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Agrarian change through sustainable agri-tech adoption in a challenging rice farming region: A panel data analysis

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Abstract: To achieve the coveted objectives of sustainable development, the Bangladesh government has devised a comprehensive strategy to promote the adoption of innovative agricultural practices capable of addressing the critical challenges at the intersection of food, energy, water, and ecosystems (FEWE). This plan prioritises the increased uptake of solar irrigation and recommended fertiliser application (SIRFA) technologies to enhance sustainable food production while effectively managing energy and water resources, and fostering ecological balance. Thus, this study analysed seven years of panel data (2015–2021) to assess the long-term impact of SIRFA technology adoption on production costs (PC) and return on investment (ROI) among Bangladeshi farmers cultivating the BRRI-dhan29 rice variety in the water-scarce, acidic soils of Dinajpur. Utilising the generalised estimating equation (GEE) with a population-averaged model, we investigated the determinants of adoption. Additionally, we applied a two-stage residual inclusion (2SRI) method alongside six linear panel-data models to analyse the impact of SIRFA adoption. Our findings revealed that adopters experienced reduced production costs and enhanced ROI through SIRFA technology adoption. These results emphasised the urgent need for region-specific policy interventions to facilitate the broader adoption of SIRFA technologies.

Keywords: correlated random effect (CRE); linear panel-data models; population-averaged (PA) model; recommended fertiliser dosage; solar irrigation; two-stage residual inclusion (2SRI)

Economic activities are influenced by environmental conditions that dictate resource production and waste management capabilities. Environmental services, such as air, water, and biomass, are vital for human prosperity and economic growth (Morales-García and Rubio 2023). As the global population is projected to reach 10 billion by 2050 (Suzuki 2019), energy and food demands will rise, consequently increasing water requirements. The food, energy, water, and ecosystems (FEWE) framework underscores the interconnections among these sectors, facilitating the evaluation of trade-offs and synergies that promote ecological balance and long-term sustainability (Probst et al. 2024). The FEWE nexus has emerged as a crucial framework for reconciling diverse interests in resource allocation across sectors and civil society. It fosters an intricate understanding of interdependencies, ultimately seeking integrated solutions in alignment with the sustainable development goals (SDGs) (Brouwer et al. 2018; Karim and Daher 2021). To enhance resilience in agricultural infrastructure in developing countries, it is essential to transform practices into sustainable

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components and shift our perception of human security, emphasising the establishment of robust resource management systems. Economically viable and socially acceptable practices aim to mitigate environmental harm from intensive agricultural input use while maximising the efficient utilisation of renewable and farm-based resources, thus epitomising sustainable agriculture (Zilberman et al. 1997; Pretty 2008). Moreover, savings from reduced input use can be reinvested in long-term growth, where return on investment (ROI) drives the development of resilient systems rather than merely assessing the financial viability of specific strategies (Meuwissen et al. 2019; Sunny et al., 2022b). Various agricultural and managerial strategies promoting sustainable practices within the framework of the FEWE nexus encompass efficient water management systems, renewable irrigation technologies, soil quality assessment tools, diversified cropping methods, judicious fertiliser application, disease-resistant and climate-adapted varieties, integrated pest management (IPM), agroforestry, cover cropping, and resource-conserving, scale-appropriate agricultural machinery (Gomiero et al. 2011; Mottaleb 2018; Sunny et al. 2022b). In developing countries like Bangladesh, agriculture serves as a crucial development engine, supporting 37% of the workforce and providing sustenance for 70% of the population (Imdad 2021; Trading Economics 2024). The government has facilitated the proliferation of agricultural technologies, such as fertiliser subsidies and diesel tax exemptions, to enhance farm productivity (Pearson et al. 2018). This has significantly increased fertiliser utilisation and expanded total irrigated acreage (IMF 1998). However, these policy reforms have adversely affected resource availability, environmental health, and farmers' economic conditions, particularly in regions experiencing water and energy crises. Diesel-powered irrigation systems exhibit suboptimal pumping efficiency, driving up operational costs, while electric systems, although more economical, impose energy constraints on the national grid. This, coupled with uneven fertiliser applications, detrimentally affects human and environmental wellbeing (Dey et al. 2017; Rahman and Zhang 2018; Islam et al. 2022).

To mitigate environmental impacts, the Bangladeshi government has devised a comprehensive strategy promoting sustainable agricultural development, emphasising the adoption of innovative farm management technologies. This approach prioritises efficient water and fertiliser usage to enhance cereal crop yields (FPMU 2021; MOA 2020). The global adoption of solar irrigation technology is growing as countries seek to lessen their reliance on non-renewable energy sources. Solar-powered irrigation systems offer a more cost-effective and sustainable alternative to traditional fossil fuels, alleviating the burdens on small-scale farmers grappling with rising fuel costs and pressure on national resources. However, most rural farmers lack access to grid electricity, making solar irrigation particularly attractive. Additionally, the recommended fertiliser application framework leverages scientific insights into nutrient production and absorption, thereby enhancing output quality and quantity while minimising adverse environmental effects (Sunny et al. 2022b). Besides, widespread implementation of solar irrigation technology could reduce carbon dioxide emissions by 20.8 million tonnes, contributing to sustainability (Hashim 2023). Optimal fertiliser management could increase crop yields by 8–14%, yielding an annual financial benefit of USD 1.8 million (Chen et al. 2022). Thus, efforts to promote careful fertiliser application are underway, with plans to install 50 000 solar-powered irrigation pumps in various areas, targeting a 75% operational rate by 2030 (Chowdhury 2020).

Research indicates that agriculturalists are inclined to adopt innovative technologies when the benefits markedly outweigh the drawbacks. Acknowledging these enduring advantages can catalyse the exploration of alternatives. Despite abundant literature addressing various agricultural practices that enhance farmers' well-being, impact assessments concerning the adoption of solar irrigation and recommended fertiliser application (SIRFA) technologies remain notably sparse. Therefore, the aim of this research was to rigorously examine the extent to which the adoption of SIRFA technologies confers advantages upon farmers.

