Technical Efficiency Measurement of Cassava Production of Thailand

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Abstract

Cassava farmers in Thailand currently face numerous economic and environmental challenges that significantly affect production efficiency. This study aims to measure the technical efficiency of cassava farmers of Thailand by applying Stochastic Frontier Analysis (SFA) with a Cobb–Douglas production function. The study represents an application of the SFA approach to cassava farming of Thailand using primary data collected from 400 farmers across eight provinces through systematic sampling. The results indicate that the average technical efficiency score was 0.853, with a maximum value of 0.970 and a minimum value of 0.591. The estimated gamma value was 0.876, suggesting that most of the variation in output was attributable to farm management practices rather than external factors beyond farmers' control. Farmer age was positively associated with technical inefficiency, whereas farming experience, training participation, and effective disease management were associated with lower levels of inefficiency. Notably, government support was found to have no statistically significant effect on technical inefficiency. These findings highlight the importance of targeted managerial and operational support, as well as farmer training programs, in enhancing the overall production efficiency of cassava farming of Thailand.

Keywords: Cassava, Technical Efficiency, Stochastic Frontier Analysis

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บทคัดย่อ

ปัจจุบันเกษตรกรผู้ปลูกมันสำปะหลังในประเทศไทยต้องเผชิญกับความท้าทายทั้งด้านเศรษฐกิจและสิ่งแวดล้อมหลายประการ ซึ่งส่งผลกระทบอย่างยิ่งต่อประสิทธิภาพการผลิต งานวิจัยนี้จึงมีวัตถุประสงค์เพื่อวัดประสิทธิภาพเชิงเทคนิคของเกษตรกรผู้ปลูกมันสำปะหลังของประเทศไทย โดยใช้การวิเคราะห์เส้นพรมแดนสุ่ม (Stochastic Frontier Analysis: SFA) ร่วมกับฟังก์ชันการผลิตแบบคอบบ์–ดักลาส (Cobb–Douglas) โดยงานวิจัยนี้เป็นการประยุกต์ใช้วิธีการวิเคราะห์แบบ SFA กับเกษตรกรผู้ปลูกมันสำปะหลังของประเทศไทยใช้ข้อมูลปฐมภูมิซึ่งได้เก็บรวบรวมข้อมูลจากเกษตรกรจำนวน 400 ราย ในแปดจังหวัด ด้วยวิธีการสุ่มตัวอย่างแบบมีระบบ ผลการศึกษาพบว่าค่าประสิทธิภาพเชิงเทคนิคเฉลี่ยเท่ากับ 0.853 โดยมีค่าสูงสุด 0.970 ค่าต่ำสุด 0.591 และค่า gamma เท่ากับ 0.876 ซึ่งบ่งชี้ว่าความผันแปรของผลผลิตส่วนใหญ่เกิดจากการบริหารจัดการฟาร์ม มากกว่าปัจจัยภายนอกที่อยู่นอกเหนือการควบคุมของเกษตรกร อายุของเกษตรกรมีความสัมพันธ์กับความไม่มีประสิทธิภาพที่สูงขึ้น ในขณะที่ประสบการณ์ การฝึกอบรม และการจัดการโรคพืชมีความสัมพันธ์กับความไม่มีประสิทธิภาพที่ลดลง ที่น่าสังเกตคือ การสนับสนุนจากภาครัฐไม่มีนัยสำคัญทางสถิติ ผลการวิจัยนี้ได้ชี้ให้เห็นถึงคุณค่าของการสนับสนุนด้านการจัดการและการดำเนินงานที่มุ่งเป้า รวมถึงการฝึกอบรม เพื่อยกระดับประสิทธิภาพการผลิตมันสำปะหลังในภาพรวมของประเทศไทยได้เป็นอย่างดี

