



Bridging the Yield Gap in Soybean Farming: Technical Efficiency and Key Determinants from a Stochastic Frontier Study in Chiang Mai Province, Thailand

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Abstract: This study aimed to analyze the technical efficiency of soybean production and identify factors influencing technical inefficiency among soybean farmers in Chiang Mai Province. Cross-sectional data from 100 farmers across Chiang Dao, Hang Dong, Phrao, and Mae Rim districts were analyzed using stochastic frontier analysis (SFA) with a Cobb–Douglas production function integrated with a copula model, allowing for flexible modeling of the dependency between error components. The average technical efficiency score was 0.77, indicating moderate efficiency, with a 23% potential yield improvement through optimized resource use. Labor hours, fertilizer expenditure, and seed quantity significantly increased yields, while land ownership and farming experience reduced inefficiency; larger farm size was linked to higher inefficiency. Land rental emerged as a key factor for improving efficiency, suggesting policy support for agreements with rice farmers who leave land fallow after harvest. Given soybeans short growth cycle and low water demand, targeted interventions—such as farmer-to-farmer knowledge exchange, structured training on optimal input use, and scale-specific strategies from low-cost improvements for smallholders to precision agriculture for commercial farms could enhance productivity, resource efficiency, and profitability in northern Thailand.

Keywords: Copula function; Soybean production; Stochastic frontier analysis; Technical efficiency

1. Introduction

Soybean is a crucial food crop for Thailand's economy, serving as both a dietary staple and a primary raw material for the oil extraction, food processing, and animal feed industries. Thailand produces approximately 50,000–60,000 tons of soybeans annually [1], while domestic demand reaches nearly 3.4 million tons. Consequently, domestic production satisfies only around

1–2% of total demand, and the country relies heavily on imports, which account for over 98% of domestic consumption [2].

Thailand's food and animal feed industries are expanding and growing significantly while domestic soybean production continues to decline. As a result, the government and businesses relying on soybeans as a key raw material have greatly emphasized encouraging farmers to cultivate more leguminous crops. They have also supported initiatives to enhance the efficiency of legume crop production. Consequently, soybeans have been classified as a substitute crop for imports to increase domestic production, meet rising demand, and mitigate trade deficits resulting from the impact of free trade agreements (FTAs). Additionally, increasing domestic soybean production helps mitigate the risks associated with price volatility in other agricultural products, such as rainy-season feed corn and dry-season rice. This strategy aims to ensure food security and sustain local livelihoods, laying the foundation for sustainable agricultural production.

The uncertainty in global trade, particularly due to the ongoing conflict between Russia and Ukraine, has increased transportation costs driven by rising fuel prices and higher prices for oilseed crops [2–3]. Despite ongoing efforts in both the public and private sectors to promote soybean production through improved efficiency, cost reduction, and better land management, challenges persist. Soybeans are short-season crops with lower returns than other crops, requiring significant labor, especially during harvest. Additionally, the high cost of production input discourages farmers from growing soybeans. In years when water availability is sufficient, many farmers opt to grow alternative crops that require less labor and yield higher returns, such as off-season rice and feed corn [4]. This shift in cultivation patterns has led to a continuous decline in Thailand's soybean production, from 22,802 tons in 2020 to 20,802 tons in 2022. To address the shortage of soybean raw materials, Thailand has significantly increased its imports of soybeans and soybean products, with 3.20 million tons of soybeans imported in 2023 to meet domestic demand, particularly for food processing [5–6]. According to the Food and Agriculture Organization of the United Nations (FAO), in 2021, Thailand's average soybean yield was 1.65 tons per hectare, which was higher than the average yields in several Southeast Asian countries, such as Vietnam, Cambodia, Indonesia, the Philippines, and Myanmar, where yields ranged from 1.37 to 1.60 tons per hectare. However, Thailand's yield was still lower than that of Laos, which achieved an average of 1.80 tons per hectare. Compared to global soybean production, which has an average yield of 2.87 tons per hectare, Thailand's production remains relatively low in terms of yield per unit area and total output [7].

