SCIENTIA AGROPECUARIA

Scientia Agropecuaria

Web page: http://revistas.unitru.edu.pe/index.php/scientiaagrop

Facultad de Ciencias Agropecuarias

Universidad Nacional de Trujillo

RESEARCH ARTICLE

Analysis of rice (*Oryza sativa* l.) bioeconomy: Data Envelopment Analysis method highlights the need for cooperation to improve productivity and sustainability

Marcelo David Castro-Alvarez[1]; Carlos Alberto Zuniga-Gonzalez[2]*; Waldemar Mercado[1]; Robert Santiago Andrade[3]

[1] Universidad Nacional Agraria La Molina, Doctorado en Economía de los Recursos Naturales y el Desarrollo Sustentable. Perú.

[2] Universidad Nacional Autónoma de Nicaragua, León. Research Center of Knowledge Area of Agrarian and Veterinary Sciences. Unit Research in Bioeconomics and Climate Change. Nicaragua.

[3] Centro Internacional de Agricultura Tropical (CIAT). Colombia.

* Corresponding author: czuniga@ct.unanleon.edu.ni (C. A. Zuniga-Gonzalez).

Received: 12 December 2025. Accepted: 13 May 2026. Published: 26 May 2026.

Abstract

Rice (*Oryza sativa L.*) production is a cornerstone of Ecuador's economy. This research evaluates the efficiency of 609 production units during 2019, addressing the need for statistical robustness in agricultural efficiency estimators. Using a national representative survey, Data Envelopment Analysis (DEA) was applied under Variable Returns Scale (VRS) and Constant Returns to Scale (CRS). To account for sampling noise, the Simar and Wilson (2007) bootstrap procedure (2,000 replications) was implemented to provide bias-corrected scores and 95% confidence intervals. The bootstrap-corrected analysis revealed a mean technical efficiency of 0.632 (95% CI: 0.596 – 0.668), suggesting a potential 36.8% input reduction without output loss. Significant provincial heterogeneity was observed: Manabí led in technical efficiency (0.743), while El Oro achieved the highest cost efficiency (0.435) due to superior allocative performance. Conversely, Loja showed high technical proficiency (0.645) but the lowest allocative efficiency (0.197). Findings underscore that "one-size-fits-all" policies are inadequate; instead, province-specific interventions, focusing on scale optimization and financial training, are required to enhance the sustainability of Ecuador's rice bioeconomy.

Keywords: sustainability; environment; cost efficiency; allocative efficiency; technical efficiency.

DOI: https://doi.org/10.17268/sci.agropecu.2026.040

Cite this article:
Castro-Alvarez, M. D., Zuniga-Gonzalez, C. A., Mercado, W., & Andrade, R. S. (2026). Analysis of rice (*Oryza sativa* l.) bioeconomy: Data Envelopment Analysis method highlights the need for cooperation to improve productivity and sustainability. *Scientia Agropecuaria*, *17*(3), 583-592.

1. Introduction

Rice is one of the most important staple crops for food security in Ecuador, both for its contribution to the basic diet of the population and its economic significance in various regions of the country (Zúniga-González et al., 2024b; Christopher et al., 2020; Seck et al., 2012). However, rice producers face several challenges that impact their productivity and competitiveness (Castro-Alvarez et al., 2025; Zúniga-González, 2024a; Antriyandarti, 2015). These challenges include inefficiencies in resource use, limited access to appropriate technology, and the threats posed by climate change, which disrupt optimal growing conditions (Pérez et al., 2026; Gregory et al., 2005). Despite rice being a strategic crop, productivity in Ecuador varies significantly across regions and producers, raising concerns about the sustainability and future of rice production (Portalanza et al., 2022).

In recent years, efficiency in agricultural production has become a critical issue for improving profitability and competitiveness among farmers. Economic efficiency in rice production refers to optimizing the use of available resources (such as land, labor, inputs, and water) to achieve the highest possible output at the lowest cost (Zúniga-González, 2024a; Medina-Litardo et al., 2022). Meanwhile, technical efficiency concerns the ability of producers to maximize rice yields with the same set of inputs. On the other hand, allocative efficiency refers to the capacity of farmers to allocate resources in proportion to their relative prices, ensuring that resources are used in the most economically optimal way (Cai et al., 2026; jasim & Zanzal, 2022).

Climate variability and limited access to advanced farming technologies are factors contributing to inefficiencies in rice production (Sarker et al., 2026). In many regions of Ecuador, farmers lack the knowledge or tools needed to adapt their agricultural practices to changing climatic conditions or to implement technologies that could boost productivity (Portalanza et al., 2024). This results in inefficient resource use and often suboptimal yields. Additionally, limited market access or a lack of information about best management practices further exacerbates the situation.

To address these issues, this study employs Data Envelopment Analysis (DEA), a technique that allows for the evaluation of the efficiency of production units (in this case, rice producers) by measuring the relationship between their inputs (such as labor, land, seeds, and fertilizers) and outputs (such as rice yield and revenue) (Zúniga-González, 2024a; Castro et al., 2023). Through DEA, it can assess three key types of efficiency: technical efficiency, economic efficiency, and allocative efficiency (Abdul Wadud, 2003). The analysis will focus on identifying the efficiency levels among rice producers in Loja province, one of the most productive regions in Ecuador, and will provide recommendations for improving resource-use efficiency (Zuniga-Gonzalez et al., 2024a).

For policymakers, this study offers a solid data foundation to design public policies that support rice producers in adopting more efficient technologies, improving crop management practices, and mitigating the effects of climate change. The findings will help identify efficiency gaps within the sector and provide an evidence-based approach for the implementation of agricultural extension programs and technology adoption strategies (Marc Jim et al., 2012).

