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Advances in Environmental and Engineering Research

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Original Research

Climate Variability, Carbon Emissions and Rice Yield in Malaysia: Evidence from an ARDL Approach

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Academic Editor: Hanuman Singh Jatav

Adv Environ Eng Res
2026, volume 7, issue 3
doi:10.21926/aeer.2603023

Received: March 23, 2026
Accepted: July 20, 2026
Published: August 03, 2026

Abstract

Climate variability and environmental change have increasingly become critical challenges affecting agricultural sustainability and global food security. Rice yield is particularly sensitive to climate-related factors, including rainfall variability, temperature changes, and environmental pressure. In Malaysia, rice cultivation is central to national food security and rural livelihoods, yet it remains exposed to changing climatic and environmental conditions. This study examines the relationship between climate variability, environmental pressure, agricultural intensification, and rice productivity in Malaysia using annual time series data from 1980 to 2023. To avoid confounding climatic effects with changes in cultivated area, rice yield (output per hectare) is used as the dependent variable, and fertilizer consumption is included alongside rainfall, temperature, and carbon emissions as explanatory variables. The Autoregressive Distributed Lag (ARDL) bounds testing approach is employed to investigate both short- and long-run dynamics, and the robustness of the long-run estimates is verified using the FMOLS, DOLS, and CCR estimators. The results indicate that carbon emissions exert a positive and statistically significant long-run effect on rice yield, a relationship best interpreted as reflecting the parallel influence of economic development, energy use, and agricultural modernisation rather than a direct agronomic benefit of CO_2. Rainfall, temperature, and fertilizer consumption do not exhibit statistically significant long-run effects, while the error correction term is negative and significant, confirming a stable long-run relationship. The findings suggest that structural and technological factors are more influential than direct climatic conditions in shaping rice productivity in Malaysia, with important implications for agricultural modernisation, water management, balanced fertilizer use, and the integration of environmental sustainability into agricultural policy.

Keywords

Climate variability; rice yield; rainfall; temperature; carbon emissions; fertilizer; Malaysia; ARDL

1. Introduction

Climate variability and environmental change have emerged as major global challenges affecting agricultural productivity and food security. Changes in rainfall patterns, rising temperatures, and increasing environmental pressure associated with economic development have intensified the vulnerability of agricultural systems worldwide [1]. Since agricultural production is closely linked to climatic and environmental conditions, understanding the relationship between climate variables and crop productivity has become increasingly important.

Rice is one of the most important staple foods globally and serves as the primary source of calories for more than half of the world's population [2]. In Malaysia, rice production plays a strategic role in ensuring national food security and supporting rural livelihoods. The Malaysian government has consistently prioritised the development of the rice sector through various agricultural policies aimed at strengthening domestic production and reducing reliance on imports.

However, rice cultivation is highly sensitive to climatic and environmental conditions. Adequate rainfall is required to maintain water levels in paddy fields, while temperature influences plant growth processes such as photosynthesis, respiration, and grain formation [3]. In addition to these climatic factors, environmental pressures associated with economic growth and rising carbon emissions may also influence agricultural productivity through broader climate change processes.

In recent decades, Malaysia has experienced noticeable climatic changes, including rising temperatures and increasing environmental pressure resulting from economic development and industrialization. These changes may affect agricultural production through multiple channels, including changes in precipitation patterns, temperature variability, and environmental degradation.

A growing body of literature has examined the relationship between climate change and agricultural productivity. Previous studies have shown that rainfall and temperature play important roles in determining crop yields [4-6]. More recent studies have also incorporated environmental indicators such as carbon emissions in analysing agricultural productivity and climate change dynamics [7, 8].

Despite the growing literature, empirical evidence on the long-run relationship between climate variability, environmental pressure, and rice productivity in Malaysia remains limited. Many previous studies focus on cross-country comparisons or short-term climate effects, and they often use total rice production, which can confound climatic effects with changes in cultivated area. Furthermore, relatively few studies jointly consider climatic variables, environmental pressure, and agricultural inputs within a unified econometric framework. Therefore, this study examines the relationship between climate variability, environmental pressure, agricultural intensification, and rice productivity in Malaysia using annual time series data from 1980 to 2023. To address the confounding of area and productivity, rice yield (output per hectare) is adopted as the dependent variable, and the analysis investigates the roles of rainfall, temperature, carbon emissions, and fertilizer consumption in determining rice yield using the Autoregressive Distributed Lag (ARDL) modelling approach.

This study contributes to the literature in several ways. First, it provides updated empirical evidence on the climate–agriculture nexus in Malaysia using a long-term dataset spanning more than four decades. Second, it adopts rice yield rather than total production as the dependent variable, thereby isolating productivity effects from changes in cultivated area. Third, it incorporates fertilizer consumption as a key agricultural input alongside climatic variables and carbon emissions, providing a more complete specification of the determinants of rice yield. Fourth, it applies the ARDL framework, complemented by the FMOLS, DOLS, and CCR estimators, to examine both short-run and long-run relationships and to verify robustness. Finally, the findings provide useful policy insights for strengthening climate-resilient and resource-efficient agricultural strategies and improving long-term food security in Malaysia.

2. Literature Review

Climate variability has long been recognised as an important determinant of agricultural productivity. Changes in rainfall, temperature, and atmospheric conditions can affect water availability, crop development, and agricultural output [1]. Since rice is particularly climate-sensitive, understanding the relationship between climate variables and rice productivity remains essential for both researchers and policymakers.

Rainfall is widely regarded as a fundamental factor in rice cultivation. Rice requires a substantial water supply during different growth stages, especially in irrigated and semi-irrigated production systems. Adequate rainfall improves water availability and supports crop growth, while prolonged shortages may reduce yield through water stress [2]. Empirical evidence has shown that rainfall often has a significant effect on rice productivity, although the direction and magnitude may differ across regions and production systems [9].

Temperature is another important determinant of crop performance. Rice plants are highly sensitive to temperature fluctuations, particularly during flowering and grain-filling stages. Moderate increases in temperature may support crop growth under certain conditions, but excessive temperatures can reduce grain quality and yield due to heat stress [3]. The study by [4] showed that climate variability is closely related to crop yield outcomes at the global level [4], while [5] emphasised the threat of climate change to food security through its impact on agricultural productivity.

In addition to rainfall and temperature, broader climate-related pressures may also influence agricultural output. Carbon emissions are often used as an indicator of climate change pressure because they are associated with rising temperatures, altered precipitation patterns, and environmental degradation. From an empirical perspective, including carbon emissions in agricultural production models may help capture the wider environmental dimension of climate change. The study by [6] examined the symmetric and asymmetric effects of climate change on rice productivity in Malaysia and found that rainfall, temperature, and cultivated area significantly influence rice production. In contrast, the asymmetric climate effects are particularly important in the long run. Recent studies have increasingly applied time-series econometric approaches to analyse the climate–agriculture nexus. Another study [10] used the ARDL framework to investigate the impact of climate change on rice production in Punjab and reported that rainfall and temperature significantly affect rice production in both the short run and long run. Similarly, [11] established the ARDL bounds testing approach as a useful econometric method for examining long-run relationships among variables with mixed orders of integration.

It is important to clarify the interpretation of carbon emissions in this context. Although CO_2 emissions are commonly treated as an indicator of climate-related pressure, in a single-country time-series setting they co-move strongly with economic development, energy consumption, and industrialisation. Accordingly, the carbon emissions variable in this study is best understood as a proxy for the broader process of economic development and agricultural modernisation rather than as a direct measure of the environmental stress experienced by the rice production system. Beyond climatic factors, agricultural inputs—particularly fertilizer—are central determinants of rice yield. Adequate fertilisation raises soil-nutrient availability and supports grain formation, but excessive or imbalanced application can produce diminishing or even negative returns through nutrient burn, soil degradation, and environmental externalities. Incorporating fertilizer consumption therefore provides a more complete and realistic specification of the yield function [12].