While three previous studies have focused on this subject within the same geographical region, two have employed single-year data, whereas the third utilised panel data. The inaugural study by Sunny et al. (2022c) examined the determinants influencing Boro rice farmers' decisions regarding the adoption of recommended fertiliser dosages. It identified significant influences such as farmers' age, land typology, soil water retention, knowledge, and the availability of cow dung. The second study by Sunny et al. (2022a) investigated the drivers and impacts of solar irrigation facilities (SIFs) adoption on irrigation costs, return on investment (ROI), and production cost (PC). The results demonstrated that farmers embracing this method could reduce irrigation costs by between 1.88% and

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2.22%, achieve a 4.48% to 8.16% enhancement in ROI, and lower overall PC by between 0.06% and 0.98% compared to non-adopters. Additionally, it revealed that factors such as farming experience, knowledge, environmental awareness, soil fertility, and ownership of irrigation machinery significantly swayed adoption decisions. In contrast to the aforementioned studies, our manuscript's principal distinction lies in its investigation of the long-term effects of adoption, utilising a seven-year panel dataset, as opposed to the one-year data employed in previous works that focused on short-term evaluations.

The third study by Sunny et al. (2023) also employed a seven-year panel dataset and addressed endogeneity; however, it concentrated solely on the adoption impact of solar irrigation technology. In contrast, the contribution of this manuscript lies in its comprehensive examination of SIRFA as an integrated technological suite. This research evaluates the synergistic effects of both technologies, presenting a cohesive assessment of their collective impact on productivity and ROI. Such an approach provides a deeper understanding of how technological integration can enhance economic performance within agriculture.

While the aforementioned studies examined comparable regions, this manuscript specifically accentuates the implementation and scaling of SIRFA technologies within a more localised context. This analysis centres on how soil characteristics and tailored policy recommendations can stimulate technology adoption, an area that has received insufficient attention in prior works. This thorough examination offers region-specific policy interventions targeting localised challenges alongside strategies to promote broader adoption of SIRFA technologies through customised recommendations that address the socio-economic and environmental hurdles encountered by farmers, extending beyond the general factors of adoption discussed in previous studies.

Furthermore, this paper employed advanced statistical methodologies, including the generalised estimating equation (GEE) and two-stage residual inclusion (2SRI). These approaches facilitate a more precise handling of endogeneity and bias, thereby providing a robust and nuanced understanding of the long-term effects associated with adopting SIRFA technologies. Moreover, our manuscript's longitudinal perspective effectively captures temporal variations that short-term studies might overlook. Understanding the long-term ramifications of technology adoption is crucial, particularly in the context of complex agricultural practices; without such knowledge, farmers may be reluctant to embrace sustainable technologies.

Finally, our study region is characterised by acidic soil conditions that significantly impact overall production cost, including fertilisation and irrigation costs. Therefore, grasping the adoption impacts of these technologies is vital for fostering sustainable agricultural development in the area. Ultimately, this research enriches the existing body of literature by offering critical insights for policymakers aimed at advancing the implementation of SIRFA technology in regions suffering from water scarcity and acidic soils, thus enhancing farmers' welfare and ensuring the long-term sustainability and productivity of agricultural systems in Bangladesh.

MATERIAL AND METHODS

Study area, sampling procedure, and data source. This study focuses on Dinajpur for several compelling reasons. The tropical wet-dry climate in this north-western region, which encompasses the largest of the nation's sixteen districts, faces significant food scarcity and pervasive poverty. Furthermore, rice cultivation occupies 41.40% of the net-planted area, with Boro rice being the predominant variety (Shirazy et al. 2018). We selected the BRRI- dhan29 rice due to its higher acceptability compared to other Boro varieties in our research area (BRRI 2019). Most importantly, given the acidic soils in these regions, it was crucial to analyse the long-term impact of SIRFA adoption on agricultural productivity (Islam et al. 2017; SRDI 2020). Policymakers must grasp the variations in sustainable water and fertiliser management practices among different agroecological zones (AEZ) to inform effective decision-making. To procure our sample, we first utilised a randomised sampling technique to select three sub-districts (Birganj, Khanshama, and Kaharol) from the thirteen within Dinajpur. We then determined the sample size using the Krejcie and Morgan formula, detailed in Equation (1). Here, s represents the sample size, N denotes the population of 643 431, χ^2 is 3.841 (corresponding to a 95% confidence interval with one degree of freedom), P is 0.50 (the population proportion yielding maximum variance), and d is 0.05 (the margin of error), as recommended by statistical experts (Krejcie and Morgan 1970).

$$s = \frac{\chi^2 NP(1-P)}{d^2(N-1)+\chi^2 P(1-P)} \tag{1}$$

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The calculated sample size (n) was 384. However, we gathered an additional 5% of samples to prevent unforeseen future issues. Hence, 135 farmers were randomly chosen from each sub-district in the initial phase between February and April 2015. These farmers consented to annual interviews until 2021, leading to the formation of a well-balanced panel comprising 2 835 farmers. Interviews were scheduled between December and June, aligning with the peak of rice production during the Boro Season (BBS 2020). The sample was categorised into two groups: adopters and non-adopters, based on their irrigation practices and the application of chemical fertiliser for the BRRI-dhan29 rice variety, with usage ranging from 336 to 525 kg/ha (BRRI 2021).

Determinants of SIRFA technologies adoption. SIRFA technology adoption by farmers followed a discrete choice model using latent variables. The rationality hypothesis states that farmers adopt new technology if it increases their expected utility (Hess et al. 2018). The utility function is not directly observable. Modelling SIRFA technology adoption requires inferring the unobservable utility function Y_{it}^* that drives the i-th farmer's decision-making at time t by analysing post-adoption behaviour (Cramer 2003). The untapped potential of a farmer's decision-making process, as captured through the lens of a binary choice model, can be articulated as follows:

$$Y_{it}^{*} = X_{it}\beta^{*} + \nu_i + \varepsilon_{it}^{*} \text{ ; where } Y_{it} = \begin{cases} 1 & \text{if } Y_{it}^{*} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For Equation (2), Y_{it}^* is described earlier, β^* is the function of X_{it} explanatory variables.

