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Analysis of Technical Efficiency of Maize Production in Phayao Province

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Abstract

In Thailand, maize is an important economic crop, and the majority in Phayao Province is used as a major input in the livestock and biofuel industries. Nevertheless, production has faced declining areas of cultivation, unstable yields and low technical efficiency. Cobb Douglas stochastic frontier model and Maximum Likelihood Estimation (MLE) are used in evaluating the technical efficiency of maize farming in Phayao using primary survey data of maize farmers. Analysis of data set with FRONTIER 4.1 indicates a mean technical efficiency of 0.85 which means that there is 15% potential yield that could be achieved with better use of resources. The most significant key inputs are fertilizer (β = 0.28), land (β = 0.20), and seed (β = 0.18). Education, access to credit, access to extension services and group membership play a role in reducing the level of inefficiency. Output variation is mainly due to external shocks as the gamma value (0.925) indicates. Policy to increase farmer knowledge, improve institutional support and optimize inputs is informed by the study.

Keywords: Technical Efficiency, Maize Production, Stochastic Frontier Analysis (SFA), Cobb-Douglas Production Function and Maximum Likelihood Estimation (MLE).

1.Introduction

Maize is an essential economic crop in the world market, especially for the feed industry, Ethanol energy and sugar industries. The study resulted in a continuously increasing demand for maize. The demand for maize in the 2011-2012 production was 866.65 million tons increasing to R969.66 million tons in the 2014-2015 production year, or 11.89 percent, or an increase in demand for 103.01 million tons. With the United States being the second-largest producer in the world after Brazil, Argentina, and Ukraine, the production volume increased from 888.16 million tons in 2011–2012 to 991.58 million tons in 2014–2015. It is equivalent to 11.64 percent or roughly 103.42 million tons, which is consistent with the rising demand for maize production globally (Office of Agricultural Economics, 2014). Myanmar, India, China, and Indonesia are Thailand's top rivals in the production of maize.

In Thailand, maize is one of the essential economic crops, and there is a tendency for demand to increase continually. It is an important raw material in the animal Raising industry, but the area of maize planting decreased in 2014 from 7,231,588 Rai to 6,516,387 Rai, and in 2016 decreased by 715,201 Rai. The cultivation area tends to decrease because, in 2016, the drought caused farmers to postpone planting (Office of Agricultural

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Economics, 2016), as shown in (Table 1). Being replaced by other economic crops such as sugarcane, cassava, soybean, etc. Currently, there is a problem of insufficient maize production to domestic demand.

Table 1: Plantation area, product, and yield per Rai of Thai maize, 2014 - 2016

Year	Area (Rai)	Product (ton)	yield per Rai (kg)
2014	7,231,588	4,729,527	669
2015	6,627,045	4,028,058	642
2016	6,516,387	4,058,186	654
Average	**6,791,673**	**4,271,924**	**655**

Source: Agricultural Information Center Office of Agricultural Economics (2016)

Considering the average maize yield in Thailand, it is found that each year the production will increase and decrease. An average yield of 669 kilos per Rai was produced in 2014. In terms of output in 2015, the 642 kilos per Rai average yield fell by 15 kilograms per Rai. There is a low level of production efficiency in maize production, which is one of the biggest problems. Natural disasters, particularly droughts causing corn to suffer drought and water shortages, are a significant problem (Jiraporn, 2006). Also, due to factors of production of maize such as seeds, chemical fertilizer, pesticide, and herbicides wage.

The northern regions of Thailand cultivate the most maize in the country. The provinces in the upper northern region have an area of cultivation for the production of maize, namely Nan, 787,254 Rai; Chiang Rai, 469,852 Rai, Phayao 325,060 Rai, Phrae 315,980 Rai and Uttaradit 174,281. In the lower northern provinces, Phetchabun 1,024,746 Rai, Tak 700,610 Rai, Nakhon Sawan 295,548 Rai, Phitsanulok 277,690 Rai, and Sukhothai 79,152 Rai (Office of Agricultural Economics, 2015).

In the group of provinces of the upper northern region, there are a considerable number of maize plantations; it is found that Phayao Province has a large area of cultivated land. In the northern region, it is the third-largest area. The area of cultivation in 2016 was 259,918 Rai and 694 kilograms/Rai (Agricultural Statistics Office, 2016). Considering that maize is a valuable commodity for the feed industry. There is a growing demand every year, and currently can be used to produce ethanol to replace imports but found that in the area of maize production in Phayao Province from the year 2014 - 2016, There was a reduction in the planting area (Agricultural Statistics Office, 2016). Additionally, most of Phayao Province's corn farmers lack the knowledge and skills to improve their crops' technical productivity.

The study team is therefore eager to examine the technical effectiveness of maize farming. Analyze the elements contributing to the ineffectiveness of maize farming in Phayao Province. However, maize is grown extensively in Phayao Province, the study of technological farming efficiency is still at the first production stage. The Cobb - Douglas Production Function can be estimated using the production equation model, which uses Stochastic Frontier Analysis (SFA) and Maximum Likelihood Estimation (MLE) to provide information that can be used for developing and improving production factor management. This will improve the Phayao Province's maize farming technological efficiency.