The upper northern region of Thailand is a major soybean cultivation area and a significant contributor to the country's soybean production. This region consists of six provinces: Mae Hong Son, Nan, Chiang Rai, Phrae, Chiang Mai, and Lampang, covering a total soybean cultivation area of 6,785.60 hectares, which accounts for 49.30% of the total national soybean planting area of approximately 13,761.76 hectares. In 2022, Chiang Mai province had a soybean cultivation area of over 663.2 hectares, representing 12.6% of the soybean growing area in the upper northern region or 5.3% of the total national soybean cultivation area [8]. Chiang Mai ranked third in soybean cultivation within the upper northern region, following Mae Hong Son and Nan. Additionally, Chiang Mai has been actively promoted as a province for soybean cultivation using the "Chiang Mai 60" variety, which was developed and improved by the Chiang Mai Field Crops Research Center. This variety is well-suited to the northern region's conditions and has been trial-planted in Chiang Mai to optimize production. The province was also selected as a model province for a project aimed at increasing soybean yields and reducing production costs [9]. During the 2019/20 planting season, Chiang Mai cultivated soybeans across nine districts, covering 796.32 hectares and producing 1,243 tons. The total production quantity decreased from the 2018/19 planting season, when the cultivated area was 1,063.2 hectares, and the total production was 1,744 tons. Mae Taeng district had the largest soybean growing area, followed by Mae Rim and San Pa Tong districts.

An analysis of Chiang Mai's average soybean yield per rai in the 2019/20 planting season revealed an average yield of 1.56 tons per hectare, which is lower than the national average of 1.68 tons per hectare. Chiang Mai's yield was also lower than Mae Hong Son's (1.86 tons/ha) and Nan's (1.74 tons/ha). Furthermore, Chiang Dao, Hang Dong, Phrao, and Mae Rim districts recorded relatively low average yields, ranging from 1.40 to 1.60 tons per hectare, which was lower than the yields of five other districts, where production ranged between

1.71 and 1.88 tons per hectare [9–10]. This suggests that narrowing the yield gap offers significant potential to enhance soybean production in Chiang Mai, particularly among smallholder farmers, and can be realized through improvements in technical efficiency. Several studies have quantified technical efficiency in soybean production using stochastic frontier analysis (SFA). For instance, Sharma et al. [11] explored soybean farmers in Madhya Pradesh, India, and reported a mean efficiency score of 0.72, indicating a 28% potential output gain through the adoption of best-practice technologies. They also identified labor and machine usage as under-utilized inputs, while better contact with extension services significantly reduced inefficiencies. In northern Ghana, Etwire et al. [12] found an average technical efficiency of 0.53 (i.e., a 47 % output gap), with key determinants including farm location, farmers' age, and participation in an Agricultural Value Chain Mentorship Project. Musaba et al. [13] examined small-scale soybean producers in Zambia using a Cobb–Douglas SFA model. They found an average efficiency of 0.503, corresponding to a 49.7% potential output increase, with factors such as education, household size, market distance, extension access, and herbicide use affecting inefficiency levels. These findings demonstrate that while substantial inefficiencies persist, targeted institutional support and extension services can meaningfully improve productivity. Beyond India, Ghana, and Zambia, efficiency assessments have surfaced in other contexts. Alabi et al. [14] examined soybean producers in Northwest Nigeria using a stochastic frontier production model. They found an average efficiency of 0.5377, corresponding to a 46.23% potential output increase, with factors such as household size, age, education level, experience, number of extension contacts, and membership in cooperatives influencing efficiency levels. Based on research conducted by Otitoju and Arene [15], the translog stochastic frontier model is applied to examine the level and determinants of technical efficiency of soybean farmers in Benue State, Nigeria. The average technical efficiency score was 0.73, indicating that there is an opportunity to improve soybean productivity by 27%. The factors significantly impacting efficiency were gender, age, and experience. Besides that, a study in Indonesia's Tabanan Regency found that the average technical efficiency of soybean production was 0.77. The study also identified farming experience as a key driver of inefficiency, as noted by Rinaldi et al. [16].

In Thailand, numerous researchers have applied the stochastic frontier analysis framework to assess technical efficiency and its determinants across various agricultural commodities at both national and regional levels. For rice production, Puphoun [17] investigated farm-level efficiency and reported relatively high performance, with paddy field size, education, experience, participation in a farmer group, and debt identified as key positive determinants. Similarly, Somcom and Wana [18] found that irrigation management, farming experience, training participation, affiliation with agricultural organizations, and diversification of farming activities significantly enhanced the efficiency of rice farmers, while Rahman et al. [19] highlighted farm size as an influential factor affecting the level of technical inefficiency. For cassava, Sriwichai [20] identified land preparation practices and access to credit as critical determinants of efficiency differences among farmers. In chili production, Krasachat [21] employed a stochastic frontier production function approach to compare farms adopting Good Agricultural Practices (GAP) and those without GAP certification, concluding that GAP adoption significantly increased technical efficiency; Sornin and Athipanyakul [22] emphasized that the Cobb–Douglas SFA model is well suited for estimating the technical productivity of chili pepper production, with cultivated area, labor force, and input value identified as significant factors influencing output. Regarding soybeans, Phummuong [23] analyzed rainfed soybean production using stochastic frontier analysis (SFA) and found an average technical efficiency of 0.66. Key factors positively associated with efficiency included labor and herbicide use. Conversely, increased seed use, farm flooding, and excessive application of liquid fertilizer had adverse effects. The findings emphasize the importance of enhancing farmers' access to information and promoting crop rotation prior to planting soybeans to improve efficiency under rainfed conditions. Further, Lesak [24] employed the Stochastic Nonparametric Envelopment of Data (StoNED) approach to analyze soybean farmers operating in irrigated areas of Chiang Mai Province, reporting an average technical efficiency score of 0.620. The study further identified that higher educational attainment of the household head and female labor participation were positively and significantly associated with improvements in technical efficiency.

