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# Can sustainable practices optimise fertiliser use and economic efficiency? A micro-panel analysis

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**Abstract:** The intensification of agricultural practices in Bangladesh has caused significant environmental challenges. This has also undermined farmers' economic sustainability, mainly due to the excessive use of subsidised chemical fertilisers. To address these issues and align with the United Nations Sustainable Development Goals (SDGs), Bangladesh has prioritised the adoption of sustainable farming practices, including the recommended fertiliser application (RFA). However, whether the adoption of RFA ensures economic sustainability remains uncertain. This study evaluates how the Bangladesh Rice Research Institute's (BRRI) proposed RFA affects fertiliser use and cost-efficiency. Drawing on five years (2017–2021) of panel data from 2 025 households across three acidic soil regions in Dinajpur, the findings reveal that RFA adoption reduces fertiliser use by 12% while improving cost efficiency by 4.9–5.1%. These results highlight the potential of RFA to mitigate environmental degradation while enhancing economic outcomes, thereby supporting the SDG agenda. In light of these benefits, the study offers key insights for policymakers and development practitioners, emphasising the need for targeted interventions to accelerate RFA adoption and promote sustainable agriculture.

**Keywords:** Bangladesh; control function; correlated random effects; efficiency; stochastic frontier cost function; sustainable agriculture

Agriculture plays a crucial role in global food production and economic development, particularly in developing countries, where it remains a key source of livelihood. The transition from traditional to intensified agricultural practices, spurred by the Industrial Revolution, has significantly supported food security and reduced rural poverty (Xie et al. 2019; Guo and Wang 2021). However, the environmental consequences of such intensification – especially the overreliance on chemical inputs such as fertilisers – have become increasingly apparent, resulting in soil degradation, biodiversity loss, and pollution (Shah and Wu 2019; Kishore et al. 2021; Huan and Zhan 2022). In particular, the indiscriminate use of chemical fertilisers in rice production presents a major challenge in Asia, adversely affecting both soil health and the wider environment. Bangladesh, a country heavily dependent on rice cultivation, exemplifies this issue. To boost productivity and efficiency, the Bangladeshi government provides fertiliser subsidies, which have helped achieve higher rice productivity (Pearson et al. 2018). However, this policy has also led to increased fertiliser consumption (Pearson et al. 2018; Sunny et al. 2024), making Bangladesh the world's 12th-largest fertiliser consumer,

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with a usage rate of over 390 kg per hectare (World Bank 2025). While these efforts have enhanced agricultural output, they have also led to imbalanced fertiliser application, causing inefficiencies, environmental degradation, and undermining farmers' economic sustainability (Rahman and Zhang 2018; Sunny et al. 2022a).

Recognising these challenges, the adoption of sustainable agricultural practices has become a national priority. In line with the United Nations' Sustainable Development Goals (SDGs), Bangladesh has launched initiatives to promote the use of recommended fertiliser application (RFA) tailored to specific crops. This sustainable practice aims to optimise fertiliser use, enhance crop productivity, and reduce environmental damage (MOA 2020; FPMU 2021; Sunny et al. 2024).

Similar strategies have been successfully adopted in other countries where excessive fertiliser use has impeded agricultural sustainability. For example, Germany, Egypt, and Ethiopia have implemented recommended fertiliser application (RFA) programmes, which have reduced fertiliser consumption while improving efficiency (Jate 2010; Shaaban et al. 2018; Wako and Usmane 2020; El-Nasharty et al. 2022). In India, site-specific fertilisation techniques have reduced nitrogen use by 18%, increased production by 4% to 12%, and decreased greenhouse gas emissions by up to 22.5% (Sapkota et al. 2021). Similarly, studies from Pakistan demonstrate that balanced fertiliser use enhances profitability (Yousaf et al. 2020). Research in China highlights improvements in soil organic matter, enzyme activity, and bacterial abundance through balanced fertilisation (Xiao et al. 2022). Findings from Indonesia and Vietnam underscore the potential of balanced fertilisation to increase productivity and improve soil properties (Hindersah et al. 2022; Trinh et al. 2023).

In Bangladesh, farmers who adopt RFA practices report higher yields and profit margins compared to those using traditional fertiliser methods. For instance, Mamun et al. (2018) examined various fertiliser management guidelines for Boro rice cultivation in the Barisal district in the south of the country, while Afrad et al. (2018) focused on the Sunamganj district in the northeast. However, these studies not only explored different regions but also relied on single-year data and small sample sizes. Although Sunny et al. (2022c; 2024) investigated the impact within the same geographical context, their research examined joint technology adoption – specifically, the integration of solar irrigation with recommended fertiliser use – and its effects on production costs and return on investment.

This article addresses a notable gap in the existing literature by providing new insights into whether the adoption of recommended fertiliser application (RFA) positively or negatively impacts fertiliser use and cost efficiency. To our knowledge, no prior studies have examined this relationship using panel data in the context of Bangladesh. By deepening the understanding of the factors influencing RFA adoption and the associated opportunities, this research aims to offer valuable evidence to support policy decisions promoting sustainable agricultural practices in Bangladesh.

Moreover, farmers' decision-making is shaped by their ability to evaluate evidence and weigh alternative options (Bukchin and Kerret 2020; Yeo and Keske 2024). Therefore, the actual benefits of adopting RFA in the Bangladeshi context require further exploration. This is especially important given that yield improvements do not always lead to reduced fertiliser use or enhanced efficiency. Consequently, a more thorough investigation of the real-world impacts of RFA adoption is warranted.

Given that fertiliser constitutes a significant share of production costs for water-intensive crops such as BRRI dhan29 rice (Mainuddin et al. 2021), the cost-effectiveness of RFA could be a key factor in farmers' adoption decisions. If RFA proves more economical in terms of fertiliser consumption and efficiency compared to traditional methods, it could encourage farmers to optimise other inputs and manage costs more effectively (Emerick et al. 2016; Abay et al. 2018; Buisson et al. 2024). Such changes may lead to more efficient resource allocation, better financial outcomes for farmers, and contribute to the development of a more sustainable rice production system. In light of the above, this article seeks to answer the following research question:

What factors influence the adoption of the Bangladesh Rice Research Institute's (BRRI) recommended fertiliser dosage (RFA), and how does RFA adoption affect fertiliser consumption and cost efficiency among BRRI dhan29 rice growers?

This study hypothesises that farmers adopting BRRI-recommended RFA will reduce fertiliser use and achieve greater efficiency than non-adopters. In the long term, the adoption of balanced fertilisation practices is expected to enhance not only economic sustainability but also broader agricultural sustainability objectives (Dobermann et al. 2022; Pandian et al. 2024). If supported, the adoption of BRRI-recommended RFA could foster more responsible farming, help mitigate climate change, and improve food security, thereby advancing SDGs 12, 13, and 2.

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## MATERIAL AND METHODS

**Study area, sampling procedure, and data source.** This research focuses on the Barind Tract, specifically the Dinajpur region, the largest of Bangladesh's sixteen districts in the northwest. This area is of particular interest for several reasons. Firstly, its tropical wet-dry climate results in limited rainfall, contributing to drought, food insecurity, and poverty. Secondly, rice cultivation is predominant, with the 'BRRI dhan29' variety widely adopted during the Boro season, also known as the dry season (BRRI 2019). Most importantly, given the region's acidic soils and the limited research on fertiliser application practices and their efficacy during the Boro season, it is essential to assess the long-term impact of BRRI-recommended fertiliser application on agricultural productivity (Islam et al. 2017; Shirazy et al. 2018; SRDI 2020; Islam et al. 2022). For effective policy-making, it is crucial to understand how sustainable fertiliser management practices vary across different agro-ecological conditions.