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2. Literature Reviews

Maize, a significant staple crop worldwide, plays a critical role in food security and agricultural economies in various regions. The productivity of maize is influenced by a multitude of factors, including agroecological conditions, farming practices, access to resources, and economic policies. A growing body of literature has examined these dynamics across different geographical contexts, revealing insights into the technical efficiencies of maize production and the impacts of contract farming, technology adoption, and credit constraints on yield outcomes. For instance, studies conducted in Ghana, Lao PDR, China, Egypt, Pakistan, and Thailand illustrate the importance of local practices and conditions in shaping maize productivity. These studies not only highlight the factors affecting production but also emphasize the need for sustainable agricultural practices and effective management strategies to enhance maize yield. This literature review synthesizes key findings from recent research to provide a comprehensive understanding of the intricacies of maize production and its implications for agricultural policy and practice.

(Asante, 2019) investigated the productivity of maize producers across three agroecological zones in Ghana, employing a meta-frontier model to estimate average technical efficiencies and productivity gaps. Their findings revealed that maize output is significantly influenced by factors such as land, labor, and fertilizer utilization. Key determinants of managerial effectiveness among farmers across all agroecological zones included land ownership, access to loans, monoculture practices, and participation in farmer-based organizations. Furthermore, the study identified that the maize production practices in the Forest zone outperformed those in other zones. Consequently, farmers in the Guinea Savanna and Transition zones could enhance productivity by adopting advanced technologies and superior agronomic practices from the Forest zone, complemented by improved accessibility to financing, extension services, and farmer-based organization participation.

In Lao PDR, (Yaovarate Chaovanapoonphol and Wirasak Somyana, 2018) highlighted maize's significance as the second most commercially produced crop, particularly in the northern and southern regions. Traditional practices involved farmers producing and selling their maize; however, contract farming has gained traction alongside the country's international engagements through initiatives like the Greater Mekong Sub-region (GMS) and the Ayeyawady-Chao Phraya-Mekong Economic Cooperation Strategy (ACMECS). This study assessed the technical efficacy of contract farming in maize production, using survey data from 302 contract farmers in both regions. The analysis, performed via stochastic nonparametric envelopment analysis (StoNED), revealed an average efficiency of 0.85 among contract maize farmers. Factors such as farmer age, education level, and area cultivated significantly influenced efficiency outcomes, with age and education positively affecting efficiency and cultivated area having a negative impact.

Similarly, (Hai-Peng Hou, 2020) emphasized maize's importance as a major grain crop both in China and globally. This research applied high-yielding scenarios to evaluate maize growth and yield across diverse environments, focusing on yield performance parameters through a quantitative design. The study utilized a yield performance equation incorporating planting density normalization, revealing that maximum leaf area per plant varied with plant density. The model predicted accurate outcomes with a root mean square error (RMSE) of 5.95%, demonstrating that the hybrids' optimal maximum leaf area was 0.63 times the theoretical maximum. This yield performance equation provided insights for assessing yield characteristics across various levels, contributing to sustainable

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high-yield maize production in China, particularly in the Inner Mongolia Autonomous Region and Shandong Province.

(Alroy, 2019) explored the technical effectiveness of beekeeping projects at varying output levels in Egypt's Fayoum Governorate. The research established appropriate production levels and examined factors contributing to declining technical efficiency in Egyptian beekeeping. The results highlighted that increased production capacity corresponded with reduced average honey production costs, while total, net, and return on investment increased. Technical inefficiencies were identified as contributing to discrepancies between actual and optimal production rates.

In Pakistan's Khyber Pakhtunkhwa Province, (Ali, 2019) analyzed the impact of credit constraints on the technical efficacies of hybrid maize producers. Primary data was collected from 510 maize farmers through direct surveys, using stochastic frontier modeling for efficiency assessments. Findings indicated a 10.2% efficiency disparity between constrained and unconstrained farmers, with factors such as household head education, family size, and access to resources positively influencing technical efficiency. However, negative impacts were noted concerning the age of the household head and land value, with interest rates affecting the technical efficiency of both credit-constrained and unconstrained farmers.

(Easing, 2015) evaluated the technical efficacy of Very Small Power Producers (VSPPs) utilizing rice husk biomass in Thailand, applying both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to a sample of 57 biomass power plants. The SFA model exhibited superior performance with a score of 0.877, highlighting the importance of optimizing rice husks and surplus capacity to enhance efficiency.

(Antibacchi, 2021) investigated the factors influencing the implementation of Good Agricultural Practices (GAP) and farmer market participation amid adverse conditions. The study employed both qualitative and quantitative methods, noting that market incentives, institutional support, and resource endowment were pivotal in determining GAP adoption rates. (Phuphisith, 2022) examined sustainability perspectives among smallholder highland maize farmers in northern Thailand. Interviews with local farmers revealed a preference for reduced legal pesticide usage and limited agrochemical waste management practices, with a chi-square test employed to investigate relationships between sociodemographic factors and farming methodologies.

