

Technical Efficiency and Its Determinants in Rice Production: A Stochastic Frontier Approach to Aus, Aman, and Boro Seasons

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Abstract

This study estimates the technical efficiency and its determinants among rice farmers in three seasons (Aus, Aman, and Boro) in Natore District in Bangladesh, employing the Cobb-Douglas SF approach using farm-level cross-sectional data. There were noticeable differences in the efficiency scores across the three seasons. Aman rice had the highest average efficiency score at 0.98, followed by Boro at 0.86 and Aus at 0.79. The closely clustered efficiency scores of Aman indicated that these farms were producing close to their feasibly optimal efficiency and, thus, the opportunity for improvement is limited. On the contrary, Aus and Boro appeared to have a wider gap between their average scores and optimal efficiency, implying they had significant room for improvement. On average, Aus farms could increase their output by 21% and Boro farms by 14% if they operated at the efficiency levels of the most efficient farmers. Of note is that Aman farmers had limited potential at 3% if they operated at the efficiency level of the most efficient Aman farmers. For those farmers experiencing the lowest efficiency potential, they could increase their output by 58% for Aus and 53% for Boro farms if they operated at the efficiency level of the most efficient farmers. Input elasticity indicated that among the rice farmers, the most important efficiency drivers across all seasons were land, fertilizer, pesticides, and irrigation. Labour was a significant factor only for Aus farmers. The inefficiency effects model also indicated that farm size and awareness of climate change contributed significantly to measuring technical efficiency. Although larger farms displayed greater efficiency levels, most noticeably for Aus farmers, this was not the case for Aman farmers. In contrast, age, education, and experience in farming had limited sensory effects in measuring the efficiency levels across the seasons. Findings suggest that environmental and structural factors more significantly contributed to measuring efficiency improve-

ment than individual preferences and characteristics of the farmers. This finding further signifies the need for season-based, environmental, and structural tailored strategies to optimise the use of farm size, distribution of inputs, and availability of inputs to build capacity for the improved technical efficiency of farmers across the Aus, Aman, and Boro seasons.

Keywords

Technical Efficiency, Cobb-Douglas Stochastic Frontier Production Function, Rice-Growing Seasons (Aus, Aman, Boro), Bangladesh Agriculture

1. Introduction

The United Nations Development Programme (UNDP) presents 17 Sustainable Development Goals (SDGs) to be reached by 2030. One of the most important is to eradicate global hunger and poverty, which aims to achieve food security, and to improve nutrition and promote sustainable livelihoods for everyone. The global population has increased three times since the mid-20th century [1] from an estimated 2.5 billion in 1950 to 8.0 billion as of November 15, 2022. The global population is projected to grow from the current 8 billion to 9.7 billion by 2050, an increase of more than 1.7 billion people [1]. A huge amount of food must be produced to feed such a large population on a diminishing amount of farmland. The world faces multiple crises of a global, overlapping nature in terms of an inevitably desperate worldwide hunger situation, the world's exhausted food systems, and populations impacted by hunger everywhere [2]. In the last few years, progress against hunger has generally declined due to the conflict in Ukraine, the impacts of climate change, and the global impact of the COVID-19 pandemic [2] [3].

One of the key sectors of the economy of Bangladesh is the agriculture sector. The role of this sector is due to the employment it creates, the dependence of the rural population of the country on agriculture for their livelihood, and the major contribution made by agriculture to the GDP of the country. Since the development of agriculture will have a considerable bearing on the fulfilment of the declared macro-economic objectives of full employment; reduction of poverty and hunger; increased food security, economic growth, and prosperity; and the development of the economy of Bangladesh, it is important that agricultural production be both efficient and productive so that a country as populated as Bangladesh can secure these objectives. It is noteworthy that during the Census of Agriculture 2019, it was found that there were more than 35.55 million households in Bangladesh, of which 16.9 million families, that is, 48% of all the families in the country, are engaged in agriculture [4]-[6]. It can be deduced from the above that to bring about improvements to the agriculture sector and protect the livelihood of the vulnerable rural population of the country, the government departments, politicians, and stakeholders should prioritise improvements to agricultural production and to the efficiency of agriculture with the aim of achieving sufficient food secu-

rity.

Rice, the most important food crop in Bangladesh, plays a very significant role in the economy of Bangladesh. The production of rice not only provides food security in the country but also makes an immense contribution to the foreign currency earnings of the country. However, despite these benefits, the country is still suffering from food shortages, and to cope with this shortage, the country is resorting to food imports while also increasing the production of crops in the country. Due to the increasing price of food globally, it has become very difficult for the country to sustain this position. Furthermore, there has been a great increase in the current prices of the modern inputs of agriculture, which has made it impossible for farmers in Bangladesh to benefit from such inputs [7]. Rice, like many other crops, is being regarded by many governments as a strategic crop, as it is not only the staple food of the people who are poor but is also a major source of employment and income [8]-[11]. There are about 118 rice-producing countries in the world; Asian countries accounted for about 86% of the land cultivated for rice and supplied about 90% of the global rice production from 2017 to 2019 [12]. According to the FAO (2022) report, the rice consumption level per year per capita is highest for the Asian countries (76 kg), followed by the South American, African, Australian, and North American countries, while the consumption rate in Europe is the lowest. As mentioned previously [1], the world population is estimated to increase by another 2 billion in the year 2050, and it is expected that most of the increase will be taking place in Asia and Africa. Accordingly, additional rice will need to be produced for these continents.

Rice is the staple food of a major portion of the populations of Asia, including Bangladesh, and rice is increasingly the daily food for African consumers [11]. In addition to this, output from rice farms has been increased to ensure that rice production is as efficient as possible. Hence, there is a global concern to find a way to produce rice in such a way as to be able to shoulder the burden of these various problems, such as climate change, increasing volatility of the market, and socio-economic problems, because rice is the staple food of 50% of the world population [13] [14].

In Asia, rice retains its status as a food grain, and due to consumers' food habits, forms a major part of the population's diet. Of course, rice supply and demand vary according to grades and rise in per capita earning [15]. Nonetheless, food security must be achieved, and according to [16], this is a precondition for rice security of Bangladesh, which according to the population and housing census, 2022, is experiencing an annual growth of 1.22% [4]. Food production efficiency of agriculture of Bangladesh must be improved significantly. This means there is ample room for growth and development of the national agriculture, which gives hope for the future.

Bangladesh has an extremely difficult task to attain food security and achieve SDG1 "No Poverty" and SDG2 "Zero Hunger". The area under cultivation is very small, and there is a huge population in a very congested area, while every year

sees a reduction in area of cultivation due to the intense pressure of an increase in population and urbanisation. It makes the position of food security precarious. However, the limit represented by the geographical area and territory restricts any further extension for the additional cultivation of land and does not permit any increase in cropping intensity.

Therefore, this study attempts to identify methods of increasing rice production. One method is to reduce the inefficiency in farm production; this might be accomplished by the proper utilisation of agricultural inputs and by determining and improving other factors that give rise to farm efficiencies. In a country that is poor in resources like Bangladesh, where there is very little likelihood of the development and use of new inventions, empirical investigation of the technical inefficiency of the production of rice, and identifying its determinants is of vital importance [13]. Factors such as age, educational attainment, off-farm income, farming experience, climate knowledge, farmers' awareness about climate changes, and farm size are some of the determinants of inefficiency that lead to variations in the efficiency of production. This study will evaluate the technical inefficiency of production as determined by the stochastic frontier production function. The SF production function and inefficiency effects are estimated simultaneously in a single-stage mode [17] using the STATA/SE 15.1 statistical software package. The remainder of this section of the thesis has been organised as follows. There is a review of related academic literature in Section 2. In Section 3, the analytical framework/message is shown. Section 4 includes clear and detailed information about the methodology, the area of study, and the survey method, and the table of the variables gives the data. This, in turn, enhances the credibility in the methodology of the research. Section 5 gives clear and precise details of the several models and hypotheses of the research, while Section 6 includes an analysis of the findings. Lastly, Section 7 presents a conclusion to the research.

