Bridging the Yield and Efficiency Gap of Smallholder Rice Farming in Rote Ndao, Semi-Arid Eastern Indonesia

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ABSTRACT

Smallholder rice farming in the semi-arid archipelagos of Eastern Indonesia faces a dual challenge of ecological vulnerability and allocative inefficiency. This study examines the production structure and economic performance of 40 rice farming households in Rote Ndao Regency using a Cobb-Douglas production function and farm-level financial analysis. The objective is to estimate the elasticity of key inputs, namely land, seed, fertilizer, pesticide, and labor, and to derive policy-relevant implications for closing the yield and efficiency gaps. The estimated model indicates Increasing Returns to Scale (RTS = 1.05), suggesting the presence of scale economies and structural constraints associated with fragmented landholdings. Land size is the dominant determinant of output ($\widehat{\beta_1} = 0.55$), while fertilizer ($\widehat{\beta_3} = 0.12$) and labor ($\widehat{\beta_5} = 0.15$) exhibit low elasticities, reflecting diminishing marginal returns and inefficiencies in nutrient management and labor use. Financial analysis shows that rice farming is economically viable, with an R/C ratio of 2.70, yet average farm-level productivity of about 3.8 tons per hectare remains substantially below the district-level potential of around 5.0 tons per hectare. The coexistence of scale inefficiency, low input responsiveness, and a persistent yield gap indicates that productivity constraints are primarily structural rather than purely agronomic. The study therefore advocates a cluster-based intensification strategy emphasizing land consolidation, balanced fertilization, and targeted mechanization to enhance input efficiency, exploit scale economies, and improve the sustainability and competitiveness of smallholder rice systems in semi-arid Eastern Indonesia.

1. Introduction

Rice remains the staple food and the main source of caloric intake for the majority of the Indonesian population, making stable and sufficient domestic rice production a strategic priority for national food security [1], [2]. While substantial productivity gains have been achieved in irrigated lowland systems, particularly in the volcanic regions of Java through technological transformation and improved crop management [3], [4], many peripheral and semi-arid regions continue to experience persistent yield stagnation and structural inefficiencies. This is especially evident in Eastern Indonesia, where rainfed and dryland rice systems dominate and production is highly vulnerable to climate variability, limited irrigation infrastructure, and low cropping intensity, resulting in large exploitable yield gaps [5], [6].

Understanding the production structure and the responsiveness of output to key inputs is therefore essential for designing effective policies to close yield gaps and enhance the economic viability of smallholder farming in semi-arid environments. The Cobb–Douglas production function provides a robust analytical framework to estimate input elasticities, assess returns to scale, and distinguish between random shocks and technical inefficiency in smallholder agriculture [7], [8]. When complemented with financial feasibility and efficiency analysis, this approach enables an integrated assessment of both technical and economic performance, thereby offering a sound empirical basis for policy formulation aimed at strengthening rice-based food security systems [9], [10].

This study focuses on smallholder rice farming in Rote Ndao Regency, East Nusa Tenggara, with three main objectives. First, it estimates the output elasticities of key production inputs, namely land, seed, fertilizer, pesticide, and labor, using a Cobb–Douglas production function to characterize the underlying production structure and returns to scale. Second, it evaluates the economic performance and cost structure of rice farming through a detailed farm budget and R/C ratio analysis. Third, it integrates the econometric and financial evidence to formulate policy-relevant strategies for reducing input inefficiency and narrowing the yield gap.

By explicitly linking scale effects, input responsiveness, and cost structure, this study contributes empirical evidence to support a cluster-based intensification approach, emphasizing land consolidation, balanced nutrient management, and targeted mechanization as key instruments to enhance technical efficiency and long-term productivity of rice-based farming systems in semi-arid Eastern Indonesia.

2. Method

2.1. Study Area and Data Collection

The study was conducted in Rote Ndao Regency, East Nusa Tenggara Province, Indonesia, a semi-arid region characterized by a monsoonal climate with a short and highly variable rainy season. Rice production in the area is dominated by rainfed lowland systems and smallholder farming with fragmented landholdings. Primary cross-sectional data were collected during the 2025 main planting season from 40 rice farming households located in six districts, namely Rote Barat Laut, Rote Tengah, Rote Barat Daya, Lobalain, Rote Timur, and Pantai Baru.

