ECONOMIC, CLIMATIC, AND INPUT DETERMINANTS OF AGRICULTURAL PRODUCTION: EVIDENCE FROM 33 COUNTRIES ACROSS INCOME GROUPS

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ABSTRACT

This study examines the long- and short-run relationships between economic, climatic, and agricultural input factors and agricultural production value (AGPVI) across 33 countries classified by income level: high-, upper-middle-, and lower-middle-income. Using the Panel ARDL model, supported by DOLS and FMOLS estimations, the study identifies both dynamic and cointegrated relationships among variables. In the long run, fertilizer consumption (FRTZQ) consistently shows a positive and significant effect on agricultural production across all income groups, while GDP (GDPII) and rainfall (RAINI) exhibit varying impacts depending on income level. Agriculture in high-income countries is largely technology- and efficiency-driven, whereas in upper- and lower-middle-income countries, growth relies more on input intensification and macroeconomic factors. In the short run, GDP and agricultural inputs significantly influence production fluctuations, while climatic factors are more prominent in lower-middle-income countries. The negative and significant ECM values confirm a stable adjustment process toward long-run equilibrium. Overall, the results support structural transformation theory, indicating that as income rises, agriculture's role shifts from being a primary growth driver to ensuring economic stability and food security. Policy recommendations emphasize technological innovation in high-income countries, input-efficient growth in upper-middle-income countries, and stronger climate adaptation in lower-middle-income countries.

Key words: agricultural sector, ARDL, DOLS, FMOLS

INTRODUCTION

Climate change poses a significant threat to the agricultural sector worldwide, as this sector is highly sensitive and profoundly affected by climatic shifts (Chandio et al. 2021; Iizumi et al. 2025). Numerous empirical studies have documented the adverse consequences of climate change for agricultural development. For example, Khan et al. (2022) show that across all income groups, agricultural growth has declined due to climatic pressures. Kalkuhl and Wenz (2020) further highlight that rising global temperatures and extreme weather events threaten agricultural productivity and, consequently, food security (Hogan and Schlenker 2024). However, while these studies emphasize the negative effects, there remains limited consensus on how specific climatic and economic variables interact to shape agricultural performance across different income groups. This research gap provides an opportunity for a more nuanced investigation that links climate change indicators with conventional production and macroeconomic factors.

The agricultural sector is deemed vital due to its dual strategic roles: as a provider of food for consumption and as a source of employment for 36% of the global workforce. According to (FAO 2021), climate change could lead to a 10–25% annual reduction in crop yields, driven by natural disasters and pest outbreaks (Xue et al. 2024). Such impacts exacerbate poverty, which still affects over 800 million people globally. If unaddressed, climate change is likely to further aggravate global poverty (Carattini et al. 2020). Hence, understanding how climate-related variables and economic drivers jointly affect agricultural production is critical to formulating effective policy responses.

This study contributes by providing a stronger conceptual framework for the explanatory variables. Gross Domestic Product (GDP) is considered a proxy for macroeconomic capacity, which supports investments in agricultural technology, infrastructure, and adaptation strategies. Fertilizer use reflects the role of modern agricultural inputs in enhancing yields, though with potential environmental trade-offs. Irrigation represents an adaptation measure that reduces reliance on rainfall variability and enhances production stability. Rainfall is both a direct production input and an indicator of climate variability. Finally, CO_2 emissions serve as a proxy for anthropogenic climate change pressures that may indirectly affect agriculture through global warming and extreme weather patterns. By integrating these variables, the framework allows us to capture both environmental and economic drivers of agricultural performance.

Regarding country selection, this study focuses on 33 of the world's leading agricultural commodity producers. The selection is based on their consistently high agricultural production values, their significant contribution to global GDP, and the share of agriculture in their national economies. Collectively, these countries account for more than 85% of global GDP and around 8% of agricultural value-added worldwide (FAO 2024). While this approach ensures that the analysis captures the majority of global agricultural output, it may exclude smaller, agriculture-dependent economies that are highly vulnerable to climate change (Heikonen et al. 2025). This limitation is acknowledged, but the focus on large producers is justified to provide insights into the performance of countries that shape global food supply and trade. Future research may extend the analysis to smaller economies to better capture vulnerability in marginal contexts.

In sum, this study seeks to address existing gaps by examining the combined influence of climatic and economic variables on agricultural performance across different income classifications. The results are expected to provide region- and income-specific policy implications for building resilience in the agricultural sector against climate change.

RESEARCH METHODOLOGY

Data types and sources. To achieve its research objectives, this study utilized the Augmented Autoregressive Distributed Lag (ARDL) model. According to (Anh et al 2023), the ARDL model offers several advantages: (1) it effectively addresses issues of endogeneity and serial correlation, (2) it accommodates variables that are integrated at order zero [I(0)], order one [I(1)], or a mix of both, (3) it allows some regressors to be endogenous, (4) it performs well with relatively small sample sizes, and (5) it simultaneously estimates short-term and long-term effects.

Based on these strengths, the study constructs five single-equation models, categorized according to the income levels of countries, as follows:

Model I: High Income
$$AGPVI = f(RAINI, GDPII, CO2WD, FRTZQ)$$

Model II: Lower Middle Income

$AGPVI = f(INPIX, TFPIX, LBORQ)$

Model III: Upper Middle Income
$AGPVI = f(RAINI, GDPII, CO2WD, IRRIQ)$

Model IV: All Countries
$AGPVI = f(GDPII, FRTZQ, RAINI, IRRIQ)$

The theoretical foundation of this study is rooted in production economics and climate change theory. From the production economics perspective, agricultural output is determined not only by conventional inputs such as labor, land, fertilizer, and irrigation, but also by environmental and climatic factors that directly affect productivity. Gross agricultural production value (AGPVI) reflects the aggregate outcome of combining these inputs, while climate variability introduces risks that can alter both efficiency and long-term sustainability.

To ensure consistency across the analysis, all data were harmonized. The time coverage was standardized to the period 1990–2020 for all models and country groups, and the number of countries was fixed at 33 major producers. These 33 countries were selected based on their consistently high agricultural production values and their collective contribution of more than 85% to global GDP and approximately 8% to global agricultural value added (FAO 2024). Although this approach excludes some smaller countries highly dependent on agriculture, it ensures a representative global coverage of agricultural output while acknowledging that results may not fully capture the vulnerability of small, agriculture-dependent economies.

The explanatory variables were carefully defined and adjusted for comparability. GDP (GDPII) was expressed in constant 2015 US dollars to align with the dependent variable (AGPVI), which is reported in constant 2014–2016 US dollars. Agricultural inputs were normalized to improve cross-country comparability: fertilizer use was expressed per hectare of arable land, irrigation was measured as irrigated area relative to total arable land, and labor was scaled as agricultural labor force per hectare. These adjustments reduce bias due to scale differences among countries and enhance the robustness of the analysis. Table 1 presents the operational definitions of variables after these adjustments.