2. Literature Review

Technical efficiency plays an important role in enhancing agricultural productivity, profitability, and sustainability. This becomes particularly important in the rice sector, as rice is the staple food for nearly half of the world's population. Therefore, by efficiently producing rice, it is possible to secure a supply of food to the masses, provide a livelihood for the producers, and increase food security [14] [18]. The impact of the efficient production of rice results not only in the welfare of individual households but also has an influence on the national economic growth. This complements agricultural growth, conserves foreign exchange for the country, provides raw materials for other sectors of the economy, and aids in the development of the economy as a whole. In the case of Bangladesh, with its agriculture largely dependent on rice, poor efficiency in agriculture relating to rice has a direct bearing on the country achieving the SDGs of meeting food security and reducing poverty. This section of the thesis presents a comprehensive review of the literature that has been published pertaining to farm efficiency and those cru-

cial elements driving performance in various countries.

The last quarter of the 20th century saw agricultural research being neglected due to the low global prices for agricultural produce [19]. However, recently, agricultural research has gained importance in academic settings and is a subject that must now be considered in policy-making. There is a renewed recognition of the need to understand that to achieve sustained increases in agricultural productivity requires not only technological improvements but also improvement in the efficiency with which the existing resources are utilised.

Research undertaken in various rice-producing countries shows there is scope for increasing efficiency considerably, though this increase is highly influenced by some special features of the farms producing the rice together with particular economic and environmental conditions. Studies in Vietnam [20] have revealed that water distribution and pollution affect the efficiency of rice production very considerably. In India, the rice growers in U.P. attained an average efficiency of 72% from their wheat growing, indicating a significant scope for increasing productive power by the use of existing technology [21]. It is evident from investigations that in Nepal, rice-growers have a generally high efficiency but that this fluctuates with sugar-cane cultivation [22]. Another study from Nigeria has shown that lowland farmers had higher efficiency compared to upland farmers [23]. There are two studies in Ghana and Ethiopia that have shown the importance of advanced technology, training and extension work, and education in producing higher technical efficiency [24] [25].

There is a fluctuation in agricultural efficiency, as seen in long-term surveys. For example, in Thailand, the overall efficiency declined on average until 2000. This again would indicate that irrigation systems and the correct management of resources were necessary for the continuance of the production [26]. Studies on agricultural efficiency have also been conducted in Malaysia, Sri Lanka, and Indonesia, where it has been shown that land use, co-operation among the farmers, and training in agricultural methods are important in producing efficiency [27]-[29]. In general, investigations of other countries across the world indicate that not only does institutional support help, but the environmental and social conditions produce important effects on the efficiency of rice farmers, in addition to the farming methods adopted.

Recent research on agricultural efficiency in Bangladesh has drawn attention to rice as not only a food staple and important product for the overall food security of households but also as a key output of the country's agricultural sector. Research reveals that the main determinants of agricultural output are labour, land, and irrigation [30]. Detailed investigations into the efficiency of rice cropping seasonal periods reveal some important information while repeatedly disclosing inefficiencies in the manufacturing process. For instance, [31] observed that the Boro farmers in areas that are not saline have, on average, been more efficient than their host farmers in saline areas, though the latter have been found to possess a greater trait of general adaptability to environmental conditions. In addition to

this, [32] stated that Aman farms have an average efficiency rating of 85%, but the efficiency is seriously impaired by the size of the family, low educational attainments, the salinity of the land, and the lack of any access to finance. Many investigations indicate that rice cultivators in Bangladesh are moderately to highly efficient, generally from 80% to 90% efficient [33]-[35]. These findings appear to show that a huge yield of rice can be achieved with improved management of the resources but without the necessity of improved methods of production through greater technological advances. The main factors that generally affect efficiency are the experience of the agriculturists, extension work, the availability of credit, and the character of the land. Other investigations on agricultural efficiency in this country clearly show the necessity of having not only mechanisation of agriculture but also financial inclusion. According to [36], farms using a greater percentage of machinery were found to obtain a higher efficiency. However, on the contrary, [37] found that through the provision of proper sources of acquiring credit, efficiency improved greatly among rice farmers. [38] have shown that it is not only important to increase the efficiency of agriculture, but it is also important to diminish the post-harvest losses to improve food security. Again, studies by [39] [40] show that although total productivity has improved from year to year, inefficiencies still exist, and age, education, and farming experience are all factors that influence performance.

Many researchers have looked at the efficiency of producing rice in Bangladesh, but they often focus on one rice-growing season at a time or on how one type of rice performs. As a result, there is little understanding of how well farmers grow rice (technical efficiency) and how sensitive they are to changes in inputs (output elasticities) across the three major growing seasons for rice (Aus, Aman, and Boro) when they are measured together under the same framework. The inability to assess and compare efficiencies and output elasticities across three rice-growing seasons in this way limits the potential to develop seasonally specific strategies for improving the efficiency of rice production in Bangladesh.

To fill this knowledge gap, this study employs the stochastic frontier approach to compare technical efficiencies, output elasticities and determinants of inefficiency for the Aus, Aman, and Boro rice-growing seasons. By comparing efficiency estimates among seasons, this study includes to the existing literature on SFA and provides direction for policymakers in Bangladesh that support the development of new agricultural policies based on productivity enhancements related to specific rice-growing seasons.

3. Analytical Framework

Technical efficiency refers to the ability of a firm to produce maximum attainable output using a given amount of inputs and available technology. [41] proposed that the dimension of technical efficiency of a farm should be measured by actual production as compared with the production that a fully efficient farm can turn out from the same supply of inputs. The stochastic frontier model is theoretically

respectable and empirically satisfactory in the study of technical efficiency. The model considers measurement error, the errors of statistics, and factors in external random shocks beyond the control of the firm so that farmers will tend to adjust the frontier at random [42] [43]. This study attempts to measure the technical efficiency of rice cultivation in the Aus, Aman, and Boro seasons by using the Ordinary Least Squares (OLS) model and SFA model. The OLS model assumes that there are no inefficiency effects in the model, while the SFA takes into account the inefficiency effects and applies the measure of technical efficiency.

A Likelihood Ratio (LR) test was performed to examine whether the SFA model was adequate. The null hypothesis of the LR test is that the data contain no inefficiency effects, which means that the OLS model is sufficient. Meanwhile, the alternative hypothesis is that the data contain inefficiency effects, which means that the SFA model is a good fit. In this study, the LR statistic is evaluated for each of the three seasons of rice (Aus, Aman, and Boro) against the critical value of the chi-square, at the 5% significance level. The LR test showed that the LR statistic exceeded the critical value for the three crops, which led to the conclusion that the null hypothesis (H_0) is rejected. This means that SFA model is a better fit than the OLS model. As the SFA model achieves a better fit by introducing inefficiency effects in the production process, the SFA model is selected for the purpose of further analysis. [8] showed that the stochastic frontier production function and the inefficiency effects model should be estimated simultaneously. According to these specifications, the general SFA model is defined as follows:

$$y_i = f(x_i; \beta) + \varepsilon_i; \quad i = 1, 2, \dots, N \quad (1)$$

Indeed, in this case, y_i refers to the rice revenue of the i -th farm, and x_i is a vector of k inputs (or their associated costs). The vector β consists of unknown parameters that are important and require estimation. The function $f(\cdot)$ is a suitable function form for the frontier, which might be Cobb-Douglas, trans-log, or quadratic. ε_i is an error term, and N is the total number of observations available for analysis. The stochastic frontier production model, better known as “the composite error model”, is based on the idea that the error term ε_i can be broken into two distinct components consisting of the stochastic random error component, which consists of random shocks (white noise), and a technical component of inefficiency, defined as follows:

$$\varepsilon_i = v_i - u_i \quad (2)$$

The symmetric double-sided, normally distributed random error (v_i) is one of the factors of this compound statistical model, which reflects a great many random happenings over which farmers have no control, such as those due to weather conditions, natural disasters, other unaccounted-for phenomena, external shocks, errors in measurement, and variability of other kinds of statistical noise. The variables of which it consists are identically independent and normally distributed as $v_i \sim N(0, \sigma^2)$ and are independent of the u_i . Consequently, this random error allows the production frontier to vary between farm and farm or within farms,

showing that the production frontier essentially is stochastic. The asymmetrical, non-negative error term u_i representing a one-sided ($u_i \geq 0$) element of efficiency measures the technical inefficiency of the i -th farm. The distribution of this parameter may be in the form of half-normal, exponential, truncated normal, or gamma distributions [42]–[44]. The assumption made here is that u_i is exponentially distributed, which is in accordance with assumptions made in other literature that has been published in applied stochastic frontier theory. The truncated normal distribution can be arrived at by applying truncation at zero to the normal distribution, having as characteristics mean μ and variance σ_u^2 . If μ is set as equal to zero, the distribution is said to be in the form of a half-normal distribution. The variance parameters of the model will be expressed in the following manner:

$$\sigma_s^2 = \sigma_v^2 + \sigma_u^2 \text{ and } \gamma = \sigma_u^2 / \sigma_s^2 \text{ so that } 0 \leq \gamma \leq 1 \quad (3)$$

