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Optimizing Inputs Consumption and Reducing Pollution through Environmental Efficiency Analysis: An Approach to Achieving Sustainable Agricultural Production

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Abstract

While agriculture relies on inputs to produce desired outputs; however, it also generates unintended environmental impacts. Given rising global food demand, reducing environmental impacts through production cuts, is often impractical. Thus, this study employs Data Envelopment Analysis with Material Balance Principle model to evaluate rice farmers' eco-efficiency. Additionally, it examines optimal input allocation with and without environmental consideration. The study focuses on rice farmers in the Gotvand region of Khuzestan Province, Iran. The primary data were collected through 153 questionnaires administered to local rice farmers in 2022. The findings revealed that the average technical efficiency of rice farmers in Gotvand region is 87% under conventional efficiency measures, but this drops to 73% when environmental pollution is factored in. To achieve optimal efficiency, inefficient Decision-Making Units must reduce their carbon dioxide emissions by an average of 8%. To improve eco-efficiency, the study identifies different optimization patterns: substantial reductions are needed for nitrogen fertilizer (-41.1%), fuel (-38.5%), and machinery operation hours (-33.6%), while increases are recommended for animal manure (612%), potassium fertilizer (6.25%), and phosphate fertilizer (2.7%). Therefore, key contributors to the inefficiency among the studied producers include inadequate animal manure application, excessive nitrogen fertilizer use, diesel fuel consumption, and machine operation hours. Notably, electricity usage has a minimal impact on inefficiency, with no significant changes detected. These findings underscore the necessity of optimized input management, especially chemical fertilizer reduction , to enhance both economic and environmental sustainability in rice farming.

Keywords: Ecoefficiency, Material Balance Principle**,** Environmental Impacts, Carbon Dioxide, Rice production.

Introduction

Agriculture is an essential economic sector that transforms inputs into valuable outputs, yet it inevitably generates undesirable byproducts ((Ramli & Munisamy, 2015). In light of growing

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environmental degradation and the global emphasis on sustainability, protecting agricultural ecosystems and ensuring sustainable farming practices have become key priorities for policymakers and researchers (Wang et al., 2024). Recognizing the long-term costs of environmental damage, governments worldwide have established dedicated environmental agencies and implemented policies to encourage responsible natural resources management (Abdollahi & Faryadi, 2010).

Among economic sectors, agriculture has the strongest connection with the environment**.** On one hand, environmentally conscious agriculture seeks to achieve sustainable development by striking a delicate balance between the economic benefits of agricultural production and environmental conservation (Li et al., 2012). On the other hand, sustainable agriculture not only shouls addresses current food demands but also ensures resource availability for future generations (Robertson, 2015). This approach balances environmental improvements, efficient input use, food security, and societal well-being. A fundamental aspect of sustainable farming is replacing chemical inputs with organic alternatives, to minimize reliance on harmful inputs (Patel et al., 2010).

However, given the limited water and soil resources in agriculture, chemical fertilizers and pesticides remain essential for increasing productivity. Nevertheless, their overapplication fails to proportionally boost yields while creating severe ecological consequences including environmental pollution, biodiversity reduction, ecosystem disruption, and increased production costs (Lin et al., 2013). Thus, researchers face the dual challenge of ensuring food security while minimizing environmental harm. This necessitates developing innovative methods for eco friendly agricultural practices with reduced environmental footprints (Tilman et al., 2011).

In Iran, fertilizer consumption has risen substantially due to national self-sufficiency policies and progressive land degradation (Maghrebi et al., 2020; Naghavi et al., 2022). Official statistics from 2019 indicate usage of 2.15 million metric tons of fertilizers and 270,000 tons of pesticides nationwide. Climate change impacts, particularly temperature increases and altered rainfall patterns, have further exacerbated pesticide demands (Naghavi et al., 2022). These trends have prompted critical reassessment of conventional farming's heavy reliance on chemical inputs (Taheri-Rad et al., 2017).

Developing indicators to measure the impact of agricultural activities on natural resources and environment is crucial for policymakers (Robaina-Alves et al., 2015). Production eco-efficiency refers to the capacity of economic systems to manufacture products and deliver services while minimizing negative consequences for ecosystems. In recent years, this metric has evolved into a key concern for policymakers and economic stakeholders, with both private enterprises and governmental institutions now systematically incorporating it into their project planning and implementation processes (Emrouznejad et al., 2023). Eco-efficiency studies provide a systematic approach to detect key variables affecting production efficiency and sustainability outcomes, facilitating integrated decision-making across policy and operational levels (Angulo-Meza et al., 2019). This concept is particularly important in farming, where the complex interactions among various production factors makes decisions much more complicated than in other industries (Rodríguez-Fernández et al., 2025).