Despite the growing literature, studies focusing specifically on Malaysia remain limited, particularly those using long-term annual data and incorporating rainfall, temperature, carbon emissions, and cultivated area in a single empirical framework. Given Malaysia's tropical climate, monsoon rainfall patterns, and food security concerns, a deeper understanding of these relationships is necessary. This study addresses that gap by providing updated empirical evidence on the long-run and short-run effects of climate variability on rice yield in Malaysia.

3. Data and Methodology

3.1 Data Sources

This study examines the relationship between climate variability, environmental pressure, agricultural intensification, and rice productivity in Malaysia using annual time series data covering 1980 to 2023. Rice yield (YIELD), defined as total paddy production divided by cultivated area (tonnes per hectare), is employed as the dependent variable. Following the reviewers' suggestion, yield is used instead of total rice production to avoid confounding climatic effects with changes in cultivated area. The explanatory variables are rainfall (RF), temperature (TEM), carbon emissions (CO_2), and fertilizer consumption (FERT). Rainfall is measured as the annual total precipitation (millimetres), and temperature as the annual mean near-surface air temperature (degrees Celsius). Carbon emissions are measured as metric tons per capita and proxy the environmental pressure associated with economic development. In contrast, fertilizer consumption is measured in kilograms per hectare of arable land and captures agricultural input intensity. Data on rice production and cultivated area, from which yield is computed, were obtained from the Department of Statistics Malaysia (DOSM) and the Department of Agriculture (DOA). Rainfall, temperature, carbon emissions, and fertilizer consumption were obtained from the World Bank World Development Indicators (WDI). A detailed description of the variables is presented in Table 1.

Table 1 Description of variables. Source: Authors' calculations.

Variable	Description	Unit	Source
RP	Rice production	Tonnes	DOSM/DOA
CA	Cultivated area	Hectares	DOSM/DOA
YIELD	Rice yield (production ÷ area)	Tonnes per hectare	Computed from DOSM/DOA
RF	Rainfall (annual total)	Millimetres	World Bank (WDI)
TEM	Temperature (annual mean)	Degrees Celsius	World Bank (WDI)
CO_2	Carbon emissions	Metric tons per capita	World Bank (WDI)
FERT	Fertilizer consumption	kg per hectare	World Bank (WDI)

Note: All variables are transformed into natural logarithmic form before estimation.

It should be acknowledged that the analysis relies on national-level annual data. Such aggregation cannot fully capture conditions specific to major rice-producing regions (for example, the granary areas of Kedah and Perlis), individual cropping seasons (main and off-season), or critical growth stages, and it may understate localised climatic stress. Ideally, region-, season-, or growth-stage-specific climate data would be used; however, consistent long-run series at these scales are not publicly available for the full 1980-2023 period in Malaysia. In addition, several potentially relevant factors—including irrigation coverage, rice-variety improvement, mechanisation, government subsidies, import policy, labour, and pest and disease pressure—could not be incorporated because continuous national series spanning the study period are unavailable. Irrigation coverage, for instance, is reported in the WDI only from 2013 onward, and a consistent long-run national flood series could not be obtained. Fertilizer consumption is included as the agricultural input for which a complete 1980-2023 series exists. These data constraints are treated as limitations and revisited in the conclusion.

3.2 Model Specification

Following previous climate–agriculture studies and using rice yield as the dependent variable, the relationship between climate variability, environmental pressure, agricultural input intensity, and rice productivity can be expressed as:

$$\ln RY_t = \beta_0 + \beta_1 \ln RF_t + \beta_2 \ln TEM_t + \beta_3 \ln CO_{2_t} + \beta_4 \ln FERT_t + \varepsilon_t \tag{1}$$

Equation (1) is estimated with all variables expressed in natural logarithms. The model can equivalently be written in functional form as RY = f(RF, TEM, CO_2, FERT). Cultivated area is excluded as a separate regressor because the dependent variable, yield, already expresses output per unit of cultivated area.

where:

RY = Rice yield (paddy production per hectare)

RF = Rainfall (annual total, mm)

TEM = Temperature (annual mean, °C)

CO_2 = Carbon emissions (metric tons per capita)
FERT = Fertilizer consumption (kg per hectare)
ε_t = error term

3.3 The Autoregressive Distributed Lag Approach

To examine the relationship between climate variability and rice yield in Malaysia, this study employs the Autoregressive Distributed Lag (ARDL) bounds testing approach developed by [11]. The ARDL approach is widely used in time series analysis because it allows the estimation of both short-run and long-run relationships simultaneously.

One of the major advantages of the ARDL technique is that it can be applied when the variables are integrated at different orders, namely I(0) or I(1), or a combination of both. Unlike traditional cointegration techniques such as the Johansen method, the ARDL approach does not require all variables to be integrated at the same order. However, the ARDL model cannot be applied if any variable is integrated at order I(2) [13].

Another advantage of the ARDL approach is that it performs well with relatively small sample sizes and helps address potential endogeneity problems among the explanatory variables. Furthermore, the ARDL framework enables the estimation of both short-run dynamic relationships and long-run equilibrium relationships within a single reduced-form equation.

The long-run relationship between rice yield and the explanatory variables can be expressed as follows:

$$\begin{aligned}\ln RY_t = c + \sum_{i=1}^{p} \varphi_i \ln RY_{t-i} + \sum_{j=0}^{q_1} \beta_j \ln RF_{t-j} + \sum_{k=0}^{q_2} \theta_k \ln TEM_{t-k} \\ + \sum_{l=0}^{q_3} \delta_l \ln CO_{2_{t-l}} + \sum_{m=0}^{q_4} \omega_m \ln FERT_{t-m} + u_t \end{aligned} \quad (2)$$

where:
RY = Rice yield
RF = Rainfall
TEM = Temperature
CO_2 = Carbon emissions
FERT = Fertilizer consumption

The unrestricted error correction representation of the ARDL model can be written as:

$$\begin{aligned}\Delta \ln RY_t = c + \sum_{i=1}^{p} \varphi_i \Delta \ln RY_{t-i} + \sum_{j=0}^{q_1} \beta_j \Delta \ln RF_{t-j} + \sum_{k=0}^{q_2} \theta_k \Delta \ln TEM_{t-k} \\ + \sum_{l=0}^{q_3} \delta_l \Delta \ln CO_{2_{t-l}} + \sum_{m=0}^{q_4} \omega_m \Delta \ln FERT_{t-m} + \lambda_1 \ln RY_{t-1} + \lambda_2 \ln RF_{t-1} \\ + \lambda_3 \ln TEM_{t-1} + \lambda_4 \ln CO_{2_{t-1}} + \lambda_5 \ln FERT_{t-1} + \varepsilon_t \end{aligned} \quad (3)$$

The existence of a long-run relationship among the variables is tested using the ARDL bounds test. The null hypothesis of no cointegration is defined as:

$$H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0 \tag{4}$$

against the alternative hypothesis:

H_a: At least one coefficient is not equal to zero

The calculated F-statistic is compared with the critical values provided by [11]. If the F-statistic exceeds the upper bound critical value, the null hypothesis of no cointegration is rejected, indicating the existence of a long-run relationship among the variables. Once cointegration is established, the short-run dynamics of the model can be estimated using the Error Correction Model (ECM), which can be expressed as:

$$\begin{aligned}\Delta\ln RY_t = c + \sum_{i=1}^{p} \varphi_i \Delta\ln RY_{t-i} + \sum_{j=0}^{q_1} \beta_j \Delta\ln RF_{t-j} + \sum_{k=0}^{q_2} \theta_k \Delta\ln TEM_{t-k} \\ + \sum_{l=0}^{q_3} \delta_l \Delta\ln CO_{2_{t-l}} + \sum_{m=0}^{q_4} \omega_m \Delta\ln FERT_{t-m} + \psi ECT_{t-1} + \varepsilon_t\end{aligned} \tag{5}$$

where ECM_{t-1} represents the lagged error correction term obtained from the long-run equation. The coefficient λ indicates the speed at which deviations from the long-run equilibrium are corrected. A negative and statistically significant ECM coefficient confirms the existence of long-run equilibrium adjustment among the variables.