More broadly, this analysis will contribute to improving Ecuador's rice bioeconomy by enhancing the competitiveness of the agricultural sector, promoting more sustainable and efficient farming practices, and ensuring food security in the country (Torres Álava et al., 2022). In a context of climate change and rising food demand, improving rice production efficiency is critical to ensure that Ecuador can meet its population's needs and remain a key player in global rice production (Zuniga-Gonzalez et al., 2024b; Zuniga-Gonzalez, 2023; Ortega-Pacheco et al., 2021).

This study aims to provide valuable insights for rice producers in Ecuador, helping them understand how they can improve their technical efficiency to achieve higher yields with the same resources. By analyzing economic efficiency, the study seeks to identify ways in which farmers can reduce production costs and increase profitability by optimizing input use and agricultural practices (Tey & Brindal, 2014; de Wit, 1992). Moreover, by addressing allocative efficiency, this research will enable farmers to make more informed decisions about resource allocation based on relative costs and benefits, thus contributing to the sustainability of their farming operations (Mivumbi & Yuan, 2023).

2. Methodology

2.1. Data collection

Data for this study were collected from 612 rice-producing farms across Ecuador during the 2019-2020 production cycle. The final sample consisted of 609 rice production units, after removing 2 outliers during the data cleaning process. The provinces studied included Guayas (located in the southwest of Ecuador), Los Rios (in the center-west), Loja (in the south), Manabi (on the central coast), and El Oro (in the south of Ecuador) (Castro Alvarez et al., 2025).

The variables considered for analysis include Area (Area x Ha), Output from Rice Sale, Wages for Fertilization (Input 1), Price for Fertilization (Input 1), Wages for Weed Control (Input 2), Price for Weed Control (Input 2), Wages for Pest and Disease Control (Input 3), Price for Pest and Disease Control (Input 3), Wages for Planting (Input 4), and Price for Planting (Input 4).

These variables, along with other characteristics like Planting Method, were included based on their relevance to understanding the economic efficiency of rice production, covering aspects such as technical efficiency, allocative efficiency, and cost efficiency.

2.2. Descriptive statistics and data distribution

Table 1 summarizes the descriptive statistics for the data, including the key variables related to agricultural production and input costs for 609 observations. Area x Ha ranges from 0.50 to 120 hectares, with a median of 3 hectares and a mean of 6.05 hectares, suggesting a relatively small average plot size with some larger outliers. Output rice sales show a wide variation, from 0 to 529,018, with a median of 6,541 and a mean of 13,444. This indicates significant variability in rice sales across the sample, with some higher-value sales skewing the mean. Input 1 wage for fertilization ranges from 0 to 360, with a mean of 13.25, and most values fall between 3 and 14, indicating that most wages for fertilization are on the lower end. Price for Input 1 has a narrow range, from 5 to 30, with a mean of

$11.57, suggesting a relatively stable cost for this input. Input 2 wage for weed control ranges from 1 to 120, with a mean of 5.80, indicating that wages for weed control also vary, but most fall on the lower side. Price for Input 2 ranges from 5 to 20, with a mean of 11.91, showing a similar distribution to Input 1 price. Input 3 wage for pest and disease control ranges from 0 to 240, with a mean of 12.06. There is a wide range of wages, but most values are concentrated around lower amounts. Price for Input 3 ranges from 10 to 60, with a mean of 12.00, reflecting a consistent price point for this input. Input 4 wage varies dramatically from $0 to 2,400, with a mean of 81.03. This indicates that wages for planting vary significantly, with some extreme values skewing the distribution. Price for Input 4 is relatively stable, ranging from 10 to 60, with a mean of 12.00.

These descriptive statistics reveal significant variability across inputs, both in terms of wages and prices, with some extreme values for certain inputs. This may suggest the presence of outliers or diverse farming practices across the observations (Castro Alvarez et al., 2025).

2.3. Data Envelopment Analysis (DEA) models

In this study, Data Envelopment Analysis (DEA) is used to measure the economic efficiency of rice production across the farms. DEA is a non-parametric method that evaluates the efficiency of decision-making units (DMUs) in terms of their input-output relationships (Figure 1). The efficiency analysis is conducted using Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) models to assess the technical efficiency, allocative efficiency, and cost efficiency of each farm. In the VRS model under Banker, Charnes, and Cooper (BCC) (Banker, Charnes & Cooper, 1984) assumptions, the focus is on minimizing the cost to achieve a given level of output (income or yield), while considering the variable returns to scale. The CRS model under Charnes, Cooper, and Rhodes (CCR) (Charnes, Cooper & Rhodes, 1978) assumes constant returns to scale in the relationship between inputs and outputs (Farrell, 1957).

a. Technical Efficiency (TE): This refers to the ability of a farm to produce the maximum output (yield in tons per hectare) from a given set of inputs (land, water, seed, etc.). It measures how well the farm uses its resources to produce output.
b. Allocative Efficiency (AE): This measures the farm's ability to allocate resources optimally according to their prices, minimizing costs. It assesses whether the farm is using the appropriate mix of inputs in line with input prices to maximize output.
c. Cost Efficiency (CE): This examines whether the farm is achieving the lowest cost for producing a given level of output, considering the prices of inputs.
d. Economy Efficiency (EE): Represents the overall ability to produce at the lowest cost, incorporating both technical and allocative efficiencies (Coelli, 1997; Battese & Coelli, 1992).
e. The DEA models are applied to evaluate the efficiency of 609 rice-producing farms. Specifically, the following variables are used in the analysis:
    - Inputs: Wages for Fertilization (Input 1), Price for Fertilization (Input 1), Wages for Weed Control (Input 2), Price for Weed Control (Input 2), Wages for Pest and Disease Control (Input 3), Price for Pest and Disease Control (Input 3), Wages for Planting (Input 4), and Price for Planting (Input 4).
    - Outputs: Total income by Rice Sale (ti), reflecting the financial performance of the farm.