คำสำคัญ: มันสำปะหลัง ประสิทธิภาพเชิงเทคนิค การวิเคราะห์เส้นพรมแดนสุ่ม

Introduction

Cassava is a crucial economic crop for the national economy, particularly in the ethanol and renewable energy industries. Cassava is considered an energy crop on par with sugarcane and oil palm. In recent years, cassava has often been cheaper than other starch-producing food crops and can be used as a raw material across various industries, resulting in a steady increase in global market demand. This demand has made cassava the fifth most important food crop worldwide, following corn, rice, wheat, and potatoes, when measured by total production volume (Sowcharoensuk, 2024). In 2021, global cassava production was approximately 324.7 million tons (Food and Agriculture Organization of the United Nations [FAO], 2022). By country, Nigeria is the leading producer (63.03 million metric tons), followed by the Democratic Republic of Congo (45.67 million metric tons), Thailand (30.11 million metric tons), Ghana (22.68 million metric tons), Brazil (18.10 million metric tons), and Indonesia (17.75 million metric tons) (Shahbandeh, 2023).

Thailand ranks as the world's third-largest cassava producer, producing 28-31 million tons annually on 8-9 million hectares with over 580,000 farming households, contributing 150 billion baht to the economy (ASEAN Cassava Centre, 2024). However, despite its production volume, Thailand’s cassava production management area is expected to decline in 2024, with a harvested area of 8.682 million rai, a production volume of 26.877 million tons, and a yield of 3,096 kilograms per rai, down 6.32%, 12.22%, and 6.27% from the previous year, respectively (Sowcharoensuk, 2024). The main causes are the ongoing cassava mosaic disease outbreak in recent years and occasional drought, both significant risk factors for cassava production. Katepan et al. (2023) documented how this outbreak forced farmers in Nakhon Ratchasima Province to fundamentally adapt their farm management practices, illustrating the operational disruption caused by the disease at the farm level. Alongside environmental factors, labour shortages in agriculture further challenge cassava production in Thailand, especially in rural areas where labour availability is declining as younger generations shift toward industrial and service sectors. Additionally, the shortage of quality cuttings and outdated agricultural technology results in cassava production remaining heavily reliant on traditional, high-risk inputs, highlighting a need for development and improvements to ensure long-term production efficiency.

Despite how important cassava is to Thailand economically, there is surprisingly little empirical work measuring the technical efficiency of Thai cassava farmers using SFA – particularly at a scale large enough to draw meaningful conclusions. Most existing studies come from Africa or Southeast Asian countries other than Thailand. Among the limited Thai evidence, Thipbharos (2016) applied SFA to agricultural producers in Thailand but focused on other crops rather than cassava, leaving a significant gap in the evidence base for cassava-specific efficiency measurement. This gap in the evidence base is the starting point for the present study.

Given these challenges – environmental, labour, production, and market-related – this study has two main aims: first, to measure the technical efficiency of cassava production of Thailand using SFA with a Cobb-Douglas production function; and second, to identify the key factors that drive technical inefficiency among Thai cassava farmers. The contribution of this study lies in providing the first large-scale empirical SFA-based measurement of technical efficiency for this crop and country, with findings that have direct implications for agricultural managerial and operational support policy and farm management. Based on the literature, we propose three research hypotheses: H1 – cultivated area and fertilizer use are significant determinants of cassava output; H2 – farmer experience, training, and production risk management significantly reduce technical inefficiency; H3 – government support significantly reduces technical inefficiency.

Beyond its agronomic dimensions, cassava production in Thailand must be understood within the broader context of agri-business competitiveness and sustainable operations management. Thailand's cassava industry is a critical upstream supplier for global starch and ethanol markets, meaning that farm-level production efficiency directly affects supply chain efficiency, industrial competitiveness, and export performance (Sowcharoensuk, 2024). From a business management perspective, improving technical efficiency at the farm level is fundamentally a question of resource allocation efficiency, input cost management, and operational productivity – not merely an agronomic challenge.

Furthermore, the sustainability of Thailand's cassava agri-business depends on the managerial capability of individual farm operators to manage production risks, optimize input use, and adapt to changing market and environmental conditions. Efficiency under resource constraints, managerial decision-making, and sustainable production management are therefore central to the long-term competitiveness of Thailand's cassava sector in both domestic and export markets (ASEAN Cassava Centre, 2024). This study addresses this gap by framing cassava production efficiency as a business and operations management problem, providing evidence that is directly relevant for agricultural business practitioners, supply chain managers, and policymakers.