Previous research in Thailand and internationally has demonstrated the utility of Stochastic Frontier Analysis (SFA) in identifying technical efficiency and productivity gaps, as well as their determinants, across

a range of crops. As a parametric approach, SFA can be employed to estimate a range of production functions, such as Cobb–Douglas, Translog, and others [25]. While existing work contributes valuable insights, notable methodological and contextual gaps persist. More recently, some studies have advanced this framework by integrating SFM with copula analysis, which enables the modeling of potential dependency between the two error components in the SFM structure, thereby offering greater flexibility and precision in efficiency estimation [26]. However, this methodological innovation has been applied primarily to rice production [25, 27], with limited attention to soybean production in Thailand, despite the crop’s economic and nutritional importance, particularly in regions such as Chiang Mai Province, where farming systems are highly diverse. Building on these methodological advantages, this study applied a copula-integrated SFA framework to examine technical efficiency in soybean production. This approach allowed for potential dependence between inefficiency and random shocks, thereby enhancing the robustness and precision of efficiency estimates. Applied to Chiang Mai Province, it also addresses a notable gap in the literature by providing region-specific evidence on both the level and determinants of technical inefficiency in soybean farming. This study aimed to estimate the technical efficiency of soybean production in Chiang Mai Province using a copula-integrated stochastic frontier model, identify the socioeconomic, farm management, and resource-use factors influencing technical inefficiency, and provide targeted recommendations to enhance production efficiency. The results will inform farmers on how to improve productivity and input use, while offering policymakers evidence to design strategies for strengthening soybean production efficiency at both regional and national levels.

2. Materials and Methods

This study utilizes cross-sectional data from a survey on soybean cultivation in Chiang Mai during the 2020/21 production year. The research focuses on the production efficiency of soybean farms in four districts: Chiang Dao, Hang Dong, Phrao, and Mae Rim. These districts account for 50% of Chiang Mai’s total soybean cultivation area and have an average yield per rai lower than the province’s average.

The sample size was determined using the Taro Yamane formula [28] at a 90% confidence level. The formula used is:

$$n = \frac{N}{1 + N(e^2)}$$

Where:

- n = required sample size
- N = total population (965 soybean farmers in the selected districts)
- e = acceptable margin of error (0.1)

The calculation resulted in a sample size of 90.61. However, to enhance the reliability of the analysis, the study rounded the sample size to 100 farmers. A stratified random sampling method was employed, ensuring the proportion of farmers from each district was represented. Random selection was applied within each stratum, as soybean farmers in the selected districts share similar socioeconomic characteristics. Field data were collected between February and July 2022 using a structured questionnaire consisting of both open-ended and closed-ended questions. Subject matter experts reviewed the questionnaire to ensure content validity and subsequently pilot-tested it with 40 farmers in Mae Taeng District to assess clarity, appropriateness, and reliability. Feedback from the pilot was used to refine the wording and sequencing of the questions. Prior to the survey, four research assistants participated in a one-day training program covering interview techniques, ethical considerations, and the use of the questionnaire. The primary data collection was conducted mainly by the lead researcher (approximately 80% of interviews), with support from the trained assistants. Face-to-face interviews were conducted after obtaining informed consent from each respondent, resulting in a 100% response rate. To ensure data quality, daily checks were performed to verify the completeness and consistency of responses, and any discrepancies were clarified with respondents on the same day. The study employed the Stochastic Frontier Analysis (SFA) method to evaluate technical efficiency in soybean production. SFA is particularly suitable for agricultural contexts because production efficiency

among farmers often exhibits high variance, and this method can separate the impacts of uncontrollable external random factors from those arising from inefficiencies in production practices [29]. In the SFA framework, the composite error terms consist of two components: v , representing external noise or randomness beyond the control of farmers, and u , representing inefficiency caused by production-related factors. Under the traditional distributional assumption, these two error components are assumed to be statistically independent [25–26, 29].

