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Research Paper

Analyzing Trends in Technical Efficiency of Paddy Production in Sri Lanka (2004 -2019)

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Abstract

This study evaluates the technical efficiency (TE) of paddy production in Sri Lanka over a 16-year period (2004–2019) using an extensive cost of cultivation dataset from seven major paddy-producing regions, providing one of the most comprehensive regional assessments to date. Stochastic Frontier Analysis revealed notable regional variations in TE, with a generally improving trend over the study period. The estimated input elasticities indicate that urea (0.15), triple superphosphate (TSP) (0.11), and labour (0.1) positively influence output, underscoring the role of balanced nutrient application and timely labour allocation. The significant and positive interaction term between urea and TSP (0.04) highlights the productivity gains from coordinated fertilizer management, while the squared term for urea shows diminishing marginal returns from excessive application. These findings suggest that productivity improvements are closely linked to the efficiency of input use and complementary application strategies. Although TE has increased over time, the analysis does not establish a direct causal relationship between current agricultural support mechanisms and the observed improvements, and such inferences require dedicated causal research. The results emphasise the importance of identifying region-specific drivers of TE, considering agro-ecological conditions, input price dynamics, and farm management practices. Future research integrating climatic, soil quality, and farmer behavioural variables with longitudinal datasets could provide a more complete understanding of efficiency determinants. Such evidence would strengthen the basis for developing targeted and sustainable agricultural policies aimed at enhancing productivity while ensuring resource efficiency in paddy cultivation across diverse production environments in Sri Lanka.

Keywords: Agricultural policy, Paddy, Stochastic frontier approach, Technical efficiency

Introduction

Paddy cultivation plays a pivotal role in the Sri Lankan economy, serving as the primary source of livelihood for many farming households. With an annual cultivated extent of 1.2 million hectares, paddy contributes significantly to the country's food security, producing approximately five million metric tons annually at an average yield of 4.3 metric tons per hectare (Department of Census and Statistics, 2022). The sector has witnessed dynamic transformations over the years, influenced by government policies, technological advancements, and shifts in resource use patterns. Technical efficiency (TE) is a critical determinant of agricultural productivity and sustainability. Several studies in Sri Lanka have highlighted regional and contextual disparities in TE in paddy production systems due to variations in farming systems, irrigation access, and resource use. For instance, Shantha *et al*. (2012) reported TE values of 0.69 in paddy farms under minor irrigation schemes, attributing inefficiencies to inadequate managerial skills. Similarly, Warnakulasooriya and Athukorale (2016) observed TE levels between 0.67 and 0.78 in rainfed farming systems, indicating potential for cost savings and productivity gains. Thibbotuwawa, Mugera, and White (2013) emphasized irrigation as a key driver of efficiency, noting that rainfed farms performed worse than irrigated ones. These findings underscore the pressing need for targeted interventions such as improved irrigation systems, enhanced extension services, and better resource optimization. Among the many factors influencing TE, government policies-particularly those related to fertilizer subsidies have played a crucial role in shaping paddy productivity. Fertilizer subsidies in Sri Lanka were introduced during the Green Revolution era in 1962 and have since evolved through various forms, including cash grants and in-kind fertilizer distributions (Weerahewa *et al*., 2010). Empirical evidence highlights both the benefits and limitations of these subsidy programs. For example, Ekanayake (2009) observed correlations between fertilizer usage and paddy yields, while Wijetunga and Saito (2017) found that removing fertilizer subsidies could lead to a decline in production and a rise in rice prices. Additionally, Kanthilanka and Weerahewa (2019) noted that efficient farmers tend to continue using chemical fertilizers even in the absence of subsidies, suggesting a strong link between fertilizer use and productivity. Globally, subsidies have been recognized as an effective short-term policy measure for boosting agricultural productivity, particularly in developing countries (Adiraputra *et al*., 2021; Bayes *et al*., 1985). However, as Renfro (1992) cautioned, subsidies can distort market dynamics and hinder private-sector competition. In Sri Lanka, research by Dulanjani and Shantha (2022) reported a positive relationship between fertilizer subsidies and paddy yields, and another study shows national productivity improvement and area expansion due to fertilizer subsidy (Weerahewa *et al*., 2022). This study seeks to analyze trends in TE within Sri Lanka's paddy sector from 2004 to 2019. This study estimates TE levels in paddy production and use. Stochastic Frontier Analysis (SFA) is commonly used in productivity analysis of paddy in Sri Lanka; however, pseudo-panel data was not used, and very limited studies on panel data analysis, and addressing a gap in prior research often constrained by small samples through the use of a large, multi-year, regionally diverse dataset.

