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RESEARCH ARTICLE

Determinants of Technical Efficiency of Harumanis Mango Production in Perlis, Malaysia

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ABSTRACT

The Harumanis mango (*Mangifera indica L.*) is renowned in Malaysia for its distinctive taste and strong market appeal. Despite the potential for exporting Harumanis mangoes to Japan, productivity in Perlis remains low. This study aims to analyse the determinants of technical efficiency in Harumanis production across two key regions in Perlis, Mata Ayer and Chuping, which are known for having the highest mango yields in Malaysia. Using Stochastic Frontier Analysis (SFA) and the Cobb-Douglas production function, a dataset of 150 observations was collected from 50 mango farms over three consecutive growing seasons. The analysis examined the impact of various production inputs—such as labour, agrichemicals, plot size—and environmental factors, including temperature and rainfal on mango yield. The findings revealed significant disparities in the efficiency and effectiveness of inputs between Mata Ayer and Chuping. Labour positively influenced mango yield in both regions, although the magnitude of its effect differed. Agrichemical use showed positive correlations in Mata Ayer but insignificant or negative associations in Chuping. Temperature emerged as a critical environmental factor, particularly in Chuping, where higher temperatures were linked to reduced output. The interaction between inputs underscores the importance

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of tailored management strategies that consider specific local conditions and input combinations. The technical efficiency analysis revealed greater inefficiencies in Mata Ayer compared to Chuping. This study enhances the understanding of mango production dynamics and provides insights for targeted interventions to improve yield and sustainability in Harumanis mango cultivation.

Keywords: Mango; Stochastic Frontier Analysis; Technical Efficiency; Food Security; Malaysia

1. Introduction

Malaysia has established itself as a notable producer of diverse tropical fruits, including pineapples, bananas, mangoes, rambutans, durians, mangosteens, jackfruits and starfruits [1]. However, Malaysia's participation in the international fruit trade remains limited despite the growth of the global tropical fruit market. Notably, the self-sufficiency ratio (SSR) for mangoes is significantly lower compared to other tropical fruits cultivated in the country.

As illustrated in **Figure 1**, the SSR for mangoes in Malaysia was a modest 32% in 2022, highlighting a substantial disparity between domestic production and consumption. This gap highlights the necessity for targeted strategies to enhance mango production and address domestic consumption needs. Recognising the economic and nutritional value of mangoes, the Malaysian government is actively formulating initiatives to strengthen production in response to the growing demand for this tropical fruit. One such initiative, implemented by the Department of Agriculture in 2016, involved incentivising farmers to replant specific tropical fruits by providing an input subsidy of RM6,000 per hectare [2].

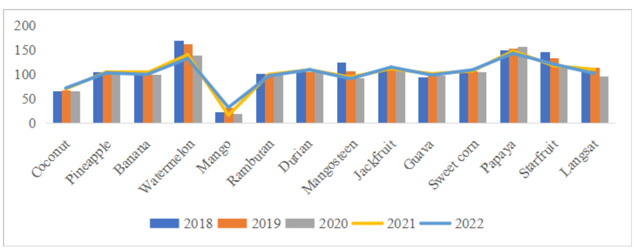

Figure 1. Self-Sufficiency Ratio of Selected Fruits, Malaysia (2018–2022).

Insights from the 2022 report by the Department of Statistics Malaysia highlight the challenges associated with mango self-sufficiency, prompting an intensified focus on policies and interventions to elevate mango production. These initiatives are crucial not only for meeting domestic consumption needs but also for seizing potential export opportunities. Furthermore, the emphasis on boosting mango production aligns with identified prospects for the future development of tropical fruits, including mangoes, in international markets like Japan [3]. The mango industry in Malaysia faces challenges in self-sufficiency and technical efficiency due to a heavy reliance on imports and inefficient resource utilisation in domestic production. This scenario suggests a need for improvements in farming practices, technology and resource management.

One of the premium mango varieties, known as Harumanis, is considered the "King of Mangoes" and is highly popular in Malaysia. This variety is commercially grown primarily in Perlis, and previously, for export. The high demand for Harumanis mangoes is due to their unique sweetness and aroma compared to other varieties [4]. However, due to their sensitivity to environmental and climatic conditions, Harumanis are mostly found in Perlis and several parts of Kedah [5].

Harumanis require a significant dry period to initiate flowering, while their productive phase can be significantly affected by changes in weather. The different climates across regions adversely affect flowering time, fruiting, yield, and the quality of the fruit [6]. Despite being one of the most commercially grown mango varieties in Malaysia due to market demand and price, the supply of Harumanis remains inadequate due to their climate sensitivity [7].

Currently, research on the effect of different regions in Malaysia on Harumanis mango production and quality is insufficient. However, a number of locals in Perlis claimed that Harumanis grown outside of Perlis yield lower quality fruit, attributable to environmental factors. Nonetheless, there is no scientific evidence to support this claim [5]. This highlights the need for research assessing the interaction between farm inputs and environmental variables, such as precipitation and temperature in determining their effects on yield quantity and quality.

Between 1979 and 2015, a series of strategic initiatives aimed at enhancing Harumanis mango production were implemented. The Village Rehabilitation Project marked the beginning, replacing non-economically viable trees with economically significant Harumanis mangoes, with efforts intensifying in 1983 under group farming. The Integrated Agricultural Development Project (IADP) allocated significant resources, resulting in 1,200 hectares of Harumanis cultivation by 1990. Despite a subsequent decline to 150 hectares in 2006 due to neglect, the Department of Agriculture revived the industry in 2007 using strategies that included reclaiming fallow land and introducing the Harumanis Village Project to cultivate 1,000 hectares by 2015 under the Tenth Malaysia Plan [8].

Since 2016, as reported by BernamaNews, a noticeable reduction in yields has been reported by local farmers, such as Saidin Saad. Meanwhile, his brother Ishak Saad who operates nearby orchards claim that factors contributing to diminished harvests extend beyond the El Niño phenomenon. He added that the combination of poor tree health, inadequate maintenance, and limited fertiliser usage exacerbates the challenges faced by farmers. Studies have shown that these factors significantly reduce yield potential in tropical crop production [9–11]. Additionally, adverse weather conditions have been identified as compounding these issues, further hindering productivity [12]. Unprecedented weather anomalies, including untimely rains triggered by cold winds from the East Coast states, have significantly impacted Harumanis mango production in Perlis. These unexpected climatic conditions during the typically hot and dry season disrupted flowering, leading to substantial losses for farmers. To counter these challenges, the Perlis Agricultural Department distributed water pumps to alleviate the effects on orchards, emphasising the need for adaptive strategies in agriculture [13].

Despite extensive efforts to enhance Harumanis mango production, a declining trend has been observed since 2020 during the pandemic, with a further decline in overall mango production in 2022 (**Table 1**) [14]. It is imperative to focus on improving efficiency among inefficient farmers, rather than solely prioritising technological advancements. While the introduction of new technologies theoretically enhances agricultural productivity, the adoption of new technologies may not yield the expected outcomes in areas where inefficiency results from underutilisation of existing inputs and technologies. The level of technical efficiency among farmers has significant implications for the country's agricultural development strategy [15].

