

Impact of Rainfall on Paddy Production in Malaysia: An ARDL Approach

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Abstract: Rice is Malaysia's main staple food and plays a crucial role in the country's economy stability and social well-being. However, rice production is highly vulnerable to climate change, especially unpredictable rainfall that causes floods, droughts, and yield losses. This worsens the country's low rice self-sufficiency level (SSL) and threatens food security. This study aims to examine the effects of rainfall on paddy production in both the short and long run. Annual time series data covering the period from 1994 to 2023 were collected and analysed using appropriate time series econometric models, namely the Autoregressive Distributed Lag (ARDL) and Error Correction Model (ECM). The estimated coefficients were constructed in linear equation and logarithmic form and the model passed the relevant diagnostic tests. The estimated short-run coefficients indicate that technological factor significantly enhance rice production, particularly from the second lag period onwards. Similarly, an expansion in cultivated area demonstrates a positive relationship with rice production in both the short and long run. In contrast, rainfall exerts a significant negative effect on rice production, underscoring risks associated with flooding and waterlogging. The Error Correction Model (ECM) confirms the existence of a stable long-run equilibrium, with 90.4% of disequilibrium being corrected annually. These findings highlight the urgent need to strengthen climate adaptation strategies in Malaysia's rice sector. Key measures include improving irrigation management, promoting the adoption of climate-resilient rice varieties, and advancing technology-driven solutions. For policymakers and stakeholders, the results reinforce the importance of sustainable agricultural practices to mitigate climate-related risks and safeguard national food security.

Keywords: Paddy production, rainfall, Autoregressive Distributed Lag (ARDL), Error Correction Model (ECM).

1. Introduction

Agriculture plays a fundamental role in ensuring food security in Malaysia, with rice serving as the nation's staple food and the backbone of dietary needs. As one of the main crops cultivated, rice contributes significantly to caloric intake while supporting rural livelihoods and the wider economy. The Malaysian government has introduced policy initiatives to strengthen self-sufficiency and reduce reliance on imports through infrastructure upgrades, technological support, and productivity-enhancing programs (Saito et al., 2014). Beyond its economic role, rice cultivation is essential for maintaining social stability, as it sustains the income of farming households in rural areas. Within ASEAN, Thailand, Vietnam, and Indonesia dominate production and exports, with Thailand regarded as the "rice bowl of Asia," Vietnam ranking as the second-largest global exporter, and Indonesia steadily increasing production toward self-sufficiency (Nielsen, 2003). These regional examples highlight how rice remains central not only to food security but also to national development strategies.

In contrast, Malaysia remains a net importer, with official statistics indicating that approximately 30% to 40% of its rice consumption is met through imports rather than domestic production (DOSM, 2021). Recent data underscore the extent of this dependency. The self-sufficiency ratio (SSR), which measures domestic production against national consumption, has declined from 68.0% in 2018 to 56.2% in 2023 based on Table 1. According to Table 2, the harvested paddy area contracted from 699,860.0 hectares in 2018 to 613,238.0 hectares in 2023. While average yields stagnated at around 3.5 to 3.7 tons per hectare well below the performance improvements seen in regional competitors. These statistics clearly illustrate Malaysia's structural challenges in achieving rice security.

Table 1. Total imports of rice and Self-sufficiency Ratio (SSR) in Malaysia, 2018 – 2023.

Year	2018	2019	2020	2021	2022	2023
Total imports of rice ('000 mt)	776.1	890.1	1,109.8	1,062.0	1,112.5	1,281.8
SSR (%)	68.0	62.4	62.1	60.9	57.9	56.2

Table 2. Harvested area and average yield of rice in Malaysia, 2018 - 2023

Year	2018	2019	2020	2021	2022	2023
Harvested area (ha)	699,860.0	670,851.6	644,471.0	645,324.0	635,418.0	613,238.0
Average yield (kg/ha)	3,770.0	3,501.0	3,654.0	3,768.0	3,577.0	3,542.0

One of the critical threats to Malaysia's rice sector is climate change, particularly rainfall variability. Global average temperatures have increased by approximately 1.1°C since the pre-industrial period (1850–1900). Under sustained greenhouse gas emissions, global temperatures are projected to continue rising throughout the 21st century. Estimates suggest an increase of 1.0–1.8°C under very low emission scenarios, 2.1–3.5°C under intermediate pathways, and up to 3.3–5.7°C under high-emission trajectories (IPCC, 2021). For Malaysia, these shifts manifest in erratic rainfall prolonged droughts and recurrent floods. Climate variability and extreme weather events, particularly floods, pose significant risks to rice production in Malaysia. Flooding in paddy areas can cause substantial production losses, while changes in temperature and rainfall patterns may further affect yield stability and food security (Anuar et al., 2023; Firdaus et al., 2020). Studies also found that maximum temperature has a negative association with rice yield during the off-season in Malaysia (Tan et al., 2021).