The input-oriented DEA models will calculate the efficiency of each farm using the following formulas for CRS and VRS models.

Table 1
Descriptive statistics of rice farm data

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	N
Area x Ha	0.5	2	3	6.05	7	120	609
Output $ rice sale	0	3194	6541	13444	13585	529018	609
Input 1 wage for fertilization	0	3	6	13.25	14.75	360	609
Price for Input 1	5	10	10	11.57	12	30	609
Input 2 wage for weed control	1	2	3	5.8	7	120	609
Price for Input 2	5	10	10	11.91	14	20	609
Input 3 wage for pest and disease control	0	4	6	12.06	14	240	609
Price for Input 3	10	10	10	12	14	60	609
Input 4 wage for planting	0	10	30.5	81.03	80	2400	609
Price for Input 4	10	10	10	12	14	60	609

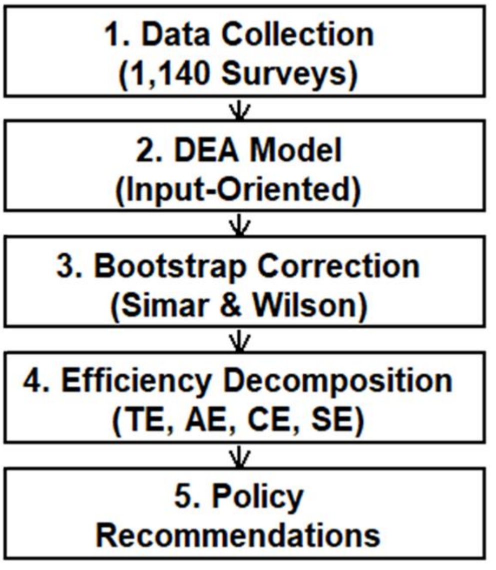

Figure 1. Methodological flowchart.

2.3.1 DEA Models for Cost Minimization (with VRS-BCC, CRS-CCR)

To evaluate the bioeconomic performance of rice production in Ecuador, a Cost Minimization DEA approach was utilized. This model identifies the minimum cost at which a farm can produce a given level of output, given the prices of input. Efficiency scores were calculated under both Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC) assumptions.

1. The BCC Model (Variable Returns to Scale- VRS)

The efficiency scores were calculated using the input-oriented BCC model (Variable Returns to Scale), expressed as: This means that the production relationship between inputs and outputs may not be linear. To account for operational scales where production is not linear, the BCC model (Banker et al., 1984) adds a convexity constraint:

Objective Function (Cost Minimization):

$$Min\ Z_0 = \sum_{i=1}^{m} \omega_{io} * \chi_i^*$$

Subject to

$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}$ (Minimum output constraint)

$\sum_{j=1}^{n} \lambda_j y_{ij} \leq \chi_i^*$ (Maximum input constraint)

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$\lambda j \geq 0$ (Convexity constraint for VRS)

$$(Equation\ 1)$$

Banker, Charnes, and Cooper (BCC) Adjustment for VRS:

Where

ϖ_{i0} represents the price of wage of input i (Wages for Fertilization (Input 1), Price for Fertilization (Input 1), Wages for Weed Control (Input 2), Price for Weed Control (Input 2), Wages for Pest and Disease Control (Input 3), Price for Pest and Disease Control (Input 3), Wages for Planting (Input 4), and Price for Planting (Input 4)). Wages and Prices were treated as separate proxies to capture different dimensions of labor and market intensity.

y_{ro} Represents "Total Income or Output from Rice Sale [ro]".

χ_j^{*0} is the cost-minimizing vector of input quantities calculated by the model. Wages and Prices were included to capture the economic dimension of the bioeconomic cycle.

This additional constraint is specific to the BCC VRS model to ensure the correct assumption of variable returns to scale.

2. The CCR Model (Constant Returns to Scale -CRS)

The CCR model [Charnes et al., 1978] assumes that any change in inputs leads to a proportional change in output.

Objective Function (Cost Minimization)

$$Min\ Z_0 = \sum_{i=1}^{m} \omega_{io} * \chi_i^*$$

Subject to

$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}$

$\sum_{j=1}^{n} \lambda_j y_{ij} \leq \chi_i^*$

$$\lambda j \geq 0 \quad (j = 1, \ldots\ldots\ldots, n)$$

$$Equation\ 2$$

In this model, the sum of weights (λ) is not constrained, assuming constant returns to scale across the production frontier.

2.4. Statistical validation

To address the deterministic nature of DEA and the lack of traditional statistical properties, the Simar & Wilson (2007) double-bootstrap procedure was implemented. This allowed for the estimation of bias-corrected efficiency scores and the construction of 95% confidence intervals through 2,000 iterations. To validate the assumptions underlying the DEA models, the Shapiro-Wilk normality test was performed to check for normality in the data distribution. Given that some data distributions were non-normal, non-parametric tests, including the Kruskal-Wallis test and Wilcoxon Rank-Sum Exact Test, were employed. These tests are robust for non-normal data and are suitable for comparing efficiency scores across different farm groups (Munim, 2020; Aliyu & Bello, 2018; Chegini et al., 2016).

2.5. Spatial analysis

A spatial analysis was conducted to explore the geographical distribution of efficiency scores across the rice-producing regions of Ecuador. This analysis helps identify regional differences in efficiency and provides insights into how factors like climate, land availability, and input usage affect rice production at the regional level (Simar & Wilson, 2007; Simar & Wilson, 1998).

2.6. Software and tools

All data analysis, including DEA modeling, Bootstrap estimation, and statistical validation, was performed using RStudio software RStudio 2024.12.1 Build 563 (Castro Alvarez et al., 2025). This platform provided the necessary tools for implementing the DEA models, performing the statistical tests, and conducting spatial analysis to evaluate the efficiency of rice production across Ecuador (Pereira et al., 2021; Battese & Coelli, 1992).

