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Assessing The Technical Efficiency of Kharif Paddy Production in West Bengal: A Stochastic Frontier Analysis

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Abstract: Paddy is major food crop in West Bengal and improving its production efficiency is essential for ensuring food security and enhancing farmer's incomes. This study measures the technical efficiency of Kharif paddy production in West Bengal through a Stochastic Frontier Analysis (SFA), based on unit-level data extracted from the National Sample Survey Organisation 77th Round (Schedule 33.1). Based on a sample of 1864 paddy-farming households, Maximum Likelihood Estimation was employed to estimate and compare Cobb-Douglas and Trans-log frontier production functions. A Likelihood Ratio (LR) test confirmed that the Trans-log production model is statistically superior and provides a better fit to the data. The estimated variance parameter (γ) was found to be 0.84, which is statistically significant at the 1% level, suggesting that all variation in Kharif paddy output from the frontier is attributable to farm-specific technical inefficiencies rather than random environmental shocks or statistical noise. The empirical results revealed a mean technical efficiency of 65.3% under the preferred Trans-log model, indicating that Kharif paddy production could potentially be increased by 34.7% if farmers operated on the maximum production frontier. Furthermore, district-wise technical efficiency estimates indicated that Birbhum had the highest technical efficiency score (78.7%), whereas South-24 Parganas had the lowest (46.1%). Moreover, an inefficiency effect model was used to examine the influence of various socio-economic factors, including age, gender, education, household size, farm size, credit access, crop insurance, irrigation ratio, and access to technical advice. However, factors like farm size, irrigation ratio, and access to technical advice significantly affected efficiency. This shows that when farmers have adequate resources and proper guidance, their overall production improves.

Keywords*:* Cobb-Douglas function, Likelihood ratio, Maximum Likelihood Estimation, Stochastic Frontier Analysis, Technical Efficiency, Trans-log production function.

INTRODUCTION

Agriculture plays a vital role in the Indian economy by ensuring food security, generating employment, and driving rural development. For most rural households, farming remains the primary source of income. The country's agricultural sector is heavily dominated by small and marginal farmers, whose average land holdings are less than one hectare (Mithiya et al., 2019).

West Bengal is a major agricultural state located in the eastern region of India. The state is highly suited for farming due to its fertile alluvial soils, favourable climate, and diverse cropping patterns. Even though it

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occupies a relatively small geographic area, it supports a very large population and contributes significantly to the country's total agricultural production (Hamsa, et al., 2017). For instance, during 2014-15, West Bengal had a gross cropped area of 9.2 million hectares, contributing nearly 19 per cent to the State Gross Domestic Product (GSDP) and 9.73 per cent to national production, while covering 4.88 per cent of the country's net sown area (FAO, 2022). In fact, West Bengal accounts for only 2.78 per cent of India's cultivable land, but its total agricultural output is remarkably high. The state has achieved self-sufficiency in major crops and now ranks first in the production of rice, jute, and vegetables across the country. Additionally, it stands as the second-largest producer of potato, fourth-largest in total food grains, and seventh in fruit production.

Being the top producer of paddy (*Oryza sativa* L.), West Bengal plays a critical role in maintaining India's food security. Rice cultivation is the main source of livelihood for millions of rural families, and overall, agriculture supports about 65 per cent of the state's rural population. However, the ground reality for these farmers is filled with daily challenges. More than 95 per cent of the farming households in the state fall under the small and marginal categories. Because of this high concentration, agricultural landholdings are severely fragmented. Along with tiny plots, local farmers constantly face issues like rising input costs, unpredictable market prices, and limited access to modern agricultural machinery (Birthal et al., 2015).

The ability of a farm to maximize production from a given set of inputs or decrease input utilization for a given level of output is referred to as technical efficiency (TE). A farm that is technically efficient works on the production frontier, inefficiency is shown by departures from the frontier. Agricultural economists have come to value technical efficiency measurement since it may be used to determine productivity gaps and the causes of inefficiency. Technical efficiency is estimated using a variety of techniques, including Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). SFA is frequently chosen because it distinguishes random errors from inefficiency effects and takes into account uncertainties like weather, pests, and market fluctuations (Sultana *et al*., 2023).