Literature Review

1. SFA Studies on Cassava Production

SFA has been applied fairly widely to study production efficiency across crops and regions. For cassava specifically, Abdul-Kareem and Isgin (2016) found a mean technical efficiency of 0.72 among cassava farmers in Ghana, with land size and credit access being key drivers. Gbigbi (2021) reported similar figures in Nigeria (mean TE = 0.74), pointing to fertilizer use and education as important factors. In Southeast Asia, Triyasari and Priyanto (2023) found a mean TE of 0.81 among cassava farmers on suboptimal dry land in Indonesia, while Ologbon et al. (2021) showed that farmers in mixed cassava-based systems in Nigeria operated at around 78% efficiency. SFA has also been widely applied beyond cassava: Chikezie et al. (2020) found significant inefficiency among rice farmers in Nigeria; Khan et al. (2022) applied SFA to rice production in Khyber Pakhtunkhwa, Pakistan, identifying experience and education as key efficiency drivers; Wu (2020) examined rice farmers in Eastern India; Priyanto et al. (2022) investigated whether climate change adaptation improves technical efficiency of rice farming in Yogyakarta, Indonesia; while Omar and Fatah (2021) applied the Cobb–Douglas SFA approach to coconut smallholders in Malaysia, demonstrating the versatility of this method across smallholder production management contexts. What these studies share is that there is a persistent and meaningful gap between what farmers are actually achieving and what is technically possible – which is precisely what this study examines in the Thai context.

2. Determinants of Technical Inefficiency in Smallholder Production Systems

Beyond estimating the production frontier itself, a large body of research has tried to understand what makes some farmers more or less efficient than others. Experience and training consistently come up as factors that reduce inefficiency – findings that sit comfortably with human capital theory. Farmer age tends to increase inefficiency, likely because older farmers are less inclined to change their practices. Access to managerial and operational support, credit, and improved inputs also matters in most contexts. Disease pressure, on the other hand, tends to push inefficiency up, consistent with the idea that biological risk introduces a stochastic element that is partly within farmers' control through preventive management and partly not.

3. Positioning and Analytical Framework of This Study

The parametric SFA approach was originally developed by Aigner and Chu (1968) and Afriat (1972), with further extensions by Richmond (1974), and remains the dominant method for estimating firm-level technical efficiency from production data. This study follows this approach with a Cobb-Douglas production function, in line with Bala et al. (2018) and Ologbon et al. (2021). This functional form is well-suited to smallholder production management contexts because it is relatively parsimonious and the parameters are easy to interpret. The one-sided error term in the SFA model allows us to separate genuine inefficiency from random noise – an important distinction in agriculture where weather, pests, and other external shocks can significantly affect output. By applying this framework to a large sample of Thai cassava farmers, this study extends the SFA literature into a context that has been underexplored.

4. Resource-Based View (RBV) and Farm-Level Competitive Advantage

The Resource-Based View (RBV), originating from Penrose (1959) and further developed by Barney (1991), provides a complementary theoretical lens for interpreting the determinants of technical efficiency in cassava production. Under the RBV, competitive advantage arises from firm-specific resources that are valuable, rare, inimitable, and non-substitutable. In the context of smallholder production systems, a farmer's accumulated experience, production risk management knowledge, and participation in training programmes can be conceptualized as strategic resources that enable superior operational performance. Farmers who possess these knowledge-based resources are better positioned to optimize input use, manage production risks, and achieve efficiency levels closer to the production frontier. This perspective reframes technical inefficiency not merely as a technical shortfall but as a consequence of unequal access to managerial and knowledge-based resources – a distinction with direct implications for agri-business development policy.