The error term, denoted by ε_{it}^*, is a random aberration that is independent of the explanatory variables and adheres to a normal distribution, and ν_i denotes time-invariant unobserved effects that are inherently correlated with the explanatory variables (McFadden 1974; Greene 2002; Wooldridge 2010). Consequently, we can predict the probability of accepting SIRFA technologies as follows:

$$Pr(Y_{it} = 1 \mid X_{it}\ , \nu_i) = \left(X_{it}\ , \nu_i\right) \tag{3}$$

The function ϕ (.) can be estimated using either a logistic or a normal distribution, which is defined by the distribution function of ε_{it}^*, a probability measure that can be modelled using various statistical distributions. To accurately quantify the parameters of interest, we concentrated on the random effect models over fixed effects, because the random effect models possess the capacity to seamlessly integrate incidental parameters and computational complexities, thereby rendering them a more effective choice for estimation.

By adopting two distinct methodologies, the supposition of conditional independence for the forecasted variable can be effectively mitigated. Firstly, by averaging out heterogeneity, we could execute a population average model that posits responses are independent, conditional on only X_i, effectively mitigating this assumption. Furthermore, when a distinct relationship between unobserved factors and explanatory variables is hypothesised, a correlated random effects (CRE) probit model incorporating the full conditional maximum likelihood (CML) approach is utilised to accommodate the specified association. To mitigate the risk of inaccurate coefficient estimates stemming from underestimating standard errors, a population-averaged clustered-robust standard errors approach is employed using the generalised estimating equation (GEE) method. This approach enabled the estimation of robust coefficients by accounting (Neuhaus 1992). Population average (PA) estimation addressed issues of autocorrelation and heteroscedasticity by assuming no independence among individual observations. The analysis focused on the alterations in the average population outcome resulting from modifications in the influential factors within the distinct grouping of the i^{th} individual's specificcluster (Hubbard et al. 2010). Furthermore, when a distinct relationship between the unobserved error and explanatory variables was evident, a CRE model, as originally conceived by Mundlak (1978) was utilised to mitigate the limitation. To tackle the heterogeneity problem, this approach relaxed the rigid assumption of the traditional random effects model, which postulated a zero covariance between the explanatory variables and error terms. Instead, it allowed for the possibility of unobservable factors being correlated with specific elements of the individual-specific vectors X_i by introducing a more nuanced assumption:

$$\nu_i \mid X_i \sim N\left(\psi + \bar{X}_i\xi, \sigma_\alpha^2\right) \tag{4}$$

where: X_i – arithmetic mean of X_{it} over a given period; $\sigma^2{}_\alpha$ – variance of α_i in equation $\nu_i = \psi + \bar{X}_i\xi + \alpha_i$.

This model enabled us to accurately quantify the isolated impacts of the constituent components of X_i on the response probability, as they would be experienced at the average value of ν_i (i.e. when ν_i was set to zero). This facilitated a meaningful comparison between the betas derived from the present model and those obtained from the PA model, which effectively

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quantified the incremental influence of each X_i on the probability of response at its average value of v_i. Verifying the null hypothesis of normality, which assumes that the underlying distribution is unconditionally normal, involves examining whether the mean (ξ) is equal to zero. Since this hypothesis was rejected across all specifications, we adopted an alternative approach, namely the CML method, to model the adoption decisions (Wooldridge 2010).

Impact assessment. To measure farmers' adoption impact of SIRFA on production costs (PC) and the return on investment (ROI) indicators, we first specified the following panel model:

$$Y_{it} = \beta_0 + \beta_1 SIRFA\ adoption_{it} + \beta_2 X_{it} + \varepsilon_{it} \quad (5)$$

where: Y_{it} – relevant outcomes (PC or ROI) indicator for household i at time t; *SIRFA adoption* – farmers' adoption status where SIRFA are considered; X_{it} – matrix of explanatory factors; β_0 – constant; β_1, β_2 – parameters to be estimated; ε_{it} – error term.

In estimating Equation (5), we had to consider that as household's adoption of SIRFA technologies is not a random decision, it is possibly correlated with the error terms. The inherent correlation between this variable and the SIRFA adoption process led to endogeneity, rendering the latter's determinants inherently intertwined. Hence, to address the potential endogeneity issue of this variable, following previous studies (Terza et al. 2008; Ma and Zhu 2020), we employed a two-stage residual inclusion (2SRI) approach.

The first stage of the 2SRI approach estimated the probability of adoption of SIRFA technologies based on the following probit model:

$$SIRFA\ adoption_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 IV_i + \varepsilon_{it} \quad (6)$$

The likelihood that a farmer i adopts SIRFA technologies, denoted by Y_{it}, was influenced by a set of explanatory factors, captured by the vector X_{it}, while being indirectly affected by the presence of an instrumental variable (IV_i), which serves as a proxy for external factors that may shape the farmer's decision-making process. The remaining variables are defined in Equation (5).

We chose the variable farmers' information-seek state as an instrumental variable (*IV*) for this study because farmers' information-seeking about SIRFA can influence adoption decisions but can not directly affect the outcomes (Kassem et al. 2021; Luo et al. 2022; Wu 2022).

The second phase of the 2SRI methodology quantified the transformative effect of SIRFA on PC, specifically assessing the impact on bottom-line profitability and the ROI. Considering the inherent characteristics of the dependent variables, a linear regression model with panel data analysis was employed in the second stage. The Hausman test was utilised to validate the preference between fixed and random effects in the static panel model, yielding a significant outcome at a 1% level, which favours a fixed effects model. Notwithstanding, we also estimated a random effects model to investigate the possibility of any significant differences in the results. Thus, the second stage of 2SRI was succinctly encapsulated as:

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 SIRFA\ adoption_{it} + \beta_2 X_{it} + \\ + \beta_3 IV_i + \beta_4 \hat{R}_{it} + \varepsilon_{it} \end{aligned} \quad (7)$$

where: Y_{it} – outcome variables (i.e. PC and ROI); $\hat{R}_{it}$ – residual term predicted after estimating Equation (6), and is included in Equation (7) to account for unobserved heterogeneity that could bias the outcome variables.

The residual term $\left(\hat{R}_{it}\right)$, obtained after adjusting for Equation (6), was a critical component that was incorporated into Equation (7) to address potential unobserved heterogeneity, which may otherwise introduce bias into the outcome variables (Ma and Zhu 2020). Other variables are already defined in the Equations (5) and (6).