The first step of the analysis aimed to determine the most suitable production function specification for modeling soybean production in Chiang Mai Province. Two commonly used functional forms in efficiency studies — the Cobb–Douglas production function and the Translog production function — were considered. The Cobb–Douglas and Translog production functions are both widely applied within the stochastic frontier analysis (SFA) framework due to their complementary strengths in modeling production technology [30]. The Cobb–Douglas form is valued for its simplicity, ease of estimation, and interpretability, making it particularly suitable for farm-level studies with limited data or potential multicollinearity issues, although it assumes constant elasticities of substitution between inputs. In contrast, the Translog function offers greater flexibility by allowing elasticities of substitution to vary and by incorporating interaction terms between inputs, enabling it to capture more complex and non-linear production relationships. Employing both functional forms within SFA enables a comparative assessment, ensuring that the chosen specification best reflects the underlying production technology while striking a balance between model interpretability and flexibility [31].

Building on the model selection process, the study further incorporated the copula-based SFA approach as an extension to both the Cobb–Douglas and Translog specifications. The copula method describes joint multivariate distributions and integrates the two error components, allowing for greater flexibility in the stochastic frontier model. Unlike traditional assumptions that require v and u to be independent, the copula approach enables them to be dependent [29]. By explicitly modeling this dependence structure, the copula-integrated SFA framework can yield more robust and precise efficiency estimates, providing a richer understanding of the determinants of technical inefficiency in soybean production. Four models were compared: the Cobb–Douglas production function and the Translog production function, both with and without incorporating the copula approach. The model selection was based on the Bayesian Information Criterion (BIC), where the best model is the one with the lowest BIC value [32]. The best model has the lowest BIC value. BIC balances model fit and complexity by penalizing models with a large number of parameters, thus reducing the risk of overfitting. Compared to the Akaike Information Criterion (AIC), BIC applies a more substantial penalty for complexity, making it more likely to select simpler models, especially as the sample size increases [33–34]. Maximum Likelihood Estimation (MLE) was employed to estimate the coefficients of the variables [35], with all computations performed using RStudio.

The production factors used in the models were derived from literature reviews, including works by Etwire et al. [12], Lesak [24], Otitoju and Arene [15], Phummuong [23], Si and Wang [36], and Sriwichai [20]. The factors used in the stochastic frontier production function, along with their definitions and measurement units, were presented in Table 1. All continuous input and output variables were log-transformed using the natural logarithm to facilitate the interpretation of estimated coefficients as elasticities, thereby enabling the evaluation of proportional changes in output relative to proportional changes in each input. For variables containing zero observations (e.g., no pesticide application during the production cycle), a constant value of one was added prior to transformation to prevent undefined logarithmic values. This adjustment ensured the retention of all observations in the dataset while maintaining the integrity and consistency of the analysis.

Table 1. Variables used in the stochastic frontier production function

Variables	Definitions	Measurement Units
Seeds (x_1)	Quantity of soybean seeds used for planting	kilograms per rai
Machinery (x_2):	Use of agricultural machinery and equipment in soybean production, such as tractors, seeders, and threshers	working hours per rai
Human labor (x_3):	Total amount of manual labor input, including family and hired labor, involved in various stages of soybean production	working hours per rai
Fertilizer (x_4):	Total expenditure incurred for using chemical and/or organic fertilizers during soybean production per rai	Thai Baht (THB) per rai
Pesticides (x_5):	Total expenditure incurred for using chemical and/or biological pesticides used to control pests, diseases, and weeds in soybean production	Thai Baht (THB) per rai

Remark: 1 rai = 0.16 hectare or 1 hectare = 6.25 rais

The Cobb-Douglas production function with the copula approach (1) and the Translog production function with the copula approach (2) can be represented as follows:

$$\ln y_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \beta_5 \ln x_{5i} + v_i - u_i \tag{1}$$

$$\begin{aligned} \ln y_i = & \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \beta_5 \ln x_{5i} + \frac{1}{2} \beta_{11} (\ln x_{1i})^2 + \frac{1}{2} \beta_{22} (\ln x_{2i})^2 + \\ & \frac{1}{2} \beta_{33} (\ln x_{3i})^2 + \frac{1}{2} \beta_{44} (\ln x_{4i})^2 + \frac{1}{2} \beta_{55} (\ln x_{5i})^2 + \beta_{12} \ln x_{1i} x_{2i} + \beta_{13} \ln x_{1i} x_{3i} + \beta_{14} \ln x_{1i} x_{4i} + \\ & \beta_{15} \ln x_{1i} x_{5i} + \beta_{23} \ln x_{2i} x_{3i} + \beta_{24} \ln x_{2i} x_{4i} + \beta_{25} \ln x_{2i} x_{5i} + \beta_{34} \ln x_{3i} x_{4i} + \beta_{35} \ln x_{3i} x_{5i} + \beta_{45} \ln x_{4i} x_{5i} + \\ & v_i - u_i \end{aligned} \tag{2}$$