As this research is based on survey data, a random sampling technique was employed to select three sub-districts – Birganj, Khanshama, and Kaharol – from a total of thirteen. The sample size was determined using the approach of Krejcie and Morgan (1970), applying a 95% confidence level, one degree of freedom, a 50% maximum population variance, and a 5% margin of error. From a population of 643 431 (BBS 2015), the required sample size was calculated to be 405 (135 farmers per sub-district), with an additional ± 5% contingency to account for unforeseen issues. Data were collected using a structured questionnaire between 2017 and 2021 through face-to-face interviews conducted annually from December to June, aligning with the Boro season (BBS 2020). All participating farmers consented to annual interviews until 2021. The interview schedule was translated into the local language and pre-tested before finalisation. The questionnaire covered various topics, including farmers' demographic and socioeconomic characteristics, adoption or non-adoption behaviour, input usage and production costs, total rice output, knowledge sources, and soil-related factors.

Following five years of data collection, a balanced panel comprising 2 025 observations (405 households over 5 years) was constructed. Farmers were classified based on their adherence to the fertiliser application rates recommended for 'BRRI dhan29' rice, as outlined in the BRRI manual. These recommended rates range from 336.8 to 524 kg per hectare, including 224.5–299.4 kg/ha of urea, 52.4–104.8 kg/ha of TSP (triple super phosphate), and 59.9–119.8 kg/ha of MOP (muriate of potash) (Sunny et al. 2024). Farmers who adhered to these guidelines were categorised as adopters, while those who did not were considered non-adopters.

**Research procedures.** This study employs the correlated random effects (CRE) model with a control function (CF) approach, alongside stochastic frontier analysis (SFA) with endogeneity correction, to assess the impact of RFA adoption on fertiliser use and cost efficiency. For cost efficiency estimation, SFA is preferred over data envelopment analysis (DEA) as it accounts for random noise and allows for statistical hypothesis testing. Endogeneity within the stochastic frontier model is addressed using the approach of Karakaplan and Kutlu (2017a, 2017b, 2017c), ensuring unbiased inefficiency estimates. A Cobb–Douglas (CD) production function is selected over translog or quadratic specifications due to its robustness against multicollinearity and its stable estimation properties. To compare efficiency between adopters and non-adopters, a fractional response model (fracreg) is used, incorporating the Mundlak (1978) approach to reduce bias. While the selected methods effectively address both endogeneity and heterogeneity, the detailed analytical procedures and the rationale for choosing these methods are provided below.

**The impact of RFA adoption on fertiliser use.** The impact of RFA adoption on fertiliser use is modelled as follows:

$$Y_{it} = \beta_0 + \beta_1 \mathrm{RFA}_{it} + \beta_2 X_{it} + v_i + \varepsilon_{it} \tag{1}$$

where: $Y_{it}$ – the total amount of fertiliser ($F$) applied by farmer $i$ at time $t$; $RFA_{it}$ – the farmers' adoption status of RFA; $X_{it}$ – a vector of predictor variables; $v_i$ – the unobserved, time-invariant household effects; $\beta_0$ – the intercept term; $\beta_1$ – the effect of RFA adoption; $\beta_2$ – the influence of predictor variables; $\varepsilon_{it}$ – the error term.

Utilising pooled ordinary least squares (OLS) to estimate Equation (1) presumes there is no correlation between error terms and the regressors. However, this approach fails to account for the panel structure of the data, potentially leading to inefficiencies due to intra-household error correlation (Tambo et al. 2020). A random effect (RE) model can be used but it holds strong assumption that the regressors are uncorrelated with the error terms (Wooldridge 2010). If farmers' decisions to adopt RFA are not random, this assumption

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is violated, leading to biased estimates (Tambo et al. 2020; Sunny et al. 2024). Although a fixed effects (FE) estimator could be applied, the model may encounter issues due to incidental parameters (Greene 2004; Wooldridge 2010; Tambo et al. 2020). Besides, other approaches such as difference-in-differences (DID) and propensity score matching (PSM) could also be considered. However, DID relies on the assumption of parallel trends (Marcus and Sant'Anna 2021), which does not hold in this context, whereas PSM fails to account for unobserved heterogeneity (Nimmo et al. 2022).

Given these limitations, the CRE model proposed by Mundlak (1978) is used. While CRE approach effectively addresses unobserved heterogeneity, it does not resolve endogeneity (Wooldridge 2010; Tambo et al. 2020). Therefore, a two-stage estimation procedure combining the CRE model with the CF approach is employed. This estimation procedure requires at least one instrumental variable (IV) that is strongly and partially correlated with $RFA_{it}$ but uncorrelated with the unobservables affecting the outcome variables (Smith and Blundell 1986; Wooldridge 2010; Tambo et al. 2020). The IV selected for this analysis is 'fertiliser information seeking state', based on the premise that farmers typically seek advice on input usage from trusted individuals. This variable is expected to influence RFA adoption decision, while not directly affecting the outcome variables (Kassem et al. 2021; Luo et al. 2022; Wu 2022; Sunny et al. 2024).

Consequently, the first stage equation, revised from Equation (1), can be expressed as:

$$\mathrm{RFA}_{it} = \beta_1 X_{it} + \beta_2 IV + \beta_3 \bar{X}_i + v_i + \varepsilon_{it} \tag{2}$$

where: $\bar{X}_i$ – the time averages of the time-varying covariates, with associated parameters $\beta_3$; $IV$ – the instrumental variable (fertiliser information-seeking state).

In the second stage, the generalised residual ($\hat{R}_{it}$) obtained from the first-stage regression [Equation (2)], is incorporated into the outcome of Equation (3):

$$Y_{it} = \beta_0 + \beta_1 \mathrm{RFA}_{it} + \beta_2 X_{it} + \beta_3 \bar{X}_i + \beta_4 \hat{R}_{it} + v_i + \varepsilon_{it} \tag{3}$$

where: $\hat{R}_{it}$ – the generalized residual; $\beta_4$ – captures the effect of $R_{it}$ after correcting for endogeneity by including the generalized residual $\hat{R}_{it}$ in the model.

The significance of $\hat{R}_{it}$ would indicate that the RFA adoption variable is endogenous (Wooldridge 2010; Tambo et al. 2020).

To ensure robustness, we employ the two-stage residual inclusion (2SRI) approach, a method used to address endogeneity. This approach has been applied in other empirical studies (Terza et al. 2008; Ma and Zhu 2020; Zhang et al. 2023), demonstrating its effectiveness in handling endogeneity concerns.

**RFA adoption impact on cost efficiency.** To understand how RFA adoption impacts efficiency levels, two commonly used methods are SFA and DEA. Coelli (1995) compared these two methods and noted that the main strengths of SFA lie in its ability to account for stochastic noise and its capacity to permit statistical testing of hypotheses related to production structure and the degree of inefficiency.

In contrast, DEA is a deterministic method that attributes all deviations from the production frontier to inefficiencies. As a result, DEA estimates are more sensitive to measurement errors or other forms of noise in the data. Moreover, SFA is particularly advantageous for evaluating efficiency in agricultural production (Reinhard et al. 2000; Bai et al. 2019; 2020).

Given these considerations, this study adopts the stochastic frontier cost function model proposed by Karakaplan and Kutlu (2017a, 2017b, 2017c), which addresses the issue of endogeneity. A previous study by Islam and Fukui (2018) also applied this method to assess the efficiency of rice production systems in Bangladesh. Following their approach, we employ the CD stochastic frontier cost function in this study.

