A Copula-Based Stochastic Frontier Analysis of Thai Jasmine Rice Production in the Northeast of Thailand

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Abstract **– Thai jasmine rice holds immense economic significance both domestically and as a major export, making it a vital contributor to the Thai economy. Traditional and modern agricultural practices, centered around rice cultivation, play a pivotal role in the culture and economy of the Northeast region. However, concerns have arisen regarding rice production efficiency in recent times due to capital and labor availability challenges. Motivated by these concerns, this study employs a copula-based stochastic frontier modeling (copula-SFM) framework to investigate production efficiency empirically. The research is based on a sample of 397 farmers in the Northeast of Thailand. The Akaike Information Criterion (AIC) is utilized to select the most appropriate model. The results indicate that the Gaussian copula-SFM outperforms other copula models. Notably, the study identifies total area, capital, and labor as critical factors significantly contributing to the positive impact on jasmine rice production. Furthermore, the research ranks provinces based on average technical efficiency (TE) scores, revealing Khon Kaen Province, Yasothon Province, and Roi Et Province as the top-performing regions.**

Keywords **– Thai jasmine rice, stochastic frontier analysis, technical efficiency, copula.**

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1. Introduction

Thailand's main crop, rice, has important historical and contemporary significance. It supports the nation's economy by acting as a crucial export product. The cultivation of rice takes up roughly 46.1% of Thai cropland, providing food for 4.9 million households, or 60.5% of all agricultural workers. As worthy of attention producer and exporter of rice, Thailand occupies a prominent place in the international market.

Thailand produces 3.7% of the world's uncooked rice, ranking sixth among the top-producing nations, according to the world rankings for 2020–2021 data. China, India, Indonesia, Bangladesh, and Vietnam, with respective contributions of 29.3%, 24.1%, 7.0%, 6.8%, and 5.4%, significantly outpace Thailand's manufacturing volume. Thailand ranks third globally in exports only, accounting for 11.9% of the global market. India leads with a 38.9% market share, followed by Vietnam (12.9%).

One of the most scrumptious rice varieties in the world, Thai jasmine rice is recognized for its excellent flavor and scent. As a result of its outstanding tenderness and alluring scent when served, this delectable species is greatly favored by many Thai households. The northeastern part of Thailand, called "Isan," is a fertile zone for quality rice cultivation. Nonetheless, the entire region confronts significant challenges and limitations, including unfavorable topography, scarcity of labor, and erratic climate fluctuations.

These factors contribute to low agricultural yields, elevated production expenses, and unpredictable farmer income. Addressing these obstacles requires a well-considered policy approach that emphasizes practical development and the effective application of farmer expertise. This includes enhancing production techniques, devising strategic marketing plans, and harnessing appropriate technologies to mitigate escalating production costs.

The sustainable development of rice farming squarely relies on production resources and efficient techniques, as is the case for all other production enterprises. Regarding research about technical efficiency in rice production, efficiency improvement is usually an area that is taken into account in crafting socio-economic policies and reforms that seek to achieve this [1]. Regarding rice production in Thailand, many economists have questioned technical efficiency considerations by farmers due to their probably inadequate knowledge of modern production decision choices that guarantee optimal outputs and, by extension, optimal profits.

In the last few decades, stochastic frontier models (SFM) have become a successful method in analyzing agricultural production efficiency. In general, SFM is a parametric method used to investigate technical efficiency and productivity. It can be applied to estimate production functions such as Cobb-Douglas, Leontief, etc.

It is commonly acknowledged that the SFM is an effective tool for evaluating the technical effectiveness of production units. It was first introduced as a cross-sectional methodology by [2] and [3], who made separate contributions to the field. The structure of the SFM shares similarities with a linear regression model, but it incorporates two distinct error components. The first component accounts for the stochastic fluctuation of the production frontier across different enterprises, leading to a two-sided error. The second component measures inefficiency relative to the frontier, resulting in a one-sided error.

In recent decades, the conventional SFM has been widely employed in numerous studies focusing on production, cost, or profit efficiency. Some notable examples are the works of [1], [4], [5], [6], [7], [8], [9], [10]. Assuming independence between the one-sided and two-sided error terms, maximum likelihood estimation and corrected OLS methods can be employed for SFM parameters.