3.4 Robustness Analysis

To ensure the robustness and reliability of the long-run estimates obtained from the ARDL model, this study further employs three alternative cointegration estimation techniques, namely Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR).

The inclusion of these additional estimators is crucial, as the ARDL framework, while flexible and efficient, may still be subject to econometric issues such as endogeneity bias, serial correlation, and small-sample distortions. Therefore, robustness checks using alternative estimators are necessary to validate the consistency of the empirical findings and strengthen the credibility of the results.

The FMOLS approach, developed by [14], modifies the ordinary least squares estimator to account for both serial correlation and endogeneity in the regressors. This method applies semi-parametric corrections to eliminate bias arising from long-run correlations between the error term and explanatory variables, thereby producing asymptotically efficient estimates.

The DOLS approach, proposed by [15], addresses endogeneity by incorporating leads and lags of the first-differenced explanatory variables into the regression model. By explicitly controlling for feedback effects, DOLS improves estimation efficiency and provides unbiased long-run coefficients even in the presence of endogenous regressors.

Meanwhile, the CCR method, introduced by [16], transforms the data so that the long-run relationship can be estimated using ordinary least squares while eliminating second-order asymptotic bias. This transformation ensures that the residuals are orthogonal to the regressors, resulting in efficient and reliable parameter estimates.

The application of FMOLS, DOLS, and CCR in this study serves as a robustness check to verify whether the long-run relationship identified by the ARDL model is stable across different estimation techniques. If the estimated coefficients remain consistent in terms of magnitude, sign, and statistical significance across these methods, it provides strong evidence that the empirical findings are not sensitive to model specification and are therefore robust.

4. Results and Discussion

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the variables used in the analysis. Rice yield (LYIELD) records a mean value of 0.737 (in logarithms) with moderate variability, consistent with the gradual productivity gains achieved in Malaysian rice farming between 1980 and 2023.

Table 2 Descriptive statistics. Source: Authors' calculations.

Variable	Mean	Std. Dev.	Minimum	Maximum
LYIELD	0.737	0.151	0.463	0.994
LRF	7.991	0.105	7.786	8.180
LTEM	3.269	0.011	3.243	3.293
LCO_2	1.608	0.453	0.770	2.117
LFERT	7.168	0.492	5.958	7.982

Note: Std. Dev. denotes standard deviation.

Rainfall (LRF) exhibits greater variability than temperature, reflecting fluctuations in precipitation across the study period, whereas temperature (LTEM) shows very small variation, indicating only gradual climatic change. Carbon emissions (LCO_2) and fertilizer consumption (LFERT) display the highest variability among the variables, mirroring Malaysia's rapid economic growth, industrial development, and intensification of agricultural input use over the past four decades. The relatively low variation in yield, combined with the larger variation in emissions and fertilizer, foreshadows the empirical finding that productivity has been shaped more by structural and input-related factors than by climatic variation alone.

4.2 Trend Analysis

To provide a preliminary understanding of the behaviour of the variables over time, graphical trend analysis is presented for rice production, rainfall, temperature, carbon emissions, and fertilizer consumption in Malaysia from 1980 to 2023. Because the econometric analysis focuses on productivity, rice yield—production per hectare—follows a broadly similar upward path and is examined directly in the model.

Rice production in Malaysia generally exhibits an upward trend over the study period, although several fluctuations can be observed in certain years (Figure 1). The gradual increase in rice production reflects improvements in agricultural productivity, technological advancement, and government initiatives aimed at strengthening the national rice industry. The increase in rice production is also likely associated with improvements in irrigation infrastructure, adoption of improved rice varieties, and better agricultural management practices. However, short-term fluctuations in production may be attributed to weather variability, market conditions, and changes in agricultural policies. Overall, the trend suggests that Malaysia has experienced steady progress in rice production despite potential challenges related to climate variability and environmental pressures.

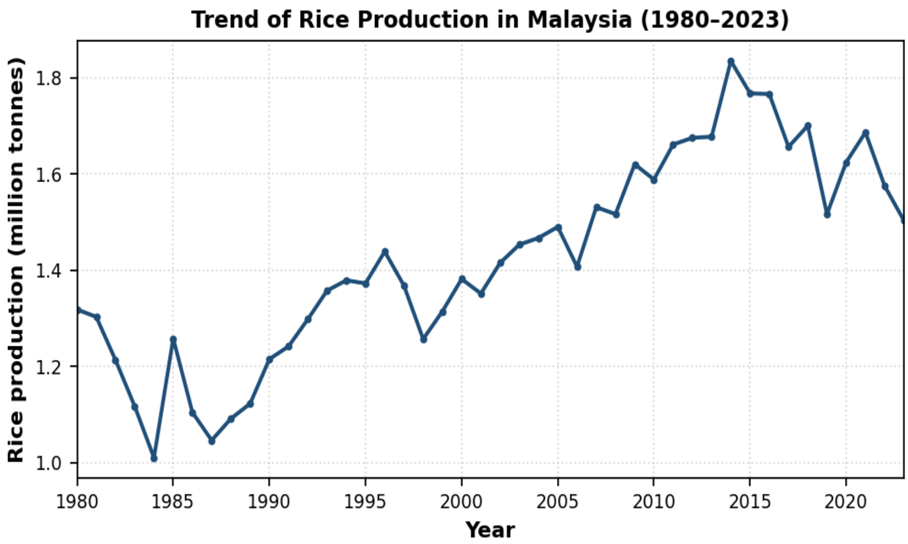

Figure 1 Trend of Rice Production in Malaysia (1980-2023).

Rainfall patterns in Malaysia show noticeable fluctuations throughout the study period (Figure 2). The variability in rainfall levels indicates that precipitation patterns are not stable and may vary significantly from year to year. Such fluctuations are common in tropical climates and may influence water availability for paddy cultivation. Although rice production in Malaysia benefits from irrigation systems, variations in rainfall may still affect water supply and agricultural productivity in certain regions. The irregular rainfall patterns observed in the figure highlight the potential vulnerability of agricultural systems to climate variability and emphasize the importance of effective water management strategies.