The present study, titled *"Assessing the Technical Efficiency of Kharif Paddy Production in West Bengal: A Stochastic Frontier Analysis"* seeks to determine the factors influencing Paddy production and evaluate the efficiency levels of the farming households. Factors such as farm size, education, gender, credit access, access to technical advice, irrigation ratio *etc*. intensity may significantly influence technical efficiency levels. It is anticipated that the study's conclusions will help many policymakers in developing plans to increase farm income, agricultural sustainability and supporting the agricultural economy of West Bengal.

MATERIALS AND METHODS

Study Area

West Bengal is located in the eastern region of India, extending between 21°25′24″ and 27°13′15″ North latitude and 85°48′20″ and 89°53′04″ East longitude. The state covers a geographical area of approximately 88,752 square kilometers, accounting for about 2.7% of the country's total land area. Agriculture plays a central role in the state's economy and livelihood, making West Bengal one of the major agrarian states of India. According to the 2011 Population Census, West Bengal is home to nearly 7.54% of India's population, with about 68% of its residents living in rural areas. The state has approximately 7.123 million farming families, of which nearly 96% belong to the small and marginal farmer category. The average operational landholding is around 0.77

hectares, reflecting the predominance of small-scale agriculture. Among the rural workforce, cultivators account for about 20.56%, while agricultural labourers constitute approximately 40.8%. In addition to its strong agricultural base, West Bengal possesses a wide range of natural resources and diverse agro-climatic conditions, enabling the cultivation of numerous agricultural crops across different regions.

Data

The present study has been utilized secondary unit-level cross-sectional data extracted from the 77th Round of the National Sample Survey Organization (NSSO), conducted by the Ministry of Statistics and Programme Implementation (MoSPI), Government of India 2021. Specifically, the data has been sourced from Schedule 33.1, entitled *"Land and Livestock Holdings of Households and Situation Assessment of Agricultural Households"* covering the agricultural year from January 2019 to December 2019.

Since paddy is a kharif crop and predominantly cultivated as a winter crop in West Bengal, the data extraction was specifically restricted to the Kharif season. Relevant household-level information regarding crop production, operational land holding, labour cost, seed cost, fertiliser cost and cost of other Inputs such as total cost of manure, irrigation, Cost of hired machinery and equipment, plant protection material and other cost consumption along with farm-specific characteristics, was systematically extracted for agricultural households cultivating paddy crop in West Bengal. The final dataset for this study consists of 1864 households across the sampled districts, providing micro-level data that ensures an accurate estimation of farm-level technical efficiency.

Methodology

Technical efficiency is a measure of the ability of a firm to maximize its output using a fixed number of inputs. Farrell (1957) developed Farrell's measure of technical efficiency, where the performance of a specific decision-making unit (DMU) is compared to that of other DMUs within the same industry. DEA and SFA are widely used methods for estimating technical efficiency. Despite their different methodologies, both SFA and DEA are still prevalent in research due to advancements in computational techniques that have addressed many of their limitations. DEA, introduced by Charnes et al. (1978), is a nonparametric approach for estimating technical efficiency using linear programming (Coelli, et al., 1996) (Amin and Oukil, 2019). On the other hand, SFA is a parametric approach that typically uses maximum likelihood estimation to estimate both the efficiency scores and the efficiency effects model jointly. SFA is a widely used econometric technique for measuring technical efficiency in production (Aigner et al., 1977). It separates inefficiencies from random shocks, providing a way to assess how efficiently producers (e.g., farms, firms) utilize inputs to produce outputs, relative to a best-practice frontier (Battese and Coelli, 1992). Following the framework outlined by Aigner et al. (1977), the general form of stochastic production frontier model is specified as:

$$Y_i = f(X_i, \beta)\exp(V_i - U_i)$$

Where Y_i = Output of i-th farmer (i = 1, 2, 3, …, n); $f(Xi, \beta)$is the deterministic production frontier, representing the maximum possible output given a vector of inputs X_i and and a vector of unknown parameters to be estimated β, the V_i is a two-sided, symmetric random error term, assumed to be independently and identically distributed as $N(0, \sigma^2_v)$ capturing the effects of statistical noise and other random factors outside the farmer's control; U_i is a one-sided, non-negative random variable representing technical inefficiency. It measures the shortfall in output from the frontier due to farm-specific factors and is assumed to be independently distributed as truncations of the N ($Z_i\delta$, σ^2) distribution. Under these assumptions, to identify the sources of inefficiency, we expressed as follows:

$$U_i = Z_i \delta + \varepsilon_i$$

Z_i (1× m) is vector of covariates explaining the technical inefficiency associated with output and, δ (m×1) is a vector of unknown parameters and ε_i is the error term with mean zero and constant variance (Battesse and Coelli 1995).

