% DEA efficiency and function at their ideal scale. The authors find that in the majority of cases, agricultural efficiency is not achieved. These areas must reduce input levels (particularly excessive labor hours concerning productivity) or raise output levels (production value) through better utilization of fixed capital and greater yields.

A study conducted by Parichatnon et al., (2017) focused on assessing the technical efficiency of durian production in different provinces of Thailand from 2012 to 2016. They utilized data envelopment analysis and employed the CCR (Charnes Cooper and Rhodes) model, developed by Charnes et al. (1978), to measure the technical performance. The study findings indicated that the technical efficiency of durian production in Thailand during the specified period was considered satisfactory. However, there is room for improvement since the technical efficiency score did not reach the optimal value of 1. Among the provinces, Chanthaburi emerged with the highest average efficiency score, earning recognition as the leading province for durian production in Thailand. In contrast, Phuket demonstrated the lowest average technical efficiency score among the provinces. Therefore, it is worthwhile to enhance both the input and output quantities in durian production. The analysis of this data can provide valuable insights and serve as a practical resource for farmers, agricultural planners, and government agencies seeking to improve the technical efficiency of durian production in Thailand. Wang et al., (2017): Efficiency data analysis with Data Envelopment Analysis to evaluate the efficiency of agricultural production of 100 major irrigation districts in northwest China in 2010.

Sokol, O., and Frýd, L. (2023). mention "DEA efficiency in agriculture: Measurement unit issues" includes the selection of inputs and outputs in Data Envelopment Analysis (DEA) models, particularly in the context of agriculture. The authors highlight the importance of different measurement units for selected inputs, which is frequently overlooked in empirical research. They demonstrate, using Czech farms as an example, that the DEA technique lacks consistent score projections or a stable ranking for many prominent metrics of labor and capital components of production. As a result, they warn that research relying on DEA efficiency values for various measured inputs should be evaluated with extreme caution. However, based on the abstract and highlights, the authors suggest that careful comparison and interpretation are required when employing DEA efficiency estimates due to the sensitivity of these results to the measurement units of inputs. They note that variation in input measurement might result in inconsistent score estimations and ranks, making comparison analyses difficult.

Yang, L., et al., (2022) combined life cycle and data envelopment analysis, which delivers complete research on the eco-efficiency of Chinese sugarcane production.

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The authors examine the effectiveness of small-holder sugarcane farms in southern China by using a combined life cycle assessment (LCA) and data envelopment analysis (DEA) paradigm. According to the report, there is a considerable yield differential across farms in the region. It also reveals significant differences in the carbon footprint and farmer profit in sugarcane cultivation. According to the authors, the combined LCA + DEA model gives insights into several elements of sugarcane farm efficiency by taking into account both agronomic and economic parameters, as well as the carbon footprint of all farm inputs and processes.

Guo, H., et al., (2022) study revealed that climate change affects agriculture's total factor productivity (TFP) in two ways: by changing the amount of output variables and by changing resource distribution. The consequences of climate change on diverse agricultural regions vary due to each region's unique influence on climatic resources, causing difficulties for global food supply and safety as well as varied degrees of agricultural productivity. The authors focus on mitigating the effects of climate change on agricultural production and minimizing weather-related dangers. They also recommend increasing media coverage and visibility to boost public knowledge of climate change.

Hamid, S., and Wang, K. (2022) investigates the environmental TFP of the agriculture sector in South Asia from 2000 to 2019 using a non-oriented generalized Luenberger-Hicks-Moorsteen (LHM) productivity indicator. Environmental LHM-TFP decomposition encompasses technical efficiency change, technological advancement, and scale efficiency change. According to the authors, boosting the environmental TFP of agriculture in South Asia needs increasing technological efficiency and maximizing economies of scale. They also advocate for nations to work together to promote sustainable agriculture practices and to encourage cleaner agricultural output to reduce emissions.

Definition of Input and Output Variables

Input and output variables were selected to reflect the appropriate use of resources and products in agricultural production systems both domestically and internationally. From this context, the input and output variables defined in this research were designed to be consistent with the study objectives and the specific characteristics of durian cultivation. These variables will help measure the efficiency and capability of durian production. Therefore, from the review of related literature, the input and output variables can be defined as shown in Table 1.