Eco-efficiency -a key metric- measures the ratio of economic output to environmental input. In agriculture, it estimates the maximum possible output with minimal resources use and pollution (Deng & Gibson, 2019). Despite limitations, this approach is favored for its cost-effectiveness in reducing environmental pressure and simpler policy implementation compared to restrictive measures (Ekins, 2005). However, traditional theory suggests that improving eco-efficiency may raise cost and reduce profit for businesses.

The Material Balance Principle (MBP), rooted in thermodynamics' first law, asserts that matter cannot be created or destroyed. This conservation law maintains the environmental inputs and outputs must balance (Field & Field, 2017; Field & Olewiler, 2005). The core principle of the material balance condition states that "what goes in must come out" (Arabi et al., 2017). Emrouznejad et al., (2023) pioneered its application in economics. Essentially, all mater entering an ecosystem must eventually leave it. When applied to biophysical-economic efficiency analysis, the MBP allows for examination of both desirable and undesirable inputs and outputs. A key methodology for evaluating environmental efficiency is the combined application of Data Envelopment Analysis (DEA) and MBP (DEA-MBP).

Numerous studies have conducted to evaluate the eco-efficiency in various sectors, particularly in agriculture. Coelli et al. (2007) measured pig farms' eco-efficiency using an input-oriented meta frontier approach and found that improved efficiency leads to notable reductions in nutrient pollution. Carberry et al. (2013) demonstrated how eco-efficient agriculture is crucial for global food security while optimizing resource use. Comparing over 3,000 farm surveys across China, Zimbabwe, and Australia revealed that Australian operated near eco-efficiency frontiers with minimal nitrogen losses, Chinese farmers can reduce inputs without yield penalties, while Zimbabwean systems require both improved efficiency and increased inputs with institutional support. In China, Pang et al. (2016) combined DEA with

Total Factor Productivity analysis to demonstrate that only four provinces achieved optimal agricultural efficiency, while Molaei et al. (2017) estimated the eco-efficiency of rice farmers in Babolsar County at 77%, revealing a 23% gap compared to their technical efficiency. Dashti et al. (2020) assessed economic and eco-efficiency using DEA and the Toda-Yamamoto test. Results showed 71% Constant Return to Scale (CRS) and 92% Variable Return to Scale (VRS) economic efficiency, alongside 88% eco-efficiency. Mohammadi et al. (2022) by integrating environmental Life Cycle Assessment (LCA) and DEA reveals significant eco-efficiency improvement opportunities (10-16% across multiple impact categories) in Northern Iran's wheat sector when modeling optimal resource allocation. This dual-method approach offers a replicable model for agricultural sustainability assessments globally. Cecchini et al. (2023) evaluated the eco-efficiency of 148 extensive beef cattle farms in Central Italy using a two-stage approach include input-oriented DEA with slack variables to measure eco-inefficiency and input reduction potential, and truncated regression to identify influencing factors. Wang et al. (2024) estimated agricultural eco-efficiency in China's Yangtze River Economic Belt (2007–2021), revealing regional disparities and key drivers (planting structure, mechanization, urbanization) for sustainable development. Rodríguez-Fernández et al. (2025) evaluated the eco-efficiency of Spain's regional agricultural systems (2004-2022) using Slack-Based Models and DEA (SBM-DEA) methodology. Results reveal national eco-efficiency scores ranging 0.644-0.837 (mean=0.772), with 47% of regions exceeding average performance.

Rice (*Oryza sativa* L.) ranks as the world's second most important cereal crop after wheat (*Triticum aestivum* L.), serving as a staple food for more than half of the global population. Asia dominates both production and consumption of this vital grain (Mohidem et al., 2022). In Iran, cereal crops constitute the most extensively cultivated agricultural products, representing 71.2% of the country's total cultivated area according to 2020 data from the Ministry of Agriculture-Jahad. Wheat occupies the largest share at approximately 69% of this cultivated area, while rice accounts for about 14% of grain consumption nationwide (Javadi et al., 2023). Iran's rice cultivation covers an estimated 529,000 hectares, yielding around 2.3 million metric tons annually. However, to satisfy domestic demand, the country must supplement this with imports of 1.7 million metric tons each year (Kouchaki-Penchah et al., 2023).

