



Original Paper

Measuring Farm-Level Technical, Allocative, and Economic Efficiency in Jute Production: A DEA Application in Southern Bangladesh

Md. Mehedi Hasan Chokdar¹, Md Elias Hossain², Md Asduzzaman Kiron^{3,*}

1) Student, Department of Economics, University of Rajshahi, Rajshahi, Bangladesh

2) Professor, Department of Economics, University of Rajshahi, Rajshahi, Bangladesh

3) Lecturer, Department of Economics, Varendra University, Rajshahi, Bangladesh

*) Corresponding Author: kiron.asduzzaman@gmail.com

Received: 10 January 2026; Revised: 16 March 2026; Accepted: 30 March 2026

DOI: <https://doi.org/10.46676/ij-fanres.v7i1.592>

Abstract—Jute production plays a major part in the economy of Bangladesh by supporting over 25 million people employed in cultivation and processing, which contributes considerably to export revenues. While earlier studies have concentrated on either technical or economic efficiency separately, the present study contributes to the field by jointly estimating technical, allocative, and economic efficiencies applying a two-stage DEA-Tobit technique to estimate the efficiency of jute production. A sample size of 360 from the district Faridpur, which is nationally known for high-quality jute production that makes it a critical focus point, has been chosen as the area of the present study. The paper also suggests that its results may serve as benchmarks that apply to comparable agroecological zones in South Asia. On average, technical, allocative, and economic efficiencies of the farms were found to be 0.87, 0.93, and 0.82, respectively, whereas their present inefficiencies are 12.4%, 17.7%, and 6.3%. Although TE and AE are 87.6% and 93.7% respectively, farmers are inefficient in producing the optimum level of output. Therefore, farmers may produce a specified amount of output at the lowest feasible cost by decreasing the cost of jute production by 17.7%, given the available resources. Moreover, a second-stage Tobit regression employed in the present study has demonstrated that farm-specific factors such as age, family size, education level, farming experience, land size, kind of seed, and the profession of the head of the household, etc. all have a substantial influence on the efficiency of the farms. These findings along with the second-stage Tobit regression that links efficiency to farm-specific factors, give empirical insights for targeted agricultural policy and rural poverty reduction, therefore attracting the educated young to choose agriculture as a career option. The research thereby fills a vacuum in multi-dimensional efficiency studies and facilitates both regional and international development policies.

Keywords— Bangladesh, Data Envelopment Analysis, Efficiency analysis, Jute production, Tobit model.

I. INTRODUCTION

Bangladesh is a densely populated and agricultural country. Agriculture is the major sector of the economy, contributing approximately 14.23% to the Gross Domestic Product (GDP) and employing about 40.60% of the overall labor force in the

nation [1][32]. Bangladesh is the second leading producer of jute crop, known as the golden fiber, with a projected yearly production of 1.6 million tons [2]. Moreover, jute as a vital cash crop has great significance in Bangladesh across different sectors including economic, agricultural, industrial, and commercial sectors. Jute cultivation may be linked back to ancient times in Bengal, which is where the name "golden fiber" was born. Even though the RMG sector dominates in employment and export earnings, every dollar exported from jute is worth more than four dollars from RMG because of the high import prices of RMG ingredients. Bangladesh ranks as the world's greatest exporter of raw jute globally [3]. Although jute has been a popular export since the 1950s, the country's monopoly on the manufacturing and sale of jute was challenged by competition from countries such as China, India, Uzbekistan, and Nepal in the 1950s and 1960s. Despite Bangladesh is still dominating jute production and export sector [4].

Bangladesh has an annual average export value of approximately one billion US dollars and the average domestic consumption of 1.16 million tons of raw jute per year [5]. White jute and tossa jute are the most popular among more than forty varieties. Jute was initially used to produce fiber for the textile and packaging sectors, but has recently extended to goods such as bags, mattresses, ropes, and carpets etc. It is also considered to be the second most significant natural fiber worldwide, behind cotton. Jute has benefits over synthetic fibers, including being more inexpensive, robust, recyclable, and biodegradable, making it an increasingly preferred eco-friendly alternative to plastic in packaging materials [6].

Prior research on Bangladesh primarily concentrated on technical or economic efficiency [7-16], without the exception of Coelli et al. [17]. Assessing production efficiency has become vital in agricultural production and development, as it gives

useful insights that can be utilized for rational management choices, optimal resource allocation, and the formulation of agricultural policy. Efficiency may be assessed in a number of ways. The most widely used approaches to efficiency measurement are Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA), and the Two-Stage DEA Model (also dubbed the Extended DEA) [18]. However, the present study employs a two-stage data envelopment analysis (DEA) with two particular objectives in mind. Firstly, this study is designed to measure the technical, allocative, and economic efficiency of jute farms. Secondly, this study also attempts to evaluate the influence of many farm-specific factors on jute farming efficiency. To meet the objectives of this study, the efficiency level was estimated by applying the Data Envelopment Analysis (DEA) model, and the impacts of different farm-specific factors on jute farming efficiencies were evaluated using the Tobit model.