The parameter γ must be within the limits of 0 and 1. This time σ_s^2 represents the total variation in the dependent variable because of both random shocks (σ_v^2) and technical inefficiency (σ_u^2). The parameter γ distinguishes between the effects of inefficiency on output. The Maximum Likelihood Estimation (MLE) of the Stochastic Frontier (SF) as derived in Equation (1) yields consistent estimators of the parameters β , γ , σ_s^2 . [43] stated the likelihood function regarding the two variance parameters, which are $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\lambda = \sigma_u / \sigma_v$. However, [9] put forth the parameter, $\gamma = \sigma_u^2 / \sigma_s^2$, since this is limited to values between 0 and 1, providing a reasonable initial estimate for an iterate maximisation procedure as opposed to the λ -parameter, which can take on values of any non-negative value. A γ estimate toward 0 implies that there is considerable variation in the observed output of the frontier, which may be attributed to random stochastic effects. γ Approach 1 indicates that the inefficiency effects or variations in technical efficiency account for considerable amounts of the arbitrary fluctuations in output.

4. Study Area, Sampling Procedure, and Data Background

4.1. Study Area and Sampling Procedure

The data used in this study were gathered from a primary dataset located in Gurudaspur Upazila in Natore District of the Rajshahi Division of northwestern Bangladesh. Gurudaspur is highly intensive in agricultural production, which is the major source of livelihood for most of the population. Other than rice, it is also dominated by rice relative to other crop production types. In this site, there are three seasonal varieties of rice, namely, Aus, Aman, and Boro rice, which are the dominant agricultural crop. Each of these rice varieties has its own season and growing season practices. The three seasonal rice varieties are the primary crop grown in Gurudaspur all year round, denoting a unique characteristic of farming practices in the region. Due to the region's focus upon rice diversity and the important contributions to farming practices for the region, Gurudaspur is an ideal area to analyse technical efficiency in rice farming.

The study compiled data from 150 households of rice-growing farmers. Pro-

duction details were collected separately for each season of rice (Aman, Aus, and Boro) that these rice farms produced and were to be analyzed for 2023-2024 crop seasons. Thus, there were 450 total household-season observations (150 households times 3 seasons), which serve as the unit of analysis in the stochastic frontier estimation.

The data for this study were collected in the first quarter of 2024, and the focus was on the production practices of the 2023-24 crop year. The research survey included a series of questions designed to elicit comprehensive data on household socioeconomic characteristics, rice production, and inputs, as well as perceived prices for inputs and outputs. The survey included a total of 150 distinct rice-farming households from each of the three rice growing seasons—Aus, Aman, and Boro. Farmers were interviewed using a semi-structured interview process. This thorough process ensured that a broad yet very detailed data collection process occurred, with every possible operational effort being made to situate and describe the agriculture production realities of Gurudaspur's rice production systems.

A multistage simple random sampling approach was used to ensure the sample was both representative and free of bias, and it was chosen for its recently highlighted ability to promote coverage of sample bias free and heterogeneous populations [45] [46]. The multistage simple random sampling technique was implemented to ensure that the sample was representative of rice-farming households as well as being heterogeneous with respect to characteristics representing households in Gurudaspur. In this study, the first stage randomly selected five unions from the six unions found in Gurudaspur Upazila. The second stage developed a complete list of rice-farming households in each of the selected villages with the help of the Upazila Agriculture Office. Three villages from each of the five unions were randomly selected with a total of fifteen households using the same approach—that is, ten households were randomly selected from a complete list of rice farming households. As such, in total, 150 rice-producing farming households were sampled in this research study.

This structured sampling approach, which is also grounded on principles of probability sampling, lends additional credibility and generalisability to the findings [47] [48]. In addition, it ensures that there is adequate representation of the heterogeneity found across villages and unions regarding practices in rice farming, input utilisation, and socioeconomic characteristics.

4.2. Brief Description of the Data Set

The data set gives information regarding the value of output, costs of inputs, and particulars of farms and households for each rice season during the year. The value of output is computed by multiplying the total production (in quintals) with that of price per quintal. The cost involved in respect of land used for the production of rice consists of the rent of the land and does not depend on who is the owner of the land. In the case of rented land, it represents the actual payments made to landowners. In the case of land cultivated by the owners, the local land rental rates

give an implicit rental value of the land, which involves the element of opportunity cost of getting the land used. The cost of seeds and seedlings involves the total expenditure incurred in obtaining the rice seeds or seedlings.

The cost of labour includes the judiciously valued contributions of the family labour and hired labour used for work before and after planting as well as for harvesting, excluding threshing. The cost of labour days multiplied by the average day's wage was obtained. The cost of fertilizers and pesticides includes the total outlay on chemical fertilizers, organic manure, herbicides, and insecticides. The cost of irrigation includes the total outlay on watering the rice fields, including the payment for irrigation by contract and the working of irrigation systems under self-management. These costs include the cost of diesel and electricity for pumping water and all other implements employed in irrigation. The cost of machinery includes all costs incurred in using agricultural machinery and implements for the preparation of soil, planting, weeding, and other work in the production process.

Initially, the total output measure and total output cost include all input costs such as land rent, seed and seedling costs, labour costs, fertilizer and pest control costs, irrigation costs, and machineries costs, and these are recorded in the local currency (Taka) initially. To aid inter-country analysis and mutual understanding, these monetary or cost values have been converted into U.S. dollars (US\$) based on the working rate of exchange between Bangladesh and the U.S. (US\$ 1 = BDT. 115.42) (<https://www.exchange-rates.org/exchange-rate-history/usd-bdt-2024>) at the time of collection of the data. This world view makes the study interesting and useful to the rest of the world. The full dataset on socioeconomic costs includes details of the main socioeconomic costs, such as age, education (all measured in terms of years), farm experience, and awareness of climate, etc. of the farm household. The total farm size measured in decimals also reflects the total area under rice cultivation. The off-farm means of livelihoods of the farm households is also expressed in US\$. For the details of the descriptive statistics of the data set, please see **Table A1**.

5. Specification of the Model

5.1. Stochastic Frontier Production Model

The empirical analysis utilises the Cobb-Douglas production function. This was originally developed by [49] and is used to estimate the stochastic production frontier, as shown in the following equation:

$$\ln Y_i = \beta_0 + \sum_{j=1}^J \beta_j \ln X_{j,i} + (V_i - U_i) \quad (4)$$

In this specification,

Y_i = Total market value of output of farm i ;

$X_{j,i}$ = Input j employed by farm i ;

β_j = Elasticity of output related to input j ;

V_i = Random error/statistical noise, which is assumed to be normally distributed as $N(0, \sigma_v^2)$;

U_i = Inefficiency term, which is non-negative;

J = Number of inputs used.

Specifically, this study applies a model characterised by the following equation.

$$\ln Y_{i,k} = \beta_{0,k} + \beta_{1,k} \ln X_1 + \beta_{2,k} \ln X_2 + \beta_{3,k} \ln X_3 + \beta_{4,k} \ln X_4 + \beta_{5,k} \ln X_5 + \beta_{6,k} \ln X_6 + (V_{i,k} - U_{i,k}) \quad (5)$$

where

$\ln Y_{i,k}$ = Total market value of rice season k for the i^{th} farm;

X_1 = Total market value of land rent cost;

X_2 = Total market value of seed, seedling & planting cost;

X_3 = Total market value of labour cost;

X_4 = Total market value of fertilizer and pesticide cost;

X_5 = Total market value of irrigation cost;

X_6 = Total market value of machinery cost;

$\beta_{0,k}$ = Rice specific intercept;

$\beta_{j,k}$ = Rice specific coefficients for input j ($j = 1, \dots, 6$);

$V_{i,k}$ = Rice specific random error;

$U_{i,k}$ = Rice specific stochastic disturbance term;

$k \in \{\text{Aus, Aman, Boro}\}$: Rice-growing season.