The CD functional form is chosen over translog or quadratic alternatives because the latter are more susceptible to multicollinearity when variables differ in nature. Additionally, the CD function yields more stable estimates even when basic assumptions are violated and is suitable for use across a range of datasets (Azad and Rahman 2017; Tenaye 2020).

Drawing from Karakaplan and Kutlu (2017a, 2017b, 2017c), our stochastic frontier model for panel data is expressed as follows:

$$\begin{aligned} Y_{it} &= x'_{ait}\beta + v_{it} - su_{it} \\ x_{it} &= Q_{it}\delta + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{bmatrix} \tilde{\varepsilon}_{it} \\ v_{it} \end{bmatrix} \equiv \begin{bmatrix} \Omega^{-1/2}\varepsilon_{it} \\ v_{it} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_\rho & \sigma_v \rho \\ \sigma_v \rho' & \sigma_v^2 \end{bmatrix} \right)$$

$$u_{it} = h\left(x'_{uit}\varphi_u\right)u_i^*$$
$$s = -1 \text{ for cost functions}$$

where: $Y_{it}$ – the logarithm of the cost of the $i^{\text{th}}$ productive unit at time $t$; $x'_{ait}$ – the vector of endogenous and exogenous variables; $\beta$ – in equation 4 represents the vector of coefficients associated with the explanatory

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variables; $x_{it}$ – a $\rho \times 1$ vector of all endogenous variables (excluding $Y_{it}$); $Q_{it} = I_\rho \otimes Q'_{it}$ ; $q_{it}$ is a $r \times 1$ vector of all exogenous variables; $v_{it}$ and $\varepsilon_{it}$ – two-sided error terms; δ – the coefficient vector linking exogenous variables to the endogenous regressors; $\tilde{\varepsilon}_{it}$ – the standardised first-stage residuals; Ω – the variance-covariance matrix of $\varepsilon_{it}$ ; $\sigma_v^2$ – the variance of $v_{it}$ ; ρ – the vector representing the correlation between $\tilde{\varepsilon}_{it}$ and $v_{it}$ ; $I_\rho$ – identity matrix used to build the instrument matrix; $u_{it} \geq 0$ – one-sided error term capturing the inefficiency; $h_{it} = h(x'_{uit}\varphi_u) > 0$ ; $x'_{uit}$ – a vector of exogenous and variables excluding the constant; $u_i^*$ – a producer-specific component independent from $v_{it}$ , and $\varepsilon_{it}$ ; $\phi_u$ – the vector of coefficients in the inefficiency equation.

Hence, $u_{it}$ and $v_{it}$ can be correlated with $x_{it}$ , yet $u_{it}$ and $v_{it}$ are conditionally independent given $x_{it}$ and $q_{it}$ . Similarly, $u_{it}$ and $\varepsilon_{it}$ are conditionally independent given $x_{it}$ and $q_{it}$.

By applying a Cholesky decomposition to the variance-covariance matrix corresponding to $(\tilde{\varepsilon}'_{it}, v_{it})'$, the decomposition can be expressed as:

$$\begin{bmatrix} \tilde{\varepsilon}_{it} \\ v_{it} \end{bmatrix} = \begin{bmatrix} I_\rho & 0 \\ \sigma_v \rho' & \sigma_v \sqrt{1-\rho'\rho} \end{bmatrix} \begin{bmatrix} \tilde{\varepsilon}_{it} \\ \tilde{w}_{it} \end{bmatrix} \tag{5}$$

where: $\tilde{\varepsilon}_{it}$ and $\tilde{w}_{it} \sim$ N (0,1) are independent; $\tilde{w}_{it}$ – an independent standard normal term from the Cholesky decomposition, representing the part of $v_{it}$ uncorrelated with $\tilde{\varepsilon}_{it}$ .

The frontier equation thus can be expressed as:

$$\begin{aligned} Y_{it} &= x'_{ait}\beta + \sigma_v \rho' \tilde{\varepsilon}_{it} + w_{it} - s u_{it} = x'_{ait}\beta + \\ &+ (x_{it} - Q_{it}\delta)'\eta + e_{it} \end{aligned} \tag{6}$$

where: $e_{it} = w_{it} - s u_{it}$ ; $w_{it} = \sigma_v \sqrt{1-\rho'\rho}\,\tilde{w}_{it} = \sigma_w \tilde{w}_{it}$ ; $\eta = \dfrac{\sigma_w \Omega^{\frac{-1}{2}} \rho}{\sqrt{1-\rho'\rho}}$ ; $w_{it}$ – the component of $v_{it}$ that is independent of $\tilde{\varepsilon}_{it}$ , scaled by its standard deviation; $\sigma_w$ the standard deviation of $w_{it}$.

This setup is important because $e_{it}$ is conditionally independent of the regressors given $x_{it}$ and $q_{it}$ . In Equation (7), the term $(x_{it} - Q_{it}\delta)'\eta$ serves as a bias correction term (Karakaplan and Kutlu 2017a, 2017b, 2017c). We assume that:

$$\begin{aligned} u_i^* &\sim N^+(\mu, \sigma_u^2) \\ h_{it}^2 &= exp(x_{uit}\varphi_u) \end{aligned} \tag{7}$$

where: μ – the mean of the inefficiency term $u_i^*$ ; $\sigma_u^2$ – the variance of $u_i^*$ across producers.

A vector of observations corresponding to the panel $i$ will be represented by a subscript $i$ . For example, $h_{i.} = (h_{i1}, h_{i2} \ldots\ldots, h_{iTi})'$ is a $T_i \times 1$ vector, where $T_i$ is the number of time periods for panel *i*. The log-likelihood function of panel *i* is given by:

$$lnL_i = lnL_{i,y|x} + lnL_{i,x} \tag{8}$$

where:

$$lnL_{i,y|x} = -\frac{1}{2}\left( T_i \ln(2\pi\sigma_w^2) + \frac{\acute{e}_{i.} e_{i.}}{\sigma_w^2} + \left( \frac{\mu^2}{\sigma_u^2} - \frac{\mu_{i*}^2}{\sigma_{i*}^2} \right) \right) +$$

$$+ ln \left( \frac{\sigma_{i*} \Phi\left( \frac{\mu_{i*}}{\sigma_{i*}} \right)}{\sigma_u \Phi\left( \frac{\mu}{\sigma_u} \right)} \right)$$

$$lnL_{i,x} = -\frac{1}{2} \sum_{t=1}^{T_i} \left( \ln(|2\pi\Omega|) + \varepsilon'_{it} \Omega^{-1} \varepsilon_{it} \right)$$

$$\mu_{i*} = \frac{\sigma_w^2 \mu - s \sigma_u^2 \acute{e}_{i.} h_{i.}}{\sigma_u^2 h'_{i.} h_{i.} + \sigma_w^2}$$

$$\sigma_{i*}^2 = \frac{\sigma_u^2 \sigma_w^2}{\sigma_u^2 h'_{i.} h_{i.} + \sigma_w^2}$$

$$e_{it} = Y_{it} - x'_{1it}\beta - \varepsilon'_{it}\eta$$

$$\varepsilon_{it} = x_{it} - Q_{it}\delta$$

where: Φ – the standard normal cumulative distribution function (Karakaplan and Kutlu 2017a, 2017b, 2017c).

