Research Article:

DETERMINANTS OF TECHNICAL EFFICIENCY IN RICE PRODUCTION: EVIDENCE FROM CHITWAN, NEPAL

Suman Shrestha [a*], **Surya Mani Dhungana**[a] **and Raj Narayan Chaudhary**[b]

[a] Department of Agricultural economics and Agribusiness management, Faculty of Agriculture, Agriculture and Forestry University, Rampur, Chitwan, Nepal

[b] College of Natural Resource Management, Agriculture and Forestry University, Pakhribas, Dhankuta, Nepal

*Corresponding author: suman.pradhanag@gmail.com

DOI: https://doi.org/10.3126/jafu.v7i1.95390

Received date: 27 Feb 2026; **Revised date:** 23 Apr 2026; **Accepted date:** 30 Apr 2026; **Published date:** 10 Jun 2026

ABSTRACT

This study aims to investigate the level of technical inefficiency as well as determine the attributes related to farmers that significantly influence the inefficiency in rice production. Multistage sampling procedure was employed to select the respondents from the primary rice cultivating areas. The data were collected through face-to-face interview with randomly selected 150 respondents from sampling frame through deployment of semi-structured questionnaire. One step stochastic frontier modelling was employed to measure the technical inefficiency, which also simultaneously estimate the inefficiency model. The estimation of the parameters in production function revealed that 1% increase in area, human labor and working capital, increases output by 0.037, 0.189, and 0.421, % respectively. The return to scale was calculated 0.647, implying diminishing return. The average technical efficiency was 82.30%, indicating, on average, farmers could increase the output by 17.70%, with the existing technologies by following best practices. The results from the inefficiency model showed that major source of household income, education, experience, cooperative membership and extension services negatively and significantly influence the inefficiency. The empirical evidences provide guidance to policy makers to target the key determinants that improve efficiency, ultimately enhancing production and productivity.

Keywords: Food security, productivity, stochastic frontier analysis, yield gap

INTRODUCTION

Rice serves as the primary staple crop in Nepal, contributing an essential role in the security of food and nutrition, accounting for 23% of protein intake and 67% of overall cereal consumption (Timsina et al., 2023). Out of the total dietary calorie intake by Nepalese people, rice contributes about 40%, as well as constitutes about 7% of national GDP and 20% of agricultural GDP (K. C. et al., 2021). As per MoALD (2023), rice is cultivated across 1477378 hectares (ha) and has documented production of 5130625 metric tons (mt) with productivity at 3.47 mt/ha.

The rise in rice demand among people of hilly and mountainous region of Nepal is primarily driven by increased income, urbanization, and better road infrastructure (CDD, 2015). To ensure food security, the current state of rice production cannot meet up demand of growing populace (Shrestha et al., 2021). While the cultivated area of rice is decreasing, the temporal study revealed a modest rise in rice productivity and production (Gairhe et al., 2021). According to section 108 of the 2020/21 budget statement, the government of Nepal envisions being self-reliant in the production of rice within five years (MoF, 2021), and to become self-reliant in such a short time seems like an unclear goal. Gairhe et al. (2021) reported an annual increment in rice quantity and import value by 24.48% and 38.11%, respectively. Reducing rice imports is essential since they deplete the nation's foreign exchange reserves and limit opportunities for investments in profitable sectors. The main issue is the high yield gap that has been caused by the low productivity of rice. In Chitwan and Kavre district, Pandey et al. (2015) reported a rice yield differential between actual and potential yield of 1.8 to 2.2 t/ha. A numerous factor has resulted in low productivity such as the misallocating of resources (Shrestha & Gairhe, 2016), limited investment in research areas to develop new technologies (Gauchan & Pandey, 2011), and insufficient resources and misutilization (Gairhe et al., 2018; Timsina et al., 2012). Similarly, limited access and utilization of new technologies, a decline in the amount of arable land per person, and insufficient inputs hurt the timely availability of inputs like machinery, fertilizer, and irrigation (Paudel et al., 2019). All of these issues make it difficult for the rice sector to grow, which presents serious difficulties for developing nations like Nepal.

Wudineh and Endrias (2016) outlined three strategies for increasing the productivity of cereal crops through developing and implementing new technologies, expanding the cultivated area horizontally, and efficiently using the inputs already in place. The strategy of horizontal expansion of cultivation areas to boost production appears difficult given the rise in urbanization and population expansion. Similar to this, the process of developing and implementing new technologies takes time and money. Therefore, out of the three strategies to boost cereal crop yield, efficient utilization of inputs is the best strategy. The prudent use of agricultural inputs and resources to obtain the highest possible production refers to technical efficiency. Therefore, it is imperative to comprehend that achieving total technical efficiency requires not just optimizing output but also optimizing output with no resource slacks (Gul et al., 2009). Inefficient use of these limited resources is the root cause of production inefficiencies (Dessale, 2019). Low yield and efficiency are the result of inadequate knowledge about the rational use of resources (Subedi et al., 2020a). Increment in output could be achieved without the need for additional inputs or production technologies through improvement in efficiency (Bravo-Ureta & Pinheiro, 1997). The primary aim of this research is to evaluate technical efficiency in order to assess the effectiveness of resource utilization and to analyze the impacts of different efficiency levels on output. Similarly, along with the way of use of production inputs, the farmer's ability to integrate these inputs with managerial techniques and entrepreneurial abilities determines the final output that the farmer can produce (Chepng’etich, 2013). Inputs, institutional, socioeconomic, environmental, and demographic factors all have a substantial influence on technical efficiency (Tamirat & Tadele, 2023). It is important to assist farmers in becoming more efficient technically which results in proper resource use and an increase in productivity leading to the economic welfare of farmers thus making it imperative not only to investigate the efficiency level but also delineate underlying factors influencing efficiency.

Determining the way of quantifying the efficiency of farmers and its measurement is essential in agriculture for many developing nations (Hazarika & Subramanian, 1999a). The deterministic statistical technique (Afriat, 1972), parametric, and non-parametric techniques (Aigner & Chu, 1968; Charnes et al., 1978) are important methods generally employed in estimating the efficiency level. Among the various methods, the parametric stochastic modelling and the non-parametric known as data envelopment analysis (DEA) are the most commonly utilized approaches for estimating efficiency, with the notable inclination toward the former approach because of its built-in stochastic nature (Coelli, 1995). Several studies have been carried out to evaluate the technical efficiency by utilizing both parametric and non-parametric methods in rice production. Dhungana et al. (2004) utilized a non-parametric method known as Data Envelopment Analysis (DEA) to assess the technical efficiency of rice growers in Nawalparasi district, Nepal. Piya et al. (2012) employed a parametric method called stochastic frontier modelling to examine technical efficiency. Khanal and Maharjan (2013) used parametric two-step frontier approach to investigate technical efficiency as well as to delineate several factors underlying those inefficiencies. Acharya et al. (2020) utilized a parametric method, specifically stochastic frontier analysis to assess technical efficiency in mechanized and traditional rice farming across Jhapa, Sunsari, and Bardiya districts to make the comparison and provide distinct pictures of the importance of mechanization to improve the efficiency level and increase productivity. Similarly, Subedi et al. (2020b) investigated technical efficiency employing a parametric stochastic frontier model and accessed the components influencing the efficiency using a Tobit model, with technical efficiency serving as the dependent variable. Thapa and Dhakal (2024) assessed the technical efficiency of rice seed producers in Chitwan and pinpointed the key determinants contributing to inefficiency by employing an advanced modelling approach known as a one-step scaling stochastic frontier technique. The majority of research studies use the parametric approach, with two-step approaches being used in particular to estimate the inefficiency model. Only a limited number of studies use the one-step approach, which produces more accurate estimation and reliable results (Thapa & Dhakal, 2024). While several prior studies have accessed inefficiency level in Nepal, there exists a gap in recent empirical evidence focusing on rice subsector in the Chitwan district using advanced one step modelling that reduce estimation bias. This study aimed to fulfil this gap by providing a localized and methodologically robust analysis of the rice subsector. The primary objectives are to analyze technical efficiency and identifies the underlying factors that contribute to technical inefficiency in Chitwan. The finding of this study is anticipated to offer valuable insights and technical guidance to farmers in the Chitwan district and Nepal in general.

RESEARCH METHODS

Conceptual framework

The conceptual framework is illustrated in Fig. 1. Within the production process, inputs are converted into output. Output is obtained through the combined use of inputs in varying proportions. The managerial competencies of farmers in effectively combining various inputs significantly influence their technical efficiency, which refers to the effectiveness with which these inputs are utilized to generate output. It is believed that the managerial attributes of farmers are shaped by variety of characteristics, including demographic, socio-economic, and institutional factors. Through the identification of significant determinants that determine technical efficiency, it is possible to enhance the output of rice, thereby improving the economic welfare of rice farmers.