3. Results and discussion

The analyzed data correspond to an efficiency assessment of rice producers in Ecuador. Three key efficiency indicators were considered in this evaluation:

Technical Efficiency (TE): Measures a producer's ability to maximize output with the available inputs.

Allocative Efficiency (AE): Evaluates whether inputs are used in optimal proportions based on their prices. Cost Efficiency (CE): Combines technical and allocative efficiency to assess overall cost efficiency.

The results reveal a high degree of heterogeneity in efficiency levels among the producers analyzed. While some demonstrate high technical efficiency (e.g., firm 5 with TE = 0.917), others exhibit extremely low values (e.g., firm 42 with TE = 0.014). This variability suggests significant differences in production practices and overall performance among producers.

The analysis indicates that cost efficiency tends to be low when either technical or allocative efficiency is low (Henderson, 2015; Ajibefun & Daramola, 2003; Coelli et al., 2002). This is expected, as a producer who does not optimize input use or has deficiencies in production is likely to face higher relative costs.

Additionally, some producers display low technical efficiency but relatively high allocative efficiency. For instance, firm 42 (TE = 0.014, AE = 1.000) effectively allocates inputs according to market prices, yet their production remains inefficient (Figure 2).

Only a small number of producers operate efficiently across all dimensions. Those with TE, AE, and CE values close to 1 can be considered highly efficient. For example, firm 162 (TE = 0.150, AE = 1.000, CE = 0.150) allocates inputs efficiently but still has room for improvement in technical efficiency, Table 2 (Appendix in Mendeley, Castro Alvarez et al., 2026).

The results highlight key areas for enhancing efficiency in rice production (Watkins et al., 2014):

Technical Efficiency: Producers with low TE could improve their production practices by adopting better technologies or more efficient agricultural strategies.

Allocative Efficiency: Those with low AE could benefit from a more rational use of inputs aligned with market conditions.

Cost Efficiency: Since CE depends on the interaction between TE and AE, simultaneous improvements in both dimensions would help reduce costs and enhance the sector's competitiveness.

Efficiency analysis and model comparison

A comparative analysis between Constant Returns to Scale (CCR) and Variable Returns to Scale (VRS) models was performed to decompose total technical efficiency. The results show a significant gap between the two models: the average deterministic VRS efficiency was 0.5478, while the CCR efficiency was considerably lower at 0.1726.

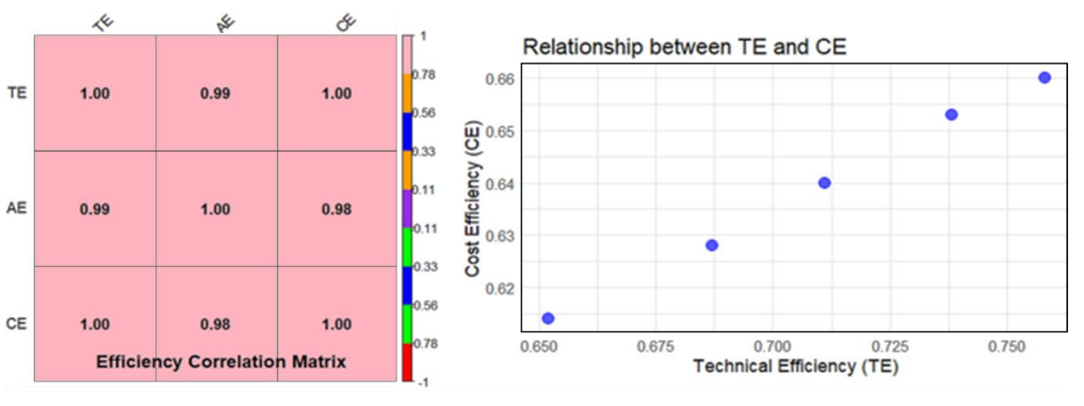

Figure 2. Efficiency correlation matrix and relationship between TE and CE.

This disparity results in an average Scale Efficiency (SE) of 0.4022, suggesting that approximately 59.8% of the observed inefficiency in the Ecuadorian rice sector is due to operating at an inappropriate scale (either too small or too large) rather than purely managerial failures. The fact that VRS scores are substantially higher than CCR scores indicates that rice producers are more efficient at managing inputs within their specific operational constraints, but they are penalized by structural factors of the rice bioeconomy, such as land fragmentation.

Consequently, the Simar & Wilson (2007) bootstrap procedure was prioritized for the VRS model to provide a robust, bias-corrected measure of "Pure Technical Efficiency," isolating managerial performance from the scale effects that dominate deterministic results.

Provincial efficiency patterns and bias correction

Significant heterogeneity in efficiencies is observed across provinces, reflecting differences in production conditions, management practices, and access to resources (Wassmann et al., 2009; Thanawong et al., 2014; Tittonell et al., 2007). The implementation of the bootstrap procedure with 2,000 replications provided a more robust estimation, correcting for inherent bias and accounting for sampling noise (Table 3).

The overall mean bias-corrected technical efficiency (TE BC) for the rice sector was 0.6325, with a 95% confidence interval of [0.596 – 0.668]. This result indicates that farmers could theoretically reduce their input consumption by approximately 36.7% while maintaining the same level of output, provided they adopt the best management practices observed in the sample.

At the provincial level, Manabí stands out with the highest average bias-corrected technical efficiency (0.7438), followed by El Oro (0.6801) and Loja (0.6459). The high performance in Manabí and El Oro could be attributed to more optimized agricultural practices and better resource management. However, Loja presents a unique case: despite its high technical skill, it shows the lowest average allocative efficiency (0.197), suggesting that these producers face significant challenges in optimizing input combinations based on market prices.