We predict the cost efficiency, $EFF_{it} = \exp(-u_{it})$, by:

$$\exp\left(-E\left[u_{it} \mid e_i\right]\right) = \exp\left[ -h_{it} \left[ \mu_{i*} + \frac{\sigma_{i*} \phi\left( \frac{\mu_{i*}}{\sigma_{i*}} \right)}{\phi\left( \frac{\mu_{i*}}{\sigma_{i*}} \right)} \right] \right] \tag{9}$$

where: ϕ – the standard normal probability density function.

Compared to standard CF methods (i.e. the two-stage approach), this model is statistically more efficient, does not require a bootstrap procedure to correct standard errors, and estimates parameters in a single stage (Karakaplan and Kutlu 2017a, 2017b, 2017c). In this model, it is necessary to include at least one IV; as noted earlier, the chosen variable is farmers' 'information-seeking state'.

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Moreover, the model facilitates the standard Durbin–Wu–Hausman test for endogeneity, conducted by assessing the joint significance of the components of the η term. If η is jointly significant, it indicates the presence of endogeneity in the model. Conversely, if η is not jointly significant, the correction term is unnecessary, and efficiency can be estimated using traditional frontier models (Karakaplan and Kutlu 2017a, 2017b).

In a cost frontier model, the condition of linear homogeneity of degree one must be satisfied; that is, $\sum_{(j=1)}^{n}\beta_j = 1$. This assumption is met by normalising the total cost and input prices by the price of one of the inputs (Jehle and Reny 2011; Islam and Fukui 2018). In this study, the seed price () is considered as the numeraire, used to normalise the total cost and prices of the other inputs.

Based on above discussion, the CD stochastic frontier cost function model, using the logarithmic form of all variables, is expressed as follows:

$$\begin{aligned}\ln\left(\frac{C_{it}}{S_{it}}\right) &= \beta_0 + \beta_1 \ln\left(\frac{K_{it}}{S_{it}}\right) + \beta_2 \ln\left(\frac{L_{it}}{S_{it}}\right) + \\ &+ \beta_3 \ln\left(\frac{LB_{it}}{S_{it}}\right) + \beta_4 \ln\left(\frac{UF_{it}}{S_{it}}\right) + \beta_5 \ln\left(\frac{TF_{it}}{S_{it}}\right) + \\ &+ \beta_6 \ln TF_{it} \ln\left(\frac{MPF_{it}}{S_{it}}\right) + \beta_7 \ln\left(\frac{I_{it}}{S_{it}}\right) + \\ &+ \beta_8 \ln\left(\frac{T_{it}}{S_{it}}\right) + \beta_9 \ln\left(\frac{P_{it}}{S_{it}}\right) + \beta_{10} \ln Q_{it} + v_{it} + u_{it}\end{aligned} \tag{10}$$

The inefficiency model is expressed as follows:

$$\begin{aligned}u_{it} &= \sigma_0 + \sigma_1 \mathrm{RFA}_{it} + \sigma_2 \mathrm{AG}_{it} + \sigma_3 \mathrm{AS}_{it} + \sigma_4 \mathrm{ED}_{it} + \\ &+ \sigma_5 \mathrm{FL}_{it} + \sigma_6 \mathrm{LS}_{it} + \sigma_7 \mathrm{LT}_{it} + \sigma_8 \mathrm{SFP}_{it} + \sigma_9 \mathrm{SWR}_{it} + \\ &+ \sigma_9 \mathrm{SWR}_{it} + \sigma_{10} \mathrm{IMO}_{it} + \sigma_{11} \ln\mathrm{OE}_{it} + \sigma_{12} \mathrm{CO}_{it} + \varepsilon_{it}\end{aligned} \tag{11}$$

where: $C$ – total production cost; *K, L, LB, S UF, TF, MPF, I, T, P* and $Q$ – the costs of other input variables, with $S$ used for the normalisation process; *RFA, AG, AS, ED, FL, LS, LT, SFP, SWR, IMO, OE* and *CO* – the inefficiency variables, a full description of all variables is provided in Table 1; β and σ – the parameters to be estimated; $i$ and $t$ – the $i^{th}$ farmer and the $t^{th}$ observation, respectively; $v_{it}$ – the error term; $u_{it}$ – the farmer-specific characteristics related to cost inefficiency (Karakaplan and Kutlu 2017a, 2017b, 2017c), as the focus of this study is to understand the impact of RFA adoption on cost efficiency, the RFA adoption variable is included in the inefficiency term ($u_{it}$) model; $\varepsilon_{it}$ – the error term in inefficiency model.

The variables used in Equations (10 and 11) are transformed using the natural logarithm to correct for skewed distributions and to mitigate the influence of large outliers. Logarithmic transformation helps to normalise the distributions, making them more appropriate for regression analysis and reducing the distortion caused by extreme values. Additionally, it enhances interpretability, as coefficients in log-linear models can be expressed in percentage terms – a feature particularly valuable in economic and efficiency analysis.

However, categorical variables used in the inefficiency or other models are not log-transformed, as they do not follow a continuous distribution where such a transformation would be meaningful. Likewise, efficiency scores – bounded between 0 and 1 – are retained in their original scale, as the logarithm of zero is undefined.

To compare which cohort (adopters or non-adopters) demonstrated superior efficiency levels, we employed a range of analytical approaches. Given that the efficiency variable is constrained within the interval (0, 1), and considering the nature of the dependent variable, we adopted a fractional response model (fracreg) incorporating the Mundlak device to mitigate potential bias (Papke and Wooldridge 2008).

Alternative approaches – such as Tobit regression, the two-part (hurdle) model, generalised linear models (GLM) with logit or probit links, and OLS with a log-odds transformation – have notable limitations. The Tobit model assumes a normally distributed latent variable, which may not be appropriate for efficiency scores. OLS with a log-odds transformation risks generating predictions outside the valid range and requires adjustment for values at 0 or 1, whereas the fractional response model naturally ensures valid predictions. Compared with GLMs using logit or probit links, the fractional response model imposes fewer distributional assumptions, offering greater flexibility when analysing real-world efficiency data. The two-part (hurdle) model is also unsuitable in this context, as efficiency scores are continuously distributed and do not exhibit a spike at 0 or 1.

Moreover, the fractional response model provides more intuitive interpretation of coefficients than OLS, which expresses effects in log-odds rather than actual efficiency scores. Given its capacity to handle fractional data effectively while maintaining interpretability and avoiding restrictive assumptions, the fractional response model is the most appropriate choice for this study. The model specification is presented as follows:

$$Y_{it} = \vartheta_0 + \vartheta_1 \mathrm{RFA}_{it} + \vartheta_2 X_{it} + \vartheta_3 \overline{X}_i + v_i + \varepsilon_{it} \tag{12}$$

