ASSESSING THE EFFICIENCY OF BLACK CARDAMOM FARMS IN HOANG SU PHI DISTRICT

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Abstract

In this comprehensive study, the efficiency of 300 Black Cardamom farms in the Hoang Su Phi district is assessed by using the Malmquist Index. The study also investigates the various factors influencing farm efficiency through the Tobit regression model. Structured interviews with farm proprietors in key communes—Ho Thau, Nam Ty, and Tung San—where Black Cardamom cultivation is concentrated, provide the data for this analysis. Preliminary findings reveal commendable efficiency levels in Black Cardamom farms in Ho Thau and Nam Ty, while those in Tung San face challenges, particularly in technological inefficiency. The study suggests that enhancing technological proficiency is crucial for farms in Tung San, and adjusting farm size strategically can significantly boost the efficiency of farms in Nam Ty, unlocking untapped potential. The Tobit regression model is employed to examine influential factors on farm efficiency. Notably, owners' demographics play a crucial role, with older farm owners exhibiting more efficient operations. Higher levels of education and professional training also correlate positively with heightened farm efficiency. Experience in Black Cardamom cultivation contributes to efficiency, emphasizing the importance of continuous learning. Furthermore, exposure to information from diverse sources, such as television, radio, newspapers, and the Internet, positively affects farm efficiency, adding 0.023 points to the overall change. Conversely, challenges such as family poverty, unexpected setbacks, and increased distances to vital services negatively impact farm efficiency.
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Keywords*: Black Cardamom, Efficiency, Malmquist Index, Tobit regression, Hoang Su Phi.*
JEL classification:O, O13.

ĐÁNH GIÁ HIỆU QUẢ CỦA CÁC VƯỜN THẢO QUẢ TRÊN ĐỊA BÀN HUYỆN HOÀNG SU PHÌ

Tóm tắt

Trong nghiên cứu toàn diện này, hiệu quả của 300 vườn Thảo Quả ở huyện Hoàng Su Phì được đánh giá bằng Chỉ số Malmquist. Nghiên cứu cũng điều tra các yếu tố khác nhau ảnh hưởng đến hiệu quả vườn, thông qua mô hình hồi quy Tobit. Các cuộc phỏng vấn có cấu trúc với các chủ vườn ở các xã trọng điểm - Hồ Thầu, Nậm Ty và Túng Sán - nơi tập trung trồng Thảo Quả, đã cung cấp dữ liệu cho phân tích này. Những phát hiện sơ bộ cho thấy các vườn Thảo Quả ở Hồ Thầu và Nậm Ty hoạt động hiệu quả một cách đáng kể, trong khi những vườn Thảo Quả ở Túng Sán phải đối mặt với những thách thức, đặc biệt là về sự kém hiệu quả về công nghệ. Nghiên cứu cho thấy việc nâng cao trình độ công nghệ là rất quan trọng đối với các vườn ở Túng Sán, và việc điều chỉnh quy mô vườn một cách chiến lược có thể làm tăng đáng kể hiệu quả của các vườn ở Nậm Ty, mở ra tiềm năng chưa được khai thác. Mô hình hồi quy Tobit đã được sử dụng để kiểm tra các yếu tố ảnh hưởng đến hiệu quả vườn. Đáng chú ý, các đặc điểm nhân khẩu học của chủ sở hữu đóng một vai trò quan trọng, với các chủ vườn lớn tuổi thể hiện hoạt động hiệu quả hơn. Trình độ học vấn cao hơn và việc được đào tạo một cách chuyên nghiệp tạo ra sự tương quan tích cực với hiệu quả vườn được nâng cao. Kinh nghiệm trồng Thảo Quả giúp gia tăng hiệu quả vườn, nhấn mạnh tầm quan trọng của việc học hỏi liên tục. Hơn nữa, việc tiếp xúc với thông tin từ nhiều nguồn khác nhau, chẳng hạn như truyền hình, đài phát thanh, báo chí và Internet, ảnh hưởng tích cực đến hiệu quả vườn – làm tăng thêm 0,023 điểm vào sự thay đổi chung. Ngược lại, những thách thức như tình trạng nghèo của hộ gia đình, những sự cố ngoài dự kiến và sự gia tăng khoảng cách đến các dịch vụ quan trọng tác động tiêu cực đến hiệu quả vườn.