The assumption made about independence in terms of estimating technical efficiency still remains a contestable one. By adopting a copula-based framework joint the marginal distribution of the two random error components, the apparent inadequacies that characterize the independence assumption can be completely resolved.

One of the first researchers to attempt this was Smith [11], who suggested an SFM incorporating dependence between the error components through copula functions. One key and powerful advantage of using copula models is their ability to adequately quantify rank correlation and tail dependence between two error terms. This introduces significant flexibility in using stochastic frontier analysis and makes the analysis more realistic. It is essential to highlight that log-likelihood functions in the copula-based SFM generally do not have a closed form, rendering analytical computations simply impossible. It is this development that makes numerical computational options a must, an exercise that can be highly complicated and computationally costly.

Our proposal uses a copula-based SFM to improve the analysis. In 2015, Wiboonponse *et al*. [12] showed that the conventional SFM severely overestimates the technical efficiencies and uses the maximum simulated likelihood estimation to evaluate the parameters in copula-based SFM. We systematically study different copula functions to investigate the nonindependence structure of the two error components in the copula-based SFM framework thoroughly. These copulas are used for cross-sectional data related explicitly to Thai jasmine rice production in northeastern Thailand. We use the lowest value of the Akaike Information Criterion (AIC) to select the suitable copula-based SFM. A significant difference is observed when comparing the calculated technical efficiency assuming independence or non-independence. The traditional approach, which assumes independence, greatly overestimates efficiency. This finding has critical implications for manufacturing analysis with SFM.

The paper has the following sections: Section 2 introduces the methods used, while Section 3 focuses on the evaluation procedures. Finally, Sections 4 and 5 present the results, discussions, and conclusions of our study.

2. Methodology

The section provides a brief overview of the methodology employed in this study. Our approach combines the Stochastic Frontier Model (SFM) with copula analysis, which is used to integrate the two error components within the SFM framework.

2.1. Stochastic Frontier Model (SFM)

To consider the traditional production function, let Y represent the maximum production output achievable with the given available technology and input material. The conventional production function states that

$$Y = f(\boldsymbol{x}, \boldsymbol{\beta}),$$

where x and β are, respectively, vectors of inputs (independent variables) and associated parameters.

Casting it in a stochastic frontier model format, we have:

$$Y = f(\boldsymbol{x}, \boldsymbol{\beta}) \cdot TE,$$

And taking log of the above, we have

$$\log(Y) = \log(\mathrm{f}(\mathbf{x}, \boldsymbol{\beta})) + \log(\mathrm{TE})$$

TE denotes technical efficiency, $\log(f(\boldsymbol{x}, \boldsymbol{\beta}))$ is a linear function, and $\log(Y)$ is the feasible output in the log scale. For x_i inputs, our regression equation can be written as

$$\log(Y_i) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \log(\mathrm{TE})$$

Aigner *et al.* (1977) defined log (TE) as a random error with two components of an independent random variable in the form

$$\log(TE) = \varepsilon = V - U.$$

Incorporating the above into the previous equation, we have

$$\log(Y) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + V - U.$$

The assumption about random variable V (efficiency error) is that it is symmetric with $E(V) = 0$ and $var(V) = \sigma_v^2$, and the random variable U (inefficiency error) is a non-negative random variable with $(E(U) > 0,\ var(U) = \sigma_u^2$.

The term V, the efficiency error, is assumed to be symmetric with $E(V) = 0$ and $var(V) = \sigma_v^2$. The random variable U (inefficiency error) is a non-negative random variable with $E(U) > 0, var(U) = \sigma_{u.}^2$

Thus, the calculation of technical efficiency (TE) can be derived using the following formula:

$$TE = e^{-U}$$

In line with the existing literature, we assume $V \sim N(0, \sigma_V^2)$ and U is the Half-normal distribution. If the two errors are independent, we can estimate the parameter by the package's frontier using R programming [13] or the maximum entropy approach [14].

2.2. Copula

Copulas are commonly utilized to build the joint distribution function of many marginal distributions. According to Sklar's theorem [15], any given cumulative distribution function (cdf) $F(x_1, x_2)$ of any two-dimensional random vector $(X_1,\ X_2)$ can be formulated as:

$$H(x_1, x_2) = C\big(F_1(x_1), F_2(x_2)\big),$$

where $F_1(\cdot)$ and $F_2(\cdot)$ are the marginals of X_1 and X_2, and C is a copula function with the following regularity conditions.