Taken together, these conditions frame the central problem addressed in this study. Malaysia's rice sector faces a convergence of challenges such as declining self-sufficiency, shrinking cultivated area, stagnant yield, climate-related risks and over-reliance on imports. Nonetheless, structural vulnerabilities including land constraints, labor shortages and climate-related production risks remain deeply embedded and continue to challenge the resilience of Malaysia's rice sector. Without systematic analysis of the key determinants of rice production, Malaysia risks continued vulnerability in its national food security.

The significance of this research lies in providing updated empirical evidence on the drivers of rice production in Malaysia, focusing specifically on cultivated area, technological adoption and rainfall as the primary explanatory variables. Unlike many descriptive studies of paddy production, this study applied the Autoregressive Distributed Lag (ARDL) approach which offers methodological strength by estimating both short and long-run relationships among variables with different integration orders. This flexibility is particularly valuable in agricultural research where climatic, technological and economic factors interact dynamically over time. The novelty of this study lies in integrating time-series econometric analysis with agricultural and environmental variables to jointly assess their influence on rice production in Malaysia. The findings are expected to inform strategies that strengthen resilience, improve productivity, and reduce import dependency, ultimately supporting Malaysia's broader goal of achieving sustainable food security in the face of mounting global and domestic challenges.

2. Literature Review

The literature on rice production consistently emphasizes the interplay between land availability, technological advancement, and climatic variable as critical determinants

of agricultural performance.

2.1 Rice Production and Land Area

The availability of cultivated land remains one of the most critical determinants of rice production. In Malaysia, the cultivated area for rice has declined markedly. One study quantified a loss of over 88,000 hectares (about 22%) in 15 years particularly acute in granary areas (Yasar et al., 2016). A comprehensive review further attributed this reduction to a combination of urbanization, population expansion, industrialization and shifting land values that divert arable land to non-agricultural uses (Mohd Ali et al., 2025). Unlike countries such as Thailand and Vietnam which continue to maintain large rice-growing areas and even expand production zones, Malaysia faces persistent land-use competition that restricts the growth of its rice sector. The relationship between land availability and rice production has also been well established internationally. For example, a regional study in China's Yangtze River Delta further illustrates how farmland conversion driven by urban expansion directly threatens regional self-sufficiency (Duan et al., 2021).

2.2 Technological Adoption in Rice Production

Technological advancement plays a decisive role in improving rice productivity and ensuring long-term food security. In Malaysia, the uptake of modern agricultural technologies such as mechanization, improved inputs and digital tools has been encouraged through various subsidies and government-led programs. Investment in rice research and development pays dividends when matched by institutional support that ensures equitable access and effective technology transfer. Meanwhile, smart farming initiatives show promising interest among rice farmers though actual implementation continues to be uneven across regions (Kamarul Zaman et al., 2023). Farmers in Sekinchan frequently rely on service providers for mechanized tasks due to affordability and scale constraints (Mohd Nawi et al., 2022). Technological innovations in Malaysia's rice sector ranging from improved seed varieties to smart farming tools, offer considerable potential to enhance productivity. However, adoption remains restrained by socio-economic constraints including low farmer education levels, complex grant procedures and inadequate extension services (Kamarul Zaman et al., 2023). Even where small-scale mechanization exists, true efficiency gains are hampered by poor technical planning and field conditions (Kamaruddin et al., 2025).

2.3 Climate Change and Rainfall Variability

Malaysia has experienced rapid climate change for decades (NAHRIM, 2006). Among the important climate factors are changes in rainfall amount and patterns, which causes floods. The historical rainfall data showed the rainfall peaked at the end of 2004 and 2009 (Tan, 2019; Malaysia Metrological Department, 2009). In general, flood-prone areas in Malaysia were estimated at 29,800 square kilometers (sq. km) or 9% of land area and affected 3.9 million people in the country (Al-Amien, 2011; Jabatan

Pengaliran dan Saliran, 2018). Higher detailed regional analysis of Providing Regional Climates for Impact Studies (PRECIS) rainfall simulations released by MMD is shown in Table 3. A significant period of increased annual rainfall is predicted to occur toward the century's end (2090-2099), with a higher increase in rainfall for PM compared to EM. During 2050-2059, North-West PM recorded the highest increase in rainfall (6.4%), followed by North-East PM, while Sabah recorded a negative anomaly. Rainfall variability plays a critical role in shaping planting decisions, crop development and yields in Malaysia's rice sector. Although temperature exerts a more pronounced influence, studies using ARDL approaches reveal that precipitation patterns particularly during sensitive growth stages (Solaymani, 2023). Model projections for Malaysia's main granary regions suggest yield losses ranging from 19% to 27% under climate scenarios with greater rainfall inconsistency and warming temperatures (Abdul Talib et al., 2024).