5. Human Capital Theory and Knowledge-Based Productivity

Schultz (1961) and Becker (1993) established that investment in human capital – through education, training, and experience – generates measurable returns in the form of enhanced productivity and decision-making capacity. In the agricultural context, this theory has been widely applied to explain efficiency differentials among farmers. Critically, from a business management standpoint, training is not simply a welfare intervention but an investment in managerial capability that yields operational returns. Farmers who receive structured training acquire knowledge-based productivity advantages: they learn to optimize input management strategy more precisely, identify early signs of disease, and apply improved farm management practices that reduce input waste. The human capital perspective thus supports a reorientation of managerial and operational support policy – away from input subsidy programmes and toward systematic capability development that builds long-term operational competence among farm managers.

6. Operations Efficiency Theory and Farm-Level Performance

Operations management theory emphasizes the role of process design, resource allocation efficiency, and operational discipline in achieving performance targets (Slack et al., 2016). Applied to cassava farming, this framework highlights that farm-level operational performance is shaped not only by what inputs are used but by how those inputs are managed, sequenced, and monitored. Production optimization, input management strategy, and risk control are operations management challenges as much as they are agronomic ones. The persistence of technical inefficiency – even when inputs are available – reflects operational gaps at the farm level: suboptimal timing of input management activities, inadequate disease monitoring protocols, and reactive rather than preventive management of production risks. Addressing these gaps requires not just more resources but better farm management practices and operational systems.

Research Methodology

Data Collection

The study uses primary data gathered through structured interviews with cassava farmers across Thailand during the 2022/23 growing season. The sample of 400 farmers was drawn from eight provinces – chosen to reflect the main cassava-growing regions – using systematic random sampling based on a sampling frame from the Office of Agricultural Economics. The sample size was determined using the Yamane (1973) formula. The questionnaire collected information on production-inputs used (cultivated area, labor quantity, fertilizer, herbicides), farm management practices, and farmer characteristics, including age, experience, training history, and uptake of government support programmes.

Data Analysis

Data were analyzed in three main stages as follows:

1. Descriptive Statistics Analysis: Calculations included percentage, mean, and standard deviation.

2. Technical Efficiency Analysis Using Stochastic Frontier Analysis (SFA): The Cobb-Douglas production function model and Maximum Likelihood Estimation (MLE) were used to estimate the coefficients of the variables, using FRONTIER 4.1 software (Coelli, 1996). The equation can be expressed as follows:

$$ln\ y_i = \beta_0 + \beta_1 lnX_1 + \beta_2 lnX_2 + \beta_3 lnX_3 + \beta_4 lnX_4 + (v_i - u_i) \quad (1)$$

Where: ln = natural log, $_i$ = Cassava Yield (kg/ha), X_1 = Cultivated Area (ha), X_2 = Labor Quantity (persons/ha), X_3 = Fertilizer (kg/ha), X_4 = Herbicides (liters/ha), β_0 = Constant, β1-β4 = coefficients of production factors, showing the elasticity of each factor, $\mathbf{v}_i$ = external random error, caused by uncontrollable factors such as weather, temperature, and Amount of rainfall, $\mathbf{u}_i$ = non-negative technical inefficiency term representing farm management inefficiency.

In this model, the error term is split into two parts: $e_i = v_i - u_i$. The first component, vi, captures random shocks outside the farmer's control – unusual weather or pest outbreaks, for instance – and is assumed to follow a normal distribution with mean zero. The second component, u_i, represents technical inefficiency: the part of the shortfall from the frontier that reflects farm management inefficiency. This follows a half-normal distribution. The gamma parameter ($\gamma = \frac{\sigma_u^2}{\sigma^2}$) tells us what share of total output variation comes from inefficiency rather than noise; a value close to 1 means most of the non-negative technical inefficiency term variation is driven by management decisions.

3. Analysis of Factors Influencing Technical Inefficiency (TI): Maximum Likelihood Estimation (MLE) was used to estimate the coefficients in the following equation:

$$TI_i = \delta_0 + \sum_{j=1}^{4} \delta_{0ji} D_{0ji} + \sum_{j=1}^{3} \delta_j Z_{ji} + e_i \quad (2)$$

where: TI = Technical Inefficiency, Z_1 = Age of the Farmer (years), Z_2 = Experience (years), Z_3 = Number of Training (Sessions), D_1 = Use of Chemical-Treated Cuttings Before Planting (Dummy: No = 0, Yes = 1), D_2 = Cutting Method (Dummy: straight cut = 0, other = 1), D_3 = Disease (Dummy: No = 0, Yes = 1), D_4 = Government Support (Dummy: No = 0, Yes = 1), δ_0 = Parameter Constant, δ_1,...,δ_7 = Coefficients of Variables, e = error term.