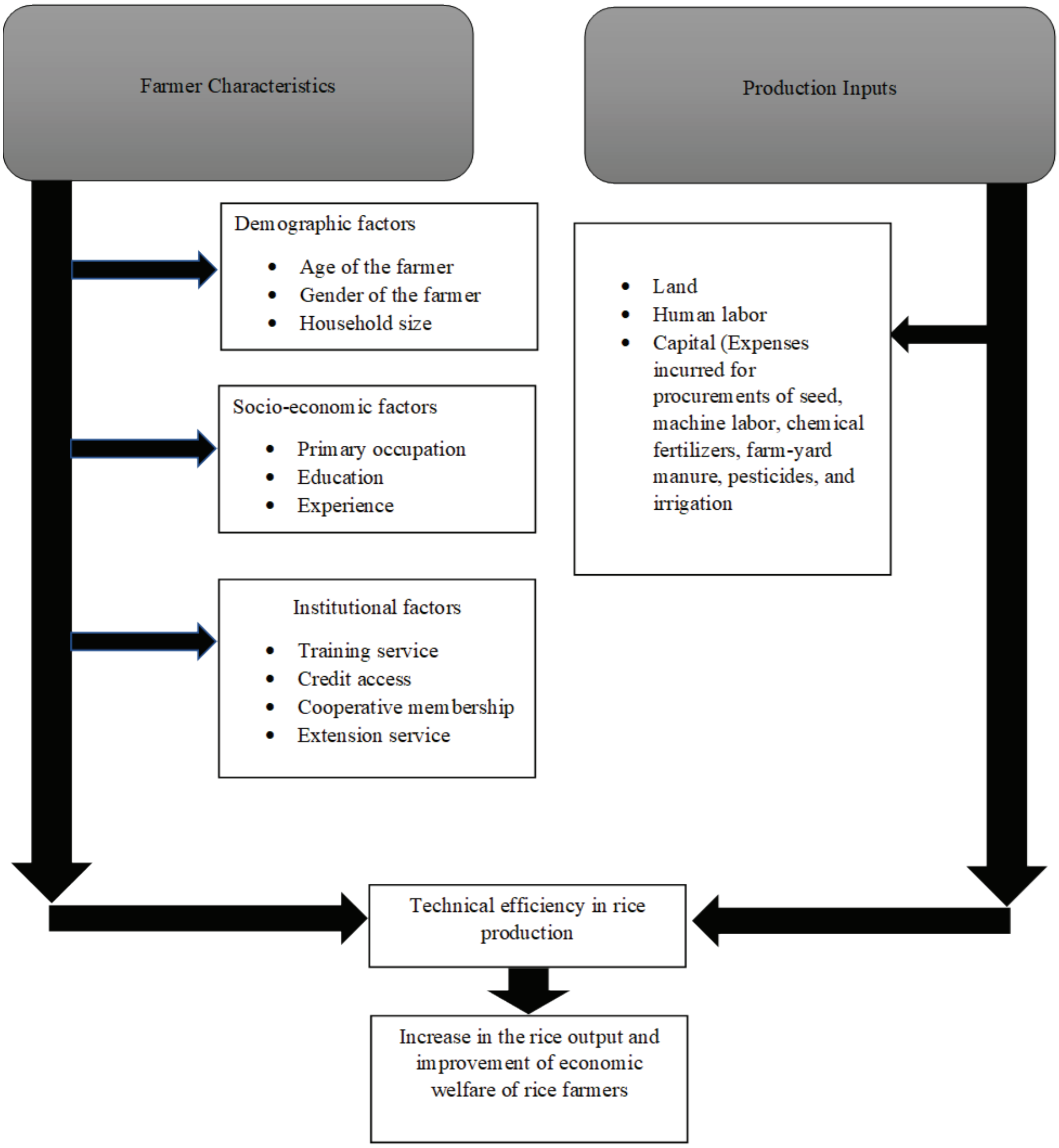

Fig 1. Conceptual framework of the study (Adapted from Anang, 2021; Tumuri et al., 2024)

Study area

Chitwan district, which is centrally located in Nepal, was selected purposively to carry out the study from a socioeconomic and environmental perspective. It is characterized by flat and fertile plains with suitable climatic conditions for the cultivation of varieties of crops. The annual average maximum and minimum temperature in the district were recorded at 30.8 degrees and 16.7 degrees respectively, while the mean annual precipitation was around 2666 mm (Paudel et al., 2014). The study mainly targeted the key rice-producing areas which were purposively selected in consultations with officials from the Agriculture Knowledge Centre, Chitwan. The selected areas were the Parbatipur region of Bharatpur Metropolitan, Kalika wards 6 and 2 from Kalika Municipality, Kathar and Kumroj region from Khairahani Municipality, Gadhyauli region from Rapti Municipality, and Bachhauli region from Ratnanagar Municipality. Most of these regions were listed as the rice zone by the Project Implementation Unit, PMAMP, Chitwan.

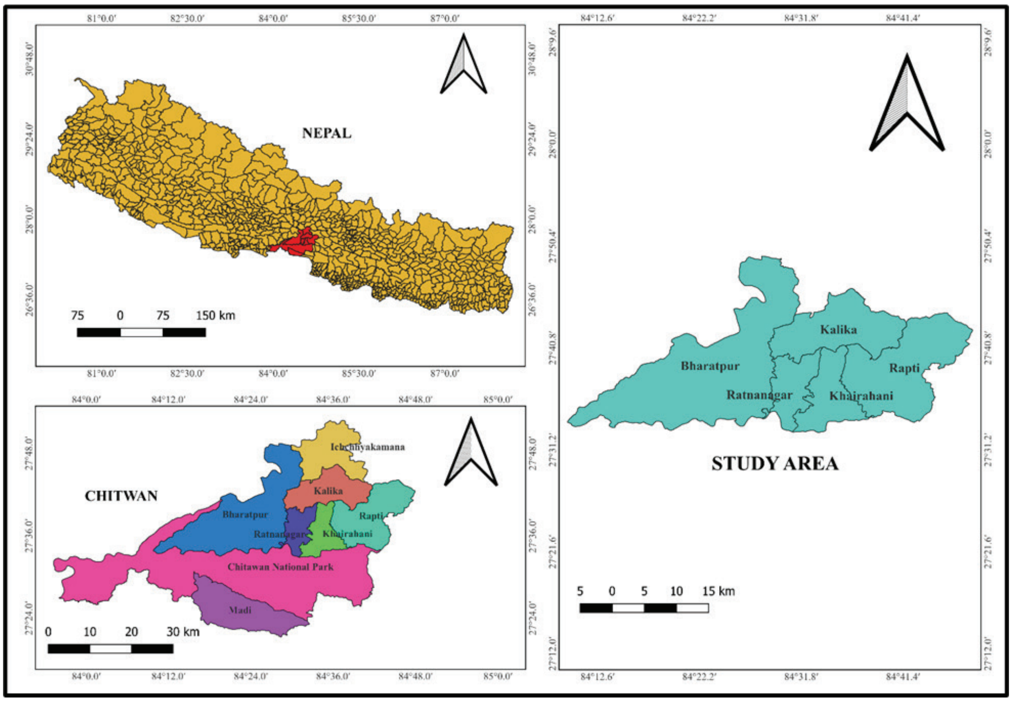

Fig 2. Map showing the study location (Source: QGIS, 2023)

Sample size and sampling methods

Multistage Sampling techniques were employed for the study. First of all, purposive sampling method was used to select the district. In the subsequent stage, the key rice cultivating regions within the districts were identified in consultation with officials from the Agriculture Knowledge Centre in Chitwan. Finally, simple random sampling method was implemented to select respondents from the sampling frame. The sampling frame consisted of 1500 rice growing households. This list was compiled by using the updated farmer roster which were obtained from the agriculture sections of the respective local government offices (Bharatpur Metropolitan, Kalika, Khairahani, Rapti, and Ratnanagar Municipalities) for the 2022/23 cropping season. The Raosoft software was employed to obtain the optimum sample size, which is widely recognized for its scientific and standardized calculation. Using confidence interval of 95%, and an error margin of 8%, it recommended minimum sample size of 137. However, we collected the sample of 150 respondents by employing the simple random sampling technique, which represents 10% of the population recorded in the sampling frame. From selected areas of each local level, we obtain the sample size proportionately to number of respondents recorded in the sampling frame (Table 1).

Table 1. Determination of sample size

Municipality	Key sites	Sampling frame (N)	Sample size (n)
Bharatpur Metropolitan	Parbatipur	323	32
Kalika Municipality	Kalika ward 2 and 6	240	24
Khairahani Municipality	Kumroj and Kathar	315	32
Rapti Municipality	Gadhyauli	313	31
Ratnanagar Municipality	Bachhauli	309	31
Total		1500	150

Source: Author calculation (Note: *Primary data was supplemented by 4 Focus Group Discussions (FGDs), 10 Key Informant Interviews (KIIs), and field observations to cross validate survey results*

Data collection and analytical methods

To obtain the information in line with the study objective, semi-structured questionnaire was developed and deployed. Before the deployment, it was vital to check the efficacy of the questionnaire. Therefore, the pretesting was conducted by taking the five respondents from each local level to assess the limitations and rectify it accordingly. After the successful completion of pretesting and incorporation of the limitations, a field survey was conducted to obtain the data for further analysis. Both primary and secondary data were meticulously collected for the study. The primary data were obtained through field surveys, Focus Group Discussion (FGD), Key Informant Interviews (KII), and direct observations, while secondary data were sourced from various reputable publications, government documents, journal articles and academic books. Both the descriptive as well as inferential analytical approaches were used for data analysis. MS Excel was used for refinement purpose, while Stata version 14.2 was used for data coding and statistical analysis.

Technical efficiency analysis

To investigate technical efficiency, the production frontier modelling was employed. This model comprises error terms that can be decomposed into two distinct error components. The first components represent the one-sided error term, indicative of inefficiency, while the second component accounts for random error that is beyond farmer's control. The production frontier is estimated using the stochastic model as shown in Equation 1.

$$Y_i = \beta_0 + \beta_i X_i + \varepsilon_i \tag{1}$$

In the above Equation 1, Y_i refers to the amount of output i.e., the yield obtained by the i^{th} farmer, β_0 represents the intercept term, β_i represents the vector of parameters that are associated with each input, X_i represents vectors of inputs utilized in the production process. In addition, ε_i refers to the composite error term, which is defined as follows.

$$\varepsilon_i = v_i - \mu_i \tag{2}$$

In Equation 2, the term v_i represents stochastic variation in output Y_i, which is outside of the farmer's control. The parameter μ_i denotes the one-sided error components, which represents the controllable factors that impact inefficiency. The distribution of random variation in output, specifically v_i, is assumed to follow a normal distribution and is distributed identically and independently with a mean value of 0 and a variance of $\sigma^2 v$. To accurately estimate the frontier model, it is essential to establish a distribution for the one-sided error term, which pertains to inefficiency. Several researchers have made different assumptions for the distribution of the inefficiency components. Some commonly used distributions for inefficiency components are half normal distribution (Aigner et al., 1977), truncated normal distribution (Stevenson, 1980), gamma distribution (Greene, 1980a, 1980b, 2003), and exponential distribution (Meeusen & van Den Broeck, 1977).

