DETERMINANTS OF RICE SUPPLY RESPONSE IN THE PHILIPPINES: EVIDENCE FROM AN ARDL APPROACH

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ABSTRACT: *Rice remains central to food security and agricultural development in the Philippines, yet domestic production continues to face productivity, profitability, and import-related challenges. This study analyzes rice supply response by examining the effects of net returns, rice imports, and productivity on harvested rice area in the Philippines. Annual data from 2000 to 2025 were obtained from the Philippine Rice Research Institute and the Philippine Statistics Authority. An autoregressive distributed lag (ARDL) model was employed after confirming stationarity and evidence of cointegration among the variables. Results show that rice yield has a positive and significant long-run effect on harvested area (elasticity = 0.3959, p = 0.004), indicating that productivity improvements strengthen domestic rice supply response. Net returns also exert a positive and significant long-run effect (elasticity = 0.0691, p = 0.001), while rice imports exhibit a negative but statistically insignificant long-run coefficient (−0.0064, p = 0.371). In the short run, changes in net returns, rice imports, and rice yield significantly influence harvested area. The error-correction coefficient (−1.3706, p = 0.001) confirms rapid adjustment toward long-run equilibrium following short-term shocks. The findings highlight the importance of productivity enhancement, profitability improvement, and balanced trade policies in strengthening domestic rice production, food security, and long-term sector resilience in the Philippines.*

Keywords: rice supply response, ARDL model, productivity, rice imports, profitability, Philippines.

INTRODUCTION

Rice remains central to food security, rural livelihoods, and agricultural development in the Philippines, supporting millions of farming households and contributing substantially to agricultural output and employment. Because rice accounts for a major share of caloric intake, maintaining stable domestic supply remains a national priority aligned with Sustainable Development Goal 2: Zero Hunger [1, 2]. At the same time, rice production places increasing pressure on land and water resources, making sustainable intensification essential. Existing studies emphasize that future growth in rice production must depend more on productivity improvements than land expansion to enhance resource-use efficiency and reduce environmental stress [3, 4, 5].

Regional production data further reveal persistent spatial disparities in Philippine palay output. From 2013 to 2023, national production increased modestly from 18.4 million to 20.1 million metric tons. Production remained concentrated in Luzon, which consistently accounted for about 58–59% of total output, while Mindanao posted slight gains and the Visayas experienced relative stagnation. Major rice-producing regions included Region I (Ilocos Region), Region II (Cagayan Valley), Region III (Central Luzon), Region VI (Western Visayas), and Region XII (SOCCSKSARGEN), although regional growth patterns were uneven. Between 2018 and 2023, BARMM recorded the highest production growth at 40%, whereas CAR and Region VIII experienced declines, reflecting substantial regional heterogeneity. Yield disparities further reinforced these inequalities, with higher productivity concentrated in Luzon due to stronger irrigation systems, technological adoption, and production conditions. These patterns suggest that long-term rice self-sufficiency depends on targeted investments in productivity and climate resilience rather than uniform nationwide interventions [5].

Recent developments in the Philippine rice sector reflect increasingly complex interactions among trade, productivity, and environmental constraints. Rice imports are projected to reach 4.8 million metric tons in 2026, highlighting continued dependence on external supply amid policy adjustments and domestic production shortfalls [6,7]. Although imports can stabilize short-term supply, they may weaken domestic production incentives and shift environmental pressures abroad [8]. Meanwhile, rice production faces rising input costs, adverse weather conditions, and uneven productivity growth [9,10]. These constraints underscore the importance of irrigation, technological innovation, and climate-resilient resource management in sustaining agricultural productivity [11,12,13].

Rice supply dynamics are also shaped by price transmission and market inefficiencies. Domestic rice prices respond to international shocks, trade policies, and production costs, while weak marketing systems generate regional price disparities that distort resource allocation decisions [14,15]. Combined with evidence of limited land expansion and slow productivity growth [5], these conditions highlight the need to analyze rice supply response as a function of both economic incentives and resource constraints.

Agricultural supply response theory explains how farmers adjust land, labor, and input allocation in response to expected profitability, production conditions, and institutional constraints [16, 17]. Harvested area is particularly important because it reflects long-run land-use adjustment. The Nerlove partial adjustment framework posits that farmers gradually move toward a desired production level based on expected prices, while later studies emphasize the importance of irrigation, technological change, and productivity growth in shaping supply behavior [18, 19, 20, 21]. Empirical studies similarly identify price and non-price factors—including irrigation, technology adoption, and institutional conditions—as key determinants of rice supply response [22, 23, 24, 25]. In the Philippines, responsiveness to price incentives remains constrained by land availability, irrigation capacity, and climate-related production risks [26, 27, 28, 29].