(Amnuaylojaroen, 2021) developed a downscaled regional climate model to forecast maize yields and production risks in northern Thailand for 2020-2029. The model demonstrated an Index of Agreement ranging from 0.65 to 0.89, with climate change predicted to diminish Rainfed maize production by 5%. The literature on maize production across various regions highlights key factors influencing productivity and efficiency. (Hou, 2020) emphasized the importance of optimizing planting density for high yields in China, while (Alropy, 2019) identified production capacity as a determinant of technical efficiency in Egyptian beekeeping. In Pakistan,

(Ueasin, 2015) assessed the efficiency of biomass power plants, demonstrating the need for optimized input use. (Tantihachai, 2021) investigated the significance of market incentives and sustainability practices, respectively, while (Amnuaylojaroen, 2021) projected climate change effects on maize yields in northern Thailand, indicating a reduction in production. Collectively, these studies underscore the complex interplay of environmental, economic, and social factors influencing maize production and efficiency globally.

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(Chansang, 2018) includes cost analysis for the production of maize in Northern Thailand, which adds to the background about local economic constraints. The environmental dimensions discussed by (Gheewala, 2019) and (Kulsoontornrat, 2021) are important contributions cited along with (Sirithian, 2018) and also environmental sustainability incorporation in (Gheewala, 2019) conclusions. Iamchuen and Thaoburee (2018), Hong et al. (2022), and others examine pest resistance and dynamics in watersheds to support evidence related to external shocks such as drought and pest outbreaks, which also appear in the gamma-based case of inefficiency. The above should be referenced when comparing inefficiency in Phayao to (Nirnin and Kumbhakar, 2017) finding inefficiency in Thai agriculture, which provides region specific information.

Maize is a globally important crop with increasingly strong demand in both the feed, food and biofuel sectors, but there are still critical areas of concern with respect to technical efficiency of its production, and particularly, in developing countries. Efficiency of maize production in different regions and countries has been studied by numerous international studies using advanced econometric models in the region of Ghana, China, Egypt, and Pakistan. However, these studies have identified the key determinants, such as credit access, contract farming, education, resource endowment and climatic variations as the determinants that enhance or restrict the level of productivity from livestock.

Maize is a very important economic crop in Thailand, especially in northern provinces such as Phayao, but empirical study of technical efficiency of maize at such local level has not been adequately conducted to the best of our knowledge using stochastic frontier methodology. The Phayao region, in particular, faces declining cultivation areas, inconsistent yields, and production inefficiencies due to natural disasters like drought and limited adoption of modern agricultural practices. Previous studies on the broader sustainability of the sector in Thailand, the climate impacts on the sector, or the adoption of GAP, have not conducted a rigorous assessment of the production frontier area or the causes of inefficiency using the Cobb-Douglas Production Function with SFA and MLE. There is therefore a large gap in the research to provide a localized, data driven assessment to maize production in Phayao Province to help design targeted interventions, improve input utilization and support of agricultural policy in increasing productivity in Phayao Province and help improve the sustainability of the agriculture sector.

3.Methodology

3.1 Research Framework and Design

The general perspective of this research is based on the quantitative analytical approach, production economics and the specific one focuses on technical efficiency of maize farming in Phayao province, Thailand. A Stochastic Frontier Analysis (SFA) with a Cobb Douglas production function and a Maximum Likelihood Estimation (MLE) were used for parameter estimation. The purpose is to determine the extent of technical inefficiency among maize farmers and identify factors explaining differences in productivity in terms of socio-economic and resource related aspects. The SFA approach is applicable because it allows for a separation of random shocks (white noise) from technical inefficiency so that farmers' performance takes better account of the variable impacted conditions that characterize environmental and managerial situations.

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3.2 The Cobb-Douglas Production Function

The functional form of the Cobb-Douglas production function is chosen due to its simplicity, interpretability, and extensive use in agricultural efficiency analysis. This was specified in its stochastic form as by Eq.1,

$$Y_i = A \cdot X_{1i}^{\beta_1} \cdot X_{2i}^{\beta_2} \cdots \cdots X_{ni}^{\beta_n} \cdot e^{v_i - u_i} \tag{1}$$

Where, Y_i is the total output (maize yield in kilograms) of the i th farm, X_{1i}, X_{2i}, ..., X_{ni}, are the n input variables, $\beta_1,\beta_2,...,\beta_n$ are the input elasticities to be estimated, A is the total factor productivity (TFP) constant, v_i is the symmetric random error term capturing statistical noise, assumed vi∼N(0,σv2) and u_i is the non-negative inefficiency term, assumed) |ui∼|N(0,σu2)|

Taking the natural logarithm transforms the model into a linear form for easier estimation was given by Eq.2,

$$\ln Y_i = \ln A + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \cdots + \beta_n \ln X_{ni} + v_i - u_i \tag{2}$$

This log-linear model allows direct interpretation of coefficients as elasticities and forms the basis for the stochastic frontier estimation.