II. METHODOLOGY

A. Study Area and Data Collection

The research is focused on Faridpur district in southern Bangladesh, renowned for its significant contribution to the jute industry and considered the top jute-growing region in Bangladesh. The sample respondents have been selected using a three-stage random sampling technique. Three upazilas of Faridpur have been initially assigned in increasing order according to the area cultivated during the 2024-2025 jute-growing season. In the first step, three upazilas named Sadarpur, Boalmari, and Madhukhali were picked at random to offer a representative sample. In the second step, 3 villages were selected at random from each of these chosen upazilas. Finally, 40 jute farmers were picked at random from each of these nine villages, generating a sample size of 360 farmers. A comprehensive and unbiased representation of jute producers in the region was assured by this multi-stage sampling approach. A pre-tested and planned interview schedule was employed to conduct in-person interviews to acquire primary data for the crop year 2024-25. Excel has been used for putting together data and R version 4.41 was used for the evaluation of efficiency. We also applied Stata version 18 to assess the influence of several farm-specific factors on the efficiency of jute farms employing Tobit Regression Model.

B. Analytical Framework

Farrell (1957) implies that estimating efficiency may be undertaken employing two major approaches, namely parametric and non-parametric frontier models. The parametric technique named, the Stochastic Frontier Production Function, demands the specification of a functional form and error distribution facilitating hypothesis testing and model fit

estimation [18]. The non-parametric approach named Data Envelopment Analysis (DEA) eliminates hypotheses on the production function and error distribution, hence reducing possible errors in specification.

C. Model Specifications

1) Resource Use Efficiency

This study measures the resource-use efficiency of jute farming using farm-level data from 360 farmers across several agro-climatic zones of Faridpur for the crop year 2024–2025. Resource use efficiency refers to a farm's capacity to maximize output from a given amount of input which is vital for boosting agricultural production and ensuring food security, particularly in resource-constrained environments. According to Coelli et al. (1996), efficiency is a relative principle assessed by comparing each farm's performance to the "best practice" frontier generated from the sample [19]. There are multiple methods available such as Data Envelopment Analysis (DEA), the Stochastic Frontier (SF) Production Function to assess resource use efficiency. This study implemented Data Envelopment Analysis (DEA) developed by Charnes et al. (1978), a robust and non-parametric approach ideal for evaluating the technical, allocative, and economic efficiency of multiple decision-making units (DMUs) that employ various inputs to produce various outputs [20]. These assessments of efficiencies provide significant insight into how efficiently resources are being used and suggest possible areas for enhancing cost-effectiveness and productivity for the jute producers.

2) Data Envelopment Analysis (DEA) Approach

Data Envelopment Analysis (DEA) is a linear programming method that employs actual input and output data to develop a non-parametric piecewise linear frontier for estimating efficiency in agricultural production. Efficiency is described as the degree to which input is employed to achieve a given level of output. More efficiency is demonstrated by producing more output with the same inputs or the same output with fewer inputs. Efficiency analysis assesses the ratio of output to inputs. In the present study, DEA has been employed to obtain the relative efficiency score of each farm with respect to farms with the lowest input-output ratio for all inputs. The score of the most efficient farms being one, the score of each farm will range between zero and one. TE indicates how efficiently a farm optimizes output from a set of inputs or minimizes inputs for a given output level, depending on whether an output-oriented or input-oriented method is adopted. AE represents the best usage of input based on its costs, whereas EE combines TE and AE to estimate a unit's capacity to produce output at minimum cost. An economically efficient unit is both technically and allocatively efficient.

The variables used in efficiency measures are output of jute (q/hectare) and inputs such as working hours of human labor (per hectare), working hours of machine labor (per hectare), NPK quantity (kg/ ha), quantity of seed (Kg/ha) and groundwater used for irrigation (cum/ha). The efficiency estimation approaches employed in this research draw inspiration from the framework created by Färe et al. (1994), which is built upon the pioneering work of Farrell (1957), Afriat (1972), and Charnes et al. (1978) [20-23]. In order to establish the mathematical formulation of the model, we suppose that we have K farmers' Decision-Making Units (DMU) using n inputs to produce m outputs.