The Gotvand irrigation and drainage network is located in southwestern Iran, within Khuzestan province. Agriculture is vital to the local economy, supporting around 70% of the population, with rice being a key crop. However, the area has struggled with droughts and water shortages, highlighting the need for better land assessment and efficient farming methods. Enhancing rice production is essential to boost food security, create rural jobs, raise incomes, and ensure long-term economic viability for farmers. Achieving these objectives would align with broader sustainable development goals for the region.

So far, no study in Iran has assessed eco-efficiency using the MBP. This study aims to address this gap by evaluating the eco-efficiency of rice farmers through the DEA-MBP model. Furthermore, it examines variations in optimal input usage when accounting for environmental pressures compared to scenarios that disregard them.

The primary objective of this study is to estimate the technical and eco-efficiency of rice farmers in the Gotvand Irrigation and Drainage Network. In addition, the study will calculate the percentage changes in farmers' input usage required to achieve the computed efficiency levels. Accordingly, the present study makes two significant contributions to the extant literature. Firstly, it is a pioneering application of the DEA-MBP framework in the domain of agricultural research, with a particular focus on rice farming. Secondly, it proposes an innovative method for quantifying environmental pollution, thereby enhancing the analysis of trade-offs between ecological and economic performance. Contrary to the approach of previous studies, which predominantly measured undesirable outputs in conjunction with desirable ones, this research employs an alternative methodology. It incorporates undesirable inputs, such as fertilizers and pesticides, along with desirable inputs, including water and labor, in eco-efficiency assessments.

Materials and Methods

This study employs the DEA-MBP framework (Arabi et al., 2017) to evaluate farm-level eco-efficiency in rice production, integrating MBP with environmental pressure metrics. Figure 1 visualizes the rice eco-efficiency assessment framework, with further methodological details elaborated in later sections.