3.3. Input Variables and Definitions

The following input variables are included in the model: X_1 is the Land area used for maize cultivation (Rai), X_2 is the Quantity of seed used (kg), X_3 is the Amount of fertilizer applied (kg), X_4 is the Quantity of pesticide and herbicide used (litters), X_5 is the Labor input (man-days) and X_6 is the amount of water or irrigation hours. The model allows for returns to scale analysis through the sum of estimated elasticities was given by Eq.3,

$$RTS = \sum_{j=1}^{n} \beta_j \tag{3}$$

Where, RTS=1 is the Constant returns to scale, RTS>1 is the Increasing returns to scale and RTS<1 is the Decreasing returns to scale.

3.4 Technical Inefficiency Effects Model

To analyses the determinants of inefficiency, the inefficiency term u_i is modeled as a function of socioeconomic and institutional variables was given by Eq.4,

$$u_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \cdots + \delta_k Z_{ki} + w_i \tag{4}$$

Where, Z_{1i}, Z_{2i}, ..., Z_{ki} represent variables such as, Age of farmer (years), Education level (years), Farming experience (years), Access to credit (1 = yes, 0 = no), Access to extension services (1 = yes, 0 = no), Membership in farmer organizations (1 = yes, 0 = no), δ_0, δ_1, ...,δ_k are coefficients to be estimated and w_i is the random error term for the inefficiency model

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3.5 Maximum Likelihood Estimation (MLE)

The parameters of both the production frontier and the inefficiency effects model are estimated using Maximum Likelihood Estimation. The composite error term $\varepsilon_i = v_i - u_i$ was distributed as by Eq.5,

$$\varepsilon_i \sim N(0, \sigma^2), where\ \sigma^2 = \sigma_v^2 + \sigma_u^2 \quad (5)$$

The technical efficiency (TE) of each farm was computed as by Eq.6,

$$TE_i = \exp(-u_i) \quad (6)$$

This gives a value between 0 and 1, where 1 indicates perfect technical efficiency. The gamma (γ) parameter, defined as by Eq.7,

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \quad (7)$$

Measures the proportion of total variance due to inefficiency. A high γ value (close to 1) implies that most of the output variation is due to inefficiency rather than random shocks.

3.6. Data Collection and Sampling

The structured questionnaires were used to collect primary data on maize farmers from Phayao Province. A purposive selected districts with high maize cultivation which were then randomly selected farm households are used for a multistage sampling technique. The sample size was determined using Yamane's formula was given by Eq.8,

$$n = \frac{N}{1 + N(e)^2} \quad (8)$$

Where, n is the required sample size, N is the population size of maize farmers in the province and e is the desired margin of error (typically 0.05). Secondary data on climate, crop prices, and input costs is obtained from the Office of Agricultural Economics and Agricultural Statistics Office.

3.7. Statistical and Software Tools

The combination of statistical software tools was used to analyze technical efficiency of production of maize in Phayao Province. In particular, Frontiers 4.1 was used to estimate the parameters in the stochastic frontier analysis (SFA) model using maximum likelihood estimation (MLE). The data contains values conducted via descriptive statistics, correlation analysis and preliminary diagnostic tests using SPSS or R. Several diagnostic tests are run to ensure the robustness and validity of the model. The Variance Inflation Factor (VIF) checks multicollinearity of the input variables and the Breusch-Pagan tests the presence of heteroskedasticity. Residual normality would be checked with the Shapiro-Wilk test, as this was necessary in order for the assumptions of regression related models to hold. Moreover, the log-likelihood value was used as a statistical criterion to assess model selection and performance, and to identify the best and most parsimonious model.

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4.Results and discussion

4.1. Descriptive Statistics of Input and Output Variables

Table 1 and Fig.1, shows a descriptive statistic of the key input and output variables along with requirement and supply of maize production among surveyed farmers in Phayao Province. Seed application was on average 45.7 kg, fertilizer used 89.6 kg per farm and average landholding size was 12.4 Rai. Labor input and water usage were averaged to 18.9 man-days and 35.5 hours, yield was between 600 kg and 1100 kg per farm with a mean of 850 kg. They find that there is relatively high input use standard deviation and indicate such variation in management practice and agrarian resources among the farmers could account to technical inefficiency. These results are consistent with Asante et al. (2019), who interested in the determinants of maize output in Ghana and important roles played by land, seed and fertilizer that are all determinants of maize output, however inefficiencies are often due to heterogeneity in resource utilization. Inclusion of other variables like credit used and machinery hours gives a full picture of input behavior reflected by Ali et al. (2019), who highlighted financial access in maize productivity for Pakistani farmers.