We also conducted a series of tests to identify heteroscedasticity, autocorrelation, and cross-sectional dependence (CD) within our dataset. The highly significant results ($P < 0.01$) for both heteroscedasticity and autocorrelation [Table S1 in the Electronic Supplementary Material (ESM)] underscored the persistence of these issues. Furthermore, the Pesaran and Frees test for cross-sectional dependence rejected the null hypothesis, indicating notable inter-sectional correlations. Given that the study period spanned merely seven years, testing for data stationarity is not advisable (Wooldridge 2012). Consequently, we employed various panel-data linear models, including feasible generalised least squares (XTGLS), linear regression with panel-corrected standard errors (XTPCSE), Newey-West standard errors (NEWEY), Driscoll-Kraay standard errors (XTSCC), fixed effects linear models with a first-order autoregressive (AR-1) disturbance term (XTREGAR), and Prais-Winsten regression (PRAIS) to ensure a more objective conclusion (Wu 2008; Popp et al. 2011; Kumar et al. 2016; Bai et al. 2021; Hasan and Adnan 2023).

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Table 1. Description of the variables used in different models

Variables	Measurement unit	Description
Outcome variables		
SIRFA adoption (*SA*)	dummy variable	1 = SIRFA adopters, 0 = otherwise
Production cost (*PC*)	BDT/ha	log value of total production cost
Return on investment (*ROI*)	ratio	ratio of net earnings to total expenditures
Explanatory variables		
Age (*AG*)	dummy variable	1 = farmers age is above 30 years, 0 = otherwise
Education (*ED*)	dummy variable	1 = farmer is literate, 0 = otherwise
Household size (*HS*)	dummy variable	1 = number of family members is > 4, 0 = number of family members is ≤ 4
Family labour (*FL*)	number	number of active labour in a household
Land size (*LS*)	ha	Respondent‘s farm size in hectare
Land ownership (*LO*)	dummy variable	1 = farmer owned, 0 = otherwise
Land typology (*LT*)	dummy variable	1 = mid-highland, 0 = low or mid-low
Farming experience (*FE*)	years	number of years actively engaged in farming
Soil fertility perception (*SFP*)	dummy variable	1 = farmer perceives their farmland as fertile, 0 = otherwise
Soil water retention (*SWR*)	dummy variable	1 = farmland can hold water long, 0 = otherwise
Irrigation machine ownership (*IMO*)	dummy variable	1 = farmer owns irrigation machine, 0 = otherwise
SIRFA knowledge (*SK*)	dummy variable	1 = farmers have proper knowledge of SIRFA, 0 = otherwise
Credit availability (*CA*)	dummy variable	1 = availability of credit during cropping season, 0 = otherwise
Secondary income (*SI*)	BDT	log value of secondary income
Instrumental variable		
Farmer’s information seeking state (*FIS*)	dummy variable	1 = farmers seek information of SIRFA from others, 0 = otherwise

BDT – the currency for Bangladesh and USD 1 = BDT 110 approximately; 1 ha = 247.13 decimal; SIRFA – solar irrigation and recommended fertiliser application
Source: Author’s own elaboration

Measurement of key variables. The dependent variable in the determinants analysis was SIRFA adoption, represented as one for adopters and zero otherwise. The impact analysis employed PC and ROI as outcome metrics. To facilitate estimation, the production cost was converted to logarithmic form. ROI effectively gauges investment performance by assessing the ratio of net profit to total expenses. Table 1 presents additional variables utilised in this study, derived from an extensive review of existing research (Idrisa et al. 2012; Ndiritu et al. 2014; Sunny et al. 2022b, 2023; Rizzo et al. 2023).

RESULTS AND DISCUSSION

Descriptive statistics. Table 2 presents a descriptive study highlighting significant distinctions between adopters and non-adopters across various metrics. For example, both cohorts exhibited similar production costs, with adopters averaging 10.88, slightly lower than non-adopters at 10.90. However, standard deviations revealed that non-adopters’ costs exhibited less variability. Adopters demonstrated a markedly higher ROI (2.70) in contrast to non-adopters (2.10). Demographically, both groups were comparable in age (adopters: 0.97, non-adopters: 0.92) and education (adopters: 0.88, non-adopters: 0.85), with modest standard deviations suggesting consistent demographics within each cohort.

Household size reflected minor differences (adopters: 0.47, non-adopters: 0.42), while family labour averages were identical (1.15), indicating similar levels of reliance on domestic labour. Non-adopters possessed marginally more land and ownership, yet both groups boasted high land ownership rates (over 90%). The median land size remained consistent across both cohorts. Adopters exhibited slightly larger farming experience (30.60 years) than non-adopters (29.81 years), with substantial variability in both instances. Furthermore, adopters had a more favourable percep-

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Table 2. Descriptive statistics of variables

Variable	Mean value		Standard deviation		Minimum		Maximum	
	adopter	non-adopter	adopter	non-adopter	adopter	non-adopter	adopter	non-adopter
PC	10.88	10.90	0.08	0.11	10.47	10.43	11.10	11.47
ROI	2.70	2.10	1.32	1.17	0.10	0.00	9.80	13.30
AG	0.97	0.92	0.16	0.27	0.00	0.00	1.00	1.00
ED	0.88	0.85	0.33	0.36	0.00	0.00	1.00	1.00
HS	0.47	0.42	0.50	0.49	0.00	0.00	1.00	1.00
FL	1.15	1.15	0.51	0.47	0.00	0.00	3.00	3.00
LS	0.36	0.39	0.35	0.32	0.06	0.05	2.83	2.83
LO	0.96	0.94	0.20	0.24	0.00	0.00	1.00	1.00
LT	0.13	0.23	0.34	0.42	0.00	0.00	1.00	1.00
FE	30.60	29.81	8.85	10.21	9.00	6.00	60.00	63.00
SFP	0.39	0.33	0.49	0.47	0.00	0.00	1.00	1.00
SWR	0.79	0.64	0.41	0.48	0.00	0.00	1.00	1.00
IMO	0.38	0.49	0.49	0.50	0.00	0.00	1.00	1.00
SK	0.39	0.21	0.49	0.41	0.00	0.00	1.00	1.00
CA	0.56	0.58	0.50	0.49	0.00	0.00	1.00	1.00
SI	10.68	10.56	0.43	0.44	8.99	8.70	11.74	12.01
FIS	0.64	0.17	0.48	0.38	0.00	0.00	1.00	1.00

PC – production cost; *ROI* – return on investment; *AG* – age; *ED* – education; *HS* – household size; *FL* – family labour; *LS* – land size; *LO* – land ownership; *LT* – land typology; *FE* – farming experience; *SFP* – soil fertility perception; *SWR* – soil water retention; *IMO* – irrigation machine ownership; *SK* – SIRFA knowledge; *CA* – credit availability; *SI* – secondary income; *FIS* – farmer's information seeking state

Source: Authors' own elaboration

tion of soil fertility and water retention (0.39 and 0.79) compared to non-adopters (0.33 and 0.64). Ownership of irrigation machinery was less prevalent among adopters (0.38) compared to non-adopters (0.49).