Technical efficiency is generally the ability of a firm to produce as much output as possible with a specified level of inputs, given the existing technology [16–18]. Conversely, technical inefficiency arises from excessive input use in production [19, 20]. The preferred method for assessing agricultural efficiency, due to inherent stochasticity [21, 22], is the stochastic frontier approach. In agriculture, technical efficiency signifies a farmer's capacity to achieve maximum output given inputs and technology [23, 24]. Variations in farmers' technical efficiency may be attributed to managerial decisions, environmental conditions, non-technical and non-economic factors, and specific farm characteristics influencing the use of production technology [17].

The Stochastic Frontier Analysis (SFA) method allows for the assessment of changes in input use, technology, and efficiency. This method assumes data characteristics and imposes a functional production form to determine efficiency levels and the usefulness of each resource in the data. Additionally, it identifies sources of inefficiency and error within the data. In most cases, SFA models commonly employ the Cobb-Douglas and Translog production functions [25].

Given the importance of Harumanis mango for domestic consumption, export potential, income generation and the livelihoods of numerous smallholders, it is crucial to conduct empirical analyses exploring the correlation between technical efficiency and socioeconomic variables among farmers. However, empirical evidence is scarce on farm-level technical efficiency in Harumanis production, while knowledge about Harumanis production, especially in Malaysia, remains inadequate.

Table 1. Production (tonne) of selected fruits in Malaysia (2018–2022).

Selected Fruits	2018	2019	2020	2021	2022
Pineapple	322,551	314,627	323,420	375,423	537,231
Banana	331,225	325,447	313,811	330,253	330,601
Jackfruit	31,175	31,281	35,624	41,047	40,220
Cempedak	30,041	27,893	24,469	25,486	20,003
Mangosteen	26,170	28,764	23,297	26,831	23,508
Mango	15,329	16,509	12,834	12,208	9,219
Durian	342,170	377,251	390,635	448,272	455,458
Starfruit	6,920	8,054	9,296	7,895	6,616
Papaya	52,917	53,681	61,776	60,980	54,753
Guava	34,495	35,962	37,881	36,900	33,292
Langsat	19,633	18,933	17,470	15,207	10.905

Source: Selected agricultural indicators 2023 [2], Department of Statistics, Malaysia (2023) [2, 14].

This study bridges a crucial gap in the literature by examining the technical efficiency of Harumanis production in specific regions of Perlis, Malaysia. The evaluation of efficiency levels informs resource allocation for farmers and guides targeted government policies. Findings from this research will substantially shed light on the formulation of effective agricultural strategies, the improvement of productivity and the enhancement of farmers' livelihoods. This research is also of utmost importance for strengthening Malaysia's position in the global tropical fruit market, strategically addressing domestic demand and fostering self-sufficiency in Harumanis production.

2. Materials and Methods

This study was conducted in Chuping and Mata Ayer, both of which are the main Harumanis production areas in the state of Perlis, Peninsular Malaysia. Both regions are located in the northern state of Perlis, Malaysia, and share similar agro-climatic conditions, such as high humidity and consistent rainfall patterns. However, slight variations in soil type and elevation differentiate them, potentially affecting mango production. **Figure 2** illustrates the geographic location of these regions within Perlis.

The sample size consisted of 50 farmers, purposively selected for assessing technical efficiency across three consecutive production seasons: 2020/2021, 2021/2022, and 2022/2023. Data collection was primarily conducted through a structured questionnaire and face-to-face interviews. The questionnaire was divided into several sections, including sociodemographics, inefficiency determinants, as well as farm input and output data.

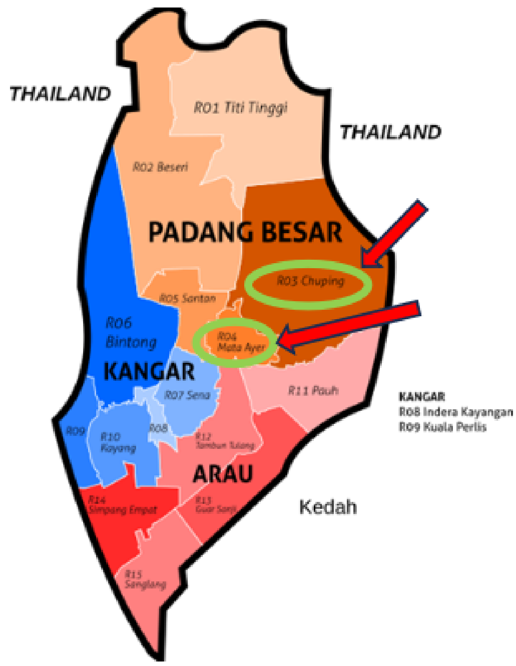

Figure 2. Geographical location of Mata Ayer and Chuping in Perlis, Malaysia.

Source: Wiki commons.

The Stochastic Frontier Analysis (SFA) production function was utilised to estimate the technical efficiency of Harumanis mango production in Chuping and Mata Ayer, Perlis, Malaysia. The SFA model, specifically employing a Cobb-Douglas production function, was selected to analyse the relationship between key inputs (labour, plot size, fertiliser and agrichemicals) and mango output.

The Cobb-Douglas production function was chosen owing to its effectiveness in capturing the non-linear relationships often present in agricultural production systems. This model enables the estimation of the average production function and the level of technical inefficiency across different production units. **Table 2** provides a summary of the variables included in the analysis.

SFA, first introduced by Farrell[16], was further developed by Aigner, Lovell and Schmidt[26] and Meeusen and van Den Broeck[27] to independently estimate technical efficiency and stochastic models. SFA is an econometric and parametric approach that incorporates a random variable to account for stochastic elements. Unlike other methods, SFA differentiates between random errors (or noise) and inefficiency. The stochastic frontier model is expressed as $y = f(x, z) + v - u$ where y represents log-output, v accounts for noise and u represents inefficiency. The production function, $f(x, z) + v$, forms the basis of the stochastic frontier, with the term "stochastic" reflecting the inclusion of random variations.

This approach allows the distinguishing between random components, which include measurement errors and stochastic effects (weather or climate changes), and deviation components, which represent inefficiency. The general form of the SFA, as proposed by Aigner, Lovell and Schmidt[26], and the production frontier described by Coelli, Rao and O'Donnell[28], can be represented in Equation (1):

$$y_{it} = f(x_{it};\ \beta) +\ v - u \tag{1}$$

where: f is a suitable functional form (such as Cobb-Douglas or Translog); y_{it} represents the output of the i-th farm at time t; x_{it} is the corresponding level of input; and β is a vector of unknown parameters to be estimated. The error term comprises two elements: u_i, is a non-negative variable associated with technical inefficiency; while v_i, a symmetric random error accounting for statistical noise or unsystematic deviations from the frontier.