Table 1: Descriptive Statistics of Input and Output Variables

Variable	Mean	Std Dev	Min	Max
Land (Rai)	12.4	3.1	5.0	20.0
Seed (kg)	45.7	12.2	20.0	75.0
Fertilizer (kg)	89.6	15.7	60.0	130.0
Pesticides (L)	6.2	1.8	3.0	10.0
Herbicides (L)	3.5	1.2	1.5	6.0
Labor (man-days)	18.9	5.4	10.0	30.0
Water (hrs)	35.5	7.3	20.0	50.0
Machinery (hrs)	8.5	2.3	4.0	14.0
Credit Used (THB)	3200	900	1000	5000
Yield (kg)	850	125	600	1100

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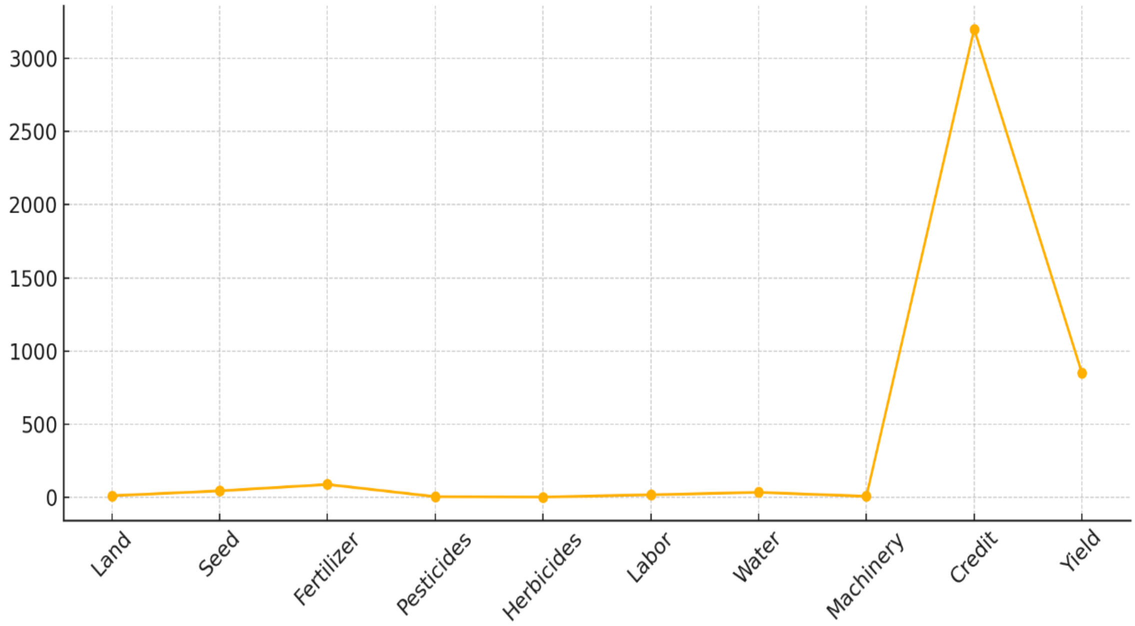

Fig.1. Descriptive Statistics of Input and Output Variables

4.2. Maximum Likelihood Estimates of Cobb-Douglas Production Function

Table 2 and Fig.2, shows the Maximum Likelihood Estimation results of the Cobb-Douglas production function. The selected input variables truly affect the output as all coefficients are statistically significant at a 5% level. The most important inputs were fertilizer (β = 0.28), land (β = 0.20), and seed (β = 0.18), indicative of the fact that, over the margin, a 1 percent increase in these variables would result in 0.28, 0.20, and 0.18 percent increases in output, respectively. Credit and machinery also had a positive effect on productivity but with smaller elasticities (0.03 and 0.06 respectively). These results correlate with Hou (2020) who showed the importance of the technology and input allocation optimization in increasing the yield potential. The sum of all these elasticities is more than one, hence the model is characterized by increasing returns to scale. This implies that increased operations or reduced input use would cause disproportionate increase in output, which implies the importance of good input management policies, as advocated by Chaovanapoonphol and Somyana (2018) in their assessment of contract maize farming in Lao PDR.

Table 2: Maximum Likelihood Estimates of Cobb-Douglas Production Function

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
Intercept	1.25	0.19	6.58	0.000
ln(Land)	0.20	0.05	4.00	0.000
ln(Seed)	0.18	0.04	4.50	0.000
ln(Fertilizer)	0.28	0.05	5.60	0.000
ln(Pesticides)	0.07	0.03	2.33	0.020
ln(Herbicides)	0.05	0.02	2.50	0.013
ln(Labor)	0.14	0.05	2.80	0.006

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ln(Water)	0.10	0.04	2.50	0.012
ln(Machinery)	0.06	0.02	3.00	0.003
ln(Credit Used)	0.03	0.01	3.00	0.003