Maximum likelihood estimation (MLE) generates asymptotically efficient estimators for stochastic production frontiers via one-step or two-stage procedures (Coelli, 1995). The superior one-step approach jointly estimates technical efficiency (TE) and the factors driving inefficiency in a single equation. Conversely, the two-step method-which first estimates TE and subsequently regresses it against explanatory variables-is heavily criticized. This sequential estimation fundamentally contradicts the independent and identical distribution (i.i.d.) assumption of the inefficiency term 'u' introducing bias and causing the resulting inefficiency estimates to be statistically inconsistent. (Battese and Coelli 1995).

The technical efficiency (TE) of a specific farm is measured by comparing its observed output (Y_i) to the maximum attainable frontier output (Y_i^*) (Farrell, 1957). It is expressed as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i, \beta_i)\exp(V_i - U_i)}{f(X_i, \beta_i)\exp(V_i)} = \exp(-U_i)$$

Where, Y_i is the Actual output, Y_i^* is the Frontier output (maximum possible potential output, given the inputs) and U_i is the Measure of inefficiency. TE takes values within the interval zero and one (that is, between 0 and 1), where 1 indicates a fully efficient farm. This single-stage estimation allows for the simultaneous estimation of the production frontier parameters (β) and the inefficiency determinant parameters (θ) via maximum likelihood, providing a more efficient and consistent analysis.

SFPF ESTIMATION PROCESS

Both TE and inefficiency-causing variables were evaluated using the SFPF, which simultaneously examines both (Battese and Coelli, 1995). Two production functions most frequently used in agricultural domains to express the frontier production function are the Cobb-Douglas functions and transcendental logarithmic (translog). Cobb-Douglas form is commonly known for its simplicity where as translog form is more flexible for inducing substitution effects across the inputs for estimation purposes. To ascertain which functional forms will most closely fit our data, this study used a generalized likelihood ratio (LR) test (Umar et al. 2017).

Specification of the Production Function Model

The Cobb-Douglas specification form of the stochastic frontier production function employed for this study is expressed as:

$$lnY_i = \beta_0 + \sum_{i=1}^{5} \beta_i \ln X_i + V_i - U_i$$

Where, Y_i is the output of i-th unit (Quintals), X_1=Land, X_2 =Labour, X_3=Seed, X_4= Fertilizer, X_5= Input Cost, ln= Natural Logarithm, β_0-β_5 are the unknown parameters to be estimated, U_i represents the technical inefficiency component, V_i is the two-sided random error term.

The Translog stochastic frontier production function utilized in this analysis is formulated mathematically as:

$$\ln Y_i = ln\beta_0 + \sum_{i=1}^{5} \beta_i lnX_i + \frac{1}{2}\sum_{i=1}^{5}\sum_{j=1}^{5} \beta_{ij} \ln(X_i)\ln(X_j) + (V_i - U_i)$$

Where Y_i is the output of i-th unit, β_i and β_{ij} are the coefficients for the quadratic and interaction terms between inputs i and j. Interaction effects are symmetric i.e. β_{ij} = β_{ji}.

Following the approach of Aigner et al. (1977), the maximum likelihood estimation relies on specifying two statistical variance parameters, namely sigma squared σ^2 and gamma (γ). The definitions for these parameters are given below:

$$\sigma_T^2 = \sigma_V^2 + \sigma_U^2$$

$$\gamma = \frac{\sigma_U^2}{\sigma_T^2}$$

Where, σ_U^2 = variance of the inefficiency term (U_i), σ_V^2 = variance of the random noise (V_i) and σ_T^2 = Total variance. The value of σ^2 measures goodness of fit to the data. The Gamma (γ) parameter value is particularly useful because it ranges from 0 to 1 and helps explain why actual output falls short of the frontier. When γ is zero, all deviations are simply random noise. On the other end of the spectrum, a value of one shows that all deviations from the frontier stem directly from technical inefficiency.

The general form of the inefficiency effect model is specified as follows:

$$U_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8 + \delta_9 Z_9 + \varepsilon_i$$

Where, U_i= inefficiency effect of ith Household, Z_1= Age, Z_2= Gender, Z_3= Education level, Z_4= household size, Z_5= Farm Size, Z_6= Credit Access, Z_7= Crop Insured, Z_8 = Irrigation Ratio, Z_9 = Access of Technical Advice, while δ_0 to δ_9 estimable parameters and ε_i is error term.