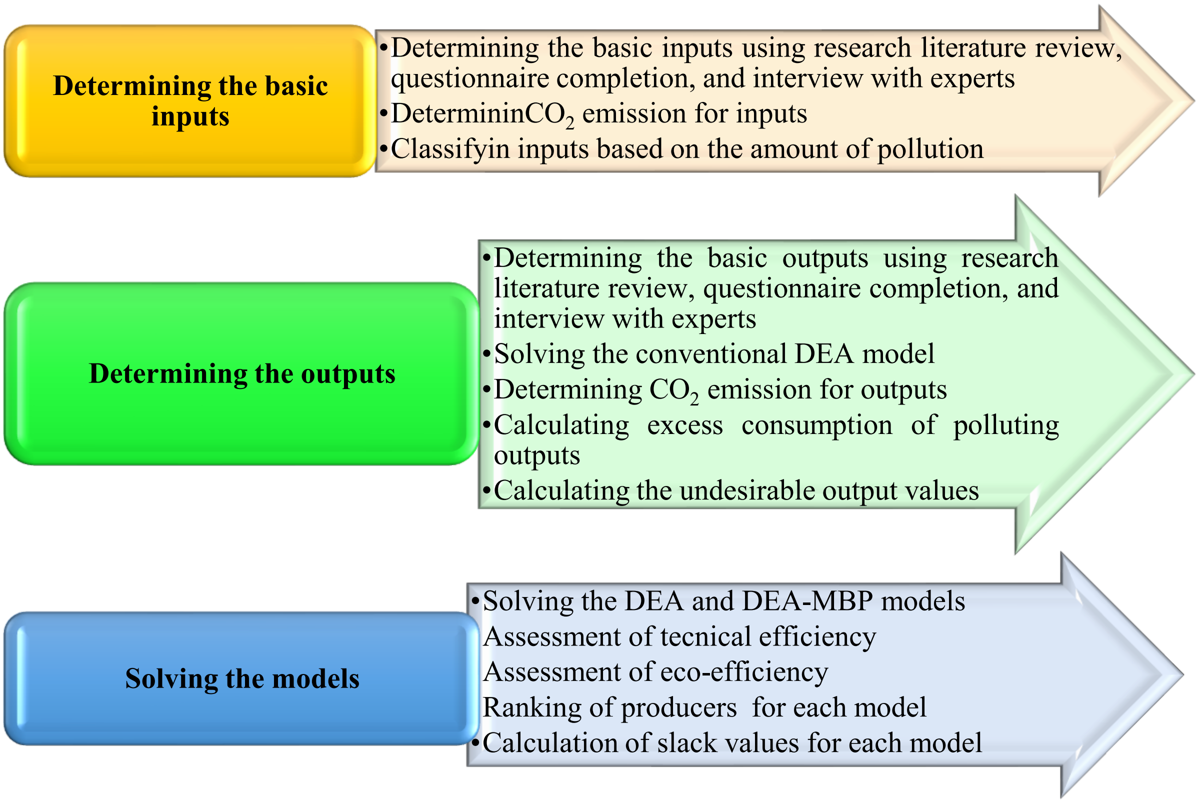

Figure 1. Conceptual framework for determining technical and co-efficiency of rice producers.

Originally, Farrel (1959) introduced the theoretical framework for measuring efficiency. Later, DEA—a linear programming technique for assessing the efficiency of Decision-Making Units (DMUs) —was developed by Charnes, Cooper, and Rhodes (CCR, 1978), who derived generalized mathematical equations under CRS assumptions. This approach uses the production frontier of DMUs as a reference point for efficiency measurement, calculating efficiency scores through input-to-output ratios. Efficiency analysis can be divided into input-oriented approaches (minimizing inputs while holding outputs constant) and output-oriented approaches (maximizing outputs given fixed inputs). Banker, Charnes, and Cooper (1984) subsequently extended the CCR model by introducing a convexity constraint on linear combinations, replacing the CRS assumption with VRS, and decomposing technical efficiency into pure technical efficiency and scale efficiency components.

DEA has emerged as a principal tool for eco-efficiency assessment over the past three decades, with ongoing model refinements being crucial for achieving net-zero emissions targets (Emrouznejad, 2023). Pioneering work by Schaltegger and Sturm first conceptualized environmental efficiency as the ratio of economic growth to environmental impacts during a specified timeframe (Cui & Wang, 2023). Subsequent research has classified environmental efficiency evaluations into two paradigms: those treating environmental pressures (e.g., pollution emissions, waste generation) as undesirable outputs and those modeling them as inputs in efficiency frameworks (Tyteca, 1997).

Among other approaches developed for measuring eco-efficiency that have attracted researchers' attention is the MBP. It relates to the interplay between ecological systems, encompassing economic and social aspects, and involving production and consumption. These systems are influenced by the flow of materials and energy, such as extraction, utilization, recycling, and waste disposal, in the natural environment. The Law of Conservation of Matter/Energy asserts that the inflow and outflow in the environment should be balanced. Nevertheless, Lauwers (2009) argues that MBP has been largely overlooked in most studies in this field. The Directional Distance Function (DDF) model, introduced by Charnes et al., (1997), is a commonly used model that incorporates undesirable outputs into efficiency measurement models. Despite the popularity of this and other models used to estimate eco-efficiency, Lauwers (2009) have raised significant criticisms regarding the compatibility of these models with MBP. The DEA-MBP model, introduced by Coelli et al., (2007), has both advantages and limitations when implemented in various industries. By considering N DMUs, this model can be expressed through equations (9) to (11).

$$\mathrm{Min}\ \lambda X_o^e a_o^e \tag{1}$$

$$\mathrm{s.t.:} \sum_{n=1}^{N} X_{ni} \leq X_{oi}^e \quad i = 1, 2, \ldots, I \tag{2}$$

$$\sum_{n=1}^{N} \lambda_n y_{nj} \leq y_{oj} \quad j = 1,2, \ldots, J \qquad \lambda_n \geq 0 \quad n = 1, 2, \ldots, N \tag{3}$$

Where o denotes the DMU being analyzed, X_{eoi} represents input variables for optimizing pollution reduction, and a_o^e reflects nutrient content. Inputs (X_{ni}) and outputs (y_{nj}) of n_{th} unit are weighted by constants λ_n. However, the model has limitations: it ignores actual pollution levels (often hard to quantify in agriculture) and oversimplifies pollution production/disposal processes. While it identifies input-efficient pollution-minimizing combinations, its accuracy declines with numerous inputs, reducing result reliability.