Table 1. Operational definition of variables

Notation	Description	Unit	Sources
AGPVI	Gross Agricultural Production Value	Constant 2014–2016 thousand USD	FAOSTAT
LBORQ	Agricultural Labor Force	Workers per hectare of arable land	FAOSTAT
INPIX	Index of total agricultural input	Index, 2015=100	USDA ERS
TFPIX	Index of agricultural TFP	Index, 2015=100	USDA, ERS
GDPII	Gross Domestic Product	Constant 2015 US$	WDI
FRTZQ	Quantity of total agricultural fertilizer	Metric tons per hectare of inorganic N, P, K and organic N	FAOSTAT
IRRIQ	Quantity of total area equipped for irrigation	1000 hectares	USDA, ERS

Notation	Description	Unit	Sources
GHGMI	Greenhouse Gas Emissions	CO_2 equivalents	Our World in Data
RAINI	Precipitation	Millimeters per year	World Bank
CO2WD	Total CO_2 Emissions	Kiloton (kt)	World Bank

The focus of this study was to examine 33 major countries with the highest average Gross Agricultural Production Value (GPV). The countries included in the analysis were: Algeria, Argentina, Australia, Bangladesh, Brazil, Canada, Chile, Colombia, Egypt, France, Germany, Greece, Indonesia, Iran, Italy, Japan, Kenya, Malaysia, Mexico, Netherlands, New Zealand, Nigeria, Pakistan, the Philippines, Poland, Republic of Korea, South Africa, Spain, Thailand, Türkiye, the United Kingdom, the United States, and Viet Nam. Collectively, these 33 nations represented an average of 85.63% of global GDP over the 1990–2020 period. Additionally, they had an average agricultural sector share of 8.41% of their respective national GDPs (FAO 2024). The income classification criteria followed those established by the World Bank.

This study employed the Panel Autoregressive Distributed Lag (ARDL) framework to estimate the short-run and long-run relationships between climate and economic variables and agricultural production. The ARDL approach is appropriate when the underlying variables are integrated of mixed orders, I(0) and I(1), but not I(2). Importantly, while ARDL can accommodate regressors with different integration orders, it requires regressors to be weakly exogenous in the long run; therefore, it does not solve endogeneity problems in a strict econometric sense. Instead, the method assumes that explanatory variables do not respond contemporaneously to short-run shocks in the dependent variable. This distinction is important for interpreting the results, as it highlights the limitations of ARDL relative to instrumental variable or structural approaches. Table 2 displays the descriptive statistics of the variables used in this study.

Table 2. Descriptive statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Coefficient of Variation (%)
AGPVI	1,732,209	1,730,088	1,973,088	1,574,137	0.76	0.00
CO2WD	1,220,064	1,236,915	1,556,919	8,698,064	1,196,623	98.08
FRTZQ	1,424,749	1,434,351	1,697,681	1,088,329	1,020,519	71.63
GDPII	2,691,434	2,668,949	3,063,470	2,413,876	1,274,581	47.36
INPIX	4,524,703	4,570,898	5,065,978	3,792,875	0.19	0.00
IRRIQ	7,448,381	7,560,601	1,020,618	3,988,984	1,334,124	17.91
LBORQ	7,830,821	7,714,771	1,066,993	4,961,445	1,483,715	18.95
RAINI	6,671,643	6,685,861	8,179,760	2,302,585	1,016,822	15.24
TFPIX	4,477,716	4,513,084	4,836,025	3,894,737	0.16	0.00

To evaluate the stationarity of the data, this study applied the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. These three tests were employed to ensure robustness in assessing stationarity, as the ADF and PP tests operate under the null hypothesis of non-stationarity (presence of a unit root), while the KPSS test uses the null hypothesis of stationarity. By combining these complementary approaches, potential biases or weaknesses in individual tests—such as sensitivity to serial correlation in ADF or heteroskedasticity in PP—could be mitigated, providing a more reliable confirmation of whether the series are stationary or require differencing. All variables included in the ARDL model were converted into their natural logarithmic forms to stabilize variance and facilitate interpretation in terms of elasticities. Additionally, a cointegration test was performed to verify the existence of a long-run relationship among the variables. The outcomes of the stationarity tests are summarized in Table 3.

Table 3. Panel unit root test results (ADF, PP, and KPSS)

Country Groups	Variables	ADF Test		PP Test		KPSS Test	
		Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
High-income countries	AGPVI	46.99**	232.84*	96.29*	1,313.50*	0.41***	0.11***
	RAINI	125.03*	280.43*	504.98*	3,343.78*	0.78***	0.05***
	GDPII	159.11*	274.06*	233.83*	3,611.03*	3.14***	0.28***
	CO2WD	6.64	87.95*	3.76	191.41*	0.46***	0.07***
	FRTZQ	41.55***	180.50*	57.68*	519.37*	0.48***	0.09***
Lower-middle countries	AGPVI	12.10	71.46*	23.09***	193.93*	0.74***	0.05***
	INPIX	4.49	61.19*	8.24	616.62*	0.15***	0.03***
	TFPIX	10.49	62.38*	21.35***	399.84*	0.21***	0.05***
	LBORQ	4.17	30.18*	3.61	72.49*	0.45***	0.09***
Upper-middle countries	AGPVI	37.99**	205.24*	50.51*	931.16*	0.17***	0.08***
	GDPII	299.35*	1,368.79*	1,597.11*	2,684.20*	2.85***	0.05***
	FRTZQ	37.14**	150.77*	37.28**	623.95*	0.37***	0.10***
	RAINI	62.73*	181.95*	124.66*	2,078.52*	0.32***	0.12***
All countries	AGPVI	97.09*	509.55*	169.89*	2,438.59*	0.21***	0.02***
	GDPII	39.78	160.84*	31.01	473.33*	0.17***	0.02***
	FRTZQ	97.08*	436.22*	128.14*	2,024.92*	0.30***	0.04***
	RAINI	229.36*	579.26*	740.69*	7,095.22*	0.37***	0.02***
	IRRIQ	351.35*	434.80*	113.44*	534.86*	0.14***	0.02***

Note: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

The stationarity test results in Table 3 indicate that the variables across different income groups are integrated at mixed orders, namely I(0) and I(1). The combination of I(0) and I(1) integration levels justifies the use of the ARDL approach, which can appropriately handle regressors with mixed orders of integration but not I(2). This finding further confirms the robustness of the subsequent cointegration test and supports the validity of employing the Panel ARDL model to capture both short-run and long-run dynamics among the variables.

The general ARDL (p, q_1, …, q_k) model can be written as:

$$AGPVI_{it} = \alpha_i + \sum_{j=1}^{p} \phi_{ij}\, AGPVI_{i,t-j} + \sum_{m=1}^{k}\sum_{j=0}^{q_m} \beta_{imj}\, X_{m,i,t-j} + \varepsilon_{it}$$

where AGPVI denotes the agricultural production value for country i at time t; X_m represents the explanatory variables (GDP, fertilizer use, irrigation, rainfall, etc.); and ε_{it} is the error term.

The short-run dynamics are captured through the corresponding Error Correction Model (ECM), in which the coefficient of the lagged error correction term (ECM_{t-1}), denoted by λ, measures the speed of adjustment toward the long-run equilibrium. A significant and negative λ confirms the existence of a stable long-run relationship.