Regarding knowledge, adopters scored higher in SIRFA comprehension (0.39) than non-adopters (0.21), while credit availability remained similar across both groups. Average secondary income was also alike, with negligible differences in both mean and variability. Notably, adopters exhibited a significantly greater inclination towards information-seeking behaviour (0.64) relative to non-adopters (0.17), indicating a stronger propensity to pursue agricultural information.

Factors affecting SIRFA adoption. Table 3 shows our estimation of the key factors of SIRFA adoption across three models. We used robust standard errors to mitigate serial correlation across time. Since the coefficients simply indicate the direction of change, we assessed average marginal effects (AMEs) to understand better how a unitary change in a covariate affects the dependent variable's conditional mean (Greene 2002; Wooldridge 2010). Besides, the variance inflation factor (VIF) analysis showed that all variable values, from 1.05 to 1.85, were below 10, indicating satisfactory multicollinearity (Maddala 1983).

Table 3 illustrates a significant correlation ($P < 0.01$) between age and the adoption of SIRFA technology, with the estimated marginal effect indicating that farmers over 30 were 13.4% more inclined to adopt this technology. This finding reinforces prior research suggesting that older generations, with their extensive experience and understanding of intra-firm structures and operations, were more receptive to sustainable agricultural practices. Senior farmers who appreciated indigenous farming methods were more likely to engage in sustainable agriculture than their younger counterparts (Rizzo et al. 2023). The CRE probit model revealed a noteworthy relationship ($P < 0.05$) between household size and technology adoption, with households comprising more than four individuals exhibiting a 5.8% increase in SIRFA adoption. This implies that larger family units may influence technology uptake, managerial decisions, and specific needs, potentially facilitating the adoption of innovative practices that enhance economic advantages (Idrisa et al. 2012). Moreover, landowners of fertile plots were 3.6% to 3.9%

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Table 3. Factors affecting SIRFA adoption

Variables	GEE-PA logit	GEE-PA probit	CRE probit	*VIF*
	d*y*/d*x* (SE)			
Age	0.130 (0.065)**	0.134 (0.063)**	0.132 (0.121)	1.29
Education	0.046 (0.063)	0.059 (0.061)	0.017 (0.042)	1.07
Household size	0.045 (0.041)	0.045 (0.040)	0.058 (0.025)*	1.12
Family labour	0.045 (0.049)	0.044 (0.047)	0.020 (0.028)	1.16
Farm size	–0.078 (0.090)	–0.072 (0.091)	–0.039 (0.053)	1.38
Land ownership	0.048 (0.114)	0.040 (0.112)	0.020 (0.078)	1.08
Land typology	–0.021 (0.085)	–0.020 (0.084)	–0.016 (0.059)	1.79
Farming experience	–0.002 (0.003)	–0.002 (0.003)	–0.002 (0.002)	1.41
Soil fertility perception	0.039 (0.014)***	0.036 (0.014)**	0.015 (0.009)	1.16
Soil water retention state	0.141 (0.070)**	0.125 (0.071)*	0.059 (0.047)	1.76
Irrigation machine ownership	–0.106 (0.048)**	–0.110 (0.047)**	–0.064 (0.033)*	1.13
SIRFA knowledge	0.170 (0.032)***	0.169 (0.033)***	0.138 (0.022)***	1.11
Credit availability	–0.019 (0.023)	–0.021 (0.021)	–0.014 (0.014)	1.35
Secondary income	0.180 (0.048)***	0.177 (0.049)***	0.102 (0.102)**	1.12
Time dummy	0.051 (0.004)***	0.052 (11.85)***	0.031 (0.005)***	1.15
Mundlak's devices	no	no	yes	–
Observations	2 835	2 835	2 835	–

*, **, *** *P*-value < 0.10, *P*-value < 0.05, and *P*-value < 0.01, respectively; *z*-statistics with robust adjustment are reported in parentheses; SIFRA – solar irrigation and recommended fertiliser application; GEE – generalised estimated equation approach; *VIF* – variance inflation factor; *PA* – population average; *CRE* – correlated random effect; mean of time-varying variables (Mundlak's devices) was incorporated in the model, but not reported in the interest of brevity

Source: Author's own elaboration

more likely to accept SIRFA than those with less fertile fields, corroborating previous studies linking soil fertility to sustainable intensification techniques (Ndiritu et al. 2014). Further data indicated that farmers cul-

Table 4. Impact of SIRFA adoption on production cost using the 2SRI regression model

Variables	First stage	Second stage FE	Second stage RE
	d*y*/d*x* (SE)		
Dependent variable	SIFRA adoption	*PC*	*PC*
SIRFA adoption	–	–0.0764*** (0.0048)	–0.0757*** (0.0044)
Age	0.1015 (0.0941)	–0.0046 (0.0065)	–0.0042 (0.0061)
Education	0.0113 (0.0408)	–	–0.0041 (0.0026)
Household size	0.0186 (0.0250)	–0.0015 (0.0075)	–0.0019 (0.0052)
Family labour	0.0145 (0.0312)	–	–0.0291*** (0.0025)
Farm size	–0.0389 (0.0456)	–1.3319* (0.6604)	–0.0865*** (0.0044)
Land ownership	0.0262 (0.0602)	–	0.0346*** (0.0038)
Land typology	–0.0121 (0.0532)	–	0.0187*** (0.0031)
Farming experience	–0.0011 (0.0018)	0.0238*** (0.0008)	0.0001 (0.0001)
Soil fertility perception	0.0392*** (0.0132)	0.0014 (0.0031)	0.0001 (0.0028)
Soil water retention state	0.0167 (0.0425)	–	–0.0284*** (0.0024)
Irrigation machine ownership	–0.0519* (0.0282)	–	0.0224*** (0.0025)
SIRFA knowledge	0.1172*** (0.0287)	–0.0001 (0.0055)	–0.0017 (0.0046)
Credit availability	–0.0296 (0.0213)	0.0064 (0.0049)	0.0023 (0.0039)
Secondary income	0.1041*** (0.0264)	–0.0399*** (0.0093)	–0.0220*** (0.0065)
Time dummy	0.0252*** (0.0043)	–	0.0229*** (0.0007)
IV (seek information)	0.2217** (0.0216)	–	–
Residual	–	0.0015*** (0.0005)	0.0016*** (0.0004)
Observations	2 835	2 835	2 835