Model and Data

The methodology employed in this study addresses the complexities of rice production analysis, with due consideration to the uncertainties inherent in this agricultural domain. Variations in output, primarily stemming from input fluctuations, technical inefficiencies, and uncontrollable random shocks, are central to understanding the dynamics of rice producers.

A dual approach was taken to disentangle the impact of input variations, technical inefficiency (reflected in the suboptimal use of resources), and random shocks (such as uncontrollable events like droughts, floods, and economic issues). Firstly, a production function specification was utilized to capture the output fluctuations attributable to input variations. Secondly, the stochastic production frontier approach (Aigner *et al*., 1977; Meeusen & van Den Broeck, 1977) was employed to dissect and quantify the influences of technical inefficiency and random shocks on output fluctuations.

$$y_i = \int(x_i, \beta) e^{v_i - u_i} \quad \text{......................} \ (1)$$

In equation (1), y denotes output, x denotes input, v represents statistical noise (two-sided random error capturing factors beyond the producer's control), and u denotes the non-negative inefficiency term, assumed to be independently and half-normally distributed, truncated at zero, and associated with technical inefficiency of production.

$$TE_i = e^{-ui} \quad \text{......................} \ (2)$$

Previous research by Battese & Coelli (1995) utilized the Cobb-Douglas production function to demonstrate that technical inefficiency (TIE) is time-invariant. In contrast, Greene (2005) proposed that TIE is a combination of time-invariant true error and random error. However, Kumbhakar & Heshmati (1995) using trans-log production function shows that TIE is a combination of firm-specific (time-invariant) and time-varying residual component. In addition, Kumbhakar *et al*. (2014) showed that the time-invariant component has two parts: firm effect and noise. Additionally, the time-varying component consists of persistent technical inefficiency and time-varying inefficiency. According to Kumbhakar and Heshmati (1995), TE measures are distorted with specification errors and difficulty of accurate measurement and suggest use of standard practices, since this kind of Maximum Likelihood Estimation models are rarely used in econometrics. The combined model is as follows.

$$ln\,(Y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j\, l\,n\big(X_{jit}\big) + \sum_{j=1}^{k} \sum_{m=1}^{k} \gamma_{jm}\, ln\,(X_{jit}) ln\,(X_{mit}) + v_{it} - u_{it} \quad \text{......................} \ (3)$$

Y_{it} is the production of i[th] farm in t[th] time. X_{jit} are the inputs that include chemical fertilizer usage, farm extent, labour usage and seed rate, β is the vector of the parameters to be estimated, while *γjm* represents the interaction effects between the inputs. v_{it} is the noise, and u_{it} is the time-varying panel level effect.

The justification for using the paddy production function stems from its ability to estimate the combined effects of multiple inputs while accounting for potential interactions between these inputs. Given the complexity of agricultural production, where inputs do not operate in isolation but interact with one another, paddy production function offers a more nuanced understanding of their relationships. Moreover, it provides flexibility in modeling both time-invariant and time-varying inefficiencies, which aligns with previous findings in the literature, such as those by Kumbhakar *et al*. (2014), who highlight the importance of distinguishing between persistent and time-varying inefficiencies.

For the time-invariant model,

$u_{it}=u_i$ where, $u_i \sim N^{+} (\mu, {}^{\sigma 2}{}_{u})$ is a non-negative, truncated normal (or half-normal) distribution. The noise term $v_{it} \sim N(0, \sigma 2_v)$ is normally distributed.

For the time decay model,

$$u_{it}=exp\{-\eta(t-T_i)\}u_i \quad \text{.........................} (4)$$

Where, T_i is the last period considered and η is the decay parameter and u_is are assumed to be independent and identically distributed non-negative truncation of the N $(\mu,\sigma 2_u)$ distribution, where μ is the mean (non-negative) of uis and $\sigma 2_u$ is the variance of u_is, and v_i $(0, \sigma 2_v)$ are normally distributed (Battese & Coelli,1992).