Despite extensive literature, limited studies apply modern time-series approaches such as the Autoregressive Distributed Lag (ARDL) framework to Philippine rice supply response, particularly in the post–Rice Tariffication Law period. The effects of import competition on domestic supply elasticity and land-use dynamics, as well as the role of productivity growth in long-run supply adjustment, also remain insufficiently examined. This study addresses these gaps by analyzing how profitability, rice imports, and productivity affect harvested rice area in the Philippines using the ARDL framework of Pesaran [30]. The findings provide policy-relevant evidence for improving productivity, optimizing resource use, and strengthening long-term resilience in the Philippine rice sector.

Research Objective

This study aims to analyze the supply response of rice production in the Philippines by examining the effects of profitability, rice imports, and productivity on harvested rice area.

Specifically, the study seeks to:

1. examine the long-term trends in harvested rice area, net returns, rice imports, and rice yield in the Philippines from 2000 to 2025; and
2. analyze the short-run and long-run effects of net returns, rice imports, and rice productivity on harvested rice area as a proxy for rice supply response.

METHODS

Research Design

This study employed a descriptive–correlational quantitative time-series design to examine rice supply response in the Philippines. Descriptive analysis was used to assess trends in harvested rice area, net returns, rice imports, and rice yield, while econometric analysis examined their short-run and long-run relationships. Harvested rice area served as the proxy for rice supply response. The study focused on the Philippines because rice remains central to food security, rural livelihoods, and agricultural development. Major rice-producing regions include Central Luzon, Cagayan Valley, Western Visayas, and parts of Mindanao, although the sector continues to face structural constraints such as limited arable land, climate vulnerability, rising production costs, and import competition. The national context is particularly relevant given ongoing policy interventions, including irrigation expansion, agricultural modernization, and the Rice Tariffication Law.

Data Gathering and Preparation

Annual time-series data from 2000 to 2025 were obtained primarily from the Philippine Rice Research Institute (PhilRice), including harvested rice area, yield per hectare, production cost, and gross returns from rice farming. Rice import data were sourced from the Philippine Statistics Authority (PSA). The dataset was reviewed for consistency and completeness prior to estimation. Missing observations were addressed through interpolation, extrapolation, and accounting identities. A small number of missing observations were reconstructed prior to estimation. Missing production cost and gross return values were estimated using linear interpolation based on adjacent observations, while missing 2025 values were obtained through forward extrapolation using the most recent available observation. Gross returns for 2000 and 2001 were reconstructed through backward extrapolation using the observed growth rate from the earliest available period. Net returns were subsequently derived using the accounting identity of gross returns minus production costs. In addition, an identified inconsistency in the 2010 net return series was corrected using the same accounting relationship. These procedures were applied to maintain a complete and internally consistent time series for econometric analysis. Gross return growth rates were estimated as:

$$Growth\ Rate = \frac{GR_t - GR_{t-1}}{GR_{t-1}}$$

where GR_t represents gross returns per hectare in year t. Net returns were reconstructed using:

$$Net\ Returns = Gross\ Returns - Production\ Cost$$

All variables were transformed into natural logarithmic form to improve statistical properties and interpret estimated coefficients as elasticities.

Data Analysis

This study employed a time-series econometric framework to examine rice supply response in the Philippines. To address the first objective, descriptive trend analysis of harvested rice area (ln_area), net returns ($\ln Net_t$), rice imports ($\ln Imports_t$), and rice yield (ln_yield) using graphical inspection and semi-log trend regression was employed:

$$\ln(Y_t) = \alpha + \beta_t + \varepsilon_t$$

where Y_t represents the variable of interest, t denotes the time trend, α is the intercept, and β measures the average annual growth rate. Because the variables are expressed in natural logarithms, the estimated coefficient β approximates the percentage change per year.

To address the second objective, the econometric analysis then examined the short-run and long-run relationships among harvested rice area, net returns, rice imports, and rice productivity using the Autoregressive Distributed Lag (ARDL) framework. The ARDL approach was selected because it accommodates variables integrated at different orders, provided none are integrated of order two (I(2)), and is appropriate for small-sample time-series analysis. Prior to estimation, multicollinearity was evaluated using the Variance Inflation Factor (VIF), where values below 5 indicate low multicollinearity and values above 10 indicate severe multicollinearity. Lag length selection was based on the Akaike Information Criterion (AIC), Hannan–Quinn Information Criterion (HQIC), and Schwarz Bayesian Information Criterion (SBIC), although a maximum lag length of two was adopted to preserve model parsimony.