To accurately assess eco-efficiency, a robust model compatible with MBP requirements is essential – one that maintains its validity even when MBP constraints are applied. While multiple MBP-compliant models exist, selection should be context-dependent. The Färe and Grosskopf (2010) framework is particularly recommended for eco-efficiency calculations.

$$D_0(x,y) = \mathrm{Max} f(z) = \sum_{i=1}^{I} a_i + \sum_{j=1}^{J} b_j \tag{4}$$

$$\mathrm{S.t.:} \sum_{n=1}^{N} \lambda_n X_{ni} = X_{i0} - a_i.1 \qquad i = 1, 2, \dots, I \tag{5}$$

$$\sum_{n=1}^{N} \lambda_n y_{jn} = y_{j0} + b_j.1 \qquad j = 1, 2, \dots, J \tag{6}$$

$$\lambda_n \geq 0, \quad b_j \geq 0, \ a_j \geq 0 \qquad n = 1, 2, \dots, N$$

The model under consideration employs non-radial slack-based models (SBM) that evaluate efficiency through simultaneous output maximization and input minimization approaches. The selection of this model is predicated on its distinguishing characteristic from traditional radial DEA models in that it separately measures inefficiency slacks in inputs and outputs without requiring proportional adjustments. This methodological approach offers enhanced flexibility by permitting differential improvement rates for each variable. Additionally, SBM possesses the capacity to incorporate undesirable outputs, such as pollution, which are frequently ignored by conventional models. A comparison of SBM with radial methods reveals that the former provides more precise and practical results in real-world, complex efficiency analyses. Based on the aforementioned model, Arabi et al. (2017) proposed their DEA-MBP alternative model to calculate the eco-efficiency under the CRS technology. CRS are frequently employed in the DEA model as opposed to VRS for a number of salient reasons. Firstly, CRS operates under the assumption of perfect scalability, rendering it more appropriate for theoretical benchmarks or long-term analyses, where scale effects are deemed irrelevant. Secondly, it quantifies technical efficiency without the necessity of isolating scale inefficiencies, a process which is beneficial when evaluating overall productivity as opposed to operational scale impacts. Thirdly, CRS is consistent with classical economic models that assume optimal long-term production scales. Fourthly, in instances where firms operate within similar sizes or where data is limited, CRS is able to circumvent unnecessary complexity. Finally, in instances where the study focuses on ranking units rather than scale effects, CRS provides a more straightforward comparison.The model incorporates equations (7) to (14) in which inputs are classified into two categories: high-pollutant inputs and low pollutant inputs.

$$D_0(x,y) = Max \sum_{l=1}^{L} a_l + \sum_{h=1}^{H} a_h + \sum_{m=1}^{M} a_m + \sum_{j=1}^{J} b_j + \sum_{k=1}^{K} \gamma_k \tag{7}$$

$$\text{s.t.:} \sum_{n=1}^{N} \lambda_n X_{ln} \leq X_{lo} + a_l.01 \qquad l = 1,2,\dots,L \tag{8}$$

$$\sum_{n=1}^{N} \lambda_n X_{hn} \leq X_{ho} + a_h.01 \qquad h = 1,2,\dots,H \tag{9}$$

$$\sum_{n=1}^{N} \lambda_{nm} X_{nm} \leq X_{mo} + a_m.01 \qquad m = 1,2,\dots,M \tag{10}$$

$$\sum_{n=1}^{N} \lambda_n y_{jn} \geq y_{jo} + b_j.01 \qquad j = 1,2,\dots,J \tag{11}$$

$$\sum_{n=1}^{N} \lambda_n z_{kn} \leq z_{ko} - \gamma_k.01 \qquad k = 1,2,\dots,K \tag{12}$$

$$\sum_{l=1}^{L} a_l - \sum_{h=1}^{H} a_h = 0 \tag{13}$$

$$\gamma_k - \sum_{j=1}^{J} b_{jk} B_j = \sum_{h=1}^{H} a_{hk}\, a_h - \sum_{l=1}^{N} a_{lk}\, a_l \tag{14}$$

$$\lambda_n \geq 0,\ a_l \geq 0,\ a_h \geq 0, \gamma_k \geq 0,\ a_m \geq 0 \quad B_j \geq 0,\ n = 1,2,\dots,N$$

This model classifies inputs as: X_l (low-pollution), X_h (high-pollution), and X_m (non-polluting, e.g., capital). Outputs are categorized as desirable (y) and undesirable (z). Key parameters include: α_l and α_h (reduction/expansion rates for low/high-pollution inputs), α_m (non-polluting input reduction rate), and γ/β (undesirable/desirable output reduction rates). Notably, $\alpha_h > \alpha_l$ ensures proper pollution-level differentiation.