The choice between fixed effects and random effects models was made using the Hausman test (Hausman, 1978), which evaluates whether the unique errors are correlated with the regressors. The test statistic is given by,

$$H=(b_{FE}-b_{RE})' \,(var\,(b_{RE})-var(b_{FE}))^{\dagger}\,(b_{FE}-b_{RE}) \quad \text{.......} (5)$$

Where, b_{FE} and b_{RE} are the coefficient vectors from the fixed effects and random effects models, respectively, and † stands for the Moore-Penrose pseudo inverse. Under the null hypothesis that the random effects estimator is consistent, *H* follows a chi-squared distribution with degrees of freedom equal to the rank of var (b_{RE})-var (b_{FE}), A statistically significant H indicates that the fixed effects model is preferred.

Utilizing pseudo-panel data from seven major cultivation areas represent 40% of total paddy cultivating extent and irrigation method (DCS, 2022), this analysis encompasses both rain-fed regions (Kalutara and Kurunegala) and major irrigation areas (Anuradhapura, Hambantota, Kurunegala, Mahaweli System H, and Polonnaruwa) over the period 2004 to 2019 (Department of Agriculture, 2004-2019). A pseudo-panel dataset was constructed using representative farmer samples from each region, selected based on specific locations served by Agrarian Service Centers (ASCs). These locations were chosen because detailed cost of cultivation data for paddy production were available from the Department of Agriculture (DOA). Within each selected location, a representative farmer was identified for each season and year based on DOA survey records. Since the individual farmers representing each location may vary across seasons and years, a pseudo-panel approach—rather than a traditional panel of the same individuals—was adopted to capture temporal and regional variations in production. Pseudo-panel data is effective in analyzing the fixed effects of cohorts in heterogenic panels (Deaton, 1985). The Maximum Likelihood Estimation (MLE) method within the production frontier approach was employed to dissect production efficiency with a pseudo-panel data approach (Heshmati & Kumbakar, 1997). Subsequently, a series of one-tail t-tests were conducted to scrutinize the regional disparities and the impact of various subsidy schemes on technical efficiency.

However, the regional effect was not captured. Data analysis was conducted using the STATA MP17 statistical package, ensuring robustness and accuracy in evaluating the multifaceted dimensions of the fertilizer subsidy policies' effects on rice production efficiency across selected regions.

Results and Discussion

Table 1 presents the summary statistics of the key variables included in the analysis.

Table 1. Summary Statistics

Variable	Unit of Measurement	Mean (SD)
Yield	kg ha^{-1}	4,641 (2344)
Cultivated extent	ha	0.74 (0.64)
Seed rate	kg ha^{-1}	124 (35)
Labour	MD ha^{-1}	71 (135)
Chemical fertilizer	kg ha^{-1}	520 (149)
Family labour	MD ha^{-1}	44 (42)
Quality of seed	Certified-1, 0 otherwise	
Pre weedicide	Applied-1, 0 otherwise	
Weedicide	Applied-1, 0 otherwise	
Pesticide	Applied-1, 0 otherwise	
Machinery	Applied-1, 0 otherwise	
Urea	kg ha^{-1}	372 (140)
TSP	kg ha^{-1}	67 (40)
MOP	kg ha^{-1}	63 (36)
Mix fertilizer	kg ha^{-1}	8 (23)
TDM	kg ha^{-1}	8 (23)
Time trend	Years	15
Regions*ASC	Cohorts	210

Note: Figures in parenthesis are Standard Deviation (SD)

The yield (Y) averages 4,641 kg ha^{-1} with a standard deviation (SD) of 2,344 kg ha^{-1}, indicating substantial variability. The average cultivated extent is 0.74 ha per farmer (SD = 0.64), and the seed rate is 124 kg ha^{-1} (SD=35). The averages of labour input, including total and family labour, are 71 MD ha^{-1} (SD = 135) and 44 MD ha^{-1} (SD = 42), respectively. Chemical fertilizer (urea, MOP, TSP, TDM and fertilizer mixtures) use average is 520 kg ha^{-1} (SD = 149). The dataset includes information on seed quality, pre-weedicide use, weedicide use, pesticide use, and machinery application, recorded as binary (yes/no) variables. Specific fertilizer types, such as urea, TSP, MOP, mix fertilizer, and TDM. The dataset spans 15 years and includes information on 210 regional cohorts, comprising 8,087 total observations.

The results from the production efficiency analysis, detailed in Table 2, describe the relationships between various input factors and the efficiency of rice production. This comparative assessment contrasts the outcomes derived from the time decay model with those obtained from the time-invariant model.