1. $0 \le\ C\big(F_1(\cdot) \le 1,\ \ F_2(\cdot)\big) \le 1$
2. $C(F_1(\cdot), 0)$ and $C\big(0, F_2(\cdot)\big) = 0$
3. $C(F_1(\cdot), 1) = F_1(\cdot)$ and $C\big(1, F_2(\cdot)\big) = F_2(\cdot)$
4. If $a < b$ and $c < d$, then
$$C\big(F_1(b), F_2(d)\big) - C\big(F_1(a), F_2(d)\big) - C\big(F_1(b), F_2(c)\big) + C\big(F_1(a), F_2(c)\big)$$

We assign $W_1 = F_1(x_1)$ and $W_2 = F_2(x_2)$, $0 \le W_1, W_2 \le 1$.

The function of the copula density expresses the joint density as $f(x_1, x_2)$ follows.

$$f(x_1, x_2) = \frac{\partial^2 C(\mathrm{W}_1, W_2)}{\partial \mathrm{F}_1(\mathrm{x}_1)\, \partial \mathrm{F}_2(x_2)}$$

$$= f_1(x_1) \cdot f_2(x_2) \cdot c(W_1, W_2).$$

Where $f_1(x_1)$ and $f_2(x_2)$ are the marginal densities function,$c(W_1, W_2)$ is the copula density function. Next, we present a set of copula families below.

1. Gaussian Copula:

$$C(W_1, W_2; \rho) := \Phi_2(\Phi^{-1}(W_1), \Phi^{-1}(W_2); \rho)$$

$$\phi(x_1, x_2; \rho) \coloneqq \frac{1}{2\pi\sqrt{1-\rho^2}} \times$$

$$\mathrm{e}^{-\frac{x_1^2 - 2\rho x_1 x_2 + x_2^2}{2(1-\rho^2)}},$$

$$\Phi(x_1, x_2; \rho) := \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \varphi(x_1, x_2; \rho)\, dx_2\, dx_1$$

given the bivariate standard normal distribution, along with its density and distribution function and a correlation parameter $\rho \in (-1,1)$.

2. Clayton Copula:

$$\left[max\left\{W_1^{-\theta} + W_2^{-\theta} - 1, 0\right\}\right]^{-1/\theta}, \theta \in [-1, \infty) \setminus \{0\}$$

3. Frank copula:

$$C(W_1, W_2) =$$

$$C(-\frac{1}{\theta}\log\left[1 + \frac{\left(e^{-\theta W_1} - 1\right)\left(e^{-\theta W_2} - 1\right)}{e^{-\theta} - 1}\right],$$

$$\theta \in R\setminus\{0\}$$

4. Gumbel copula:

$$C(W_1, W_2) = \mathrm{e}^{-\left((-\log(W_1))^{\theta} + (-\log(W_2))^{\theta}\right)^{\frac{1}{\theta}}}, \theta \in [1, \infty)$$

5. Joe Copula:

$$C(W_1, W_2) = 1 - \left[(1 - W_1)^{\theta} + (1 - W_2)^{\theta} - (1 - W_1)^{\theta}(1 - W_2)^{\theta}\right]^{\frac{1}{\theta}}, \theta \in [1, \infty).$$

2.3. Copula-Based Stochastic Frontier Model (copula-based SFM)

The noise (error) terms V and U are considered to be independent under the first-generation SFM framework. However, Smith (2008) relaxed this assumption and, in turn, modeled V and U as being dependent using copula. Following Smith (2008), the density function $f_\theta(\varepsilon)$ can be obtained from $f(u, v)$ as

$$f(u, v) = f(u, u + \varepsilon)$$

$$= c_\theta\left(F_U(u), F_V(u + \varepsilon)\right) \cdot f_U(u) \cdot f_V(u + \varepsilon),$$

Marginalizing out U

$$f_\theta(\varepsilon) = \int_0^\infty f(u, u + \varepsilon)du$$

$$= \int_0^\infty c_\theta\left(F_U(u), F_V(u + \varepsilon)\right) \cdot f_U(u) \cdot f_V(u + \varepsilon)\mathrm{d}u$$

or, equivalently,

$$f_\theta(\varepsilon) = E_u\left[\left(c_\theta\left(F_U(U), F_V(U + \varepsilon)\right) \cdot f_V(U + \varepsilon)\right]$$

where $E_u[\cdot]$ is the expectation function from the density function of U and θ is a parameter space of copula and all marginal density functions.