The model incorporates the constraint H + L + M = I (total inputs) for mathematical consistency. Constraints 1 & 5 originate from conventional SBM models Färe and Grosskopf (2010), with constraints 1-2 reflecting preferences for low-pollution inputs. Constraints 3-5 mirror standard SBM applications for non-polluting inputs and outputs. The sixth constraint ($\alpha_h = \alpha_l = 0$ for efficient DMUs) and seventh constraint maintain thermodynamic consistency in the Production Possibility Set (PPS) - without which no DMU would satisfy the first law of thermodynamics.

This study presents an analytical framework assessing agricultural systems using dual outputs: crop yield and CO_2eq emissions. The model integrates various inputs - land, labor, fertilizers (N, P, K), pesticides, manure, seeds, machinery, fuel, and water. Building on (Khan et al., 2018), it highlights environmental consequences: nitrogen degrades soil quality while phosphate pollutes water systems, with GHG emissions converted to CO_2eq following Soni et al. (2013). Inputs are classified by emission intensity: high-polluting (>1 kg CO_2eq/unit: nitrogen, fungicides, machinery, diesel), low-polluting (<1 kg CO_2eq/unit: potassium, phosphate, manure, labor, electricity), and neutral (seeds, water). By simultaneously evaluating crop production and emissions, the model enables holistic sustainability analysis of farming practices.

Primary data were collected through farmer questionnaires during 2022. The questionnaire included questions covering various input quantities used by rice farmers as well as their production output quantities. Using Kotrlik and Higgins (2001) adjusted Cochran formula with a total population of approximately 420 rice farmers, we determined a representative sample size of 153 participants. The sampling procedure employed simple random selection to ensure unbiased representation for subsequent analysis.[2]

Results and Discussion

Table 1 presents descriptive statistics of input and output variables, revealing significant heterogeneity in application pattern. potassium fertilizers demonstrate the greatest variability (CV=4.94), followed by phosphate (CV=2.44), nitrogen (CV=0.92) and animal manure (CV=0.56). This dispersion likely reflects differential substitution patterns between chemical and organic inputs across farmers. Notably, the carbon dioxide equivalent, as an indicator of environmental pollution potential, indicating the substantial variations in the use of inputs among DMUs. Hence, strategic input optimization reduces both environmental impact and agricultural costs.

The eco-efficiency analysis presented in Table 2 reveals critical insights into rice production systems. The results demonstrate a mean technical efficiency of 87% among producers, which decreases to 73% when considering environmental pollution, indicating a 14% overestimation of efficiency in conventional assessments. This discrepancy highlights the significant impact of environmental factors on production efficiency. The distribution of efficiency scores shows notable variation across farmers. While 40.5% (62 DMUs) achieved full technical efficiency, only 33.3% (51 DMUs) attained complete eco-efficiency. The range of efficiency scores was substantially wider for eco-efficiency (2-100%) compared to technical efficiency (40-100%), with corresponding coefficients of variation of 0.38 and 0.08, respectively. The analysis further

2- The data file and GAMS code are available indicates that 54% of units exceeded 90% technical efficiency, compared to just 42% achieving similar levels of eco-efficiency. These findings consistent with Ramli and Munisamy (2015) that emphasize two key implications for agricultural policy: conventional efficiency assesment systematically overestimate true performance by neglecting environmental costs, and significant potential exists for improving both economic and environmental outcomes through targeted interventions.

Table 1. Statistical description of inputs and outputs used in rice cultivation (hectares).

Input/output	Variable type	Variable		Mean	SD[3]	Min.	Max.	CV[4]
Inputs	Low Pollution Input	Potassium	Kg	1.6	7.9	0.00	65	4.94
		Phosphate	Kg	11.1	27.1	0.00	100	2.44
		Animal Manure	Tone	31.7	17.8	10	90	0.56
		Labor Force	Hour	981.6	421	227	2000	0.43
		Electricity	Kwh	21735	4771	8384	39300	0.22
	High Pollution Input	Nitrogen	kg	51.3	47	0.00	350	0.92
		Fungicide	Kg	1.6	0.9	0.00	3	0.56
		Machinery	Hour	41.7	16.1	8.66	89.06	0.39
		Fuel (Diesel)	Liter	473.5	227	94	1535	0.48
	Independent Input	Seeds	Kg	281.5	51.1	185	397	0.18
		Water	Cubic meter	4898	1118	3000	6500	0.23
Outputs	Desirable Output	Crop	kg	6006	1489	4000	9000	0.25
	Undesirabe Output	Carbon Dioxide Equivalents	Kg	7289	4455.5	0	15379	0.61

Table 2. Calculated technical and eco-efficiency of rice farmers.