The ARDL bounds testing approach was applied to identify both short run and long-run effects, which are represented in the following linear equation:

High income

$$\begin{aligned}\Delta AGPVI_t = {} & \alpha_0 + \alpha_1 AGPVI_{t-1} + \alpha_2 RAINI_{t-1} + \alpha_3 GDPII_{t-1} + \alpha_4 CO2WD_{t-1} + \alpha_5 FRTZQ_{t-1} \\ & + \sum_{i=1}^{p} \alpha_{6i} \Delta AGPVI_{t-i} + \sum_{i=1}^{q} \alpha_{7i} \Delta RAINI_{t-i} + \sum_{i=1}^{r} \alpha_{8i} \Delta GDPII_{t-i} \\ & + \sum_{i=1}^{s} \alpha_{9i} \Delta CO2WD_{t-i} + \sum_{i=1}^{t} \alpha_{10i} \Delta FRTZQ_{t-i} + u_t\end{aligned}$$

Lower middle income

$$\begin{aligned}\Delta AGPVI_t = {} & \alpha_0 + \alpha_1 AGPVI_{t-1} + \alpha_2 INPIX_{t-1} + \alpha_3 TFPIX_{t-1} + \alpha_4 LBORQ_{t-1} \\ & + \sum_{i=1}^{p} \alpha_{5i} \Delta AGPVI_{t-i} + \sum_{i=1}^{q} \alpha_{6i} \Delta INPIX_{t-i} + \sum_{i=1}^{r} \alpha_{7i} \Delta TFPIX_{t-i} \\ & + \sum_{i=1}^{s} \alpha_{8i} \Delta LBORQ_{t-i} + u_t\end{aligned}$$

Upper middle income

$$\begin{aligned}\Delta AGPVI_t = {} & \alpha_0 + \alpha_1 AGPVI_{t-1} + \alpha_2 GDPII_{t-1} + \alpha_3 FRTZQ_{t-1} + \alpha_4 RAINI_{t-1} \\ & + \sum_{i=1}^{p} \alpha_{6i} \Delta AGPVI_{t-i} + \sum_{i=1}^{q} \alpha_{7i} \Delta GDPII_{t-i} + \sum_{i=1}^{r} \alpha_{8i} \Delta FRTZQ_{t-i} \\ & + \sum_{i=1}^{s} \alpha_{9i} \Delta RAINI_{t-i} + u_t\end{aligned}$$

All countries

$$\begin{aligned}\Delta AGPVI_t = {} & \alpha_0 + \alpha_1 AGPVI_{t-1} + \alpha_2 GDPII_{t-1} + \alpha_3 FRTZQ_{t-1} + \alpha_4 RAINI_{t-1} + \alpha_5 IRRIQ_{t-1} \\ & + \sum_{i=1}^{p} \alpha_{6i} \Delta AGPVI_{t-i} + \sum_{i=1}^{q} \alpha_{7i} \Delta GDPII_{t-i} + \sum_{i=1}^{r} \alpha_{8i} \Delta FRTZQ_{t-i} \\ & + \sum_{i=1}^{s} \alpha_{9i} \Delta RAINI_{t-i} + \sum_{i=1}^{t} \alpha_{10i} \Delta IRRIQ_{t-i} + u_t\end{aligned}$$

Where Δ denotes the change in the variable, and p, q, r, s, and t represent the optimal lag lengths for each respective variable.

Following this, the short-run dynamics within the ARDL framework are represented by the equation below:

High income

$$\Delta AGPVI_t = \alpha_{11} + \sum_{i=1}^{p} \alpha_{12i} \Delta AGPVI_{t-i} + \sum_{i=0}^{q} \alpha_{13i} \Delta RAINI_{t-i} + \sum_{i=0}^{r} \alpha_{14i} \Delta GDPII_{t-i} + \sum_{i=0}^{s} \alpha_{15i} \Delta CO2WD_{t-i} + \sum_{i=0}^{t} \alpha_{16i} \Delta FRTZQ_{t-i} + \lambda ECM_{t-1} + u_t$$

Lower middle income

$$\Delta AGPVI_t = \alpha_{11} + \sum_{i=1}^{p} \alpha_{12i} \Delta AGPVI_{t-i} + \sum_{i=0}^{q} \alpha_{13i} \Delta INPIX_{t-i} + \sum_{i=0}^{r} \alpha_{14i} \Delta TFPIX_{t-i} + \sum_{i=0}^{s} \alpha_{15i} \Delta LBORQ_{t-i} + \lambda ECM_{t-1} + u_t$$

Upper middle income

$$\Delta AGPVI_t = \alpha_{11} + \sum_{i=1}^{p} \alpha_{12i} \Delta AGPVI_{t-i} + \sum_{i=0}^{q} \alpha_{13i} \Delta RAINI_{t-i} + \sum_{i=0}^{r} \alpha_{14i} \Delta GDPII_{t-i} + \sum_{i=0}^{s} \alpha_{15i} \Delta CO2WD_{t-i} + \sum_{i=0}^{t} \alpha_{16i} \Delta IRRIQ_{t-i} + \lambda ECM_{t-1} + u_t$$

All countries

$$\Delta AGPVI_t = \alpha_{11} + \sum_{i=1}^{p} \alpha_{12i} \Delta AGPVI_{t-i} + \sum_{i=0}^{q} \alpha_{13i} \Delta GDPII_{t-i} + \sum_{i=0}^{r} \alpha_{14i} \Delta FRTZQ_{t-i} + \sum_{i=0}^{s} \alpha_{15i} \Delta RAINI_{t-i} + \sum_{i=0}^{t} \alpha_{16i} \Delta IRRIQ_{t-i} + \lambda ECM_{t-1} + u_t$$

Based on the equation, a negative and statistically significant coefficient of ECM_{t-1} (λ) indicates the existence of cointegration within the model. This reflects the speed at which any temporary deviation in the relationship between the dependent and independent variables returns to the long-run equilibrium. Table 4 presents the results of the panel cointegration test.

Table 4. Panel cointegration test results (Pedroni and Kao Tests)

Country Groups	Panel v-stat.	Panel rho-stat.	Panel PP-stat.	Panel ADF-stat.	Group rho-stat.	Group PP-stat.	Group ADF-stat.	Kao ADF-stat.
High-income countries	-2.16	2.63	1.51	4.26	1.68	-1.88*	2.47	2.42*
Lower-middle countries	6.23**	-4.04**	-6.39*	-0.49	-1.43***	-4.36*	-0.47	-3.62*

Upper-middle countries	-2.48	0.61	-1.49	1.20	1.39	-1.34***	1.75	-3.30*
All countries	-1.11	0.21	-1.36***	1.57	1.29	-1.07	2.65	-1.25***

Note: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

The results of the Pedroni and Kao residual cointegration tests confirm the presence of a long-run equilibrium relationship among the variables across most country groups. Several Pedroni statistics, both within and between dimension, are significant for high-income, upper-middle-income, and the full sample, while the Kao test also consistently rejects the null of no cointegration. Although the evidence is weaker for lower-middle-income countries, at least one of the tests indicates cointegration. These findings validate the suitability of the Panel ARDL model, which is capable of capturing both short-run dynamics and long-run relationships in the presence of cointegration.

Three dynamic panel estimators were considered: the Mean Group (MG), the Pooled Mean Group (PMG), and the Dynamic Fixed Effects (DFE). The MG estimator allows full heterogeneity across groups, while the PMG restricts long-run coefficients to be homogeneous but permits heterogeneous short-run dynamics. The DFE estimator imposes homogeneity on both long- and short-run coefficients. To determine whether PMG is appropriate, Hausman tests were conducted, comparing PMG against MG to test the null hypothesis that the long-run coefficients are homogeneous across groups. If the null is not rejected, PMG is preferred due to its efficiency gains, while rejection of the null suggests that the MG estimator, which allows for full heterogeneity, provides more reliable estimates.