In contrast, El Oro shows the most balanced and integrated performance, leading in both allocative efficiency (0.640) and cost efficiency (0.435). This indicates superior financial planning and greater sensitivity to input costs. On the other hand, Guayas exhibits the lowest technical efficiency (0.5413), signaling the need for urgent interventions to improve management and overcome technological limitations (Figure 3).

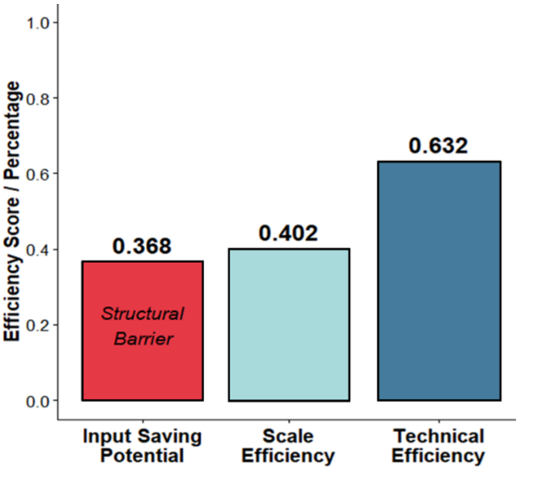

Figure 3. The Efficiency Gap & Policy Path.

The statistical reliability of these findings, supported by the bootstrap procedure across the 609 analyzed farms, confirms that the main challenge for the Ecuadorian rice sector is the gap between technical potential and price-based resource allocation. It is recommended to promote the exchange of best practices between provinces, particularly from El Oro to other regions, to improve the overall efficiency of the sector (Castro-Alvarez et al., 2026). Implementing training programs tailored to each province, with an emphasis on cost management, remains a crucial policy implication (Bui et al., 2018).

Table 3
Comprehensive efficiency analysis by province: decomposition of technical, allocative, and scale effects

Provincia	TE (CCR)	TE (VRS)	TE (BC)*	95% Conf. Interval	Allocative (AE)	Cost (CE)	Scale (SE)
EL ORO	0.092	0.229	0.680	[0.641 – 0.718]	0.640	0.435	0.402
GUAYAS	0.058	0.152	0.541	[0.510 – 0.572]	0.403	0.218	0.385
LOJA	0.109	0.264	0.645	[0.608 – 0.683]	0.197	0.127	0.415
LOS RÍOS	0.070	0.177	0.551	[0.520 – 0.582]	0.313	0.172	0.398
MANABÍ	0.084	0.204	0.743	[0.701 – 0.786]	0.311	0.231	0.411
Mean	0.172	0.205	0.632	[0.596 – 0.668]	0.373	0.236	0.402

Note: CE=TE(BC)*AE; SE= CCR/VRS; (BC)*= Bias-Corrected (Bootstrap VRS), using the Simar & Wilson bootstrap procedure).

Table 4 (Appendix in Mendeley, Castro Alvarez et al., 2026) provides a detailed summary of the input quantities (labor days) used across the 609 analyzed firms, categorized into four key agricultural activities: fertilization (Input 1), weed control (Input 2), pest and disease control (Input 3), and planting (Input 4). The data reveals significant heterogeneity in resource allocation. This variation suggests that Ecuadorian rice producers employ diverse production strategies and face different levels of access to technology and resources (Minten et al., 2013; Barrett et al., 2004). Specifically, the wide range observed in Input 1 (fertilization) and Input 2 (weed control) indicates that these are flexible inputs, highly sensitive to the specific management practices of each farmer.

From an efficiency perspective, the variability in Input 3 (pest control) and Input 4 (planting) highlights potential areas for standardization. The fact that some firms achieve similar output levels with substantially lower input quantities is consistent with the bias-corrected technical efficiency results (mean = 0.5156) discussed in Section 3.3. This confirms that a considerable number of firms are operating far from the production frontier, likely due to suboptimal input combinations or labor-intensive traditional technologies (Serraj et al., 2011). Furthermore, the differences in input usage intensity across firms suggest potential input substitution (e.g., between manual weed control and chemical alternatives) and reflect the presence of economies of scale, where larger-scale producers may optimize labor more effectively (Pokharel & Featherstone, 2018). These descriptive insights provide the empirical basis for the technical, allocative, and cost inefficiencies identified in the main DEA model.

The comparative analysis presented in Table 5 situates the performance of Ecuadorian rice producers within a global technological context, highlighting significant gaps between local practices and the international production frontier. While the technical efficiency (TE) found in this study (0.632) is statistically robust due to the bootstrap correction, it remains considerably lower than the scores reported in recent 2025 and 2026 studies from high-performing Asian systems.

Research by Yuan et al. (2026) and Tran et al. (2026) reports efficiency scores exceeding 0.850, primarily driven by the adoption of mechanical side-deep fertilization and rigorous management of conventional plots. The Ecuadorian score suggests a potential input reduction of 36.8% if local farmers adopted these "Best Management Practices".

Comparing the current results with those of Dey et al. (2024) and Yuan et al. (2026) reveals that systems integrating environmental criteria—such as SBM-DEA and eco-efficiency models—achieve robust scores between 0.680 and 0.950. This demonstrates that economic efficiency and environmental sustainability are complementary; optimizing nitrogen and energy use is the primary pathway for enhancing the competitiveness of Ecuador's rice bioeconomy.

The work of Li et al. (2025) identifies an "inverted U-shaped" relationship between plot scale and efficiency, setting an optimal threshold of approximately 0.49 hectares. Given that the present study identified an average scale efficiency (SE) of only 0.402 for Ecuador, international evidence confirms that extreme land fragmentation is a dominant structural barrier. This fragmentation prevents local producers from reaching the meta-frontier observed in Vietnam or China, regardless of their individual managerial skills.

In summary, while the Ecuadorian rice sector shows technical proficiency in certain regions, it is currently in a technological transition phase. The evidence suggests that closing the gap with global leaders requires a shift toward moderate-scale operations and the implementatio0n of precision agriculture to address the structural and allocative shortcomings identified in this research.