Efficiency	Mean	Min	Max	C.V.	Number (percentage) of DMUs in efficiency categories				
					<0.6	0.6-0.8	0.8-0.9	0.9-1	1
Technical	0.87	0.4	1	0.08	4 (2.6%)	48 (31.4%)	18 (11.8%)	21 (13.7%)	62 (40.5%)
Eco-	0.73	0.02	1	0.384	53 (36%)	18 (11.8%)	15 (9.8%)	14 (9.2%)	51 (33.3%)

Table (3) presents a comparative analysis of actual versus optimal input and output values based on slack/surplus measures derived from the models. The findings reveal that in the eco-efficiency model, inefficient DMUs exhibit a positive percentage change in the optimal use of low-pollution inputs compared to actual usage, suggesting that these inputs should be increased. Conversely, High-pollution inputs show a negative percentage change, indicating a need for reduction in inefficient DMUs. The analysis highlights significant adjustments needed to enhance eco-efficiency in agricultural practices. The most notable change concerns nitrogen fertilizer, where DMUs should reduce application rates by

3- Standared Deviation
4- Coefficient of Variation

approximately 41% to achieve optimal eco-efficiency. This substantial reduction reflects nitrogen's significant environmental impact. Conversely, among Low-pollution inputs, animal manure demonstrates the greatest potential for increased utilization (612%). This results indicate that substituting nitrogen fertilizer with animal manure could significantly reduce environmental pollution. The model also indicates that current phosphate and potassium application rates are below optimal levels, requiring increased usage by 2.7% and 6.25% respectivelly. While eco-efficiency demands a 26.3% reduction in water use, tecnichal efficiency achieves comparable gains with just a 6.8% decrease.

Table 3. The average optimal use of inputs and the percentage changes in their use relative to the actual use.

Input/ output	Variable type	Variable		Technical Efficiency		**Eco-efficiency**	
			Mean	Mean	Change%	Mean	Change%
Inputs	Low Pollution Input	Potassium	1.6	1.4	-12.5	1.7	6.25
		Phosphate	11.1	6.5	-41.4	11.4	2.7
		Animal Manure	31.7	27.5	-13.2	225.7	612
		Labor Force	981.6	881.1	-10.2	1005	2.4
		Electricity	21735	20156	-7.3	21735	0.00
	High Pollution Input	Nitrogen	51.3	41.8	-18.5	30.2	-41.1
		Fungicide	1.6	1.4	-12.5	1.2	-25
		Machinery	41.7	37.2	-10.8	27.7	-33.6
		Fuel (Diesel)	473.5	420.1	-11.3	291	-38.5
	Independent Input	Seeds	281.5	260.3	-7.5	230	-18.3
		Water	4898	4565	-6.8	3611	-26.3
Outputs	Desirable Output	Crop	6006	6006	0.00	6027	0.35
	Undesirable Output	Carbon Dioxide Equivalents	7289	-	-	6722	-7.8

Results indicate that current rice production levels are already optimal, as both technical and eco-efficiency models show minimal required changes in output (0.00% and 0.35%). However, achieving eco-efficiency requires an average of 8% reduction in carbon dioxide emissions along with significant input adjustments.

The analysis reveals distinct input optimization requirements for enhancing both technical and eco-efficiency in rice production. For technical efficiency gains, the study highlights three critical inputs needing significant reduction: phosphate fertilizers (-41.4%), nitrogen (-18.5%), and animal manure (-13.2%). More modest reductions are suggested for water (-6.8%), seeds (-7.3%), and electricity (-7.5%). Regarding eco-efficiency improvements, the study identifies different optimization patterns: substantial reduction are needed for nitrogen fertilizer (-41.1%), fuel (-38.5%), and machinery operation hours (-33.6%), while increases are recommended for animal manure (612%), potassium fertilizer (6.25%), and phosphate fertilizer (2.7%). These findings collectively identify the root causes of eco-inefficiency in the