Table 3. Projection annual rainfall change (%) for 2020-2099 relative to 1990- 1999 period

Region	2020-2029	2050-2059	2090-2099
North-West PM	-11.3	6.4	11.9
North-East PM	-18.7	6.0	4.1
Central PM	-10.2	2.3	14.1
Southern PM	-14.6	-0.2	15.2
East Sabah	-17.5	-12.8	-3.6
West Sabah	-8.9	-1.2	0.3
East Sarawak	-9.1	-1.3	6.2
West Sarawak	-8.8	3.8	14.6

(Source: MMD, 2009)

Previous studies demonstrate that rainfall variability combined with rising temperatures disrupts cultivation cycles and leads to reduced yields (Mohd Ekhwan, 2014; Zhang et al., 2023). Rising night time temperatures rather than daytime highs or precipitation changes led to substantial yield declines in irrigated rice, estimating a roughly 10% drop in grain yield for every 1°C increase in minimum temperature during the dry season (Peng et al., 2004). Kedah is widely acknowledged as the “rice bowl” of the nation accounting for nearly 40% of the country's total paddy production with about 85% of the nation's main rice crop produced in northern Peninsular Malaysia. This centralization means that localized climate and environmental shocks such as floods or droughts in Kedah can disproportionately impact national rice supply making Malaysia's rice security particularly fragile. International evidence supports

the idea that climate variability undermines crop yields.

2.4 ARDL Applications in Agriculture

The Autoregressive Distributed Lag (ARDL) model is a dynamic econometric technique widely used to examine both short-run and long-run relationships among time-series variables. It is particularly suitable when variables are integrated of different orders, $I(0)$ and $I(1)$, but not $I(2)$. Pesaran, Shin, and Smith introduced the bounds testing procedure that accommodates variables integrated at different levels and performs well with small samples (Pesaran et al., 2001). Moreover, the ARDL model enables forecasting and policy simulation providing valuable insights for assessing climate impacts on agricultural productivity and guiding adaptation strategies. It is widely used to disentangle the short- and long-run effects of climatic and non-climatic factors on agricultural productivity. For instance, ARDL analysis revealed that temperature negatively impacts rice yields in the long run while variables such as fertilizer use and cultivated area yield positive effects in Pakistan (Gul et al., 2022). Similarly, an ARDL-based study in Turkey found that climatic factors like temperature and precipitation differently influence rice and wheat outputs across time horizons (Asante et al., 2021). In Malaysia, while regression and other static analyses have explored climate and production links, the use of ARDL models remains sparse. Recently, Afroz et al. (2022) used ARDL at Kedah state levels, found that long-run increases in temperature reduced rice output by about 7% while rainfall had state-specific impacts (Herath et al., 2019). Even more robust is the symmetric and asymmetric analysis using NARDL, which confirms statistically significant effects of cultivated area and rainfall shocks on rice production over time. These examples underscore ARDL's potential to advance understanding of Malaysia's rice sector dynamics amid climate variability, yet much remains unexplored especially regarding the combined influence of land, technology and rainfall.

3. Methods

The methodology of this study was designed to analyze the relationship between climatic and non-climatic factors influencing paddy production in Malaysia. A quantitative approach using time-series data was applied to capture both short-term fluctuations and long-term dynamics. Econometric techniques, particularly the ARDL framework were employed to ensure robust and reliable results.

3.1 Conceptual Framework

This study applied a conceptual framework in Figure 1 to illustrate the expected relationships among the variables. The framework aligns the research objectives with the chosen methodology to ensure coherent conclusions. The conceptual framework posits that cultivated area, technology and rainfall causally influence the rice production. Cultivated area determines production scale, the technology proxy captures improvements in input efficiency and yield and rainfall represents climatic

conditions that directly affect paddy performance.

3.2 Research Area

This research was carried out in Malaysia which has a total land area of 330,803 km² with about 77,000 hectares allocated to paddy cultivation. The study relied on secondary data covering the period from 1994 to 2023 obtained from a range of authoritative sources. Production of paddy and land-use statistics were sourced from the Department of Statistics Malaysia (DOSM) and the Food and Agriculture Organization (FAOSTAT). While annual mean rainfall data was provided by the Malaysian Meteorological Department (MMD).