The estimated model will be interpreted, therefore, as a stochastic frontier based on value (not in terms of physical output). Since all the variables are expressed in a common monetary unit, there are fewer comparability problems due to differences in the physical measurement units on the different inputs.

5.2. Inefficiency Effect Model

We determine the technical inefficiency (u) by calculating the difference between unity and TE. In its most basic form, the TE effect can be shown as a linear function of the socioeconomic and farm management factors of a household. The following equation was used to define the effect [17] [50] [51]:

$$u_i = \delta_0 + \sum_{k=1}^6 \delta_k z_{ik} \quad (6)$$

In the context of the above equations, u_i represents the technical inefficiency effect, while δ_k refers to the coefficient of the explicative variables (inefficiency factors). The variable z_i indicates the socioeconomic condition of the farm, which explains inefficiency and does not necessarily depend on Y . From the literature review, it has been indicated that the use of inputs leads to inefficiency, and factors such as age, education, farming experience, awareness of the climate, size of the farms, and off-farm income also contribute to the TE of rice farms [38] [39] [52]-[55]. These variables will be used in the inefficiency effect model to analyse the effect of these factors on inefficiency. Thus, the inefficiency effects model may be expressed as:

$$u_{i,k} = \delta_{0,k} + \delta_{1,k} Z_1 + \delta_{2,k} Z_2 + \delta_{3,k} Z_3 + \delta_{4,k} Z_4 + \delta_{5,k} Z_5 + \delta_{6,k} Z_6 + \omega_{i,k} \quad (7)$$

where,

$u_{i,k}$ = Production inefficiency resulting from exogenous or farm-specific socio-economic factors and climate adaptation for farm i and crop k ;

Z_1 = Age of household head;

Z_2 = Education level of household head;

Z_3 = Farming experience;

Z_4 = Length of time aware of climate change;

Z_5 = Area of farm;

Z_6 = Off-farm income;

$\delta_{j,k}$ = Crop-specific coefficients for the inefficiency factors Z_j , these are unknown parameters to be estimated ($j = 1, \dots, 7$);

$\omega_{i,k}$ = Stochastic disturbance term for farm i and crop k ;

$k \in \{\text{Aus, Aman, Boro}\}$: Rice-growing season.

5.3. Technical Efficiency Model

The TE model is based on the SFA and the previously stated inefficiency effect models. The terminology used in the TE model aligns with those models. In the following model, $TE_{i,k}$ implies the TE of farm i for rice-growing season k , while $\delta_{j,k}$ indicates crop-specific coefficients for the j -th inefficiency factor. Assuming that k is a rice variety {Aus, Aman, Boro}, the TE for the i -th farm is expressed as [56]:

$$TE_{i,k} = \exp(-u_{i,k}) \quad (8)$$

where $u_{i,k}$ is derived from the inefficiency effects model (Equation (7)).

Thus, the TE for rice-growing season k is defined as:

$$TE_{i,k} = \exp\left(-\left(\delta_{0,k} + \delta_{1,k}Z_1 + \delta_{2,k}Z_2 + \dots + \delta_{6,k}Z_6 + \omega_{i,k}\right)\right), k \in \{\text{Aus, Aman, Boro}\} \quad (9)$$

5.4. Hypothesis Tests

Each rice season had these tests performed on it for the purpose of evaluating the functional forms, their inefficiency effects, and coefficients of determination:

Hypothesis 1

Null hypothesis (H_0): The inclusion of second-degree terms does not affect, in a meaningful manner, the conformance of the function to the observations. If the null hypothesis is true, then the Cobb-Douglas functional form is satisfactory in its representation of the relation. From a mathematical standpoint, the following is used:

$$H_0: \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = 0$$

The coefficients associated with the squared terms (land, seed, labour, fertilizer and pesticides, irrigation, machinery) are all determined to be zero.

Alternative hypothesis (H_1): At least one squared term has a significant impact on the model, suggesting that the quadratic functional form (modified trans-log) provides a better fit than the Cobb-Douglas model. From a mathematical perspec-

tive, there exists at least one β_j that is not equal to zero, specifically

$$H_1: \beta_j \neq 0, \text{ for } j = 7, 8, \dots, 12$$

This means that at least one square input contributes heavily to the output variation, thus making a quadratic functional form necessary.

Hypothesis 2

Null hypothesis (H_0): The inclusion of square and interaction terms does not significantly increase the goodness of fit of the model, implying that the Cobb-Douglas functional form gives a satisfactory representation of the relationship. Mathematically,

$$H_0: \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = 0$$

The coefficients associated with the squared and interaction terms (land, seed, labour, fertilizer and pesticides, irrigation, machinery) are all determined to be zero.

Alternative hypothesis (H_1): At least one squared or interaction term has a significant impact on the model, suggesting that the trans-log functional form provides a better fit than the Cobb-Douglas model. From a mathematical perspective, there exists at least one β_j that is not equal to zero, specifically

$$H_1: \beta_j \neq 0, \text{ for } j = 7, 8, \dots, 18$$

This suggests that at least one of the squared input variables significantly contributes to the variation in output, highlighting the need for a quadratic functional form.

Hypothesis 3

The null hypothesis (H_0) states that no inefficiency effects exist in the model, indicating that inefficiency effects are not important for the explanation of efficiency. Accordingly, the OLS is the model of choice ($\gamma = 0$).

The alternative hypothesis (H_1) states that inefficiency exists, implying that SFA is the model of choice ($\gamma > 0$). This means that the inefficiency factor has a significant role to play in the determination of technical efficiency.

Hypothesis 4

Null hypothesis (H_0): The coefficients of the determinants in the inefficiency model are found to be zero ($H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$).

Alternative hypothesis (H_1): At least one of the coefficients of the determinants in the inefficiency model is not zero ($H_1: \delta_i \neq 0; i = 1, 2, \dots, 6$).

The generalised LR test was used to test the hypotheses. To obtain the LR, the formula is $LR = -2[L(H_0) - L(H_1)]$ where $L(H_0)$ is the value of the likelihood function of the frontier model under the null hypotheses, and $L(H_1)$ is the value of the likelihood function of the frontier model under the alternative hypotheses. If the resulting LR exceeds the critical chi-square (χ^2) value for the given level of significance (e.g., 5%), the null hypothesis (H_0) will be rejected in favour of the alternative hypothesis (H_1). If, however, the resulting LR for the null hypotheses is less than or equal to the critical chi-square (χ^2) value for the given level of significance (e.g., 5%), the null hypothesis (H_0) will not be rejected.

6. Analysis and Interpretation of Results

6.1. Model Selection

This study compares the OLS model and the SFA model to determine the most suitable approach for analysing TE. The SFA model was chosen for further analysis because it demonstrates a superior fit by effectively incorporating inefficiency effects in the production process. To find the parameters of the Cobb-Douglas stochastic frontier production function, the quadratic production function, and the trans-log model, the advanced capabilities of the Stata/SE 15.1 software were utilised. This was accomplished using Maximum Likelihood Estimation (MLE), and **Table 1** presents the resulting estimates.

To discover the best applied functional form of the stochastic frontier model with a various assumption on the error distribution, tests were performed on the Cobb-Douglas, quadratic, and trans-log forms. The log LR test was subsequently employed in deciding whether to reject or not one of the model specifications in favour of another as indicated from the analysis of the chi-square probability table, by comparing the values obtained with the critical value in the 5% region. First, the Cobb-Douglas model was compared with the quadratic model to see if the Cobb-Douglas model gave a better result from the analysis of the data. The null hypothesis was not rejected, and the quadratic model was rejected from further consideration. Finally, the results of the comparison between the Cobb-Douglas and the trans-log function showed that the Cobb-Douglas model gave a good description of the data with regard to the value of coefficients of input, and the test on the null hypothesis was not rejected.

6.2. Evaluation of the Hypothesis Test

Table 2 provides a summary of the hypothesis testing. To test hypothesis 1, in case of choosing the functional form of the stochastic frontier production, the LR test results for Aus, Aman, and Boro demonstrate that the Cobb-Douglas (CD) functional form offers a more parsimonious and adequate fit than the Quadratic (QD) functional form of the SF production model, as the LR statistic for each comparison was below the critical value for chi-squared (12.59) with the appropriate degrees of freedom (d.f. = 6) at the 5% significance level. In addition, for hypothesis 2, when choosing between Cobb-Douglas (CD) and Trans-Log (TL), CD is the better choice according to the LR test.