Further, technical efficiency can be estimated by the ratio of observed output y_{it} to the maximum feasible output $y_{max} = \textit{exp}\,(x_{it};\ \beta) * v_{it}$ under an appropriate environment. Using an output-oriented measure of technical efficiency, this ratio is illustrated in Equations (2) and (3).

$$TE_{it} = \frac{Y_{it}}{expf\,(x_{it};\beta) * expv_{it}} = \frac{expf\,(x_{it};\beta) * expv_{it}(-u_{it})}{expf\,(x_{it};\beta) * expv_{it}} \tag{2}$$

$$TE_{it} = exp(-u_{it}) \tag{3}$$

As a parametric approach, SFA requires an assumption regarding the specific functional form, with the frontier econometrically estimated using least squares or maximum likelihood methods[23]. SFA is grounded in an econometric regression model where the frontier is smooth and curved.

A production function model is necessary under SFA, with options including Cobb-Douglas, Constant Elasticity of Substitution (CES), Translog, generalised Leontief, or normalised quadratic and their variants. However, the Translog and Cobb-Douglas production functions are the most favoured in empirical studies for production and frontier analysis[23]. Despite the availability of various stochastic frontier function forms, the data were fitted to the Cobb-Douglas production function using R software. The empirical model of the stochastic frontier Cobb-Douglas production function for analysing the technical efficiency of Harumanis production is specified in Equation (4) as follows:

$$\begin{gathered} lny_i = t +\ \beta_0 +\ \beta_1 lnx_1 +\ \beta_2 lnx_2 +\ \beta_3 lnx_3 + \\ \beta_4 lnx_4 +\ \beta_5 ln(x_1)^2 +\ \beta_6 ln(x_1.x_2) + \\ \beta_7 ln(x_1.x_3) +\ \beta_8 ln(x_1.x_4) + \beta_9 ln(x_2)^2 + \\ \beta_{10} ln(x_2.x_3) +\ \beta_{11} ln(x_2.x_4) + \beta_{12} ln(x_3)^2 + \\ \beta_{13} ln(x_3.x_4) +\ \beta_{14} ln(x_4)^2 +\ lnz_1 +\ lnz_2 + \\ v_i +\ u_i \end{gathered} \tag{4}$$

In the analysis of Harumanis mango technical efficiency, several variables and parameters were utilised. The output of Harumanis mango (tonnes), denoted as y_1, was examined alongside a time trend t. The model included a constant term β_0, representing the intercept; while β_1 through β_{14} were coefficients to be estimated. Various input factors were considered, including plot size x_1, measured in relung; 1 relung = 0.288 hectares), labour (x_2, quantified in man-days), quantity of fertiliser

Table 2. Summary of agricultural inputs and environmental variables for mango production in Mata Ayer and Chuping.

		Mata Ayer				Chuping			
Variable	**Description**	**Min**	**Max**	**Mean**	**Std. Error**	**Min**	**Max**	**Mean**	**Std. Error**
Plot size (relung)	Size of the farming plot in relung (1 relung = 0.288 hectares)	1	3	1.508	0.75	0.5	6	1.72	0.88
Labour (man-days)	Total labour input per relung	17	207	72.71	46.75	19	239	76.36	50.31
Fertiliser (kilogramme)	Quantity of fertiliser applied per relung	15	425	144.21	135.58	0.28	3008	514.28	125
Agrichemical (litres)	Quantity of agrichemicals applied per relung	0.24	2006.1	159.97	582.3	2.14	742.8	95.36	552.23
Rain precipitation (millimetre)	Rain precipitation during flowering phase	17.7	52.6	33.04	7.95	13.8	44.2	26.57	6.87
Temperature (degree Celsius)	Temperature during flowering phase	23.7	27.2	25.19	2.44	27	29	28.04	2.35

Source: Field survey data (2023) & Meteorological Department (2023).

(x_3, expressed in kilograms) and quantity of agrochemicals (x_4, measured in litres). Additionally, environmental factors such as rainfall precipitation (z_1, in millimetres) and temperature (z_2, in degrees Celsius) were incorporated into the model. The presence of random error (v_i) accounts for unexplained variability; while u_i represents the technical inefficiency effect predicted by the model, with the subscript i denoting the i-th farmer in the sample.

The determinants of technical efficiency among mango farmers adapted from Mensah and Brummer [29], Raimondo et al. [30] and Krasachat [31] were modelled according to the specific characteristics of farmers in the study area. The model equation incorporated various components, with technical inefficiency u_i represented in Equation (5) as:

$$u_i = \alpha_0 + \Sigma_{r=1}^{7} \alpha_r z_r + k \quad (5)$$

where: α_0 and α_r represent parameters subject to estimation; while k denotes a truncated random variable. The variables z_1 through z_7 capture various dimensions of farmer characteristics and agricultural practices, including the number of trees, household size, attendance at training sessions, years of farm experience, membership status (as indicated by dummy variables), availability of irrigation (also represented by a dummy variable) and farm accreditation (likewise represented by a dummy variable).

3. Findings and Discussion

3.1. Description of Respondents

The socio-economic characteristics of the Harumanis mango farmers surveyed in Chuping and Mata Ayer revealed distinct patterns that may significantly influence farm productivity and technical efficiency. As demonstrated in **Table 3**, the entire sample from both regions consisted exclusively of male respondents. This finding aligns with broader trends in agricultural practices, where labour-intensive activities, including mango harvesting, are predominantly undertaken by men. The physically demanding nature of these tasks often limits female participation, a phenomenon supported by prior research highlighting the gendered division of agricultural labour [32, 33].

The age distribution of farmers in Chuping and Mata Ayer exhibited notable regional differences. In Chuping, most respondents (60%) fell within the 41–50 age group, whereas the largest proportion (40%) in Mata Ayer were aged between 51–60 years. This suggests that Chuping's farming population is relatively younger. The predominance of middle-aged farmers in both regions indicates a workforce that, while experienced, may be increasingly challenged by the physical demands of mango farming. The presence of older farmers, particularly in Mata Ayer, raises concerns about long-term productivity, as advancing age may reduce physical capacity for labour-intensive tasks [34].

Table 3. Descriptive analysis of farmers' demographic in Mata Ayer and Chuping.

		Mata Ayer		Chuping	
Variable	**Categories**	**Number of Respondents**	**Percentage (%)**	**Number of Respondents**	**Percentage (%)**
Gender	Male	25	100	25	100
	Female	0	0	0	0
Age (years old)	31–40	2	8	1	4
	41–50	1	4	15	60
	51–60	10	40	6	24
	61–70	9	36	3	12
	71–80	3	12	0	0
Marital status	Single	4	16	2	8
	Married	21	84	23	92
	Divorced	0	0	0	0
Household size	1–5	24	96	13	52
	6–10	1	4	11	44
	11–15	0	0	1	4
Education level	Non-formal	1	4	0	0
	Primary	4	16	1	4
	Secondary	16	64	21	84
	Tertiary	4	16	1	4
	Others	0	0	2	8
Race	Malay	25	100	25	100
	Chinese	0	0	0	0
	Indian	0	0	0	0
	Others	0	0	0	0
Planting mode	Full-time	7	28	8	32
	Part-time	18	72	17	68
Experience (years)	1–10	21	84	17	68
	11–20	1	4	6	24
	21–30	3	1270	0	
	31–40	0	0	2	8
Plot size (relung)	less than 1	0	0	3	12
	1–2	23	92	18	72
	2.1–3	2	8	2	8
	3.1–4	0	0	0	0
	above 4	0	0	2	8

Source: Field survey data (2023).