Inputs are denoted by:

$$x_{jk} \quad (j = 1, 2, 3, \dots, n) \quad (1)$$

Outputs are denoted by:

$$y_{ik} \quad (i = 1, 2, 3, \dots, m) \quad (2)$$

Therefore, for each farmer k

$$(k = 1, 2, 3, \dots, K)$$

The technical efficiency (TE) of the farmers can be estimated as follows:

$$TE_k = \frac{\sum_{i=1}^m u_i y_{ik}}{\sum_{j=1}^n v_j x_{jk}} \quad (3)$$

Where y_{ik} is the quantity of i th output produced by k th farmer, x_{jk} is the quantity of j th input used by the k th farmer, u_i and v_j are the output and input weights respectively. The farmer maximizes technical efficiency.

TE_k subject to,

$$TE_k = \frac{\sum_{i=1}^m u_i y_{ik}}{\sum_{j=1}^n v_j x_{jk}} \leq 1 \quad (4)$$

where u_i and $v_j \geq 0$. Given the input and output weights are positive, the preceding equation shows that a farmer's technical efficiency measure cannot be more than one. The weights are selected in such a way that the farmer maximizes its technical efficiency which is executed separately. The linear programming model mentioned below is used to choose the best weights:

Min TE_k Subject to,

$$\sum_{i=1}^m u_i y_{ik} - y_{ik} + \omega \geq 0 \quad (5)$$

where, $k = 1, 2, \dots, K$

and,

$$x_{jk} - \sum_{j=1}^m u_j x_{jk} \geq 0 \quad (6)$$

where u_i and $v_j \geq 0$

The model mentioned above assumes that $w = 0$ and displays TE under constant returns to scale (CRS).

Technical Efficiency (TE): In general, it may be stated as the ratio of the total weighted inputs to the total weighted outputs. Technical efficiency has a number between zero and one; a value of one indicates that the DMU is the best performer on the production frontier and has very little opportunity for decrease. A TE value is less than one indicates inefficient input use by the DMU.

Cost or Economic Efficiency (CE): To obtain behavioral goals like revenue maximization or cost reduction, one may assess both technical and cost or economic efficiency. Cost minimization DEA is expressed as,

$$\text{Min } Y_{kk}^* w_k^* X_k^*$$

$$\text{Subject to } -y_k + Y Y \geq 0,$$

$$X_k^* - X Y \geq 0,$$

$$Y \geq 0, \quad (7)$$

Where w_k is a vector of input prices for the k th farmer and X_k^* (which is calculated by LP) is the vector of cost minimization of input quantities for the k th farmer, given the input prices w_k and the output level y_k .

Total cost efficiency (CE) or economic efficiency of the k th farmer can be calculated as:

$$CE = \frac{w X_{kk}^*}{w X_{kk}} \quad (8)$$

That is the ratio of the minimum cost to the observed cost.

Allocative efficiency (AE): It is calculated as the ratio of cost efficiency to technical efficiency:

$$AE = \frac{CE}{TE} \quad (9)$$

Efficiency, also known as performance analysis, is a concept that is related to production analysis and uses a ratio to quantify productivity. When technology demonstrates continuous returns to scale, TE measures how much a farmer can produce from a given bundle of inputs or how few inputs are needed to create a certain level of output. The terms output-oriented and input-oriented efficiency metrics, respectively refer to these two interpretations of TE. A farm's capacity to utilize inputs in the best possible proportions given their various prices is reflected in its AE, or price efficiency. Technical and allocative efficiency could coexist with economic efficiency.

3) Tobit Regression Model

Tobit model is employed to determine the variables influencing TE, AE, and CE of jute production the studied farms. According to Suh et al. (2002), it is standard practice to regress the DEA efficiency ratings on the relevant control variables [24]. Since efficiency is a censored variable with an upper limit of one, we can apply the Tobit model, a censored regression model that is appropriate in situations when the dependent variable is restricted. The Tobit model is defined as:

$$Y = \begin{cases} y^*; & 0 \leq y^* \leq 1 \\ 0; & y^* < 0 \\ 1; & 1 < y^* \end{cases}$$

$$y^* = \beta x_i + e_i \quad (10)$$

Where y is the DEA efficiency score; $e \sim N(0, \sigma^2)$ y^* is a latent (unobservable) variable; β is the vector of unknown parameters that determines the relationship between the independent variable and the latent variable. Therefore, the Tobit model that was used in this study might be defined as:

$$Y^* = \beta_0 + \beta_1AG + \beta_2EDU + \beta_3FS + \beta_4FE + \beta_5LS + \beta_6ST + \beta_7OCU + e_i \quad (11)$$

Where Y^* is the dependent variable, and x_i is the vector of explanatory variables. (TE, AE, and CE of the jute farm).

III. RESULTS

A. Data Envelopment Analysis (DEA)

This study employed Data Envelopment Analysis (DEA) using R programming to evaluate the technical, allocative, and economic efficiency of farms. The DEA model assessed production value per bigha in relation to inputs such as land, labor, seeds, fertilizer, and irrigation. Farms were classified as efficient or inefficient, with a score of 1 denoting optimal resource use, which is attained by the most productive farms. The results emphasize the necessity for increased resource management to increase overall productivity.