Từ khóa: *Thảo quả, Hiệu quả, Chỉ số Malmquist, Hồi quy Tobit, Hoàng Su Phì.*

1. Introduction

Black Cardamom, renowned not only as a cherished spice in culinary endeavors but also as a valuable medicinal ingredient, holds a significant place in various cultures and industries (Aghasi et al., 2019; Anwar, Abbas, & Alkharfy, 2016; Fatemeh et al., 2017; Rajpur & Samratha, 2018; Sengottuvelu, 2011; Souissi, Azelmat, Chaieb, & Grenier, 2020; Vinmec, 2020). In Vietnam, the Northwestern provinces, particularly Ha Giang, have emerged as the primary hub for Black Cardamom cultivation. The communes of Ho Thau, Nam Ty, and Tung San within the Hoang Su Phi district are especially noteworthy for their ideal climate and soil conditions conducive to Black Cardamom growth (Dai Tam, 2018). The cultivation of Black Cardamom in this region has been instrumental in elevating ethnic minorities from poverty, contributing to the agricultural restructuring in Ha Giang province during the 2016-2020 period (Ha Giang People's Committee, 2015). However, the economic efficiency of these Black Cardamom farms extends beyond agricultural practices, encompassing market dynamics, economic returns, and the challenges of price fluctuations and value chain complexities. The global and local market trends for Black Cardamom indicate varying demands and prices, which significantly impact the profitability and sustainability of farming practices. Additionally, the current reliance on traditional methods, primarily seed-based cultivation with limited use of intensive farming techniques or modern science and technology, restricts the potential for maximizing productivity and market resilience (Dai Tam, 2018). The primary objective of this study is to assess the productivity of Black Cardamom farms in the Thau, Nam Ty, and Tung San communes of the Hoang Su Phi district. This includes an analysis of the key factors influencing the efficiency of these Black Cardamom farms, such as owner demographics, education, experience, and access to information. By understanding these dynamics, the study aims to provide practical solutions to enhance the overall effectiveness of Black Cardamom cultivation operations, with a particular focus on strategies that bolster market resilience and ensure long-term profitability.

2. Data collection, research methodology, variable selection and regression model

2.1. Data collection

Data for this study were obtained through structured interviews with farm proprietors in three key communes in Hoang Su Phi district: Ho Thau, Nam Ty, and Tung San, where Black Cardamom cultivation is most concentrated. In every commune, we randomly selected 100 Black Cardamom farm owners to be interviewees from a list furnished by the respective commune president. Black Cardamom typically undergoes a fundamental growth cycle, spanning an average duration of approximately 6 years from the initial planting of seedlings to the harvesting of the final products. Consequently, our efficiency analysis focused exclusively on farms with a minimum age of 8 years or more to ensure a comprehensive evaluation. The interviews were carried out via telephone throughout June and July 2023, with a total sample size of 300 farm owners. These farm owners were requested to furnish details encompassing their demographic information as well as comprehensive data regarding their farms, which included inputs and outputs. Data collection encompassed the years 2020 to 2022. Given that 2020 served as the reference year, findings from this particular year will not be presented.

2.2. Research methodology

The analysis of farm efficiency typically employs conventional methods like Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) when dealing with cross-sectional data to provide a snapshot of a farm’s efficiency. However, it’s crucial to recognize that efficiency not only varies among the examined farms but also changes over time. In response to the ever-evolving landscape of dynamic changes, the dynamic settings of the Malmquist index approach, as pioneered by Malmquist (1953), provide an optimal solution, as underscored by Cooper, Seiford, & Zhu in their (2011) work.

This study capitalizes on the availability of panel data spanning 2020-2022 for Black

Cardamom farms in the three communes of Hoang Su Phi district to assess total factor productivity change and its components. This approach is expected to yield more comprehensive insights into farm efficiency. The Malmquist Total Factor Productivity (TFP) Index, first introduced by Caves, Christensen, and Diewert in their 1982 publications (1982a, 1982b), and later refined by Färe, Grosskopf, Norris, and Zhang in (1994), quantifies the change in TFP between two specific data points, where 'k' represents the base period, and 'k+1' signifies the reference period. This index derives its calculation by assessing the relative distances of each data point concerning a common technological benchmark. In this context, the Malmquist TFP index is computed through a comparison of the output distances between the base and reference periods, utilizing the base period technology ('k') as the reference point for technology assessment:

$$\mathrm{MQI}_o^k\left(y_i^k, x_i^k, y_i^{k+1}, x_i^{k+1}\right) = \frac{d_o^k\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^k\left(y_i^k, x_i^k\right)} \quad (1)$$