The marital status data indicated that many farmers in both regions were married; 92% in Chuping and 84% in Mata Ayer. This high prevalence of married respondents aligns with existing research, which suggests that marital stability often enhances household labour contributions, thereby potentially increasing farm productivity [35]. Household sizes were predominantly between 1–5 individuals in both regions, with Chuping reporting 52% and Mata Ayer a substantial 96%. The trend towards smaller household sizes may reflect broader demographic changes, potentially impacting the availability of family labour for farming activities [36].

The educational background of the farmers revealed significant regional disparities. In Chuping, 84% of respondents had completed secondary education, compared to 64% in Mata Ayer. Higher levels of education in Chuping may contribute to more effective farm management practices and greater productivity, as education equips farmers with critical skills and knowledge essential for navigating the complexities of modern agriculture [37, 38]. These findings are in line with evidence from other regions, such as the Offinso Municipality and broader Southeast Asia, where education has been shown to significantly enhance agricultural productivity [39, 40]. The relatively lower tertiary education levels across both regions suggest a potential barrier to adopting advanced farming technologies and methods, which are often linked to higher agricultural output [41]. Nonetheless, the predominance of secondary education is pivotal, as it lays a foundational understanding necessary for improved decision-making and resource management on farms.

It was also found that all farmers in both Chuping and Mata Ayer were of Malay ethnicity, reflecting the homogeneity of the farming communities in these regions. Regarding farming modes, a significant proportion of farmers were engaged in part-time farming; 68% in Chuping and 72% in Mata Ayer. This suggests that many farmers are balancing mango farming with other occupations, which may dilute their focus and commitment to agriculture, potentially leading to lower productivity [42]. Part-time farming has been associated with reduced efficiency, as it often results in less intensive farm management compared to full-time farming.

The analysis of farming experience revealed that most farmers in both regions had relatively short tenures in Harumanis mango farming. In Chuping, 68% of farmers had 1–10 years of experience, while in Mata Ayer, this figure was higher at 84%. The presence of newer entrants to the industry is a positive sign for the sector's growth; however, experience is critical for enhancing productivity. Farmers with more years of experience are generally more adept at optimising input use and improving farm efficiency from the cumulative benefits of experiential learning [43, 44]. The small subset of farmers with over 30 years of experience represents a valuable source of knowledge that could be leveraged to improve agricultural practices within the community.

Plot size distribution is another critical factor influencing productivity. In Chuping, 72% of farmers managed plots between 1 and 2 relung (0.288 to 0.576 hectares); while in Mata Ayer, a similar distribution was observed, with 92% of farmers operating within this range. This indicates that small to medium-sized plots are common in both regions. Efficient management of smaller plots can lead to more intensive and effective utilisation of land resources, contributing to higher productivity per unit area [45]. However, the few farmers in Chuping with larger plots (above 4 relung) may have the potential to achieve economies of scale, further enhancing productivity [46] as observed in maize production where plot size and management practices significantly influenced efficiency [47].

The socio-economic characteristics identified in this study highlight the need for targeted policy interventions to address the specific needs of each region. The higher educational levels in Chuping, for instance, could be harnessed to introduce and promote advanced agricultural practices, while the older age profile of farmers in Mata Ayer might necessitate support for less physically demanding farming methods or the introduction of labour-saving technologies. Additionally, encouraging full-time farming could enhance productivity by enabling farmers to devote more time and resources to their agricultural activities. By addressing these factors, stakeholders can improve the sustainability and efficiency of mango farming in these regions, thereby contributing to enhanced economic outcomes for the farmers and their communities [48].

3.2. Estimation of Cobb-Douglas Production Function in Harumanis Mango Production

The production function for Harumanis mango in the regions of Mata Ayer and Chuping for the three consecutive seasons was estimated using a stochastic frontier analysis with a Cobb-Douglas production function approach. The analysis was executed through the Ordinary Least Square (OLS) method to provide robust estimates of the production parameters. **Table 4** outlines the detailed results of this estimation.

Hypothesis tests were conducted to select the functional form using the likelihood ratio (LR) = $-2[\ln L(H_0) - \ln L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses respectively. LR has approximately a Chi-square (or mixed Chi-square) distribution if the given null hypothesis is true, with a degree of freedom equal to the number of parameters assumed to be zero in (H_0). Kodde and Palm [49] proposed that all critical values can be obtained from the appropriate Chi-square distribution. However, if the test of hypothesis involves $\gamma = 0$, then the asymptotic distribution necessitates the mixed Chi-square distribution.

In this study, all variables which are planting area,

Table 4. Stochastic frontier analysis for Harumanis mango production: Cobb Douglas production function (Ordinary Least Square).

Variable	Mata Ayer		Chuping	
	Coeff. β	**Std. Error**	**Coeff. β**	**Std. Error**
Constant	3.5129e+00***	1.0526e+00	1.1583e+01***	9.9666e–01
Year (dummy)	7.9803e–01	5.1500e–01	–4.4188e–01*	2.1971e–01
Ln plot size/relung	2.6204e–01	9.5797e–01	2.3266e–01	1.0321e+00
Ln labour/man-days	7.0781e–02*	3.3976e–02	5.3685e–02**	1.9002e–02
Ln fertiliser/kilogramme	–1.6338e–02	1.6311e–02	–1.9547e–03	1.9297e–03
Ln agrichemical/litre	3.2556e–02*	1.4585e–02	–1.4067e–02	1.5413e–02
Ln (plot size)^2	–7.1843e–01	8.3370e–01	–1.8664e–01	4.2714e–01
Ln (plot size*labour)	1.7543e–02	1.7024e–02	2.1175e–03	1.8003e–02
Ln (plot size*fertiliser)	–2.4160e–03	1.4144e–02	–1.4663e–04	8.0647e–04
Ln (plot size*agrichemical)	1.3625e–02**	5.2809e–03	1.1707e–03	6.8420e–03
Ln (labour)^2	–5.1483e–04**	1.8272e–04	–1.1944e–04	8.3468e–05
Ln (labour*fertiliser)	2.5620e–04	1.6903e–04	5.0337e–06	3.2398e–05
Ln (labour*agrichemical)	–4.8744e–04**	1.5402e–04	8.4121e–06	4.6703e–05
Ln (fertiliser)^2	1.5559e–05	3.1013e–05	5.1969e–07	8.8847e–07
Ln (fertiliser*agrichemical)	–6.2933e–05.	3.2713e–05	6.3190e–06	9.6029e–06
Ln (agrichemical)^2	5.9748e–06	4.0783e–06	1.0416e–05	1.4313e–05
Ln rain precipitation/millimetre	5.0803e–03	3.7974e–02	–2.9954e–02	2.4511e–02
Ln temperature/degree Celsius	–2.8573e–01**	9.2545e–02	–4.2527e–01***	6.2429e–02
Sigma-squared u (σ_u^2)	9.9586e+00***	1.3315e+00	5.8575e+00***	5.6628e–01
Sigma-squared v (σ_v^2)	1.4817e–07	1.0455e–06	5.8575e–08	8.9269e–07
Sigma-squared (σ^2)	9.9586e+00***	1.3315e+00	5.8575e+00***	5.6628e–01
Sigma u (σ_u)	3.1557e+00***	2.1096e–01	2.4202e+00	1.1699e–01
Sigma v (σ_v)	3.8493e–04	1.3580e–03	2.4202e–04	1.8442e–03
Lambda ($\lambda = \sigma_u / \sigma_v$)	8.1983e+03	2.8996e+04	1.0000e+04	7.6315e+04
Number of observations	75		75	
Log likelihood	–145.7136		–136.4858	