Farmers were selected using simple random sampling to represent the existing variability in farm size, ranging from subsistence plots of 0.15 ha to semi-commercial holdings of about 3.00 ha. The survey gathered detailed information on output, land area, seed use, fertilizer application, pesticide use, labor input, and production costs through structured questionnaires and direct field observation.

2.2. The Econometric Model

To analyze the production structure and input responsiveness, the study employed a Cobb–Douglas production function in log-linear form, estimated using Ordinary Least Squares (OLS), a specification widely applied in farm-level production analysis because it allows direct interpretation of coefficients as output elasticities and can be efficiently estimated using linear regression techniques [8], [11]:

$$\ln Y = \beta_0 + \beta_1 lnX_1 + \beta_2 lnX_2 + \beta_3 lnX_3 + \beta_4 lnX_4 + \beta_5 lnX_5 + \varepsilon \ldots (1)$$

Where Y denotes rice production measured in kilograms, X_1 represents land size in hectares based on real observation data, X_2 is the quantity of seed used (kg), X_3 refers to the amount of fertilizer applied (kg, including urea and NPK), X_4 denotes pesticide use (liters), and X_5 is labor input measured in person-days (HOK). The parameters β_i are the estimated output elasticity coefficients of each input, while ε is the stochastic error term capturing unobserved factors affecting production. The use of a log-linear Cobb–Douglas model estimated by OLS is consistent with empirical studies on crop production systems, including maize, potatoes, and other smallholder crops, which rely on this framework to assess input productivity and scale properties [12].

Returns to Scale (RTS) were computed as the sum of all estimated input elasticities, $RTS = \sum_{i=1}^{5} \beta_i$, where RTS > 1 indicates increasing returns to scale, RTS = 1 constant returns to scale, and RTS < 1 decreasing returns to scale. This classification follows standard production theory and is commonly applied in Cobb–Douglas studies of agricultural systems to infer scale efficiency and structural constraints [13], [14].

2.3. Diagnostic Tests

To ensure the validity of the OLS estimates, a set of classical assumption tests was conducted in line with the requirements for the Best Linear Unbiased Estimator (BLUE). Normality of residuals was examined using the Kolmogorov–Smirnov test, which is commonly applied in regression studies to verify that the error term is normally distributed before conducting statistical inference [15], [16]. Multicollinearity among explanatory variables was assessed through the Variance Inflation Factor (VIF), a standard diagnostic tool for detecting linear dependence among regressors and ensuring the stability of coefficient estimates [17], [18]. Heteroscedasticity was tested using the Glejser method, which regresses the absolute residuals on the explanatory variables to identify non-constant error variance [19]. These diagnostics were applied to confirm that the estimated model satisfies the classical OLS assumptions and thus fulfills the BLUE properties, allowing the regression coefficients to be interpreted reliably [20], [21].

2.4. Financial Feasibility Analysis

Economic performance was evaluated using a farm budget analysis standardized per hectare and per planting season, a common approach in smallholder rice studies [22]. Total revenue was calculated based on observed paddy output, milling recovery rate, and prevailing farm-gate rice prices, consistent with the standard formulation of revenue as the product of yield and output price in rice farm economics [23], [24]. Production costs were classified into variable and fixed components, including seed, fertilizer, pesticides, labor, machinery services, land tax, and depreciation, following conventional cost disaggregation in rice farming and smallholder budgeting studies [25].
Farm profitability was assessed using net income and the Revenue–Cost (R/C) ratio, defined as the ratio of total revenue to total production cost. An R/C ratio greater than one indicates that the farming system is financially feasible, equal to one indicates break-even, and less than one implies economic unviability, in line with standard criteria applied in rice farm feasibility analyses [26], [27].
This integrated econometric and financial approach allows simultaneous assessment of technical relationships among inputs, scale efficiency, and economic viability, thereby providing a comprehensive basis for policy-oriented analysis of smallholder rice production systems [7].

3. Results and Discussion

3.1. Socioeconomic Profile of Sample Farmers

To contextualize the econometric and financial analyses, it is essential to first describe the socioeconomic characteristics of the sampled rice farmers. Table 1 summarizes the average age, educational attainment, farming experience, and household dependency of the respondents in Rote Ndao Regency.