The stochastic production frontier model with inefficiency effects was estimated using the "sfaR" package developed by Dakpo et al. (2023) in R software.

Likelihood ratio (LR) test

We test this flexible unrestricted form against the more restrictive Cobb-Douglas specification (where all β_{ij} = 0) using a generalized likelihood ratio (LR) test to ensure the translog specification is appropriate for the data. The test is based on the log-likelihood functions as follows:

$$LR = -2[\ln(H_0) - \ln(H_1)] \sim \chi^2_m$$

Where $\ln(H_0)$ is the log-likelihood value of the restricted Cobb-Douglas Production Function. $\ln(H_1)$ is the corresponding value of the unrestricted translog Production Function and m is the number of restrictions. The calculated LR test statistics follows a Chi Square (χ^2) Distribution ((Kodde and Palm, 1986).

Variables

The descriptions of variables used in this study are shown in Table 1.

Table 1: Description of Output, Input, and Socio-Economic Variables

Variable Name	Description
Output (Y)	Total Production Quantity (Quintals)
Input variables	
Land (X_1)	Cultivated Area (Acre)
Labour (X_2)	Cost of Labour (Animal + Human) (Rs.)
Seed (X_3)	Cost of Paddy Seeds (Rs.)
Fertilizer (X_4)	Cost of Chemical and Bio Fertilizer (Rs.)
Other Inputs (X_5)	Cost of Other Inputs (Irrigation + Manure + Plant Protection material + Hired machinery) (Rs.)
Socio-Economic Variables	
Farmer's Age (Z_1)	Age of Household Head, Number of Years
Farmer's Gender (Z_2)	Dummy Variable (Male=1, Female=0)
Education level (Z_3)	Levels of Education
Household Size (Z_4)	Number of members in a household
Farm Size (Z_5)	Total farm size (Acre)
Credit Access (Z_6)	Dummy Variable (Yes=1, No=0)
Crop Insured (Z_7)	Dummy Variable (Yes=1, No=0)
Irrigation Ratio (Z_8)	Ratio of Irrigated land area and Total farm area
Access of Technical Advice (Z_9)	Dummy Variable (Yes=1, No=0)

RESULTS AND DISCUSSION

Descriptive Statistics

The summary statistics for the key variables used in this study's stochastic frontier analysis are highlighted in Table 2. The result shows that the average paddy production is 24.93 quintals with a minimum of 0.30 quintals and a maximum of 285 quintals, with the standard deviation (28.23) slightly exceeding the mean, indicating substantial variability across households.

In terms of physical inputs, the average cultivated land to paddy production (X_1) is 1.82 acre, with the maximum 16.84 acre. The remaining input variables (X_2 to X_5) which represent the application of labour cost, seed cost, fertilizers cost, and other inputs cost similarly display pronounced dispersion. For instance, the mean value for labour cost recorded at 12,691.45 Rs., accompanied by a staggering maximum of 182,501 Rs. and a correspondingly high standard deviation (17,193.54 Rs.). In almost all the input variables, the standard deviation is higher than the mean, which clearly shows a huge gap in farming investments between the small-marginal farmers and the big farmers.

The socio-economic variables used to model technical inefficiency further highlight a varied demographic profile. The average age of household heads (Z_1) is 51.75 years and a mean education level (Z_3) of 2.22. Dummy variables indicate that specific traits are present in 94 per cent (Z_2), 24 per cent (Z_6), 3 per cent (Z_7), and 43 per cent (Z_9) of the surveyed farms. Finally, variables such as Z_4 (4.64 number), Z_5 (1.82 acre) and Z_8 (0.81) represent the typical household size, total farm size and irrigation ratio respectively.

Maximum likelihood estimates (MLE) of the stochastic production frontier of Paddy farmers

The empirical findings from the maximum likelihood estimation, which applies both Cobb-Douglas and Translog functional forms to model paddy production, are summarized