Source: Field survey data (2023).
Note: ***, **, and * denote significance at 0.01, 0.05 and 0.1 respectively.

labour, fertiliser and agrichemicals are used to estimate Cobb Douglas production function in order to determine the technical efficiency among Harumanis mango farmers in Mata Ayer and Chuping, Perlis. The variable ln plot size is the log-transformed plot size, lnlabour is the log-transformed labour, lnfertiliser is the log-transformed fertiliser, ln agrichemicals is the log-transformed agrichemicals, and meanwhile lnproduction is the log-transformed production of Harumanis mango. Average rain precipitation and average daily temperature during flowering month are also included in the model where they are treated as input and log-transformed as ln rain precipitation and ln temperature.

The Ordinary Least Squares (OLS) method was employed to derive robust estimates of the production parameters. Detailed results of this evaluation are presented in **Table 4**. The coefficients indicate the marginal effects of each input variable on Harumanis mango production in the Mata Ayer and Chuping regions. These regions exhibit distinct agro-climatic and socio-economic conditions that contribute to the variability in the observed production outcomes.

The stochastic frontier model components, including sigma-squared (σ^2), sigma-squared u (σ_u^2), and sigma-squared v (σ_v^2), were significantly estimated. The relatively high value of sigma-squared u in both regions indicates considerable inefficiencies in production, which could be targeted for improvement. The lambda (λ) values, representing the ratio of variance from inefficiency effects to random noise, were exceedingly high, emphasizing the predominance of inefficiencies over stochastic variations in production.

The models for both regions demonstrated adequate fit with the data, evidenced by the log-likelihood values (–145.7136 for Mata Ayer and –136.4858 for Chuping). The number of observations (N = 75 for both regions) provides a reasonable basis for the robustness of the statistical estimates.

The analysis of Harumanis mango production in Mata Ayer and Chuping demonstrated several significant findings that contribute to understanding productivity dynamics in these regions. The present findings indicated that labour input is a critical determinant of mango yield in both regions. In Mata Ayer, labour input showed a positive and statistically significant impact on yield ($\beta = 0.0708$, $p < 0.05$), with an increase in man-days leading to a corresponding increase in yield by 0.0708 tonnes. This result aligns with previous research [29, 50], reinforcing the role of labour in enhancing mango productivity.

The use of agrichemicals also significantly influences mango yield in Mata Ayer. The positive coefficient ($\beta = 0.0326$, $p < 0.05$) suggests that an increase in agrichemical application enhanced productivity by 3.3%, consistent with findings from [51]. These results highlight the importance of agrichemicals in boosting mango production, although their use should be carefully managed to avoid potential negative effects from over-application.

Conversely, the negative coefficient for fertiliser input ($\beta = -0.0163$) in Mata Ayer suggests that excessive fertiliser application may adversely impact yield. This finding aligns with observations in agricultural research [52], where high levels of fertiliser can lead to nutrient imbalances and reduced productivity. Thus, while fertiliser is essential, its application must be optimised to prevent detrimental effects on mango yield.Temperature during the flowering stage also plays a significant role. In Mata Ayer, lower temperatures were associated with higher yields ($\beta = -0.286$), which underscores the sensitivity of mango cultivation to temperature variations during critical growth periods [53, 54]. Cooler temperatures appear to create a more favourable environment for fruit development. Sukhvibul et al. [55], suggesting that temperature management strategies could enhance mango productivity.

The analysis in Chuping identified a statistically significant decline in mango production over time ($\beta = -0.44188$, $p < 0.05$), highlighting ongoing challenges in maintaining yield levels. Despite this trend, labour input remained a significant factor influencing productivity, with a positive coefficient ($\beta = 0.0537$, $p < 0.01$), consistent with the findings of Saina et al and Dessale [38, 56]. Additionally, the negative coefficient for temperature in Chuping supports the observation that lower temperatures during the flowering period are related to higher mango yields, corroborating results reported by Legave, Normand and Lauri [54].

The discussion highlights the importance of both significant and non-significant variables in agricultural productivity. Findings from different regions reveal complex interactions among plot size, agrichemicals, and labour input, emphasising the need for integrated farming approaches [57]. Labour input consistently influences mango productivity; while the quadratic effect of plot size suggests optimising farm size to avoid diminishing returns. Although non-significant variables are secondary, they contextualise the findings and suggest future research avenues, informing sustainable agricultural interventions.

Although the discussion primarily emphasises statistically significant variables, acknowledging non-significant variables is also valuable. The discussion highlights the value of considering both significant and non-significant variables in agricultural productivity analysis. Findings from both regions reveal complex interactions among plot size, agrichemicals, and labour input, emphasising the need for integrated farming approaches [40]. The quadratic effect of plot size underscores the importance of optimising farm size to avoid diminishing returns. Furthermore, differing impacts of fertiliser application between Mata Ayer and Chuping may result from variations in soil fertility and agronomic practices. Excessive fertiliser use could disrupt soil nutrient balance; while optimal agrichemical use may enhance yields. According to Silva and Araújo [52], continuous mineral fertiliser application can alter soil properties and nutrient balance.

While previous studies have generally indicated a positive relationship between labour and yield [44, 50], the negative coefficients and elasticities observed for labour input in Mata Ayer underscore the critical role of skilled labour in mango cultivation. Activities such as pruning, irrigation, and harvesting are directly linked to yield outcomes, highlighting the importance of skillful labour for successful cultivation practices. This observation aligns with Khai and Yabe [58], which notes that yield does not always have a positive relationship with agricultural labour utilisation in developing countries. Additionally, favourable climatic conditions, including moderate rainfall and optimal temperature ranges, may further enhance mango productivity in both regions.

Overall, the findings from both regions emphasise the need for targeted management practices tailored to specific agro-climatic conditions. Efficient use of labour and agrichemicals, combined with effective temperature management, can optimise mango productivity. Future research should continue to explore the nuanced relationships between these variables and develop strategies to address inefficiencies and enhance productivity in Harumanis mango cultivation.