When the subsequent reference technology period, denoted as (k+1), is chosen as the reference technology, the computation of the Malmquist Total Factor Productivity (TFP) index is executed as follows:

$$\mathrm{MQI}_o^{k+1}\left(y_i^k, x_i^k, y_i^{k+1}, x_i^{k+1}\right) = \frac{d_o^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^{k+1}\left(y_i^k, x_i^k\right)} \quad (2)$$

When M_0 surpasses one, it signifies a positive TFP growth, while an M_0 of one indicates a stable TFP. A value less than one implies a decline in TFP.

Drawing upon the insights from the studies by Caves et al. (1982b) and Fisher (1922) , the Malmquist Total Factor Productivity (TFP) index can be reformulated as follows:

$$\mathrm{MQI}_o\left(y_i^k, x_i^k, y_i^{k+1}, x_i^{k+1}\right) = \left\{\frac{d_o^k\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^k\left(y_i^k, x_i^k\right)} * \frac{d_o^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^{k+1}\left(y_i^k, x_i^k\right)}\right\}^{\frac{1}{2}} \quad (3)$$

Equation 3 can be rearranged as demonstrated below:

$$\mathrm{MQI}_o\left(y_i^k, x_i^k, y_i^{k+1}, x_i^{k+1}\right) = \frac{d_o^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^k\left(y_i^k, x_i^k\right)} * \left\{\frac{d_o^k\left(y_i^{k+1}, x_i^{k+1}\right)}{d_o^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)} * \frac{d_o^k\left(y_i^k, x_i^k\right)}{d_o^{k+1}\left(y_i^k, x_i^k\right)}\right\}^{\frac{1}{2}} \quad (4)$$

In Equation 4, the initial segment evaluates changes in technical efficiency, while the subsequent portion quantifies shifts in technological efficiency. To put it differently:

TFPCH (TFP change) = EFFCH (Technical efficiency change) * TECHCH (Technological efficiency change) (5)

where: TFPCH represents changes in total factor productivity, EFFCH signifies changes in technical efficiency, and TECHCH denotes changes in technological efficiency.

Technical efficiency change assesses a farm’s competence in managing and optimizing input resources for output production. When a farm could have achieved the same level of output with fewer inputs, it is considered inefficient. Conversely, if it could have produced greater outputs with the same input resources, it is operating inefficiently.

Technology is anticipated to evolve over time, and a farm's efficiency is intricately tied to its ability to embrace and adapt to new technological advancements. A farm that can effectively integrate modern technology, thereby reducing input consumption or enhancing output yields, is more likely to be considered efficient. The availability of panel data enables the tracking of this evolving trend. Technological efficiency change mirrors a farm's capability to stay in step with current technology, optimizing input utilization for output production, as emphasized by Coelli, Rao, O'Donnell, and Battese (2005).

Färe et al. (1994) decomposed the technical efficiency change into two distinct components for a more comprehensive analysis, namely pure efficiency change (PECH) and scale efficiency change (SECH), as demonstrated below:

EFFCH = PECH * SECH (6)

where:

$$PECH = \frac{d_u^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}{d_u^k\left(y_i^k, x_i^k\right)} (7)$$

$$SECH = \frac{\dfrac{d_b^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}{d_u^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right)}}{\dfrac{d_b^k\left(y_i^k, x_i^k\right)}{d_u^k\left(y_i^k, x_i^k\right)}} (8)$$

$$SECH = \frac{d_b^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right) * d_u^k\left(y_i^k, x_i^k\right)}{d_u^{k+1}\left(y_i^{k+1}, x_i^{k+1}\right) * d_b^k\left(y_i^k, x_i^k\right)} (9)$$

In this particular context, the symbol ‘b’ represents a state of constant returns to scale, while ‘u’ is indicative of variable returns to scale.

PECH primarily encompasses changes in managerial efficiency, including factors such as the adoption of best management practices and the optimization of input combinations within farming operations. On the other hand, SECH signifies variations in the scale or size of farms.