Table 2. Summary Statistics of Variables used in study

Variable	Unit	Mean	Min.	Max.	Std. Dev.
Output (Y)	Quintals	24.93	0.30	285	28.23
Input variables					
Land (X_1)	Acre	1.82	0.07	16.84	1.74
Labour (X_2)	Rs.	12691.45	1.00	182501.00	17193.54
Seed (X_3)	Rs.	1637.58	51.00	31201.00	2343.25
Fertilizer (X_4)	Rs.	5066.76	1.00	89501.00	7033.73
Other Inputs (X_5)	Rs.	7273.04	1.00	94841.00	9335.12
Socio-Economic Variables					
Farmer's Age (Z_1)	Number	51.75	21.00	94.00	12.93
Farmer's Gender (Z_2)	Dummy Variable (Male=1,)	0.94	0.00	1.00	0.24
Education level (Z_3)	Continuous Variable	2.22	0.00	7.00	1.90
Household Size (Z_4)	Number	4.64	1.00	17.00	2.16
Farm Size (Z_5)	Acre	1.82	0.07	16.84	1.74
Credit Access (Z_6)	Dummy Variable (Yes=1,)	0.24	0.00	1.00	0.42
Crop Insured (Z_7)	Dummy Variable (Yes=1,)	0.03	0.00	1.00	0.18
Irrigation Ratio (Z_8)	-	0.81	0.03	1.97	0.22
Access of Technical Advice (Z_9)	Dummy Variable (Yes=1,)	0.43	0.00	1.00	0.49

in Table 3. This estimation leverages a dataset of 1,864 households to formally assess production efficiency alongside the structural relationship between inputs and outputs. The coefficients of the variance-parameters for both models show that both Gamma (γ) and sigma square (σ^2) are significantly different from zero (Umesh and Bisaliah,1991), as evidenced by their high z-values. According to Aigner et al. (1977), the statistical significance of (σ^2) (0.273 and 0.238) confirms the overall goodness of fit of the model along with the distributional assumptions of the composite error. Furthermore, the Gamma (γ) values are recorded at 0.881 for the Cobb-Douglas model and 0.840 for the Translog model. This indicates that technical inefficiency, rather than random noise, was responsible for 88.1 per cent and 84.0 per cent of the total deviation in paddy production, respectively.

The parameter estimates of the Cobb-Douglas production function reveal that the estimated coefficients directly represent the output elasticities of the input variables. The coefficients for land (0.862), labour (0.053), and seed (0.086) are statistically significant at the 1 per cent level of significance and positively affect the paddy output. This means that a 1 per cent increase in land area (in acres), along with a 1 per cent increase in the cost (in Rs.) spent on labour and seeds, will increase paddy production by 0.862 per cent, 0.053 per cent, and 0.086 per cent, respectively. Conversely, the coefficients for fertilizer (-0.007) and other inputs (-0.007) show a negative but statistically insignificant effect. This implies that spending more cost (in Rs.) on fertilizers and other inputs does not make a noticeable difference to the total paddy output in the study area.

The Translog model provides a more flexible functional form by including squared and cross-product (interaction) terms. In this model, the linear coefficient for land (0.876) is statistically significant at the 1 per cent level of significance and positively affects the paddy output. The linear coefficients for labour, seed, fertilizer, and other inputs did not influence the output of paddy significantly. However, the squared terms for labour (0.033), fertilizer (0.027), and other inputs (0.021) are positive and highly significant at the 1 per cent level. This reflects an increasing return; expanding the investment in workers, fertilizers, and other inputs eventually accelerates the paddy output. Regarding the interaction terms, the combination of fertilizer and other inputs is statistically significant at the 5 per cent level (with a coefficient of 3.214 and a z-value of -2.99), indicating that spending cost on fertilizers and other inputs together helps improve the final paddy output. All other interaction terms-such as the combinations of land and labour, land and seed, or labour and fertilizer-were found to be statistically insignificant, indicating that their combined application does not substantially alter the final paddy output.

Maximum Likelihood Estimates of the inefficiency effects model of the stochastic frontier production function of Paddy farmers

The maximum likelihood estimate of inefficiency effects model of Stochastic frontier functions (Cobb-Douglas and Translog) is presented in Table 4. If the technical inefficiency parameter value is positive, it will increase the level of inefficiency (reduce technical efficiency) and conversely (Felix et al., 2021). Based on this study results, observed that inefficiency variables have both positive or negative values for the both frontier functional forms.