Table 2. Estimated input elasticities and technical efficiency analysis from the log-log production model

Factor	Value of time decay model	Value of time-invariant model
Urea	2.87** (0.77)	
Labour* Labour	-0.02* (0.01)	-0.03*(0.01)
TSP*TSP	0.15** (0.05)	
Urea*Urea	-0.36**(0.08)	
Labour*Urea	0.10**(0.04)	0.10*(0.03)
TSP*MOP	0.18**(0.07)	
TSP*Extent	-0.12**(0.03)	
Urea*Seed rate	0.15*(0.07)	
Extent*Extent		0.06**(0.01)
Labour*TSP		-0.22**(0.05)
TSP*Urea		-0.20**(0.07)
TSP*Extent		-0.17**(0.04)
TSP*Seed rate		-0.29**(0.08)
σ_u (inefficiency)	0.60** (0.01)	0.70**(0.01)
σ_v (noise)	0.22**(0.01)	0
λ (signal to noise)	2.79 (0.01)	636119.5**(0.01)
Log-likelihood ratio	-3501.52	-2245.45
N	6141	6059

*Note: Figures in parenthesis are standard errors (SE), level of significance * 5% ,**1%*

The effect of urea on rice yield incorporates the direct coefficient (2.87), a significant negative quadratic effect (–4.26) reflecting diminishing returns at higher application rates, and positive interactions with labour (0.43) and seed rate (0.72). Combining these effects yields a net marginal elasticity of –0.24, indicating that beyond average application levels, increased urea use may slightly reduce yield efficiency.

The marginal effect of TSP on rice yield is driven by its positive quadratic term (1.26) and a small positive interaction with cultivated extent (0.04), resulting in a net elasticity of approximately 1.30, which indicates a positive contribution to yield with some diminishing effect as cultivated extent increases.

Labour's effect on rice yield combines a negative quadratic term (-0.17), suggesting diminishing returns at higher labour levels, with a positive interaction with urea (0.59), resulting in a net elasticity of 0.42, indicating moderate positive returns to labour input.

The time decay and time-invariant models differ primarily in their assumptions about inefficiency dynamics: the time decay model allows inefficiency to change and decrease over time, while the time-invariant model assumes a constant inefficiency effect. The smaller sample size in the time-invariant model (6059 vs. 6141) results from excluding incomplete observations necessary for balanced panel estimation. Although the time-invariant model shows a substantially higher Lambda value (636,119.5) and better log-likelihood (-2245.45 vs. -3501.52), indicating a stronger signal-to-noise ratio and improved fit, the time decay model is preferred for capturing the realistic nature of technical inefficiency in rice production over time. Reporting both models allows for comprehensive comparison of dynamic versus static inefficiency assumptions.

The production elasticities derived from the time decay model were calculated by integrating main effects, quadratic terms, and interaction effects evaluated at the mean values of input variables following the translog elasticity framework. The net marginal elasticity of urea was estimated at –0.24, reflecting an initial positive effect (2.87) offset by a substantial negative quadratic term (–4.26), and moderated by positive interactions with labour (0.43) and seed rate (0.72). Although the urea–TSP interaction was not significant in this model, notable interactions such as labour–urea and urea–seed rate demonstrate complementary input relationships. Labour exhibited a net elasticity of 0.42, incorporating diminishing marginal returns via its negative quadratic term (–0.17) and enhanced productivity through interaction with urea (0.59). TSP showed a positive net elasticity of 1.30, primarily driven by its quadratic term (1.26) and a modest positive interaction with cultivated extent (0.036). In contrast, cultivated extent had a negative net elasticity (–0.50), attributed to its negative interaction with TSP, suggesting diminishing returns at higher levels of land use. Seed rate contributed positively with a net elasticity of 0.89, largely through its synergistic interaction with urea.

The Hausman Test outcomes, detailed in Table 3, serve as a critical determinant in model selection between the time decay and time-invariant models. This statistical assessment decisively favours the time decay model over its time-invariant counterpart. The statistical evidence strongly supports the superior explanatory power and suitability of the time decay model in elucidating the dynamics inherent in production efficiency within rice cultivation.

The presented data in Table 4 delineates the temporal dynamics of technical inefficiency within rice production across selected 7 production regions major production areas from 2004 to 2019.