Microeconomic theory asserts that one of the foremost goals of a farm is to operate at its optimal size. When a farm's scale deviates significantly from this optimum, it can encounter challenges in efficiently managing input costs and maximizing output in terms of revenue and profitability. In the context of this study, SECH clarifies the extent to which the farm's scale aligns with the optimization of output utilizing fixed inputs or the minimization of inputs for peak efficiency.

Beyond internal factors, external influences that encompass social, economic, political, and geographical attributes can wield a significant impact on a farm's efficiency. To thoroughly investigate the effects of these factors on farm efficiency, as ascertained through non-parametric analysis, we conducted a parametric analysis using the following latent variable model:

$$y_i^* = \beta x_i + \varepsilon_i (10)$$

Within this model, the following components are present: x_i, signifying a vector of influential variables; β, representing a vector of parameters to be estimated; and ε_i denoting a random error. The latent variable y_i^* is linked to the observed technical efficiency scores through the subsequent measurement model.

$$y_i = \begin{cases} y_i^* \text{ if } 0 < y_i^* < 1 \\ 1 \text{ if } y_i^* \geq 1 \\ 0 \text{ if } y_i^* \leq 0 \end{cases} (11)$$

In the realm of agricultural efficiency analysis, the Tobit model offers distinct advantages in handling censored data, identifying determinants, and assessing technical efficiency. One of the primary strengths of the Tobit model lies in its ability to effectively manage efficiency scores that are constrained within a zero to one range, a common occurrence in agricultural studies (Greene, 2003). The model is particularly well-suited for situations where the dependent variable is censored, as it accounts for the presence of observations falling below or above a certain threshold. This is essential in scenarios where the efficiency scores are bounded, reflecting the inherent limitations of agricultural production systems.

Identification of determinants influencing efficiency is another noteworthy advantage of the Tobit model. By explicitly modeling the censored nature of efficiency scores, Tobit regression facilitates a more accurate assessment of factors affecting agricultural efficiency. Researchers can discern the impact of various determinants on both the probability of observing a censored score and the magnitude of the score itself, providing a comprehensive understanding of the efficiency determinants within the specified range (Cameron & Trivedi, 2013).

Moreover, the Tobit model is instrumental in conducting technical efficiency assessment in agriculture. It allows for the estimation of the frontier production function, separating inefficiency from random error, and thus enabling a more precise evaluation of technical efficiency levels among different agricultural units (Battese & Coelli, 1995). This capacity to disentangle inefficiency from random variation contributes to the robustness and reliability of efficiency assessments.

However, the Tobit model is not without its drawbacks in agricultural efficiency analysis. Sensitivity to model assumptions is a notable limitation, as the results can be influenced by the underlying assumptions regarding the distribution of the error term and the linearity of the relationships (Wooldridge, 2010). The assumption of normality in the distribution of inefficiency, for instance, may impact the accuracy of efficiency estimates. Researchers employing the Tobit model should therefore exercise caution and conduct sensitivity analyses to gauge the robustness of their findings.

Furthermore, the Tobit model has a limited scope for heterogeneity, as it assumes a uniform relationship between the determinants and efficiency across all observations (Cameron & Trivedi, 2013). This may oversimplify the complex and heterogeneous nature of agricultural systems, potentially leading to biased efficiency estimates. Researchers should be mindful of this limitation and explore alternative models or incorporate additional variables to capture the diversity inherent in agricultural practices.

Dependency on linearity is another concern associated with the Tobit model. The model assumes a linear relationship between the determinants and the latent variable underlying the censored observations. If this assumption is violated, it can lead to biased parameter estimates and compromise the validity of efficiency assessments (Cameron & Trivedi, 2013). Nonlinear relationships may be better captured by alternative modeling approaches, and researchers should carefully consider the linearity assumption when employing the Tobit model in agricultural efficiency analysis.

In conclusion, while the Tobit model presents valuable advantages in handling censored data, identifying determinants, and conducting technical efficiency assessments in agricultural efficiency analysis, researchers must be cognizant of its limitations, including sensitivity to model assumptions, limited scope for heterogeneity, and dependency on linearity. By acknowledging these drawbacks and employing robust methodologies, researchers can enhance the accuracy and reliability of their efficiency assessments in the agricultural context.

2.3. Variable selection

In the assessment of agricultural efficiency, the selection of inputs and outputs is crucial for accurate and meaningful analysis. The study on the efficiency of Black Cardamom farms includes inputs such as farm size, the quantity of Black Cardamom trees, annual investment, labor days, and frequency of technical consultations, and outputs such as production, annual revenue, and price. Details are discussed below.