4. Conclusions

The efficiency assessment of rice producers in Ecuador reveals a significant gap between current practices and the production frontier, with an overall bias-corrected technical efficiency (TE) of 0.632 (95% CI: 0.596 – 0.668).

Table 5
Comparative analysis of efficiency score in rice production across different regions and methodologies

Region / System	Method	Efficiency Score	Source
Ecuador (Rice)	DEA-Bootstrap	0.632 (Technical)	Current Study
China (Yangtze River Delta)	DEA	0.85-0.95 (Eco-Efficiency)	Yuan et al., (2026)
Central Vietnam (Conventional)	Meta-Frontier DEA	0.888-0.906	Tran et al., (2026)
Li et al. (2025)	DEA-BCC & Tobit	0.750-0.850	Li et al. (2025)
Andhra Pradesh, India	SBM-DEA	0.680 – 0.760 (Eco)	Dey et al. (2024)

These results indicate that farmers could theoretically reduce input consumption by 36.8% without decreasing output levels if they adopted best-management practices. A critical bottleneck is the low average scale efficiency of 0.402, which, when compared to recent findings in China, identifies land fragmentation and sub-optimal plot sizes as primary structural barriers to competitiveness. The striking heterogeneity across provinces, ranging from highly efficient units in Manabí and El Oro to lower performance in Guayas (0.541), highlights a profound gap in technology adoption and resource management that places Ecuador behind contemporary international benchmarks in Vietnam and China.

Given these regional disparities, a "one-size-fits-all" policy is insufficient; instead, interventions must be province-specific and focus on both technical and financial dimensions. Technological modernization through precision farming and mechanical side-deep fertilization is urgently required in provinces like Guayas to bridge the gap between traditional practices and the production frontier. Simultaneously, financial training programs should target regions like Loja, which exhibits high technical proficiency (0.645) but the lowest allocative efficiency (0.197), suggesting that technically skilled farmers still struggle to optimize input combinations in response to market price dynamics. Promoting the exchange of best practices from El Oro, the most balanced province in terms of cost efficiency (0.435), can serve as a national model for superior financial planning and input substitution.

In conclusion, the Ecuadorian rice sector must transition toward sustainable, technology-driven systems to ensure long-term food security and economic resilience. The use of robust bootstrap methods confirms that cost competitiveness is hindered by technical and allocative shortcomings, further exacerbated by operational scale failures. Future research should delve into the socio-economic determinants, such as land tenure, credit access, and education, that influence these efficiency disparities. By addressing these structural gaps through targeted modernization and energy-optimized conservation cropping systems, Ecuador can enhance the overall competitiveness and sustainability of its small and medium-scale rice producers within the global bioeconomy.

Competing interests

The authors declare no conflict of interest. The data source is from a public national survey, ensuring anonymity and ethical handling of producer information.

Acknowledge

The authors express sincere gratitude for the valuable collaboration and support provided by the International Center for Tropical Agriculture - CIAT and the Agricultural and Livestock Ministry- MAG of Ecuador in providing access to the database that has been fundamental for the development of our scientific article.

Author Contributions

M. D. Castro-Alvarez: Conceptualization, Methodology, Formal Analysis, Visualization, Writing-Review & Editing Original Draft. C. A. Zuniga-Gonzalez: Supervision, conceptualization, Methodology, Review original draft. W. Mercado: Supervision, Conceptualization, Methodology, Formal Analysis, Visualization, Writing original draft. R. S. Andrade: Conceptualization, Methodology, Formal Analysis, Writing Review & Editing. Data.

ORCID

M. D. Castro-Álvarez https://orcid.org/0000-0002-8066-0687
C. A. Zúniga-González https://orcid.org/0000-0002-2545-8304
W. Mercado https://orcid.org/0000-0001-7167-9581
R. S. Andrade https://orcid.org/0000-0002-5764-3854

References

Aliyu, A., & Bello, K. (2018). Data envelopment analysis of rubber smallholders: BCC and CCR models and bootstrapping technique. *International Journal of Research-Granthaalayah*, *6*, 346-368. https://doi.org/10.29121/granthaalayah.v6.i5.2018.1463

Antriyandarti, E. (2015). Competitiveness and Cost Efficiency of Rice Farming in Indonesia. *Journal of Rural Problems*, *51*(2),74-85, https://doi.org/10.7310/arfe.51.74

Abdul Wadud, M. (2003). Technical, Allocative, and Economic Efficiency of Farms in Bangladesh: A Stochastic Frontier and DEA Approach. *The Journal of Developing Areas*, 37(1), 109–126. http://www.jstor.org/stable/4192941 .

Ajibefun, I. A., & Daramola, A. G. (2003). Determinants of technical and allocative efficiency of micro-enterprises: firm-level evidence from Nigeria. *African development review*, *15*(2-3), 353-395. https://doi.org/10.1111/j.1467-8268.2003.00077.x

Bui, T. L., Tran, H. C., Azadi, H., & Lebailly, P. (2018). Improving the technical efficiency of Sengcu rice producers through better financial management and sustainable farming practices in mountainous areas of Vietnam. *Sustainability*, *10*(7), 2279. https://doi.org/10.3390/su10072279

Barrett, C. B., Moser, C. M., McHugh, O. V., & Barison, J. (2004). Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. *American Journal of Agricultural Economics*, *86*(4), 869-888. https://doi.org/10.1111/j.0002-9092.2004.00640.x

Battese, G. E., & Coelli, T. J. (1992). Frontier Production Functions. Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *J. Prod. Anal.*, *3*, 153–169. https://doi.org/10.1007/BF00158774

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9),1031-1142. https://doi.org/10.1287/mnsc.30.9.1078