Table 3. Specification test results for model selection between time-invariant and time-decay models

Variable	Time invariant	Time decay	Difference	Standard error	Chi-square value and probability
Chemical fertilizer	-0.20	-0.40	0.20	0.25	99.08
Labour*Labour	-0.03	-0.02	-0.00	0.00	0.00*
TSP*TSP	0.10	0.15	-0.05	0.03	
Urea*Urea	0.01	-0.36	0.37	0.00	
MOP*MOP	-0.07	-0.00	-0.07	0.04	
Extent*Extent	0.06	0.01	0.04	0.01	
Seed rate*Seed rate	-0.03	-0.04	0.01	0.00	
Labour*TSP	-0.22	-0.04	-0.18	0.03	
Labour *Urea	0.10	0.10	-0.00	0.00	
Labour*MOP	-0.02	0.05	-0.07	0.03	
Labour*Extent	-0.01	-0.01	0.00	0.01	
Labour*Seed rate	0.01	-0.07	0.08	0.00	
TSP*Urea	-0.20	0.03	-0.22	0.03	
TSP*MOP	0.04	0.18	-0.14	0.05	
TSP*Extent	-0.17	-0.12	0.06	0.02	
TSP*Seed rate	-0.29	-0.15	0.14	0.02	
Urea*MOP	0.06	-0.05	0.11	0.03	
Urea*Extent	0.03	0.02	0.01	0.00	
Urea*Seed rate	-0.01	0.15	-0.16	0.03	
MOP*Extent	-0.04	0.01	-0.05	0.02	
MOP*Seed rate	0.09	0.17	-0.08	0.04	

*Note: * 5% level of significance*

Table 4. Technical inefficiency change

Year	All Island	Anuradhapura (irrigated)	Hambantota (irrigated)	Kalutara (rainfed)	Kurunegala (irrigated)	Kurunegala (rainfed)	Polonnaruwa (irrigated)	System H (irrigated)
2004	0.12 ± (0.02)						0.12 ± (0.02)	
2005	0.12 ± (0.01)	0.10 ± (0.01)	0.13 ± (0.02)	0.27 ± (0.02)			0.10 ± (0.01)	
2006	0.16 ± (0.01)	0.12 ± (0.01)	0.10 ± (0.00)	0.34 ± (0.02)			0.10 ± (0.01)	
2007	0.15 ± (0.00)	0.11 ± (0.01)	0.10 ± (0.00)	0.27 ± (0.01)	0.12 ± (0.01)	0.27 ± (0.03)	0.10 ± (0.00)	0.13 ± (0.00)
2008	0.15 ± (0.00)	0.12 ± (0.01)	0.10 ± (0.00)	0.26 ± (0.01)	0.12 ± (0.00)	0.24 ± (0.02)	0.09 ± (0.00)	0.12 ± (0.00)
2009	0.15 ± (0.00)	0.11 ± (0.01)	0.10 ± (0.00)	0.25 ± (0.01)	0.10 ± (0.00)	0.25 ± (0.02)	0.10 ± (0.00)	0.12 ± (0.00)
2010	0.15 ± (0.00)	0.11 ± (0.01)	0.09 ± (0.00)	0.25 ± (0.01)	0.11 ± (0.01)	0.27 ± (0.02)	0.09 ± (0.00)	0.12 ± (0.00)
2011	0.15 ± (0.01)	0.10 ± (0.01)	0.09 ± (0.00)	0.25 ± (0.02)	0.11 ± (0.01)	0.31 ± (0.02)	0.09 ± (0.00)	0.12 ± (0.00)
2012	0.15 ± (0.01)	0.10 ± (0.00)	0.09 ± (0.00)	0.25 ± (0.02)	0.11 ± (0.01)	0.30 ± (0.02)	0.08 ± (0.00)	0.11 ± (0.01)
2013	0.14 ± (0.01)	0.09 ± (0.00)	0.08 ± (0.00)	0.23 ± (0.02)	0.11 ± (0.01)	0.29 ± (0.02)	0.08 ± (0.00)	0.11 ± (0.01)
2014	0.15 ± (0.01)	0.09 ± (0.01)	0.08 ± (0.01)	0.23 ± (0.02)	0.10 ± (0.01)	0.28 ± (0.02)	0.08 ± (0.00)	0.10 ± (0.01)
2015	0.13 ± (0.01)	0.09 ± (0.00)	0.08 ± (0.00)	0.22 ± (0.02)	0.10 ± (0.01)	0.27 ± (0.02)	0.07 ± (0.00)	0.10 ± (0.01)
2016	0.13 ± (0.01)	0.09 ± (0.00)	0.08 ± (0.00)	0.21 ± (0.01)	0.09 ± (0.01)	0.26 ± (0.02)	0.07 ± (0.00)	0.10 ± (0.01)
2017	0.13 ± (0.01)	0.08 ± (0.01)	0.07 ± (0.00)	0.20 ± (0.01)	0.09 ± (0.01)	0.26 ± (0.01)	0.07 ± (0.00)	0.09 ± (0.01)
2018	0.13 ± (0.01)	0.08 ± (0.00)	0.07 ± (0.00)	0.21 ± (0.02)	0.10 ± (0.01)	0.23 ± (0.02)	0.07 ± (0.01)	0.09 ± (0.00)
2019	0.12 ± (0.00)	0.08 ± (0.01)	0.07 ± (0.00)	0.19 ± (0.01)	0.09 ± (0.01)	0.23 ± (0.02)	0.06 ± (0.01)	0.09 ± (0.00)
2005-2015	0.15 ± (0.01)	0.11 ± (0.01)	0.09 ± (0.00)	0.25 ± (0.02)	0.11 ± (0.01)	0.27 ± (0.01)	0.09 ± (0.00)	0.11 ± (0.01)
2016-2019	0.13 ± (0.01)	0.08 ± (0.00)	0.07 ± (0.00)	0.21 ± (0.01)	0.09 ± (0.01)	0.25 ± (0.01)	0.07 ± (0.00)	0.09 ± (0.01)
t-test (p-value)	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**