Inputs

- Farm Size (measured in hectares): Farm size is a fundamental input in agricultural efficiency studies. It represents the physical capacity for production and can significantly impact productivity and efficiency. Larger farms may benefit from economies of scale, while smaller farms might be more efficient due to more intensive use of resources. Previous studies, such as those analyzing periurban farming systems, have used land size in hectares as a key input variable (Gaviglio, Filippini, Madau, Marescotti, & Demartini, 2021).

- Quantity of Black Cardamom Trees (trees): The number of trees directly relates to the potential output of a farm. This input is crucial for crops like Black Cardamom, where production is directly tied to the number of trees.

- Annual Investment (measured in VND millions – the Vietnamese currency. Currently, \$1.00 = VND 24,205.963 (XE, 2022)): Investment is a critical input that includes costs related to infrastructure, equipment, seeds, fertilizers, etc. It reflects the financial resources allocated for production activities. Investment level can influence the productivity and efficiency of the farm, as it often correlates with the adoption of modern farming techniques and technology.

- Labor Days (measured in days): Labor is a primary input in agriculture. The amount of labor used, often measured in labor days, affects the farm's operational efficiency. It's an essential factor, especially in labor-intensive farming practices like Black Cardamom cultivation.

- Frequency of Technical Consultations (measured in times): This input reflects the extent of technical knowledge and support received by the farm. Technical consultations can include guidance on best practices, pest control, and crop management, which are crucial for improving farm efficiency and productivity.

Outputs

Tirkaso and Hansson (2023) conducted a study in Ethiopia using the 2015 Ethiopia Rural Socioeconomic Survey compared efficiency assessments using quantities versus costs and revenues. The study found differing efficiency scores and rankings based on the type of data used, highlighting the importance of considering both physical quantities and monetary values in efficiency assessments. The outputs they used as follow:

- Production (measured in kilograms): The total quantity of Black Cardamom produced is a direct measure of output. It's essential to gauge the efficiency of the farm in converting inputs into tangible produce.

- Annual Revenue (measured in VND thousands): Revenue is a financial measure of output, indicating the economic return from farming activities. It's a comprehensive output indicator, encompassing both the quantity produced and the market value of the crop.

- Price (measured in VND thousands per kilogram): The price obtained per kilogram of produce is crucial in understanding the market value and demand for the crop. It reflects the economic viability of farming Black Cardamom, directly influencing the profitability and efficiency of the farms.

In conclusion, the selected inputs and outputs for assessing the efficiency of Black Cardamom farms are aligned with common practices in agricultural efficiency studies. They provide a comprehensive view of both the resource utilization and the economic performance of the farms, which are crucial for understanding the overall efficiency and sustainability of agricultural operations.

Influential factors

In the analysis of the efficiency of Black Cardamom farms, various influential factors have been identified, categorized into three groups: demographic characteristics of farm owners, characteristics of the farm owners' families and the selected farms, and characteristics related to the locations of the farms. Let's discuss these factors with references to previous studies that have used similar variables.

- Demographic Characteristics of Farm Owners are often characterised by: Age, Gender, Education, Professional Training, Experience in Cultivating Black Cardamom: Studies in agricultural efficiency often consider these socio-economic factors. For instance, a study on farm productivity and income in Northern Ghana examined factors like gender, age, education, and farming experience, finding significant impacts on farm income and participation in extension programs (Danso-Abbeam, Ehiakpor, & Aidoo, 2018). These factors are expected to influence efficiency positively, with education and experience correlating with better farm management and adoption of effective practices.

- Characteristics of the Farm Owners' Families and the Selected Farms are generally illustrated through: Number of Dependents, Poverty Status, Shocks Experienced, Sources of Information: The impact of family characteristics on agricultural efficiency is less straightforward, but it can be inferred that larger families might require more resources, potentially impacting efficiency. The poverty status and shocks experienced by a farm can significantly affect its productivity and resilience, as indicated in studies examining the impact of natural disaster shocks on farm household poverty vulnerability (Lu, Zheng, Ou, Liu, & Li, 2022). Conversely, access to information from diverse sources is expected to positively influence farm efficiency by providing farmers with updated knowledge and practices.