Table 1. definition of input and output variables

No	Variable	Definition	Author/year
1.	Perennial area, (hectare)	The area used for perennial crops, this variable reflects areas managed to grow crops that can produce long-term crops.	Toma et al., 2015, Guo et al., 2022
2.	Fruiting area, (hectare)	The area where perennial crops in each plot are beginning to produce. This variable indicates the potential for agricultural land management, especially when crops are beginning to be ready for harvest.	Parichatnon et al., 2017, Yang et al., 2022

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3.	Yield, (metric tons)	Productivity from cultivated areas, this variable reflects the results of land, water, and labor resource allocation, as well as production technology.	Wang et al., 2017, Hamid & Wang, 2022, Guo et al., 2022, Yang et al., 2022

Source: from the literature review of the researcher

Data Selection

This paper uses secondary data of durian cultivation in Thailand using data from 2011 to 2020. The data covers durian cultivation areas in 4 regions, which include; Northern, Northeast, Central, and Southern regions as shown in Table 2.

Table 2. data of durian cultivation in each region of Thailand using data from 2011 to 2020.

DMU	2011	2011	2011	2012	2012	2012
	Perennial space	Harvest area	Yield	Perennial space	Harvest area	Yield
Northern Region (DMU1)	28,406	24,327	11,506	28,610	24,239	14,708
Northeast (DMU2)	1,814	1,345	1,108	1,878	1,315	1,061
Central (DMU3)	298,069	266,526	349,741	290,873	254,962	311,524
Southern Region (DMU4)	336,264	312,303	147,080	327,332	301,135	197,174
Total	664,553	604,501	509,435	28,610	581,651	524,467
DMU	**2013**	**2013**	**2013**	**2014**	**2014**	**2014**
	Perennial space	Harvest area	Yield	Perennial space	Harvest area	Yield
Northern Region (DMU1)	28,717	24,820	15,924	40,815	35,958	22,771
Northeast (DMU2)	2,042	1,294	1,160	3,228	2,343	2,416
Central (DMU3)	289,057	253,517	329,177	293,490	250,214	354,431
Southern Region	336,670	297,558	223,050	392,474	332,056	293,312

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(DMU4)						
Total	656,486	577,189	569,311	689,192	620,571	672,930
DMU	**2015**	**2015**	**2015**	**2016**	**2016**	**2016**
	Perennial space	Harvest area	Yield	Perennial space	Harvest area	Yield
Northern Region (DMU1)	44,052	36,826	21,905	48,246	37,467	8,390
Northeast (DMU2)	3,997	2,339	2,142	4,499	2,431	1,677
Central (DMU3)	303,341	251,710	342,964	315,449	257,722	281,657
Southern Region (DMU4)	419,858	330,012	250,201	435,123	331,433	255,265
Total	771,248	620,887	617,212	803,317	629,053	546,989
DMU	**2017**	**2017**	**2017**	**2018**	**2018**	**2018**
	Perennial space	Harvest area	Yield	Perennial space	Harvest area	Yield
Northern Region (DMU1)	53,120	37,644	32,138	56,651	38,596	34,936
Northeast (DMU2)	5,131	2,891	2,927	8,571	3,454	4,480
Central (DMU3)	328,464	262,543	427,909	338,704	274,158	408,572
Southern Region (DMU4)	451,999	339,952	200,092	475,887	360,041	311,840
Total	838,714	643,030	663,066	823,162	676,249	724,892
DMU	**2019**	**2019**	**2019**	**2020**	**2020**	**2020**
	Perennial space	Harvest area	Yield	Perennial space	Harvest area	Yield
Northern Region (DMU1)	55,245	41,045	23,749	55,652	47,636	25,881
Northeast (DMU2)	11,872	3,886	3,722	16,872	6,352	5,056
Central (DMU3)	361,719	293,600	504,130	391,515	299,184	558,890
Southern Region (DMU4)	503,504	387,944	482,140	528,556	437,993	522,101
Total	932,340	726,475	1,013,741	992,595	791,165	1,111,928

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Source: Bureau of Agricultural Economics, 2021
Note: Perennial space = unit (hectare), Harvest area unit (hectare), Yield = (metric ton)

The screening of input and output variables uses a conceptual model derived from the study of Dyson et al. (2001), Which can be summarized as follows: In the first step, list the input and output variables that are related to this paper. In the second step, the input and output variables are examined by statistical analysis of the correlation between the variablesThe result in Table 3 shows descriptive statistics of input and output variables and the distribution of the data selection, which is confirmed by the arithmetic mean and standard deviation.