Lag length selection was based on the Akaike Information Criterion (AIC), balancing goodness of fit and parsimony across specifications. Consistent lag lengths were applied across groups to facilitate comparability.

Because climate and market shocks often affect many countries simultaneously, the possibility of cross-sectional dependence was formally tested. Robustness checks were conducted using the Common Correlated Effects (CCE) ARDL specification, which augments the standard ARDL with cross-sectional averages of the dependent and independent variables. This specification accounts for unobserved common factors, ensuring that global shocks do not bias long-run coefficients. The CCE approach is widely recognized as a reliable method to address cross-sectional dependence in panel data, particularly in studies involving global phenomena such as climate change. By incorporating common factors, the CCE-ARDL provides more consistent and unbiased estimates, allowing the results to better reflect both country-specific dynamics and shared global shocks.

Overall, the empirical strategy involved four steps: (1) testing for stationarity and cointegration, (2) estimating panel ARDL models across income groups, (3) conducting robustness checks with alternative estimators (MG, PMG, DFE, CCE), and (4) validating results through Hausman tests and sensitivity analyses. This comprehensive methodological framework ensures that the estimated effects of climate and economic factors on agricultural production are reliable and robust across model specifications.

RESULTS AND DISCUSSION

After confirming cointegration, the subsequent step involved identifying and estimating the short-run and long-run effects. The long-run ARDL estimation results are reported in Table 5, complemented by robustness checks using the Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS) methods. Table 6 reports the short-run ARDL results. All tables have been reformatted to ensure clarity, with units, measures, and standard errors reported in parentheses. Each table is now self-contained and designed to be interpretable without reference to the main text, thereby allowing readers to directly assess the magnitude, significance, and robustness of the estimated coefficients across country groups.

Table 5. Long-run Estimation Results Using ARDL, DOLS, and FMOLS

Country Groups	Variables	ARDL		DOLS		FMOLS	
		Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
High income	RAINI	0.57* (0.02)	23.05	0.09 (0.14)	0.64	0.05 (0.06)	0.83
	GDPII	-0.02* (0.00)	-3.79	-0.01 (0.01)	-0.48	0.00 (0.00)	0.03
	CO2WD	0.15 (0.02)	7.00	0.26* (0.07)	3.69	0.25* (0.04)	5.23
	FRTZQ	0.40* (0.02)	23.87	0.26* (0.06)	4.79	0.25* (0.04)	5.98
	Constant	6.54* (0.37)	17.88				
	R2			0.99		0.99	
	Adjusted R2			0.99		0.99	
	Standard error of the estimate			0.08		0.09	
Lower middle income	RAINI	-0.10*** (0.05)	-1.82	0.08 (0.12)	0.63	0.01 (0.08)	0.09
	FRTZQ	0.03 (0.09)	0.27	0.37* (0.07)	5.56	0.49* (0.06)	8.16
	LBORQ	0.19 (0.15)	1.27	0.12 (0.13)	0.88	0.25** (0.11)	2.25
	GHGMI	-0.02 (0.14)	-0.15	0.65* (0.08)	8.28	0.53* (0.07)	7.51
	Constant	15.93* (4.46)	3.57				
	R2			0.98		0.96	
	Adjusted R2			0.97		0.95	
	Standard error of the estimate			0.09		0.11	
Upper middle income	GDPII	0.20** (0.10)	2.09	0.06 (0.09)	0.65	0.02* (0.02)	1.04
	FRTZQ	0.76* (0.22)	3.43	0.74* (0.06)	12.06	0.71 (0.05)	15.13
	RAINI	0.69 (0.32)	2.17	0.20 (0.25)	0.80	0.17 (0.13)	134
	Constant	-2.33 (5.69)	-0.41				

Country Groups	Variables	ARDL		DOLS		FMOLS	
		Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
	R2			0.97		0.96	
	Adjusted R2			0.96		0.96	
	Standard error of the estimate			0.04		0.06	
All countries	GDPII	0.28* (0.02)	14.52	0.37* (0.02)	16.32	0.37* (0.02)	20.56
	FRTZQ	0.36* (0.02)	16.83	0.27* (0.03)	10.09	0.28* (0.02)	13.12
	RAINI	0.45* (0.03)	17.36	0.08 (0.06)	1.35	-0.00 (0.03)	-0.02
	IRRIQ	0.22* (0.01)	16.17	0.23* (0.03)	7.72	0.23* (0.03)	8.48
	Constant	0.10 (0.48)	-0.20				
	R2			0.99		0.99	
	Adjusted R2			0.99		0.99	
	Standard error of the estimate			0.00		0.02	

Note: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

Long-Run Analysis

High-income countries. Based on the long-run estimation results of the ARDL model for the high-income country group, it was found that rainfall (RAINI), gross domestic product (GDPII), and fertilizer consumption (FRTZQ) have a significant influence on agricultural production (AGPVI), while carbon emissions (CO2WD) show no significant effect (Ruane et al. 2024). The positive and significant coefficient of rainfall (0.57) indicates that a 1% increase in rainfall can raise agricultural production by 0.57%. This finding suggests that although developed countries possess advanced irrigation and water management technologies, rainfall availability remains a vital factor in maintaining the stability of their agricultural systems. Meanwhile, the GDPII variable exhibits a negative and significant coefficient (-0.02), indicating an inverse relationship between economic growth and the contribution of the agricultural sector. This result is consistent with the structural transformation theory proposed by Kuznets (1955) and Timmer (1988), which explains that as income levels and industrialization rise, the share of agriculture in total economic output tends to decline due to the reallocation of labor and capital toward the industrial and service sectors. In contrast, fertilizer consumption (FRTZQ) shows a strong and significant positive relationship with agricultural production (coefficient 0.40), confirming that agricultural intensification through modern inputs remains a key factor in sustaining land productivity in developed economies (Bracho-Mujica et al., 2024).

In contrast, the DOLS estimation results reveal variations in the level of significance across variables. In this model, only carbon emissions (CO2WD) and fertilizer consumption (FRTZQ) have a positive and significant impact on agricultural production, whereas rainfall and GDP are statistically insignificant. The positive and significant coefficient of CO2WD (0.26) suggests that higher carbon emissions, which typically result from energy-intensive economic activities, are associated with increased agricultural productivity (Li et al. 2025). This may reflect the higher levels of modernization and mechanization in developed countries, where the use of energy and fossil-fuel-based machinery contributes to greater production efficiency. Meanwhile, the insignificance of rainfall and GDP in the DOLS model indicates that after accounting for short-run dynamics and time trends, these variables no longer serve as dominant factors in explaining variations in agricultural output among high-income countries.

A relatively consistent pattern is also observed in the FMOLS model, where carbon emissions (CO2WD) and fertilizer consumption (FRTZQ) continue to exert a positive and significant effect on agricultural production, while rainfall (RAINI) and GDP (GDPII) remain insignificant. The insignificance of rainfall in both the DOLS and FMOLS models reinforces the notion that agricultural systems in advanced economies have become relatively insulated from climatic fluctuations through the adoption of adaptive technologies such as greenhouses, precision irrigation systems, and climate-resilient crop varieties. Similarly, the insignificance of GDP in explaining agricultural production implies that agriculture in developed countries is no longer the main driver of economic growth but rather a technologically advanced and mature sector with stable output that is relatively independent of macroeconomic dynamics.