Hypothesis 3 provides the LR test results covering the comparison of the OLS and SFA models for the Aus, Aman, and Boro rice seasons. The null hypothesis ($H_0: \gamma = 0$) is such that there is no inefficiency effect, and therefore, the OLS model is suitable. In all the rice seasons, the LR statistic exceeds the critical chi-square value of 2.71, indicating a rejection of the null hypothesis. This shows the existence of inefficiency effects, and the SFA model is therefore preferred to the OLS model. The results indicate that TE plays an important part in the variation of outputs, and it is for this reason that the SFA method is most suitable in the efficiency analysis among the three rice-growing seasons.

Table 1. Maximum likelihood estimates of cobb-douglas, quadratic, and trans-log stochastic frontier production functions.

Functional form	Variables	Cobb-Douglas ML Estimates			Quadratic ML Estimates			Trans-log ML Estimates		
		Rice-growing Seasons			Rice-growing Seasons			Rice-growing Seasons		
		Aus	Aman	Boro	Aus	Aman	Boro	Aus	Aman	Boro
Cobb-Douglas	Intercept	β_0	2.49*** (0.14)	1.71*** (0.106)	1.943*** (0.183)	1.762*** (0.652)	2.324*** (1.157)	0.454 (1.053)	2.325** (0.756)	1.046 (1.421)
	Inland	β_1	0.284*** (0.066)	0.446*** (0.055)	0.336*** (0.131)	0.545 (0.405)	0.000 (0.929)	0.98** (0.494)	0.419 (0.417)	0.395 (0.593)
	Inseed_seedling	β_2	0.078 (0.073)	0.219*** (0.045)	0.539*** (0.164)	-0.097 (0.260)	0.695 (0.707)	0.048 (10.014)	-0.443 (0.440)	0.771 (1.108)
	Inlabour	β_3	0.099*** (0.037)	0.049 (0.031)	0.092 (0.059)	-0.066 (0.208)	0.134 (0.352)	0.218 (0.192)	-0.346 (0.309)	1.576 (0.684)
	Infert_pest	β_4	0.159*** (0.037)	0.096*** (0.032)	0.151*** (0.056)	0.215 (0.219)	0.377 (0.365)	0.708 (0.479)	0.168 (0.452)	0.585 (0.689)
	Inirrigation	β_5	0.233*** (0.052)	0.182*** (0.038)	0.091* (0.054)	0.388*** (0.191)	0.125 (0.298)	-10.03 (0.679)	0.622 (0.406)	-0.148 (0.487)
	Inmachinery	β_6	0.164* (0.097)	0.013 (0.021)	-0.197** (0.092)	0.013 (0.096)	-0.443 (0.394)	0.611 (10.039)	0.546* (0.296)	-2.17*** (0.828)
	$[\ln(\text{land})]^2$	β_7				-0.010 (0.038)	0.028 (0.084)	-0.082 (0.056)	0.001 (0.039)	-0.019 (0.090)
	$[\ln(\text{seed})]^2$	β_8				0.039 (0.032)	-0.017 (0.084)	0.372 (0.624)	-0.164 (0.326)	-3.31*** (1.19)
	$[\ln(\text{labour})]^2$	β_9				0.014 (0.022)	-0.006 (0.037)	-0.137 (0.152)	0.145 (0.097)	-0.681** (0.291)
Quadratic	$[\ln(\text{fert_pest})]^2$	β_{10}				-0.013 (0.025)	-0.021 (0.038)	0.184 (0.168)	-0.201 (0.145)	-0.364 (0.472)
	$[\ln(\text{irrigation})]^2$	β_{11}				-0.035 (0.031)	-0.004 (0.034)	-0.69** (0.29)	-0.095 (0.128)	-0.294 (0.274)
	$[\ln(\text{machinery})]^2$	β_{12}				0.000 (0.016)	0.031 (0.050)	-0.819 (0.850)	-0.060 (0.104)	-1.457* (0.815)
	Inseed. Infert_pest	β_{13}						-0.71** (0.36)	0.549* (0.325)	0.915 (1.088)
	Inseed. Inirrigation	β_{14}						-0.182 (0.607)	-0.127 (0.365)	2.333*** (0.806)
	Inseed. Inmachinery	β_{15}						0.134 (1.357)	-0.039 (0.255)	3.237* (1.734)
	Inlabour. Inmachinery	β_{16}						0.279 (0.308)	-0.274 (0.186)	1.370** (0.590)
	Infert_pest.	β_{17}						0.236 (0.316)	-0.154 (0.299)	-0.163 (0.523)
	Inirrigation.	β_{18}						1.396 (.878)	0.412* (0.213)	-1.57*** (.553)
	Inmachinery									
Variance parameters										
Trans-log	$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.677	0.747	0.526	0.681	0.736	0.495	0.748	0.774	0.576
	$\sigma_v^2 = (\sigma_u^2 + \sigma_v^2)$	0.115	0.087	0.097	0.113	0.087	0.095	0.115	0.084	0.092
	Log likelihood	174.04	216.88	195.49	177.52	218.78	197.66	182.54	222.38	205.43
	sigma_v	0.038	0.022	0.046	0.036	0.023	0.048	0.029	0.019	0.039
	Sigma_u	0.077	0.065	0.051	0.077	0.064	0.047	0.086	0.065	0.053

Note: Standard errors in parenthesis; *p < 0.10, **p < 0.05, ***p < 0.01.

The findings of LR test of hypothesis 4 serves to show the important contribution of farm and household characteristics to the inefficiency of rice production in all the three seasons (Aus, Aman, and Boro). The null hypothesis is that the entire set of coefficients of the inefficiency determinants, namely, the age, the education, the farming experience, the awareness of climate change, the farm size, and the off-farm income, are equal to zero. The results show that these are not an important factor in the determination of inefficiency. Thus, it can be concluded that a model that does not include them will be appropriate. For the Aus and Aman rice varieties, the LR statistic exceeds the critical chi-square value of 12.59. The addition of the inefficiency determinants helps the model considerably. The null hypothesis is rejected. Therefore, farm and household characteristics are important factors in the determination of inefficiency in Aus and Aman seasons of rice growing. The case of Boro rice is different because the LR statistic of 2.79 is less than the critical value (12.59). The determinants of inefficiency therefore do not contribute to any great extent to the model, and therefore, the null hypothesis is not rejected.

Table 2. Synopsis of hypothesis testing for parameters in stochastic frontier and inefficiency effect models.

Null Hypotheses	LL (H ₀)	LL (H ₁)	LR	χ^2 Critical Value	Decision
Aus Rice					
1) Cobb-Douglas functional form sufficiently represents the relationship against quadratic functional form (H ₀ : $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = 0$)	174.04	177.52	6.96	12.59	Do not reject H ₀
2) Cobb-Douglas functional form sufficiently represents the relationship against trans-log functional form (H ₀ : $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = 0$)	174.04	182.54	17.00	21.03	Do not reject H ₀
3) There is no inefficiency effect, indicating that OLS is the appropriate model (H ₀ : $\gamma = 0$)	114.94	174.04	118.20	2.71	Reject H ₀
4) The coefficients of the determinants in the inefficiency model equal zero (H ₀ : $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$)	174.04	186.65	25.23	12.59	Reject H ₀
Aman Rice					
1) Cobb-Douglas functional form sufficiently represents the relationship against quadratic functional form (H ₀ : $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = 0$)	216.88	218.78	3.81	12.59	Do not reject H ₀
2) Cobb-Douglas functional form sufficiently represents the relationship against trans-log functional form (H ₀ : $\beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = 0$)	216.88	222.38	11.00	21.03	Do not reject H ₀
3) There is no inefficiency effect, indicating that OLS is the appropriate model (H ₀ : $\gamma = 0$)	192.72	216.88	48.32	2.71	Reject H ₀

Continued

4) The coefficients of the determinants in the inefficiency model equal zero ($H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$)	216.88	225.37	16.98	12.59	Reject H_0
Boro Rice					
1) Cobb-Douglas functional form sufficiently represents the relationship against quadratic functional form ($H_0: \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = 0$)	195.49	197.66	4.34	12.59	Do not reject H_0
2) Cobb-Douglas functional form sufficiently represents the relationship against trans-log functional form ($H_0: \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = 0$)	195.49	205.43	19.89	21.03	Do not reject H_0
3) There is no inefficiency effect, indicating that OLS is the appropriate model ($H_0: \gamma = 0$)	189.11	195.48	12.74	2.71	Reject H_0
4) The coefficients of the determinants in the inefficiency model equal zero ($H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$)	195.49	196.88	2.79	12.59	Do not reject H_0

Therefore, the farm and household characteristics do not contribute greatly to the explanation of the inefficiency of Boro rice. It is better, therefore, to use a simpler model excluding these characteristics in determining the efficiency of Boro rice, as it is a seasonal product.