Table 1. Socioeconomic Profile of Sample Rice Farmers in Rote Ndao Regency

Variable	Average
Age (Years)	49
Education (Years)	8.2
Farming Experience (Years)	29.3
Number of Household Dependents	4.6

Source: Primary Data Analysis (2025)

The average farmer age is 49 years, indicating an ageing agricultural workforce, a phenomenon widely observed in developing-country smallholder systems, where older farmers are generally more conservative, more risk-averse, and less inclined to adopt new and complex agricultural technologies such as mechanization and precision input management [28], [29]. This demographic structure has important implications for labor availability, physical work capacity, and the pace of technological adoption, particularly in rainfed and semi-arid environments where innovation often involves higher production risks and learning costs [29]. The mean education level of 8.2 years (junior secondary) suggests that while basic literacy is adequate, limited formal schooling may constrain the ability to absorb and implement more knowledge-intensive technologies, further reinforcing age-related adoption barriers [28].

Farmers in the study area exhibit a long average farming experience of 29.3 years, reflecting substantial accumulation of tacit and location-specific knowledge. However, such extensive experience may also be associated with path dependency and conservative production behavior, as older and more experienced farmers tend to rely on established practices and exhibit stronger aversion to technological and management changes [28]. Furthermore, the average household dependency ratio of 4.6 persons indicates a relatively high consumption burden. This condition is likely to increase farmers' risk aversion and preference for low-variance production strategies, since households with higher dependency and limited asset buffers tend to avoid uncertain but potentially high-return technologies and modern inputs [30], [31]. Such risk-averse behavior can lead to cautious input use and reinforce sub-optimal adoption of fertilizer, mechanization, and other productivity-enhancing innovations.

Overall, the socioeconomic profile suggests that productivity constraints in the study area are not solely technical in nature, but are also shaped by demographic ageing, education, and risk behavior associated with household dependency, which together influence technology adoption, input allocation, and the effectiveness of intensification and mechanization policies in smallholder agriculture.

3.2. Classical Assumption Tests

Prior to interpreting the estimated production elasticities, the reliability of the Cobb–Douglas regression model was evaluated through a series of classical assumption tests to ensure that the Ordinary Least Squares (OLS) estimator satisfies the Best Linear Unbiased Estimator (BLUE) properties [20], [21]. The results of the normality, multicollinearity, and heteroscedasticity tests are summarized in Table 2.

Table 2. Summary of Classical Assumption Tests

Test Type	Indicator/Variable	Statistic Value	Cut-off Value	Result
Normality	Kolmogorov-Smirnov	0.584	-	Normal Distribution
	Asymp. Sig. (2-tailed)	0.892	> 0.05	H_0 Accepted
Multicollinearity	Variance Inflation Factor (VIF)			No Multicollinearity
(Dep. Var: Ln_Production)	VIF - Ln Land (X_1)	8.450	< 10.00	
	VIF - Ln Seed (X_2)	6.120	< 10.00	
	VIF - Ln Fertilizer (X_3)	7.300	< 10.00	
	VIF - Ln Pesticide (X_4)	4.250	< 10.00	
	VIF - Ln Labor (X_5)	6.800	< 10.00	
Heteroscedasticity	Glejser Test (Sig.)			Homoscedastic
(Dep. Var: $\|e\|$)	Ln Land (X_1)	0.655	> 0.05	
	Ln Seed (X_2)	0.380	> 0.05	
	Ln Fert. (X_3)	0.540	> 0.05	
	Ln Pesticide (X_4)	0.812	> 0.05	
	Ln Labor (X_5)	0.751	> 0.05	

Source: Primary Data Analysis (2025)

The Kolmogorov–Smirnov test indicates that the residuals are normally distributed, as evidenced by an Asymp. Sig. (2-tailed) value of 0.892, which is well above the 5 percent significance level. This confirms that the normality assumption is not violated, allowing valid statistical inference on the estimated parameters.

Multicollinearity was examined using the Variance Inflation Factor (VIF). All explanatory variables, namely land, seed, fertilizer, pesticide, and labor, exhibit VIF values below the critical threshold of 10, ranging from 4.25 to 8.45. These results suggest the absence of severe linear dependence among input variables and imply that the estimated coefficients are stable and interpretable.

Heteroscedasticity was tested using the Glejser procedure. The significance levels of the auxiliary regressions for all input variables exceed 0.05, indicating homoscedastic residuals. This confirms that the variance of the error term is constant across observations, and therefore the OLS estimates are efficient.