The need to account for the distribution of inefficiency necessitated the application of maximum likelihood technique for estimating the stochastic frontier model, while alternative estimation methods, such as ordinary least squares and generalized method of moments could be utilized, albeit less efficient (Belotti et al., 2013). Evaluation of the stochastic model is performed in two steps. First, the parameters are estimated by maximizing the loglikelihood function. In the next stage, we can derive the point estimates of inefficiency by utilizing the conditional distribution of the mean/ mode. Estimation of technical efficiency by differentiating unobserved components from combined error terms is the major objective of the frontier model. To address this issue, Jondrow et al. (1982) proposed a commonly used method by leveraging the conditional distribution of μ given ε. For each unit of observations, inefficiency ($\mu|\varepsilon$) is obtained through the conditional distribution of μ, where the μ is represented as, $\mu = \varepsilon + v$.

$$E\left(\frac{\mu}{\varepsilon}\right) = \sigma 2 \left[\frac{f\left(\frac{\varepsilon\lambda}{\sigma}\right)}{1-F\left(\frac{\varepsilon\lambda}{\sigma}\right)} - \frac{\varepsilon\lambda}{\sigma}\right] \qquad (3)$$

In Equation 3, f refers to standard normal density, while F refers to cumulative distribution function. Point estimation of inefficiency can be obtained using the conditional mean $E(\mu|\hat{\varepsilon})$. After obtaining the estimate of μ, we can calculate the technical efficiency using formulae $Eff = \exp(-\hat{\mu})$, where $\hat{\mu}$ is given as $E(\mu|\hat{\varepsilon})$.

$$\lambda = \sigma_u/\sigma_v \qquad (4)$$

The estimation of the ratio as presented in equation 4 between two standard errors, quantifies the portion of total output deviation from the frontier which could be explained by technical efficiency (Jondrow et al., 1982), while the calculated value of γ indicates the proportion of inefficiency variance μ out of total variance. It is estimated using the formulae that is represented in Equation 5.

$$\gamma = \sigma_\mu^2/\sigma^2 \qquad (5)$$

σ^2 is given as, $\sigma^2 = \sigma_\mu^2 + \sigma_v^2$, where, σ_μ^2 and σ_v^2, represents variance of the technical inefficiency and stochastic (systematic) component respectively, and σ^2 represents the total variance.

According to Greene (2012), researchers often used the two-step method to incorporate the exogenous effect. In this process, efficiency is estimated first without considering the explanatory factors, and the efficiency estimated is then regressed on explanatory variables in the next step, which led to biased estimation of parameters (Wang & Schmidt, 2002). One effective method for incorporating exogeneous variables into the inefficiency model is outlined by Kumbhakar et al. (1991), who proposed parametrizing the mean of pretruncated inefficiency distribution as $\mu_i \sim N^+(\mu_i, \sigma^2_u)$.

$$\mu_i = z'_i\psi \qquad (6)$$

Where, μ_i is the technical inefficiency of ith observation derived from the truncated normal distribution of random variables, with z_i representing the vector of exogenous variables that includes the constant term. ψ represents coefficients of exogenous variables required to be estimated, also known as inefficiency effects. The coefficients obtained from the inefficiency model illustrates the influence of exogenous variables on the inefficiency component; a negative value indicates positive effect on technical efficiency, while a positive value suggests a negative effect.

Model specification: One step stochastic frontier model

Recent studies of production analysis frequently employ two functional forms, namely Cobb Douglas and Translog. Each of these functional forms has its own unique benefits and drawbacks. However, many researchers stated that Cobb Douglas function form offers several benefits over its counterparts by striking the balance between fitting the data well as well as being computationally efficient. The straightforward nature provides simplicity in the interpretations of production elasticities and its parsimonious use of degree of freedom makes it a popular choice for the production frontier analysis (Hazarika & Subramanian, 1999b). However, the Cobb-Douglas model made several assumptions such as, the elasticity of substitution between inputs remains fixed at unity, constant elasticity, and a production process exhibiting constant returns to scale (Coelli et al., 1998). Despite its limitations, its simplicity and ease of interpretation make it an appropriate choice for study. Hence, Cobb Douglas as the functional form was proposed to investigate the technical inefficiency. The empirical representation of the Cobb-Douglas production frontier with a double logarithm is expressed in the following equation.

$$\mathrm{Ln}(Y) = \beta_0 + \beta_1 \mathrm{Ln}(A) + \beta_2 \mathrm{Ln}(L) + \beta_3 \mathrm{Ln}(C) + v_i - u_i \qquad (7)$$

In the Equation 7, Ln indicates natural logarithm, Y refers to rice output or yield measured in kg per hectare (kg/ha), $\beta_0 - \beta_3$, refers to the parameters to be estimated, A refers to the area under rice cultivation measured in hectare (ha), L refers to the total number of human labor required for the rice cultivation measured in man-days per hectare (man-days/ha), and C refers to the overhead capital expenditure which is the summation of the expenses incurred during the procurement of inputs in rice cultivation such as seed, machine labor, chemical fertilizer, farmyard manure, and pesticide cum irrigation measured in NRs/ha. v_i represents the error component which is outside of farmer control and follows normal distribution denoted as N (0, σ^2_v). This is a two-sided error that indicates random variation in the model and is identically and independently distributed. u_i refers to a one-sided error component that could be controlled by the farmer. This error term is presumed to follow a truncated normal distribution which is denoted as $N^+(\mu_i, \sigma^2_u)$.

As previously mentioned, the two-step method for estimating the impact of exogenous variables on the inefficiency components tends to yield a significantly biased estimate. Therefore, the single step estimation method was used for inefficiency modelling, as delineated by Kumbhakar et al. (1991). In this context, the command line recommended by Belotti et al. (2013) in Stata for estimation of the one-step stochastic frontier modelling was followed. The formulation of the inefficiency model can be expressed as follows:

$$\mu_i = \delta_0 + \sum_{k=1}^{10} \delta_k Z_{ik} \tag{8}$$

Where, μ_i represents the technical inefficiency component and δ_k represents the vector of coefficients for the k exogenous variable. Z_i refers to exogenous variables representing the characteristics of farmers i.e., demographic, socio-economic, and institutional characteristics. The variables that were used for modelling the inefficiency model are listed in Table 2.

Table 2. Key determinants influencing inefficiency in rice production

Variables	Description	Expected sign
Age	Age of the farmer in years	+/-
Gender	1: Male and 0: Female	+/-
Household size	Number of members in the family living together under the same roof	+/-
Education	Number of years in formal schooling	+
Major source of household income	1: Agriculture and 0: Other sectors	+
Training	1= Received training on rice cultivation practices, and 0= otherwise	+
Credit service	1 = Access and 0= otherwise	+
Experience	Years of experience in the cultivation of rice	+
Cooperative membership	1= Yes and 0 = No	+
Extension service	1= Access and 0 = otherwise	+

Hypothesis testing for assessing presence of inefficiency in the model

Technical inefficiency is a fundamental aspect of the stochastic frontier modelling. It is essential to assess its presence, as the absence of an inefficiency component would render the model a conventional regression, with ordinary least squares (OLS) estimates being sufficient. Two methodologies were evaluated for the assessment of the existence of inefficiency in the SFA model. The first methodology involves implementing the skewness test on ordinary least squares

(OLS) residuals, as proposed by Schmidt and Lin (1984), to validate the stochastic production frontier. The skewness test is straightforward and serves as preliminary steps before proceeding with the more intricate maximum likelihood estimation. This test is grounded on the principle that a stochastic frontier model with composite error term, which is represented as v_i- μ_i, where $\mu_i \geq 0$, indicates that the error component reflecting random variation i.e., v_i is symmetrically distributed around zero. Consequently, the OLS residuals obtained from OLS regression should exhibit negative skewness. The null hypothesis posits the absence of skewness and is evaluated against the alternative hypothesis. The observation of negative skewness with significant p-value allows for the rejection of null hypothesis, thereby providing sufficient evidence of an inefficiency component. However, it is important to acknowledge that this test does not consider the specific distribution function selected for μ_i in the estimation procedures. To overcome this, an alternative method is the generalized likelihood ratio test (LR), which compares the log-likelihood values, derived from the stochastic frontier (unrestricted) and OLS (restricted) models. The LR test is tailored to specific model, however it necessitates the initial estimation of the maximum likelihood (Kumbhakar et al., 2015). It is computed using formula as follow.

$$LR = -2\,[L(Ho) - L(H1)] \tag{9}$$

In Equation 9, LR denotes the likelihood ratio test statistics, while L(H0) and L(H1) represent log-likelihood values, which are derived from restricted OLS regression and the unrestricted stochastic frontier modeling, respectively. The number of constraints applied in the test is determined by the degrees of freedom. The resulting LR statistic is subsequently compared with critical values obtained from the mixed distribution of chi-square, as provided by Kodde and Palm (1986). It is important to highlight that the LR test does not conform to the standard chi-square distribution. Coelli (1995) observed that the LR test follows a mixed distribution rather than the conventional chi-square distribution.