- Characteristics Related to the Locations of the Farms are regularly denoted by: Distance to the Nearest Bank, Market, and Availability of Concrete/Tarred Roads: Proximity to markets and financial institutions is crucial for farm efficiency. A study in Southwest Ethiopia highlighted that the distance to the nearest market significantly affects market participation among smallholder farmers, with those closer to markets more likely to participate (Haile, Gebre, & Workye, 2022). Hence, longer distances to essential services and infrastructure are likely to negatively impact farm efficiency.

In conclusion, these factors are integral to understanding the multifaceted influences on agricultural efficiency. While demographic characteristics of farm owners are expected to have a direct impact on efficiency, factors related to family characteristics and farm location play a more complex role, influencing the farm's operational environment and access to resources and markets. For a detailed overview of the selected variables and influential factors, please refer to Table 1.

Table 1: *Descriptive statistics of the selected inputs, outputs and influential factors*

Variable	Mean	S. D.^{a}	Min	Max
Influential factors				
Farm owner's age (years)	45.81	9.64	22.00	69.00
Farm owner's gender (1=male)	N/A	N/A	N/A	N/A
Farm owner's education (schooling years)	7.03	2.62	2.00	12.00
Farm owner's professional training (1=yes)	0.09	0.33	0.00	2.00
Farm owner's experience in growing Black Cardamom (years)	19.74	8.38	3.00	38.00
Farm owner's family dependants (persons)	1.61	1.03	0.00	4.00
Farm owner's family poverty status (1=poor/near poor)	N/A	N/A	N/A	N/A
Number of shocks farm experienced	0.33	0.47	0.00	1.00
Farm information sources (1=TV/radio/newspapers/Internet)	N/A	N/A	N/A	N/A
Distance to the nearest bank (km)	23.47	7.88	9.00	38.00
Distance to the nearest market (km)	23.41	7.98	1.00	38.00
Distance to the nearest concrete/tarred road (km)	0.87	0.72	0.00	2.00
Inputs				
Farm size (ha)	1.10	0.62	0.20	3.20
Number of trees	1,341.43	791.20	250.00	4,200.00
Farm production age (years)	16.62	5.67	5.00	34.00
Annual investment (VND millions)	4.37	3.64	1.00	84.00
Labour days	21.38	8.23	5.00	61.00
Consultations (times)	1.33	0.47	1.00	2.00
Outputs				
Production (kg)	857.60	470.22	150.00	2,900.00
Revenue (VND thousands)	36,950.45	24,849.50	4,950.00	182,700.00
Price (VND thousands)	43.00	14.40	32.00	64.00

Note. [a]Standard deviation.

Source. Authors' calculation, using the interviewed data.

3. Results and Discussion

3.1. Efficiency of the Black Cardamom farms

The efficiency of Black Cardamom farms was evaluated through the application of the Malmquist Index. Detailed results can be found in Table 2.

Table 2: *Efficiency of the Black Cardamom farms*

	EFFCH[a]	TECHCH[b]	PECH[c]	SECH[d]	TFPCH[e]
Ho Thau	1.0140	1.0080	1.0060	1.0080	1.0220
Nam Ty	1.0030	1.0300	1.0050	0.9980	1.0330
Tung San	1.0280	0.9700	1.0200	1.0080	0.9970

Note. [a]Technical efficiency change, [b]Technological change, [c]Pure technical efficiency change, [d]Scale efficiency change, [e]Total factor productivity change.

Source. Authors' calculation, using the interviewed data.

Among the three distinct study locations, it's quite evident that Black Cardamom farms in Ho Thau and Nam Ty have showcased commendable efficiency levels. Specifically, their total factor productivity changes have remarkably reached 102.2% and 103.3%, respectively. What's particularly noteworthy is the considerable potential for further enhancing efficiency, especially in Nam Ty, where focusing on scale efficiency change appears to be an avenue for improvement, given the current rate of 99.8%. Optimizing the size of their farms stands out as a crucial strategy to fortify their overall efficiency, emphasizing the significance of this factor.

Conversely, in the case of farms situated in Tung San, they have attained noteworthy technical efficiency levels, registering at 102.8%. Nevertheless, their overall efficiency has been impacted by technological inefficiency, which is currently standing at 97%, leading to a total factor productivity change of 99.7%. It's clear that adopting advanced technology holds significant promise in elevating the efficiency of these farms, signifying that embracing modern techniques is a valuable path toward improvement.