6.3. Estimation of Technical Efficiency (TE)

The TE values indicate the efficiency of operation of the farm relative to the estimated production frontier. The estimates of TE of the Aus, Aman, and Boro rice-growing periods are provided in **Table 3**. The average TE for the three rice-growing periods is characterised by greatly differing degrees of efficiency. The average TE for Aus rice is nearly 0.79, while for Aman and Boro rice, the mean TE values are greater at about 0.98 and 0.86, respectively. This result indicates that Aman farms on average have their operations nearer to their respective production frontiers than Aus and Boro farms have. The lower TE in Aus and Boro farms indicates considerable possibilities for improvement in the efficiency of cultivation practices.

Table 3. Summary of technical efficiency for Aus, Aman, and Boro seasons.

Rice Variety		Aus			Aman			Boro		
TE Level ↓	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.	
≤0.80	264	58.67	58.67	10	2.22	2.22	157	34.89	34.89	
>0.80 & ≤0.90	44	9.78	68.44	20	4.44	6.67	9	2.00	36.89	
>0.90	142	31.56	100	420	93.33	100	284	63.11	100	
Total Farms	450	100		450	100		450	100		
TE Distribution ↓	Value	Percentage		Value	Percentage		Value	Percentage		
Mean	0.7903	79.03		0.9765	97.65		0.8586	85.86		

Continued

Standard Deviation		0.1355		0.0479		0.1519
Minimum	0.4196	41.96	0.6644	66.44	0.4706	47.06
p25	0.6814	68.14	0.9782	97.82	0.6932	69.32
p50 (Median)	0.7610	76.10	0.9973	99.73	0.9560	95.60
p75	0.9444	94.44	0.9984	99.84	0.9790	97.90
Maximum	0.9920	99.20	0.9990	99.90	0.9918	99.18

6.4. Distribution of Technical Efficiency among Rice-Growing Seasons

The distribution of the TE of rice among the Aus, Aman, and Boro crops exhibits a distinct pattern, which is confirmed from the average of given in **Table 3** and the box plot (**Figure 1**). Among the three seasons, Aman rice gives a high average TE, which is equal to 0.9765, and the average TEs of Aus and Boro are 0.7903 and 0.8586, respectively.

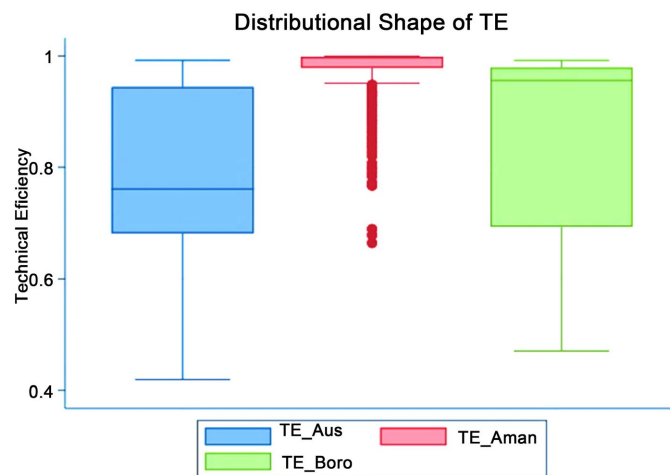


Figure 1. Distributional shape of technical efficiency.

That means farmers are on average 97.65% technically efficient in cultivating Aman rice and 79.03% and 85.86% efficient in cultivating Aus and Boro rice, respectively. The Aman crop also shows the minimum variability among the TE values; this is observed from the standard deviation, which is equal to 0.0479, while for the Boro and Aus crops it is 0.1519 and 0.1355, respectively. This difference is also confirmed by the minimum of the TE, since the Aman crop shows a very high minimum efficiency value (0.6644) compared to Aus (0.4196) and Boro (0.4706) rice.

The Interquartile Range (IQR) provides additional information on the distributional characteristics of TE. Aman rice has a very high median efficiency of 0.9973 and a very low IQR ($p25 = 0.9782$, $p75 = 0.9984$), which indicates that most Aman farmers produce near the efficiency frontier. The existence of multiple observations below the 1st quartile provides evidence that a subset of the Aman farmers is less efficient. Aus and Boro, in contrast, exhibit wider IQRs, with Boro hav-

ing the greater upper extreme value, giving a maximum TE of 0.9918. The boxplot confirms the above conclusions, outlining the close distribution of TE scores for Aman rice, with only a small number of TE scores being on either side of the mean efficiency.

On the other hand, Aus and Boro rice have a wider distribution, with Boro having a larger concentration of farms near the upper quartile, so that it shows some considerable spread towards the lower values of TE. It is apparent that on average, Aman rice farms are more efficient than Aus and Boro ones, coupled with a smaller variability. The greater dispersion of TE for Aus and Boro rice would tend to indicate that there are less efficient farms in existence and that factors such as management of inputs, farm characteristics, or production conditions may have a bearing upon the efficiency differences.

6.5. Implication of Variations in Technical Efficiency

Findings on the distribution of TE indicate that for Aus rice, if the average farmer in the sample were to realise the TE level of the most efficient farmer, the average farmer could increase, on average, by about 21% [$1 - (0.79/0.99)$] the output of their farm. Likewise, the least technically efficient farmer could increase their TE about 58% [$1 - (0.42/0.99)$] by attaining the TE levels of the most efficient farmer. With respect to the Aman and Boro varieties, if the average farmer in the sample could obtain the TE levels of the most efficient farmer, they could increase their output respectively by about 3% [$1 - (0.97/0.99)$] and 14% [$1 - (0.86/0.99)$].

In the same sense, the lowest technically efficient farmer could increase TE by about 34% [$1 - (0.66/0.99)$] and 53% [$1 - (0.47/0.99)$] respectively for Aman and Boro rice by achieving the levels of TE reached by the most efficient farmer. The mean TE values of 79%, 97%, and 86% result in output losses of 21%, 3%, and 14% respectively due to inefficiencies in Aus, Aman, and Boro rice production. Therefore, this result indicates there are possibilities of efficiency improvement of 21%, 3%, and 14% respectively, for these rice-growing seasons.

6.6. Examination of the Distribution Shapes of TE across Rice-Growing Seasons

As various SF models are applied for each rice-growing season, a direct comparison of the TE for various rice seasons is practically not possible, as it is necessary to realise that each rice-growing season shows its own frontier, which must inevitably have different assumptions and aspects. However, despite using different frontiers by means of the box plot, it will be possible to obtain a relative view of the distribution of the TE for each rice-growing season in its own group. This gives an idea of the central tendency (median) of the IQR, and the outliers, where necessary, of the TE distribution for each rice-growing season. Not only will this distribution shape of the TE permit a comparison of the shape of the TE distribution for each rice-growing season separately, but it will also aid in obtaining a rough comparison of the extent of the TE distributions, hence permitting an overview of the effect of the various rice-growing conditions on this characteristic of

the rice crop when planted in the various rice-growing seasons.

Aman and Boro rice have greater median TE, ranging near 1 than Aus rice. Aus has a notably lower median TE, which indicates that its efficiency is, on average, less than that of Aman and Boro. Aman has a small IQR, which shows that the TE values are closely clustered about the median. Aus and Boro have a wider IQR, indicating greater variability in TE among farms growing Aus and Boro rice. Aman has many outliers under the main distribution of TE, which indicates that some farms are showing considerably lower efficiencies. Aus and Boro have a greater number of very low outliers, indicating a greater variability of TE among the Aus and Boro crops. Aman has shorter whiskers, which indicates a greater uniformity of TE.