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Table 1. Variables used in different models

| Variables | Description |
|---|---|
| *RFA* (recommended fertiliser application) | 1 = farmer has adopted RFA, 0 = otherwise |
| Production (*C*) | production cost (USD/ha) |
| Capital (*K*) | capital assets (i.e. machinery) cost after depreciation (USD) |
| Land (*L*) | land rent (USD/ha) |
| Labour (*LB*) | labour wage (USD/man-days) |
| Seed (*S*) | seed price (USD/kg) |
| Urea (*UF*) | urea fertiliser price (USD/kg) |
| TSP (*TF*) | TSP fertiliser price (USD/kg) |
| MOP (*MPF*) | MOP fertiliser price (USD/kg) |
| Tilling (*T*) | mechanical ploughing price (USD/ha) |
| Pesticide (*P*) | pesticide and insecticide price (USD/ha) |
| Irrigation (*I*) | irrigation cost (USD/ha) |
| Rice Produce (*Q*) | total rice production (kg/ha) |
| Fertiliser (*F*) | total amount of fertiliser uses (kg/ha) |
| Age (*AG*) | age of the respondents in years |
| Age square (*AS*) | squared value of the respondents age |
| Education (*ED*) | 1 = farmer is literate, 0 = otherwise |
| Household size (*HS*) | 1 = more than 4 family members, 0 = otherwise |
| Family labour (*FL*) | number of active labours in household |
| Land size (*LS*) | land area (ha) |
| Land typology (*LT*) | 1 = mid-highland, 0 = low or mid-low |
| Land ownership (*LO*) | 1 = farmer owned, 0 = otherwise |
| Soil water retention (*SWR*) | 1 = farmland can hold water long, 0 = otherwise |
| Soil fertility perception (*SFP*) | 1 = farmer perceives their farmland as fertile, 0 = otherwise |
| Knowledge of RFA (*KF*) | 1 = farmers know about recommendation doses, 0 = otherwise |
| Credit obtainability (*CO*) | 1 = farmers obtain credit during cropping season, 0 = otherwise |
| Off-farm earning (*OE*) | log value of secondary income (USD) |
| Irrigation machine ownership (*IMO*) | 1 = farmers own irrigation machine, 0 = otherwise, |
| Instrumental variable (*IV*): fertiliser information seeking state (*FIS*) | 1 = farmers seek information of fertiliser doses from others, 0 = otherwise |

MOP – muriate of potash; TSP – triple super phosphate; ha – hectare

Source: Author's elaboration

where: $Y_{it}$ – the cost efficiency score; $X_{it}$ – other explanatory variables; $\overline{X}_i$ – the time averages of the time-varying covariates with associated parameters $\vartheta_3$; $v_i$ – the time-invariant unobserved household effects, assumed to be normally distributed with zero mean and constant variance; $\vartheta_0$ – the intercept term; $\vartheta_1$ – the effect of adoption on fertiliser use; $\vartheta_2$ – the effects of other explanatory variables; $\varepsilon_{it}$ – the error term.

For robustness checks, beta regression is employed, as it effectively models dependent variables within the (0,1) range while accounting for varying dispersion (Pirani et al. 2018; Cribari-Neto 2023). This approach enhances the reliability of the results by ensuring consistency across different modelling frameworks. Beta regression serves as a useful complement to the fractional response model, preserving the fractional nature of efficiency scores while offering an alternative specification. The combined use of the fractional response model as the primary method and beta regression for robustness strengthens the comprehensiveness and credibility of the analysis.

**Variables description.** All variables used in this study are presented in Table 1 and are selected based on existing research and academic literature (Azad and

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Rahman 2017; Islam and Fukui 2018; Tambo et al. 2020; Sunny et al. 2022a, 2022b, 2022c).

## RESULTS AND DISCUSSION

**Descriptive statistics.** Table 2 compares adopters and non-adopters of RFA across agronomic, demographic, and institutional characteristics. While several indicators appear similar across groups, notable differences highlight distinct behavioural and resource patterns. Adopters exhibit slightly lower average production costs (458.49 vs 477.52) and nearly identical levels of capital and land use. Labour input, seed, pesticide, and tillage use are consistent across groups, while irrigation intensity is notably higher among adopters (147.61 vs 134.13), reflecting more proactive water management. Fertiliser component usage remains unchanged; however, adopters apply less total fertiliser (437.85 vs 505.99) with lower variation, indicating more targeted application. Although non-adopters report marginally higher yields (6 166.86 vs 6 071.16), adopters show more stable output with a lower standard deviation.

Table 2. Descriptive statistics of variables

| Variables | Mean | | SD | |
|---|---|---|---|---|
| | Adopt | Non-adopt | Adopt | Non-adopt |
| C | 458.49 | 477.52 | 46.08 | 43.96 |
| K | 350.92 | 351.72 | 53.20 | 53.44 |
| L | 205.50 | 205.65 | 55.49 | 55.43 |
| LB | 3.00 | 3.00 | 0.51 | 0.50 |
| S | 0.40 | 0.39 | 0.10 | 0.10 |
| UF | 0.17 | 0.17 | 0.02 | 0.02 |
| TF | 0.21 | 0.21 | 0.02 | 0.02 |
| MPF | 0.31 | 0.31 | 0.06 | 0.06 |
| T | 42.26 | 42.00 | 13.36 | 13.10 |
| P | 42.12 | 42.23 | 13.39 | 13.27 |
| I | 147.61 | 134.13 | 40.63 | 25.89 |
| Q | 6 071.16 | 6 166.86 | 474.32 | 633.24 |
| F | 437.85 | 505.99 | 53.49 | 103.33 |
| AG | 45.15 | 43.21 | 9.44 | 10.37 |
| AS | 2 127.46 | 1 974.05 | 894.22 | 981.54 |
| ED | 0.86 | 0.87 | 0.35 | 0.34 |
| HS | 0.45 | 0.48 | 0.50 | 0.50 |
| FL | 1.15 | 1.15 | 0.50 | 0.42 |
| LS | 0.36 | 0.44 | 0.34 | 0.27 |
| LT | 0.10 | 0.56 | 0.30 | 0.50 |
| LO | 0.96 | 0.90 | 0.20 | 0.30 |
| SWR | 0.80 | 0.26 | 0.40 | 0.44 |
| SFP | 0.36 | 0.30 | 0.48 | 0.46 |
| KF | 0.35 | 0.30 | 0.48 | 0.46 |
| CO | 0.54 | 0.69 | 0.50 | 0.46 |
| OE | 5.87 | 5.77 | 0.43 | 0.43 |
| IMO | 0.43 | 0.56 | 0.49 | 0.50 |

Variables as explained in Table 1.

Source: Author's elaboration

Demographic characteristics differ modestly. Adopters are marginally older (45.15 vs 43.21), with a higher age-squared value, suggesting greater farming experience. Education, household size, and reliance on family labour are broadly similar across groups.

Regarding resource endowments, adopters cultivate smaller plots (0.36 ha vs 0.44 ha) but enjoy higher land ownership rates (0.96 vs 0.90). Land typology values indicate that non-adopters face greater fragmentation (0.56 vs 0.10). Adopters also benefit from stronger soil water retention (0.80 vs 0.26) and slightly more favourable soil fertility perceptions (0.36 vs 0.30).

Institutionally, adopters demonstrate greater awareness of RFA (0.35 vs 0.30) but have less access to credit (0.54 vs 0.69), suggesting that adoption is not credit-driven. Irrigation machinery ownership is more common among non-adopters (0.56 vs 0.43), reflecting different capital strategies. Finally, off-farm income is nearly identical across groups (5.87 vs 5.77), suggesting that reliance on non-agricultural earnings does not differ meaningfully between adopters and non-adopters.