In addition to hypothesis testing, several diagnostic tests were performed. In our study, the Breusch-Pagan test was used to investigate the presence of heteroskedasticity in our data. To evaluate the degree of multicollinearity among the explanatory variables in SFA, the Variance Inflation Factor (VIF) was used. A VIF values exceeding 10 indicates the presence of multicollinearity among the explanatory variables (Ahmad et al., 2006). Both the problem of heteroskedasticity and multicollinearity impose a significant challenge in econometrics for robust estimation (Emmanuel & Maureen, 2021). Additionally, the Shapiro-Wilk test and histogram plot were used to assess the normality of residuals obtained from the OLS regressions.

RESULTS AND DISCUSSION

Descriptive statistics of key variables

The descriptive analysis of the variables representing production, demographic, socioeconomic, and institutional characteristics of rice farmers are summarized in Table 3. The average rice production was found 4.65 mt/ha, which align with Subedi et al. (2020) at 4.5 mt/ha, while Dhakal et al. (2019) reported a slightly higher productivity of 5.2 t/ha in the plain region of Chitwan. The average land owned by farmers was found 0.46 hectares, with 0.32 hectares allocated for rice cultivation, which indicates the potentiality of horizontal area expansion. Rice is a labor-intensive crop, requiring an average of 80.81 man-days per hectare. The recent outmigration has exacerbated the issue of labor shortage, impacting timely establishment and cultivation of crop (Maharjan et al., 2013), leading to higher wages and costs. Total inputs cost was found NRs. 91296.59/ ha, which included expenses on seed, machine labor, chemical fertilizer, farm-yard manure, pesticide, and irrigation. The increase in average production expenses is mainly driven by rising labor, machinery, and fertilizer prices (Bhandari et al., 2015; Sapkota & Sapkota, 2019). The agricultural mechanization has been identified as a potential strategy to reduce production cost by lowering dependency on human labor and improving operational efficiency (Poudel et al., 2021; GC et al., 2019; Acharya et al., 2021).

The average farmer age engaged in rice cultivation was found 47.99 years, with approximately 71% being male. The mean household size was found 5.19, which was higher than national (4.37) and district (4.01) averages (CBS, 2021). The mean years of formal education was 8.51 years, lower than global average of 8.7 years (UNDP, 2022). Agriculture was reported as the primary income source for nearly 48% of households, while others rely on services, business, manufacturing, or remittances. Only 17% of the respondents reported to have received cultivation training, which is essential for technology adoption and improve productivity (Nakano et al., 2018). Credit access was found limited to 23%, despite its necessity for increasing productivity (Mohsin et al., 2011; Zabatantou Louyindoula et al., 2023). The average experience among farmers was found 19.88 years, which ranged between 3 to 50 years. Experience is positively correlated with agricultural productivity (Chou & Lau, 1978). Only 33% of the respondents reported being members of cooperatives. Cooperative membership aids in poverty reduction by enhancing economies of scale and bargaining power (Latynskiy & Berger, 2016). Extension services was limited to 17% of the respondents. It is crucial to strengthen extension system to improve dissemination of knowledge and promote sustainable agro-practices (Adebayo et al., 2015).

Table 3. Descriptive statistical analysis of the variables under study

Variable	Unit	Mean	St. Deviation	Minimum	Maximum
Output	Metric ton/ Hectare	4.651	0.726	3	6
Area under rice	Hectare	0.32	0.23	0.03	2
Human Labor	Man-day/ Hectare	80.81	10.44	30	120
Capital	NPR/ha	91296.59	20509.3247	46862.22	140340
Land Owned	Hectare	0.46	0.36	0.02	2.67
Age	Year	47.99	10.11	24	72
Gender	Male: 1 Female: 0	0.71	0.45	0	1
Household size	Number	5.19	1.51	2	10
Education	Year	8.51	3.33	0	16
Major source of household income	Agriculture: 1 Other: 0	0.48	0.50	0	1
Training	Yes: 1 No: 0	0.17	0.38	0	1
Credit service	Yes: 1 No: 0	0.23	0.42	0	1
Experience	Year	19.88	9.67	3	50
Cooperative membership	Yes: 1 No: 0	0.33	0.47	0	1
Extension service	Yes: 1 No: 0	0.17	0.38	0	1

Hypothesis testing for technical inefficiency

The residuals derived from the OLS regression were subjected to skewness test for affirming the existence of inefficiency within the model. In Table 4, variable e represents the OLS residuals, which showed a skewness value of -0.2704, implying inefficiency. However, the p-value was found 0.1642, which exceeded the significant level of 5%. This result indicates that the null hypothesis cannot be rejected. Consequently, the skewness test was unable to substantiate the existence of inefficiency within the model. As previously mentioned, the skewness test does not take into account of the distributional assumption related to inefficiency term, whereas the likelihood ratio test incorporates such considerations, thereby making more precise for the specific model. Table 5 reported a log-likelihood value of 129.96, obtained from a stochastic frontier model with unrestricted specification and distributional assumption of truncated normal for the inefficiency component. Similarly, the restricted model or OLS model, yielded a log-likelihood value of 104.64. The calculated likelihood ratio test statistic was found 50.64. According to the mixed chi-square distribution from Kodde and Palm (1986), the tabulated value for 12 degrees of freedom at a 1% significance level was 25.549. Given that the calculated value of likelihood ratio test statistic exceeded the tabulated value, the null hypothesis was rejected at the 1% significance level, indicating the presence of inefficiency in frontier model.

Table 4. Skewness test of the residuals obtained from the OLS regression

Variable	Observation	Mean	Standard deviation	Variance	Skewness	P value
E	150	-2.24e-10	0.1209	0.0146	-0.2704	0.1642

Table 5. LR test assessing the presence of inefficiency within the frontier model

Statistic	OLS	Stochastic Frontier Model (SFM)
Degree of Freedom	5	17
Loglikelihood value	104.64	129.96
Likelihood ratio	-	50.64
Critical value at 1% level	-	25.549 (12)

Note: Figures in the parentheses indicate the number of restrictions (degree of freedom) which represents the difference in the estimated number of inputs and inefficiency variables between SFA and OLS.

Estimates of one stochastic production frontier

In the Table 7, the maximum likelihood estimates of the stochastic frontier model are presented. The Wald chi-square value ($\chi^2 = 110.38, p<0.01$) suggests the joint significance of the explanatory variables to capture the variability within the dependent variable. The findings revealed that a 1% increase in area, human labor, and overhead capital expenditure leads to increase in rice output by 0.037% ($p<0.05$), 0.189% ($p<0.01$), and 0.421% ($p<0.01$), respectively. These findings are consistent with previous studies, which reported a positive and significant influence of land, human labor, and inputs cost on crop production (Thapa and Dhakal, 2024; Anik and Rahman, 2021; Girma et al., 2024; Fakasin and Akinbode, 2020). The estimated elasticities indicated that output of rice was relatively inelastic with respect to these inputs. The return to scale, which is calculated as the summations of all estimated inputs coefficients, was found 0.647, indicating diminishing return to scale. It inferred that a 1% increment for all inputs results in only a 0.647% increase in output. Similar findings have been documented in previous studies for rice production in Nepal (Subedi et al., 2020; Dhakal et al., 2019).

The estimates of the loglikelihood parameter, given as, $\lambda=\sigma_u/\sigma_v$, was calculated 4.032, significantly rejecting the null hypothesis of absence of technical inefficiency at 1% level (Aigner et al., 1977). The estimate of sigma square was found 0.014, which significantly differs from zero at 1% significance level. It indicates a well-fitting model and validates the appropriateness of the specified truncated normal distribution for the inefficiency component. Similarly, the gamma value of the model was found 0.942, statistically significant at 1%. It indicated that 94.2% of output variation are attributable to technical inefficiency. The observed discrepancy from the maximum possible output was predominantly driven by technical inefficiency.

Several diagnostic tests, such as multicollinearity, heteroskedasticity, and normality of the residual, are presented in Table 6. The mean and maximum value of VIF were calculated 1.17 and 1.25, respectively, which indicated no multicollinearity among the independent variables. The Breusch-Pagan/Cook-Weisberg test was employed to assess heteroskedasticity, which yielded a chi-square value of 0.16 and a p-value of 0.688, failing to reject the null hypothesis. It inferred that the residuals have constant variance or homoscedastic. The Shapiro-Wilk test was used to evaluate the normality of the residuals, which yielded W value of 0.983 and a p-value of 0.0632, indicating that the residuals are normally distributed at a significance level of 5%. The histogram, which is presented in Fig. 3, confirmed the normal distribution of residuals by showing the bell-shaped symmetric distribution with no presence of any outliers.

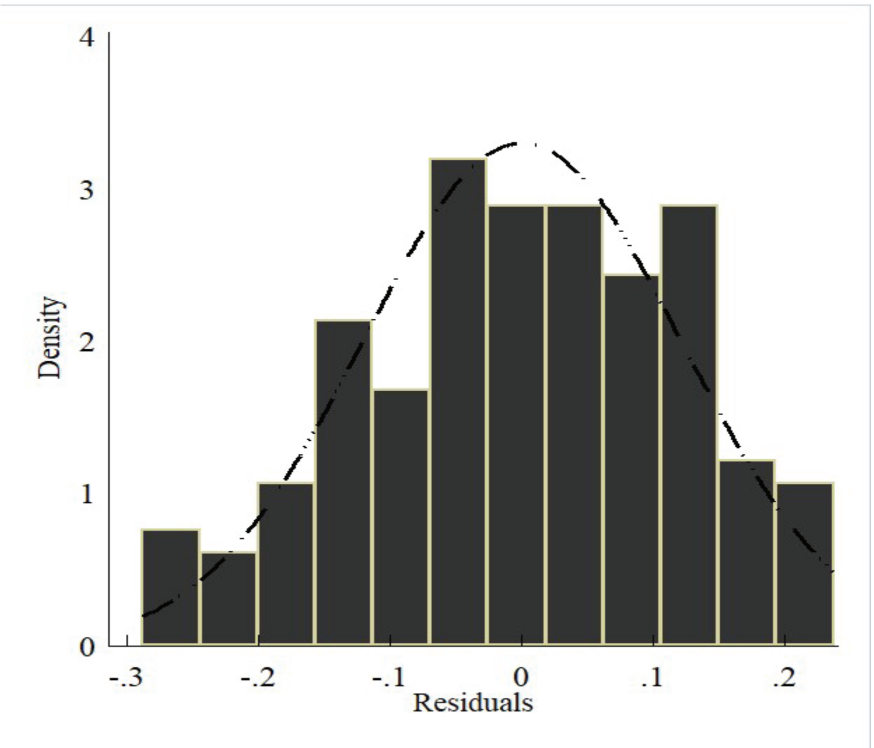

Fig 3. Histogram plot displaying the normal distribution of residuals in the SFA modeling.