, * 5% and 1% significance level, respectively; FE – fixed effects model; RE – random effect model; SIRFA – solar irrigation and recommended fertiliser application; PC – production cost

Source: Author's own elaboration

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tivating on particularly water-retentive soil exhibit a 12.5% to 14.1% increase in SIRFA adoption. Preserving soil health necessitated water retention to foster crop growth and maintain organic richness, supporting earlier findings that the capacity of soil to retain water promotes sustainable agriculture (Sunny et al. 2022c). The result also demonstrated a significant negative relationship ($P < 0.05$) between ownership of irrigation devices and SIRFA adoption, suggesting that possessing any irrigation system decreased the likelihood of adoption by 6.4–11%. Besides, farmers with higher secondary incomes were 1.85% to 6.25% more likely to embrace new technologies compared to their peers, supporting earlier studies indicating that increased off-farm income positively impacts the adoption of innovative practices, considering additional costs (Sunny et al. 2022b). Lastly, the data revealed that farmers knowledgeable about SIRFA technologies were 13.8%

Table 5. Impact of SIRFA adoption on production cost using the different regression models

Variables	xtgls	xtscc	xtpcse	xtregar	newey	prais
	dy/dx (SE)					
SIRFA adoption	–0.0700*** (0.0025)	–0.0711*** (0.0091)	–0.0738*** (0.0040)	–0.0806*** (0.0041)	–0.0544*** (0.0035)	–0.0830*** (0.0035)
Age	–0.0038 (0.0043)	0.0010 (0.0019)	0.0010 (0.0065)	–0.0022 (0.0074)	0.0017 (0.0072)	–0.0010 (0.0074)
Education	–0.0026 (0.0040)	–	–0.0054 (0.0063)	–	–0.0066 (0.0042)	–0.0113 (0.0160)
Household size	0.0052* (0.0028)	0.0009 (0.0048)	0.0018 (0.0043)	0.0131* (0.0074)	–0.0004 (0.0034)	0.0054 (0.0059)
Family labour	–0.0287*** (0.0030)	–	–0.0301*** (0.0053)	–	–0.0316*** (0.0037)	–0.0208* (0.0117)
Farm size	–0.0831*** (0.0067)	–1.3868*** (0.1749)	–0.0908*** (0.0095)	–2.2410*** (0.4963)	–0.0782*** (0.0074)	0.0022 (0.0176)
Land ownership	0.0356*** (0.0073)	–	0.0384*** (0.0091)	–	0.0368*** (0.0062)	0.0155 (0.0247)
Land typology	0.0215*** (0.0053)	–	0.0247*** (0.0079)	–	0.0223*** (0.0056)	–0.0164 (0.0180)
Farming experience	0.0000 (0.0002)	0.4493*** (0.0052)	–0.0001 (0.0003)	0.0275*** (0.0009)	0.0001 (0.0002)	0.0008 (0.0006)
Soil fertility perception	–0.0024 (0.0016)	0.0031* (0.0015)	–0.0023 (0.0025)	0.0008 (0.0021)	–0.0141*** (0.0037)	0.0006 (0.0020)
Soil water retention state	–0.0294*** (0.0043)	–	–0.0251*** (0.0059)	–	–0.0259*** (0.0046)	–0.0111 (0.0151)
Irrigation machine ownership	0.0101*** (0.0034)	–	0.0217*** (0.0051)	–	0.0207*** (0.0037)	–0.0350*** (0.0113)
SIRFA knowledge	–0.0039 (0.0025)	0.0065 (0.0087)	–0.0011 (0.0037)	0.0023 (0.0049)	0.0032 (0.0034)	–0.0050 (0.0037)
Credit availability	–0.0025 (0.0021)	0.0056*** (0.0005)	–0.0067** (0.0033)	0.0030 (0.0029)	–0.0243*** (0.0040)	0.0031 (0.0027)
Secondary income	0.0074** (0.0032)	–0.0340** (0.0135)	0.0047 (0.0047)	–0.0131** (0.0064)	0.0172*** (0.0043)	–0.0168*** (0.0055)
Time dummy	0.0221*** (0.0006)	–0.4238*** (0.0043)	0.0209*** (0.0008)	–	0.0225*** (0.0009)	0.0218*** (0.0033)
Observations	2 835	2 835	2 835	2 835	2 835	2 835

, * 5% and 1% significance level, respectively; SIRFA – solar irrigation and recommended fertiliser application; xtgls – panel-data linear models by using feasible generalized least squares; xtscc – regression with Driscoll-Kraay standard errors; xtpcse – linear regression with panel-corrected standard errors; xtregar – fixed- and random-effects linear models with an AR(1) disturbance; newey – regression with Newey–West standard errors; prais – Prais-Winsten and Cochrane-Orcutt regression

Source: Author's own elaboration

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to 17% more likely to utilise them, further supporting previous research that underscores the role of knowledge in shaping perceptions, intentions, and environmentally responsible behaviours (Liu et al. 2020).

Effect of SIRFA adoption on production cost. The estimates from the 2SRI method are presented in Table 4. Due to the complexities of coefficient interpretation, we provide marginal effects instead. The first-stage results revealed that farmers' cognitive skills, supplementary income, soil fertility, and water retention capacity enhanced the adoption of SIRFA. The instrumental variable demonstrated a positive and statistically significant association, indicating that farmers exhibiting greater curiosity regarding SIRFA were more inclined to embrace the technology.