Empirical Results

Factors Affecting Cassava Production

The analysis of factors affecting cassava production using the Stochastic Frontier approach estimated parameters through Maximum Likelihood Estimation (MLE), with the results presented in Table 1. Based on the Likelihood Ratio (LR) test, compared to the critical value under constraints at a 5% error level, equaling 6.13, the LR value was found to be 56.92, which exceeds the critical limit. This indicates that the coefficients of variables in the model impact inefficiency, differing from zero. This implies that each variable used in the model affects the level of inefficiency in cassava production. The results further demonstrate that the frontier production function can adequately explain the data on technical inefficiency in cassava production.

Of the inputs examined, fertilizer and cultivated area had statistically significant effects on cassava output. Input management strategy showed a strong positive relationship (coefficient = 4.728, t = 5.341, $p < 0.01$), consistent with agronomic research showing that cassava responds well to nutrient supplementation, particularly on depleted soils (Omondi & Yermiyahu, 2021; Luar et al., 2018). Cultivated area, on the other hand, showed a negative and significant coefficient (-2.763, t = -2.992, $p < 0.01$). This likely reflects diminishing returns: larger farms in this sample tended to be managed less intensively per hectare, which dragged down output per unit of input. Labour and herbicide use were not statistically significant, suggesting that at current input levels, adding more of these resources would not meaningfully improve output.

Table 1. Parameter Estimation of The Stochastic Frontier Production Function

Variable	Coefficient	Standard error	t-ratio
Constant	4.566	0.705	6.473
Cultivated Area	-2.763	0.924	-2.992***
Labor Quantity	0.351	0.888	0.395
Fertilizer	4.728	0.885	5.341***
Herbicides	0.684	0.613	1.116
sigma-squared	0.365	0.130	2.808***
gamma (γ)	0.876	0.104	8.430***
Log likelihood function	-95.400		
LR test of the one-sided error	56.920		

Note: *** = significant at α 1% (2.687)

Technical efficiency of cassava production

Looking at technical efficiency scores across the sample, the maximum was 0.970, the minimum was 0.591, and the mean was 0.853. In practical terms, the average Thai cassava farmer in this sample was achieving about 85.3% of the output they could theoretically produce with their current inputs – leaving a gap of roughly 14.7% that could, in principle, be closed through better farm management without adding more resources.

At the individual level, most farmers exhibited-high technical efficiency ($0.701 \leq TE \leq 0.900$), accounting for 63.00%, followed by those with very high efficiency ($0.901 \leq TE \leq 1.000$) at 31.25%, and moderate

efficiency (0.501 ≤ TE ≤ 0.700) at 5.75% (Table 2). These findings indicate that farmers with efficiency levels below 1 need to improve their input use to achieve optimal production levels. Improvements should focus on factors impacting production, such as the quantity of fertilizer and cultivated area. These findings may also reflect limitations related to farmers' experience, knowledge, and access to support.

Table 2. Distribution of farmers based on the technical efficiency of cassava production

Efficiency Level	Technical efficiency scores	Frequency	Percentage
Very Low	0.000 - 0.300	-	-
Low	0.301 - 0.500	-	-
Medium	0.501 - 0.700	23	5.75
High	0.701 - 0.900	252	63.00
Very High	0.901 - 1.000	125	31.25
Total		400	100.00
Max	0.970		
Min	0.591		
Mean	0.853		

Factors Affecting Technical Inefficiency

In examining factors that contribute to technical inefficiency in cassava production among Thai farmers, seven variables were identified: farmer age, production experience, training frequency, use of chemical-soaked cuttings, cutting methods, production risk management, and government support. The analysis of parameters for technical inefficiency shows that the statistically significant factors at the 0.01 level include production experience, with a coefficient of -0.394. This negative coefficient indicates that as farmers gain more experience or have engaged in cassava production for many years, inefficiency decreases. Another significant factor is training frequency, with a coefficient of -0.298, also negative, meaning that farmers with more training sessions acquire new production techniques, thus reducing technical inefficiency. At the 0.05 level, age is significant with a coefficient of 0.108, suggesting that as farmers age, inefficiency increases due to reduced physical capability. Disease prevalence also affects inefficiency, with a coefficient of 0.197, indicating that inadequate production risk management leading to outbreaks contributes to increased inefficiency (Table 3).