6.7. Estimation of Cobb-Douglas Stochastic Production Frontier (Output Elasticity)

We estimate a Cobb-Douglas stochastic frontier for production using data from three rice-growing seasons to evaluate the impact of inputs on rice output. The model accounts for technological inefficiency, which is represented by stochastic error components. $\ln\sigma^2_v$ (log of variance of random error, σ^2_v) reflects the level of statistical noise or measurement error in the production process. The results (Table 4) demonstrate that each of the three rice-growing seasons—Aus, Aman, and Boro—shows negative and highly significant $\ln\sigma^2_v$ values. This suggests that σ^2_v has a minor effect, meaning external noise has a limited influence on output variation. The lowest $\ln\sigma^2_v$ value is found in Aman (−7.67), indicating its production is less affected by random shocks compared to Aus (−6.32) and Boro (−6.12).

The Cobb-Douglas stochastic frontier model, a crucial tool for analysing rice production, measures the output elasticity of different inputs across the three rice-growing seasons—Aus, Aman, and Boro. With all other inputs held constant, these elasticities indicate the percentage change in output resulting from a 1% change in each input. Changes in these inputs influence rice output across the Aus, Aman, and Boro seasons, as shown by the estimated elasticity for land, seed, labour, fertilizer, pesticides, irrigation, and machinery.

Significant positive elasticity has been found to have statutory significance with regard to all the inputs excepting seed. In Aus rice, land, machinery, and irrigation have been found to be the most important inputs. The coefficient of seed has not been found to be significant; hence, variation in the seed input does not significantly affect the output of Aus rice. The most elastic and significant inputs of Aman rice are land and seed. Thus, if land and seed are increased, there is a significant increase in the production. The input of fertilizers, pesticides, and irrigation is also of some importance, showing the significance of chemical inputs and the supply of land water in the production of Aman rice. The study has found that the labour is either made optimum, or the mechanisation is not being properly handled, as the labour and machinery inputs do not significantly affect the output. The most

important inputs of Boro rice have been found to be land, seed, fertilizer, and pesticides. The significance of these inputs is that an increase in them leads to an increase in output. The change in output consequent on variations in irrigation level is not significant; this is shown by the non-significant effect of irrigation. However, the negative coefficient of machinery shows that an addition of machinery input, with other inputs remaining constant, leads to a decrease in output.

The coefficient of land is estimated to be 0.27 for Aus, 0.46 for Aman, and 0.37 for Boro rice production, all of which are significant at the 1% level. From this, it has been found that a 1% increase in the cultivated area will mean an increase in the production of Aus rice by 0.27%, of Aman rice by 0.46%, and of Boro by 0.37%. The greater elasticity of Aman rice shows that land is a comparatively more important factor in its production in this season than it is for Aus and Boro rice. The whole year shows that the increase in seed brings about a positive effect and is statistically significant for Aman and Boro rice only, while it is insignificant for Aus rice.

Table 4. Maximum likelihood estimates of the Cobb-Douglas stochastic frontier model and inefficiency effects model.

Cobb-Douglas Stochastic Frontier Model				
Variables	Parameters	Rice-growing Seasons		
		Aus	Aman	Boro
Intercept	β_0	2.53*** (0.142)	1.65*** (0.095)	1.89*** (0.187)
lnland	β_1	0.27*** (0.066)	0.46*** (0.050)	0.37*** (0.132)
lnseed_seedling	β_2	0.04 (0.070)	0.21*** (0.043)	0.50*** (0.163)
lnlabour	β_3	0.11*** (0.035)	0.05 (0.029)	0.09 (0.060)
lnfert_pest	β_4	0.16*** (0.035)	0.10*** (0.030)	0.15*** (0.056)
lnirrigation	β_5	0.20*** (0.047)	0.17*** (0.036)	0.09** (0.053)
lnmachinery	β_6	0.22** (0.086)	0.02 (0.019)	-0.19** (0.091)
Log likelihood		186.65	225.37	196.88
lnsigma_v	$\ln \sigma_v^2$	-6.32*** (0.195)	-7.67*** (0.326)	-6.12*** (0.270)
Inefficiency Effects Model				
Constant	δ_0	-2.94 (4.195)	-5.28 (3.803)	0.16 (5.037)
lnage	δ_1	0.53 (1.197)	-0.84 (1.149)	-1.40 (1.661)
lneducation	δ_2	1.06 (0.672)	-0.52(0.531)	0.001 (0.653)
lnfarming_experience	δ_3	0.29 (0.498)	-0.11 (0.530)	0.23 (0.889)
lnclimate_awareness	δ_4	0.39 (0.373)	0.96*** (0.350)	-0.16 (0.400)
lnfarm_size	δ_5	-1.46*** (0.401)	0.77*** (0.290)	0.07 (0.384)
lnoff-farm_income	δ_6	-0.42 (0.328)	-0.12 (0.252)	-0.25 (0.326)

Note: Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

The labour coefficient for Aus rice is 0.11 and is statistically significant at the 1% level but insignificant for Aman and Boro rice. This finding shows that the impact of labour employed is statistically significant on production in the Aus

crop, in which it is noted that an increase of 1% in its use in cultivation will bring about a positive increase of 0.11% in the output of Aus rice.

The non-significance of the use of labour in the case of Aus and Aman rice may suggest that mechanisation and other forms of capital-intensive effort lessen the reliance on labour. The degrees of significance of fertilizer and pesticides are positive and significant for Aus (0.16), Aman (0.10), and Boro (0.15) rice. This means that a 1% increase in the use of fertilizer and pesticides will give an increase in production in Aus, Aman, and Boro rice of 0.16%, 0.10%, and 0.15%, respectively. The values for the elasticity of irrigation are 0.20 for Aus, and 0.17 for Aman, and 0.09 for Boro rice, all of which are significant at 1% and 5%. This means that 1% increase in the use of irrigation will give an increase in production in Aus, Aman, and Boro rice of 0.20%, 0.17%, and 0.09%, respectively. The coefficient value for the machinery as regards Aus is positive (0.22) but is negative for Boro (−0.19) and is significant. The negative coefficient for machinery as regards Boro suggests that there is a tendency to over-rely on machinery and the lack of an increase in production proportionate to the increase in costs is probably due to inefficiencies in the use made of such machinery or is due to high operational costs.

6.8. Determinants of Inefficiency

The estimates of the effects of age, education, farming experience, knowledge of climate change, farm size, and off-farm income on inefficiency for the Aus, Aman, and Boro rice-growing seasons provided by the inefficiency model are shown in the lower section of **Table 4**. A positive coefficient would indicate that a greater increase in the factor would result in greater inefficiency, while a negative coefficient would indicate that a greater increase in the factor would result in a smaller amount of inefficiency and hence greater efficiencies on the part of the producer. The constant would indicate the inherent inefficiency in the producer in respect of each of the rice-growing seasons under consideration. Although Aus (−2.94) and Aman (−5.28) have negative values, the fairly high standard error (probably due to the absence of a significant number of producers) would suggest that the estimates are not of a statistically reliable nature. In Boro (0.16), however, there is what would appear to be a slight but positive inefficiency figure with a greater standard deviation.

In Aus (0.53), inefficiency increases with age, which may imply that older farmers may have difficulty adopting different agricultural technologies or coping with changes in the pattern of farming. In Aman (−0.84) and Boro (−1.40), age increases are accompanied by decreases in inefficiency, which may mean that the older farmers possess experience and better decision-making ability, both of which lead to greater efficiency. With Aus, increasing education results in increased inefficiency (1.06), which may indicate that the more educated farmers may be directing their resources to non-farming purposes, and consequently, they are less efficient in their efforts to improve farm efficiency. In Aman (−0.52), education appears to reduce inefficiency; this may be due to improved knowledge and ability, which will assist

farmers in making better farming decisions. The effect of education on the inefficiency in Boro (0.001) is negligible.

As farming experience increases, there is a slight rise in inefficiency for Aus (0.29) and Boro (0.23). Farming experience alone will not bring about full efficiency. On the other hand, there is a slight decrease in inefficiency for Aman (−0.11) with the increase in farming experience, but this is rather negligible. It seems that farming experience alone is not a very reliable measure of efficiency and that it gives varied results with respect to the different seasons of rice cultivation. Thus, it can be concluded that the effects of age, education, and farming experience are not themselves statistically significant.