Table 3. descriptive statistics of input and output variables

	Perennial space (hectare)	Harvest area (hectare)	Yield (metric tons)
Max	528,556	437,993	558,890
Min	1,814	1,294	1,061
Average	197,944.2	161,769.3	174,722.7
SD	181,117.8	147,635.1	181,476.5

Source: the researcher's calculation

In addition, the results in Table 4 show that the correlation coefficient analysis indicated that input and output variables had a positive relationship with the independent variables, with more than half having a correlation index higher than 0.80 and a strong relationship between all variables, reflecting a significant relationship between input and output variables.

Table 4. correlation coefficient analysis of input and output variables

	Perennial space (hectare)	Harvest area (hectare)	Yield (metric tons)
Perennial space (hectare)	1	0.995329	0.891167
Harvest area (hectare)	0.995329	1	0.88904
Yield (metric tons)	0.891167	0.88904	1

Source: the researcher's calculation

Results and Discussion

Efficiency Analysis Results

As the data of durian cultivation by region from the Bureau of Agricultural Economics 2021, using historical data from 10 years 2011 to 2020, with decision-making units consisting of Decision Unit 1 Northern Region (DMU1), Decision Unit 2 Northeastern Region (DMU2), Decision Unit 3 Central Region (DMU3) and Decision Unit 4 Southern Region (DMU4) with the use of Data Envelopment Analysis (DEA) and CCR and BCC models under Variable returns to scale (VRS) scale to analyze Thailand's macro-efficiency by considering the input variables, namely: Perennial area, unit (hectare), fruiting area, unit (hectare), and the output or yield variables are: The yield of durian in Table 5.

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Table 5. the efficiency and production capacity of durian consists of 4 regions in Thailand using data from 2011 to 2020.

Order	Firm / (DMU1)	crste	vrste	scale	Goals for improvement
1	Northern Region (DMU1)	0.378	1.000	0.378	IRS
2	Northeast (DMU2)	0.005	0.741	0.007	IRS
3	Central (DMU3)	1.000	1.000	1.000	CRS
4	Southern Region (DMU4)	1.000	1.000	1.000	CRS
Mean		0.596	0.935	0.596	IRS

Source: from the calculations of the researcher, software DEAP 2.1

Note: crste = technical efficiency from CRS DEA, vrste = technical efficiency from VRS DEA and scale = scale efficiency = crste/vrste.

From the efficiency analysis of 2011 to 2020, in Table 5 was found that the technical efficiency under the CRS model in durian production in the northern region (DMU1) was 0.378. The technical efficiency under the VRS model was 1 and the efficiency per scale was 0.378. The improvement goal was IRS or increasing return to scale. Similarly, the technical efficiency under the CRS model in durian production was 0.378. In the Northeast region (DMU2), the technical efficiency under the VRS model was 0.741 and the efficiency per scale was 0.007. The improvement goal was IRS or increasing return to scale. In durian production, it was also found that the central region (DMU3) and southern region (DMU3) had the same technical efficiency in durian production. The technical performance values under the CRS and VRS models were 1 for both sectors and the efficiency per scale was 1 for both sectors as well. The goal of improving durian production is CRS or constant return to scale. In Thailand, the technical efficiency under the CRS model was 0.596, the technical efficiency under the VRS model was 0.935, and the efficiency per scale was 0.596. The improvement goal was irs or increasing return to scale.

Productivity Analysis Results

Using the Malmquist index helps to raise awareness and understanding of changes in performance from the side of import variables or inputs as a whole (Malmquist, 1953), such as Technological changes in durian cultivation, real technical efficiency, and the production change of the cultivation sector.