Table I indicates the factors employed to assess efficiency. However, several variables, such as irrigation frequency and power tiller usage, were omitted due to their similarity throughout the sample.

TABLE I. DESCRIPTIVE STATISTICS OF THE VARIABLES USED IN DEA

Variables	Unit	Mean	Std. Deviation	Min	Max
Output Value	Tk/Bigha	28950	3541.12	22400	34500
Land Cultivated	Bigha	5.80	4.10	1	15
Human Labor	Man-day/Bigha	23.07	2.05	20	26

Labor Wage	Tk/Day	543.33	40.96	500	600
Seed	Kg/Bigha	1.61	0.40	1	2
Seed Price	Tk/Kg	292.33	7.73	280	300
Fertilizer	Kg/Bigha	49.00	5.31	40	60
Fertilizer Price	Tk/Kg	33.13	0.73	32	34
Insecticide Cost	Tk/Bigha	983.06	83.56	850	1100
Irrigation	Frequency/Bigha	4.50	0.97	3	6
Irrigation Cost	Tk/Per Irrigation	1156.6	79.58	1000	1250

Source: Field Survey, 2025

The mean land area was found to be 5.80 bigha, and labor input was expressed in man-days per bigha; it was found to be 23.07 man-days on average (standard deviation = 2.05), which indicates significant variance among farms. The present study found the average daily labor wage to be 543.33 Tk (with contributions from both hired and family labor in agriculture), which is consistent with local rates. To increase production, the majority of farmers used hybrid or high-yield seeds, applying an average seed rate of 1.61 kg per bigha at a cost of Tk 292.33 per kg. Chemical fertilizers such as urea, TSP, and MOP were intensively used at an average of 49 kg per bigha at an average price of Tk 33.13 per kg. Insecticides were frequently used at an average rate of 983.06 Tk per bigha to solve local pest problems. Irrigation usage frequency on average was found to be 4.50 times per bigha at a per-application cost rate of 1,156.66Tk. The variables presented in Table I provide insight into the factors that influence production efficiency in the region, indicating substantial variation among farms.

Table II displays key summary statistics for three important efficiency measures of jute production, namely Technical Efficiency (TE), Economic Efficiency (EE) and Allocative Efficiency (AE). Each of these measures demonstrates how well jute farmers are performing in different aspects of efficiency.

TABLE II. DESCRIPTIVE STATISTICS OF TE, EE & AE OF FARMERS

	TE	EE	AE
Mean	0.876	0.823	0.937
Standard Deviation	0.102	0.120	0.045
Minimum	0.657	0.618	0.819
Maximum	1.00	1.00	1.00

Source: Field Survey, 2025

Technical Efficiency (TE): The degree to which farmers maximize their output by optimizing their input usage is evaluated by technical efficiency. Mean TE was found to be

0.876, which suggests that, on average, jute farmers in the study area produce at 87.6% of their maximum efficiency. In other words, this means that a normal farmer can increase production by 12.4% with the same level of input. The input use of the farmers varies substantially as demonstrated by the standard deviation of 0.102, with the majority deviating from the mean TE by 10.2%. TE ranges from a minimum of 0.657 to a maximum of 1.00. The least efficient farmer functions at 65.7% of maximum efficiency, while some farms achieve maximum efficiency (100%). This means that even when the majority of farmers are fairly efficient, those at the lower end of the range still have an opportunity for progress.

Economic Efficiency (EE): Economic efficiency refers to the capacity of farmers to produce maximum output at the lowest possible cost, which takes into account both technical and allocative efficiency. In the present study, average economic efficiency was found to be 82.3%, according to the mean EE of 0.823. This means that if farmers were perfectly efficient, they could have cut costs by 17.7% while keeping production of output at the same level. The standard deviation of 0.120 indicates that the economic efficiency of farms varies more (by 12%) than their technical efficiency. This suggests that the sample has a wider range of economic efficiency. The least economically efficient farmer operates at 61.8% efficiency with a minimum EE of 0.618 compared to the most efficient farmer, who works at 100% efficiency. This range shows that there is a greater variation in economic efficiency, with some farmers working much below their capacity.

Allocative Efficiency (AE): Allocative efficiency is the ability of a farmer to use input in the most cost-effective proportions given their prices. The average allocative efficiency of the farmers was found to be 93.7% with a mean AE of 0.937. This indicates that they nearly perfectly use resources to reduce costs. Given that allocative efficiency is greater than technical and economic efficiency, it may be assumed that farmers are more efficient at determining the right combination of inputs than they are at increasing production or decreasing input costs. The standard deviation of 0.045 shows that most farmers are closely clustered around the mean with very little variation across farms. Given that the minimum AE was found to be 0.819, the least efficient farmer in this regard operates at an efficiency of 81.9%. On the other hand, the maximum value, which is 1.00, suggests that some farmers have perfect allocative efficiency applying inputs in an appropriate proportion to decrease costs.