Where:

- y_i represents the average soybean yield of farmers (kg per rai/ 1 rai = 0.16 hectare)
- x_{1i}, \dots, x_{5i} are the production input variables
- β_0 is the constant term
- $\beta_1, \beta_2, \dots, \beta_5$ are the parameters to be estimated
- \ln denotes the natural logarithm (logarithm base e)
- v_i represents errors due to uncontrollable external factors
- u_i represents errors due to internal factors that can be controlled
- i represents individual farmers cultivating soybeans, with values ranging from 1 to 100

The technical efficiency of soybean production among farmers in Chiang Mai can be estimated using a production function, where the efficiency score ranges from 0 to 1. If soybean production's technical efficiency (TE) equals 1.0, the producer has achieved the highest possible level of technical efficiency. Conversely, if the TE score is less than 1.0, it implies the presence of inefficiency [37]. According to Adinya et al. [38], the estimated technical efficiency levels can be classified into five categories:

- Very low (< 0.60)
- Low (0.61 - 0.70)
- Moderate (0.71 - 0.80)
- High (0.81 - 0.90)
- Very high (> 0.90)

This study employs a linear model estimated using multiple regression analysis with the Ordinary Least Squares (OLS) method to analyze factors affecting technical inefficiency in soybean production. This approach is chosen because multiple independent variables may influence the dependent variable, allowing for the simultaneous analysis of multiple factors [18]. The selection of variables for the analysis follows the stepwise regression method [39]. Six independent variables expected to influence technical inefficiency in soybean production are included, while each farmer's technical inefficiency (TI) is the dependent variable. The model is expressed in equation (3)

$$TI = \delta_0 + \delta_1DOWN + \delta_2DIRR + \delta_3DLAB + \delta_4DSUPP + \delta_5EXP + \delta_6SIZ + \varepsilon \tag{3}$$

Where:

- TI* = Technical inefficiency
- δ_0 = Constant term
- $\delta_1, \delta_2, \delta_3, \dots, \delta_6$ = Parameters to be estimated
- DOWN* = Dummy variable representing land ownership (1 = rented land, 0 = owned land)
- DIRR* = Dummy variable indicating whether the land is in an irrigated area (1 = irrigated, 0 = non-irrigated)
- DLAB* = Dummy variable representing labor type (1 = mixed labor, including household labor, 0 = hired labor only)
- DSUPP* = Dummy variable indicating support from relevant agencies (1 = received support, 0 = did not receive support)
- EXP* = Experience in soybean farming (years)
- SIZ* = Total soybean cultivation area (rai)
- ε = Error term

In equation (3), if an independent variable contributes to reducing technical inefficiency, its corresponding parameter will have a negative sign (-). Conversely, if an independent variable increases inefficiency, its parameter sign will be positive (+). The variables included in the analysis are based on a literature review of studies by Chubtong [40], Phummuong [23], and Si and Wang [36].

3. Results and Discussion

3.1 Technical Efficiency Analysis of Soybean Production

The analysis of basic data for the variables used in the stochastic frontier production function of soybean production in Chiang Mai Province, based on a sample of 100 farmers, revealed the following important statistics (Table 2): The average soybean yield per farmer was 310.13 kilograms per rai (approximately 1.94 tons per hectare). The average amount of soybean seed used was 16.68 kilograms per rai (0.10 tons per hectare). The average machine hours used for production were 3.12 hours per rai (19.5 hours per hectare). The average labor hours used for production were 12.39 hours per rai (77.45 hours per hectare). The average expenditure on fertilizer was 125 THB per rai (781.25 THB per hectare), and the average expenditure on pesticides was 99 THB per rai 618.75 THB per hectare. The improved soybean yields during the study period may be attributed to the favorable climatic conditions in the year of data collection, which were conducive to soybean cultivation. Additionally, rising domestic soybean prices are likely to encourage farmers to intensify their production efforts, resulting in increased productivity.

Table 2. Descriptive statistics of variables for the stochastic frontier production function

Variables	Average	S.D.	Minimum	Maximum
Production of soybean (Y) (kg/rai)	310.13	72.84	150.00	446.667
Amount of soybean seeds (X ₁) (kg/rai)	16.68	3.40	12.00	30.00
Farm machinery used (X ₂) (hours of work/rai)	3.12	3.49	1.00	22.00
Labour used (X ₃) (hours of work/rai)	12.39	12.39	1.50	72.33
Cost of fertilizers (X ₄) (THB/rai)	125.00	13.52	98.00	152.00
Cost of pesticides (X ₅) (THB/rai)	99.00	15.25	82.00	143.00