production system: inadequate application of organic manure combined with excessive use of nitrogen-based fertilizers, diesel fuel consumption, and machinery utilization. Notably, the research found electricity consumption has minimal influence on overall system efficiency.
These findings demonstrate that while output levels are optimized, substantial efficiency gains can be achieved through strategic input reallocation- particularly by reducing chemical fertilizer use and increasing organic alternatives- without compromising productivity. The results emphasize the importance of input restructuring for achieving both technical and environmental efficiency in rice production systems. The results also revealed a 14% gap between eco-efficiency (87%) and technical efficiency (73%), indicating that conventional efficiency measurements overestimate actual performance by 14% when environmental factors are excluded.
eco-efficiency assessment requires a dual focus: optimizing input-output ratios while strategically managing pollution levels through input substitution. True efficiency isn't achieved merely by maximizing output with minimal inputs, as this approach overlooks the environmental degradation that ultimately reduces overall efficiency. Environmentally efficient DMUs distinguish themselves by both optimizing production inputs and systematically replacing high-pollution inputs with cleaner alternatives.
Supporting evidence comes from Huang et al. (2022), whose research on Chinese rice cultivation demonstrated that cutting fertilizer and pesticide use by half - while switching to eco-friendly alternatives - boosted bio-economic efficiency by 6%. This finding underscores the tangible benefits of pollution-conscious input management.
This study shows that despite adopting optimal technical practices, rice farmers fail to achieve satisfactory environmental sustainability. This issue not only raises production costs due to chemical fertilizer use but also degrades soil and water resources. To address these challenges, reducing chemical fertilizer use and optimizing their application is essential for improving eco-efficiency in the region. This measure is critical for public health and preventing excessive chemical buildup in soil. Additionally, farmers should decrease reliance on phosphorus, potassium, and nitrogen inputs while increasing organic manure usage to enhance both environmental and economic efficiency. These findings align with Biswas et al. (2021), who demonstrated the benefits of balanced chemical and organic fertilizer use on production, as well as the negative effects of excessive pesticide application.
The optimal production level, when considering environmental impacts, closely aligns with traditional technical efficiency values. However, inefficient units must reduce CO_2 emissions

by approximately 8% to reach optimal efficiency. Gancone et al. (2017) assessed eco-efficiency in Latvia's agriculture, showing that production can stabilize at a certain level while enhancing both technical and environmental efficiency. Their findings also indicate that greenhouse gas emissions can grow at a slower rate than under current conditions. Given the similarities in economic and eco-efficiency objectives between these studies, such results are consistent with the present research.

The results reveal that optimal input usage in rice production is lower than actual consumption, indicating inefficiency due to overuse. Efficient farms already match optimal input levels, requiring no adjustments. However, inefficient farms should shift from labor, manure, phosphates, and potassium to more polluting inputs like nitrogen, machinery, diesel, and fungicides to maximize efficiency. Given the region's high unemployment (Ghojagh et al., 2023), replacing labor with machinery is a viable option. Additionally, Mardani Najafabadi and Ashktorab (2023) suggest that modifying cropping patterns can reduce fertilizer and pesticide use by 6–8% without cutting profits.

The results also indicate that the Spearman rank correlation between the two efficiency rankings was 0.697, statistically significant at the 5% level. Since eco-efficiency accounts for environmental pressures, it leads to a greater reduction in polluting inputs than expected. By integrating both economic and environmental factors, this approach provides a more suitable framework for policymakers, especially in developing economies with limited resources. Simultaneously considering these aspects significantly influences rice producers' efficiency measurements. Similarly, Mardani Najafabadi et al. (2023) observed that saffron growers had higher technical efficiency than eco-efficiency, with the difference being statistically significant at the 1% level.

Conclusions

This study evaluated eco-efficiency through analysis of three input categories - high-pollution, low-pollution, and pollution-neutral inputs - while maintaining MBP. The study demonstrates that conventional efficiency measurements overestimate producer performance by about 14% when they fail to account for environmental pollution and material balance. This discrepancy highlights the necessity of incorporating negative environmental outputs in agricultural efficiency assessments.

Eco-efficient DMUs optimize production not only by minimizing inputs but also by substituting high-pollution inputs with cleaner alternatives. Chemical fertilizers emerge as particularly problematic, showing the widest gap from optimal usage levels among all environmentally damaging inputs. To address these challenges, government intervention should focus on two key areas: comprehensive farmer education programs for optimal input utilization and development of supportive policy frameworks to encourage organic production methods. Additionally, upgrading obsolete farming equipment in rice cultivation and implementing long-term machinery modernization programs would significantly improve operational efficiency. A key limitation of the DEA-MBP model is - it doesn't incorporate uncertainty factors. Future studies could substantially enhance the model's reliability and practical application by integrating uncertainty analysis methods such as fuzzy set theory, stochastic programming, or robust optimization techniques.

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