Other factors in Table 3, including the use of chemical-soaked cuttings, cutting methods, and government support, were found to have no statistically significant effect on technical inefficiency in cassava production.

Table 3. Technical Inefficiency Estimation

Variable	Coefficient	S.E.	t-ratio
Constant	5.861	1.167	5.023
Age of the Farmer	0.108	0.046	2.336**
Experience	-0.394	0.117	-3.361***
Number of Training	-0.298	0.085	-3.495***

Table 3. Technical Inefficiency Estimation (Cont)

Variable	Coefficient	S.E.	t-ratio
Use of Chemical-Treated Cuttings Before Planting	-0.115	0.095	-1.220
Cutting Method	0.064	0.063	1.003
Disease	0.197	0.091	2.165**
Government Support	-0.179	0.182	-0.982

Note: ** = significant at α 5% (2.021)
*** = significant at α 1% (2.687)

Conclusion and Discussion

The production frontier analysis confirms that cassava output in Thailand is most strongly shaped by fertilizer use and cultivated area. Fertilizer had the largest positive effect on yield, consistent with evidence from across the cassava-growing world (Omondi & Yermiyahu, 2021). The negative coefficient on cultivated area points to diminishing returns at larger farm sizes – a finding consistent with Sheng and Chancellor (2019), who showed that beyond a certain scale, larger farms tend to be managed less intensively per unit area, reducing overall output efficiency. This has direct implications for how managerial and operational support is targeted. Labour and herbicide use did not emerge as significant, which may reflect relatively uniform practices across the sample on these dimensions.

The mean technical efficiency of 0.853 suggests that Thai cassava farmers, on average, are performing reasonably well – but there is still a meaningful gap between actual and potential output. The gamma value of 0.876 confirms that most of this gap reflects farm-level management decisions rather than external shocks, which means it is, in principle, addressable through better information and practices. Some farmers face more binding constraints than others, and the results point to experience, training, and production risk management as the factors that matter most.

The mean TE of 0.853 found in this study is higher than what has been reported in comparable cassava SFA studies elsewhere. Abdul-Kareem and Isgin (2016) found 0.72 in Ghana, Gbigbi (2021) reported 0.74 in Nigeria, and Triyasari and Priyanto (2023) found 0.81 in Indonesia. The relatively higher efficiency in Thailand likely reflects better input access, more established extension systems, and the generally higher level of agricultural development in the country. That said, the presence of farmers with scores around 0.591 shows there is still meaningful variation within Thailand that warrants attention.

Among the factors driving technical inefficiency, farmer age increased inefficiency significantly (coefficient = 0.108, $p < 0.05$)—a pattern also observed in Chandel et al. (2022) and Salam et al. (2024) and generally attributed to older farm operators being less likely to adopt new production practices. Experience worked in the opposite direction (coefficient = -0.394, $p < 0.01$), as did the number of training sessions attended (coefficient = -0.298, $p < 0.01$). Both findings align with Human Capital Theory (Schultz, 1961), suggesting that farm operators who accumulate knowledge through experience and formal training are more capable of managing production resources efficiently. Production risk factors increased inefficiency (coefficient = 0.197, $p < 0.05$), reflecting the operational disruptions and output uncertainty associated with disease outbreaks. Government support did not emerge as statistically significant (coefficient = -0.179, t = -0.982),

consistent with findings from similar studies (Ho & Shimada, 2019; Omar & Fatah, 2021). This may indicate that existing managerial and operational support programmes are not yet sufficiently aligned with farm-level capability development and operational performance improvement.