Source: author’s calculation

Remark: 1 rai = 0.16 hectare or 1 hectare = 6.25 rais

Testing the functional form of the stochastic frontier production function for soybean production in Chiang Mai Province involved four alternative specifications: the Cobb-Douglas model, the Cobb-Douglas model integrated with the copula approach, the Translog model, and the Translog model integrated with the

copula approach. As shown in Table 3, the Cobb-Douglas specification with the copula approach achieved the lowest BIC value (-210.9685), indicating the most favorable balance between model fit and parsimony. This outcome confirmed that the Cobb-Douglas form, when combined with the copula framework, is the most appropriate for capturing the production structure in the study area. Consequently, this specification was adopted for the subsequent estimation of production function coefficients and technical efficiency scores for soybean farmers.

Table 3. Bayesian Information Criterion (BIC) for model selection

	Cobb-Douglas	Cobb-Douglas +Copula	Translog	Translog +Copula
Bayesian Information Criteria (BIC)	-206.8829	-210.9685*	-190.6069	-184.1074

Source: author's calculation.

Note: * the lowest value of BIC

The estimation results of the coefficients for the stochastic frontier production function of soybean production by farmers in Chiang Mai province, using the Cobb-Douglas function combined with the copula model (Table 4), show that the variables for the number of labor hours used in production and the expenditure on fertilizer have a statistically significant impact on soybean yields at the 0.01 level. Meanwhile, the variable for the amount of soybean seed used in production has a statistically significant impact on soybean yields at the 0.05 level. All three factors have positive coefficients, indicating a positive relationship with soybean production. The estimation results of the coefficients for the stochastic frontier production function of soybean production by farmers in Chiang Mai province, using the Cobb-Douglas function combined with the copula model (Table 4), show that the variables for the number of labor hours used in production and the expenditure on fertilizer have a statistically significant impact on soybean yields at the 0.01 level. Meanwhile, the variable for the amount of soybean seed used in production has a statistically significant impact on soybean yields at the 0.05 level. All three factors have positive coefficients, indicating a positive relationship with soybean production. Table 4 presents the estimated parameters from the Cobb–Douglas stochastic production frontier with the copula specification. Holding other factors constant, the elasticity estimates indicate that a 1% increase in soybean seed use leads to a 0.286% increase in output, while a 1% increase in labor hours results in a 0.350% increase in output. Fertilizer expenditure also has a positive and statistically significant effect, where a 1% increase raises yield by 0.024%. In contrast, the number of farm machinery hours and pesticide expenditure do not significantly affect soybean yield in this sample, suggesting that there are limited productivity gains from additional spending on these inputs under current production conditions. The results highlight labor and seed use as the most influential inputs in soybean production, with labor showing the most significant elasticity. This suggests that interventions targeting labor productivity, such as training programs or labor-saving technologies, could yield substantial improvements in output. Likewise, optimizing seed use through improved seed quality or better planting techniques may further enhance productivity. Additionally, the sum of these elasticities is 0.752, indicating decreasing returns to scale in soybean production.

Table 4. Estimated parameters for the stochastic production frontier of Cobb-Douglas with Copula

Variables	Coefficient	Standard error
constant	1.684***	0.192
Amount of soybean seeds (X_1) (kg/rai)	0.286**	0.127
Farm machinery used (X_2) (hours of work/rai)	0.085	0.057
Labor used (X_3) (hours of work/rai)	0.350***	0.060
Cost of fertilizers (X_4) (THB/rai)	0.024***	0.007
Cost of pesticides (X_5) (THB/rai)	0.007	0.008

Source: author's calculation. Note: *** and ** represent statistical significance at 0.01 and 0.05 levels (or confidence at 99 and 95 percent levels), respectively.

Remark: 1 rai = 0.16 hectare or 1 hectare = 6.25 rais

The estimation results of the technical efficiency of soybean production by farmers in Chiang Mai province, as shown in Table 5, reveal that 13% of the farmers have a high level of technical efficiency (0.81-0.90). Meanwhile, 3% of farmers have a low level of technical efficiency (0.61-0.70), while the majority, over 84%, have their technical efficiency levels clustered in the range of 0.77-0.79. The value of technical efficiency indicates that most farmers have a medium level of technical efficiency (0.71-0.80). None of the sample farmers has achieved the highest technical efficiency (greater than 0.90). This distribution reflects a moderate level of efficiency overall, indicating scope for improvement in both production practices and technology adoption. The average technical efficiency of the farmers is 0.77, or 77.0%, indicating that there is still room for improvement in soybean production under the current technology available during the research period by 23.0%. The observed mean technical efficiency of 0.77 aligns with production theory under the stochastic frontier framework, where deviations from the frontier reflect suboptimal input allocation, managerial inefficiencies, or environmental constraints. The significant positive elasticities for labor, seed quantity, and fertilizer expenditure indicate that these inputs contribute directly to marginal output gains, consistent with neoclassical production theory, which posits that diminishing returns are gradual within the optimal input range. The lack of significance for machinery hours and pesticide expenditure suggests either overutilization or a mismatch between their application and yield response.