The study's exploration of Black Cardamom farms in Ho Thau, Nam Ty, and Tung San offers valuable insights when considered within the wider context of Black Cardamom cultivation research. By examining environmental impacts, growth conditions, and farming practices, the findings contribute to a nuanced comprehension of the factors influencing farm efficiency. The current study's results echo a parallel investigation in Bhutan, underscoring the significance of agroforestry species composition and growth patterns across different altitudinal habitats. Specifically, the emphasis on shade trees like Alnus nepalensis creating optimal bioclimatic conditions aligns with the observed efficiency in Ho Thau and Nam Ty, suggesting a potential correlation with similar agroforestry practices and favorable habitat conditions (Koirala, Suberi, Sherub, Chhetri, & Gyeltshen, 2022). Corroborating evidence emerges from a study in the Indian Cardamom Hills, shedding light on the ecological and environmental implications of intensive cardamom cultivation. This broader perspective aids in understanding the efficiency dynamics in Tung San, where technological inefficiency has impacted overall efficiency. The focus on microclimatic conditions, pest and disease incidence, and the influence of shade levels on cardamom growth in the Indian context contributes to comprehending the technical efficiency observed in Tung San (Murugan et al., 2022). In summary, the efficiency levels noted in Ho Thau, Nam Ty, and Tung San Black Cardamom farms can be linked to broader research findings. The success in Ho Thau and Nam Ty may be attributed to optimal agroforestry practices and habitat conditions, while challenges in Tung San appear tied to the complexities of intensive cultivation, environmental impacts, and the need for technological advancements. This underscores a nuanced relationship between environmental conditions, cultivation practices, and farm efficiency, emphasizing the importance of adopting sustainable and context-specific agricultural strategies.

3.2. The impact of influential factors on efficiency of the Black Cardamom farms

The impact of influential factors on the efficiency of Black Cardamom farms was scrutinized using the Tobit regression model. The outcomes are presented in Table 3.

***Table 3:** The impact of influential factors on efficiency of the Black Cardamom farms*

Efficiency of the Black Cardamom farms	Coef.[a]	S.E.[b]	*p-value*
Farm owner's age (years)	0.0243	0.0337	0.0470
Farm owner's gender (1=male)	0.0299	0.0384	0.4360
Farm owner's education (schooling years)	0.0832	0.0443	0.0600
Farm owner's professional training (1=yes)	0.0416	0.0085	0.0000
Farm owner's experience in growing Black Cardamom (years)	0.0231	0.0320	0.0447
Farm owner's family dependants (persons)	-0.0284	0.0365	0.3342
Farm owner's family poverty status (1=poor/near poor)	-0.0790	0.0421	0.0570
Number of shocks farm experienced	-0.0395	0.0081	0.0000
Farm information sources (1=TV/radio/newspapers/Internet)	0.0226	0.0314	0.0438
Distance to the nearest bank (km)	-0.0278	0.0358	0.0335
Distance to the nearest market (km)	-0.0775	0.0412	0.0559
Distance to the nearest concrete/tarred road (km)	-0.0387	0.0079	0.0000
Constant	1.0650	0.1826	0.0000

Note. [a]Coefficient, [b]Standard Error. *Source. Authors' calculation, using the interviewed data.*

Table 3 provides significant insights into the determinants of farm efficiency among Black Cardamom producers. Notably, the age of farm owners emerges as a key factor, with farms owned by individuals of advanced age demonstrating higher efficiency levels. This finding aligns with previous research, such as Tauer (1995), which observed a positive correlation between age and farm efficiency in diverse agricultural contexts. The study confirms this trend, indicating that an additional year of the farm owner's age is associated with a noteworthy increase in total factor productivity change (0.024 points), with statistical significance at the 5% level. However, it is important to note that this impact follows the diminishing law, implying a potential slowdown in efficiency gains as owners age.

Educational attainment, professional training, and experience in Black Cardamom cultivation also play crucial roles in determining farm efficiency. These results are consistent with findings from studies such as Luh (2017) and Bartel and Lichtenburg (1988), emphasizing the positive influence of education and training on agricultural productivity. In this study, an additional year of education for the farm owner corresponds to a substantial increase in total factor productivity change (0.083 points), achieving significance at the 10% level. Similarly, farms owned by individuals with professional training exhibit significantly higher total factor productivity changes, surpassing the baseline by nearly 0.042 points (significant at the 1% level). Experience in Black Cardamom cultivation also contributes positively to efficiency, with each additional year linked to an increase of approximately 0.023 points (significant at the 5% level).