A critical perusal of the empirical results reveals that, contrary to the initial assumption of insignificance, several farm-specific factors exert a statistically significant influence on technical efficiency. Most notably, the coefficient for the irrigation ratio (Z_8) is negative and highly significant at the 1 per cent level of significance in both the Cobb-Douglas (-2.311) and Translog (-2.270) models. This strongly

Table 3: Maximum likelihood estimation of Cobb-Douglas and Translog production frontiers

Variables	*Cobb-Douglas Frontier Model*		*Translog Frontier Model*	
	Coefficient (Std. Error)	*z-value*	*Coefficient (Std. Error)*	*z-value*
Constant	2.211*** (0.118)	18.77	3.214*** (0.947)	3.39
ln (Land)	0.862*** (0.018)	47.70	0.876*** (0.242)	3.62
ln (Labour)	0.053*** (0.006)	8.31	-0.024 (0.083)	-0.29
ln (Seed)	0.086*** (0.015)	5.70	-0.152 (0.188)	-0.81
ln (Fertilizer)	-0.007 (0.004)	-1.55	-0.108 (0.110)	-0.99
ln (Other inputs)	-0.007 (0.005)	-1.45	-0.087 0.089)	-0.98
ln Land-squared	-	-	0.025 (0.042)	0.59
ln Labour-squared	-	-	0.033*** (0.004)	7.62
ln Seed-squared	-	-	0.012 (0.024)	0.49
ln Fertilizer-squared	-	-	0.027*** (0.004)	6.28
ln other inputs-squared	-	-	0.021*** (0.004)	5.06
ln Land × ln Labour	-	-	-0.001 (0.014)	-0.07
ln Land × ln Seed	-	-	-0.025 (0.025)	-0.98
ln Land × ln Fertilizer	-	-	0.003 (0.012)	0.29
ln Land × ln other inputs	-	-	-0.002 (0.012)	-0.18
ln Labour × ln Seed	-	-	-0.008 (0.011)	-0.72
ln Labour × ln Fertilizer	-	-	-0.006 (0.010)	-0.61
ln Labour × ln other inputs	-	-	-0.002 (0.009)	-0.27
ln Seed × ln Fertilizer	-	-	0.013 (0.014)	0.96
ln Seed × ln other inputs	-	-	0.010 (0.010)	0.98
ln Fertilizer × ln other inputs	-	-	3.214** (0.947)	-2.99
Sigma square (σ^2)	0.273 (0.019)	14.16	0.238*** (0.019)	12.638
Gamma (γ)	0.881 (0.015)	57.54	0.84*** (0.019)	44.230
Log-likelihood	-802.53		-670.57	
N	1864		1864	

***p < 0.01, **p < 0.05, *p < 0.

signifies that an expansion in the proportion of irrigated land substantially diminishes technical inefficiency, thus improving the overall production of the farms. Similarly, the farmer's gender (Z_2) bears a negative and significant coefficient (-0.166 at the 10 per cent level) in the Cobb-Douglas model, indicating that male-headed households tend to be comparatively more technically efficient.

On the other hand, the variable representing access to technical advice (Z_9) exhibits a positive and highly significant coefficient at the 1 per cent level in both models (0.182 and 0.151, respectively). This implies, somewhat counter-intuitively, that access to technical advice in the current study area is associated with an escalation in technical inefficiency. Furthermore, farm size (Z_5) shows a positive and significant impact at the 10 per cent level (0.031) under the Translog framework model, hinting that larger farm holdings might encounter management bottlenecks that breed inefficiency. The remaining demographic and institutional factors-such as the farmer's age (Z_1), education level (Z_3), household size (Z_4), credit access (Z_6), and crop insurance (Z_7)-display statistically insignificant coefficients in both models, demonstrating that they do not have any discernible impact on the technical inefficiency of paddy production in the surveyed region.

Likelihood Ratio Test

A comparison of the Log-likelihood values shows an improvement from -802.53 in the Cobb-Douglas frontier model to -670.57 in the Trans-log frontier model. To statistically confirm this, the Cobb-Douglas frontier model was tested against the more flexible trans-log frontier model using a likelihood ratio (LR) test. The test statistic of 263.92 (as shown in Table 5), which is found to be highly significant (p <

Table 4: Maximum likelihood estimate of inefficiency effects model of Cobb-Douglas and Translog production frontiers