The Malmquist index for Thailand's durian production over 10 years (2011-2020) was summarized in Figure 4 and Table 6. It revealed that Thailand's overall change in durian production efficiency during this period was 1.416. Specifically, the efficiency values in years 3 to 10 were 0.560, 1.357, 1.176, 0.506, 0.506, 1.115, 4.160, 0.892, and 0.995, respectively. Year 8 exhibited the highest performance change, followed by year 4, while year 6 had the least change in durian efficiency. Regarding technology change, the values for years 2 to 10 were 0.830, 1.971, 0.495, 1.018, 0.822, 1.599, 0.771, 1.697, and 1.002, respectively. On the other hand, the actual technical efficiency changes were observed in years 2 to 10, with values of 1.078, 0.748, 1.245, 1.075, 0.791, 0.710, 1.384, 1.220, and 0.874, respectively. Year 8 had the most significant change in technical efficiency, followed by years 4 and 7, which showed minimal change in actual technical efficiency for durian production. Regarding efficiency change per size, the values for years 2 to 10 were 1.314, 0.748, 1.090, 1.094, 0.639, 1.572, 3.005, 0.731, and 1.138, respectively. Year 8 had the highest efficiency change, followed by year 7, while year 9 exhibited the least efficiency change concerning the size of durian production. Additionally, the change in the productivity of durian production in Thailand during the same period showed values of 1.176, 1.103, 0.672, 1.197, 0.416, 1.783, 3.207, 1.513, and

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0.996 for years 2 to 10, respectively. Year 8 had the highest productivity change, followed by year 7, while year 6 displayed the least change in productivity for durian production.

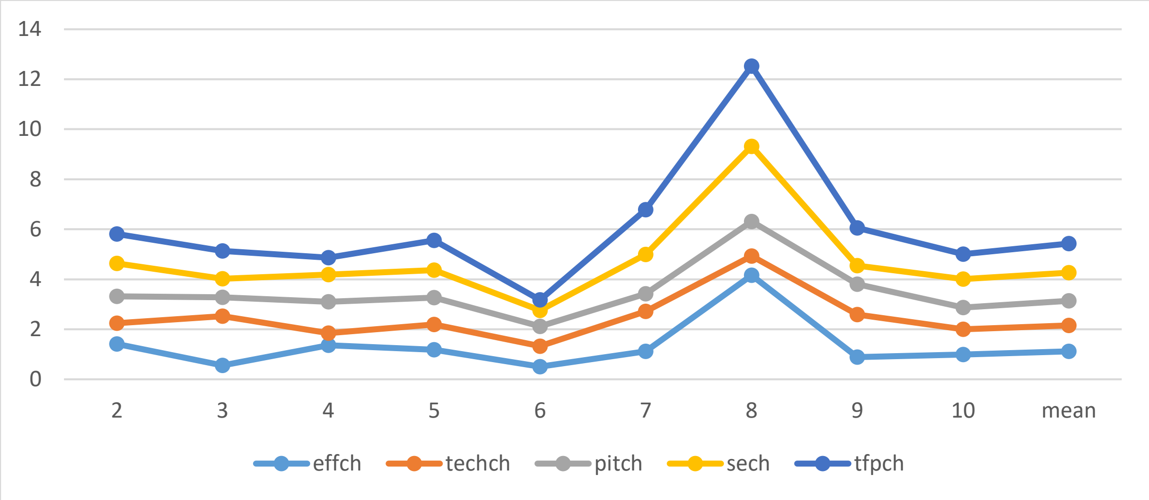

Figure 4. summarizes the Malmquist Index of Thailand's durian production in 10 years.
Source: from the calculations of the researcher

Table 6. summarizes the Malmquist Index of Thailand's durian production in 10 years.

year	effch	techch	pitch	sech	tfpch
2	1.416	0.830	1.078	1.314	1.176
3	0.560	1.971	0.748	0.748	1.103
4	1.357	0.495	1.245	1.090	0.672
5	1.176	1.018	1.075	1.094	1.197
6	0.506	0.822	0.791	0.639	0.416
7	1.115	1.599	0.710	1.572	1.783
8	4.160	0.771	1.384	3.005	3.207
9	0.892	1.697	1.220	0.731	1.513
10	0.995	1.002	0.874	1.138	0.996
mean	1.113	1.040	0.988	1.128	1.158

Source: from the calculations of the researcher, software DEAP 2.1
Note: effch= efficiency changes, techch =technical efficiency changes, pitch= pure technical efficiency changes, sech=scale efficiency changes and tfpch= total factor productivity changes.

Considering the average change in production efficiency, technology change, actual technical performance changes, performance-to-size changes, and the change in the productivity of durian production in Thailand, the values were found to be 1.113, 1.040, 0.988, 1.128, and 1.158, respectively. These values indicated satisfactory and appropriate index values for the durian production situation in Thailand. It is derived from the calculation of the Malmquist index method; every benchmark level value should be greater than 1.