**RFA adoption impact on farmers' fertiliser use amount**. Table 3 presents the results of the main model – the CRE probit model with a CF approach – alongside the robustness check using the 2SRI model. In the first stage of both models, the adoption of RFA is significantly influenced by several factors. Land typology shows a negative effect (–0.073, $P < 0.10$), indicating that certain land types are less conducive to RFA adoption. This may be attributed to variations in soil characteristics or environmental constraints in these areas. This finding is particularly relevant, as Boro rice farming requires flooded fields. Leakage issues on comparatively higher land impede the ability to retain ponded water, resulting in fertiliser wastage and increased fertiliser use (Pearson et al. 2018). Soil water retention demonstrates a substantial positive effect (0.076, $P < 0.05$), suggesting that farmers with better water-retaining soils are more likely to adopt RFA. Prior studies have shown that soil retaining

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Table 3. Impact of RFA adoption on fertiliser use amount in CRE-CF and 2SRI model

| Variables | CRE with CF | | 2SRI | |
|---|---|---|---|---|
| | First stage | Second stage | First stage | Second stage |
| | RFA adoption (0/1) | log fertiliser quantity (kg/ha) | RFA adoption (0/1) | log fertiliser quantity (kg/ha) |
| | dy/dx (SE) | dy/dx (SE) | dy/dx (SE) | dy/dx (SE) |
| RFA Adopt | – | –0.120*** (0.022) | – | –0.120*** (0.022) |
| Age (*AG*) | 0.000 (0.002) | –0.002 (0.004) | 0.000 (0.002) | –0.001 (0.004) |
| Age square (*AS*) | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) |
| Education (*ED*) | –0.005 (0.010) | –0.020* (0.012) | –0.005 (0.010) | –0.020* (0.012) |
| Household size (*HS*) | –0.003 (0.006) | 0.005 (0.006) | –0.003 (0.006) | 0.005 (0.006) |
| Family labour (*FL*) | 0.012 (0.011) | 0.013 (0.008) | 0.012 (0.011) | 0.013 (0.008) |
| Land size (*LS*) | 0.001 (0.009) | 0.054*** (0.015) | 0.001 (0.009) | 0.054*** (0.015) |
| Land ownership (*LO*) | –0.003 (0.017) | –0.025 (0.018) | –0.003 (0.017) | –0.025 (0.018) |
| Land typology (*LT*) | –0.073* (0.038) | 0.031 (0.020) | –0.073* (0.038) | 0.031 (0.020) |
| Soil fertility perception (*SFP*) | –0.002 (0.005) | 0.002 (0.006) | –0.002 (0.005) | 0.002 (0.006) |
| Soil water retention (*SWR*) | 0.076** (0.038) | –0.155*** (0.013) | 0.076** (0.038) | –0.155*** (0.013) |
| Irrigation machine ownership (*IMO*) | –0.006 (0.007) | –0.031*** (0.010) | –0.006 (0.007) | –0.031*** (0.010) |
| Knowledge of RFA (*KF*) | 0.006 (0.008) | –0.012 (0.010) | 0.006 (0.008) | –0.012 (0.010) |
| Off-farm earning (*OE*) | 0.013 (0.010) | 0.010* (0.006) | 0.013 (0.010) | 0.010* (0.006) |
| Credit obtainability (*CO*) | –0.005 (0.006) | –0.003 (0.002) | –0.005 (0.006) | –0.003 (0.002) |
| Instrumental variable *(IV):* fertiliser information seeking state (*FIS*) | 0.066** (0.031) | – | 0.066** (0.031) | – |
| Residual | – | 0.025*** (0.005) | – | 0.025*** (0.005) |
| Time dummy | yes | yes | yes | yes |
| Mean of time varying variables included | yes | yes | no | no |
| Observations | 2 025 | 2 025 | 2 025 | 2 025 |

*, ** and ***significance at 0.1, 0.05 and 0.01 levels, respectively; values in parentheses are delta-method standard errors; the mean of time-varying variables was included in the model but not reported for brevity

2SRI – two-stage residual inclusion; CF – control function; CRE – correlated random effects; RFA – recommended fertiliser application

Source: Author's elaboration

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a balanced amount of water supports crop growth and maintains soil organic matter. In contrast, soils with low water-holding capacity require greater inputs of organic and chemical fertilisers (Dong et al. 2012). The instrumental variable, farmers' fertiliser information-seeking behaviour, displays a positive relationship with RFA adoption.

The second-stage results from both the CRE-CF and 2SRI models are highly consistent. Most notably, RFA adoption exhibits a significant negative effect on fertiliser use, reducing it by 12% (coefficient: –0.120, $P < 0.01$) in both models.

Several control variables also display significant effects on fertiliser use. For instance, education level shows a marginally significant negative effect (–0.020, $P < 0.10$), suggesting that more educated farmers tend to use less fertiliser. Previous studies have indicated that education enhances farmers' allocative efficiency by enabling them to think critically and utilise information sources effectively, thereby restricting the quantity of fertiliser applied to some extent (Tan et al. 2022). Land size shows a strong positive association (0.054, $P < 0.01$), implying that larger farms tend to use more fertiliser per hectare. In contrast, soil water retention shows a substantial negative effect (–0.155, $P < 0.01$), consistent with the idea that soils with better moisture capacity make more efficient use of nutrient (Sunny et al. 2022c). Similarly, ownership of irrigation machinery is associated with lower fertiliser use (–0.031, $P < 0.01$). This finding aligns with earlier studies, which argue that the high fixed costs associated with machinery ownership can constrain the availability of working capital for other inputs (Schimmelpfennig 2016). Besides, off-farm earnings (0.010, $P < 0.10$) positively influence adoption, indicating that households with off-farm income sources are more likely to adopt RFA, possibly due to greater financial capacity or reduced risk aversion. This aligns with previous findings suggesting that adopting new technologies often incurs additional costs (Rahman et al. 2021). Finally, the significance of the residual term (0.025, $P < 0.01$) in both models confirms the presence of endogeneity, thereby validating the instrumental variable approach. The consistency of results across both models – despite differences in specification – strengthens the robustness and credibility of the findings.

**Estimation of overall cost efficiency.** Table 4 presents the estimation results of both the endogenous and exogenous cost stochastic frontier production functions using the Cobb–Douglas specification. The model statistics for the endogeneity test of RFA adoption are significant ($\chi^2 = 4.33$, $P < 0.05$), indicating that the endogenous model provides more appropriate estimates for inference, particularly regarding the impact of RFA adoption on efficiency. In validating the IV, we found it statistically significant at the 1% level, with a $z$-value of 11.51 (Supplementary Table S1), thereby justifying the use of an endogeneity correction model. Previous studies have noted that for a single endogenous variable, a commonly used rule of thumb for IV validation is a $z$-value exceeding $\sqrt{10} \cong 3.16$ (or $F$-value > 10). Therefore, our instrument satisfies this criterion and qualifies as a strong instrument (Karakaplan and Kutlu 2017a; Islam and Fukui 2018). We also confirmed instrument validity through the 2SLS results presented in Supplementary Table S2. Both the endogeneity tests (Durbin and Wu-Hausman) and the instrument strength (F-statistics) indicate that our instrument meets the conventional thresholds, qualifying it as a strong instrument. Furthermore, the efficiency score indicates that, after accounting for endogeneity, the mean cost efficiency slightly decreased from 0.845 7 to 0.842 8.

The estimation results from both the exogenous and endogenous stochastic frontier models yield several important insights into agricultural production efficiency. All input variables are statistically significant, though their magnitudes vary. Capital demonstrates the strongest influence, with an elasticity of 0.286 and 0.287 in the exogenous and endogenous models, respectively ($P < 0.001$). Irrigation and tilling emerge as the next most influential inputs, with coefficients ranging from 0.145 to 0.160 and 0.147 to 0.149, respectively ($P < 0.001$). TSP fertiliser also exerts a substantial effect (0.127–0.139, $P < 0.001$), while other fertilisers (MOP and urea) show more moderate influences. Notably, pesticide use demonstrates the smallest elasticity among all inputs (0.012), suggesting a relatively minor contribution to production outcomes. This finding holds important implications for input optimisation and cost management strategies.

The inefficiency effects model reveals several significant determinants of cost inefficiency. RFA adoption demonstrates a strong negative association with inefficiency (ranging from –0.257 to –0.649, $P < 0.001$), indicating that adopters tend to operate more efficiently. Household size shows a consistent positive relationship with inefficiency (0.212–0.239, $P < 0.005$), suggesting that larger households may encounter difficulties in optimal resource allocation.