A comparison of the three models shows that fertilizer consumption (FRTZQ) consistently exerts a positive and significant effect on agricultural production, emphasizing the importance of modern input factors in advanced agricultural systems. Meanwhile, carbon emissions (CO2WD) become significant only in the DOLS and FMOLS models, suggesting that the impact of agricultural modernization on productivity becomes more apparent when long-run relationships and cointegration effects are taken into account. Conversely, rainfall and GDP, which are significant in the ARDL model but not in the DOLS and FMOLS estimations, appear to have more short-term and transitional effects. Hence, the differing patterns of significance across models illustrate a structural shift from dependence on climatic and economic factors toward the predominance of technological and efficiency-related drivers in the agricultural systems of high-income countries.

These findings strengthen the argument that at higher income levels, agriculture has entered a post-productivist phase, where productivity growth is increasingly driven by innovation, energy efficiency, and environmental sustainability rather than traditional economic and climatic variables. Overall, fertilizer use—representing technological advancement—emerges as the principal factor reinforcing the resilience of the agricultural sector in developed economies against climate change. This aligns with Aggarwal et al. (2019), who emphasize the importance of technological innovation, and Kadanali and Yalcinkaya (2020), who advocate for greater collaboration among developed nations in reducing greenhouse gas emissions. High-income countries should therefore utilize their fiscal capacities effectively and efficiently, enabling them not only to strengthen domestic agricultural resilience but also to contribute to global climate finance—such as the US$100 billion annual commitment pledged by developed countries at COP15 to support mitigation and adaptation efforts in developing nations (Abebaw et al. 2025).

Lower-middle-income countries. The long-run estimation results of the ARDL model for the lower-middle-income country group reveal that most independent variables do not significantly affect agricultural production (AGPVI), except for rainfall (RAINI), which is marginally significant at the 10% level. The rainfall coefficient of -0.10 indicates a negative relationship between rainfall and agricultural production, suggesting that an increase in rainfall tends to reduce agricultural productivity in lower-middle-income countries. This finding resonates with the case of Nepal, where rice production fell by 0.01% due to rainfall (Chandio et al. 2021). This can be explained by the fact that most countries in this group possess limited agricultural infrastructure and irrigation systems, making them vulnerable to excessive rainfall that often leads to flooding, soil erosion, and farmland degradation. Consequently, climatic variables that should ideally serve as productive resources may instead become destructive forces when not accompanied by adequate adaptive capacity and water management systems. Other variables such as fertilizer consumption (FRTZQ), agricultural labor (LBORQ), and greenhouse gas emissions (GHGMI) show no significant effect in the ARDL model. This indicates that at the lower-middle-income level, key production factors such as labor and modern inputs have yet to optimally enhance agricultural productivity due to persistent inefficiencies, limited access to capital, and low technological adoption.

However, the DOLS estimation results show a notable shift in both the direction and magnitude of variable influences on agricultural production. In this model, fertilizer consumption (FRTZQ) and greenhouse gas emissions (GHGMI) have a positive and significant impact on agricultural output at the 1% level. The fertilizer consumption coefficient of 0.37 suggests that increased fertilizer use directly contributes to higher agricultural output. This finding aligns with the theory of agricultural intensification, which posits that increased utilization of modern inputs is a primary strategy for enhancing productivity in developing countries. Meanwhile, the positive and significant coefficient of greenhouse gas emissions (0.65) indicates a link between more intensive agricultural activities and higher carbon emissions. This can be interpreted as evidence that productivity growth in lower-middle-income countries is still achieved through input expansion that remains energy-intensive and environmentally inefficient. These results highlight that agriculture in these countries is still in the early stages of industrialization, where production growth is often accompanied by rising emissions and environmental degradation.

The FMOLS model produces a pattern nearly identical to that of DOLS, reinforcing the evidence that the relationship between modern input use and agricultural production is long-term in nature. In this model, fertilizer consumption (FRTZQ), agricultural labor (LBORQ), and greenhouse gas emissions (GHGMI) all exert positive and significant effects on agricultural output. The fertilizer coefficient of 0.49 confirms a strong and consistent positive influence on agricultural productivity, while the labor coefficient of 0.25 underscores that the agricultural sector in lower-middle-income countries remains labor-intensive. The significance of labor also indicates that mechanization has not yet fully replaced human labor, meaning that output growth still heavily depends on the availability and intensity of the agricultural workforce. Furthermore, the positive and significant coefficient of greenhouse gas emissions (0.53) once again emphasizes that economic expansion and intensive agricultural activities remain the main drivers of productivity—though at the cost of increasing environmental pressure.

The varying levels of significance across the ARDL, DOLS, and FMOLS models illustrate the structural dynamics currently unfolding in lower-middle-income countries. In the ARDL model, rainfall exerts a negative and marginally significant effect, suggesting that the agricultural sector in these countries remains highly vulnerable to climatic variability and weather uncertainty. However, when long-run correction models (DOLS and FMOLS) are employed, the rainfall effect disappears, and stronger relationships emerge between modern inputs, emissions, and agricultural productivity. This shift indicates a transition from dependence on natural factors toward reliance on production inputs. In other words, although agriculture in lower-middle-income countries continues to depend heavily on climatic conditions, in the long run, productivity is increasingly determined by the extent to which these countries can enhance the use of modern inputs and productive labor.

Conceptually, these findings indicate that the agricultural sector in lower-middle-income countries remains in an input-driven growth phase rather than an innovation-driven growth phase. The dominant influence of fertilizer and labor variables suggests that productivity is not yet supported by technological efficiency or sustainable agricultural systems. Moreover, the positive relationship between carbon emissions and agricultural output indicates a trade-off between economic growth and environmental sustainability. Therefore, agricultural development policies in this country group should be directed toward two main strategies: (1) Improving input efficiency through environmentally friendly technologies and sustainable farming practices, and (2) Strengthening adaptive capacity to climate change to reduce dependence on extreme weather conditions.

Overall, the findings empirically confirm that in lower-middle-income countries, agricultural development remains heavily constrained by structural limitations and incomplete economic transitions. In the long run, agricultural productivity will largely depend on these countries' ability to balance output growth with sustainable environmental management, while gradually transforming toward an innovation- and efficiency-based agricultural system.

Empirical evidence from previous studies supports these conclusions. Islam et al. (2019) highlight the vulnerability of the agriculture and fisheries sectors in Bangladesh to the impacts of climate change. Raihan et al. (2022) and Yousaf Raza et al. (2023) find that economic growth, energy use, and urbanization significantly influence agricultural productivity and climatic conditions in Bangladesh. In Egypt, Raihan et al. (2023) report that higher agricultural productivity contributes to improved environmental quality through reductions in CO_2 emissions, underscoring the importance of climate-smart agricultural practices.

These findings reinforce the urgency of an integrated strategy that combines technological innovation, institutional strengthening, and international cooperation to balance productivity growth with environmental sustainability.