Stationarity was examined using the Augmented Dickey–Fuller (ADF) unit root test:

$$\Delta Y_t = \alpha + \lambda Y_{t-1} + \sum_{i-1}^{k} \gamma_i \Delta Y_{t-i} + \varepsilon_t$$

where:

Y_t represents the variable under investigation

Δ denotes the first difference operator

k is the number of lagged differences included to correct for serial correlation.

The general ARDL specification was expressed as:

$$\ln Area_t = \alpha_0 + \sum_{i=1}^{p} \beta_i lnArea_{t-i} + \sum_{j=0}^{q1} \gamma_j lnNet_{t-j} + \sum_{k=0}^{q2} \delta_k lnImports_{t-k} + \sum_{m=0}^{q3} \emptyset_m lnYield_{t-m} + \varepsilon_t \, lnYield_{t-m}$$

where:
$lnArea_{t-i}$ represents the harvested rice area
$lnNet_{t-j}$ represents net returns
$lnImports_{t-k}$ represents rice imports
$lnYield_{t-m}$ represents rice productivity.

Once cointegration was established, short-run dynamics were estimated using the Error Correction Model (ECM):

$$\Delta \ln Area_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta lnArea_{t-1} + \sum_{j=0}^{q1} \gamma_j \Delta lnNet_{t-j} + \sum_{k=0}^{q2} \delta_{k\Delta} lnImports_{t-k} + \sum_{m=0}^{q3} \emptyset_m \Delta lnYield_{t-m} + \lambda ECM_{t-1} + \varepsilon_t$$

Long-run equilibrium relationships were tested using the ARDL bounds testing procedure of Pesaran [30], where cointegration is confirmed when the computed F-statistic exceeds the upper critical bound.

Model robustness was evaluated through diagnostic tests, including the Breusch–Godfrey LM test for serial correlation, Breusch–Pagan and White tests for heteroskedasticity, ARCH LM for conditional heteroskedasticity, Ramsey RESET for model specification, Jarque–Bera for residual normality, and the Durbin–Watson statistic for autocorrelation. Parameter stability was assessed using the CUSUM test, where coefficients are considered stable when recursive residuals remain within critical bounds.

RESULTS AND DISCUSSION

Trend Analysis of Rice Sector Variables in the Philippines (2000–2025)

To examine the long-term evolution of the key variables in the rice sector, both graphical inspection and semi-log linear trend regression were employed. Visual inspection provides an initial understanding of the direction and variability of the series, while the regression analysis quantifies the average growth rate over time.

Graphical Trends in Rice Sector Variables

Figure 1 illustrates the time-series patterns of harvested area, net returns, rice imports, and yield from 2000 to 2025.

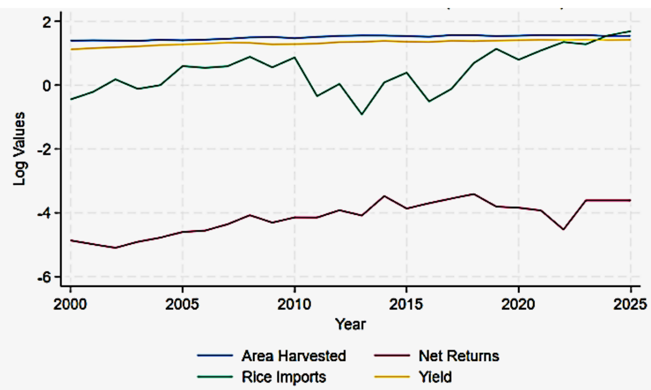

Figure 1. The trends in rice sector variables (2000-2025)

First, harvested rice area shows a gradual upward movement over the study period, suggesting a modest expansion in rice cultivation. The trajectory appears relatively smooth with limited volatility, indicating that land allocation decisions in rice production tend to adjust gradually over time. Second, net returns display a stronger upward trajectory, although with greater fluctuations compared with harvested area. This variability likely reflects changes in market prices, production costs, and policy interventions affecting farm profitability. Third, rice imports exhibit a pronounced upward trend with noticeable variability across years. The increasing import volumes indicate a growing reliance on external supply to meet domestic rice demand. Finally, rice yield demonstrates a steady and consistent upward movement throughout the sample period. The relatively smooth trend suggests continuous productivity improvements, possibly driven by technological advancement, improved crop varieties, and better farm management practices.

Therefore, the graphical evidence indicates that all four variables follow positive long-term trends, although their magnitudes and volatility differ.