Moreover, soil water retention in the exogenous model exhibits a significant negative effect (–0.400, $P < 0.05$),

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Table 4. Estimated results of the stochastic cost frontiers with inefficiency effects model

| Variables | Exogenous model | | Endogenous model | |
|---|---|---|---|---|
| | estimate | SE | estimate | SE |
| Capital (*K*) | 0.286*** | 0.012 | 0.287*** | 0.014 |
| Land (*L*) | 0.032*** | 0.006 | 0.033*** | 0.007 |
| Labour (*LB*) | 0.039*** | 0.010 | 0.040*** | 0.011 |
| Urea (*UF*) | 0.042*** | 0.009 | 0.050*** | 0.011 |
| TSP (*TF*) | 0.139*** | 0.012 | 0.127*** | 0.015 |
| MOP (*MPF*) | 0.062*** | 0.011 | 0.067*** | 0.013 |
| Pesticide (*P*) | 0.012** | 0.004 | 0.012* | 0.005 |
| Irrigation (*I*) | 0.145*** | 0.014 | 0.160*** | 0.015 |
| Tilling (*T*) | 0.149*** | 0.008 | 0.147*** | 0.009 |
| Rice produce (*Q*) | 0.079*** | 0.018 | 0.061** | 0.019 |
| Year dummy | –0.038*** | 0.002 | –0.040** | 0.002 |
| Constant | 2.915*** | 0.088 | 2.919*** | 0.098 |
| Inefficiency variables: | | | | |
| Constant | –4.549*** | 0.547 | –4.776*** | 0.540 |
| RFA adoption | –0.256*** | 0.068 | –0.649*** | 0.185 |
| Age (*AG*) | 0.023 | 0.018 | 0.030† | 0.017 |
| Age squared (*AS*) | 0.000 | 0.000 | –0.000 | 0.000 |
| Education (*ED*) | 0.218 | 0.205 | 0.216 | 0.205 |
| Household size (*HS*) | 0.239*** | 0.070 | 0.212** | 0.068 |
| Soil water retention (*SWR*) | –0.400* | 0.157 | –0.228 | 0.176 |
| Soil fertility perception (*SFP*) | –0.014 | 0.018 | –0.042† | 0.023 |
| Irrigation machine ownership (*IMO*) | 0.531*** | 0.149 | 0.465** | 0.152 |
| Off-farm earning (*OE*) | 0.013 | 0.050 | 0.049 | 0.051 |
| Knowledge of RFA (*KF*) | 0.065 | 0.150 | 0.068 | 0.150 |
| Dependent variable: ln (σ²_v) | | | | |
| Constant | –7.633*** | 0.037 | – | – |
| Dependent variable: ln (σ²_w) | | | | |
| Constant | – | – | –7.646*** | 0.037 |
| Endogeneity test: | | | | |
| *η* RFA adoption | – | – | 0.043* | 0.021 |
| *η* endogeneity test | – | – | $\chi^2$ = 4.33 | *P* = 0.037 |
| Log likelihood | 3 947.41 | | 3 225.08 | |
| Mean efficiency | 0.845 7 | | 0.842 8 | |
| Median efficiency | 0.8443 | | 0.841 7 | |
| Number of observations | 2 025 | | 2 025 | |

***, **, * and †significance at 0.1%, 1%, 5% and 10% levels, respectively

MOP – muriate of potash; RFA – recommended fertiliser application; TSP – triple super phosphate

Source: Author's elaboration

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indicating that rice cultivation on high water-retaining land reduces inefficiency. This finding underscores the link between water-holding capacity and soil health. Previous studies have indicated that soils with adequate water retention support crop growth and preserve soil organic matter (Dong et al. 2012). In addition, ownership of irrigation machinery is positively and significantly associated with inefficiency (0.465–0.531, $P < 0.05$). This aligns with earlier studies that highlight the substantial fixed costs of machinery ownership, which may constrain capital availability for other essential inputs in the production process (Schimmelpfennig 2016). Besides, farmers age is positively associated with inefficiency (0.030, $P < 0.10$). Finally, the soil fertility variable is negatively and significantly associated with inefficiency (–0.037, $P < 0.10$). This result is consistent with the findings of Salam et al. (2021), which indicate that rice productivity depends on improved soil fertility.

**Impact of RFA adoption on cost efficiency.** Table 5 presents the estimated impact of RFA adoption on efficiency using two distinct estimation approaches. The primary model employs the fractional response model, while the robustness check utilises the beta regression model. Both methodologies incorporate CRE probit framework with a CF, thereby enhancing the robustness and reliability of the analysis. The results demonstrate consistent findings across the two estimation methods, reinforcing the validity of the conclusions. RFA adoption exhibits a positive and highly significant effect on efficiency in both models. The magnitude of this effect ranges from 0.049 in the fractional response model to 0.051 in the beta regression model. This consistency suggests that RFA adoption improves efficiency by approximately 4.9% to 5.1%, reflecting a meaningful enhancement in farming productivity. These results are in line with earlier research, which indicated that balanced nutrient management constitutes a cost-effective and environmentally friendly strategy for achieving sustainable intensive rice cropping systems (Shankar et al. 2021).

Among the control variables, the inverse relationship between education and efficiency in the beta regression model aligns with recent research findings (Seok et al. 2018; Sunny et al. 2022a). While this outcome may appear to contradict human capital theory, it highlights the phenomenon of education-driven occupational shifts from agricultural to non-agricultural sectors. In Bangladesh, rural youth increasingly pursue public or private sector employment, largely due to the perceived social prestige associated with these careers (Sunny et al. 2022a). As a result, their engagement in agriculture is often part-time, necessitating reliance on hired labour. Goodwin and Mishra (2004) argue that improved educational attainment facilitates occupational mobility away from agriculture.

Table 5. Adoption impact of RFA on cost efficiency

| Variables | Fractional regression | | Beta regression | |
|---|---|---|---|---|
| | dy/dx | SE | dy/dx | SE |
| RFA Adopt | 0.049*** | 0.006 | 0.051*** | 0.006 |
| Age (*AG*) | 0.001 | 0.002 | 0.001 | 0.002 |
| Age Square (*AS*) | –0.000 | 0.000 | –0.000 | 0.000 |
| Education (*ED*) | –0.013 | 0.009 | –0.022* | 0.011 |
| Household size (*HS*) | –0.013** | 0.005 | –0.016** | 0.007 |
| Family labour (*FL*) | 0.027*** | 0.007 | 0.035*** | 0.009 |
| Land size (*LS*) | –0.007 | 0.007 | –0.013 | 0.010 |
| Land ownership (*LO*) | 0.001 | 0.008 | 0.003 | 0.009 |
| Land typology (*LT*) | –0.016** | 0.007 | –0.015** | 0.008 |
| Soil fertility perception (*SFP*) | 0.013*** | 0.005 | 0.014** | 0.006 |
| Soil water retention (*SWR*) | 0.005 | 0.007 | 0.008 | 0.008 |
| Irrigation machine ownership (*IMO*) | –0.030*** | 0.006 | –0.030*** | 0.007 |
| Knowledge of RFA (*KF*) | –0.006 | 0.005 | –0.010 | 0.006 |
| Off-farm earning (*OE*) | –0.015** | 0.006 | –0.016** | 0.007 |
| Credit obtainability (*CO*) | –0.011** | 0.005 | –0.013* | 0.007 |
| Time dummy | yes | | yes | |
| Mean of time varying variables | yes | | yes | |
| Observations | 2 025 | | 2 025 | |

*, ** and ***significance at 0.1, 0.05 and 0.01 levels, respectively; the mean of time-varying variables was included in the model but not reported for brevity

RFA – recommended fertiliser application

Source: Author's elaboration

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The negative marginal effect coefficients in both models indicate a decline in efficiency when household size exceeds four members. Supporting research suggests that larger household consumption needs often compete with the optimal allocation of farm inputs (Sunny et al. 2022a). In contrast, family labour has a significant positive effect in both models, implying that households with higher levels of family labour participation exhibit lower inefficiency. Prior research has shown that family labour availability eases capital constraints and provides vital support during peak agricultural periods (Gebeyehu 2016).