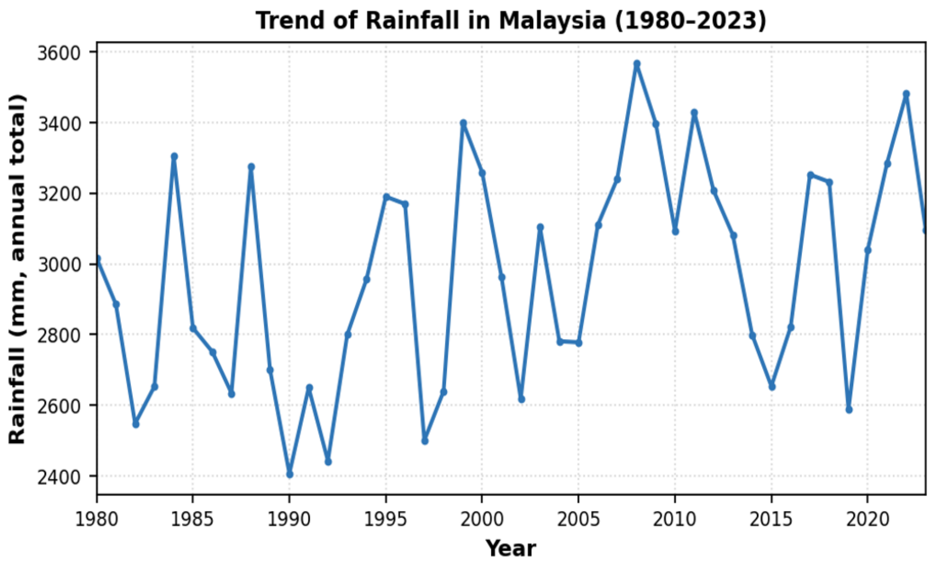

Figure 2 Trend of Rainfall in Malaysia (1980-2023).

The temperature trend shows a gradual increase over the study period (Figure 3), indicating long-term climatic change. Although the increase appears moderate, the upward trend suggests a gradual warming pattern that may be associated with global climate change. Rising temperatures can affect rice cultivation through several mechanisms, including changes in plant growth cycles, increased evapotranspiration, and potential heat stress during critical growth stages. Therefore, even moderate increases in temperature may pose long-term challenges for agricultural sustainability. The upward temperature trend observed in Malaysia is consistent with global climate change patterns reported in previous studies.

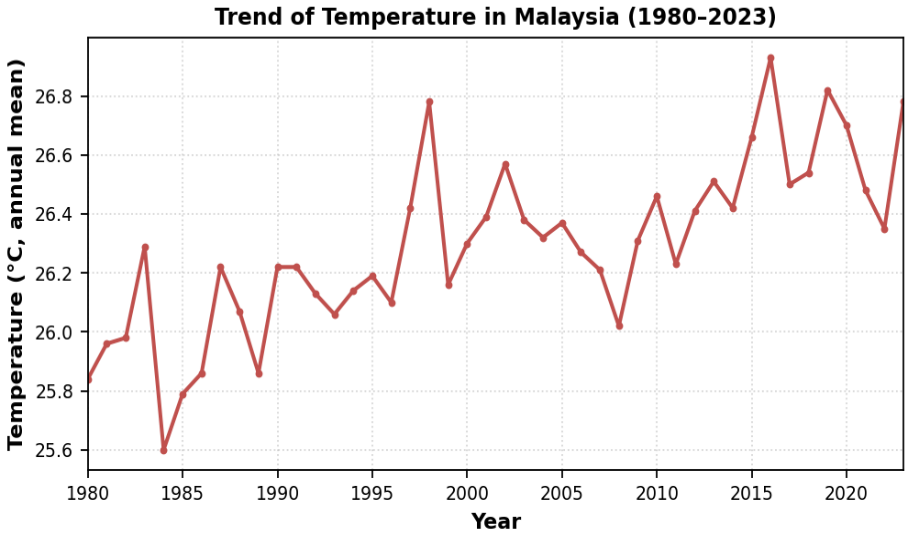

Figure 3 Trend of Temperature in Malaysia (1980-2023).

Carbon emissions display a strong upward trend throughout the study period (Figure 4). This pattern reflects Malaysia's rapid economic development, industrialization, and increasing energy consumption over the past four decades. The increase in carbon emissions may also indicate expanding industrial activities and transportation systems associated with economic growth. While economic development may contribute positively to agricultural productivity through technological advancement and infrastructure improvements, rising carbon emissions also contribute to broader climate change challenges. The increasing trend in carbon emissions highlights the importance of balancing economic development with environmental sustainability to support long-term agricultural resilience.

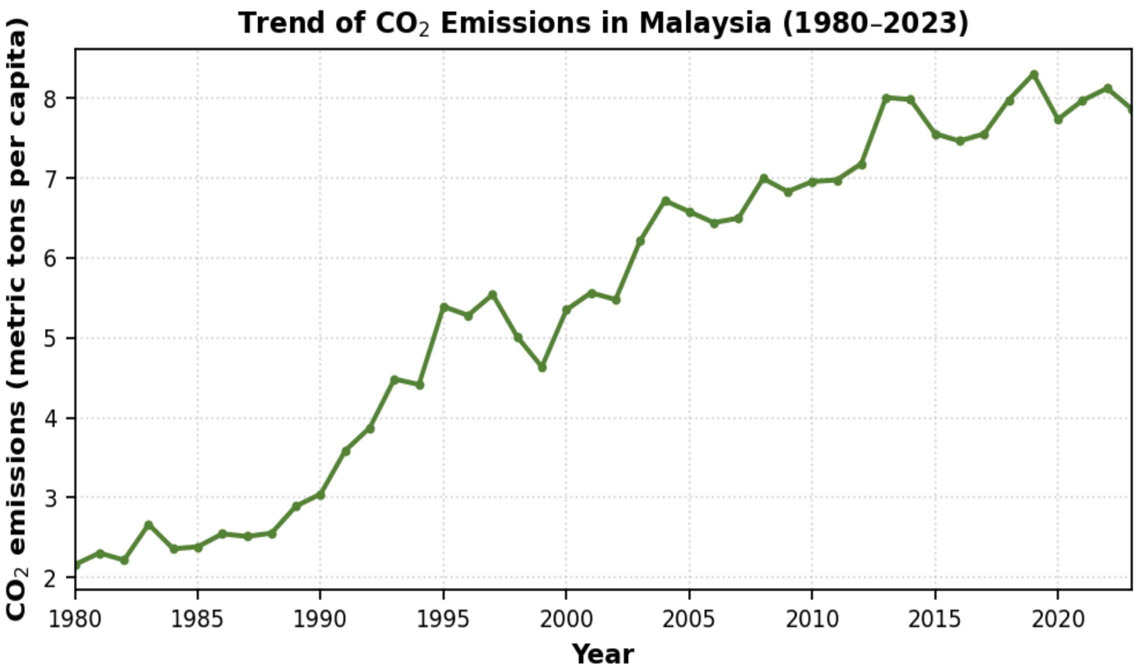

Figure 4 Trend of CO_2 Emissions in Malaysia (1980-2023).

Fertilizer consumption displays a pronounced upward trend over the study period, rising from roughly 430 kg per hectare in 1980 to above 2,900 kg per hectare in 2023, albeit with considerable year-to-year fluctuation (Figure 5). This reflects the intensification of input use in Malaysian rice farming. The high and rising application rates are relevant for interpreting the later finding that fertilizer does not exert a significant long-run effect on yield, as they suggest that the sector may already be operating in a range of diminishing marginal returns.