Table 6. Diagnostic test of the model

Statistical test	
Multicollinearity test (Variance Inflation Factor)	Mean VIF = 1.17; Maximum VIF = 1.25
Heteroskedasticity test (Breusch-Pagan test)	Chi square (1) = 0.16; p-value = 0.6889 (Constant variance)
Normality test (Shapiro-Wilk test)	W = 0.983, p-value = 0.0632 (Normal distribution of residual)

Table 7. Estimation of parameters for the one-step stochastic frontier model

Yield	Coef.	Std. Err.	Z	P>z	[95%Conf.	Interval]
Frontier						
Area	0.037*	0.015	2.430	0.015	0.007	0.066
Human labor	0.189**	0.069	2.750	0.006	0.054	0.323
Capital	0.421**	0.042	10.090	0.000	0.340	0.503
Constant	3.053**	0.552	5.530	0.000	1.970	4.135
Inefficiency model						
Age	-0.0004	0.002	-0.270	0.786	-0.003	0.003
Gender#						
Male	0.030	0.029	1.050	0.294	-0.026	0.087
Household size	0.002	0.008	0.270	0.785	-0.014	0.018
Major source of household income#						
Agriculture	-0.068*	0.031	-2.230	0.026	-0.128	-0.008
Experience	-0.004**	0.001	-2.660	0.008	-0.007	-0.001
Training#						
Received	-0.046	0.046	-0.990	0.321	-0.136	0.044
Credit service#						
Access	-0.025	0.031	-0.820	0.414	-0.085	0.035
Education	-0.009	0.004	-1.910	0.056	-0.017	0.000
Cooperative membership#						
Yes	-0.050	0.028	-1.830	0.067	-0.105	0.004
Extension service#						
Received	-0.118*	0.049	-2.380	0.017	-0.215	-0.021
Constant	0.399**	0.103	3.880	0.000	0.198	0.601
Usigma						
Constant	-4.298**	0.187	-23.020	0.000	-4.663	-3.932
Vsigma						
Constant	-7.086**	1.566	-4.520	0.000	-10.155	-4.017
sigma_u	0.117**	0.011	10.710	0.000	0.097	0.140
sigma_v	0.029	0.023	1.280	0.202	0.006	0.134
Lambda (λ)	4.032**	0.026	152.880	0.000	3.980	4.083
Sigma Sq (σ^2)	0.014**	0.003	4.806	0.000		
Gamma (γ)	0.942**	0.092	10.272	0.000		
Summary statistics of the Stochastic frontier model (normal/ tnormal)						
Total observations = 150						
Wald chi2(3) = 110.38**, Prob > chi2 = 0.0000						
Loglikelihood = 129.9572						

Note: ** p<0.01, * p<0.05, # represents the dummy variable

Technical efficiency in rice production

Table 8 showed the level of technical efficiency in rice production. U represents technical inefficiency, U_LB 95 represents the lower bound, while U_UB 95 represents the upper bound of technical inefficiency, at a 95% confidence level. Similarly, Eff denotes the technical efficiency, Eff_LB 95 indicates the lower bound, while Eff_UB 95 represents the upper bound of technical efficiency, at a confidence interval of 95%. The results revealed that all farmers were producing below the optimal frontier level, and the variation could be resulting from heterogeneity in resource use and management practices. The mean technical inefficiency was 20.13%, with an inefficiency level varying between 1.52% and 48.90%. Similarly, the average technical efficiency was 82.30%, ranging between 61.32% to 98.49%. This inferred that, on average, farmers produced 82.30% of potential output, which highlighted a 17.70% production gap. The small difference between mean inefficiency (20.13%) and efficiency gap (17.70%) arises from the nonlinear transformation, TE = e^u, where small value of u, 1-e^u ~ u. The variations in the efficiency level are likely attributable to differences in input level use, which is expected to have been influenced by farmer’s attributes.

Table 8. Measurement of efficiency level in the rice production

Variable	Observation	Mean	St. Deviation	Min	Max
U	150	0.2013	0.1152	0.0152	0.4890
U_LB 95	150	0.1488	0.1116	0.0005	0.4350
U_UB 95	150	0.2554	0.1166	0.0475	0.5440
Eff	150	0.8230	0.0930	0.6132	0.9849
Eff_LB 95	150	0.7798	0.0894	0.5804	0.9536
Eff_UB 95	150	0.8670	0.0944	0.6479	0.9995

The variance of the inefficiency, represented by σ_μ^2, was found to be 0.0136, which signifies that the majority of the observations are close to 100% efficient. Fig. 4 demonstrated the distribution of technical inefficiency, adhering to a truncated normal distribution and value ranging between 0.0152 and 0.4890. A normal density curve, which is appropriately scaled to the mean and standard deviation of the data, overlaid with the histogram with its tail extending toward the right side, illustrated that the majority of the respondents had relatively low inefficiency levels.

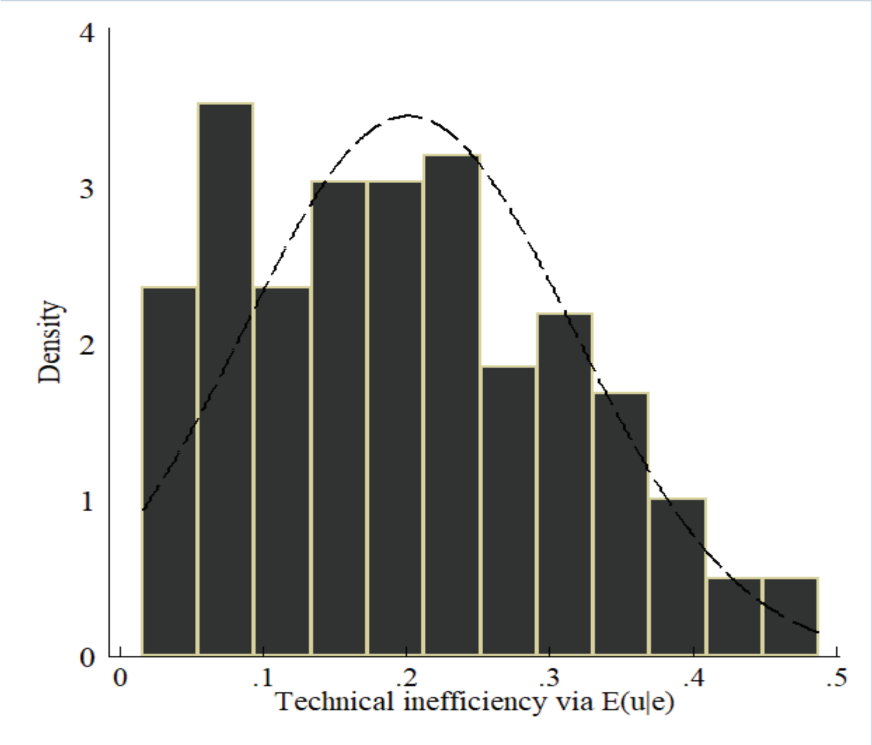

Fig 4. Histogram showing the distribution of technical inefficiency.

In addition, the distribution of technical efficiency along with mean yield is presented in Table 9, which revealed that only 57.34% of farmers had an efficiency level of 80% or higher, while 3.33% operated below 65%, and 39.33% fell between the range of 65% to 80%. Furthermore, 48.67% of farmers were performing above the mean efficiency level of 82.30%, while the rest fell below this level. The average yield of rice increased steadily with higher efficiency levels, ranging from 3621.43 kg/ha (below 65%) to 5484.97 kg/ha (95-100%), which is also illustrated in Fig. 5. The average efficient and the least efficient farmers must lower their costs by 17.97% and 39.27%, respectively, to achieve the efficiency level of the most technically efficient farmer. The positive correlation between technical efficiency and productivity suggests that efficient farmers can allocate their resources more optimally, which results in higher outputs and low input wastage. Similar findings have been noted by Amankwa et al. (2022) and Majumder et al. (2016), who reported that improvements in technical efficiency significantly increase rice production and contribute to national food security.