3.3. Determinants of Technical Efficiency

The estimated determinants of technical efficiency for Harumanis mango production in Mata Ayer and Chuping are presented in **Table 5**. A positive coefficient signifies a direct association with technical inefficiency, while a negative sign indicates an inverse relationship, suggesting an enhancement in technical efficiency for the specified variable.

In Mata Ayer, although not statistically significant, larger household sizes were associated with lower technical efficiency ($\beta = -0.0532$), suggesting potential inefficiencies arising from larger family units [59]. Conversely, in Chuping, larger household sizes were linked to higher technical efficiency ($\beta = 1.4219$, $p < 0.05$), indicating possible synergies within larger family units. Membership in farmer associations positively influenced technical efficiency in Mata Ayer ($\beta = 0.2665$, $p < 0.01$) but not in Chuping ($\beta = 0.0508$), highlighting the role of collective action in promoting best practices and resource sharing among farmers. Moreover, farmer experience had contrasting effects in the two regions, with more experienced farmers exhibiting lower technical efficiency in Mata Ayer ($\beta = -0.0185$, $p < 0.05$) but higher technical efficiency in Chuping ($\beta = 1.9373$, $p < 0.001$).

These findings indicate the region-specific nature of technical efficiency determinants in mango production that reflects the diverse socio-economic and environmental contexts of Mata Ayer and Chuping. While household size and farmer experience showed divergent effects, membership in farmer associations emerged as a common positive influencer of technical efficiency across both regions. These results highlight the importance of tailored interventions to address the unique challenges and opportunities faced by mango farmers in each region, ultimately contributing to the enhancement of agricultural productivity and sustainability.

Identifying and understanding the factors influencing technical efficiency in Harumanis mango production allowed this study to provide valuable insights for policymakers, researchers and practitioners aiming to optimise agricultural productivity and promote sustainable farming practices in diverse agro-ecological settings. Future research should explore additional variables and employ more advanced econometric techniques to further elucidate the complexities of mango production efficiency.

In Mata Ayer, the determinants of technical efficiency included the number of training sessions, farmer association membership, farm certification and farmer experience. In Chuping, the determinants were household size and farmer experience. This outcome corresponds with the findings of Murtaza and Thapa [60] and Gebrehiwot [24] regarding farmer associations, as well as Khai and Yabe [58] and Francis, Samuel and Samuel [61] concerning the number of training sessions as determinants of technical efficiency. Other studies support the relevance of household size [62] and farmer experience [29, 50]. A larger household size generally indicates greater labour availability for farm activities, which can improve technical efficiency in developing agricultural contexts. Furthermore, longer farmer experience was seen to be associated with higher technical efficiency. Among farmers with similar experience levels, younger farmers typically achieve better technical efficiency, aligning with previous findings [63]. Additionally, farm certification has been reported to enhance technical efficiency [30, 31].

Table 5. Estimation results of determinants of technical efficiency of Harumanis mango production in Mata Ayer and Chuping using Ordinary Least Square (OLS).

Dependent: Technical Efficiency	Mata Ayer		Chuping	
Variable	**Coeff. β**	**Std. Error**	**Coeff. β**	**Std. Error**
Constant	0.4261880*	0.1917458	−7.32839*	3.06454
Number of trees	−0.0009566	0.0010914	−0.28659	0.38170
Household size	−0.0532175	0.0322786	1.42192*	0.61123
Number of trainings	−0.0607186**	0.0196551	−0.21211	0.18718
Farmer association (dummy)	0.2665375**	0.1003079	0.05079	1.51549
Farm certification (dummy)	0.5887433***	0.1620959	0.04489	0.67940
Farmer experience	−0.0185496*	0.0086631	1.93727***	0.53465
Number of observations	75		75	
Breusch-Pagan (chi-square)	11.637		25.836	
F-statistics	3.31		4.148	
R-squared	0.226		0.2679	

Source: Field survey data (2023).
Note: ***, **, and * denote significance at 0.001, 0.01, 0.05 and 0.1 respectively.

3.4. Frequency Distribution and Technical Efficiency Indices in Mata Ayer and Chuping

As illustrated in **Table 6**, the frequency distribution of technical efficiency scores in Mata Ayer across three production seasons (2020/2021, 2021/2022 and 2022/2023) revealed that this region is struggling with low farm productivity. In the first production season (2020/2021), the histogram indicated that most farms operate with efficiency scores clustered between 0.20 and 0.40, suggesting widespread inefficiency.

The corresponding boxplot reinforced this observation, showing a low median efficiency score and a broad interquartile range (IQR), which reflects significant variability in farm performance (**Figure 3**). In the second production season (2021/ 2022), only a slight shift was observed in the frequency distribution, with some farms moving toward mid-range efficiency scores (0.40–0.50). However, the overall distribution remained similar to the previous season; while the boxplot continued to display a broad IQR and low median score, indicating persistent inefficiencies across the region.

Table 6. Frequency distribution and technical efficiency indices in Mata Ayer and Chuping.

Technical Efficiency	Mata Ayer 2020/2021		Mata Ayer 2021/2022		Mata Ayer 2022/2023		Chuping 2020/2021		Chuping 2021/2022		Chuping 2022/2023	
	Freq.	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
0.00–0.09	8	32	6	24	8	32	3	12	1	4	6	24
0.10–0.19	4	16	4	16	6	24	9	36	6	24	4	16
0.20–0.29	2	8	4	16	2	8	5	20	5	20	4	16
0.30–0.39	5	20	1	4	3	12	1	4	4	16	3	12
0.40–0.49	2	8	4	16	1	4	3	12	3	12	0	0
0.50–0.59	1	4	1	4	1	4	1	4	1	4	2	8
0.60–0.69	0	0	0	0	3	12	1	4	2	8	1	4
0.70–0.79	2	8	1	4	0	0	1	4	0	0	2	8
0.80–0.89	1	4	0	0	0	0	0	0	0	0	2	8
0.90–1.00	0	0	1	4	1	4	1	4	1	4	1	4
1.00	0	0	3	12	0	0	0	0	2	8	0	0
Total	25	100	25	100	25	100	25	100	25	100	25	100
Mean	0.27		0.36		0.26		0.29		0.38		0.35	
Max	0.81		1		0.92		0.92		1		0.91	
Min	0.00		0.00		0.00		0.00		0.07		0.00	

Source: Field survey data (2023).