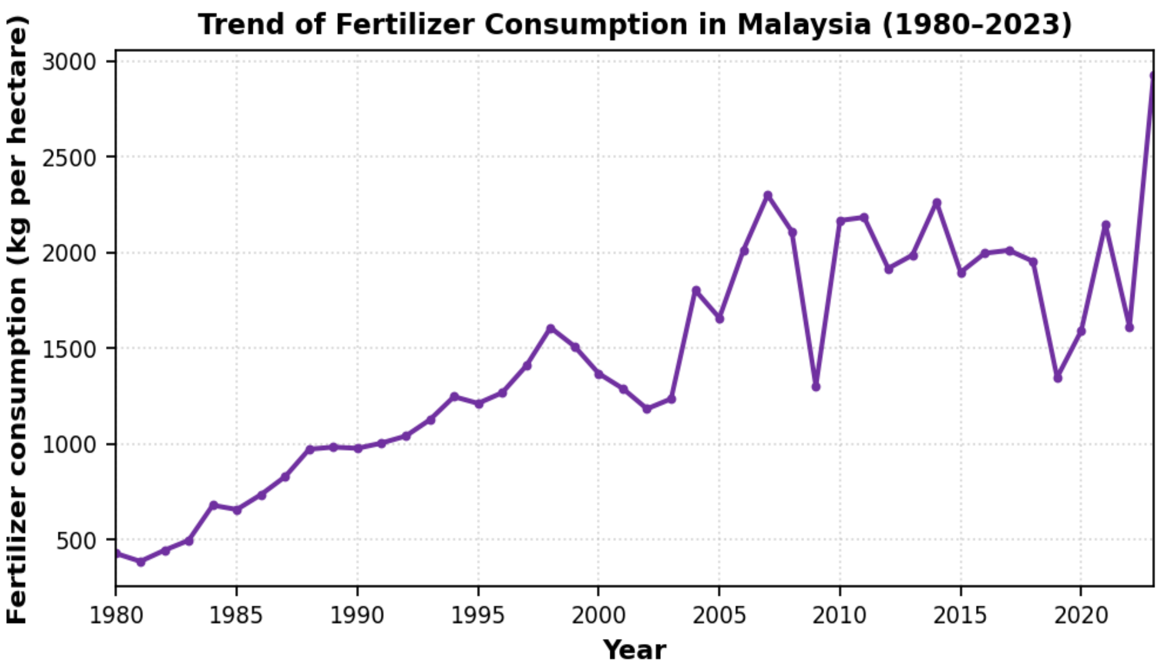

Figure 5 Trend of Fertilizer Consumption in Malaysia (1980-2023).

The graphical analysis provides preliminary evidence of the evolving patterns of climate variables and rice production in Malaysia. However, visual inspection alone cannot determine the existence of long-run relationships among these variables. Therefore, formal econometric analysis using the ARDL framework is conducted in the following section.

4.3 Correlation Analysis

Before the econometric estimation, correlation analysis is conducted to examine the strength and direction of the relationships among the variables, as well as to detect potential multicollinearity issues. The results of the correlation matrix are presented in Table 3.

Table 3 Correlation matrix and variance inflation factors. Source: Authors' calculations.

	LYIELD	**LRF**	**LTEM**	**LCO_2**	**LFERT**
LYIELD	1.000	0.370	0.658	0.909	0.783
LRF	0.370	1.000	-0.089	0.361	0.377
LTEM	0.658	-0.089	1.000	0.752	0.648
LCO_2	0.909	0.361	0.752	1.000	0.907
LFERT	0.783	0.377	0.648	0.907	1.000

Note: Values represent pairwise correlation coefficients. Variance inflation factors (VIF): LRF = 1.76, LTEM = 3.51, LCO_2 = 8.93, LFERT = 5.73. LYIELD = rice yield, LRF = rainfall, LTEM = temperature, LCO_2 = carbon emissions, and LFERT = fertilizer consumption.

The findings indicate that rice yield (LYIELD) is strongly and positively correlated with carbon emissions (0.909), fertilizer consumption (0.783), and temperature (0.658). The strong association between yield and carbon emissions reflects the role of economic development, agricultural modernisation, and technological progress in raising productivity. In contrast, the correlation with fertilizer reflects intensified input use.

Rainfall (LRF) exhibits a moderate positive correlation with rice yield (0.370), highlighting the importance of water availability, although the relationship is weaker than that of the development-related variables.

Importantly, carbon emissions and fertilizer consumption are themselves highly correlated (0.907), exceeding the conventional threshold of 0.90. Relying on pairwise correlations alone is therefore insufficient to assess multicollinearity. Variance inflation factors (VIF) were accordingly computed: the VIF values for carbon emissions (8.93) and fertilizer (5.73) are elevated—reflecting their common association with economic development and agricultural intensification—though they remain below the conventional threshold of 10. This collinearity implies that the individual coefficients on CO_2 and fertilizer should be interpreted with caution, as they partly capture the same underlying development process.

4.4 Unit Root Test

To ensure the validity of the econometric analysis and to avoid spurious regression results, the stationarity properties of the variables are examined using the Augmented Dickey–Fuller (ADF) unit root test. The results of the ADF test are reported in Table 4.

Table 4 Augmented Dickey–Fuller (ADF) unit root test. Source: Authors' calculations.

Variable	Specification	Level (t-stat)	Prob.	First Diff. (t-stat)	Prob.	Order
LYIELD	Intercept	-1.118	0.699	-7.574	0.000	I(1)
LYIELD	Intercept & Trend	-3.556	0.046	-7.481	0.000	
LRF	Intercept	-4.408	0.001	-7.588	0.000	I(0)
LRF	Intercept & Trend	-5.042	0.001	-7.464	0.000	
LTEM	Intercept	-3.053	0.037	-8.630	0.000	I(0)
LTEM	Intercept & Trend	-5.492	0.000	-8.502	0.000	
LCO_2	Intercept	-1.734	0.405	-7.480	0.000	I(1)
LCO_2	Intercept & Trend	-1.200	0.897	-7.775	0.000	
LFERT	Intercept	-2.360	0.156	-8.273	0.000	I(1)
LFERT	Intercept & Trend	-3.147	0.109	-8.351	0.000	

Note: Lag length selected by the Akaike Information Criterion. The reported probabilities are MacKinnon-type p-values. Approximate critical values for the intercept specification at the 1%, 5%, and 10% levels are -3.59, -2.93, and -2.60, respectively. The null hypothesis is the presence of a unit root; rejection indicates stationarity.

The ADF tests were conducted using both an intercept specification and an intercept-and-trend specification; the Akaike Information Criterion selected the lag length, and the corresponding probability values are reported in Table 4. The dependent variable, rice yield (LYIELD), is non-stationary at level but becomes stationary after first differencing, indicating that it is integrated of order one, I(1). Rainfall (LRF) and temperature (LTEM) are stationary at level, I(0), whereas carbon emissions (LCO_2) and fertilizer consumption (LFERT) are non-stationary at level and stationary after first differencing, I(1).

The presence of a mixture of I(0) and I(1) variables, with none integrated of order two, confirms that the ARDL bounds testing approach is appropriate for this study. This is because the ARDL framework can accommodate variables with different orders of integration, provided that none of the variables is I(2). The results therefore support the application of the ARDL model for examining both the short-run and long-run relationships among the variables.

4.5 ARDL Bounds Test for Cointegration

Based on the Akaike Information Criterion, an ARDL (1, 0, 0, 0, 0) specification is selected. To examine the existence of a long-run equilibrium relationship among the variables, the ARDL bounds testing approach is then employed, using both the F-test and the t-test. The results are presented in Table 5. The computed F-statistic is 2.705, which lies between the lower I(0) bound (2.86) and the upper I(1) bound (4.01) at the 5% level, while the bounds t-statistic (-3.322) likewise falls between its corresponding critical bounds. Both tests are therefore individually inconclusive with respect to cointegration.

Table 5 ARDL bounds test for cointegration. Source: Authors' calculations.