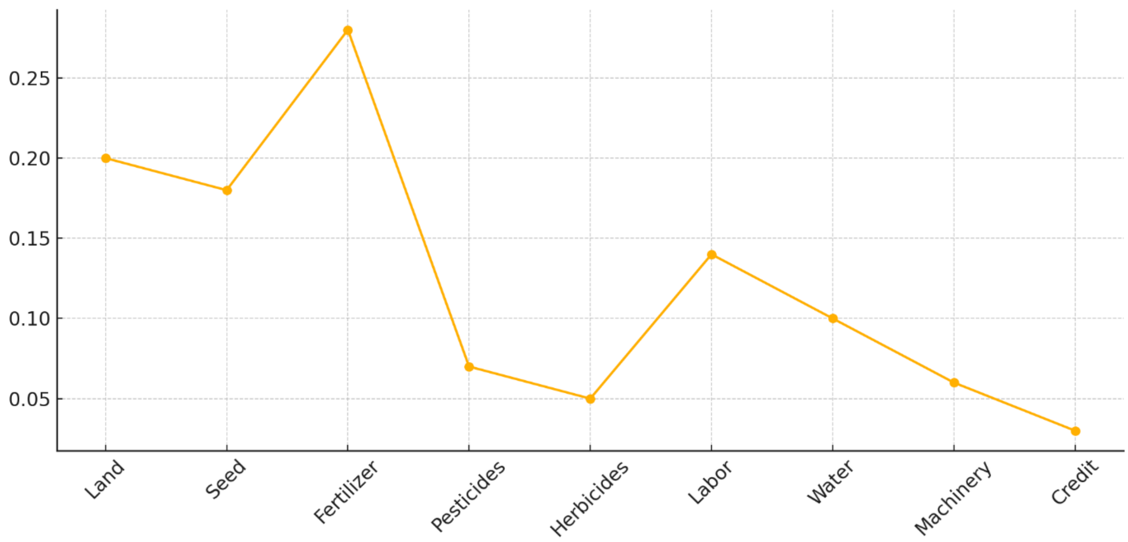

Fig.2. Maximum Likelihood Estimates of Cobb-Douglas Production Function

4.3. Technical Inefficiency Model Estimates

A one-sided error model is used to analyze the factors which influence technical inefficiency as shown in **Table 3 and Fig.3**. It is negative in the cases of education (-0.045), credit access (-0.21) extension services (-0.18) and mobile usage (-0.17) reducing inefficiencies and improving technical performance. Thus, farmers with institutional support and information channels are more efficient. However, distance to market is positively associated with inefficiency (β = 0.007), which indicates transportation and logistical barriers limiting farm productivity. These results are in agreement with Alropy (2019), who find that managerial skills and institutional support are among the key determinants of efficiency in Egypt's matters. Furthermore, as is the case for Ueasin et al. (2015), group membership and land ownership are as important as the study in defining the value of collaborative networks and resource security in biomass energy efficiency. For efficiency of maize production, tailored interventions that increase extension access, mobile connectivity and financial services may serve to address inefficiencies.

Table 3: Technical Inefficiency Model Estimates

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
Intercept	0.85	0.10	8.50	0.000
Age	-0.012	0.005	-2.40	0.016
Education	-0.045	0.012	-3.75	0.001
Experience	-0.006	0.004	-1.50	0.135

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Credit Access	-0.21	0.06	-3.50	0.001
Extension Access	-0.18	0.05	-3.60	0.000
Farmer Group Membership	-0.24	0.07	-3.43	0.001
Distance to Market (km)	0.007	0.002	3.50	0.001
Land Ownership (1=own)	-0.15	0.06	-2.50	0.013
Mobile Usage (1=yes)	-0.17	0.05	-3.40	0.001