Access to information through media channels, including TV, radio, newspapers, or the Internet, emerges as a positive determinant of farm efficiency. This finding resonates with studies like Beuermann (2015), highlighting the role of information in enhancing agricultural practices. In this study, information from these sources is associated with a higher total factor productivity change (0.023 points), with statistical significance at the 5% level.

Conversely, factors such as family poverty status, the number of shocks experienced by the farm, and greater distances to essential facilities negatively impact farm efficiency. These findings corroborate research by Addison, Ghoshray, and Stamatogiannis (2016), Devkota and Upadhyay (2013), and Thirtle, Irz, Lin, McKenzie-Hill, and Wiggins (2001), emphasizing the adverse effects of poverty, shocks, and limited access on agricultural productivity. Farms owned by individuals classified as poor or near-poor exhibit lower total factor productivity change (reduction of approximately 0.08 points, significant at the 10% level). Additionally, each additional shock experienced by the farm leads to a decrease of about 0.04 points in total factor productivity change (significant at the 1% level). Increased distances to the nearest bank, market, or concrete/tarred road are associated with significant decreases (0.03, 0.08, and 0.04 points, respectively) in total factor productivity change, highlighting the importance of proximity to essential resources and infrastructure (significant at the 5%, 10%, and 1% levels, respectively).

3.3. Practical recommendations

To enhance Black Cardamom farm efficiency, farm owners should prioritize continuous learning, encompassing education, professional development, and experience. Staying informed about cultivation techniques and market trends through various sources is crucial. Optimizing farm size, diversifying information sources, and implementing risk management strategies, such as crop diversification and sustainable practices, can boost efficiency. Improving access to essential services like banks and markets through transportation upgrades is essential. Older farm owners should plan for succession to ensure continued efficient operations. Incorporating these strategies can elevate efficiency, productivity, and overall success in Black Cardamom farming.

4. Conclusion

In this comprehensive study, an analysis of data from 300 Black Cardamom farm owners in Hoang Su Phi district was conducted to evaluate farm efficiency using the Malmquist Index. The exploration of influential factors was further undertaken through the Tobit regression model. The findings illuminate the commendable efficiency of Black Cardamom farms in Ho Thau and Nam Ty, consistently showcasing impressive total factor productivity changes of 102.2% and 103.3%, respectively. This underscores the current success of these farms, yet also reveals untapped potential for further improvement, particularly in Nam Ty, where optimizing farm size could substantially enhance overall efficiency.

Conversely, Tung San farms exhibited noteworthy technical efficiency at 102.8%, yet were hindered by a considerable 97% technological inefficiency, resulting in an overall total factor productivity change of 99.7%. To address this, embracing advanced technology emerges as a promising avenue to elevate efficiency in these farms and unlock their full productivity potential.

The study identifies key factors influencing farm efficiency, including the age of owners, where each additional year corresponds to a 0.024-point increase in total factor productivity change. Furthermore, education, professional training, and experience significantly enhance efficiency, with each contributing to respective increases of 0.083, 0.042, and 0.023 points in total factor productivity change. Information derived from various sources such as TV, radio, newspapers, and the Internet also positively affects efficiency, adding 0.023 points to the overall change.

Conversely, challenges such as family poverty status, the number of shocks experienced, and increased distances to essential services exert negative impacts on farm efficiency. Addressing these challenges, alongside the strategic adoption of technology and continuous learning initiatives, is crucial for Black Cardamom farm owners to optimize their operations and achieve enhanced efficiency and success within the industry.

Despite the valuable insights gained from this study, it is essential to acknowledge certain limitations. The study's scope is confined to a specific geographic region, and variations in environmental and socio-economic conditions across different regions may influence the generalizability of the findings. Additionally, the data collection process, while extensive, may be subject to recall bias or other limitations inherent in survey-based research.

For future studies, it is recommended to expand the geographical scope to capture a more diverse range of environmental and socio-economic conditions. Further, a longitudinal approach could provide a dynamic understanding of farm efficiency trends over time. Additionally, qualitative research methods, such as interviews and focus groups, could offer deeper insights into the nuanced factors influencing farm efficiency. Finally, exploring the role of government policies and support programs in promoting sustainable and efficient agricultural practices could contribute valuable insights for both researchers and policymakers.

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