Upper-Middle-Income Countries. The long-run estimation results using the ARDL model for the upper-middle-income country group reveal that gross domestic product (GDPII), rainfall (RAINI), and fertilizer consumption (FRTZQ) all contribute positively to agricultural production (AGPVI). Among these variables, only GDP and fertilizer consumption are statistically significant. The GDP coefficient of 0.20, significant at the 5% level, indicates that economic growth positively influences agricultural output in upper-middle-income countries. This finding suggests that economic expansion in this income group is still partially supported by the substantial contribution of the agricultural sector, where increases in domestic income enhance investment in agricultural infrastructure and technological capacity. The result reinforces the argument that agriculture continues to play a strategic role in the process of industrialization and economic development at the intermediate stage.

In addition, fertilizer consumption (FRTZQ) exhibits a strong and highly significant positive effect on agricultural production (coefficient 0.76, significant at 1%). This result implies that the intensification of modern input use, such as chemical fertilizers, remains a primary determinant of agricultural productivity in upper-middle-income countries. Such dependence on input-based growth indicates that productivity improvements are driven more by factor accumulation than by technological efficiency or systemic innovation. Meanwhile, rainfall (RAINI) also shows a positive coefficient of 0.69, although its significance is borderline (t-statistic 2.17). This suggests that climatic conditions—particularly rainfall—still play an important role in supporting agricultural productivity in upper-middle-income economies, most of which retain land-based production structures and are situated in tropical or subtropical climate zones.

Cross-regional empirical evidence supports the complexity of interactions between climate, economic growth, and agriculture. In Malaysia, climate change has significantly affected rice production over the period 1980–2019, with rainfall and agricultural land area exerting positive effects on yields, while extreme temperature and precipitation variability reduce productivity (Q. Zhang et al. 2023). In China, H. Zhang et al. (2023) find that a 1% increase in agricultural output contributes to a 0.14% rise in agricultural CO_2 emissions in the long run, highlighting the linkage between agricultural intensification and environmental impact. Conversely, Raihan et al. (2022) report that in Indonesia, a 1% increase in agricultural productivity leads to a 0.24% reduction in CO_2 emissions in the long run, reflecting the benefits of cleaner and more efficient farming practices.

The DOLS model results reveal that although the direction of relationships among variables remains consistent, the level of statistical significance changes. GDP (GDPII) continues to have a positive relationship with agricultural production, but its effect becomes statistically insignificant, while fertilizer consumption (FRTZQ) remains significant with a coefficient of 0.74. The loss of GDP significance in the DOLS model suggests that when long-run cointegration relationships and autocorrelation corrections are taken into account, the contribution of economic growth to the agricultural sector diminishes. This may be explained by ongoing economic diversification in upper-middle-income countries, where non-agricultural sectors—particularly industry and services—are becoming increasingly dominant. Hence, while agriculture continues to grow, it no longer serves as a primary driver of macroeconomic expansion.

The FMOLS model produces results broadly similar to those of the DOLS estimation. Fertilizer consumption (FRTZQ) remains the most significant variable (coefficient 0.71), whereas GDP (GDPII) and rainfall (RAINI) retain positive but statistically insignificant effects. The consistent significance of FRTZQ across all three models (ARDL, DOLS, and FMOLS) confirms that modern agricultural inputs remain a key determinant of agricultural productivity in upper-middle-income countries. However, the insignificance of GDP and rainfall in the DOLS and FMOLS models indicates a structural transition in which agriculture becomes less dependent on macroeconomic and climatic factors, and increasingly reliant on technological and input-based drivers of production.

The differences in significance levels across the three models carry both methodological and substantive implications. The ARDL model captures short-run dynamics and adjustments to economic or climatic shocks, thereby revealing significant effects of GDP and rainfall that may reflect short-term economic fluctuations or seasonal weather conditions. However, once long-run cointegration corrections are incorporated in the DOLS and FMOLS models, only variables with strong and persistent relationships—such as fertilizer consumption—remain significant. This finding underscores that, at the upper-middle-income stage, agricultural productivity is more strongly determined by internal production-system factors than by external influences such as macroeconomic growth or annual climate variation.

Overall, these results suggest that the agricultural sector in upper-middle-income countries is undergoing a transition from traditional farming toward a modern, input-intensive production system. The high dependence on fertilizers indicates that intensification remains the dominant strategy, while technological innovation and adaptive efficiency have not yet fully substituted for physical input use. In the long-term development context, this condition implies the need for policy strategies focused on improving fertilizer-use efficiency, enhancing production technologies, and strengthening adaptive capacity to climate change—thereby promoting agricultural growth that is both sustainable and less reliant on material input intensification.

All Countries (33 Countries). The long-run estimation results for the *All Countries* group—which includes 33 countries across high-, upper-middle-, and lower-middle-income levels—reveal that nearly all variables in the ARDL model exert a positive and significant influence on agricultural production (AGPVI). GDP (GDPII), fertilizer consumption (FRTZQ), rainfall (RAINI), and irrigation (IRRIQ) all display positive coefficients and are statistically significant at the 1% level. This indicates that, in aggregate, economic growth, agricultural input intensification, climatic factors, and irrigation infrastructure are the main drivers of agricultural production across countries. The GDP coefficient (0.28) suggests that economic growth remains directly associated with higher agricultural output. In other words, as national income increases, countries tend to expand investments in agriculture—

through enhanced physical inputs, improved access to agricultural finance, and the adoption of modern technologies.

Fertilizer consumption (FRTZQ), with a positive and highly significant coefficient (0.36 at the 1% level), confirms that modern input use remains a dominant determinant of agricultural productivity across income groups. This finding reinforces evidence from the previous country-group analyses, establishing fertilizer as the most consistent and significant variable explaining variations in agricultural output. Rainfall (RAINI), with a coefficient of 0.45, also exhibits a positive and significant effect, suggesting that climatic factors continue to play a crucial role in global agricultural systems—particularly in developing countries where agricultural infrastructure remains underdeveloped. This finding underscores that climatic stability remains a fundamental prerequisite for aggregate agricultural productivity. Likewise, irrigation (IRRIQ) has a positive and significant relationship (coefficient 0.22), emphasizing the importance of water management infrastructure as a primary adaptation instrument to climate variability.

However, the DOLS and FMOLS estimation results reveal shifts in the level of significance among variables. In the DOLS model, GDP, fertilizer consumption, and irrigation remain positive and significant, whereas rainfall becomes insignificant. Once cointegration and autocorrelation corrections are introduced, the influence of rainfall on agricultural output becomes statistically negligible—indicating that short-term climatic fluctuations do not exert stable long-term effects on productivity when structural and technological factors are accounted for. The FMOLS results echo this pattern, with GDP, fertilizer use, and irrigation remaining significant, while rainfall loses significance. These changes suggest that rainfall effects are short-term and context-dependent, whereas long-run agricultural productivity is more strongly driven by economic, technological, and infrastructural factors.

Conceptually, the consistent significance of GDP, fertilizer consumption, and irrigation in the DOLS and FMOLS models underscores the combined importance of macroeconomic and input-related factors in sustaining agricultural production across nations. Rising GDP reflects a country's capacity to invest in agriculture through infrastructure development, technological innovation, and farmer financing. The persistent significance of fertilizer use across all models confirms that input intensification remains a widespread strategy to boost productivity, even though its long-term effectiveness depends on usage efficiency. Meanwhile, the strong role of irrigation highlights the centrality of water management infrastructure in reducing dependency on rainfall—particularly in tropical and semi-arid regions.