Table 5. Distribution of technical efficiency of soybean production in Chiang Mai province

Technical efficiency level		Sample (n=100)	Percentage (%)
Very low	(<0.60)	0	0
Low	(0.61-0.70)	3	3
Medium	(0.71-0.80)	84	84
High	(0.81-0.90)	13	13
Very High	(>0.90)	0	0
Total		100	100
Average = 0.77		Median = 0.77	Maximum = 0.81
		Minimum = 0.66	S.D. 0.02

Source: author's calculation.

Compared with previous soybean studies, Chiang Mai's TE is higher than findings from several African contexts (0.53) in northern Ghana Etwire et al. [12], 0.503 in Zambia Musaba et al. [13], and 0.5377 in North West Nigeria Alabi et al. [14], and also exceeds the 0.72 reported for Madhya Pradesh, India, Sharma et al. [11]. It is similar to Indonesia's Tabanan Regency (0.77) [16] and somewhat higher than Benue State, Nigeria (0.73) [15]. Within Thailand, Chiang Mai's TE surpasses earlier soybean estimates under rainfed conditions (0.66) Phummuong [23] and a StoNED-based study in irrigated Chiang Mai (0.620) Lesak [24]. These differences are plausible given the context and method. First, agro-ecological and institutional conditions vary: studies with lower TE often report constraints related to extension access, market distance, input quality, or household characteristics (e.g., education, age, cooperative membership), while programs that strengthen extension and input use tend to reduce inefficiency [11-14]. Second, methodological choices matter: Chiang Mai's estimates come from a Cobb–Douglas, copula-integrated SFA, whereas some comparators use conventional SFA (assuming independent errors) or StoNED Lesak [24]. Relaxing the independence assumption can yield more precise efficiency measures. Third, temporal and regional differences in seed varieties, input price environments, and recent extension initiatives can lead to an upward shift in TE. Consistent with our results, labor and seed have the largest elasticities, while machine hours are not statistically significant. This pattern aligns with small, fragmented plots, where careful labor/seed management dominates gains, and mechanization advantages remain limited.

3.2 Analysis of Factors Affecting Technical Inefficiency in Soybean Production

The results of the multiple regression analysis examining the factors influencing technical inefficiency in soybean production indicated that the model is appropriate, as evidenced by a coefficient of determination (R^2) of 0.470. This value suggested that all independent variables in the model, including the land ownership

status, labor hiring status, irrigation zone, irrigation method, farming experience, total soybean cultivation area, and other related factors, collectively explain 47.0% of the variation in technical inefficiency. The remaining 53.0% of the variation was likely due to other factors not captured by the model, such as physical, biological, economic, or farm management variables associated with soybean production. The analysis revealed an F-statistic of 13.75 with a p-value of 0.0000, less than or equal to 0.05, indicating that the independent variables significantly explain the variation in the dependent variable at the 5% significance level. Furthermore, the Durbin-Watson statistic of 1.86, which is close to the benchmark value of 2, suggests that autocorrelation is absent among the residuals. Although the model has a relatively low R² value (Table 6), it is still considered suitable for explaining the relationship. At the 99% confidence level, the factors that significantly influence technical inefficiency in soybean production are land ownership status (1 = rented land, 0 = owned land), farming experience (in years), and the total area of soybean cultivation (in rai) (Table 6).

Table 6. Estimation of a Technical Inefficiency Model for Soybean Production in Chiang Mai Province.

Variable	Coefficient	Standard Error	T-stat
Constant	0.242***	0.006	43.575
Dummy of land ownership (DOWN)	-0.011***	0.004	-2.683
Dummy of Irrigation area (DIRR)	-0.004	0.005	-0.833
Dummy of labor involvement (family and hired) (DLAB)	-0.001	0.004	-0.329
Dummy of support from institution (DSUPP)	-0.006	0.005	-1.153
Experience of farmers in soybean production (EXP)	-0.001***	0.000	-5.485
Soybean land area (SIZ)	0.002***	0.000	4.210
R	0.686	RMSE	0.020
R-Squared	0.470	Coef. Var	9.007
Adj R-Squared	0.436	MSE	0.000
F-Statistics	13.755	MAE	0.015
Durbin-Watson	1.865		

Notes: *** represents statistically significant at 0.01 level (or confidence at 99 percent level), F-Statistic = F [6, 100] = 13.755 (p-value = 0.0000)