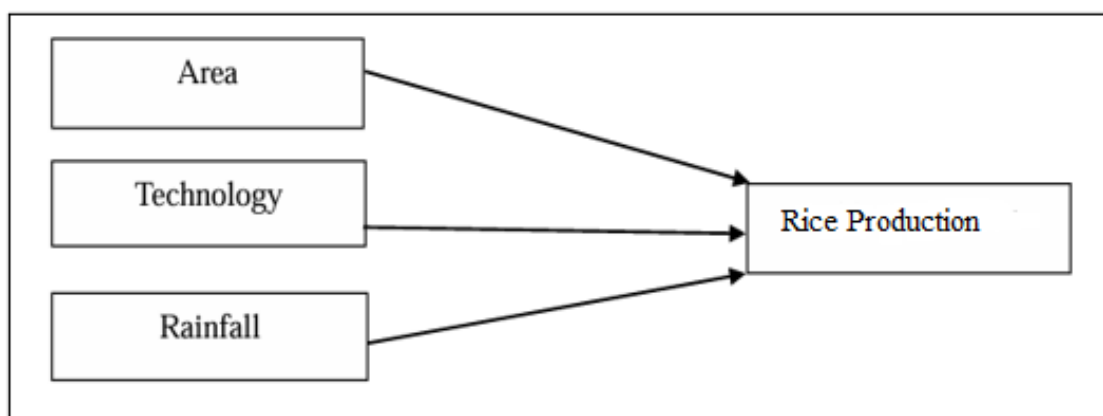


Figure 1: Conceptual framework of the study

3.3 Pearson Correlation Analysis

Pearson correlation analysis is a statistical technique used to measure the strength and direction of the linear relationship between two continuous variables. The correlation coefficient (r) ranges from -1 to +1. It is widely applied in scientific research to determine associations among quantitative variables supporting hypothesis testing and data interpretation (Pallant, 2020).

3.4 Stationary Tests

The pioneering work on testing for a unit root in time series was done by Dickey and Fuller in 1979 (Pallant, 2020). The Augmented Dickey-Fuller (ADF) and The Phillips-Perron (PP) unit root tests are the most extensively used methods for evaluating the stationarity level of data sets. The ARDL model passed a number of diagnostic tests to guarantee the accuracy of the econometric analysis. The Augmented Dickey-Fuller test is a reliable alternative for time series with bigger number of observations and it is most regularly used to verify that the errors are uncorrelated. The unit root tests developed by Phillips and Perron (1988) differ from the ADF tests primarily in how the tests manage each serial correlation and heteroskedasticity in the errors.

3.5 Model Validation

Model validation is required to establish a model's predictive capability and to boost model confidence. As observed by Spanos (2011) validation criteria include: (i) statistical (goodness of fit or prediction and statistical significance), (ii) substantive meaningfulness, and (iii) pragmatic norms (simplicity and parsimony). The diagnostic test carried out was autocorrelation, which examines whether error terms are correlated across time periods. The regression estimators are no longer effective with lowest variance even though autocorrelation is still linearly unbiased. It can be found using statistical or graphical techniques like the Breusch-Godfrey Lagrange Multiplier (LM) test and the Durbin-Watson test. The Breusch-Godfrey test is preferred for high order autoregressive errors such as AR(1) and AR(2) as it allows non-stochastic regressors, such as the lagged values of the regressand (Gujarati and Porter, 2009). Second diagnostic test was heteroscedasticity which occurs when the variance of the error term is not constant across observations. In this study, the Breusch-Pagan-Godfrey (BPG) test was applied to detect the presence of heteroskedasticity (Wooldridge, 2020).

It is crucial to evaluate the normality of data in order to prevent incorrect deductions and conclusions. Normality can be measured through visual and normality tests. The Jarque-Bera (JB) test of normality was originally proposed by Bowman and Shenton in 1975 and subsequently was derived by Bera and Jarque as the LM test in 1982 (Mantalos, 2011). The fourth diagnostic test conducted was the Ramsey Regression Equation Specification Error Test (RESET) which assesses whether the functional form of the estimated model is correctly specified. It detects specification errors such as omitted variables, incorrect functional form, or inclusion of irrelevant variables that may bias coefficient estimates (Wooldridge, 2020). The CUSUM and CUSUMSQ tests ought to be performed in tandem due to the CUSUM test's ability to identify structural changes in the regression's intercept. Nonetheless, the CUSUMSQ test has greater power if the structural change involves a slope coefficient or the error term's variance (Caporale et al., 2004). The CUSUMSQ is the best approach to detecting endogenous regressors and errors with weak serial correlations in both stationary and co-integration models (Turner, 2010). Accordingly, both tests are complementary and used in this study.

3.6 The Autoregressive Distributed Lags (ARDL)

The Autoregressive Distributed Lag (ARDL) co-integration approach or bound co-integration testing technique provides more efficient and accurate for small data sets when working with variables that are integrated in different orders, $I(0)$, $I(1)$, or a combination of the two (Omoniyi and Olawale, 2015). However, non-stationary variables of order two $I(2)$ are not compatible with ARDL (Haq and Larson, 2016). The ARDL approach offers several advantages including its applicability to small sample sizes and its ability to provide unbiased long-run estimates. The model incorporates lagged values of both dependent and independent variables allowing it to capture

temporal dynamics and adjustment processes. Through the bounds testing procedure, ARDL can determine the existence of long-run co-integration among variables. This flexibility makes it a preferred method in agricultural and environmental studies, where economic and climatic factors often interact over time (Chizari et al., 2017). ARDL bound testing approach or known as the Unrestricted Error Correction Model (UECM) was used in testing the existence of long-run relationship and was specified as follows:

$$Y = \alpha_0 + \beta_1 A + \beta_2 T + \beta_3 RF + \mu \quad \dots\dots\dots(1)$$

Logarithmic transformation was added to enhance the validity and interpretability of econometric estimations. Equation (1) above can be well presented into a time series model by adding subscript (t) in each variable with the exception of intercept (α_0). Therefore, the reorganized model becomes:

$$Y = \alpha_0 + \beta_1 \ln A_t + \beta_2 \ln T_t + \beta_3 \ln RF_t + \mu_t \quad \dots\dots\dots(2)$$

Where, Y = rice production (ton) in period t , $\ln A_t$ = Log of cultivated area (Ha) in period t , $\ln T_t$ = Log of technology in period t , $\ln RF_t$ = Log of rainfall (millimeter) in period t , μ_t = error term.