Cai, R., Zhao, H., Wang, S., & Ma, J. (2026). Subsidies and allocative efficiency in China's rice production: does farm size matter?. *Applied Economics*, *58*(15), 2909-2922. https://doi.org/10.1080/00036846.2025.2482242

Castro, M., Duarte, A. R., Villegas, A., & Chanci, L. (2023). The effect of crop insurance in Ecuadorian rice farming: a technical efficiency approach. *Agricultural Finance Review*, *83*(3), 478-497. https://doi.org/10.1108/AFR-10-2022-0122

Castro Alvarez, M. D., Zúniga-Gonzalez, C. A., Andrade, R. S. (2025). Data for Analysis of rice (*Oryza sativa* l.) bioeconomy: a DEA approach to economy efficiency. Mendeley Data, V2, https://doi.org/10.17632/rsknb2b8z6.2

Coelli, T., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach. *Journal of agricultural economics*, *53*(3), 607-626. https://doi.org/10.1111/j.1477-9552.2002.tb00040.x

Coelli, T.J. (1997). A Multi-Stage Methodology for the Solution of Oriented DEA Models, mimeo. Armidale: Centre For Efficiency and Productivity Analysis, University of New England. 50 pp.

Christopher, L.M., Orozco, F., Averett, J. Muñoz, F., Romero, M. J. and Barahona, A. (2020). Agricultural food production diversity among female small holder farmers in a region of the Ecuadorian Andes experiencing nutrition transition. *Nutrients*, *12*(8), 2454. https://doi.org/10.3390/nu12082454

Chegini, M. G., Yousefi, S., & Borojani, G. (2016). Factors affecting the efficiency of human resources in Guilan's rice processing industry. *International Journal of Agricultural Management and Development 7*(3), 383-93.

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

de Wit, C.T. (1992). Resource use efficiency in agriculture. *Agricultural Systems*, *140*(1–3), 125-151, https://doi.org/10.1016/0308-521X(92)90018-J

Dey, S., Abbhishek, K., Saraswathibatla, S., Kuttippurath, J., Singh, P. K., & Das, D. (2024). Can cropping systems be energy efficient: performance measure for various rice-based cropping systems in peninsular India. *Journal of Agriculture and Food Research*, *18*, 101516. https://doi.org/10.1016/j.jafr.2024.101516

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, A CXX, Part 3, 253-290.

Gregory, P. J., Ingram, J. S. I., & Brklacich, M. (2005). Climate change and food security. *Phil. Trans. R. Soc., 360*(1463), 2139-2148. http://doi.org/10.1098/rstb.2005.1745

Henderson, H. (2015). Considering technical and allocative efficiency in the inverse farm size-productivity relationship. *Journal of Agricultural Economics*, *66*(2), 442-469. https://doi.org/10.1111/1477-9552.12086

jasim N. J., & Zanzal, H. T. (2022). Estimating the economic efficiency of cucumber crop the protected houses in Diyala governorate (Baquba an Applied model) for the 2021 agricultural season. *Tikrit Journal for Agricultural Sciences*, *22*(3), 12-19. https://doi.org/10.25130/tjas.22.3.2

Li, G., Wang, X., Ma, D., & Zhao, C. (2025). Does the Scale of Contiguous Plots Significantly Influence Rice Production Efficiency? Empirical Evidence From China Land Economic Survey Data. *Sage Open*, *15*(4). https://doi.org/10.1177/21582440251400498

Mivumbi, M., & Yuan, X. (2023). Sustainable Environmental Economics in Farmers' Production Factors via Irrigation Resources Utilization Using Technical Efficiency and Allocative Efficiency. *Sustainability*, *15*, 4101. https://doi.org/10.3390/su15054101

Medina-Litardo, R.C., García-Bendezú, S. J., Carrillo-Zenteno, M. D., Pérez-Almeida, I., & Moran, E. (2022). Salinity of soil and irrigation water on rice productivity in the canton of San Jacinto de Yaguachi, Ecuador. *Agrociencia*, *56*(7). https://doi.org/10.47163/agrociencia.v56i7.2602

Munim, Z. H. (2020). Does higher technical efficiency induce a higher service level? A paradox association in the context of port operations. *The Asian Journal of Shipping and Logistics*, *36*(4), 57-68. https://doi.org/10.1016/j.ajsl.2020.02.001

Minten, B., Murshid, K. A. S., & Reardon, T. (2013). Food quality changes and implications: evidence from the rice value chain of Bangladesh. *World Development*, *42*, 100-113. https://doi.org/10.1016/j.worlddev.2012.06.015

Marc Jim, M., Villano, R., & Fleming, E. (2012). Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines, *Agricultural Systems*, *110*, 41-53, https://doi.org/10.1016/j.agsy.2012.03.010

Ortega-Pacheco, D., Castro-Verdezoto, P. L., Mendoza-Jiménez, M. J., Almeida Benalcázar, E., & Castro, M. P. (2021). Social and Economic Contribution of the Bioeconomic Sector in Ecuador: A Methodological Approach. In: Venkatramanan, V., Shah, S., Prasad, R. (eds) *Sustainable Bioeconomy*. Springer, Singapore. https://doi.org/10.1007/978-981-15-7321-7_3

Portalanza, D., Torres, M., Rosso, F., Zuluaga, C.F., Durigon, A., Horgan Finbarr, G., Alava, E., Ferraz, S. (2024). Climate variability and change in Ecuador: dynamic downscaling of regional projections with RegCM4 and HadGEM2-ES for informed adaptation strategies. *Frontiers in Climate*, *6*, 1344868. https://doi.org/10.3389/fclim.2024.1344868

Pérez, S. G. C., González, C. A. Z., Jurado, A. T., & Flores, Y. M. (Eds.). (2026). Sustainability in Latin America: A Bioeconomic Approach. Springer Nature. 166 pp. https://doi.org/10.1007/978-3-032-09787-3