Test	Statistic	Decision at the 5% level
Bounds F-statistic	2.705	Inconclusive
Bounds t-statistic	-3.322	Inconclusive
Critical values		
Significance	**I(0) Lower Bound**	**I(1) Upper Bound**
10%	2.45	3.52
5%	2.86	4.01
1%	3.74	5.06

Note: The null hypothesis of no cointegration is tested against the alternative of a long-run relationship. If the F-statistic exceeds the upper bound, cointegration is confirmed; if it falls below the lower bound, cointegration is rejected; and if it lies between the bounds, the result is considered inconclusive.

However, because the F-statistic does not fall below the lower bound, the null hypothesis of no long-run relationship cannot be accepted outright. In such cases, the error correction term provides additional and more decisive evidence. As reported in the subsequent section, the error correction term is negative and statistically significant at the 1% level, which confirms the existence of a stable long-run relationship among the variables. The ARDL framework therefore remains appropriate for analysing both the short-run and long-run dynamics linking climatic variables, environmental pressure, fertilizer use, and rice yield in Malaysia.

4.6 Long-Run ARDL Estimates

The long-run estimation results derived from the ARDL model are presented in Table 6. The results indicate that carbon emissions (LCO_2) have a positive and statistically significant long-run effect on rice yield at the 1% level. The estimated coefficient of 0.424 implies that a 1% increase in carbon emissions is associated with approximately a 0.42% increase in rice yield in the long run. Given the high collinearity between emissions and fertilizer and the single-country time-series setting, this relationship is best interpreted as reflecting the parallel influence of economic development, energy use, and agricultural modernisation rather than a direct agronomic benefit of CO_2. In other words, the periods of rising emissions coincide with broader investment in mechanisation, infrastructure, and improved farming practices that have raised productivity.

Table 6 Long-run coefficients. Source: Authors' calculations.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LRF	0.108	0.287	0.37	0.710
LTEM	-3.723	4.305	-0.86	0.393
LCO_2	0.424***	0.154	2.75	0.010
LFERT	-0.048	0.109	-0.44	0.663
C	11.720	-	-	-

Note: The asterisks *** indicate significance at 1% levels, respectively. All variables are expressed in natural logarithmic form.

In contrast, rainfall (LRF) and temperature (LTEM) do not exhibit statistically significant long-run effects on rice yield. The coefficient on rainfall is small and positive (0.108), while that on temperature is negative (-3.723) but imprecisely estimated; neither is statistically distinguishable from zero. These results suggest that, at the national level, productivity is not strongly driven by year-to-year climatic variation over the study period.

Fertilizer consumption (LFERT) also shows a statistically insignificant long-run coefficient, with a small negative point estimate (-0.048). This counter-intuitive sign is consistent with the descriptive evidence that application rates in Malaysia are already very high, placing the sector in a range of diminishing—or even negative—marginal returns, and with the strong collinearity between fertilizer and carbon emissions documented earlier. Overall, the long-run results highlight that structural and technological factors, proxied by carbon emissions, are more influential than direct climatic variables or fertilizer intensity in shaping rice yield in Malaysia.

4.7 Short-Run Dynamics and Error Correction Model

The short-run dynamics of the model are examined using the Error Correction Model (ECM), and the results are reported in Table 7. The ECM specification allows for the assessment of both short-run adjustments and the speed at which deviations from the long-run equilibrium are corrected.

Table 7 Error correction model (short-run dynamics). Source: Authors' calculations.

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LRF)	-0.012	0.113	-0.10	0.919
D(LTEM)	-1.285	1.447	-0.89	0.381
D(LCO_2)	0.120	0.119	1.02	0.317
D(LFERT)	-0.018	0.048	-0.39	0.700
ECM(-1)	-0.454***	0.137	-3.32	0.002
Model statistics				
Statistic	**Value**			
R-squared	0.905			
Adjusted R-squared	0.892			
F-statistic	70.29			
Durbin-Watson	2.36			

Note: The asterisks *** indicate significance at 1% levels, respectively; ECM(-1) represents the speed of adjustment toward long-run equilibrium. Durbin–Watson values close to 2 indicate no autocorrelation.

The estimated error correction term, ECM(-1), is negative and statistically significant at the 1% level, confirming the existence of a stable long-run relationship among the variables. The coefficient of -0.454 indicates that approximately 45.4% of any short-run disequilibrium in rice yield is corrected within one year, implying a moderate speed of adjustment toward long-run equilibrium. Thus, short-term shocks to rice yield gradually converge back to the long-run equilibrium path over time. Statistical inference for the short-run coefficients is reported together with the corresponding standard errors, t-statistics, and probability values in Table 7.

In terms of short-run dynamics, none of the first-differenced explanatory variables—rainfall, temperature, carbon emissions, or fertilizer—exerts a statistically significant individual effect on rice yield. This indicates that, in the short run, year-to-year changes in these variables do not translate into immediate, systematic changes in productivity.

Instead, the adjustment of rice yield operates primarily through the error-correction mechanism, whereby deviations from the long-run equilibrium are gradually corrected. This pattern is consistent with a productivity process that responds to slow-moving structural and technological factors rather than to short-term fluctuations in climate or input use.

The overall model diagnostics confirm the reliability of the estimated ARDL model. The coefficient of determination (R^2 = 0.905) indicates that approximately 91% of the variation in rice yield is explained by the model, and the high F-statistic (70.29) confirms its overall significance. At the same time, the Durbin–Watson statistic (2.36) suggests the absence of serious first-order autocorrelation in the residuals.

4.8 Diagnostic Tests

To ensure the validity and reliability of the estimated ARDL model, several diagnostic tests are conducted to examine whether the classical regression assumptions are satisfied. The results of these diagnostic tests are presented in Table 8.

Table 8 Diagnostic tests. Source: Authors' calculations.

Test	Statistic	Prob.
Breusch–Godfrey (serial correlation)	2.944	0.229
Breusch–Pagan (heteroskedasticity)	6.815	0.656
Jarque–Bera (normality)	3.411	0.182
Ramsey RESET (functional form)	0.602	0.554

Note: The null hypotheses are, respectively, no serial correlation (Breusch–Godfrey), homoskedasticity (Breusch–Pagan), normality (Jarque–Bera), and correct functional form (Ramsey RESET). A probability value greater than 0.05 indicates that the null hypothesis cannot be rejected.

The Breusch–Godfrey serial correlation test indicates that the null hypothesis of no serial correlation cannot be rejected (p = 0.229), confirming that the residuals are not serially correlated. Similarly, the Breusch–Pagan test does not reject the null of homoskedasticity (p = 0.656), indicating constant error variance.

In addition, the Jarque–Bera test does not reject the normality of the residuals (p = 0.182), and the Ramsey RESET test (p = 0.554) provides no evidence of functional-form misspecification. Taken together, the diagnostic results confirm that the estimated ARDL model satisfies the key classical assumptions—no serial correlation, homoskedasticity, normally distributed residuals, and correct functional form—so that the estimated coefficients are reliable for inference and policy interpretation.

4.9 Robustness Analysis

To further validate the reliability of the long-run estimates obtained from the ARDL model, robustness analysis is conducted using alternative cointegration estimators, namely Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR). The results are reported in Table 9.

Table 9 FMOLS, DOLS, and CCR long-run estimates. Source: Authors' calculations.