From a broader theoretical standpoint, these results fit well within a framework that emphasises the role of human capital and risk in shaping farm performance. The experience and training effects are consistent with Schultz's (1961) view that investment in farmers' knowledge generates returns in the form of better decision-making. The disease effect is a reminder that even well-managed farms face stochastic shocks that cannot be fully guarded against – though disease-resistant varieties and preventive practices can reduce the impact. Taken together, the findings suggest that policy should focus less on input subsidies and more on building the capacity of farmers to use existing inputs well.

Managerial Implications

The findings of this study carry significant implications for three groups of stakeholders in Thailand's cassava agri-business: farm operators and agricultural entrepreneurs, supply chain managers, and policymakers.

1. Implications for Agricultural Business Operators

At the farm level, the results underscore the critical importance of input management strategy and production risk management as drivers of operational efficiency. Farmers operating below the efficiency frontier may benefit from prioritizing structured investment in managerial capability – particularly around fertilizer optimization and disease prevention protocols. The significant negative effect of training on technical inefficiency demonstrates that knowledge acquisition has a direct and measurable return in the form of improved farm management practices and output efficiency. Farm operators should treat training participation not as an optional activity but as a strategic investment in operational performance.

2. Implications for Supply Chain Management

Thailand's cassava supply chain – feeding starch processing and ethanol production industries – depends critically on upstream supply chain efficiency. Technical inefficiency at the farm level creates volatility in raw material supply, raising input costs for downstream processors and undermining industrial competitiveness. The finding that farm-level management decisions account for 87.6% of output variation (gamma = 0.876) implies that targeted managerial and operational support for farmers could yield significant gains in supply chain reliability and consistency. Supply chain managers and agri-business companies operating in the cassava sector should consider co-investing in farmer capability development programmes as a risk management and competitiveness strategy.

3. Implications for Policy and Institutional Design

The non-significance of government support in this study is a signal that current programme designs are not generating measurable operational returns at the farm level. Policymakers should redesign extension programmes with a focus on managerial training rather than input subsidies – shifting from subsidy-oriented policy toward capability development initiatives that build operational competence among farm managers. Specifically, programmes should target input management strategy knowledge, production risk management (particularly disease prevention), and farm-level operational planning skills. Regional cooperatives and agri-business associations could serve as delivery channels for such capability-building programmes, complementing government extension efforts.

Suggestions

On the basis of these findings, we suggest four practical policy directions. First, the Department of Agricultural Extension (DOAE) should scale up training specifically around input management strategy– the data show clearly that training reduces inefficiency, and fertilizer use is the single biggest driver of output. Second, the Department of Agriculture (DOA) should make certified disease-resistant cassava varieties more widely available, given the high economic cost of disease. Third, cooperatives and community groups have a role to play in peer learning, particularly for older farmers who showed the highest inefficiency levels. Fourth, government support programmes should be redesigned with more attention to how they actually reach farmers – the current evidence suggests they are not having a measurable effect, which may be a question of design or delivery rather than intent. These directions connect to SDG Goal 2 (Zero Hunger) through improved smallholder productivity, and to SDG Goal 12 (Responsible Production and Consumption) through more efficient use of fertiliser and land.

Limitations

This study has a few limitations worth acknowledging. The data come from a single growing season (2022/23), so we cannot track how efficiency changes over time – a cross-sectional snapshot captures a moment but cannot speak to trends. The sample is confined to eight provinces, which means the findings may not fully represent conditions across all cassava-growing areas. We also used a Cobb-Douglas functional form, which imposes some restrictions on the production relationships; a Translog function would offer more flexibility, though at the cost of more parameters to estimate.

Future Research

Future work could address these limitations in a few ways. Panel data covering multiple seasons would allow a more dynamic picture of efficiency trends and help disentangle structural factors from year-to-year variation. Expanding the geographic coverage would strengthen generalizability. It would also be worth testing whether a Translog production function changes the results meaningfully. Beyond the methodological, there is scope for qualitative work exploring why government support programmes are not showing up as significant – whether that is a reach problem, a design problem, or something else – which would be important for policy.

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