Collectively, these diagnostic results demonstrate that the empirical model is well specified and statistically robust. Consequently, the estimated input elasticities and returns-to-scale measures can be interpreted with confidence in the subsequent analysis of production structure and allocative efficiency.

3.3. Production Structure and Returns to Scale

The estimated Cobb–Douglas production function for smallholder rice farming in Rote Ndao Regency can be expressed in its log-linear form as:

$$\widehat{ln\,Y} = 0.921 + 0.552\,ln\,X_1 + 0.181\,ln\,X_2 + 0.122\,ln\,X_3 + 0.046\,ln\,X_4 + 0.154\,ln\,X_5$$

The estimated Cobb–Douglas production function reveals important insights into the underlying production structure of smallholder rice farming in the semi-arid environment of Rote Ndao Regency. The sum of the estimated output elasticities ($\sum_{i=1}^{5} \beta_i$) is 1.05, indicating that the production system operates under Increasing Returns to Scale (IRS). Although the RTS value of 1.05 is only slightly above unity, it still indicates mild increasing returns, suggesting that scale expansion may generate efficiency gains, particularly under fragmented land structures. This implies that a proportional increase in all production inputs would result in a more than proportional increase in output, suggesting the presence of scale economies and structural inefficiencies associated with small and fragmented farm sizes.

Among the input variables, land exhibits the largest and most statistically significant elasticity, with an estimated coefficient of 0.55. This finding confirms that land size remains the dominant determinant of rice output in the study area. The magnitude of this elasticity reflects the strong influence of scale on productivity and indicates that farm fragmentation substantially constrains the realization of technical and economic efficiency. In rainfed dryland systems, where irrigation control and yield-stabilizing technologies are limited, larger operational holdings allow better synchronization of input use, mechanization, and water management, thereby enhancing marginal productivity.

In contrast, the elasticities of fertilizer and labor are relatively low, estimated at 0.12 and 0.15, respectively. The low fertilizer elasticity suggests diminishing marginal returns to chemical inputs, which may be attributed to imbalanced nutrient application, particularly the heavy reliance on nitrogen-based fertilizers (urea) without adequate supplementation of phosphorus and potassium. Such nutrient bias can lead to soil nutrient mining and physiological yield constraints [5], thereby weakening the responsiveness of output to additional fertilizer use.

Similarly, the modest labor elasticity indicates the presence of labor underutilization and declining marginal productivity of manual work. Given the average labor use of approximately 75 person-days per hectare, the results point to a situation of disguised unemployment, where additional labor inputs contribute little to output growth [7]. This condition is consistent with the observed dominance of manual operations and limited mechanization, which restricts labor-saving technological change and perpetuates inefficiencies in task allocation and timing of field operations.

Overall, the presence of Increasing Returns to Scale combined with low marginal productivity of variable inputs highlights a structural production gap. The findings suggest that productivity gains in the study area are more likely to be achieved through scale enlargement and technological upgrading, rather than through further intensification of conventional input use under the existing fragmented and labor-intensive production system.

3.4. Financial Feasibility Analysis

The economic performance of smallholder rice farming in Rote Ndao Regency was evaluated through a farm budget analysis standardized on a per-hectare and per-season basis. As presented in Table 3, rice cultivation remains financially viable under prevailing input and output prices. With an average gross revenue of IDR 30.26 million per hectare derived from a yield of approximately 3.7–3.8 tons of paddy (GKG) and a milling recovery rate of 63 percent, total production costs amount to IDR 11.21 million per hectare, resulting in a net profit of about IDR 19.05 million and an R/C ratio of 2.70. This indicates that every rupiah invested in rice farming generates a return of approximately 2.70 rupiah, confirming the economic attractiveness of the enterprise.

The cost structure reported in Table 3 shows that labor constitutes the largest component of total production costs, accounting for nearly half of total expenditures (around IDR 5.32 million or 47.4 percent). This is followed by fertilizer and machinery services, while seed and pesticide costs represent relatively smaller shares. The dominance of labor costs reflects the highly labor-intensive nature of rice production in the study area, with an average labor requirement of about 76 person-days per hectare. This pattern is consistent with the low labor elasticity estimated in the production function, indicating diminishing marginal productivity of manual labor and the presence of labor underutilization.