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Table 7. summarizes the Malmquist Durian Production Index for each region of Thailand

Region	effch	techch	pitch	sech	tfpch
Northern Region (DMU1)	0.981	1.020	0.920	1.067	1.001
Northeast Region (DMU2)	1.567	0.971	1.034	1.515	1.521
Central Region (DMU3)	1.000	1.092	1.000	1.000	1.092
Southern Region (DMU4)	1.000	1.081	1.000	1.000	1.081
Mean	1.113	1.040	0.988	1.128	1.158

Source: from the calculations of the researcher, software DEAP 2.1
Note: effch= efficiency changes, techch =technical efficiency changes, pitch= pure technical efficiency changes, sech=scale efficiency changes and tfpch= total factor productivity changes

In Table 7, which summarizes the Malmquist Index of durian production over the past 10 years, several observations were made when examining the production capacity of durian across different regions of Thailand. The central and southern regions displayed higher technology change index than Thailand's northern and northeastern regions. The central region demonstrated notably highest scores, indicating a greater focus on cultivating durian for increasing economies of scale as shown in Chart 1.

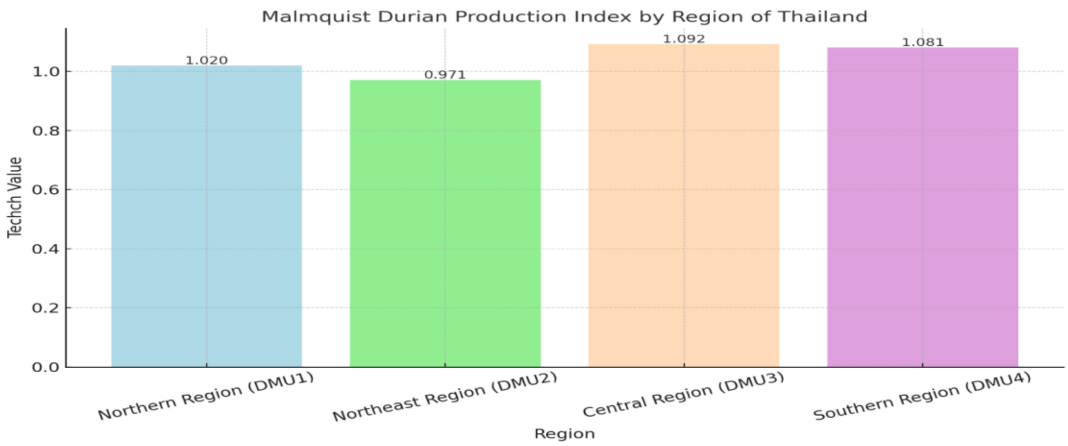

Chart 1. Malmquist Durian Production Index By Region Of Thailand
Source: from the calculations of the researcher

Conclusion

Thailand has been the world's number one cultivator and exporter of durian since 2016, after which export numbers have continued to rise yearly, with the most exported markets being China and Hong Kong. Thai durian tastes are favored by customers from China and other countries in the ASEAN region. As a result, the purchase price of durian in the country also increases according to the demand from outside the country. According to the Office of Agricultural Economics, Ministry of Agriculture and Cooperatives statistics, this represents a new record high for Thai durian production in 2020, with a volume of 1,111,928 tons (Office of Agricultural Economics, 2021), creating tremendous economic value for Thailand. From the study's results on measuring the efficiency and productivity of durian production in Thailand, problems regarding product quality and price, cultivation, and harvesting are usually encountered. In this study, the input variables were perennial area unit (hectare), fruiting unit (hectare), and yield, the production of durian that comes from classification by region. It consists of the

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northern region (DMU1), the northeastern region (DMU2), the central region (DMU3), and the southern region (DMU4). The Data Envelopment Analysis (DEA) model under the CRS and VRS models was used to analyze the technical efficiency of durian cultivation and production classified by region of Thailand. The analysis revealed that the central and southern regions had the highest technical efficiency in durian production. The value equals 1, and the next is the northern region, which equals 0.378 and 1.000, respectively. It was found that the least technical efficiency of durian production was in the Northeast region, which was equal to 0.005 and 0.741, respectively. The central and southern regions had a level of efficiency per size equal to 1 for both regions, with stable durian production that did not increase or decrease. In addition, when considering the northern region (DMU1) and the northeastern region (DMU2), it was found that the efficiency values per size were 0.378 and 0.007, respectively. Thus 2 regions, where durian production is low level, the technical efficiency of durian production should be increased (Charnes et al., 1978).