Table 9. Distribution of rice farmers by technical efficiency level and corresponding mean yield

Efficiency ranges (%)	Frequency	Percentage	Cum. Percent	Mean Output (Kg/Hectare)
95 and above	13	8.67	8.67	5484.97
90 to 95	24	16.00	24.67	5378.20
85 to 90	27	18.00	42.67	5009.72
80 to 85	22	14.67	57.34	4595.14
75 to 80	26	17.33	74.67	4311.68
70 to 75	24	16.00	90.67	4054.08
65 to 70	9	6.00	96.67	3713.28
Below 65	5	3.33	100.00	3621.43
Total	150	100.00	100.00	4651.10
Reduction in cost required to achieve maximum efficiency level				
For the average efficient farmer (1-Mean / Max) * 100			17.97%	
For the least efficient farmer (1-Min / Max) * 100			39.27%	
Mean Efficiency level			82.30%	

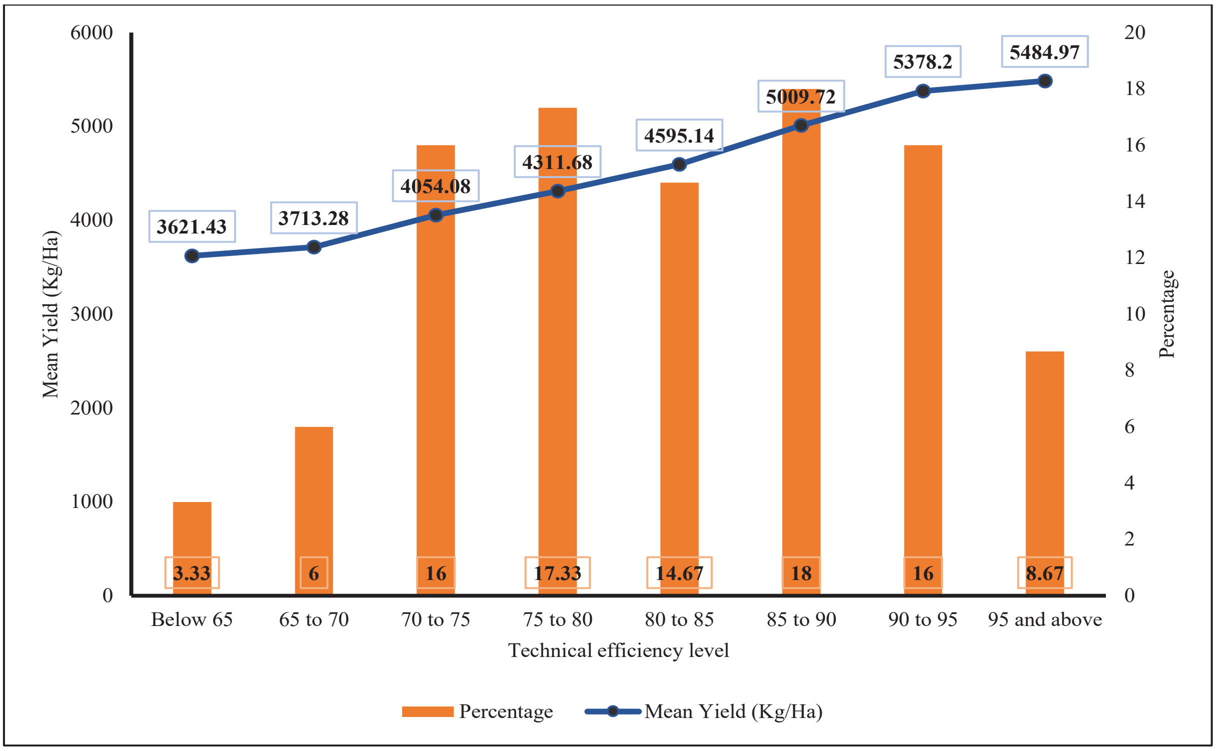

Fig 5. Level of technical efficiency of rice farmers along with their corresponding yields.

Factor affecting technical inefficiency in rice production

The study employed a one-step stochastic frontier model to identify the significant determinants of productivity differentials. Only knowing the presence of inefficiency is insufficient without understanding its sources. Therefore, this study also incorporates factors, such as demographic, socio-economic, and institutional characteristics, related to the farmers into the inefficiency component (Table 7).

In the inefficiency model, a positive coefficient indicates increased inefficiency (reduced efficiency), while a negative coefficient denotes reduced inefficiency (increased efficiency). The result from the inefficiency model revealed positive but statistically insignificant coefficients for gender and household size, indicating no significant impact on efficiency. The exogenous variables, such as age, training, and credit, showed a negative coefficient; however, the p-values for these coefficients were not statistically significant, which indicates that these variables do not influence the technical efficiency significantly. Conversely, major sources of household income ($p<0.05$), experience ($p<0.01$), education ($p<0.1$), cooperative membership ($p<0.1$), and extension services (<0.05) exhibited negative and statistically significant coefficients, signifying their pivotal roles in reducing inefficiency.

The results from the inefficiency model indicated that farming households with agriculture as their primary income source display higher technical efficiency relative to those reliant on non-agricultural sectors. These results likely from greater investment in time, capital, and labor in rice cultivation from household relying on agriculture, which results better management of crops, adoption of improved techniques and technologies, ultimately leading to increased yield and efficiency. Households with agriculture as their primary occupation are more inclined to adopt agricultural technologies (Subedi & Dhakal, 2018). Aligning with our findings, Subedi et al. (2020a) found higher technical efficiency among households with agriculture as primary income source in comparison to their counterparts. Similarly, Buba et al. (2017) found that full-time farmers are more technically efficient than part time farmers in traditional wheat cultivation in the Fezzan region.

Experience also showed a positive and significant association with technical efficiency, inferring that more experienced farmers achieve higher efficiency in comparison to less experienced ones. This is likely due to gained skills and knowledge through experience, enabling better adoption of new technologies and effective resource management (Sapkota & Joshi, 2021). Experience assists to gain valuable skills and boost technical efficiency (Okike et al., 2003). Consistent with our findings, several prior studies have reported a positive correlation between experience and technical efficiency in rice cultivation (Subedi et al., 2020a; Khanal & Maharjan, 2013); Choudhary et al., 2022). Similarly, Sapkota and Joshi (2021) also documented a significant positive relationship of experience with technical efficiency in maize seed production in mid-hills of Nepal. In addition, Girma et al., (2024) found experience in wheat production negatively impacts efficiency, implying higher efficiency among experienced farmers.

The inefficiency model reveled that higher education attainment, measured by years of formal schooling, had significant negative relations with technical inefficiency, thereby improving efficiency. Highly educated farmers are better in accessing agricultural information and skills, enabling successful planning, resource management, and adoption of improved technologies, ultimately boosting yield. Education is typically expected to have an inverse relationship with technical inefficiency (Mishra et al., 2018). Aligning with our findings, several studies have documented a significant positive relationship between education and technical efficiency in rice production (Acharya & Bhatta, 2022; Ali et al., 2022; Lema et al., 2017). In addition, Khanal and Maharjan (2023) also reported a positive significant association of education with technical efficiency in rice seed production. Similarly, Ghimire et al. (2023) found that improved education opportunities enhance technical efficiency in lentil production, while Girma et al. (2024) reported a significant negative relationship between education level and inefficiency in wheat production.

Cooperative membership had significant negative coefficient, indicating that members of cooperative had higher technical efficiency than non-members. Participation in cooperatives provide access to meetings, training, and interactions that facilitate adoption of improved technologies, which leads to higher yields and efficiency (Subedi et al., 2020a). Several studies have reported the significant positive relationship of cooperative membership with technical efficiency (Acharya & Bhatta, 2022; Subedi et al., 2020a; Tipi et al., 2009). Similarly, Ghimire et al. (2023) reported that membership of farmers in cooperatives significantly improves technical efficiency in lentil production, while Neupane et al. (2022) found that cooperative membership positively affects the technical efficiency level of goat farming in Nepal.

The coefficient for extension services was negatively and significantly associated with technical inefficiency, indicating that farmers with access to extension services demonstrated a higher technical efficiency compared to farmers with no access. Agricultural extension enhances knowledge and skills which are essential for optimal input use and resource management, which ultimately boost productivity (Abate et al., 2019; Athukorala, 2017). Consistent with our findings, Thapa and Dhakal (2024) reported that rice seed growers in Chitwan who interacted with extension agents were found less inefficient. Similarly, Biswas et al. (2021) found that rural paddy farmers receiving extension services had higher technical efficiency. Additionally, Girma et al. (2024) also reported that the frequency of contact with extension agents negatively influences technical inefficiency in wheat production.

CONCLUSION

This study assessed the inefficiency level and its sources among rice farmers in the Chitwan district of Nepal by employing one-step stochastic frontier model, which reported the mean technical efficiency of 82.30%. This indicates that farmers are relatively efficient, while there exists a significant production gap of 17.70%. There is a substantial potential to enhance the productivity level by approximately 18%, following the best management practices currently adopted by the most efficient farmers. In addition, the inefficiency model revealed that several socio-economic and institutional determinants, such as major sources of household income, education, experience, cooperative membership, and extension service, significantly reduce technical inefficiency. Furthermore, the gamma value indicates that 94.2% of variation in rice production is attributable to technical inefficiency rather than random factors, which highlights the necessities for management-based interventions. Therefore, to achieve the national objective of being self-sufficient in rice production and improve rural livelihood, policymakers should prioritize strengthening agricultural extension services, promoting cooperative networks, and enhancing formal and technical education within farming households.

ACKNOWLEDGMENTS

The authors would like to sincerely acknowledge all the farmers who participated in the survey and shared their valuable time and information. The authors are grateful to the enumerators for their assistance during data collection.

AUTHOR CONTRIBUTIONS

SS: Conceptualization, Formal analysis, Writing – original draft; **SMD:** Validation, Writing – review & editing, Supervision; **RNC:** Writing – review & editing.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ETHICAL APPROVAL AND PERMITS

Not applicable.