Table 3. Financial Feasibility of Rice Farming in Rote Ndao (Per Ha/Season)

No.	Component	Unit	Quantity	Price/Unit (IDR)	Total Value (IDR)
A	**REVENUE**				
	Production (from 3,695 kg GKG; milling recovery 63%)	Kg	2,328	13,000	30,264,000
B	**VARIABLE COSTS**				
1	Seeds	Kg	35	15,000	525,000
2	Fertilizer				
	- Urea (Subsidy/Non)	Kg	200	4500	900,000
	- NPK (Subsidy/Non)	Kg	150	18,000	2,700,000
3	Pesticides	Package	1	450,000	450,000
4	Labor	HOK	76	70,000	5,320,000
5	Machinery (Tractor)	Package	1	600,000	600,000
	Sub-Total Variable Cost				*10,495,000*
C	**FIXED COSTS**				
	Land Tax + Depreciation	Package	1	719,000	719,000
D	**TOTAL COST (B + C)**				11,214,000
E	**NET PROFIT (π)**				19,050,000
F	**R/C RATIO**				**2.70**

Source: Primary Data (2025). Standard Labor Wage: IDR 70,000/HOK.

Fertilizer expenditure, although substantial, does not translate proportionally into output gains, as evidenced by its relatively low elasticity. This suggests that current nutrient management practices are characterized more by quantitative application than by balanced and efficient nutrient use, particularly due to the predominance of nitrogen-based fertilizers. Consequently, additional fertilizer inputs generate limited yield responses while increasing production costs.

The composition of revenue and costs is further illustrated in Figure 1 using a waterfall diagram. The figure clearly visualizes the gap between gross revenue and total costs, resulting in a sizeable net profit margin, while simultaneously highlighting the overwhelming contribution of labor to total costs. This visual evidence reinforces the econometric findings of low labor and fertilizer elasticities and supports the argument that productivity and profitability gains are more likely to be achieved through labor-saving mechanization, scale-oriented operations, and balanced fertilization, rather than through further intensification of conventional inputs under the existing production structure.

Overall, the financial analysis confirms that although rice farming in Rote Ndao is economically profitable, its cost structure is inefficient and heavily skewed toward inputs with low marginal returns. This underscores the need for structural and technological interventions, particularly land consolidation, mechanization, and improved nutrient management, to enhance input efficiency and long-term competitiveness of smallholder rice systems in semi-arid environments.

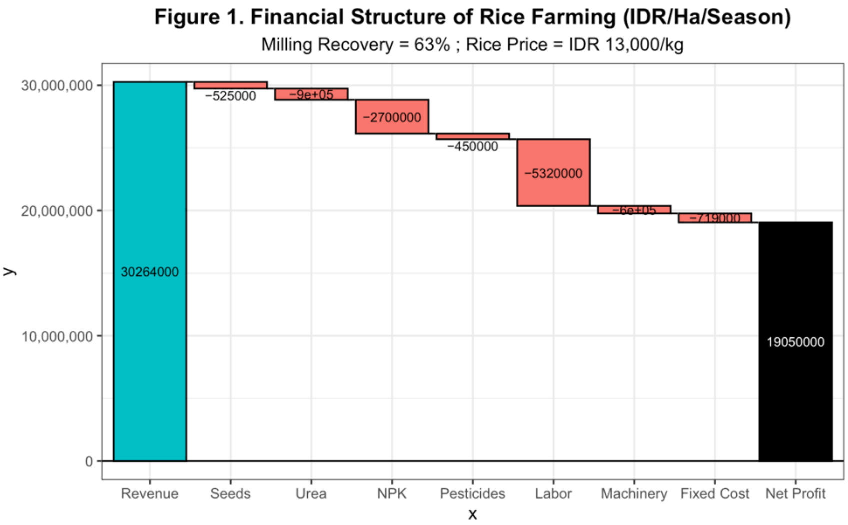

Fig 1. Waterfall chart of revenue, costs, and net profit of rice farming in Rote Ndao Regency (IDR/ha/season)
Source: Authors' visualization based on primary data (2025).