The regression analysis revealed that land ownership has a statistically significant effect on technical inefficiency in soybean production, with a coefficient of -0.011. Specifically, a 1% increase in the proportion of land rented for soybean cultivation is associated with a 0.011% reduction in technical inefficiency, indicating an improvement in technical efficiency. One possible explanation is that farmers who rent land face higher monetary costs, which may incentivize them to plan their production more efficiently and optimize the use of available inputs in order to maximize income through increased marketable output. The higher average yield per rai among farmers who rent land (324.80 kg/rai or 2.03 tons/ha) compared to those who own land (294.92 kg/rai or 1.84 tons/ha) further supports this observation. This result is consistent with the findings of Chubtong [40] and Donkor and Owusu [41], who argue that renting land tends to reduce technical inefficiency. Specifically, renting land may incentivize farmers to utilize resources more effectively, thereby increasing agricultural productivity. The analysis showed that experience in soybean cultivation significantly reduces technical inefficiency, with a coefficient of -0.001. Specifically, a 1% increase in a farmer's experience in soybean production is associated with a 0.001% reduction in technical inefficiency. This finding is consistent with the research of Omar and Fatah [42], who demonstrated that farmers' experience in crop cultivation positively influenced their decision-making in managing coconut production in Johor, Malaysia. Similarly, studies by Alabi et al. [14], Puphoung [17], and Somcom and Wana [18] found that increased experience enables farmers to address challenges and obstacles during production more effectively. Therefore, farmers with more years of experience in soybean cultivation are typically more skilled and better able to understand production conditions. Their experience enables them to select appropriate technologies and gather knowledge from

various sources, ultimately improving production efficiency. In addition, the size of the cultivated area significantly contributes to an increase in technical inefficiency in soybean production, with a coefficient of 0.002. Specifically, a 1% increase in the area dedicated to soybean cultivation is associated with a 0.002% increase in technical inefficiency. This relationship may arise from farmers' difficulties in effectively managing larger areas, leading to reduced management quality and production efficiency. These findings align with the research of Ajibefun et al. [43] and Puphoung [17], who observed that larger agricultural areas are associated with higher levels of technical inefficiency in production. Therefore, farmers should focus on comprehensive production management across the cultivated area by planning and allocating time to thoroughly monitor all areas. This approach will help increase the technical efficiency of soybean production.

4. Conclusions

This study employed the stochastic frontier analysis (SFA) framework, selecting the Cobb-Douglas production function integrated with a copula model as the most appropriate specification for analyzing the technical efficiency of soybean production by farmers in Chiang Mai Province. The methodological choice enabled a more flexible treatment of the potential dependency between inefficiency effects and random shocks, thereby improving the robustness of the efficiency estimates. The results revealed an average technical efficiency score of 0.77, implying a 23 % potential yield gain if farmers optimize input use under the existing technology set. The findings align with production economics principles, where deviations from the frontier reflect suboptimal input allocation and managerial constraints. Positive and significant elasticities for labor, seed use, and fertilizer expenditure confirm that these inputs remain within the increasing returns portion of the production function, indicating scope for productivity gains without breaching diminishing returns. The insignificance of machinery and pesticide expenditure suggests possible overuse or inefficient application, supporting the resource misallocation hypothesis. When benchmarked against international soybean studies, such as those by Otitoju and Arene [15] in Nigeria, Sharma et al. [11] in India, and Rinaldi et al. [16] in Indonesia, Chiang Mai's TE level is moderate and broadly comparable. However, contextual differences in determinants emerge: while African and South Asian contexts often emphasize education, access to extension services, and credit availability, the results highlight the roles of land ownership, farming experience, and cultivated area size. Land rental emerged as a key factor reducing inefficiency, suggesting policy support for agreements with rice farmers who leave land fallow after harvest could expand soybean cultivation. Given soybeans' short growth cycle and low water demand, such strategies align with their role as a secondary crop in Thai farming systems. Further, farmer experience was also critical, highlighting the need for structured knowledge exchange, targeted training, and improved access to agronomic information. Policies should facilitate land rental markets, strengthen farmer-to-farmer mentoring, and expand site-specific training on seed density, labor management, and fertilizer application. Interaction effects suggest that bundled interventions, such as combining improved seed use with labor training, can yield greater efficiency gains than isolated measures. Additionally, practical implications vary by scale: smallholders benefit from low-cost improvements supported by group-based extension; medium-scale farmers from semi-mechanization and input calibration; and commercial-scale farmers from integrating precision agriculture and digital monitoring. By addressing these areas, stakeholders can bridge existing efficiency gaps, enhance resource use, and improve the resilience and profitability of soybean production systems in northern Thailand.

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