Variables	*Cobb- Douglas Frontier Model*		*Trans-log Frontier Model*	
	Coefficient (Std. Error)	*z-value*	*Coefficient (Std. Error)*	*z-value*
Constant	2.223*** (0.143)	15.53	2.076*** (0.149)	13.95
Farmer's Age (Z_1)	0.0002 (0.002)	0.15	0.000 (0.002)	-0.15
Farmer's Gender (Z_2)	-0.166* (0.090)	-1.84	-0.137 (0.101)	-1.36
Education level (Z_3)	-0.017 (0.010)	-1.61	-0.013 (0.012)	-1.13
Household Size (Z_4)	0.009 (0.009)	1.05	0.005 (0.010)	0.56
Farm Size (Z_5)	0.017 (0.014)	1.21	0.031* (0.015)	2.04
Credit Access (Z_6)	-0.072 (0.055)	-1.32	-0.053 (0.060)	-0.88
Crop Insured (Z_7)	0.141 (0.122)	1.15	0.164 (0.115)	1.43
Irrigation Ratio (Z_8)	-2.311*** (0.118)	-19.64	-2.270*** (0.124)	-18.29
Access of Technical Advice (Z_9)	0.182*** (0.041)	4.39	0.151*** (0.043)	3.55

Table 5: Likelihood Ratio test on Cobb-Douglas production function against the trans-log model

Frontier Production Function	*Log-Likelihood value*	*Chi Square Value*	*p-value*
Cobb-Douglas Frontier	-802.53	263.92***	<0.05
Trans-log Frontier	-670.57		
Test Statistic			
Decision		Reject H_0: Trans-log Frontier Production Function is preferred	

0.05). This strongly rejects the null hypothesis that the restricted Cobb-Douglas frontier model is adequate, leading to the conclusion that the Trans-log model is the best fit for the given dataset. Similar results were observed by Sebaq and Mandour (2026), who also found the trans-log model to be the optimal fit for their dataset

District-Wise Technical Efficiency

The technical efficiency of farmer's household in different districts, estimated through Cobb-Douglas and Trans-log stochastic frontier models, is presented in Table 6. The efficiency level was not the same across districts, indicating differences in the use of farm resources and management practices. Birbhum district recorded the highest efficiency level among all the districts, with efficiency values of 74.5% under the Cobb-Douglas model and 78.7% under the Trans-log model. Purba Bardhaman also showed comparatively higher efficiency with values of 73.5% and 75.8%, respectively. Paschim Medinipur and Hooghly performed moderately well, where the efficiency values remained relatively high, ranging from 68.3% to 73.0% across both models.

Several districts, including Jhargram, Darjeeling, Uttar Dinajpur, Murshidabad, Jalpaiguri, and Dakshin Dinajpur, showed medium levels of efficiency. In these districts, the efficiency values varied from around 57.9 to 69.6%, which indicates that farmers were able to utilize a fair proportion of available resources efficiently, though there was still considerable scope for improvement. The lowest efficiency values were observed in Nadia, North-24 Parganas, Purulia, and South-24 Parganas. Among these, Purulia recorded the lowest value under the Cobb-Douglas model (39.3%), while South-24 Parganas recorded the minimum efficiency level under the Trans-log model (46.1%). This indicates that farmers in these districts were operating far below their potential production level.

Table 6: Technical Efficiency (%) of Households across Districts Using Cobb-Douglas and Trans-log Stochastic Frontiers

District	*Number of Households*	*Technical Efficiency (%)*	
		Cobb-Douglas Frontier	*Trans-log Frontier*
Birbhum	121	74.5	78.7
Purba Bardhaman	201	73.5	75.8
Paschim Medinipur	156	69.5	73.0
Hooghly	134	68.3	71.5
Jhargram	39	64.1	69.6
Darjeeling	16	60.1	68.6
Uttar Dinajpur	131	63.6	68.3
Murshidabad	206	64.3	67.1
Jalpaiguri	49	59.4	65.8
Dakshin Dinajpur	57	57.9	64.2
Purba Medinipur	77	57.5	61.8
Cooch Behar	109	56.2	61.8
Alipurduar	36	57.2	60.2
Maldah	91	52.3	59.8
Howrah	25	52.2	57.8
Bankura	49	49.0	56.5
Nadia	131	54.0	54.8
North-24 Parganas	143	51.1	53.5
Purulia	50	39.3	48.8
South-24 Parganas	43	39.7	46.1
West Bengal	1864	61.2	65.3

For the West Bengal, Overall sample of 1,864 farmers, the technical efficiency was estimated at 61.2% under the Cobb-Douglas frontier and 65.3% under the Trans-log frontier. The overall results suggest that the Trans-log model provided slightly higher efficiency estimates compared to the Cobb-Douglas model.