3.5. Yield Gap and Spatial Productivity Disparities

Spatial variation in rice productivity across districts in Rote Ndao Regency is presented in Table 4 based on official statistics from the Central Bureau of Statistics (BPS) for the year 2024 [32]. The data indicate that district-level average productivity ranges from 4.9 to 5.4 tons per hectare, with several districts, such as Rote Barat Laut and Lobalain, achieving yields above 5.3 tons per hectare. At the regency level, average productivity reaches approximately 5.0 tons per hectare, which can be considered the attainable yield frontier under existing agro-climatic conditions and prevailing production technologies.

In contrast, the primary survey data reveal substantially lower realized yields. As illustrated in Figure 2, the average productivity of sample farmers across all surveyed districts is clustered around 3.8–3.9 tons per hectare, with only minor spatial variation despite differences in agro-ecological conditions and sample size. Even in districts with relatively high official productivity, the observed farm-level yields remain well below the district potential. This indicates a pronounced yield gap of approximately 1.1–1.6 tons per hectare, or about 20–30 percent relative to the attainable frontier reported in Table 4.

Table 4. Harvested Area, Productivity, and Production of Wetland Paddy by District in Rote Ndao Regency, 2024

No	District	Harvested Area (Ha)	Productivity (Ton/Ha)	Production (Ton)
1	Rote Barat Daya	2,792	4.9	16,810.0
2	Rote Barat Laut	2,462	5.4	19,134.4
3	Loaholu	685	5.0	2,702.4
4	Lobalain	2,989	5.3	22,048.0
5	Rote Tengah	3,017	4.9	18,988.0
6	Rote Selatan	401	4.9	2,059.2
7	Pantai Baru	3,093	4.9	13,245.0
8	Rote Timur	2,294	4.9	13,128.9
9	Landu Leko	1,632	4.9	3,033.6
10	Rote Barat	368	4.9	3,288.0
Rote Ndao Regency (Total)		**19,733**	**5.0**	**114,437.5**

Source: Central Bureau of Statistics (BPS) of Rote Ndao Regency (2024)

The convergence of low realized yields across locations suggests that productivity constraints are largely systemic rather than location-specific [6]. The gap is therefore unlikely to be driven primarily by biophysical limitations, but instead reflects common structural and managerial bottlenecks faced by smallholders throughout the regency. These include fragmented landholdings, limited access to balanced and timely fertilizer application, and inefficiencies in labor and machinery use, as evidenced by the low elasticities of fertilizer and labor and the dominance of land scale effects in the production function.

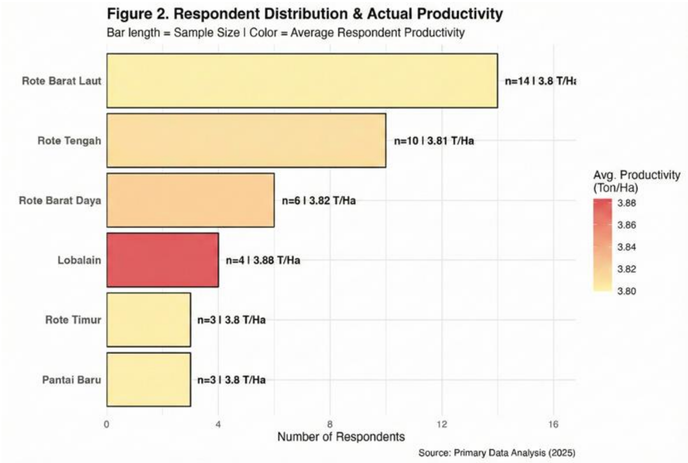

Fig. 2. Respondent Distribution & Productivity by District (Primary Data, 2025).
Source: Authors' visualization based on primary data (2025).

Overall, the comparison between official district-level productivity (Table 4) and farm-level survey results (Figure 2) provides strong empirical evidence of an "input and technology gap." Closing this gap requires interventions that go beyond incremental input intensification and instead address the structural conditions that prevent farmers from approaching the existing productivity frontier. This spatial evidence further supports the need for coordinated, scale-oriented strategies to improve technical efficiency and facilitate the adoption of modern production technologies across districts in Rote Ndao Regency.