It appears that the majority of farmers are highly efficient at choosing the optimum level of inputs, but they are not so effective at using those inputs to their maximum capacity (technical efficiency) and at reducing costs (economic

efficiency). This is affirmed by the fact that allocative efficiency, on average, is higher and has less fluctuation than technical and economic efficiency. Considering the differences in technical and economic efficiency, especially the greater variation in economic efficiency, some farmers might profit from targeted interventions that help them maximize input usage and reduce costs. Some farmers receive a perfect efficiency score (1.00) on all three parameters, indicating that the group is already employing optimal approaches. This offers an opportunity to share expertise or provide training to help other farms perform better. In conclusion, jute farmers are found to be more efficient in terms of allocative efficiency than technical and economic efficiency. This suggests that by employing more effective resource management strategies or implementing more productive agriculture practices, farms could still be able to increase their output and reduce their costs.

Table III shows the frequency distribution of efficiency scores for Technical Efficiency (TE), Economic Efficiency (EE), and Allocative Efficiency (AE) of the sampled farms. It classifies farms into several efficiency categories to illustrate how efficiency levels are distributed across the sample and provide insight into the degree of variance in efficiency among farmers in the studied region. By analyzing these trends, the table identify potential gaps in farm performance and demonstrates the opportunity for enhancing productivity and resource use efficiency.

The efficiency levels in Table III range from 50-100% providing insights into how farms operate. The positive aspect of the findings is that no farm operates at less than 50% efficiency for any of the efficiency measures. Only 8% of farms were found to have Technical Efficiency (TE) between 61-70% efficiency range. 68 farms were found to operate at 71-80% efficiency level, whereas the 81-90% efficiency range is occupied by a higher concentration, that is, by 97 farms and 27% of the sample.

TABLE III. FREQUENCY DISTRIBUTION OF THE EFFICIENCY SCORES

Efficiency Interval	Frequency (Number of Farms)		
	TE	EE	AE
50-60	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
61-70	29.00 (8.00)	79.00 (22.00)	0.00 (0.00)
71-80	68.00 (19.00)	94.00 (26.00)	0.00 (0.00)
81-90	97.00 (27.00)	83.00 (23.00)	86.00 (24.00)
91-100	166.00 (46.00)	104.00 (29.00)	274.00 (76.00)

Note: Figures in brackets indicate percentage values

A considerable portion of the sample achieves near-optimal technical efficiency as evidenced by the fact that 166 farms

(46%) operate in the largest efficiency range, which is 91–100%. This suggests that a significant fraction of the sample achieves near-optimal technical efficiency.

In terms of economic efficiency, 79 farms were found to achieve an Economic Efficiency (EE) of between 61-70%. Furthermore, there are no farms found to be functioning at 50–60% efficiency and 94 farms (26% farms) operate at 71-80% efficiency range. 23% of farms are in the 81-90% efficiency range. However, only 29% of farms were found to fall between 91% and 100% efficiency level. This suggests that while economic efficiency is typically high, fewer farms reach the maximum levels of economic efficiency in comparison to technical efficiency.

When it comes to Allocative Efficiency (AE), there are no farms in the lower efficiency intervals (50–70%), and the distribution has a skew towards the higher end. A small fraction of farms, that is, 86 farms (24%), operate between 81-90% efficiency level. In addition, it was found that the majority of the farms, that is, 274 farms (76%) operate at 91–100% efficiency range.

In conclusion, the data demonstrates that farms perform effectively in terms of technical efficiency with more than half producing at maximum efficiency. Though inputs are being used effectively, fewer farms achieve the greatest degree of economic efficiency. This suggests that there is room for reduction in costs. Furthermore, allocative efficiency is high with nearly all farms achieving near-optimal efficiency. These findings suggest that the farms might benefit from improved economic decision-making to increase overall productivity and cost-effectiveness, even though they are technically efficient.

B. Tobit Analysis

The Tobit model was used to identify the factors that influence farm TE, AE, and CE of jute production. According to Fethi et al. (2000) and Suh et al. (2008), it is standard to regress the DEA score on the corresponding control variables [24-25]. The Tobit model is a censored regression model that may be employed when the dependent variable is constrained.

TABLE IV. VARIABLES DEFINITION

Variables	Symbol	Definition
Age	AG	Age of the farmer.
Education	EDU	Years of schooling completed by the farmer.
Family Size	FS	Number of people in the household.

Farming Experience	FE	Years of farming completed by the farmer.
Land Size	LS	Land used for jute production.
Seed Type	ST	Dummy variable for seed type. The value is 1 if the farmer used local varieties and 0 otherwise.
Occupation of the Household Head	OCU	Primary occupation of the household head. The value is 1 if agriculture is the main occupation and 0 otherwise.