A comparison of the ARDL, DOLS, and FMOLS models reveals that differences in coefficient magnitude and significance reflect the contrast between short-run and long-run dynamics. The ARDL model captures both short- and long-run relationships, showing that all variables significantly influence agricultural production—implying a strong interaction among climatic, economic, and agricultural input factors. However, in the DOLS and FMOLS models—which emphasize long-run equilibrium and structural relationships—the significance of rainfall disappears, indicating that the long-term role of climate has been offset by adaptation mechanisms such as irrigation development and agricultural technology adoption. In other words, the DOLS and FMOLS estimations suggest that in the long run, global agricultural systems depend less on climatic conditions per se and more on economic and technological capacities to adapt to them.

These findings carry important implications for cross-country agricultural development policy. First, macroeconomic factors such as GDP growth must be optimized to strengthen investment in climate-resilient agriculture. Second, improving fertilizer-use efficiency and enhancing irrigation systems should be prioritized as core strategies for maintaining and increasing sustainable agricultural productivity. Third, the insignificance of rainfall in long-run models underscores the urgency of policies for climate-change mitigation and adaptation to reduce dependence on weather variability through the adoption of climate-smart agricultural technologies. Overall, the results for the *All Countries* group (33 countries) indicate that global agricultural productivity is increasingly determined by the interaction between economic, technological, and adaptive policy factors—rather than by natural climatic conditions alone.

The aggregated evidence suggests that there is no single pathway toward building agricultural resilience to climate change. Instead, an integrated approach is required—combining economic strength, technological adoption, community participation, and ecological management (Sarkodie et al. 2019). Governments play a critical role in institutional coordination, climate-resilient infrastructure development, and expanding access to agricultural technologies (Mursyid et al. 2021).

Meanwhile, farmers remain at the core of adaptation processes. Studies have shown that farmers with stronger climate awareness are more likely to invest in climate-resilient strategies (Saptutyningsih et al. 2020). Therefore, modern agricultural extension services leveraging information and communication technologies (ICT) are essential to promote the widespread adoption of adaptive practices (Hasibuan et al. 2020).

Climate change continues to pose a major challenge to global agriculture. (Khan et al. 2022) report a decline in agricultural development across 101 countries due to rising global temperatures, while (Kalkuhl and Wenz 2020) estimate that a 3.5°C increase in global surface temperature could reduce global agricultural output by 7–14% by 2100, with tropical and low-income regions being the most affected. (Dewi 2009) also identifies tropical regions as the most vulnerable areas to climate change impacts.

Although previous studies have employed different climate indicators—ranging from temperature, drought, and rainfall variability to sea-level rise—the inclusion of rainfall and CO_2 emissions in this study reflects both their empirical relevance and theoretical significance. Rainfall represents the variability of the climatic system, while CO_2 emissions capture the anthropogenic drivers of climate change. Without decisive action, climate change will exacerbate global poverty (Carattini et al. 2020), hinder economic transformation (Chandy 2023), reduce labor productivity, and raise operational costs (Wade and Jennings 2016). As a sector positioned at the intersection of food security and climate change, agriculture must remain a top priority in both adaptation and mitigation strategies.

Short-Run Analysis (ECM Regression). Based on the calculation results, Table 6 presents the short-run ARDL estimation for the model classified by countries' income levels. ECM indicate speed of adjustment to long-run equilibrium. The table is presented as follows.

Table 6. Short-run panel ARDL estimation results

Country Groups	Variables	Coefficient	t-Statistics
High income	D(LNGDPII(-1))	0.01* (0.00)	2.72
	D(FRTZQ)	-0.20** (0.08)	-2.53
	D(FRTZQ(-2))	0.14** (0.07)	2.16
	CointEq(-1)	-0.19** (0.10)	-1.96

Country Groups	Variables	Coefficient	t-Statistics
Lower middle income	D(RAINI)	0.06* (0.02)	3.23
	D(RAINI(-1))	0.05*** (0.03)	1.87
	D(LBORQ(-2))	-0.83*** (0.47)	-1.79
	CointEq(-1)	-0.13** (0.10)	-1.27
Upper middle income	D(AGPVI(-1))	-0.39* (0.06)	-6.21
	D(AGPVI(-2))	-0.18* (0.06)	-2.97
	D(FRTZQ)	0.05*** (0.03)	1.72
	D(FRTZQ(-1))	0.06** (0.03)	2.00
	CointEq(-1)	-0.03** (0.02)	-1.91
All countries	D(AGPVI(-1))	-0.19* (0.03)	-5.47
	D(GDPII)	0.18* (0.07)	2.68
	CointEq(-1)	-0.12* (0.03)	-3.83

Note: The symbols *, **, and *** signify statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

The short-run estimation results from the Panel ARDL model reveal varying dynamics across country groups, reflecting differences in income levels and economic structures. Overall, economic and agricultural input variables exert significant short-run effects on changes in agricultural production (AGPVI), while the ECM is negative and statistically significant across all groups. This confirms the presence of stable correction mechanisms that guide short-run disequilibria toward long-run equilibrium in each agricultural system.

For high-income countries, the first lag of GDP growth (D(LNGDPII(-1))) shows a positive and significant effect on agricultural production, indicating that economic expansion continues to stimulate agricultural activity, even though the sector's contribution to overall GDP is relatively modest. Meanwhile, changes in fertilizer consumption (D(FRTZQ)) exert a negative and significant contemporaneous effect but turn positive and significant after two periods (D(FRTZQ(-2))). This pattern suggests that excessive fertilizer use may initially reduce productivity due to nutrient imbalances or overapplication, but yields improve in subsequent periods once soil absorption and plant uptake reach optimal levels. The negative and significant ECM value (-0.19) indicates that approximately 19% of short-run disequilibrium is corrected each period, reflecting a relatively rapid and efficient adjustment mechanism in advanced agricultural systems facing economic or input shocks.

In upper-middle-income countries, the results indicate strong internal adjustment effects within agricultural production itself, as reflected by two negative and significant lags of AGPVI (D(AGPVI(-1)) = -0.39 and D(AGPVI(-2)) = -0.18). This implies a short-run diminishing returns effect, where increased production in one period leads to slower growth in subsequent periods due to land and input constraints. Conversely, changes in fertilizer consumption (D(FRTZQ)) and its lag exhibit positive and significant impacts, indicating that modern input intensification immediately and sustainably enhances productivity. The negative and significant ECM (-0.03) suggests a very slow adjustment speed of about 3% per period, implying that while agricultural modernization has progressed, structural rigidities and institutional constraints continue to hinder rapid re-equilibration toward the long-run path.

In contrast, the lower-middle-income countries group exhibits short-run dynamics predominantly driven by climatic factors. Rainfall (D(RAINI)) exerts a positive and significant effect both contemporaneously (0.06) and with one lag (0.05), indicating that increased and sustained precipitation enhances agricultural productivity. This underscores the continued dependence of agriculture in these economies on natural climatic conditions, with limited protection from irrigation or adaptive technologies. Conversely, agricultural labor (D(LBORQ(-2))) shows a negative and significant effect at two lags, suggesting the presence of labor redundancy and low marginal productivity within the agricultural workforce. The negative and significant ECM (-0.13) indicates that approximately 13% of disequilibrium is corrected per period, implying a slow but stable adjustment process typical of economies still transitioning toward agricultural modernization.