The non-standard asymptotic distribution of the F-test statistic is used to identify the long-term association. Since the study's sample size was below 80 observations, the critical value provided by Narayan (2005) was applied. In the higher critical limit, all variables are expected to integrate at $I(1)$, while in the lower critical bound (0), all variables are assumed to integrate at $I(2)$. The null hypothesis is rejected and co-integration is present if the calculated F-statistic is greater than the upper bound of critical values. The result is inconclusive if the F-statistic lay between the lower and upper bound value. It is important to determine the autoregressive lag length for a time series in order to have Gaussian error terms. There are various lag length selection criteria that have been employed by scholars, such as Akaike's information criterion (AIC), Schwarz Bayesian information criterion (SIC), Hannan-Quinn criterion (HQC), and final prediction error (FPE). The appropriate lag arrangement avoids being excessively small or large. A maximum of two delays for annual data from which the lag length that maximizes AIC or SIC was chosen for this study.

3.7 Error Correction Model (ECM)

The Error Correction Model (ECM) was applied in this research to examine both the short-run and long-run effects of rainfall on rice production in Malaysia. Since rainfall

and paddy yield are often co-integrated, ECM effectively captures the short-term adjustments towards long-run equilibrium. The model identifies how deviations from equilibrium caused by irregular rainfall patterns are corrected over time. The error correction term measures the speed at which rice production responds to rainfall fluctuations reflecting the system's stability. Thus, ECM provides valuable insights into the dynamic interaction between climatic variables and agricultural output ensuring robust and meaningful econometric interpretation (Gujarati and Porter, 2009).

4.0 Results and Discussion

This section presents the empirical findings of the study and interprets their implications for rice production in Malaysia. The analysis begins with stationarity test, diagnostic tests and co-integration test to establish the validity of the econometric framework. Correlation analysis is then used to provide preliminary insights into variable relationships, while the ARDL and ECM outputs are discussed in detail to highlight both short-run and long-run effects.

4.1 Pearson Correlation

The Pearson correlation coefficients presented in Table 4 provide preliminary insights into the relationships among the variables. Rice production exhibited a moderate positive correlation with technology ($r = 0.662$) suggesting that technological adoption plays a crucial role in enhancing yields. The relationship with cultivated area was weakly positive ($r = 0.137$) indicating that land expansion alone contributes only marginally to production increases. In contrast, rainfall showed a modest negative correlation ($r = -0.159$). It implying that excessive or poorly distributed rainfall may slightly reduce production due to waterlogging or related agronomic stresses. These findings are consistent with previous studies highlighting that technological advancement significantly improves rice productivity, while rainfall variability can adversely affect yields (Firdaus et al., 2020).

Table 4: Pearson correlation

	Paddy	Area	Technology	Rainfall
Paddy	1	0.137	0.662	-0.159
Area	0.137	1	-0.415	-0.211
Technology	0.662	-0.415	1	-0.001
Rainfall	-0.159	-0.212	-0.0007	1

4.2 Stationarity Results

In empirical analysis, the first step is to establish the order in which the data series are integrated. Both the ADF and PP tests were used as standard testing methods. The optimal lag length chosen based on the SIC was due to a small data set. The options of constant with trend method for variables at the level and only constant or intercept method for the variable at first difference were considered for both tests. Table 5 reveals that both tests concurred in classifying the following variables as I(1): InY (Log of rice production) and InA (Log of Area) which were not stationary in their level form except after first differencing. However, InT (Log of technology) and In RF (Log of rainfall) were confirmed to be stationary in their level form, as indicated by their critical values which are all significant at 5% level. These results validate the use of the ARDL approach as it accommodates variables with mixed integration orders (I(0) and I(1)). The presence of I(1) variables also justified testing for long-run relationships using the bounds co-integration test.

Table 5: ADF and PP unit root test

Variables	ADF		PP	
	Level	First Differencing	Level	First Differencing
<u>InY</u>	-1.704	-7.203***	-1.604	-7.240***
<u>InA</u>	-1.022	-6.142***	-1.113	-6.125***
<u>InT</u>	-4.295***	-6.334***	-4.179***	-13.691***
<u>InRF</u>	-4.319***	-6.441***	-8.363***	-13.506***

Note: (*) and (**) denote level of significance at 5% and 1%, respectively.