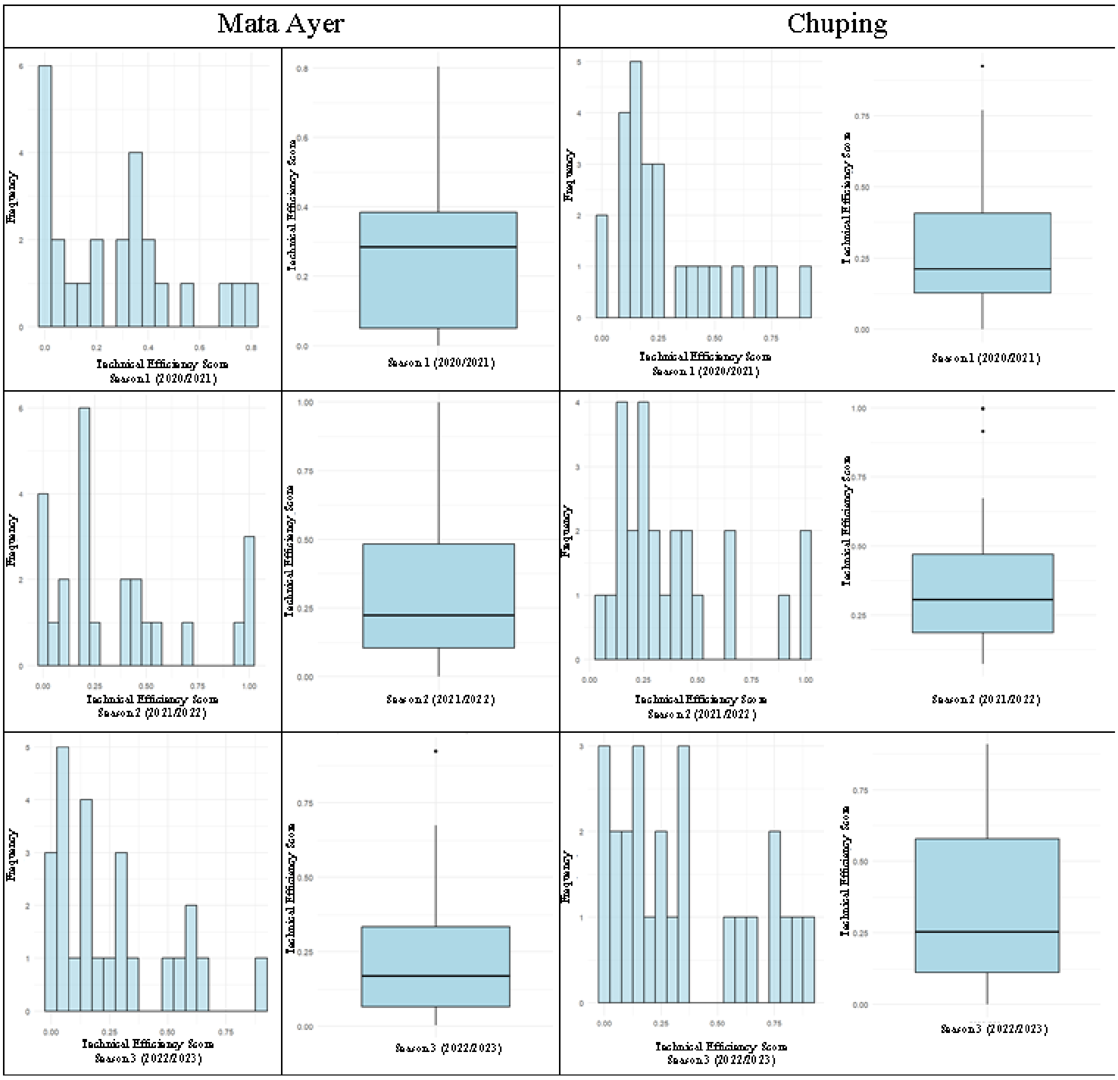

Figure 3. Histogram and box plot of frequency distribution and technical efficiency indices in Mata Ayer and Chuping (2020/2021–2022/2023).

In the second production season (2021/2022), the frequency distribution shows only a slight shift, with a minor portion of farms progressing towards mid-range efficiency scores of 40% to 50%. However, the overall distribution remains largely unchanged from the previous season, and the boxplot continues to reflect a broad IQR and a low median score, underscoring the persistence of inefficiencies across the region. By the third production season (2022/2023), the frequency distribution exhibits marginal improvement, with a few farms achieving higher efficiency scores above 40%. Despite this, the boxplot for this season reveals only a slight increase in the median efficiency score, which remains relatively low; while the IQR remains wide. This suggests that although some farms in Mata Ayer are making incremental improvements, the region continues to face substantial challenges in enhancing technical efficiency.

In contrast, the Chuping region presents a more diverse frequency distribution of TE scores. In the first production season (2020/2021), the histogram indicates a broader range of scores, with several farms achieving mid-range efficiency levels between 40% and 60%. The boxplot supports this observation, showing a slightly higher median score than that observed in Mata Ayer and a broader IQR, indicative of greater variability in farm performance. The presence of outliers within the boxplot suggests that while some farms in Chuping perform exceptionally well, others continue to struggle with low efficiency.

During the second production season (2021/2022), the frequency distribution in Chuping shifts, with a greater number of farms attaining mid-range efficiency scores. This improvement is reflected in the boxplot, which shows a modest increase in the median efficiency score and a narrowing of the IQR, indicating that farm performance is becoming more consistent across the region. However, the continued presence of outliers suggests that certain farms still deviate significantly from the norm, either excelling or underperforming relative to the majority. By the third production season (2022/2023), the frequency distribution in Chuping demonstrates further improvement, with a notable increase in the number of farms achieving efficiency scores between 40% and 70%. The corresponding boxplot displays a higher median efficiency score and a similar IQR to previous seasons, indicating progress in the region, although variability in farm performance persists. The persistence of outliers highlights the ongoing diversity in efficiency levels across farms in Chuping.

By the third production season (2022/2023), the frequency distribution in Chuping showed further progress, with a notable increase in the number of farms achieving efficiency scores between 0.40 (40%) and 0.70 (70%). The corresponding boxplot displayed a higher median efficiency score and a similar IQR to previous seasons, suggesting that while the region is making progress, variability in farm performance remains. The persistence of outliers highlights the ongoing diversity in efficiency levels across farms in Chuping.

To provide greater clarity, it is essential to interpret TE scores effectively. For instance, a TE score of 70% implies that a farm is operating at 70% of the maximum possible output given the available inputs under ideal conditions. This also indicates that the farm is not utilising 30% of its potential capacity, suggesting the possibility of increasing output by 30% through improvements in efficiency. By incorporating such an interpretation, the practical implications of TE scores become clearer, enabling a more nuanced understanding of the results.

The comparison between Mata Ayer and Chuping highlights significant regional disparities in the frequency distribution and technical efficiency indices over the three production seasons. Mata Ayer consistently presented lower median efficiency scores and greater variability, reflecting the region's struggles with farm productivity. The limited improvement over time suggests that the region may face resource constraints, slower adoption of technology, or other challenges that inhibit significant gains in efficiency.

On the other hand, Chuping exhibited a more dynamic frequency distribution, with higher median efficiency scores and a trend toward improved farm performance across the seasons. The broader range of scores and presence of outliers suggest that some farms in Chuping have successfully adopted better practices and technologies, leading to higher efficiency, while others still face challenges.