REFERENCES

Abate, T. M., Dessie, A. B., & Mekie, T. M. (2019). Technical efficiency of smallholder farmers in red pepper production in North Gondar Zone, Amhara Regional State, Ethiopia. *Journal of Economic Structures, 8*, Article 15. https://doi.org/10.1186/s40008-019-0150-6

Acharya, P., Regmi, P. P., Gauchan, D., KC, D. B., & KC, G. B. (2020). Comparative study on technical efficiency of mechanized and traditional rice farms in Nepal. *Journal of Agriculture and Natural Resources, 3*(2), 82–91. https://doi.org/10.3126/janr.v3i2.32484

Acharya, P., Regmi, P. P., Gauchan, D., KC, D. B., & KC, G. B. (2021). Comparative analysis of cost, return, profitability and labor use in mechanized and traditional rice farms in Nepal. *Food & Agribusiness Management, 2*(1), 17–22. https://doi.org/10.26480/fabm.01.2021.17.22

Acharya, R., & Bhatta, S. (2022). Gender differentials in technical efficiency of rice farmers in Jhapa district of Nepal. *Nepalese Journal of Agricultural Sciences, 23*.

Adebayo, K., Babu, S. C., Sanusi, R., & Sofola, M. (2015). Private sector participation in agricultural extension for cocoa farming in Nigeria: The case of multi-trex integrated foods. In Y. Zhou & S. C. Babu (Eds.), *Knowledge-driven development: Private extension and global lessons*. Academic Press.

Afriat, S. N. (1972). Efficiency estimation of production functions. *International Economic Review, 13*(3), 568. https://doi.org/10.2307/2525845

Ahmad, M. H., Adnan, R., & Adnan, N. (2006). A comparative study on some methods for handling multicollinearity problems. *MATEMATIKA, 22*, 109–119.

Aigner, D. J., & Chu, S. F. (1968). On estimating the industry production function. *The American Economic Review, 58*(4), 826–839.

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

Ali, S., Murtaza, Ahmad, W., Bibi, N., Khan, A., & Khan, J. (2022). Does education and farming experience affect technical efficiency of rice crop growers? Evidence from Khyber Pakhtunkhwa, Pakistan. *Sarhad Journal of Agriculture, 38*(3), 1147–1159. https://doi.org/10.17582/journal.sja/2022/38.3.1147.1159

Amankwa, L. A., Abdulai, A., & Jumpah, E. T. (2022). Technical efficiency and its determinants in rice production: The case of small-scale rice growers in the Ejisu Juaben Municipality of Ghana. *Journal of Planning and Land Management, 2*(2), 38–49. https://doi.org/10.36005/jplm.v2i2.64

Anang, B. T. (2021). Assessing technical and scale efficiency of groundnut production in Tolon district of northern Ghana: A nonparametric approach. *Journal of Agriculture and Food Research, 4*, Article 100149. https://doi.org/10.1016/j.jafr.2021.100149

Anik, A. R., & Rahman, S. (2021). Women's empowerment in agriculture: Level, inequality, progress, and impact on productivity and efficiency. *Journal of Development Studies, 57*(6), 930–948. https://doi.org/10.1080/00220388.2020.1817393

Athukorala, W. (2017). Identifying the role of agricultural extension services in improving technical efficiency in the paddy farming sector in Sri Lanka. *Sri Lanka Journal of Economic Research, 5*, 63–77. https://doi.org/10.4038/sljer.v5i1.58

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. *Stata Journal, 13*(4), 718–758.

Bhandari, N. B., Bhattarai, D., & Aryal, M. (2015). *Cost, production and price spread of cereal crops in Nepal: A time series analysis.*

Biswas, B., Mallick, B., Roy, A., & Sultana, Z. (2021). Impact of agricultural extension services on technical efficiency of rural paddy farmers in southwest Bangladesh. *Environmental Challenges, 5*, Article 100261. https://doi.org/10.1016/j.envc.2021.100261

Bravo-Ureta, B. E., & Pinheiro, A. E. (1997). Technical, economic, and allocative efficiency in peasant farming: Evidence from the Dominican Republic. *The Developing Economies, 35*(1), 48–67. https://doi.org/10.1111/j.1746-1049.1997.tb01186.x

Buba, S., Mohamed, Z. A., Latif, I. A., Abdullah, A. M., & Iliyas, A. (2017). Analysis of technical efficiency of traditional wheat farming in Fezzan region, Libya. *Journal of Agricultural Economics and Rural Development, 3*(3), 251–258.

Central Bureau of Statistics, Nepal. (2021). *National population and housing census 2021*.

Centre for Development and Documentation (CDD). (2015). *Rice varietal mapping in Nepal: Implications for development and adoption*.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chepng'etich, E. (2013). *Analysis of technical efficiency of smallholder sorghum producers in Machakos and Makindu districts in Kenya*. Kenyatta University.

Chou, E. C., & Lau, L. (1978). Farmer ability and farm productivity: A study of farm households in the Chiang Mai valley, Thailand (1972–1978).

Choudhary, D., Banskota, K., Khanal, N. P., McDonald, A. J., Krupnik, T. J., & Erenstein, O. (2022). Rice subsector development and farmer efficiency in Nepal: Implications for further transformation and food security. *Frontiers in Sustainable Food Systems, 5*, Article 740546. https://doi.org/10.3389/fsufs.2021.740546

Coelli, T. (1995). Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis. *Journal of Productivity Analysis, 6*, 247–268. https://doi.org/10.1007/BF01076978

Coelli, T., Rao, D. S. P., & Battese, G. E. (1998). *An introduction to efficiency and productivity analysis*. Springer. https://doi.org/10.1007/978-1-4615-5493-6

Dessale, M. (2019). Analysis of technical efficiency of smallholder wheat-growing farmers of Jamma district, Ethiopia. *Agriculture and Food Security, 8*, Article 25. https://doi.org/10.1186/s40066-018-0250-9

Dhakal, R., Bhandari, S., Joshi, B., Aryal, A., Kattel, R. R., & Dhakal, S. C. (2019). Cost-benefit analysis and resource use efficiency of rice production system in different agricultural landscapes in Chitwan district, Nepal. *Archives of Agriculture and Environmental Science, 4*(4), 442–448. https://doi.org/10.26832/24566632.2019.0404011

Dhungana, B. R., Nuthall, P. L., & Nartea, G. V. (2004). Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis. *Australian Journal of Agricultural and Resource Economics, 48*(2), 347–369. https://doi.org/10.1111/j.1467-8489.2004.00243.x

Emmanuel, B. O., & Maureen, N. T. (2021). Investigating heteroscedastic disturbances in some transformed economic models while eliminating multicollinearity. *International Journal of Statistics and Applied Mathematics, 6*(5), 1–7.

Gairhe, S., Gauchan, D., & Timsina, K. P. (2021). Temporal dynamics of rice production and import in Nepal. *Journal of Nepal Agricultural Research Council, 7*, 97–108. https://doi.org/10.3126/jnarc.v7i1.36932

Gairhe, S., Shrestha, H. K., & Timsina, K. (2018). Dynamics of major cereals productivity in Nepal. *Journal of Nepal Agricultural Research Council, 4*, 60–71. https://doi.org/10.3126/jnarc.v4i1.19691

Gauchan, D., & Pandey, S. (2011). Is investment in rice research in Nepal adequate and balanced across production environments? Some empirical evidence. *Quarterly Journal of International Agriculture, 50*(4), 305–324.

GC, A., Yeo, J.-H., & Ghimire, K. (2019). Determinants of farm mechanization in Nepal. *Turkish Journal of Agriculture – Food Science and Technology, 7*(1), 87–91. https://doi.org/10.24925/turjaf.v7i1.87-91.2131

Ghimire, B., Dhakal, S. C., Marahatta, S., & Bastakoti, R. C. (2023). Technical efficiency and its determinants on lentil (Lens culinaris) production in Nepal. *Farming System, 1*(3), Article 100045. https://doi.org/10.1016/j.farsys.2023.100045

Girma, M., Mehare, A., & Ketema, M. (2024). Wheat crop producers' technical efficiency and its determinants in Oromia region of Ethiopia: Evidence from West Shewa zone. *Cogent Social Sciences, 10*(1). https://doi.org/10.1080/23311886.2024.2329791

Greene, W. H. (1980a). Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics, 13*(1), 27–56. https://doi.org/10.1016/0304-4076(80)90041-X

Greene, W. H. (1980b). On the estimation of a flexible frontier production model. *Journal of Econometrics, 13*(1), 101–115. https://doi.org/10.1016/0304-4076(80)90045-7

Greene, W. H. (2003). Simulated likelihood estimation of the normal-gamma stochastic frontier function. *Journal of Productivity Analysis, 19*, 179–190. https://doi.org/10.1023/A:1022853416499

Greene, W. H. (2012). *Econometric analysis* (7th ed.). Prentice Hall.

Gul, M., Koç, B., Dağistan, E., Akpinar, M. G., & Parlakay, O. (2009). Determination of technical efficiency in cotton growing farms in Turkey: A case study of Çukurova region. *African Journal of Agricultural Economics and Rural Development, 4*(10), 944–949.

Hazarika, C., & Subramanian, S. R. (1999a). Estimation of technical efficiency in the stochastic frontier production function model: An application to the tea industry in Assam. *Indian Journal of Agricultural Economics, 54*(2), 201–211.

Hazarika, C., & Subramanian, S. R. (1999b). Estimation of technical efficiency in the stochastic frontier production function model: An application to the tea industry in Assam. *Indian Journal of Agricultural Economics, 54*(2), 201–211.