4.3 Model Validation Results

Several diagnostic tests were conducted to verify the adequacy of the ARDL model. Table 5 shows that the model passed all specification checks which is no serial correlation was detected ($p = 0.7869$). The heteroskedasticity test records a statistic of 0.4621 with a p-value of 0.8284, confirming that the error variances are constant and homoscedasticity. The Ramsey RESET test produces a statistic of 0.0368 with a p-value of 0.8496 indicating that the model is correctly specified with no functional form misspecification. Lastly, normality test records a statistic of 0.1469 with a p-value of 0.9291 indicating that the residuals are normally distributed and thus satisfy the normality assumption of the model. These findings reveal that null hypotheses could not be rejected at the 5% level of significance confirming that the estimated ARDL model is statistically sound, well-specified and suitable for reliable interpretation.

Table 5: Results of diagnostic tests

Test	Test Statistic	p-value
Serial Correlation (LM test)	0.2427	0.7869
Heteroskedasticity (Breusch-Pagan-Godfrey)	0.4621	0.8284
Stability (Ramsey RESET Test)	0.0368	0.8496
Normality (Jarque-Bera test)	0.1469	0.9291

4.4 ARDL Bound Test Co-integration

The minimum SIC and AIC values were used to establish the lag duration for each equation with a maximum lag order of two. Table 6 shows that the F-statistic laid between the lower and upper bound values confirming have inconclusive bound test. Following Kremers et al. (1992) the error correction term (which must be negative, less than one, and significant) was employed to establish co-integration in inconclusive cases. The finding suggested that the estimated model can be treated as co-integrated model.

Table 6: ARDL Co-integration Test

Equation	K	SIC (Min. Value)	F-Statistic	Narayan (2005) CV at 5%		Remark
				I(0)	I(1)	
1	3	-4.011	3.485**	3.23	4.35	Inc.

Note: (**) and (***) denote level of significance at 5% and 1%, respectively. K = Number of exogenous variables in each equation; SIC= Schwarz Information Criterion (Minimum value in each equation); CV = Critical Values at 5% level of significance.

4.5 Estimated Long-Run Coefficients

The long-run coefficients were derived from Equation 2 as presented in Table 7. The estimated long-run level equation that passed the structural stability test are depicted in Figure 2 and 3. The estimated equation appear stable as CUSUM test statistics did not exceed the bounds at a 5% level of significance. Model used was specified based on the ARDL specification of 1020.

Table 7: Estimated long-run coefficients

Independent Variable	Equation 2	t-Statistic	Prob
<u>lnA</u>		5.7871	0.000
LT	2.0163***		0.9667
LRF	0.0033	0.0422	0.0065
C	-0.2654***	-3.0216	0.0377
	-4.6752**	-2.2175	

Note: Dependent variable: rice production. (*), (**), and (***) denote level of significance at 5% and 1%, respectively.

The long-run estimation results presented in Equation 2 demonstrate distinct relationships between cultivated area, technology, and rainfall with rice production. The coefficient of cultivated area (2.0163) was positive and highly significant. When the cultivated area of paddy increases by 1%, the paddy production increases by 2.02% considering all other factors remain constant. It indicates that an expansion in cultivated area contributes substantially to increased rice production in the long run. This suggests that land availability remains an important driver of output in Malaysia's rice sector. Che Omar et al. (2019) found that cultivated area expansion directly enhances crop yields, particularly where land productivity is not yet at saturation.

The coefficient of technology (0.0033) was positive but statistically insignificant, suggesting that technological adoption has not yet translated into significant long-run productivity gains. This could be due to limited diffusion of advanced technologies, high input costs or inadequate technical support services for farmers. Similar findings were reported by Abdulai et al. (2019) and Rahman et al. (2018) who observed that the potential benefits of technology in developing agricultural systems are often constrained by socio-economic and institutional barriers. Conversely, the coefficient of rainfall (-0.2654) was negative and statistically significant at the 1% level indicating that a 1% increase in rainfall will decrease the paddy production by 0.27%. This outcome aligns with Asante et al. (2021) and Sarker et al. (2020) who emphasized that extreme rainfall disrupts planting schedules, reduces soil fertility and increases flood risks. All of which can significantly lower yields. The negative sign reflects the sensitivity of Malaysia's rice sector to climatic variability, highlighting the need for adaptive strategies such as improved irrigation, climate-resilient varieties, and precision water management.

4.6 Estimated Short-Run Coefficients

In order to estimate the short-run coefficients, the extracted residual from the co-

integrating regression in Table 7 above was used in estimating ECT. The estimated coefficient for the ECT with one period lag (ECT_{-1}) confirms the existence of a long-run relationship among the variables in the tested models since the coefficient has a negative sign and was statistically significant at 5%. The ECT_{-1} value of -0.896 indicating that a deviation from the long-run equilibrium is corrected with a period lag at a rate of 90% per year. These results appear to be well substantiated by the theoretical prediction of the partial adjustment and adaptive expectation models (Askari and Cummings, 1977) which propose that production will adjust but not fully adjusted. The value of F-statistic (35.1268 with p value less than 0.01), R^2 value of 0.9094 and Adjusted R^2 of 0.8835 suggest that the model explains approximately 88% of the variation in rice production and indicating a strong goodness of fit. The Durbin-Watson statistic of 2.0840 further suggests the absence of serial correlation, confirming model reliability.