The empirical analysis in columns 3 and 4 of Table 4 reveals compelling evidence of SIRFA adoption's significant impact on production costs in agriculture. Notably, SIRFA adoption was associated with a 7.57% to 7.64% reduction in production costs, underscoring its potential as a cost-effective sustainable farming practice. Interestingly, factors such as farm size, family labour, land ownership, land typology, farming experience, soil water retention, irrigation machine ownership and secondary income also played crucial roles in influencing production costs. These findings suggest that promoting SIRFA could lead to substantial economic benefits for farmers while contributing to environmental sustainability. Prior research indicates that innovative farming practices significantly bolster sustainable agricultural methods, enabling participants to considerably lower production expenses (Tho et al. 2021).

The comparison of the two principal models (Table 4) with alternatives reveals that the results in Table 5 exhibit analogous signs and effects. The adoption of SIRFA led to a reduction in production costs ranging from 5.44% to 8.30%. Similar to earlier results, factors such as farm size, family labour, land ownership, land typology, farming experience, soil water retention, irrigation machine ownership and secondary income also played

Table 6. Impact of SIRFA adoption on *ROI* using the 2SRI regression model

Variables	First stage	Second stage FE	Second stage RE
		dy/dx (SE)	
Dependent variable	SIFRA adoption	*ROI*	*ROI*
SIRFA adoption	–	0.2503***(0.0386)	0.2561***(0.0369)
Age	0.1015 (0.0941)	0.0052 (0.0631)	–0.0144 (0.0611)
Education	0.0113 (0.0408)	–	–0.2859*** (0.0243)
Household size	0.0186 (0.0250)	–0.1638*** (0.0514)	–0.2364*** (0.0437)
Family labour	0.0145 (0.0312)	–	0.0234 (0.0183)
Farm size	–0.0389 (0.0456)	–1.6490 (5.9201)	–0.9391*** (0.0387)
Land ownership	0.0262 (0.0602)	–	0.4790*** (0.0279)
Land typology	–0.0121 (0.0532)	–	0.4429*** (0.0253)
Farming experience	–0.0011 (0.0018)	0.1488*** (0.0071)	0.0002 (0.0010)
Soil fertility perception	0.0392***(0.0132)	–0.0009 (0.0250)	–0.0068 (0.0247)
Soil water retention state	0.0167 (0.0425)	–	0.0402* (0.0206)
Irrigation machine ownership	–0.0519* (0.0282)	–	–0.4129*** (0.0206)
SIRFA knowledge	0.1172***(0.0287)	–0.1254*** (0.0443)	–0.1182** (0.0393)
Credit availability	–0.0296 (0.0213)	–0.0966** (0.0343)	–0.1530*** (0.0328)
Secondary income	0.1041***(0.0264)	2.6558*** (0.0965)	2.3467*** (0.0677)
Time dummy[a]	0.0252***(0.0043)	–	0.1556***(0.0064)
IV (seek information)	0.2217**(0.0216)	–	–
Residual	–	–0.0140*** (0.0043)	–0.0114** (0.0040)
Observations	2 835	2 835	2 835

, * 5% and 1% significance level, respectively; SIRFA – solar irrigation and recommended fertiliser application; FE – fixed effects model; RE – random effect model; *ROI* – return on investment

Source: Author's own elaboration

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crucial roles in influencing production costs. These findings corroborate the evidence presented in Table 4.

Effect of SIRFA adoption on ROI. Table 6 shows that the residual error was statistically significant, demonstrating a strong link between first and second stage estimation error terms. The findings suggest that SIRFA technologies in BRRI-dhan29 rice production would boost ROI by 25.03% to 25.61%. This finding matches a prior study conducted in Vietnam that farmers who adopted sustainable farming techniques achieved 22% higher ROI than their counterparts (Tho et al. 2021). Besides, factors such as secondary income, land ownership, land typology, farm size, irrigation machine ownership, education, Soil water retention state, farming experience, knowledge credit availability and household size influences ROI. These results highlight the complex interplay of factors affecting farm profitability and suggest areas for potential policy intervention or further research.

Table 7. Impact of SIRFA adoption on ROI using the different regression models

Variables	xtgls	xtscc	xtpcse	xtregar	newey	prais
	dy/dx (SE)					
SIRFA adoption	0.1392*** (0.0246)	0.2024*** (0.0506)	0.2298*** (0.0418)	0.1627*** (0.0380)	0.2062*** (0.0480)	0.2436*** (0.0344)
Age	–0.0354 (0.0414)	–0.0476* (0.0212)	–0.0433 (0.0646)	–0.0220 (0.0678)	–0.0180 (0.0630)	–0.0138 (0.0678)
Education	–0.1120** (0.0443)	–	–0.2125** (0.0733)	–	–0.1479** (0.0578)	–0.0906 (0.5957)
Household size	–0.3607*** (0.0256)	–0.1871** (0.0516)	–0.4040*** (0.0441)	–0.1849* (0.0678)	–0.4050*** (0.0385)	–0.0858 (0.0626)
Family labour	0.0311 (0.0308)	–	0.0243 (0.0507)	–	0.0047 (0.0389)	0.1456 (0.4353)
Farm size	–0.7076*** (0.0600)	–1.1684 (2.5804)	–0.7808*** (0.0919)	3.8386 (4.8878)	–0.6273*** (0.0682)	–3.8851*** (0.6443)
Land ownership	0.3893*** (0.0652)	–	0.4406*** (0.0881)	–	0.4778*** (0.0610)	0.6329 (0.9250)
Land typology	0.2483*** (0.0459)	–	0.3597*** (0.0705)	–	0.3517*** (0.0506)	0.0519 (0.6737)
Farming experience	0.0010 (0.0015)	–0.9694*** (0.0406)	0.0025 (0.0025)	0.1699*** (0.0068)	0.0032 (0.0021)	–0.0149 (0.0219)
Soil fertility perception	–0.0037 (0.0144)	–0.0169 (0.0185)	–0.0146 (0.0269)	–0.0215 (0.0210)	0.0156 (0.0399)	–0.0206 (0.0185)
Soil water retention state	0.0049 (0.0392)	–	0.0341 (0.0580)	–	0.0213 (0.0420)	0.3164 (0.5628)
Irrigation machine ownership	–0.2882*** (0.0295)	–	–0.3174*** (0.0498)	–	–0.2099*** (0.0384)	–0.0412 (0.4209)
SIRFA knowledge	–0.1389*** (0.0239)	–0.1845** (0.0503)	–0.0995** (0.0372)	–0.0915** (0.0465)	–0.0981** (0.0400)	–0.0328 (0.0370)
Credit availability	–0.1552*** (0.0193)	–0.0885** (0.0272)	–0.2147*** (0.0373)	–0.0774** (0.0284)	–0.4910*** (0.0449)	–0.0705** (0.0251)
Secondary income	1.6389*** (0.0304)	2.6039*** (0.0303)	1.8014*** (0.0649)	2.7578*** (0.0615)	1.4316*** (0.0574)	2.7626*** (0.0548)
Time dummy[a]	0.1594*** (0.0051)	1.1029*** (0.0307)	0.1662*** (0.0089)	–	0.1701*** (0.0096)	1.3092*** (0.1267)
Observations	2 835	2 835	2 835	2 835	2 835	2 835