The log-likelihood function is predicated on the assumption that data on the cross-sectional observations of individual farmers are independent and identically distributed.

$$L(\beta, \sigma_u, \sigma_v, \theta) = \sum_{i=1}^{n} \log f_\theta(\varepsilon_i)$$

$$= \sum_{i=1}^{n} \log f_\theta(y_i - x_i'\beta).$$

Where y_i is the production unit from farmer i, x_i is the independent input factor from farmer i, σ_u is the scale parameter of the marginal distribution of U, and σ_v is the scale parameter of the marginal distribution of V.

The marginal function of ε can be shown as

$$f(\varepsilon) = \int_0^\infty c_\theta(F_U(u), F_V(u + \varepsilon)) \cdot f_U(u) \cdot f_V(u + \varepsilon)du$$

$$= \int_0^\infty \frac{2\mathrm{e}^{-\frac{u^2}{2\sigma_u^2}}}{\sqrt{2\pi\sigma_u}} c_\theta(F_U(u), F_V(u + \varepsilon)) \cdot f_V(u + \varepsilon)du,$$

$$= \int_0^\infty \frac{2\mathrm{e}^{-\frac{u^2}{2\sigma_u^2}}}{\sqrt{2\pi\sigma_u}} c_\theta\left(F_U(\sigma_u u_0), F_V(\sigma_u u_0 + \varepsilon)\right) \cdot f_V(\sigma_u u_0 + \varepsilon)d\sigma_u u_0,$$

$$= \int_0^\infty \frac{2e^{-\frac{u^2}{2}}}{\sqrt{2\pi}} c_\theta\left(F_U(\sigma_u u_0), F_V(\sigma_u u_0 + \varepsilon)\right) \cdot f_V(\sigma_u u_0 + \varepsilon)du_0,$$

under the assumption that U is half-normally distributed, and by the Mote Carlo simulation, we can approximate the integral function by

$$\tilde{f}(\varepsilon) = \frac{1}{N}\sum_{r=1}^{N} f_v\left(\sigma_u u_{0,r} + \varepsilon\right) \times$$

$$c_\theta\left(F_U\left(\sigma_u u_{0,r}\right), F_V\left(\sigma_u u_{0,r} + \varepsilon\right)\right),$$

where $u_{0,r}$, $r = 1,2, \ldots, N$, is a simulation number from the standard half-normal distribution (we can use function rhalfnorm from the package fdtool).

We can write the simulated maximum log-likelihood in the SFM as:

$$L(\beta, \sigma_u, \sigma_v, \theta) = \sum_{i=1}^{n} \log \left[\begin{matrix} \frac{1}{N} f_v(\sigma_u u_{0,r} + \varepsilon_i) \times \\ c_\theta \left(F_U(\sigma_u u_{0,r}), F_V(\sigma_u u_{0,r} + \varepsilon_i) \right) \end{matrix} \right]$$

With parameterization, the pair (σ_V, σ_U) is equivalent to (λ, σ) where $\lambda = \sigma_U / \sigma_V$ and $= \sqrt{\sigma_U^2 + \sigma_V^2}$. It can be easily verified from the above that the inefficiency component of the model increases with λ. The amount $\lambda = \sigma_U^2 / (\sigma_U^2 + \sigma_V^2)$ gives the global inefficiency value. To determine whether inefficiency plays a significant role in the composite error term, λ and γ are used. For more information on this method, see [16].