The differences in technical efficiency indices between the two regions can be contextualised using the broader literature on agricultural productivity. The challenges faced by Mata Ayer align with studies by Farrell [16] and Battese and Coelli [48], which emphasised the impact of resource constraints and environmental factors on farm efficiency. In contrast, Chuping's improvements may be attributed to better resource management and technology adoption, as discussed by Bravo-Ureta and Pinheiro [64]. The persistent variability and outliers in both regions are consistent with Färe, Grabowski and Grosskopf [65] who highlight the importance of understanding the diversity in farm performance to identify pathways for broader efficiency gains.

The observed improvement in TE scores in Chuping, particularly during the 2021/2022 season, could also be associated to favourable weather conditions, as suggested by Gitz et al. [66],who established a strong correlation between climatic factors and farm efficiency. Additionally, the adoption of improved farming techniques, as noted by Inkoom, Dadzie and Ndebugri [67], may have contributed to the better performance of some farms in this region. Government support, such as subsidies and training programs that facilitate the adoption of new technologies, could have further enhanced the efficiency of farms in Chuping, consistent with the findings of Latruffe [68].

Previous studies highlighted varying levels of technical efficiency among mango growers across different regions. For example, Mar, Yabe and Ogata[44] found a mean technical efficiency of 71% among 151 mango growers in Central Myanmar; while Kiet, Thoa and Nguyen[50] reported mean efficiency levels ranging from 49.38% to 55.82% in the Mekong Delta, Vietnam. Similarly, research in Shandorah village, Egypt, revealed efficiency levels averaging between 81% and 98% across different farm sizes[69]. In Muzafargarh, Pakistan, approximately 50% of mango growers had efficiency scores below the average of 0.60[70].

This current study, despite its smaller sample size, revealed lower technical efficiency levels, which can be attributed to data limitations, suboptimal farming practices, and environmental challenges. Incorporating a time trend analysis allows for monitoring efficiency changes over time, aiding in benchmarking, forecasting and policy evaluation. It underscores the importance of considering context-specific factors in assessing mango production and highlights the need for informed decision-making based on comprehensive analysis. With a larger sample size and the inclusion of inefficiency effects in the production model, it is anticipated that technical efficiency scores will improve.

In summary, the analysis of frequency distribution and technical efficiency indices in Mata Ayer and Chuping stresses the need for targeted interventions to enhance farm productivity, with a particular focus on addressing the unique challenges faced by each region. These findings provide valuable insights for policymakers and stakeholders aiming to improve agricultural efficiency in similar contexts.

4. Conclusion and Recommendations

This study has analysed the determinants of technical efficiency among Harumanis mango farmers in Mata Ayer and Chuping, Perlis, Malaysia. significant differences in the efficiency and effectiveness of production inputs between Mata Ayer and Chuping. Labour input positively influences mango yield in both regions, albeit with varying degrees of impact. Agrichemical usage demonstrates mixed effects, with significant positive associations observed in Mata Ayer and non-significant or negative relationships in Chuping. Temperature emerges as a critical environmental factor, negatively impacting mango yield, particularly in Chuping, where higher temperatures coincide with reduced output. Additionally, interaction effects between inputs highlight the importance of tailored management strategies that consider local conditions and input combinations.

Technical efficiency analysis identifies inefficiencies in production practices, with Mata Ayer exhibiting greater levels of inefficiency compared to Chuping. The determinants of technical efficiency in Mata Ayer are number of trainings, farmer association and farm certification and farmer experience; in the meanwhile, determinants of technical efficiency are household size and farmer experience; determinants of technical efficiency in Chuping are household size and farmer experience.

Overall, this analysis provides valuable insights into the efficiency of Harumanis mango production in Mata Ayer and Chuping, highlighting regional disparities and areas for improvement. By identifying and addressing factors contributing to inefficiencies, stakeholders can work towards enhancing productivity and sustainability in mango cultivation, thereby promoting economic growth and livelihood improvement in these regions.

5. Limitations and Future Research

5.1. Limitations

This study offers valuable insights into the factors influencing technical efficiency in Harumanis mango production. However, several limitations should be acknowledged.

Firstly, the analysis is only confined to data from two regions, Mata Ayer and Chuping, which may not capture the full range of variability in mango production across other regions. Expanding the geographic scope to include additional areas with diverse climatic and soil conditions could provide a more comprehensive understanding of productivity dynamics.

Secondly, this study covers only three consecutive seasons, which may not account for longer-term trends and fluctuations in productivity. Longitudinal studies that span more extended periods could offer deeper insights into the long-term effects of various factors on mango production and enhance the robustness of the findings.

Additionally, while the focus was on statistically significant variables, some non-significant factors were not extensively explored. Investigating these non-significant variables further could help assess their potential impact on productivity and refine the understanding of their roles. Moreover, this study primarily considers input variables and climate conditions, although other external factors such as market fluctuations, policy changes and socio-economic dynamics may also influence productivity. Hence, incorporating these factors into future analyses could provide a more holistic view of mango production efficiency.

Finally, the reliability of the findings depends on the accuracy of the data collected. Future research should aim to enhance data accuracy through improved data collection.

5.2. Future Research

To address these limitations and build upon this research, several avenues for future investigation are recommended. Expanding the geographic and temporal scope of studies could provide a broader understanding of mango production dynamics, such as including additional regions and extending the study period to help validate and generalise the findings.

Future research should also explore additional influential variables, including socio-economic and policy-related factors, to offer a more comprehensive analysis of mango production. Examining the impact of emerging technologies and agricultural practices on productivity could further enhance the understanding of efficiency improvements.

Investigating non-significant variables in greater detail may also yield insights into their potential effects on productivity, providing a more nuanced view of the production process. Furthermore, integrating external factors such as market conditions and policy changes into future studies could aid in developing more effective and context-specific strategies for enhancing agricultural productivity and sustainability.

These efforts will contribute to a deeper understanding of the factors affecting mango production and support the development of targeted strategies to improve productivity and sustainability in the sector.

Author Contributions

Data curation, analysis, investigation, writing—original draft, K.N.M.N.; Conceptualization, methodology, supervision, writing—review and editing, F.A.F.; Resources, methodology, supervision, writing—review and editing, C.O. All authors have read and agreed to the published version of the manuscript.

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This study was conducted in accordance with the guidelines approved by the UiTM Research Ethics Committee (REC), with reference number REC/09/2023 (PG/MR/327). The proposal titled "Technical Efficiency and Productivity of Harumanis Mango Production in Different Agro-Ecological Zones in Perlis" received ethical approval on 7 September 2023, with the approval period extending until 20 September 2024. All participants provided informed consent, and the study was assessed to involve minimal risk by the research ethics committee.

Informed Consent Statement

Informed consent was obtained from all participants involved in the study. Furthermore, written consent for the publication of this manuscript was acquired from each participant.

Data Availability Statement

The data supporting the results of this study are not publicly available due to confidentiality and privacy concerns of the respondents. Data may be available from the corresponding author upon reasonable request and subject to approval from the ethics committee and adherence to privacy regulations.

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Conflicts of Interest

All authors disclosed no conflict of interest.

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