Semi-Log Trend Regression Results

To formally quantify these trends, semi-log linear trend regressions were estimated for each variable. The regression results are summarized in Table 1.

Table 1. Trend Analysis of Rice Sector Variables

Variable	(β)	Std. Error	t-Statistic	p-value	R^2	F-Statistic
ln_area	0.0078	0.0008	9.67	0.000	0.796	93.50
ln_net	0.0546	0.0078	7.00	0.000	0.672	49.07
ln_imports	0.0536	0.0146	3.68	0.001	0.361	13.58
ln_yield	0.0104	0.0008	12.31	0.000	0.863	151.47

Harvested rice area also demonstrates a positive and statistically significant trend. The estimated coefficient for ln_area is 0.0078, corresponding to an annual growth rate of approximately 0.78%. The regression model exhibits strong explanatory power (R^2=0.796) and a highly significant F-statistic of 93.50. This result indicates a gradual expansion in rice cultivation throughout the study period, reflecting steady adjustments in land allocation for rice production.

Net returns from rice production similarly exhibit a positive and statistically significant trend. The estimated coefficient for ln_net is 0.0546, indicating an average annual growth rate of approximately 5.46%. The regression model is statistically significant (R^2=0.672; F=49.07), suggesting substantial increases in rice farming profitability over time, likely associated with improvements in output prices, productivity, and government support programs.

Rice imports also demonstrate a positive and statistically significant trend. The estimated coefficient for ln_imports is 0.0536, corresponding to an annual growth rate of approximately 5.36%. Although the explanatory power of the model is lower (R^2=0.361), the regression remains statistically significant (F=13.58). This finding indicates increasing dependence on imported rice over time to complement domestic production.

Rice yield also demonstrates a positive and statistically significant trend. The estimated coefficient for ln_yield is 0.0104, corresponding to an annual productivity growth rate of approximately 1.04%. The regression model exhibits strong explanatory power (R^2=0.863) and a highly significant F-statistic of 151.47. This result indicates consistent improvements in rice productivity throughout the study period, likely reflecting technological progress and improved agricultural practices. The combination of modest harvested area expansion and steady productivity growth suggests a pattern consistent with sustainable intensification, where agricultural growth increasingly depends on productivity improvements and more efficient resource use rather than extensive land expansion [3, 4, 8, 31, 32].

Rice Supply Response in the Philippines: Long-Run and Short-Run Dynamics

Unit Root Test

Table 2 presents the results of the Augmented Dickey–Fuller (ADF) unit root test used to determine the stationarity properties of the variables included in the rice supply response model.

Table 2. Unit Root Test Results Using the Augmented Dickey–Fuller (ADF) Test

Variable	Level Test Statistic	P-Value	First Difference Statistic	P-Value
ln_area	-1.470	0.548	-4.759	0.001
ln_net	-1.455	0.556	-4.515	0.002
ln_imports	-1.089	0.720	-4.357	0.004
ln_yield	-2.300	0.172	-3.007	0.034

Stationarity testing is essential in time-series analysis to avoid spurious regression results and unreliable statistical inference [33]. The Augmented Dickey–Fuller (ADF) test, conducted with one lag and no deterministic drift, indicates that harvested rice area (ln_area), net returns (ln_net), rice imports (ln_imports), and rice yield (ln_yield) are non-stationary at level, as their test statistics fail to reject the null hypothesis of a unit root. However, all variables become statistically significant after first differencing, with ADF statistics of −4.759 for ln_area, −4.515 for ln_net, −4.357 for ln_imports, and −3.007 for ln_yield, confirming that the series are integrated of order one (I(1)). The presence of I(1) variables justifies the use of the Autoregressive Distributed Lag (ARDL) framework, which is appropriate for estimating short-run and long-run relationships among variables integrated at mixed orders, provided none are integrated of order two (I(2)) [30].

Multicollinearity Test

Table 3 presents the multicollinearity diagnostic results using the Variance Inflation Factor (VIF) after excluding production cost from the model because it is inherently incorporated in the computation of net returns. Including both variables would introduce redundancy and increase the likelihood of multicollinearity, potentially affecting the precision and stability of the estimated coefficients. High multicollinearity can inflate standard errors and reduce the reliability of coefficient estimates; therefore, VIF values below 5 are generally considered acceptable, while values above 10 indicate serious collinearity concerns [34,35].

The multicollinearity results indicate that, after removing production cost from the specification, the remaining explanatory variables exhibit acceptable levels of correlation, with all VIF values falling below the critical threshold of 5.