*Note: Figures in parenthesis are Standard Errors (SE), **Significant at 1%*

The overall trend denotes a consistent decline in inefficiency levels observed from 2004 to 2019 across various regions, signifying an overall improvement in production efficiency. Specific regions, including Anuradhapura, Hambantota, Kalutara (rainfed), Kurunegala (irrigated), Kurunegala (rainfed), Polonnaruwa, and System H, demonstrate variable inefficiency levels throughout the years, albeit showcasing a predominant reduction in inefficiency. The analysis of the two distinct periods (2005-2015) and (2016-2019) reveals marked inefficiency alterations across all regions during these intervals, denoted by a t-test resulting in a p-value <0.01. Comparing the inefficiency changes between irrigation and rainfed systems reveals significant variation. According to Thibbotuwawa *et al*. (2013), productivity in both the systems is notably low, primarily due to the timely unavailability of water. Additionally, factors such as the scale of operation, availability of quality seeds, and skilled labour further contribute to inefficiencies in these production systems.

The inefficiency levels during the period (2005-2015) average at 0.15 (±0.01), displaying regional variations yet indicating an overall decline in inefficiency. After the initial period (2016-2019), inefficiency levels further diminished to an average of 0.13 (±0.01), underlining a sustained trend towards enhanced technical efficiency across the studied regions.

The observed reduction in technical inefficiency over the study period likely reflects cumulative improvements in rice production practices, including better access to inputs, adoption of improved seed varieties, and enhanced management skills among farmers. Although this study does not explicitly model the determinants of inefficiency, the two-stage approach captures these underlying efficiency gains by first estimating technical inefficiency through the stochastic frontier model and then analyzing inefficiency scores across time and regions. Thus, the declining inefficiency trend reflects gradual improvements in resource use efficiency, technology adoption, and possibly the impact of policy measures such as fertilizer subsidy reforms. However, isolating the precise drivers of this improvement requires further research incorporating explicit explanatory variables for inefficiency in a second-stage regression framework.

Conclusion

This study offers valuable insights into factors influencing technical efficiency (TE) in rice production, emphasizing the significant role of key inputs like urea fertilizer in the production function. However, it is important to note that urea was not included as an explanatory variable in the inefficiency model; thus, its direct impact on TE cannot be conclusively determined from this analysis. The observed improvement in TE over time coincides with the implementation of two distinct fertilizer subsidy schemes, with notable efficiency gains during the period of cash grant subsidies. Conceptually, these gains may reflect improved input accessibility and incentives, although the study does not explicitly model these mechanisms.

Efficiency improvements were consistent across diverse agro-ecological zones and irrigation types-including irrigated and rainfed systems in major rice-producing districts-indicating a broad enhancement of production efficiency that transcends specific geographic and irrigation-related limitations such as water availability and soil conditions. Nevertheless, the use of secondary cost-of-cultivation data limited the inclusion of key socio-economic and management variables affecting inefficiency. To robustly assess the determinants of TE and the causal effects of subsidy schemes, future research should adopt a two-stage modeling framework with comprehensive primary data, capturing farmer behaviour, input timing, and institutional factors to fully elucidate the complex drivers of technical efficiency in rice production.

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