There is some inefficiency present as the efficiency levels in the area of study for the production of jute were found to be less than 100%. Since farmers may be able to increase productivity without rising input costs, this inefficiency means that they are not making the most of the resources at their disposal. It is vital to know the causes responsible for this inefficiency to develop measures that can increase productivity and profitability in jute production. This study focuses on a collection of factors in Table IV that are considered to influence the efficiency levels of jute producers in order to gain deeper insight into the root causes of inefficiencies. Field observations, past research, and their application to agricultural approaches in the study area were taken into consideration in determining these parameters. Key determinants include age, agricultural experience, occupation of the household head, size of the land of the jute farmers, farm size, and farmer education level.

Estimates of the following variables, conducted using a Tobit regression analysis, are given in Table V.

TABLE V. ESTIMATION OF THE EFFECTS OF FARM-SPECIFIC VARIABLES ON JUTE FARMING EFFICIENCY

Variables	Technical efficiency (TE)	Allocative efficiency (AE)	Economic efficiency (EE)
Constant	0.6997*** (0.0569)	0.9535*** (0.0318)	0.6702*** (0.0655)
Age	0.0016 (0.0018)	-0.0021** (0.0010)	-0.0003 (0.0021)
Education	0.0060** (0.0023)	0.0008 (0.0013)	0.0065** (0.0027)
Occupation	0.1198*** (0.0157)	0.0399*** (0.0088)	0.1484*** (0.0181)

Family size	0.0033 (0.0025)	-0.0007 (0.0013)	0.0024 (0.0027)
Farming experience	0.0002 (0.0019)	0.0024** (0.0011)	0.0024 (0.0021)
Land size	0.0005 (0.0033)	0.0017 (0.0018)	0.0020 (0.0038)
Seed type	-0.0078 (0.0148)	-0.0082 (0.0083)	-0.0135 (0.0171)
Log Likelihood	123.192	180.147	109.427

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels. Standard errors are shown in parentheses.

Table V displays the findings of the Tobit model estimation for farm-specific variables and their influence on technical, allocative, and economic efficiency. The coefficient for each variable shows how much it influences efficiency and stars indicate different significance levels. The constant terms are positive and highly significant at 1% level for all efficiency types (TE: 0.6997***, AE: 0.9535***, EE: 0.6702***), demonstrating a satisfactory level of efficiency across farms. Age has very little influence on technical or economic efficiency but it has a negative and substantial impact on allocative efficiency (-0.0021**, at 5% level). This may imply that farmers who are older experience more trouble when it comes to allocating resources effectively. Education positively influences both technical efficiency (0.0060**, at 5% level) and economic efficiency (0.0065**, 5% level). This indicates that educated farmers frequently employ inputs more efficiently and reduce costs. Occupation is beneficial and very significant for all three efficiency categories (TE: 0.1198***, AE: 0.0399***, EE: 0.1484***) at 1% level, demonstrating its vital impact. This emphasizes the importance of employment as a key factor in increasing economic and technical efficiency. Household size may not directly influence the efficiency of jute production. Farming experience substantially increases allocative efficiency (0.0024***, at 1% level), whereas its impact on TE and EE is not significant. This suggests that more experienced farmers are more effective at resource allocation. Land size and seed type do not significantly influence any form of efficiency in this study, implying that changes in these factors do not have a noticeable impact on how efficiently farms are operated. The log-likelihood values show the overall fitness of the model, with higher values for allocative efficiency (AE) implying a better model fit in explaining the variance in resource allocation decisions.

This study attempted to compare estimated findings with those found in previous studies. This conclusion is consistent with the assumption that aging has little influence on technical

or economic efficiency and negatively affects allocative efficiency. This study found that this finding is comparable to what was achieved by Gupta et al. (2009) [26]. Both technical and economic efficiency are positively and considerably influenced by education. This indicates that educated farmers frequently use inputs more effectively and reduce costs. These findings are significant to the results calculated by Singh et al. (2019) [27]. Occupation is positively and significantly influenced by all three forms of efficiency, indicating that farmers whose primary occupation is farming are likely to achieve higher efficiency. This positive finding is consistent with Islam et al. (2015) [28]. There is a negligible but negative relation between family size and allocative efficiency, and a negligible but positive relation between family size, technical and economic efficiency. This means that efficiency is not substantially influenced by the size of the family. This finding is consistent with Molla et al. (2013) [29]. At 1% level, there is a substantial influence on agricultural experience and allocative efficiency, showing that more experienced farmers are less effective at allocating resources optimally. However, it has a positive but little influence on technical and economic efficiency. Land size shows a positive but insignificant relation with all forms of efficiency, indicating that larger farms do not necessarily lead to higher efficiency. Regarding land size, this finding coincides with Amin & Sarker (2023) [30]. Seed type has a negative but negligible influence on all forms of efficiency, demonstrating that changes in seed types do not have a substantial impact on farming efficiency. These results are relevant to the findings of Chakraborty & Maiti (2018) [31].