Table 8: Estimated short-run coefficients

Independent Variable	Equation 2	t-Statistic	Prob
$\ln A(-1)$		5.7443	0.0000
$\ln T(-1)$	1.8069***	-3.3231	0.0032
$\ln T(-2)$	-5.2113***	3.9136	0.0008
$\ln RF$	2.6935***	-2.7678	0.0115
ECT_{-1}	-0.2379**	-6.4828	0.0000
F-Stat	-0.8961***		0.0000
R^2	35.1268***		
Adjusted R^2	0.9094		
DW	0.8835		
	2.0840		

Note: Dependent variable: rice production. (*), (**), and (***) denote level of significance at 10%, 5% and 1%, respectively.

The estimated coefficient of cultivated area was positive and significant at 5% level at lagged one period. It suggests that a 1% increase in the cultivated area leads to a 1.81% increase in current rice production, holding other factors constant in short-run consideration. This indicates a persistent effect of land utilization over time which consistent with Ochieng et al. (2021) who observed that land expansion enhances production stability in smallholder rice systems. Specifically, the short-run elasticity of technology (-5.2113) indicates that a 1% increase in technology adoption initially reduces rice production by about 5.21% holding other factors constant. In the short run, new technologies may initially reduce output due to the learning curve, adjustment costs or temporary disruptions in production practices. However, after two periods the positive elasticity of technology (2.6935) shows that a 1% increase in

technology ultimately raises paddy production by approximately 2.69% once farmers adapt and effectively utilize the new technologies. This pattern suggests that technological adoption has short-term disruptive effects but yields long-term productivity gains. This aligning with Chandio et al. (2021) and Kassie et al. (2015) who found that the benefits of innovation in agriculture are realized after an adjustment period when users become proficient with new systems.

Rainfall plays a crucial role in rice production as it directly influences water availability, soil moisture, and crop growth stages. In this study, the estimated short-run elasticity of rainfall (-0.2379) suggests a negative and statistically significant relationship with rice output. It indicates that a 1% increase in rainfall will reduce rice production by about 0.24% holding other factors constant. This finding aligns with Nayak et al. (2019) who reported that high rainfall intensity can cause flooding, nutrient leaching and lodging of paddy plants, leading to yield reduction. Conversely, moderate rainfall is beneficial for maintaining soil fertility and supporting germination (Sarker et al., 2020). The negative coefficient observed in this model may reflect Malaysia's tropical monsoon climate, where irregular rainfall patterns and excessive precipitation can disrupt field operations and delay harvesting (Ghosh et al., 2018). Moreover, the result underscores the growing vulnerability of rice production systems to climate variability. This highlights the need for efficient water management and adaptation strategies such as improved drainage systems and the adoption of climate-smart technologies (Ali et al., 2021). Although rainfall remains a vital determinant of paddy cultivation, its increasing unpredictability poses significant risks to production stability. Therefore, greater policy emphasis is required to enhance the resilience of rice production systems against climatic extremes and hydrological uncertainties.