Table 3 - Multicollinearity Test Using Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
ln_yield	4.97	0.201
ln_net	3.85	0.259
ln_imports	1.60	0.624
Mean VIF	3.48	

Rice yield (ln_yield) recorded the highest VIF at 4.97, followed by net returns (ln_net) at 3.85, while rice imports (ln_imports) showed the lowest VIF at 1.60. The mean VIF of 3.48 further confirms the absence of serious multicollinearity. These results suggest that the explanatory variables provide sufficiently distinct information in explaining harvested rice area and that multicollinearity is unlikely to compromise the efficiency, stability, and interpretability of the ARDL estimates [34,35].

Lag Length Selection

Prior to estimating the Autoregressive Distributed Lag (ARDL) model, the optimal lag structure was evaluated using the Akaike Information Criterion (AIC), Hannan–Quinn Information Criterion (HQIC), and Schwarz Bayesian Information Criterion (SBIC), as presented in Table 4.

Table 4. Lag Length Selection Criteria

Lag	Log-Likelihood	AIC	HQIC	SBIC
0	62.703	-5.336	-5.289	-5.138
1	101.453	-7.404	-7.171	-6.412
2	122.237	-7.840	-7.419	-6.054
3	136.979	-7.725	-7.118	-5.147
4	189.867	-11.079*	-10.284*	-7.706*

The consistent selection of lag four across multiple criteria strengthens confidence in the appropriateness of the chosen lag structure and suggests that the dynamic relationships among harvested rice area, net returns, rice imports, and rice yield extend beyond a single production cycle. Consistent with the ARDL methodology, the selected lag length was subsequently used as the maximum lag order in model estimation, resulting in the ARDL(1,3,4,1) specification. The use of information-criterion-based lag selection is recommended in ARDL modeling because it helps ensure efficient estimation, minimizes specification error, and adequately captures the underlying dynamic adjustments among variables [30,34,35,36].

ARDL Bounds Test for Cointegration

To determine whether a long-run equilibrium relationship exists among the variables, the ARDL bounds testing approach was applied following the procedure proposed by Pesaran et al. [30], as shown in Table 5 below. The ARDL bounds test provides moderate evidence of a long-run equilibrium relationship among harvested rice area, net returns, rice imports, and rice yield. The computed F-statistic (4.560) exceeds the upper critical bound at the 10% significance level (4.343), while the bounds t-statistic (−3.659) provides additional support for cointegration.

Table 5. ARDL Bounds Test for Cointegration

Test Statistic	Value	10% I (0)	10% I (1)	5% I (0)	5%I (1)
F-statistic	4.560	3.130	4.343	3.904	5.317
t-statistic	−3.659	−2.600	−3.487	−2.980	−3.930

This evidence is reinforced by the negative and highly significant error-correction coefficient, ECM(-1) = −1.3706 ($p = 0.001$), indicating that short-run deviations from equilibrium are corrected over time. Taken together, these results support the estimation and interpretation of both the long-run and short-run relationships within the ARDL framework and are consistent with agricultural supply response theory [16,30].

Long-run Dynamics from the ARDL Model

Table 6. Long-Run and Short-Run Coefficients of Rice Supply Response Estimated from the ARDL(1,3,4,1) Model (n = 22)

VARIABLE	COEFFICIENT	STD. ERR.	T-STAT	P-VALUE
Long-run relationship				
ln_net	0.0691	0.0128	5.38	0.001
ln_imports	0.0064	0.0068	0.94	0.371
ln_yield	0.3959	0.1015	3.90	0.004
Constant	0.7500	0.4533	3.86	0.004
Short-run Relationships				
Δln_net(-1)	-0.0897	0.0269	-3.33	0.009
Δln_net(-2)	-0.0919	0.0251	-3.67	0.005
Δln_net(-3)	-0.0589	0.0193	-3.05	0.014
Δln_imports(-1)	-0.0208	0.0091	-2.28	0.049
Δln_imports(-2)	-0.0516	0.0123	-4.21	0.002
Δln_imports(-3)	-0.0479	0.0128	-3.74	0.005
Δln_imports(-4)	-0.0253	0.0123	-2.06	0.070
Δln_yield(-1)	-0.7411	0.2681	-2.76	0.022
Speed of Adjustment				
ECM(-1)	-1.3706	0.2599	-5.27	0.001
Model Statistic	Value	Diagnostic Test		Result
Observations	22	BG LM (lags = 4)		9.134(0.0577)
R²	0.9708	Breusch–Pagan		0.41 (0.5243)
Adjusted R²	0.9319	White test		16.51(0.400)
Log-likelihood	24.94 (p<0.001)	ARCH LM (Lag 4)		0.10(0.8676)
Log-likelihood	72.701	Ramsey RESET		1.17 (0.3949)
Root MSE	0.0139	Residual Normality		1.10 (0.5763)
AIC	−119.40	CUSUM		Stable/Stable
BIC	−105.22	CUSUMSQ		Stable
		Durbin–Watson		≈ 2.290

Table 6 presents the estimated long-run and short-run coefficients of the rice supply response model using the ARDL(1,3,4,1) specification.