IV. CONCLUSIONS AND POLICY RECOMMENDATIONS

This study examined the technical, allocative, and economic efficiencies of jute farms in Faridpur district, one of the leading jute-growing areas of southern Bangladesh, by applying the Data Envelopment Analysis (DEA) approach. The results indicate that jute farming operates with moderate efficiency scores but shows considerable scope for improvement in cost management and resource use. On average, technical efficiency (TE) was estimated to be 87.6 percent, suggesting that farmers could increase output by about 12.4 percent using the same level of input. Allocative efficiency (AE) averaged at 93.7 percent, which implies that most farmers are relatively effective in choosing the appropriate combination of inputs based on their prices. However, economic efficiency (EE) was lower at 82.3 percent, indicating that production costs could be reduced by around 17.7 percent without affecting output levels. The distribution of efficiency scores shows that while nearly half of the farmers (46 percent) achieved high technical efficiency (91–100 percent), only 29 percent reached the same range in terms

of economic efficiency. Allocative efficiency was consistently higher, with 76 percent of farms operating in the 91–100 percent range. These findings suggest that although farmers are making sound choices in input allocation, they face challenges in maximizing output and minimizing costs simultaneously.

The Tobit regression analysis further explains the variation in efficiency across farms based on farm-specific variables and their influence on technical, allocative and economic efficiency. It reveals that education was found to have a positive effect on both technical and economic efficiency, highlighting the importance of literacy and formal training in managing resources effectively. Farming as the primary occupation also showed a strong positive influence on all three efficiency measures, underlining the role of full-time engagement in agriculture. Farming experience was positively associated with allocative efficiency, indicating that experienced farmers tend to allocate resources more effectively. By contrast, age had a negative impact on allocative efficiency, possibly due to older farmers' limited adoption of modern practices. Household size, land size, and seed type did not appear to have any significant effect on efficiency measures.

Based on the findings, several recommendations can be drawn.

1. Expand farmer education and training programs to strengthen technical and economic efficiency.
2. Access to high-yielding seeds, efficient irrigation and modern machinery should be ensured to improve productivity.
3. Financial and institutional support, including affordable credit, crop insurance and stable markets would help farmers adopt improved practices and manage risks.
4. Demonstration farms and farmer cooperatives could serve as platforms for sharing successful practices among peers.
5. Undertake sustainable agriculture policies that encourage the participation of educated youth in farming by making agriculture more profitable and attractive.

In summary, jute farmers in the study area display relatively high allocative efficiency but remain constrained in technical and economic efficiency. Addressing these gaps through education, technology adoption and institutional support would enhance productivity, profitability and the long-term sustainability of the jute sector in Bangladesh.