Assessing the values of technical efficiency terms is the primary purpose of stochastic frontier modeling. Technical efficiency conditional expectations are expressed as:

$$TE_0 = E[\mathrm{e}^{-\mathrm{w}} \mid \varepsilon] = \frac{1}{f_\theta(\varepsilon)} \int_0^{+\infty} \mathrm{e}^{-\mathrm{u}} f(u, \varepsilon) du = \frac{E_U[e^{-U} f_V(U + \varepsilon) c_\theta(F_U(U), F_V(U + \varepsilon))]}{E_U[f_V(U + \varepsilon) c_\theta(F_U(U), F_V(U + \varepsilon))]}$$

3. Data

Data for this study have been sourced from the Smart Farmer Project of The International College of Digital Innovation (ICDI), Chang Mai University database on jasmine rice production. The database has data covering a sample of 397 on the following variables: total capital, number of labor, and costs of production in the following provinces: Chaiyaphum, Khon Kaen, Maha Sarakham, Roi-Et, Surin, and Yasothon. Table 1 presents the descriptive statistics of the study data additionally showing that the highest standard deviation is observed for total capital, while the lowest is observed for total area. With the exception of total capital, all other series are not normal distributions, as we fail to accept the null hypothesis. Every variable is stationary by the unit root test. Moreover, all data is transformed into a natural log. The estimation of the copula-based SFM is as follows:

$$\log(\text{Total Revenue}) = \beta_0 + \beta_1 \log(\text{Total Area}) + \beta_2 \log(\text{Total Capital}) + \beta_3 \log(\text{Total Labor}) + v_i + u_i$$

where log(Total Revenue) is the rice revenue, log(Total Area) is the amount of total area, log(Total Capital) is the amount of total capital, and log(Total Labor) is the number of total labor for each province i. We assumed error terms v_i follow normal distribution and inefficiency u_i follows half-normal distribution. Additionally, the five different copula families, Gaussian, Clayton, Frank, Gumbel, and Joe are the candidates for the copula-based SFM.

Table 1. Descriptive statistics

Variable	**log (Total Revenue)**	**log (Total Area)**	**log (Total Capital)**	**Log (Total Labor)**
Mean	10.3160	1.8430	8.7246	8.9679
Median	10.1608	1.6094	8.7796	8.6995
Maximum	12.5101	3.9512	11.5129	11.1844
Minimum	6.9217	-1.3863	4.8283	5.7038
Std. Dev	0.6937	0.6598	1.0133	0.7016
Skewness	0.2470	0.2058	0.1966	0.3508
Kurtosis	1.7480	1.9859	0.1004	1.6525
Jarque-Bera	56.006***	70.754***	2.8418	55.48***
Unit root test	-7.5764***	-7.3875***	-7.8259***	-7.5499***

*Note: ***, **, and * are significant at 0.01, 0.05, and 0.1, respectively.*

4. Empirical Results

The results of this study are presented in the following section. We begin by reporting the comparison of copula-based SFM models, and subsequently, we interpret the best-fit model to provide a comprehensive analysis of our findings.

4.1. The Copula-Based SFM Estimated Results

We evaluated five copula families to estimate our SFM and chose the suitable model with the lowest AIC value. Table 2 presents the results. It can be seen that the Gaussian copula produces the lowest AIC with *a value of* -668.0253, and, as a result, for this study, the Gaussian copula SFM is the most suitable model.

Table 2. The AIC value from the copula model

Copula families	AIC
Gaussian	-668.0253
Clayton	-645.2552
Frank	-609.3914
Gumbel	-659.5961
Joe	-630.3294

Table 3 shows the estimates of the Gaussian copula parameters of the SFM. Every parameter of independent input variables has a positive value. It has a significant impact on Thai jasmine rice production, with parameter estimates of 0.9306, 0.0067, and 0.0657 for total area, total capital, and total labor, respectively. Since all variables have been log-transformed, an increase of 1% in area or land size will increase Thai jasmine rice production by 0.9306% with a statistical significance of 1% level.

For total capital, an increase of 1% will increase rice production by 0.0067%, significant at the 10% level. In the case of the total, a 1% increase will increase Thai jasmine rice production by 0.0657% at a significant level of 1%. σ_u, it can be considered statistically significant at a level of 1%, which clearly indicates that Thai jasmine rice production is plagued with inefficiency. Our results have confirmed a pronounced positive dependence in the noise-inefficiency measure, ρ with a value of 0.7379. This finding proves that a copula-based SFM should be preferred to the traditional SFM.