In addition, from the study on efficiency measurement and productivity of durian production in Thailand over the past 10 years, it was also found that the average of the index changes in production efficiency, technology changes, and real technical efficiency changes were increasing almost every year when classified by region. The Malmquist Index of Durian Production in each region in the past 10 years showed that the Central and Southern regions had higher index values than Thailand's Northern and Northeastern regions. Previous research has studied measuring the productivity trend of durian production in Thailand from 2012 to 2016. By using input and output variables, which consist of planted area, harvested area, human labor, fertilizer, pesticide, and machinery, it was found that the central region has the highest productivity growth and also has the highest technical change and efficiency change, followed by the southern region, the northeast region, and the northern region, respectively. When comparing the results, it was found that there was a consensus among productivity trends (Parichatnon et al., 2017) with the research topic, "The measurement of efficiency and productivity change in durian in Thailand, it learned more about the subject's essential causes of change in productivity, technical change, and efficiency". By considering the change in the input and output variables, the study's results can be summarized as follows: The farmers in the central region are using technology to increase yields better than in other regions. When comparing farmland with the yield obtained after harvest, increasing or using technology more effectively makes the production of the central region higher than other regions. Therefore, technology and innovation in every region of Thailand is an important mechanism to drive the ability and efficiency of durian cultivation in Thailand.

Using the system for measuring PH, moisture, and minerals in the soil and a drone for spraying fertilizer and pesticides in durian cultivation has proven beneficial for growth and maintenance efficiency in durian orchards. By selecting appropriate durian varieties that are resistant to diseases and pests, farmers can achieve improved quality and quantity of durian yields. Adopting smart farming technology has emerged as a highly efficient and water-saving approach. These systems utilize sensors to detect soil moisture levels and deliver precise amounts of water directly to the base of durian trees. Furthermore, farmers can provide water based on the individual demands of the durian trees by monitoring and measuring soil moisture. Controlling the use of chemical fertilizers is essential for regulating the amount of nutrients suited for durian growing. The nutrients in the soil can be accomplished by employing fertilizers designed based on soil component analysis. Additionally, the use of foliar spray chemicals helps control plant pests and diseases that affect durian leaves. These chemicals penetrate the leaf surface and effectively combat plant pests and diseases, such as insecticides and

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fungicides, consistent with previous research by Datepumee et al. (2019), who studied the factors affecting the production of export-quality durians by farmers in Thailand. This study used binary logistic regression to analyze the data set. The study's results found that the sample of 393 durian farmers in the central region highlighted soil texture, training attendance, durian maturity inspection, spread of pests, branch pruning, fertilizer application on fruit maturity, and income as factors that affected the farmers' production capability.

Thus, these technologies significantly enhance the efficiency of durian cultivation and maintenance. They lead to the development of healthier and more productive durian trees in Thailand, ensuring improved yields and overall farm profitability. By integrating these technologies into their practices, durian farmers can optimize the growth and health of their durian trees, resulting in successful and sustainable durian production. The governments or agencies involved in durian cultivation should focus on the use of technology and innovation to aid in the cultivation of production and harvesting of durian to be most efficient and of the lowest cost. However, climate change, such as inconsistent rainfall and drought, can affect yields. Farmers must adapt by using technology to balance the growing environment, which can effectively reduce costs and increase yields. Therefore, external factors and technology are essential in supporting farmers in producing durian sustainably and competing better in the global market.

Limitation and Suggestion

Most of the analysis is quantitative, such as planting area and yield, but lacks qualitative factors, such as farmer satisfaction or on-site management. Although the impact of climate change is mentioned, there is still a lack of in-depth analysis of long-term impacts, such as changes in planting seasons or future soil suitability. There is also a lack of comparison of the impact of traditional and modern technologies on durian yield and quality, making it impossible to identify the most appropriate approach for comprehensive production development.

In future studies, in-depth studies should be conducted in low-production areas, such as the North and the Northeast, to identify factors contributing to low efficiency and find ways to improve them. Qualitative factors such as farmers' attitudes and knowledge management should also be analyzed for a more comprehensive perspective. The impacts of traditional and modern technologies on productivity and cost should be compared to find the most suitable approach. Finally, the government should study ways to support farmers, such as providing technology funding, developing infrastructure, and expanding export markets to promote more efficient and sustainable durian production.

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