The results provide insights into how harvested rice area responds to economic incentives, import dynamics, and productivity factors within the Philippine agricultural sector. Net returns (ln_net) have a positive and highly significant long-run coefficient of 0.0691 ($p < 0.001$), indicating that a 1% increase in net returns is associated with a 0.07% increase in harvested rice area. Although the elasticity is relatively modest, the result confirms the central proposition of Nerlovian supply response theory that farmers respond positively to economic incentives when making long-run production decisions [16,17,19]. The relatively small magnitude suggests that land allocation decisions in Philippine rice farming are influenced not only by profitability but also by structural constraints such as land availability, tenure arrangements, irrigation access, and production risks. Nevertheless, the significance of net returns indicates that policies aimed at improving farm profitability through productivity enhancement, cost reduction, or price stabilization can contribute to sustaining domestic rice production.

Rice imports (ln_imports) exhibit a positive but statistically insignificant long-run coefficient of 0.0064 ($p = 0.371$). This finding suggests that import volumes do not significantly influence long-run harvested rice area. While import liberalization may affect domestic market conditions in the short run, farmers' long-term land allocation decisions appear to be driven more strongly by domestic profitability and productivity considerations than by fluctuations in import volumes. This result differs from studies suggesting that import competition discourages domestic production through downward pressure on farmgate prices [26,27,42]. One possible explanation is that Philippine rice producers adjust to import competition through productivity improvements and technological adaptation rather than reducing cultivated area. Consequently, imports may affect prices and incomes without necessarily altering long-run production decisions.

Rice yield (ln_yield) exhibits a positive and statistically significant long-run elasticity of 0.3959 ($p = 0.004$), indicating that a 1% increase in rice yield is associated with an approximately 0.40% increase in harvested rice area, ceteris paribus. This finding suggests that productivity improvements encourage farmers to maintain or expand rice cultivation by increasing expected output per unit of land and improving production efficiency. The result is consistent with the agricultural development literature emphasizing technological progress, improved seed varieties, irrigation investments, and better crop management practices as fundamental drivers of agricultural growth and supply expansion [21,37,38]. Productivity-enhancing technologies reduce production risk and improve land-use efficiency, thereby strengthening incentives for sustained rice cultivation [3,8,31,32]. In the Philippine context, historical gains in rice productivity during and after the Green Revolution contributed significantly to increases in domestic rice production despite limited opportunities for extensive land expansion [38].

Therefore, the long-run results indicate that productivity growth and farm profitability remain the most important determinants of rice supply response in the Philippines. The findings support policies that promote yield-enhancing technologies, efficient resource use, and improvements in farm-level profitability as mechanisms for strengthening domestic rice production and food security [3,8,21].

Short-Run Dynamics

The short-run dynamics reveal that rice supply adjustments are influenced by lagged changes in profitability, imports, and productivity. Several lagged differences of net returns and rice imports are statistically significant, indicating that farmers respond to short-term economic signals when making production and land-use decisions.

Net Returns. The lagged changes in net returns are all negative and statistically significant. Specifically, Δln_net(-1), Δln_net(-2), and Δln_net(-3) have coefficients of −0.0897 ($p = 0.009$), −0.0919 ($p = 0.005$), and −0.0589 ($p = 0.014$), respectively. These results indicate that increases in net returns during previous periods are associated with reductions in harvested rice area in the short run.

At first glance, this finding appears contrary to conventional supply response theory, which predicts a positive relationship between profitability and production. However, in agricultural systems, short-run responses often differ from long-run adjustments due to biological production cycles, land constraints, and adaptive expectations. Farmers may experience unusually high net returns during periods of limited supply or favorable market conditions, but they may be unable to expand cultivated area immediately because of fixed land resources, labor constraints, and seasonal production schedules [16,17,43]. Moreover, high profitability in one period may induce subsequent adjustments in production decisions that temporarily reduce net returns because of increased input use or changing market conditions. Consequently, the negative short-run coefficients may reflect transitional dynamics and adjustment costs rather than a true inverse relationship between profitability and rice cultivation.