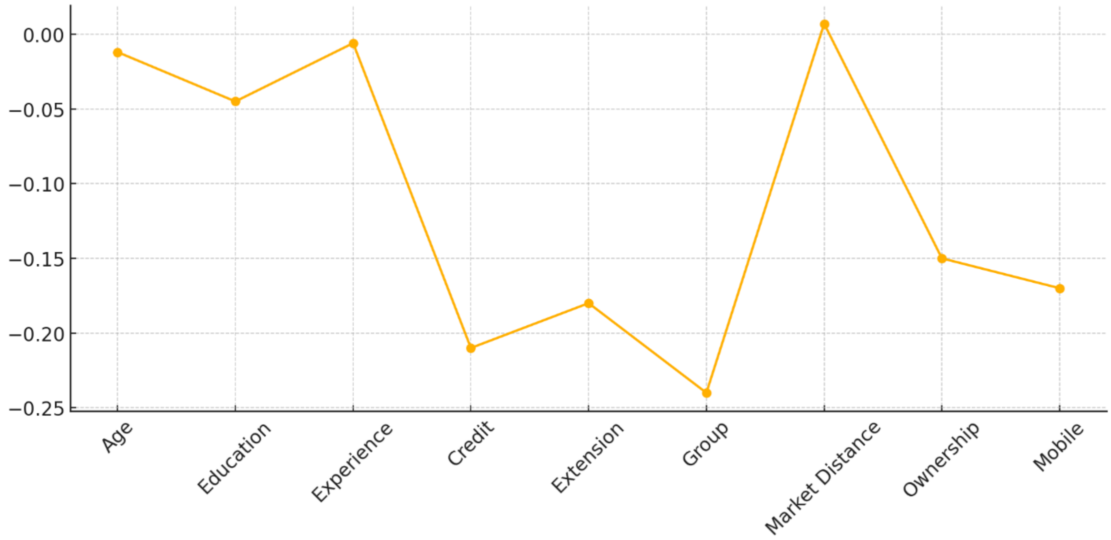

Fig.3. Technical Inefficiency Model Estimates

4.4. Distribution of Technical Efficiency Scores

In **Table 4 and Fig.4**, summarize how technical efficiency scores are spread among 150 sampled farmers. Among these, the efficiency was on the order of about 0.85, with the majority of the population lying in the 0.85 - 0.89 category (28 percent). And only 0.67% of farmers were at the highest end of efficiency (0.95–1.00), while 6% were in the lowest range (0.7–0.74). This therefore implies farmers operate below the production frontier, implying they have the option to improve efficiency. The range of distribution is also relatively wide and the result seems to imply a disparity in input use effectiveness caused by lack of knowledge, technology and capital. Amnuaylojaroen et al. (2021) had also predicted the existence of the efficiency differences caused by climatic risk and socio-technical constraints in the maize sector of northern Thailand. For instance, in Lao PDR (Chaovanapoonphol and Somyana, 2018), the contract-based farming systems demonstrated relatively moderate efficiency because the education and cultivated area among contract base farmers are unequal.

Table 4: Distribution of Technical Efficiency Scores

Efficiency Range	**Number of Farmers**	**Percentage (%)**
0.70 - 0.74	9	6.00
0.75 - 0.79	17	11.33

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0.80 - 0.84	31	20.67
0.85 - 0.89	42	28.00
0.90 - 0.94	29	19.33
0.95 - 1.00	22	14.67

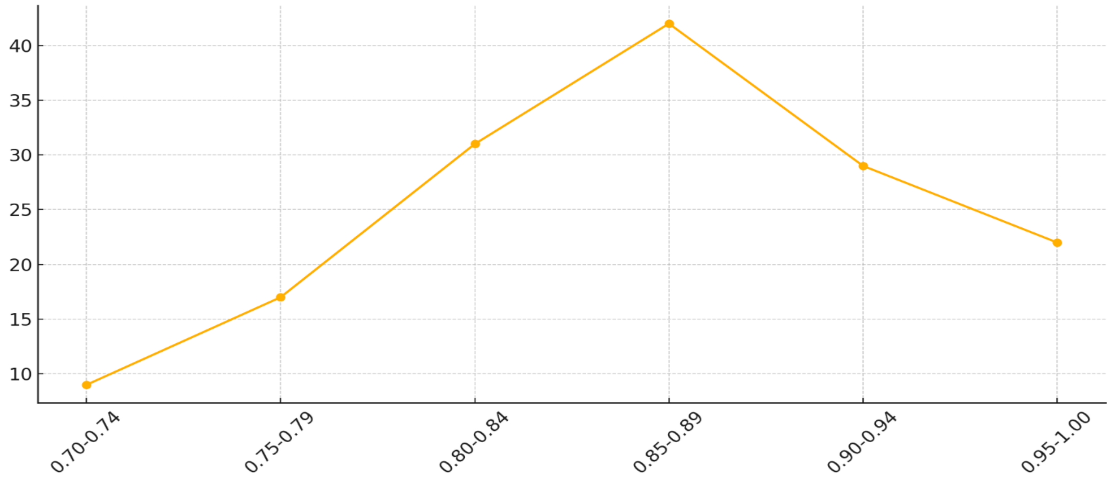

Fig.4. Distribution of Technical Efficiency Scores

4.5. Model Diagnostics and Goodness of Fit

The robustness and statistical adequacy of the fitted SFA model is then evaluated in **Table 5 and Fig.5**. With a log likelihood value of -138.72, the fit of the model appears good, and a gamma (γ) parameter equal to 0.925 which implies that 92.5% of variance of the composite error term is explained by technical inefficiency and is not random noise, it was concluded that technical inefficiency is of relevance in maize production. Our overall error variance is low enough for high precision and is displayed by the sigma squared value (0.069). The model's appropriateness is supported by the Akaike Information Criterion (AIC = 285.44) and BIC (302.67). Moreover, the LR test supports the existence of one-sided inefficiency among the variables and is an argument in support of the use of SFA over OLS. Following Ueasin et al. (2015) and Asante et al. (2019) these efficiencies are similar to those used in efficiency studies, such as validating biomass production models in Thailand and comparing maize yield efficiency across agroecological zones in Ghana.