References

- [1] Alam, M. S., & Kiron, M. A. (2025). Understanding Agrochemical Overuse in Bangladesh: Evidence from Farmers in Naogaon District. *International Journal on Food, Agriculture and Natural Resources*, 6(3), 67-73.
- [2] BBS (2019) Estimates of jute 2018-2019, Bangladesh Bureau of Statistics, Ministry of Planning, Dhaka, Bangladesh.
- [3] Ahsan, N. (2022). Jute industry of Bangladesh: Reclaiming the lost glory, Industrial Development Leasing Company of Bangladesh Limited, Dhaka, Bangladesh.
- [4] Rahman, S., Kazal, M. M. H., Begum, I. A., & Alam, M. J. (2017). Exploring the future potential of jute in Bangladesh. *Agriculture*, 7(12), 96.
- [5] BIDA (2021) Jute: Bangladesh's contribution to GOING GREEN, Bangladesh Investment Development Authority, Prime Minister's Office, Dhaka, Bangladesh.
- [6] Paulsen, P. S. (2022). Jute Farmers in Bangladesh: a study on institutional influences. Second cycle, A2E. Uppsala: SLU, Dept. of Economics, *Swedish University of Agricultural Sciences*.
- [7] Bolaji, M., Babatunde, R. O., & Omotesho, O. A. (2023). Assessment of The Technical Efficiency and Cost and Returns on Seed Yam Farms in North-Central. *International Journal on Food, Agriculture and Natural Resources*, 4(3), 37-42.
- [8] Wadud, A., & White, B. (2000). Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics*, 32(13), 1665-1673.
- [9] Rahman, K. M., Schmitz, P. M., & Wronka, T. C. (2002). Comparison of Technical Efficiencies for Rice Production in Bangladesh under Two Alternative Tenurial Systems. *The Bangladesh Development Studies*, 137-160.
- [10] Balcombe, K., Davidova, S., & Latruffe, L. (2008). The use of bootstrapped Malmquist indices to reassess productivity change findings: an application to a sample of Polish farms. *Applied Economics*, 40(16), 2055-2061.
- [11] Ara Begum, I., Buysse, J., Alam, M. J., & Van Huylenbroeck, G. (2009). An application of Data Envelopment Analysis (DEA) to evaluate the economic efficiency of poultry farms in Bangladesh. In *27th Conference of the International Association of Agricultural Economists (IAAE)*.
- [12] Chowdhury, S. A., Aziz, S., & Hossain, M. B. (2022). Cost Efficiency Evaluation of Thermal Power Plants in Bangladesh Using a Two-Stage DEA Model. *Economics of Energy & Environmental Policy*, 11(1).
- [13] Vortia, P., Nasrin, M., Bipasha, S. K., & Islam, M. M. (2021). Extent of farm mechanization and technical efficiency of rice production in some selected areas of Bangladesh. *Geo Journal*, 86, 729-742.
- [14] Mitra, S., Khan, M. A., Nielsen, R., & Islam, N. (2020). Total factor productivity and technical efficiency differences of aquaculture farmers in Bangladesh: do environmental characteristics matter? *Journal of the World Aquaculture Society*, 51(4), 918-930.
- [15] Paz, B., Hailu, A., Rola-Rubzen, M. F., & Rashid, M. M. (2024). Conservation agriculture-based sustainable intensification improves technical efficiency in Northern Bangladesh: The case of Rangpur. *Australian Journal of Agricultural and Resource Economics*, 68(1), 125-145.
- [16] Arefin, M. S. (2023). Measuring Efficiency of Non-Bank Financial Institutions in Bangladesh: A Non-Parametric Data Envelopment Approach. *London Journal of Research in Management & Business*, 23(3), 1-9.
- [17] Coelli, T., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach. *Journal of Agricultural Economics*, 53(3), 607-626.
- [18] Bezat, A. (2009). Comparison of the deterministic and stochastic approaches for estimating technical efficiency on the example of non-parametric DEA and parametric SFA methods. *Metody ilościowe w badaniach ekonomicznych*, 10(1), 20-29.
- [19] Coelli, T. J., & Battese, G. E. (1996). Identification of factors that influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics*, 40(2), 103-128.

- [20] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European journal of operational research*, 2(6), 429-444.
- [21] Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, 66-83.
- [22] Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253-281.
- [23] Afriat, S. N. (1972). Efficiency estimation of production functions. *International Economic Review*, 568-598.
- [24] Fethi, M. D., Jackson, P. M., & Weyman-Jones, T. G. (2000). Measuring the efficiency of European airlines: an application of DEA and Tobit Analysis.
- [25] Suh, D., Hwang, J., & Oh, D. (2008, October). Do software intellectual property rights affect the performance of firms? case study of South Korea. In 2008, the Third International Conference on Software Engineering Advances (pp. 307-312). IEEE.
- [26] Gupta, D., Sahu, P. K., & Banerjee, R. (2009). Forecasting jute production in major contributing countries in the world. *Journal of Natural Fibers*, 6(2), 127-137.
- [27] Singh, A. K., Jha, S. K., Majumdar, B., Roy, M. L., Sarkar, S., & Ghorai, A. K. (2019). Impacts of climate-smart jute farming on resource use efficiency, productivity and economic benefits in rural Eastern India. *Outlook on Agriculture*, 48(1), 75-82.
- [28] Islam, M. M., Xiaoying, J., Uddin, M. E., & Bhuiyan, F. (2015). Status and constraints of jute cultivation in Bangladesh: an experience from selected upazilas under Chandpur district. *Asian Journal of Agriculture and Rural Development*, 5(8), 175.
- [29] Molla, M. M. U., Sabur, S. A., & Akhtar, S. CURRENT SCENARIO OF JUTE SECTOR IN BANGLADESH: DOMESTIC AND WORLD PERSPECTIVE. First issue: Volume 01 Issue 01, July-December 2013 Current Issue: Volume 02 Issue 02, October-December 2014.
- [30] Amin, M. A., & Sarker, S. (2023). Jute industry of Bangladesh: challenges and opportunities.
- [31] Chakraborty, C., & Maiti, S. (2018). Technical Efficiency of Jute Industry in India: A Nonparametric Approach. *Int. J. Social Science and Economic Research*, 3(09), 4931-4938.
- [32] Kiron, M. A., Hossain, M. E., & Hasan Chokdar, M. M. (2025). Assessing the Economic Impact of Climate Change on Rice Production in Bangladesh: A Ricardian Approach for Sustainable Agriculture. *Economics of Disasters and Climate Change*, 9(2), 359-373.