James Fasakin, I., & Akinbode, B. B. (2020). Technical efficiency of maize farmers in Oyo State, Nigeria. *Agricultural Journal, 14*(4), 70–74. https://doi.org/10.36478/aj.2019.70.74

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics, 19*(2–3), 233–238. https://doi.org/10.1016/0304-4076(82)90004-5

K. C., B., Pandit, R., Kandel, B. P., Kanchan, K. K., K. C., A., & Poudel, M. R. (2021). Scenario of plant breeding in Nepal and its application in rice. *International Journal of Agronomy, 2021*. https://doi.org/10.1155/2021/5520741

Khanal Prasad, N., & Maharjan Lall, K. (2013). Technical efficiency of rice seed growers in the Tarai region of Nepal. *Journal of Rural Problems, 49*(1), 27–31. https://doi.org/10.7310/arfe.49.27

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

Kumbhakar, S. C., Ghosh, S., & McGuckin, J. T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms. *Journal of Business & Economic Statistics, 9*(3), 279–286. https://doi.org/10.2307/1391292

Kumbhakar, S. C., Wang, H.-J., & Horncastle, A. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press. https://doi.org/10.1017/cbo9781139342070

Latynskiy, E., & Berger, T. (2016). Networks of rural producer organizations in Uganda: What can be done to make them work better? *World Development, 78*, 572–586. https://doi.org/10.1016/j.worlddev.2015.10.014

Lema, T. Z., Tessema, S. A., & Abebe, F. A. (2017). Analysis of the technical efficiency of rice production in Fogera district of Ethiopia: A stochastic frontier approach. *Ethiopian Journal of Economics, 26*(2), 88–108.

Maharjan, A., Bauer, S., & Knerr, B. (2013). Migration for labour and its impact on farm production in Nepal. *Centre for the Study of Labour and Mobility*.

Majumder, S., Bala, B. K., Arshad, F. M., Haque, M. A., & Hossain, M. A. (2016). Food security through increasing technical efficiency and reducing postharvest losses of rice production systems in Bangladesh. *Food Security, 8*, 361–374. https://doi.org/10.1007/s12571-016-0558-x

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*(2), 435–444. https://doi.org/10.2307/2525757

Mishra, A. K., Bairagi, S., Velasco, M. L., & Mohanty, S. (2018). Impact of access to capital and abiotic stress on production efficiency: Evidence from rice farming in Cambodia. *Land Use Policy, 79*, 215–222. https://doi.org/10.1016/j.landusepol.2018.08.016

Ministry of Agriculture and Livestock Development, Nepal. (2022). *Statistical information on Nepalese agriculture*.

Ministry of Finance, Nepal. (2021). *Budget speech 2021/22 (2078/79)*.

Mohsin, A. Q., Ahmad, S., & Anwar, A. (2011). Impact of supervised agricultural credit on farm income in the Barani areas of Punjab. *Pakistan Journal of Social Science, 31*(2), 241–250.

Nakano, Y., Tsusaka, T. W., Aida, T., & Pede, V. O. (2018). Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. *World Development, 105*, 336–351. https://doi.org/10.1016/j.worlddev.2017.12.013

Neupane, H., Paudel, K. P., Adhikari, M., & He, Q. (2022). Impact of cooperative membership on production efficiency of smallholder goat farmers in Nepal. *Annals of Public and Cooperative Economics, 93*, 337–356. https://doi.org/10.1111/apce.12371

Okike, I., Jabbar, M. A., Manyong, V. M., Smith, J. W., & Ehui, S. K. (2003). Factors affecting farm-specific production efficiency in the savanna zones of West Africa. *Journal of African Economies, 12*(1), 134–165. https://doi.org/10.1093/jae/13.1.134

Pandey, P. R., Pandey, H., GC, A., & Khanal, M. P. (2015). Climatic variability, rice-based cropping systems and impacts on livelihoods: A comparative study of Chitwan and Kavre districts, Nepal. *Nepalese Journal of Agricultural Economics*, 167–179.

Paudel, B., Acharya, B. S., Ghimire, R., Dahal, K. R., & Bista, P. (2014). Adapting agriculture to climate change and variability in Chitwan: Long-term trends and farmers' perceptions. *Agricultural Research, 3*(2), 165–174. https://doi.org/10.1007/s40003-014-0103-0

Paudel, G. P., KC, D. B., Rahut, D. B., Khanal, N. P., Justice, S. E., & McDonald, A. J. (2019). Smallholder farmers' willingness to pay for scale-appropriate farm mechanization: Evidence from the mid-hills of Nepal. *Technology in Society, 59*, Article 101196. https://doi.org/10.1016/j.techsoc.2019.101196

Piya, S., Kiminami, A., & Yagi, H. (2012). Comparing the technical efficiency of rice farms in urban and rural areas: A case study from Nepal. *Trends in Agricultural Economics, 5*, 48–60. https://doi.org/10.3923/tae.2012.48.60

Poudel, U., Kattel, R. R., Gurung, B., Shrestha, S., Paudel, A., & Paudel, A. (2021). Economic analysis of rice (Oryza sativa L.) cultivation in Gorkha district of Nepal. *Archives of Agriculture and Environmental Science, 6*(4), 489–497. https://doi.org/10.26832/24566632.2021.0604011

Sapkota, M., & Joshi, N. P. (2021). Factors associated with the technical efficiency of maize seed production in the mid-hills of Nepal: Empirical analysis. *International Journal of Agronomy, 2021*, Article 5542024. https://doi.org/10.1155/2021/5542024

Sapkota, S., & Sapkota, S. (2019). Benefit-cost analysis of different rice varieties in Kapilvastu district, Nepal. *International Journal of Applied Sciences and Biotechnology, 7*(2), 222–226. https://doi.org/10.3126/ijasbt.v7i2.24210

Schmidt, P., & Lin, T.-F. (1984). Simple tests of alternative specifications in stochastic frontier models. *Journal of Econometrics, 24*(3), 349–361.

Shrestha, H. K., & Gairhe, S. (2016). Is investment in maize research balanced and justified? An empirical study. *Journal of Nepal Agricultural Research Council, 2*, 27–32. https://doi.org/10.3126/jnarc.v2i0.16118

Shrestha, J., Subedi, S., Kushwaha, U. K. S., & Maharjan, B. (2021). Evaluation of rice genotypes for growth, yield and yield components. *Journal of Agriculture and Natural Resources, 4*(2), 339–346. https://doi.org/10.3126/janr.v4i2.33967

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics, 13*(1), 57–66. https://doi.org/10.1016/0304-4076(80)90042-1

Subedi, S., & Dhakal, D. (2018). Economics of poultry manure as an alternative to chemical fertilizer for agricultural production in Nepal. *Journal of the Institute of Agriculture and Animal Science, 33–34*, 259–268. https://doi.org/10.3126/jiaas.v33i0.20713

Subedi, S., Ghimire, Y. N., Kharel, M., Adhikari, S. P., Shrestha, J., & Sapkota, B. K. (2020a). Technical efficiency of rice production in Terai district of Nepal. *Journal of Agriculture and Natural Resources, 3*(2), 32–44. https://doi.org/10.3126/janr.v3i2.32301

Subedi, S., Ghimire, Y. N., Kharel, M., Adhikari, S. P., Shrestha, J., & Sapkota, B. K. (2020b). Technical efficiency of rice production in Terai district of Nepal. *Journal of Agriculture and Natural Resources, 3*(2), 32–44. https://doi.org/10.3126/janr.v3i2.32301

Subedi, S., Ghimire, Y. N., Kharel, M., Sharma, B., Shrestha, J., & Sapkota, B. K. (2020). Profitability and resource use efficiency of rice production in Jhapa district of Nepal. *International Journal of Social Sciences and Management, 7*(4), 242–247. https://doi.org/10.3126/ijssm.v7i4.32487

Tamirat, N., & Tadele, S. (2023). Determinants of technical efficiency of coffee production in Jimma Zone, Southwest Ethiopia. *Heliyon, 9*(4), Article e15030. https://doi.org/10.1016/j.heliyon.2023.e15030

Thapa, R., & Dhakal, S. C. (2024). Technical efficiency of rice seed production and their determinants in Chitwan, Nepal: A one-step scaling stochastic frontier approach. *Cogent Food & Agriculture, 10*(1), Article 2353668. https://doi.org/10.1080/23311932.2024.2353668

Timsina, K. P., Gauchan, D., Gairhe, S., Subedi, S. R., Pokhrel, B. B., Upadhyay, S., Joshi, K. D., Pandey, S., & Shrestha, J. (2023). Rice demand and production projections for 2050: Opportunities for achieving self-sufficiency in Nepal. *Nepal Agriculture Research Journal, 15*(1), 163–180. https://doi.org/10.3126/narj.v15i1.51926

Timsina, K., Shrestha, K. P., & Pandey, S. (2012). Factors affecting adoption of new modern varieties of rice in eastern Terai of Nepal. *Agriculture Research for Development: Proceedings of Fourth Society of Agricultural Scientist-Nepal (SAS-N) Convention*, 4–6.

Tipi, T., Yildiz, N., Nargeleçekenler, M., & Çetin, B. (2009). Measuring the technical efficiency and determinants of efficiency of rice (*Oryza sativa*) farms in Marmara region, Turkey. *New Zealand Journal of Crop and Horticultural Science, 37*(2), 121–129. https://doi.org/10.1080/01140670909510257

Tumuri, A., Geleta, D., & Sime, G. (2024). Technical efficiency of maize production and their determinants among smallholder farmers in Ethiopia: A case study in Sidama Region. *Cogent Food & Agriculture, 10*(1). https://doi.org/10.1080/23311932.2024.2392045

United Nations Development Programme. (2022). *Human development report 2021–22: Uncertain times, unsettled lives: Shaping our future in a transforming world*. https://hdr.undp.org/

Wang, H. J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis, 18*, 129–144. https://doi.org/10.1023/A:1016565719882

Wudineh, G. T., & Endrias, G. (2016). Technical efficiency of smallholder wheat farmers: The case of Welmera district, Central Oromia, Ethiopia. *Journal of Development and Agricultural Economics, 8*(2), 39–51. https://doi.org/10.5897/jdae2015.0660

Zabatantou Louyindoula, H., Bouity, C. A., & Owonda, F. (2023). Impact of agricultural credit on productivity. *Theoretical Economics Letters, 13*(6), 1434–1462. https://doi.org/10.4236/tel.2023.136081