Rice Imports. The coefficients of lagged changes in rice imports are also negative and statistically significant. The estimated effects range from −0.0208 for Δln_imports(-1) ($p = 0.049$) to −0.0516 for Δln_imports(-2) ($p = 0.002$), while Δln_imports(-3) remains significant at −0.0479 ($p = 0.005$). The fourth lag, Δln_imports(-4), is marginally significant at the 10% level ($\beta = -0.0253$, $p = 0.070$).

These findings suggest that increases in rice imports reduce harvested rice area in the short run. Greater import inflows increase the supply of rice in domestic markets, placing downward pressure on farmgate prices and reducing farmers' expected revenues. As a result, producers may temporarily reduce planting intentions or postpone investments in rice production [26,27,42]. The stronger effects observed at the second and third lags imply that farmers do not respond immediately to import shocks; rather, the impact emerges gradually as market information becomes incorporated into production decisions. This delayed response is consistent with the seasonal nature of rice cultivation, where decisions regarding land preparation, planting, and input allocation are made months before harvest.

Importantly, while imports exert significant short-run effects, the long-run coefficient is statistically insignificant. This suggests that import shocks primarily influence short-term production behavior and market expectations rather than permanently altering land allocation decisions. Over time, farmers appear to adjust through productivity improvements and adaptation strategies, thereby neutralizing the long-run impact of imports on harvested area.

Rice Yield. The coefficient for Δln_yield(-1) is negative and statistically significant ($\beta = -0.7411$, $p = 0.022$), indicating that a 1% increase in rice yield in the previous period is associated with an approximately 0.74% decrease in harvested area in the current period.

This inverse short-run relationship may reflect a land-saving effect of productivity gains. When farmers achieve higher yields, they can produce more output from existing land resources, reducing the immediate need to expand cultivated area. Under the sustainable intensification framework, productivity improvements often increase output without requiring proportional increases in land use [3,8,31]. Consequently, short-term gains in yield may encourage more efficient land utilization rather than expansion of harvested area.

Another explanation is that exceptionally high yields in one season may lead farmers to reallocate land temporarily toward alternative crops in subsequent periods, particularly when expected returns from rice decline because of increased market supply. Thus, while productivity growth stimulates rice cultivation in the long run, short-run fluctuations in yield may generate temporary adjustments in land-use decisions.

Taken together, the short-run results indicate that harvested rice area responds negatively to lagged changes in profitability, imports, and yield. These findings highlight the presence of adjustment costs, adaptive expectations, and production rigidities within the Philippine rice sector. Unlike the long-run equilibrium relationship, where profitability and productivity encourage expansion of rice cultivation, short-run responses are shaped by temporary market conditions, delayed production decisions, and resource constraints. Such dynamics are consistent with Nerlovian supply response theory, which emphasizes that farmers adjust gradually to economic signals rather than instantaneously [16,17,19]. The results therefore underscore the importance of distinguishing between short-run fluctuations and long-run structural drivers when formulating agricultural and food security policies.

Speed of Adjustment

The coefficient of the error correction term, ECM(-1) = −1.3706 ($p = 0.001$), is negative and highly significant, confirming the existence of a stable long-run equilibrium relationship among harvested area, net returns, imports, and yield. The magnitude of the coefficient implies that approximately 137.1% of deviations from long-run equilibrium are corrected within one year. Because the coefficient exceeds unity in absolute value, the adjustment process exhibits overshooting, whereby the system initially adjusts beyond its long-run equilibrium before converging back toward equilibrium in subsequent periods. Such behavior is not uncommon in agricultural markets characterized by delayed production responses, adaptive expectations, and cyclical adjustments in land allocation and resource use [16,43].

The highly significant error-correction coefficient indicates that the Philippine rice sector possesses a strong capacity to restore equilibrium following economic or production shocks. Changes in profitability, productivity, or market conditions may generate temporary deviations from equilibrium, but the adjustment mechanism operates rapidly to re-establish the long-run relationship. This finding highlights the resilience of the rice production system and underscores the importance of policies that support productivity growth, profitability enhancement, and adaptive capacity in the face of market and climatic uncertainties [11,13,44]. The ECM results demonstrate that while short-run responses may fluctuate because of economic and market shocks, the long-run equilibrium relationship remains stable and economically meaningful, providing strong empirical support for the estimated ARDL framework [30,36].