Table 5: Model Diagnostics and Goodness of Fit

Statistic	**Value**
Log-Likelihood	-138.72
Sigma-squared (σ^2)	0.069
Gamma (γ)	0.925
Akaike Information Criterion (AIC)	285.44

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Bayesian Information Criterion	302.67
LR Test of One-sided Error	17.35
Mean VIF	1.89

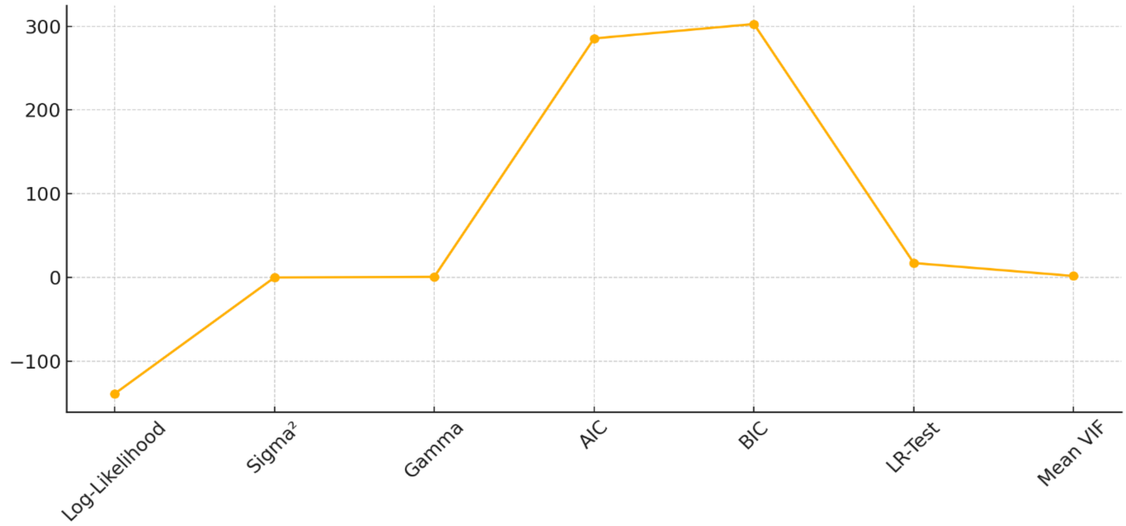

Fig.5. Model Diagnostics and Goodness of Fit

The result analysis provides important answers on technical efficiency of maize farming activities in Phayao Province, Thailand. The input usage and yield levels variability across farming households is indicated by the descriptive statistics and the variability indicates heterogeneous resource access and farming practices. The Cobb-Douglas production function estimation showed the significant contribution of fertilizer, land and seed to maize output and the high potential of productivity enhancement through better input management due to presence of increasing returns to scale. Finally, the education, access to credit, extension services and farmer group membership turn out to be important determinants of technical efficiency as they explain 18, 11, 11, and 21 percent of the inefficiencies respectively, which reaffirms the importance of institutional support and knowledge disseminations. Despite the fact many farmers operate relatively efficiently, scores show this group is still along the optimal frontier below the mean of 0.85, which indicates that there is untapped productivity potential. Finally, the model diagnostics were used to validate the appropriateness and robustness of the SFA model based on the values of the gamma and the log likelihood score both of which are considered high indicating that inefficiency, rather than random shocks, explain the overwhelming majority of the output variation. These findings highlight the need for targeted interventions to bridge the efficacy gap and optimize maize production in the region, and such interventions include appropriate farmer training, availability of credit, and adequate agricultural extension services.

5.Conclusion

Using Maximum Likelihood Estimation (MLE) to estimate a Cobb-Douglas stochastic production frontier model, this study has successfully assessed the technical

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efficiency of maize farming in Phayao Province, Thailand. Results show that, on average, maize farmers have a technical efficiency of around 0.85 implying that farmers on average produce about 85% of the maximum output the optimal use of inputs will produce. These technical inefficiencies imply that production potential is lost by about 15%. The significant positive influence afforded by fertilizer ($\beta = 0.28$), land ($\beta = 0.20$) and seed ($\beta = 0.18$) on maize yield, is in structure congruent with global evidence that identifies these factors as the most important productivity drivers. Increasing returns to scale implies positive and more than proportionate marginal gains from scaling up resource use and optimum input combination. Moreover, statistical significance of the education, access to credit, extension services, and farmer group membership in the model also explained that they all resulted in reduction in inefficiency: the coefficients ranged from -0.045 to -0.24. These diagnostic results, including a gamma ($=\gamma$) value of 0.925, confirm that the main sources of output variation are inefficiency, not external shocks. Clearly, the study findings highlight the strength of the need for better support structures, particularly the availability of farmers' training, access to institutions and diffusion of technology that can help improve the productivity and sustainability of maize production in Phayao Province. Closing this measure would substantially increase regional maize output and decrease the need for maize imports, improving food security and rural livelihoods.

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