The increase in efficiency with the increase in knowledge of climate change has been pointed out. It appears that with the increase in knowledge of climate change, there is a marked increase in inefficiency for Aman (0.96) and for Aus (0.39). This shows that the knowledge of more climate mindful farmers may not be strong enough with respect to the efficient adoption of methods to respond to climate change, which manifests as increased inefficiency. At the same time, for Boro (−0.16), the increased knowledge of climate gives rise to a slight fall in inefficiency.

For increasing size of farm, inefficiency decreases significantly in the case of Aus (−1.46), so larger farms take advantage of economies of scale and better management of resources. On the contrary, in the case of Aman (0.77), the size of larger farms is associated with greater inefficiency, probably due to farmers' inability to manage effectively the bigger areas. The effect of farm size on inefficiency in the case of Boro (0.07) is negligible. These results show the different effects of farm size in the different rice seasons; larger farms improve efficiency in Aus, whereas large farm size increases inefficiency for Aman. The increase in off-farm income has resulted in a small decrease in inefficiency for Aus (−0.42), but off-farm income has a positive effect on overall efficiency, as seen by the fact that it will produce a small decrease in inefficiency. However, off-farm income did not prove to be statistically significant, which indicates that there are no encouraging signs in the results, and as stated above, off-farm income should not be considered to be a very valuable item in terms of minimising inefficiency.

Nonetheless, **Table 2** illustrates that the determinants of inefficiency can not be jointly significant—thus the individual estimates for “Boro” should be viewed with caution and as inadequate evidence to support any true pattern of systematic inefficiencies affecting “Boro”.

7. Conclusions

In this study, technical efficiency and its determinants in rice farms during the Aus, Aman and Boro seasons were studied in Natore District in Bangladesh. In a comparison of the OLS model function and various SF specifications, the SFA is found to be superior to the OLS model. The SFA is capable of adequately capturing inefficiency factors prevalent in the production process. The LR tests of the Cobb-Douglas (CD) functional form are very acceptable compared with the quad-

ratic and trans-log form of functional forms, and the Cobb-Douglas (CD) functional form is both more parsimoniously specified and statistically significant. Therefore, it was decided to choose the CD functional form to achieve the aims of the efficiency analysis.

The examination of TE was clearly different for all the three rice-growing seasons. Aman rice obtained the highest average efficiency score of 0.98, while Boro and Aus obtained the scores of 0.86 and 0.79, respectively. The relatively high and closely related TE for Aman rice indicates that most of the farms are nearing the production frontier and little chance is left to gain TE. On the other hand, the lower and more varied TE for Aus and Boro rice indicates that there is scope for large-scale improvement of TE. A close examination of the distributions demonstrates this difference very clearly: Aman rice was found to have the least variation in TE, while Aus and Boro rice had a greater variation in the TE rating, showing clearly those farms that were working far below the potential TE and indicating that a possible increase in production was desirable.

The distribution of TE indicates that there is considerable opportunity for increased productivity within Aus and Boro rice production, as, on average, Aus farms would increase their production of rice by 21% and Boro farms by 14% if they attained the efficiency of the best farms within each group. On the other hand, the potentialities of the Aman farmers are very small, at only 3%. For the least efficient farmers, the possibilities of increased efficiency are, in fact, much larger, as possible increased production of 58% for Aus and 53% for Boro farmers are indicated. From these figures, it can be seen that it will mean a considerable total increased growth in rice production if increased efficiency is secured by means of better management of Aus and Boro rice growing.

The SF estimates derived from Cobb-Douglas point to a significant impact of inputs on production efficiency through the three rice-growing seasons. From the results for the elasticity estimates, it is seen that land was consistently the most important input, and the greatest elasticity occurred during the Aman season, which indicates that it is of foremost importance in rice production. There was a significant positive effect of fertilizers and pesticides and of irrigation during all the seasons, though the effects varied in magnitude. Labour was significant during the Aus season, indicating a dependence on manual labour during this rice-growing season. On the other hand, the negative coefficient for machinery during the Boro season indicates that it might be inefficient or that there is excessive use of machines. The latter may be due to rising costs or poor management practices. These findings indicate the need for balance in input usage and the allocation of resources based on requirements specific to conditions, all of which would help output and efficiency.

The inefficiency effects model yielded useful information related to farm/household characteristics and TE. The analysis indicated that farm size and climate change awareness have a significant influence on TE. Larger farms were more efficient in the Aus-growing season but less so during the Aman season. This reflects

the situation where farm size permits farms to realise the advantages of being a larger economic unit, but where they also have to face management problems due to their size. Climate change awareness was indicated to be a significant factor, in that longer periods of exposure to information on climate change variability were associated with less inefficiency according to the model. This emphasises the entire concept of being prepared and informed about climate issues and shows that this is vital in any effort to further improve farm efficiency. The factor of off-farm income was also found to be weakly associated with inefficiency but consistently negatively related. This indicates that additional income earned by farmers could assist them to adopt practices conducive to improving their efficiency. The effects of age, education, and farming experience were found to have varying degrees of very insignificant effects on farm efficiency/inefficiency over the various rice-growing seasons studied. This seems to indicate that environmental and structural qualities were more important than farmer characteristics in the determination of efficiency gains.

The results of this research show that, although Aman rice production is a very efficient part of the agricultural system, there are still many opportunities to improve efficiency in Aus and Boro rice production. Targeted actions that promote balanced input use, improve the mechanisation process, and enhance farmers' understanding of climate variability would significantly reduce the inefficiency that occurs in the total agricultural system. This study highlights the requirement for specific plans to be developed for the rice seasons rather than a broad-spectrum approach since the factors leading to inefficiency change from season to season. By grading the policies according to the aspects of each season, which are different in terms of inefficiency, there is a greater possibility to try to encourage improved efficiency in production on a farm basis, with all the advantages that this would bring with regard to higher productivity, profitability, and food security in Bangladesh.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Descriptive statistics.

Variables	Output Value (US\$)	Land Rent (US\$)	Seed and Seedling Cost (US\$)	Labour Cost (US\$)	Fertilizer & Pesticide Cost (US\$)	Irrigation Cost (US\$)	Machinery Cost (US\$)	Age (Years)	Education (Years)	Farming Experience (Years)	Climate Awareness (Years)	Farm Size (Decimal)	Off-farm Income (US\$)
Aus													
Mean	415.18	148.58	33.56	30.72	40.56	10.29	21.58	48	8	26	7	77.33	859.24
Std. dev.	410.42	138.12	31.86	32.04	43.70	10.47	20.39	11	3	12	4	73.45	771.62
Min	40.91	30.93	6.59	5.12	6.96	1.85	4.21	28	3	2	2	16.5	96.22
Max	3715.18	1229.84	296.04	294.33	434.01	94.42	183.88	80	18	50	20	660	4115.84
Aman													
Mean	598.34	282.19	72.01	111.29	115.36	25.52	34.75	48	8	24	7	110	859.24
Std. dev.	660.24	314.79	78.55	130.93	129.88	28.46	39.77	11	3	10	4	121.24	771.62
Min	90.05	40.01	9.91	14.90	15.06	3.68	4.51	28	3	4	2	16.5	96.22
Max	5888.47	2603.06	620.35	1223.05	1071.68	232.12	324.65	80	18	45	20		4115.84
Boro													
Mean	1365.74	416.67	87.03	186.03	179.32	116.58	62.84	48	8	24	7	146.41	859.24
Std. dev.	1638.39	480.94	99.79	217.36	206.88	134.02	71.66	11	3	10	4	170.22	771.62
Min	256.45	90.48	19.04	37.92	35.86	22.19	12.98	28	3	7	2	33	96.22
Max	11300.51	3320.54	697.17	1373.22	1336.57	898.81	534.57	80	18	50	20	1188	4115.84

The dataset contains key variables that provide a detailed picture of the farm household's characteristics, inputs, and outputs. With a mean age of 48 years, the household heads range in age from 28 to 80. Household heads' educational backgrounds vary widely, with an average of 8 years of education ranging from 3 to 18 years. An average period of farming experience is 24 years, with a range of 2 to 50 years. Climate awareness lasts for an average of 7 years, although it may range from 2 to 20 years. Farm size shows variation by household, with the average farm size in Aus being 77.33 decimals, Aman being 110 decimals, and Boro being 146.41 decimals.