Soil fertility shows a positive and significant relationship with efficiency, reinforcing earlier findings that link improved soil fertility with enhanced productive performance (Fan et al. 2005). Conversely, both off-farm income and access to credit during cultivation periods are negatively associated with efficiency. This finding is noteworthy, as credit availability does not always lead to optimal input use (Rizwan et al. 2019; Ouattara et al. 2020; Sunny et al. 2023).

Similarly, ownership of irrigation machinery is associated with lower cost efficiency (–0.030, $P < 0.01$). This finding is consistent with earlier studies, which highlight that diesel-based irrigation systems are more expensive and therefore constrain the availability of capital for other essential inputs in the production process (Sunny et al. 2024). Finally, farmers cultivating highland areas exhibit lower efficiency levels, a result that accords with previous research suggesting that highland cultivation leads to greater input wastage (Sunny et al. 2022b).

The results of this study demonstrate that the adoption of the recommended fertiliser application dosage (RFA) significantly reduces fertiliser use and improves cost efficiency in rice cultivation, particularly among farmers growing the BRRI dhan29 variety in the Dinajpur region of Bangladesh. Adoption of RFA led to a 12% reduction in fertiliser use among adopters compared to non-adopters. This decline in usage mitigates the risk of environmental contamination through nutrient runoff – especially relevant in Bangladesh's acidic soil regions, where fertiliser over-application has been a common practice. By reducing the amount of fertiliser applied, RFA helps to lower nutrient loads entering water bodies, thereby decreasing eutrophication, and protecting aquatic ecosystems. Furthermore, the improved soil management practices associated with RFA help prevent soil degradation and support soil health, fostering a more sustainable agricultural environment.

Economically, RFA adoption has been shown to enhance cost efficiency. Empirical findings from both fractional and beta regression models indicate that adopters attain greater cost efficiency than non-adopters, with efficiency gains ranging from 4.9% to 5.1%. This economic benefit translates into reduced input costs, thereby increasing the profitability of rice farming. Moreover, cost savings associated with RFA adoption strengthen farmers' resilience to fluctuations in fertiliser prices – an especially valuable outcome in a developing country such as Bangladesh. Notably, only 8.7% of small and marginal farmers in the country have access to finance from the state-owned Bangladesh Krishi Bank, whose lending policies are often misrepresented by commercial banks or poorly understood by farmers (FAO 2023).

These results support the alternative hypothesis that farmers adopting the BRRI-recommended RFA can reduce fertiliser usage and achieve greater efficiency compared to non-adopters. This finding is consistent with earlier research highlighting the dual benefits of RFA: reducing environmental harm while improving economic outcomes. For example, Jate (2010) found that balanced mineral fertiliser adoption yielded the highest nutrient use efficiency in Germany. Similarly, Afrad et al. (2018) observed that the use of fertilisers recommended by the Bangladesh Agricultural Research Council (BARC) produced the highest benefit-cost ratio (BCR) for rice farmers in Bangladesh's Haor region. In addition, Chen et al. (2021) revealed that the adoption of balanced fertilisation practices reduced excessive fertiliser use by between 35% and 93% in China.

The new evidence presented in this study provides a strong rationale for promoting RFA as a sustainable agricultural practice. It supports both national and international sustainability goals, and the robustness of the findings – evident in their consistency across multiple estimation methods – reinforces the reliability of these conclusions.

## CONCLUSION

This study, based on survey data from 2 025 households collected between 2017 and 2021, investigates the factors influencing the adoption of BRRI-recommended fertiliser dosages. It also evaluates the impact of RFA adoption on fertiliser consumption and cost efficiency, with a particular focus on economic sustainability.

The findings indicate that RFA adoption is influenced by several factors, including the availability of family labour, soils with good water retention, and off-farm income. However, farmers cultivating rice in highland

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areas are less inclined to adopt RFA. To address this challenge, further research is needed to refine fertiliser application guidelines tailored to highland soil conditions. In addition, the development and promotion of location-specific fertiliser management techniques could enhance nutrient uptake efficiency and encourage broader adoption among farmers.

Impact analysis confirms that RFA adoption results in a 12% reduction in fertiliser use and a 4.9% to 5.1% improvement in cost efficiency compared to non-adopters. These findings highlight both the environmental and economic advantages of RFA adoption, demonstrating its potential to promote sustainable agricultural practices while advancing several SDGs. Specifically, the reduction in fertiliser use supports SDG 12 (responsible consumption and production) by promoting efficient resource use and minimising environmental harm. It also contributes to SDG 13 (climate action) by reducing greenhouse gas emissions associated with excessive fertiliser application, and supports SDG 2 (zero hunger) by preserving soil health and ensuring sustainable food production. Furthermore, the cost efficiency gains align with SDG 8 (decent work and economic growth) by strengthening farmers' financial resilience and enhancing livelihoods, while also supporting SDG 9 (industry, innovation and infrastructure) by encouraging advancements in agricultural productivity and resource management.

This study represents the first longitudinal investigation into the impact of RFA adoption on fertiliser use and cost efficiency, offering novel insights that extend current knowledge. The findings present compelling evidence in favour of RFA as a viable practice for sustainable rice cultivation. However, transitioning from traditional fertiliser application methods to more sustainable practices may be slow unless farmers perceive clear and long-term benefits. Therefore, beyond targeted initiatives such as field demonstration programmes, efforts must also focus on addressing farmers limited scientific knowledge. Notably, nearly 13% of farmers in the sample are illiterate, which poses a barrier to understanding and adopting improved fertiliser techniques. Moreover, as observed during the survey, farmers tend to seek information from non-experts such as fertiliser sellers rather than trained extension personnel. These non-expert sources may lack technical knowledge or may have commercial incentives that discourage optimal application, potentially hindering widespread RFA adoption. Addressing this issue requires strengthening extension services, improving training programmes for both farmers and fertiliser vendors, and leveraging peer influence by encouraging early adopters to serve as role models.

While this study makes a significant contribution to understanding the impact of RFA adoption on fertiliser use and cost efficiency, these findings are somewhat limited due to their site-specific nature. To improve the generalisability of results, future research should encompass a broader range of agricultural zones, crop varieties, and soil types. Additionally, tackling socio-economic barriers, evaluating the long-term effects of RFA on soil health, and assessing the effectiveness of district-level initiatives through advanced modelling and robust monitoring frameworks will be essential to developing comprehensive strategies for sustainable agriculture in Bangladesh. Future studies should also consider employing methodologies such as randomised control trials or DID approaches to measure outcomes before and after intervention, providing a more rigorous assessment of the impact of RFA adoption. Ultimately, fostering collaboration among researchers, policymakers and farmers is vital to ensuring that RFA adoption leads to long-term sustainability and resilience in agriculture. By integrating scientific advancements with practical knowledge and targeted policy support, the agricultural sector can move towards a more efficient, climate-resilient and economically viable future.

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