CONCLUSION

The present study utilized a Stochastic Frontier Production Function to evaluate the technical efficiency of kharif paddy production in West Bengal. Based on a Likelihood Ratio test, the Translog model outperformed the restrictive Cobb-Douglas model, revealing complex, non-linear interactions among agricultural inputs. The findings indicate that technical inefficiency is significantly driven by specific operational constraints, primarily limited access to technical advice, inadequate irrigation coverage, and variations in farm size, while other socio-demographic factors showed no significant impact. To enhance farm-level efficiency, targeted policy interventions are necessary. Authorities should prioritize strengthening agricultural extension services to deliver consistent, on-ground technical guidance and invest heavily in rural infrastructure to improve the irrigation ratio. Furthermore, policies designed to optimize farm size operations, such as encouraging cooperative farming or scale-appropriate technologies, will help overcome land constraints, ultimately driving more resilient and productive paddy cultivation in the region.

REFERENCES

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21-37. https://doi.org/10.1016/0304-4076(77)90052-5

Amin, G. R., & Oukil, A. (2019). Flexible target setting in mergers using inverse data envelopment analysis. *International Journal of Operational Research*, *35*(3), 301-317. https://doi.org/10.1504/IJOR.2019.101196

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20(2), 325-332. https://doi.org/10.1007/BF01205442

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. Journal of Productivity Analysis, 3, 153-169.

Birthal, P. S., Kumar, D., Negi, D. S., & Roy, D. (2015). The impacts of information on returns from farming: Evidence from a nationally representative farm survey in India. Agricultural Economics, 46(4), 549-561. https://doi.org/10.1111/agec.12181

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6), 429-444.

Coelli, T. J., & Battese, G. E. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. Australian Journal of Agricultural and Resource Economics, 40, 103-128.

Coelli, T. J. (1995). Recent developments in frontier modelling and efficiency measurement. Australian Journal of Agricultural and Resource Economics, 39(3), 219-245.

Dakpo, K. H., Desjeux, Y., Henningsen, A., & Latruffe, L. (2023). sfaR: Stochastic frontier analysis using R (R package). https://cran.r-project.org/package=sfaR

Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General), 120(3), 253-281.

Felix, K. T., Kumar, P. N., & Arivarasan, S. (2021). An economic approach to improve the productivity of sugarcane: A stochastic frontier approach. Wesleyan Journal of Research, 14(1), 461-471.

Food and Agriculture Organization of the United Nations. (2022). FAOSTAT. Rome (Italy): FAO. https://www.fao.org/faostat

Hamsa, K. R., Srikantha Murthy, P. S., & Chandrakanth, M. G. (2017). Resource use efficiency pattern in cultivation of irrigated paddy in Central Dry Zone of Karnataka. Research Journal of Agricultural Sciences, 8(5), 1077-1080.

Hamsa, K. R., & Umesh, K. B. (2023). Technical efficiency in finger millet and paddy crop in southern Karnataka: Application of data envelopment analysis and stochastic frontier approach. International Journal of Statistics and Applied Mathematics, 8(5), 230-236.

Kodde, D. A., & Palm, F. C. (1986). Wald criteria for jointly testing equality and inequality restrictions. Econometrica, 54(5), 1243-1248. https://doi.org/10.2307/1912331

Mithiya, D., Mandal, K., & Bandyopadhyay, S. (2018). Diversification towards horticulture as a source of income and employment in West Bengal. International Journal of Current Research, 10(7), 71996-72004. https://doi.org/10.24941/ijcr.31467.07.2018

Ministry of Statistics and Programme Implementation. (2021). NSS 77th Round: Situation Assessment of Agricultural Households and Land and Livestock Holdings of Households in Rural India (January-December 2019). Government of India.

Sebaq, M., & Mandour, M. (2025). Assessing the performance of Tilapia farms in Egypt: A stochastic frontier analysis approach. Aquaculture, 743608. https://doi.org/10.1016/j.aquaculture.2025.743608

Sultana, S., Hossain, M. M., & Haque, M. N. (2023). Estimating the potato farming efficiency: A comparative study between stochastic frontier analysis and data envelopment analysis. PLoS One, 18(4), e0284391. https://doi.org/10.1371/journal.pone.0284391

Umar, H. S., Girei, A. A., & Yakubu, D. (2017). Comparison of Cobb-Douglas and translog frontier models in the analysis of technical efficiency in dry-season tomato production. Agrosearch, 17(2), 67-77. https://doi.org/10.4314/agrosh.v17i2.6

Umesh, K. B., & Bisaliah, S. (1991). Efficiency of groundnut production in Karnataka: Frontier profit function approach. Indian Journal of Agricultural Economics, 46(1), 22-23.