Diagnostic Tests

Diagnostic tests confirm the adequacy and robustness of the ARDL(1,3,4,1)-ECM model [30]. The Breusch–Godfrey LM test ($\chi^2 = 9.139$, $p = 0.0577$) indicates no evidence of serial correlation at the 5% significance level, while the Durbin–Watson statistic of 2.290, which is close to the benchmark value of 2, suggests the absence of first-order autocorrelation in the residuals. The Breusch–Pagan ($p = 0.5243$), White ($p = 0.3995$), and ARCH LM ($p = 0.8676$) tests confirm homoscedastic residuals, while the Ramsey RESET test ($p = 0.3949$) suggests correct model specification. The residual normality test ($p = 0.5763$) further indicates normally distributed errors. Overall, the model demonstrates strong explanatory power ($R^2 = 0.9708$; Adjusted $R^2 = 0.9319$), a highly significant overall fit ($F = 24.94$, $p < 0.001$), low prediction error (Root MSE = 0.0139), and favorable information criteria (AIC = −119.40; BIC = −105.22) [34,35].

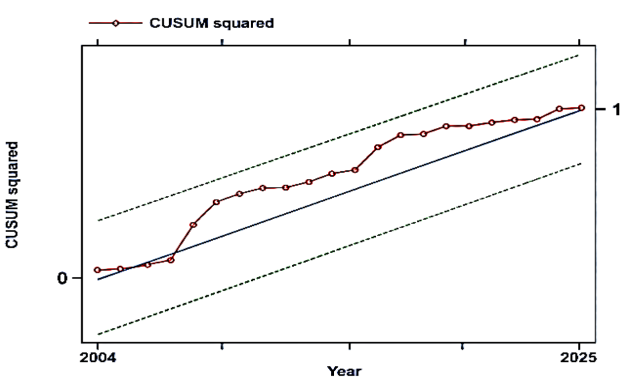

Figure 2. CUSUMSQ Stability Test for the ARDL Model

Figure 2 shows that the CUSUMSQ statistic remains within the 5% critical bounds throughout the sample period, confirming parameter stability and the absence of structural breaks. The ARDL bounds test also indicates cointegration, with the F-statistic (4.560) exceeding the upper critical bound at the 10% level and the bounds t-statistic (−3.659) providing additional support. This finding is reinforced by the negative and highly significant error-correction coefficient, ECM(-1) = −1.3706 ($p = 0.001$), confirming a stable long-run equilibrium relationship among the variables [16,30,36].

CONCLUSION AND RECOMMENDATIONS

This study demonstrates that rice supply response in the Philippines is shaped not only by economic incentives but also by productivity conditions, trade dynamics, institutional support, and broader structural constraints within the agricultural sector. The ARDL results indicate that farm profitability and rice yield are the primary long-run determinants of harvested rice area. While profitability remains an important driver of production decisions, improvements in rice yield exert the strongest positive influence on harvested area, suggesting that farmers respond more consistently to gains in productivity and production efficiency than to short-term market signals alone. Rice imports, although not statistically significant in the long run, exert significant short-run effects, indicating that import flows and trade policies can temporarily influence domestic production incentives and farmers' expectations.

The findings further suggest the existence of a long-run equilibrium relationship among harvested area, net returns, rice imports, and rice yield, supported by the ARDL bounds test and the negative and highly significant error-correction coefficient. The rapid adjustment toward equilibrium indicates that the Philippine rice sector is capable of correcting short-run deviations arising from economic, market, or production shocks. The results highlight the importance of strengthening both productivity and profitability as complementary drivers of domestic rice production.

A limitation of the study is the potential endogeneity between harvested area and rice yield, since both may be jointly influenced by irrigation development, technological adoption, climatic conditions, and other unobserved factors. Future studies may employ instrumental variable techniques, panel-data approaches, or additional control variables to further address this issue and strengthen causal inference.

To strengthen rice supply and improve food security, policymakers should adopt integrated and forward-looking strategies: (1) intensify investments in irrigation, mechanization, and climate-resilient technologies; (2) expand access to certified seeds, affordable credit, crop insurance, and productivity-enhancing farm inputs; (3) strengthen agricultural extension services and digital agriculture initiatives that improve farmer decision-making and technology adoption; (4) improve post-harvest systems, storage facilities, and market infrastructure to reduce inefficiencies and production losses; and (5) balance trade liberalization policies with targeted support mechanisms that enhance the competitiveness and resilience of domestic rice producers. Agricultural modernization programs should remain responsive to the realities faced by Filipino farmers and be continuously evaluated to ensure long-term effectiveness. Such coordinated interventions can contribute to a more resilient and competitive rice sector, with potential benefits for farmer welfare, food security, and sustainable agricultural development in the Philippines.

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