Table 3. The estimated parameters of Thai jasmine rice production on copula-based SFM

Variable	Gaussian copula-based SFM		P-Value
	Estimates	S.E.	
Intercept	8.1549***	0.0006	0.0000
log(Total Area)	0.9306***	0.0028	0.0000
log(Total Capital)	0.0067*	0.0035	0.0597
log(Total Labor)	0.0657***	0.0031	0.0000
σ_v	0.0196***	0.0031	0.0000
σ_u	0.2495***	0.0041	0.0000
ρ	0.7379***	0.1149	0.0000

*Note: ***, **, and * are significant at 0.01, 0.05, and 0.1, respectively.*

4.2. Technical Efficiency (TE) Estimates

Table 4 below presents the TE estimates, which indicate the ratio of observed Thai jasmine production to the maximum feasible output. The TE score has a specific interpretation that is relevant to measuring jasmine rice production efficiency. If the TE value is less than 1, it means that Thai jasmine rice production is not achieving its full potential efficiency. On the other hand, if the TE value is equal to 1, it implies that production has reached its full possibility boundary. The results indicate that Khon Kaen Province holds the top average TE score of 0.8548, while Roi Ed Province scored the lowest average TE with 0.7660.

Trace plots and box plots of Gaussian copula-based technical efficiency for jasmine rice production in Northeast Thailand provinces are shown in Figures 1 and 2.

Table 4. Average TE of Northeast in Thailand

Variable	Average TE
Chaiyabhum	0.8278
Khon Kaen	0.8548
Maha Sarakham	0.8220
Roi Ed	0.7660
Surin	0.8152
Yasothon	0.8348

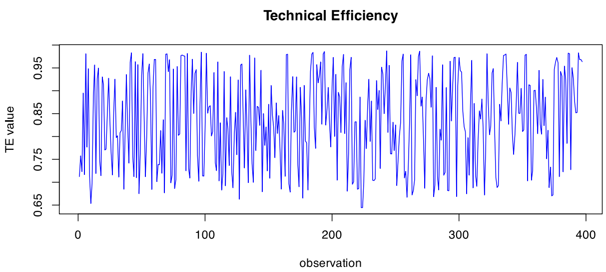

Figure 1. The TE value of Northeast of Thailand

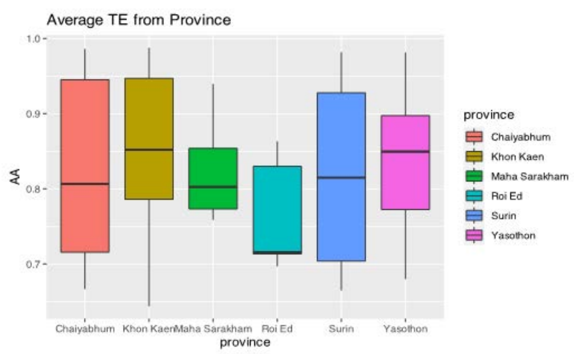

Figure 2. A box plot of the average TE of Northeast Provinces

5. Conclusion

This paper employed a copula-based SFM to analyze Thai jasmine rice production in Northeast Thailand. Model selection was done using the lowest AIC approach, and our study shows that Gaussian copula SFM is the best model. Total area, total capital, and total labor have been found to have a positive impact and significant effects on Thai jasmine rice production in the selected provinces, with the following parameter estimates: 0.9306, 0.0067, and 0.0657, respectively. Regarding average TE scores, Khon Kaen has the highest TE of 0.8548, followed by Yasothon with 0.8348, while Roi Ed has the lowest TE score of 0.7660.

The results of this study will serve as practical guidelines for developing Thai jasmine rice production. The TE result for the province with the maximum score will serve as a benchmark or a reference point for other provinces that intend to replicate the underlining factors in the well-performing province. The findings about the low-performing provinces also offer a valuable and critical policy opportunity. In Thailand, the government has made efforts to boost Thai jasmine rice production by expanding cultivated areas. However, low productivity remains a significant concern in Thailand's primary rice production. The government has actively encouraged farmers to adopt new technologies, resulting in a consistent increase in rice production. An analysis using the copula-based SFM models has unveiled that area, capital, and labor have significant and positive impact on the average major rice output in Thai farming. Therefore, we hope that important rice production policies will take these current findings into account when formulating their policy initiatives to enhance efficient rice production in these regions. In future research, the copula-SFM model could be applied to study Thai jasmine rice production in other regions not covered in the current study, including Southern, Northern, and Central Thailand.

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