3.6. Policy Implications for Closing the Yield and Efficiency Gap

The combined econometric and financial evidence indicates that productivity constraints in smallholder rice farming in Rote Ndao are primarily structural rather than purely agronomic. The presence of Increasing Returns to Scale (RTS = 1.05), the dominant role of land as the main determinant of output, the low marginal productivity of fertilizer and labor, and the substantial yield gap relative to the district-level productivity frontier together suggest that further intensification through additional use of conventional inputs alone will be insufficient to close the productivity gap. Similar patterns of scale inefficiency, low input responsiveness, and persistent yield gaps have been documented in smallholder rice systems in Asia and Africa, indicating that structural constraints rather than input scarcity constitute the main binding factors [33], [34].

First, cluster-based operational land consolidation should be promoted to exploit scale economies. The strong elasticity of land and the evidence of increasing returns to scale indicate that fragmented farm sizes constrain the realization of technical and economic efficiency. Empirical studies show that block farming, cooperative clusters, and reduced plot fragmentation significantly improve technical efficiency and productivity by enabling synchronized operations and better access to machinery and services [33], [35]. Such operational consolidation can raise productivity without altering land ownership structures, while facilitating mechanization and coordinated input management.

Second, targeted mechanization through shared service schemes is required to address labor inefficiency and high production costs. Labor accounts for the largest share of total production costs but exhibits relatively low output elasticity, indicating diminishing marginal returns and underutilization of manual labor. Evidence from China and sub-Saharan Africa shows that custom hiring centers and agricultural service providers supplying appropriate-scale machinery substantially reduce labor bottlenecks, improve the timeliness of field operations, and enhance technical efficiency, particularly when combined with clustered production systems [36], [37].

Third, balanced and site-specific nutrient management should be prioritized to improve fertilizer use

efficiency. The low fertilizer elasticity, despite substantial expenditure on chemical inputs, reflects imbalanced nutrient application dominated by nitrogen. Studies across rice-based systems demonstrate that soil-test-based, site-specific N–P–K management and the integrated use of organic and inorganic fertilizers significantly improve nutrient use efficiency and close yield gaps more effectively than uniform input intensification [38], [39].
Taken together, these three policy directions, operational land consolidation, targeted mechanization, and balanced nutrient management, directly address the core structural and allocative constraints identified in the analysis and provide a coherent strategy for enhancing productivity, efficiency, and competitiveness of smallholder rice farming systems in the semi-arid environment of Rote Ndao Regency.

4. Conclusion

This study provides empirical evidence on the production structure, input responsiveness, and economic performance of smallholder rice farming in the semi-arid region of Rote Ndao Regency, East Nusa Tenggara. The estimated Cobb–Douglas production function reveals that the system operates under Increasing Returns to Scale (RTS = 1.05), indicating the presence of scale economies and underscoring the structural constraints imposed by fragmented landholdings. Land size is the most influential determinant of output, whereas fertilizer and labor exhibit relatively low elasticities, reflecting diminishing marginal returns and allocative inefficiencies associated with imbalanced nutrient management and labor-intensive production practices.

The financial analysis confirms that rice farming is economically viable, as indicated by an R/C ratio well above unity. However, the cost structure is heavily dominated by labor and chemical inputs with low marginal productivity, and average farm-level yields remain substantially below the attainable district-level productivity frontier. The coexistence of profitability with low technical efficiency and a persistent yield gap suggests that productivity constraints in Rote Ndao are not primarily biophysical, but rather stem from structural and managerial inefficiencies.

Taken together, the findings indicate that further productivity gains are unlikely to be achieved through conventional input intensification alone. Instead, a structural transformation of the production system is required. Accordingly, the study identifies three key policy priorities: (i) promoting cluster-based operational land consolidation to exploit scale economies and reduce fragmentation; (ii) expanding access to appropriate-scale mechanization through shared service schemes to enhance labor productivity and improve the timeliness of field operations; and (iii) strengthening balanced and site-specific nutrient management to increase fertilizer use efficiency and yield responsiveness. The implementation of these integrated strategies would enable smallholder farmers to move closer to the existing productivity frontier, reduce input inefficiencies, and improve the long-term sustainability and competitiveness of rice farming in semi-arid Eastern Indonesia.

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Data and Software Availability Statement

The data used in this study consist of primary cross-sectional observations collected from rice farming households in Rote Ndao Regency, East Nusa Tenggara, Indonesia, during the 2025 production season. Statistical analyses and visualizations were performed using R software, and reference management was carried out with Mendeley. Extracted data are available from the corresponding author upon reasonable request.

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