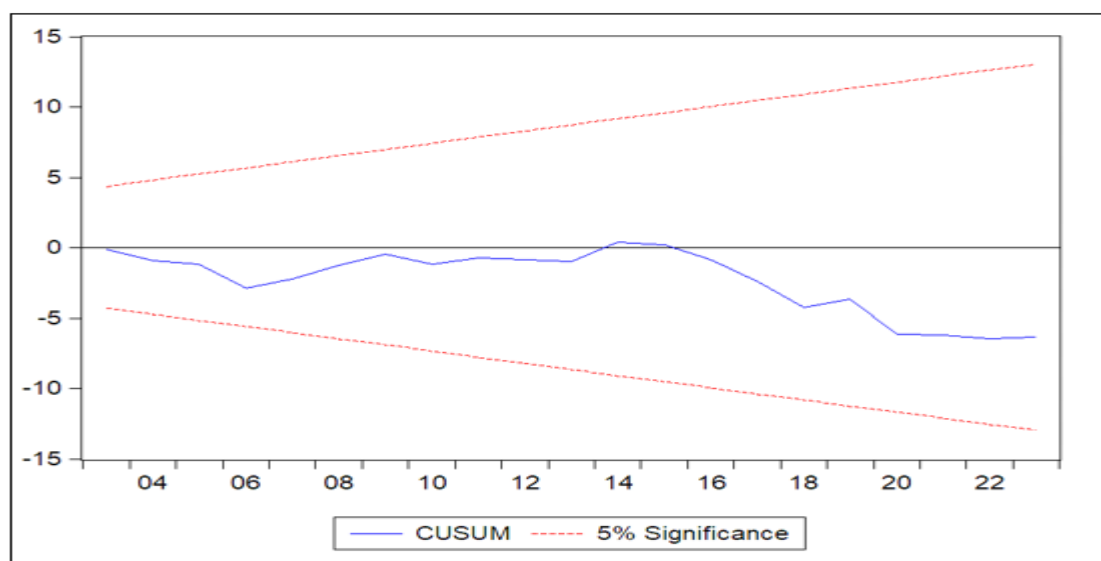


Figure 2: CUSUM Test for Model Stability

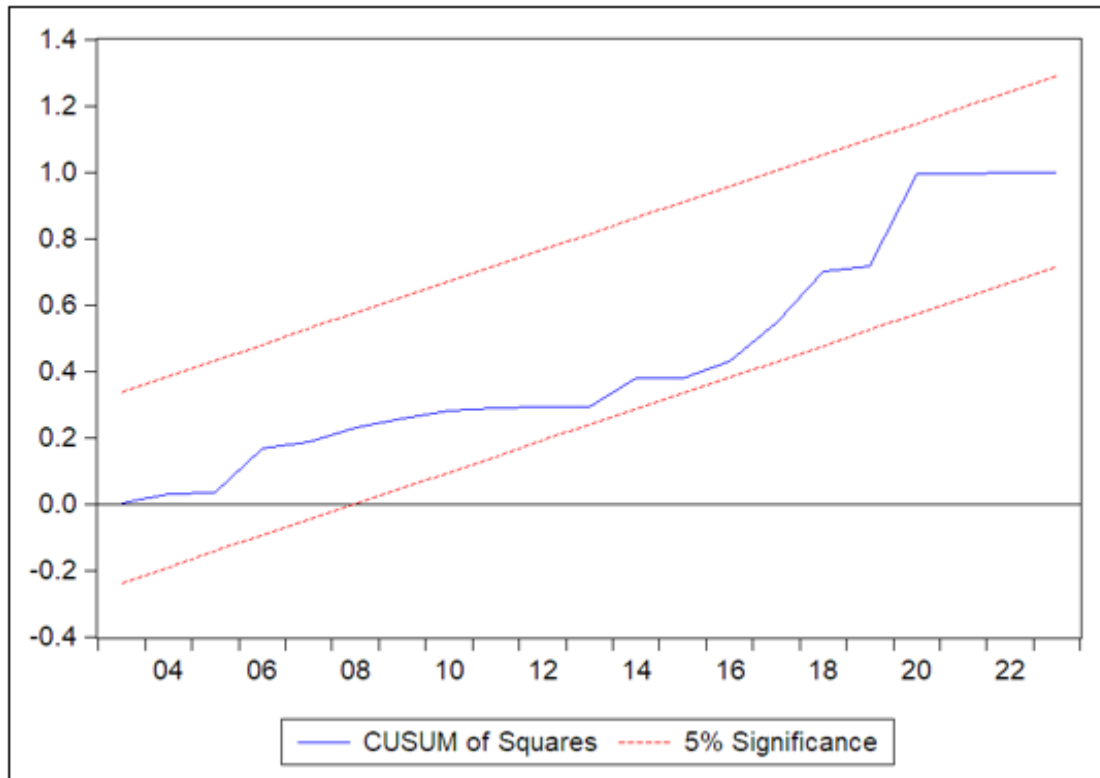


Figure 3: CUSUMSQ Test for Model Stability

5. Conclusion

This study investigated the dynamic effects of cultivated area, technology and rainfall on rice production in Malaysia using the ARDL model to capture both short- and long-run relationships. The results revealed that cultivated area and technology exert a positive and statistically significant influence on rice output underscoring their critical roles in driving production growth and ensuring food security. Expansion of cultivated land enhances the scale of production while technological progress through improved mechanization, precision farming and modern seed varieties contributes to efficiency gains and yield improvements. However, the study also found that rainfall has a negative and significant impact on rice production suggesting that excessive or poorly distributed rainfall adversely affects crop performance. In Malaysia's monsoon climate, irregular rainfall patterns often lead to flooding, nutrient leaching, and delays in planting and harvesting which collectively undermine productivity and increase vulnerability among smallholder farmers.

The findings emphasize the need for integrated strategies that address both productivity enhancement and climate resilience. Policymakers should prioritize investment in irrigation and drainage infrastructure to manage water more efficiently, especially in flood-prone areas. Promoting climate-smart agricultural practices such as the use of flood-tolerant rice varieties, weather-based decision support systems and sustainable land-use planning can strengthen adaptive capacity and reduce risk. In

addition, strengthening institutional support through extension services, farmer training and financial incentives will encourage greater adoption of technology and climate-resilient practices. Future research should explore spatial and temporal variations in rainfall effects, considering regional differences in soil, hydrology, and farming systems. Incorporating additional climatic factors, such as temperature and evapotranspiration would provide a more comprehensive understanding of environmental influences on rice productivity. Further studies could also assess the role of institutional frameworks and farmer behaviour in technology adoption and climate adaptation. Overall, this study underscores that sustaining Malaysia's paddy sector requires the integration of technological innovation, efficient land utilization and adaptive climate strategies to enhance productivity, resilience and long-term food security in the face of increasing climatic uncertainty.

Competing interests

The authors declare that they have no competing interests.

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