Variable	FMOLS	DOLS	CCR
LRF	0.091	-0.175	0.148
LTEM	-0.419	-4.316	0.560
LCO_2	0.392***	0.568***	0.295***
LFERT	-0.085	-0.146**	-0.025

Note: *** and ** denote statistical significance at the 1%, and 10% levels, respectively. All models are estimated in logarithmic form, with rice yield (LYIELD) as the dependent variable. FMOLS corrects for serial correlation and endogeneity, DOLS includes leads and lags of differenced regressors, and CCR applies a data transformation to achieve efficient estimation.

The findings indicate a high degree of consistency for the key result across the three estimation techniques. In particular, carbon emissions (LCO_2) remain positive and statistically significant across the FMOLS, DOLS, and CCR estimators. This consistency provides strong evidence that the development- and modernisation-related process captured by carbon emissions plays a significant role in raising rice yield in Malaysia.

The magnitude of the LCO_2 coefficient remains in a broadly similar range across the estimators. This implies that a 1% increase in carbon emissions is associated with a positive and economically meaningful increase in rice yield in the long run, and that the relationship is robust and not an artefact of a single estimation method.

Fertilizer consumption (LFERT) is statistically insignificant under the ARDL, FMOLS, and CCR estimators, consistent with the earlier finding that high application rates have pushed the sector toward diminishing returns and that fertilizer is highly collinear with carbon emissions.

Rainfall (LRF) and temperature (LTEM) remain statistically insignificant across the estimation methods, reinforcing the earlier ARDL results and suggesting that climatic variables do not exert a strong long-run influence on national rice yield over the study period.

Overall, the robustness analysis confirms that the central long-run relationship identified by the ARDL model—the positive and significant effect of carbon emissions—is stable across the FMOLS, DOLS, and CCR estimators, indicating that the principal finding is not driven by potential endogeneity or serial correlation.

4.10 Stability Tests

To examine the stability of the estimated ARDL model over the sample period, the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests were employed. These tests are widely used to assess the stability of model parameters and detect possible structural changes in time series models. The CUSUM test evaluates the cumulative sum of recursive residuals and determines whether the estimated coefficients remain stable throughout the sample period. Meanwhile, the CUSUMSQ test examines the cumulative sum of squared recursive residuals and is particularly useful for identifying sudden structural shifts in the model.

The graphical results of the CUSUM and CUSUMSQ tests, as presented in Figure 6 and Figure 7, show that the plotted statistics remain within the 5% critical bounds throughout the sample period. This indicates that the estimated coefficients of the ARDL model are stable and do not exhibit systematic structural changes over time.

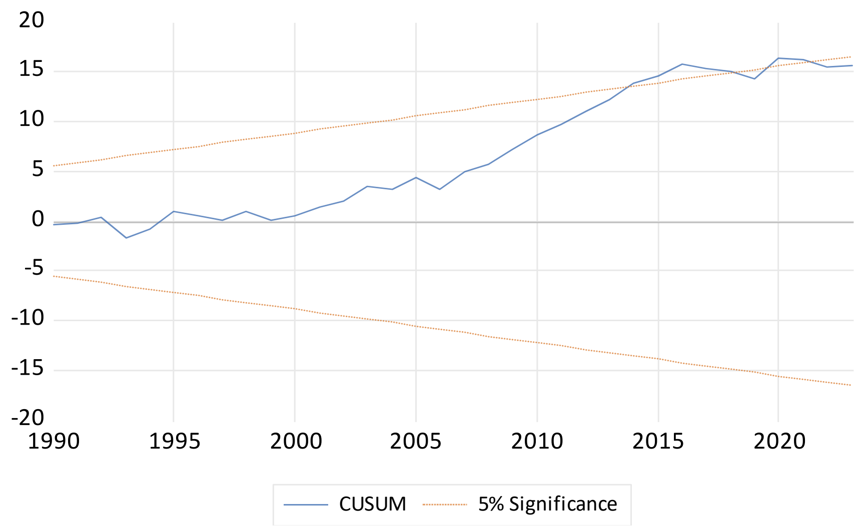

Figure 6 The CUSUM of residuals plot.

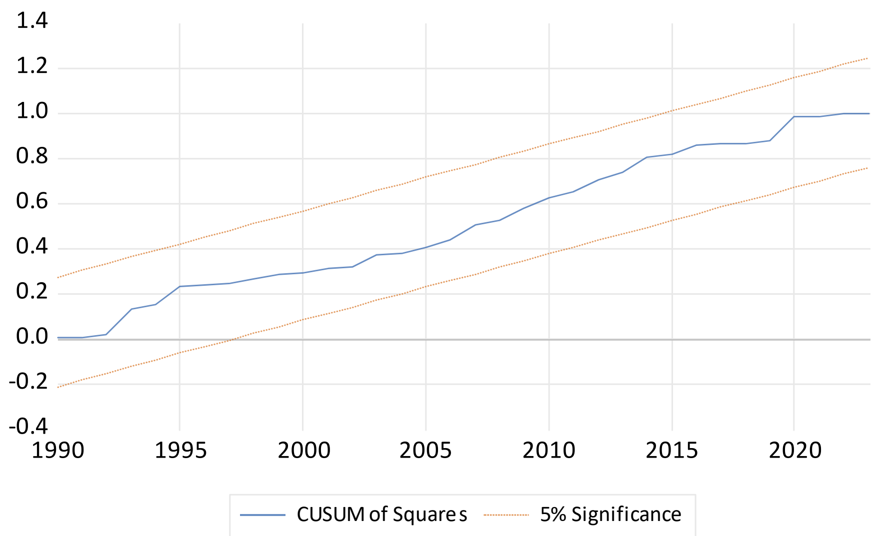

Figure 7 The CUSUM of squares of recursive residuals plot.

The stability of the CUSUM plot suggests that the recursive residuals do not deviate significantly from zero, implying parameter constancy in the model. Similarly, the CUSUMSQ plot confirms the absence of sudden structural shifts, further supporting the stability of the estimated parameters. These findings indicate that the ARDL model is structurally stable over the period from 1980 to 2023. Consequently, the estimated relationships between climate variables, environmental pressure, and rice production remain consistent across the sample period. Overall, the stability test results reinforce the robustness and reliability of the estimated model, confirming that the empirical findings are not influenced by structural instability or parameter shifts.

5. Discussion

The empirical results provide several important insights into the relationship between climate variability, environmental pressure, agricultural intensification, and rice productivity in Malaysia. First, carbon emissions have a positive and statistically significant long-run effect on rice yield. As argued above, this relationship should not be read as a direct agronomic benefit of CO_2; in a single-country setting, emissions are tightly correlated with economic development, energy use, industrialisation, and fertilizer intensity. The result is therefore most plausibly interpreted as evidence that the broad process of economic development and agricultural modernisation—rather than atmospheric CO_2 itself—has driven productivity gains, through investment in mechanisation, irrigation infrastructure, research, and improved farming practices.

This interpretation is consistent with studies that link economic development and technological progress to agricultural productivity, while cautioning against a causal reading of the emissions–yield association. It also helps reconcile the present results with earlier Malaysian studies, such as those reporting significant rainfall and temperature effects on rice output: differences in the dependent variable (yield versus total production), the level of aggregation, and the sample period can all materially affect which determinants appear significant [6, 17].

A critical qualification concerns grain quality. While elevated atmospheric CO_2 can stimulate biomass accumulation in C3 crops such as rice, a growing body of experimental evidence shows that higher CO_2 concentrations reduce the protein, zinc, iron, and B-vitamin content of rice grains. For a population such as Malaysia's, in which rice is a dietary staple, such declines in nutritional quality could heighten the risk of micronutrient deficiencies, anaemia, and related health burdens, particularly among lower-income households. The positive association between emissions and yield observed here should therefore not be construed as an unambiguous benefit: potential gains in quantity may be partly offset by losses in grain quality. This reinforces the argument for interpreting the CO_2 result through a development-and-modernisation lens and for monitoring the nutritional composition of domestically produced rice as emissions continue to rise [18, 19].