, * 5% and 1% significance level, respectively; SIRFA – solar irrigation and recommended fertiliser application; xtgls – panel-data linear models by using feasible generalized least squares; xtscc – regression with Driscoll-Kraay standard errors; xtpcse – linear regression with panel-corrected standard errors; xtregar – fixed- and random-effects linear models with an AR(1) disturbance; newey – regression with Newey–West standard errors; prais – Prais-Winsten and Cochrane-Orcutt regression

Source: Author's own elaboration

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Table 7 shows that SIRFA adopters had a greater ROI than other models. Despite modest differences from Table 6, the findings showed similar signs and effects. Factors such as secondary income, land ownership, land typology, farm size, irrigation machine ownership, education, farming experience, knowledge, credit availability, and household size influenced ROI, supporting the results shown in Table 6.

Our findings emphasise the broader significance and potential advantages of sustainable agricultural practices, particularly within the realm of BRRI-dhan29 rice cultivation. For example, while Sunny et al. (2022b) observed a modest 1.36% reduction in PC and an 8.92% increase in ROI following the short-term effects of technology adoption, this manuscript uncovered considerably more substantial and enduring impacts over time. Specifically, it demonstrated that the adoption of SIRFA led to a reduction in PC ranging from 5.44% to 8.30%, and an increase in ROI in between 13.92% to 25.61%. This indicates that the implementation of SIRFA confers more pronounced long-term benefits compared to transient advantages.

CONCLUSION

This study, leveraging seven years of panel data, examined the determinants of SIFRA technology adoption and its impact on rice farmers in the Dinajpur region, where acidic soil predominates. Findings revealed that factors such as the respondent's age, household size, soil fertility, water retention capacity, ownership of irrigation equipment, and environmental considerations substantially influenced adoption choices. The impact analysis shows that SIFRA adoption reduced PC by 5.44% to 8.30% while enhancing ROI by 13.92% to 25.61%. These results underscore the significance of integrating advanced technologies to elevate productivity and improve economic outcomes in agriculture. They also highlight SIFRA's critical role in strengthening farming resilience against potential disasters, whether natural or anthropogenic, supported by effective capacity-building frameworks within established systems. Additionally, farmers who recognised the significance of resource management were more inclined to adopt eco-friendly methods. It is plausible that as farmers enhance productivity through innovations like SIFRA, policymakers may be increasingly motivated to support environmentally sustainable policies. However, transitioning from existing technologies may take time unless farmers see the new solutions as offering superior utility and long-term benefits. Therefore, policy implications are derived from the key findings of this study.

Firstly, our results indicate that younger farmers cultivating the BRRI-dhan29 rice variety are less likely to adopt SIFRA. Consequently, a uniform extension approach may not be the most effective strategy. Tailoring extension strategies to address the diverse characteristics, adoption statuses, and specific challenges of different farmer groups is likely to meet their needs better. Further research is necessary to explore how such targeted designs can enhance SIFRA adoption rates.

Secondly, policymakers should rethink the implementation of conflicting schemes within the same regions, such as permitting both small portable solar irrigation systems and large immovable systems. These discrepancies could lead to disputes between farmers and service providers, complicating business operations and loan repayments. Additionally, strategies for providing backup in low sunlight conditions must be developed, which could involve connecting solar sites to the national electricity grid. This would allow for the transfer of unused energy during optimal conditions, providing irrigation support when needed. Furthermore, educating farmers about abiotic and biotic factors and adjusting fertiliser application according to soil acidity could improve the adoption process.

Given that rural families often involve multiple members in decision-making, a higher likelihood of adoption relies on these individuals possessing adequate knowledge of the benefits. Therefore, disseminating information through extension officers, service providers, and fertiliser distributors is expected to facilitate SIFRA adoption.

Moreover, launching public-private initiatives to establish group-farming models supported by microfinance institutions could significantly enhance the adoption process. Group farming encourages small farmers to pool resources, creating larger enterprises while sharing costs and benefits, all without relinquishing rights to their land. Reforming agricultural cooperatives and encouraging family farms to join could serve as a platform for regular exchanges among farmers. Through technical guidance and knowledge sharing, SIFRA technologies can be promoted more effectively among geographically proximate family farms. Additionally, establishing region-specific water extraction regulations can mitigate unforeseen groundwater abstraction issues. Encouraging farmers to conduct soil tests annually and establishing more affordable soil-testing laboratories will empower them to manage their soil effectively, tailoring fertiliser application accordingly.

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It is essential to note that the findings of this study may not be universally applicable to all SIFRA adopters in different regions of Bangladesh due to their diverse characteristics. However, as the first longitudinal study focused on technology adoption among BRRI-dhan29 rice variety farmers in acidic soils within a water-scarce area, it accentuates the need for further research across various regions. Investigating this rice variety in different contexts will yield valuable insights into overcoming inefficiencies and formulating appropriate policies to promote sustainable agriculture. Furthermore, we advocate for additional research to elucidate the precise mechanisms through which SIFRA technologies impact ROI in rice production. Assessing the influence of SIFRA adoption on farmers' technical efficiency is essential. A deeper understanding of these mechanisms can inform targeted interventions and strategies aimed at fostering sustainable farming practices and improving farmers' livelihoods.

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