Portalanza, D., Horgan, F. G., Pohlmann, V., Vianna Cuadra, S., Torres-Ulloa, M., Alava, E., Ferraz, S., Durigon, A. (2022). Potential Impact of Future Climates on Rice Production in Ecuador Determined Using Kobayashi's 'Very Simple Model'. *Agriculture* *12*, 1828. https://doi.org/10.3390/agriculture12111828

Pereira, M. A., Ferreira, D. C., Figueira, J. R., & Marques, R. C. (2021). Measuring the efficiency of the Portuguese public hospitals: A value modelled network data envelopment analysis with simulation. *Expert systems with applications*, *181*, 115169. https://doi.org/10.1016/j.eswa.2021.115169

Pokharel, K. P., & Featherstone, A. M. (2018). Estimating multiproduct and product-specific scale economies for agricultural cooperatives. Agricultural Economics, *50*(3), 279-289. https://doi.org/10.1111/agec.12483

Tittonell, P., Vanlauwe, B., de Ridder, N., & Giller, K. E. (2007). Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: soil fertility gradients or management intensity gradients*? Agricultural systems*, *94*(2), 376-390. https://doi.org/10.1016/j.agsy.2006.10.012

Thanawong, K., Perret, S.R., & Basset-Mens, C. (2014). Eco-efficiency of paddy rice production in Northeastern Thailand: a comparison of rain-fed and irrigated cropping systems. *Journal of Cleaner Production*, *73*, 204-217. https://doi.org/10.1016/j.jclepro.2013.12.067

Tey, Y. S., & Brindal, M. (2014). Factors Influencing Farm Profitability. In: Lichtfouse, E. (eds) Sustainable Agriculture Reviews. Sustainable Agriculture Reviews, Chapter 15.Springer Nature Link. https://doi.org/10.1007/978-3-319-09132-7_5

Torres Álava, F., Guerrero F, Varas Maenza, C., & Solis Barros, T. (2022). Circular economy vision for local development focused on waste derived from two agricultural crops in Ecuador. *Journal of Business and Entrepreneurial Studie*, *6*(4). https://doi.org/10.37956/jbes.v6i4.318

Sarker, J. R., Rolfe, J. & Ananda, J. (2026). Bangladeshi coastal rice farmers navigate environmental uncertainty through adaptive management strategies. *Discover Food*, *6*, 87. https://doi.org/10.1007/s44187-026-00836-w

Seck, P. A, Diagne, A., Mohanty, S., Wopereis, S. M. C. (2012). Crops that feed the world 7: Rice. *Food Sec.*, *4*, 7–24 https://doi.org/10.1007/s12571-012-0168-1

Serraj, R., McNally, K. L., Slamet-Loedin, I., Kohli, A., Haefele, S. M., Atlin, G., & Kumar, A. (2011). Drought resistance improvement in rice: an integrated genetic and resource management strategy. *Plant Production Science*, *14*(1), 1-14. https://doi.org/10.1626/pps.14.1

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *J. Econom.*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Simar, L., Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Manag. Sci.*, *44(*1),49–61. https://doi.org/10.1287/mnsc.44.1.49

Tran, H. H., Datai, H., & Haiu Nu., A. T. (2026). Technical Efficiency of Organic and Conventional Rice Farming in Central Vietnam: A Meta-frontier DEA Analysis. *J. Glob. Innov. Agric. Sci.*, *14*(2), 711-719. https://doi.org/10.22194/JGIAS/26.1805

Watkins, K. B., Hristovska, T., Mazzanti, R., Wilson Jr, C. E., & Schmidt, L. (2014). Measurement of technical, allocative, economic, and scale efficiency of rice production in Arkansas using data envelopment analysis. *Journal of Agricultural and Applied Economics*, *46*(1), 89-106. https://doi.org/10.1017/S1074070800000651

Wassmann, R., Jagadish, S.V. K., Sumfleth, K., Pathak, H., Howell, G., Ismail, A.,& Heuer, S. (2009). Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation. *Advances in agronomy*, *102*, 91-133. https://doi.org/10.1016/S0065-2113(09)01003-7

Yuan, M., Wang, J., Wu, G., Jin, J., Hu, Y., Liu, C., Miao, Q., Wu, P., & Sun, Y. (2026). Mechanical Side-Deep Fertilization Synergizes with Controlled-Release Fertilizer to Drive Low-Carbon and High-Efficiency Rice (*Oryza sativa* L.) Production. *Agriculture*, *16*(6), 651. https://doi.org/10.3390/agriculture16060651

Zuniga-Gonzalez, C. A., Quiroga-Canaviri, J. L., Brambila-Paz, J. J., Ceballos-Pérez S. G., & Rojas-Rojas, M. M. (2024a). Formulation of an innovative model for the bioeconomy. *PLoS ONE*, *19*, e0309358. https://doi.org/10.1371/journal.pone.0309358

Zúniga-González, C. A., López, M. R., Icabalceta-Mairena, J. L., Vivas-Viachica, E. A., & Blanco-Orozco, N. V. (2024b). Study of the Efficiency and Productivity of the Productive Paths of the Bioeconomy in the CNU Universities. In Handbook on Data Envelopment Analysis in Business, Finance, and Sustainability: Recent Trends and Developments (pp. 221-250). https://doi.org/10.1142/9781800615786_0007

Zuniga-Gonzalez, C. A. (2023). TFP Bioeconomy Impact post Covid-19 on the agricultural economy. *PLoS ONE*, *18*(11), e0288885. https://doi.org/10.1371/journal.pone.0288885

Zúniga-González, C. A. (2024). Productivity growth and technical efficiency changes in Rice farms: An input-oriented study using biosolid. In Handbook on data envelopment analysis in business, finance, and sustainability: Recent trends and developments (pp. 551-574). https://doi.org/10.1142/9781800615786_0019