Second, rainfall does not have a statistically significant long-run effect on rice yield in Malaysia. The weak effect may partly reflect the role of irrigation and water management in the country's granary areas, which can buffer paddy fields against year-to-year rainfall variability. It should be emphasised, however, that the present national-level data do not allow this mechanism to be tested directly; the irrigation explanation therefore remains a plausible interpretation rather than an established empirical finding, and disaggregated, season-specific data would be required to confirm it [20, 21].

Third, temperature does not exhibit a statistically significant long-run effect, which may reflect Malaysia's relatively stable tropical climate, where temperature fluctuations are less extreme than in temperate regions, as well as the adoption of improved varieties and modern practices. Fourth, fertilizer consumption is statistically insignificant and carries a small negative point estimate, consistent with already-high application rates and diminishing returns, and with the strong collinearity between fertilizer and the development-related emissions variable. Taken together, these findings indicate that, over the study period, Malaysian rice productivity has been shaped more by slow-moving structural and technological factors than by short-run climatic conditions or marginal increases in input intensity—an interpretation that is robust across the alternative estimators but that should be tested further with disaggregated regional and seasonal data.

6. Policy Implications

The empirical findings of this study provide important policy implications for strengthening the sustainability and resilience of Malaysia's rice production sector. These implications are closely aligned with several United Nations Sustainable Development Goals (SDGs), particularly those related to food security, climate action, and sustainable economic development.

First, the significant positive association between carbon emissions and rice yield is interpreted here as a reflection of development-driven productivity gains. This points to the value of continued investment in agricultural modernisation—mechanisation, infrastructure, and research and extension—as a means of sustaining productivity, in line with SDG 2 (Zero Hunger) and SDG 9 (Industry, Innovation and Infrastructure). At the same time, because the underlying driver is economic development rather than emissions per se, productivity growth should be progressively decoupled from carbon intensity, consistent with SDG 12 and SDG 13. The result should not be read as a justification for higher emissions.

Second, the finding that fertilizer consumption has no significant long-run effect—and a small negative point estimate—carries a direct, model-based policy implication: at current high application rates, additional fertilizer is unlikely to raise yield and may impose environmental costs. Policy should therefore prioritise balanced and efficient fertilizer management (for example, soil-testing-based and site-specific nutrient application) rather than further increases in input volume, supporting SDG 12 (Responsible Consumption and Production).

Third, although rainfall and temperature are not statistically significant in the long run, their variability remains a precautionary concern for agricultural planning, consistent with SDG 6 (Clean Water and Sanitation) and SDG 13 (Climate Action). Maintaining and improving irrigation and water-management systems can help stabilise production under climatic variability. We note, however, that the buffering role of irrigation is not directly tested in this national-level model and is advanced as a precautionary, rather than empirically established, rationale.

Fourth, the evidence that productivity is shaped by structural and development-related factors, together with the nutritional-quality concerns associated with rising CO_2, suggests that food-security policy should look beyond output volume to the resilience and nutritional quality of the rice supply. Monitoring the protein and micronutrient content of domestically produced rice, and supporting biofortified or quality-preserving varieties, would align with SDG 2 (Zero Hunger) and SDG 3 (Good Health and Well-being).

Finally, several widely discussed measures—such as precision agriculture, climate-smart practices, and the development of high-yield, climate-resilient varieties—are promising but are not directly examined in this study. They are therefore presented as forward-looking directions consistent with the broader modernisation narrative rather than as conclusions derived from the present model. Ensuring that such development remains environmentally sustainable, by promoting green technologies and reducing carbon intensity, is consistent with SDG 12 and SDG 13.

7. Conclusion

This study set out to determine whether climate variability and environmental pressure, or structural and input-related factors, more strongly shape rice productivity in Malaysia. The analysis reaches a clear overall conclusion: over the period 1980-2023, rice yield in Malaysia has been driven primarily by development- and modernisation-related factors—captured here by carbon emissions—rather than by direct climatic conditions or fertilizer intensity. This conclusion challenges the common assumption that climatic variables are the dominant determinants of national rice productivity and instead foregrounds the role of long-run structural change.

Specifically, carbon emissions exert a positive and statistically significant long-run effect on rice yield, a relationship interpreted as reflecting economic development and agricultural modernisation rather than a direct agronomic effect of CO_2. Rainfall, temperature, and fertilizer consumption do not exhibit statistically significant long-run effects. In contrast, the negative and significant error correction term confirms a stable long-run relationship with a moderate speed of adjustment. These results are robust across the FMOLS, DOLS, and CCR estimators and pass the standard diagnostic and stability tests.

Several limitations should be acknowledged. The analysis uses aggregate national-level annual data, which cannot capture regional, seasonal, or growth-stage-specific climatic conditions; consistent long-run series at these finer scales, as well as continuous data on irrigation coverage, flood incidence, rice-variety improvement, mechanisation, subsidies, labour, and pest and disease pressure, were not available for the full study period. The strong collinearity between carbon emissions and fertilizer also means that their individual effects cannot be sharply separated, and the emissions–yield association should be interpreted as a development proxy rather than a causal climatic effect. Finally, the potential decline in the nutritional quality of rice under rising CO_2 is an important dimension not captured by yield data alone. Future research should therefore incorporate disaggregated regional and seasonal data, additional input and policy variables, and indicators of grain nutritional quality to provide a more complete understanding of the determinants of sustainable rice production in Malaysia.

Author Contributions

All authors contributed to the development of this manuscript. M.H.O was responsible for conceptualization, research design, methodology development, literature synthesis, analysis, drafting, and overall supervision of the study. N.Z.M.S provided academic guidance, mentorship under the FRGS-EC grant framework, and contributed to the critical review and refinement of the manuscript. S.S.S.S. contributed to proofreading, language editing, and improving the clarity and presentation of the manuscript. All authors read and approved the final version of the manuscript prior to submission.

Funding

This research was supported by the Ministry of Higher Education Malaysia under the Fundamental Research Grant Scheme - Early Career Researcher (FRGS-EC/1/2024/SS06/UITM/02/16).

Competing Interests

The authors have declared that no competing interests exist.

Data Availability Statement

The data used in this study are obtained from publicly accessible and official sources. Rice production and cultivated area, from which rice yield is computed, were obtained from the Department of Statistics Malaysia (DOSM) and the Department of Agriculture (DOA). Rainfall, temperature, carbon emissions, and fertilizer consumption were obtained from the World Bank World Development Indicators (WDI). To ensure consistency, all climate, environmental, and input series are cited as WDI throughout the manuscript.

The datasets are publicly available without restriction and can be accessed through the official portals of the Department of Statistics Malaysia (https://www.dosm.gov.my), the Department of Agriculture Malaysia (https://www.doa.gov.my), and the World Bank World Development Indicators (https://databank.worldbank.org/source/world-development-indicators).

https://www.doa.gov.my/index.php/pages/view/622?mid=239https://climateknowledgeportal.worldbank.org/.

AI-Assisted Technologies Statement

The authors declare that artificial intelligence (AI)-assisted tools were used to support the writing process of this manuscript, specifically for language refinement, structuring of content, and improvement of academic expression. No AI tools were used for data analysis, data interpretation, or generation of results. All analyses, interpretations, and conclusions presented in this study were conducted and verified by the authors.

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