For the aggregated sample of all countries (33 countries), short-run estimates show that GDP growth (D(GDPII)) exerts a positive and significant effect on agricultural production, while the first lag of production (D(AGPVI(-1))) is negative and significant. The positive GDP effect suggests that economic expansion stimulates agricultural investment and demand, while the negative production lag reflects a natural post-expansion adjustment following previous output surges. The ECM (-0.12), significant at the 1% level, indicates that approximately 12% of short-run disequilibrium is corrected toward long-run equilibrium each period, reflecting a moderate yet efficient global adjustment mechanism.

Taken together, the short-run ARDL results demonstrate that the determinants of agricultural production vary systematically with countries' income levels. High-income economies exhibit rapid and efficient adjustment mechanisms supported by strong technological and institutional capacity. Upper-middle-income countries show transitional behavior, with slower adjustment reflecting structural and institutional rigidities. Lower-middle-income countries remain highly dependent on climatic conditions and constrained by infrastructural and efficiency limitations. The consistently negative and significant ECM across all groups confirms that, despite varying adjustment speeds, agricultural systems tend to converge toward long-run equilibrium following short-run shocks.

In essence, the short-run dynamics underscore that the global agricultural sector's long-run stability depends critically on efficient adjustment mechanisms, technological availability, and adaptive capacity to both climatic variability and economic fluctuations.

CONCLUSION

This study provides a comprehensive examination of the relationship between economic, climatic, and agricultural input factors on agricultural production (AGPVI) across income-based country classifications. The combined evidence from the long-run and short-run analyses demonstrates that while the direction and magnitude of these relationships differ across groups, a consistent pattern emerges: modern agricultural inputs (such as fertilizer use) and macroeconomic factors (such as GDP) play dominant roles in shaping global agricultural productivity, whereas the influence of climatic variables (particularly rainfall) diminishes as countries advance economically and enhance their technological adaptive capacity.

In the long run, the results of the ARDL, DOLS, and FMOLS estimations indicate that high-income countries have reached the stage of *post-productivist agriculture*, where agricultural performance no longer depends on economic growth or climatic conditions, but rather on technological efficiency and the optimized use of modern inputs. In contrast, upper-middle-income countries exhibit a transitional pattern—from macroeconomic dependence toward a more modern, input-efficient agricultural system. Lower-middle-income countries, however, remain strongly influenced by climatic conditions and physical input intensification (e.g., fertilizer and labor), rendering their productivity more vulnerable to rainfall fluctuations and climate variability. At the aggregate level (33 countries), the long-run findings confirm that economic growth, fertilizer use, and irrigation infrastructure constitute the primary drivers of agricultural productivity, while the significance of climatic variables weakens as adaptation capacity and mitigation policies are increasingly internalized within national agricultural systems.

In the short run, the fluctuations in agricultural production are mainly driven by changes in economic and input-related factors. GDP growth generally exerts a positive effect—particularly in upper-middle-income and developing economies—by stimulating agricultural investment and demand. However, fertilizer use exhibits delayed effects: in some cases (e.g., high-income countries), its short-run impact is negative but turns positive in subsequent periods, suggesting a lag in soil and crop responsiveness to nutrient application. Climatic variables, such as rainfall, remain significant in the short run—especially in lower-middle-income countries—but lose significance in the long-run estimations. The negative and significant ECM across all country groups confirm that global agricultural systems possess stable adjustment mechanisms, whereby short-run shocks are gradually corrected toward long-run equilibrium.

Conceptually, these findings reinforce the structural transformation theory advanced by (Kuznets 1955) and Timmer (1988)—which posits that as income levels rise, economic structures shift from agriculture toward industry and services, while agriculture evolves from a growth engine to a stabilizing sector that ensures food security and social resilience. Nevertheless, the results of this study reveal that agriculture continues to play an essential role in sustaining macroeconomic balance and supporting long-term development—primarily through technological innovation and resource-use efficiency.

From a policy perspective, the findings generate several important implications: (1) For high-income countries, agricultural policy should prioritize technological innovation, energy efficiency, and the adoption of low-emission sustainable farming systems to maintain a balance between productivity and environmental integrity. (2) For upper-middle-income countries, policies should focus on improving input-use efficiency, strengthening agricultural research and technology adoption, and advancing institutional reforms to accelerate the structural transition from input intensification to innovation-driven agriculture. (3) For lower-middle-income countries, policy priorities should emphasize building adaptive capacity to climate change, expanding irrigation and water management infrastructure, and enhancing farmers' access to agricultural inputs and finance—thereby improving both resilience and productivity.

Overall, this study underscores that the success of sustainable agricultural development does not depend solely on economic growth or climatic conditions, but rather on a country's ability to integrate economic, technological, and environmental policies in a coherent and balanced manner. With adaptive, evidence-based approaches—such as those employed through the ARDL, DOLS, and

FMOLS models—agriculture can play a pivotal role in global sustainable development strategies: not merely as a provider of food, but as a cornerstone of economic stability, social resilience, and ecological sustainability in the decades ahead.

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REFERENCES CITED

Abebaw, S. E., Tesfaye, D. and Mengistu, A. 2025. A global review of the impacts of climate change and variability on agriculture and livestock. Food Science & Nutrition. 13: 2231–2248.

Aggarwal, P., Vyas, S., Thornton, P., Campbell, B.M. and Kropff, M. 2019. Importance of considering technology growth in impact assessments of climate change on agriculture. Global Food Security. 23: 41–48.

Anh, D. L. T., Anh, N. T. and Chandio, A. A. 2023. Climate change and its impacts on Vietnam agriculture: A macroeconomic perspective. Ecological Informatics. 74: 1-12.

Bracho-Mujica, G., López, D., Carrillo, R. and Rojas, R. 2024. Effects of changes in climatic means, variability, and agro-technology on crop yields. Agricultural Systems. 218: 103741.

Carattini, S., Gosnell, G. and Tavoni, A. 2020. How developed countries can learn from developing countries to tackle climate change. World Development. 127: 104829.

Chandio, A. A., Jiang, Y., Ahmad, F., Adhikari, S. and Ain, Q. U. 2021. Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. Technology in Society. 66: 1-14.

Chandy, L. 2023. Economic Development in an Era of Climate Change. Carnegie Endowment for International Peace. 1-9.

Dewi, P. P. 2009. Climate change impacts on tropical agriculture and the potential of organic agriculture to overcome these impacts. Asian Journal of Food and Agro-Industry. 2: 10-17.

FAO. 2021. Climate change impacts on 20 major crop pests in Central Asia, the Caucasus and Southeastern Europe. Univ. Bonn. Ankara.

FAO. 2024. World Food and Agriculture-Statistical Yearbook 2024. Rome.

Hasibuan, A. M., Gregg, D. and Stringer, R. 2020. Accounting for diverse risk attitudes in measures of risk perceptions: A case study of climate change risk for small-scale citrus farmers in Indonesia. Land Use Policy. 95: 1-18.

Heikonen, S., Lehtonen, H. and Peltonen-Sainio, P. 2025. Climate change threatens crop diversity at low latitudes. Nature Food. 6: 150–159.

Hogan, D. and Schlenker, W. 2024. Non-linear relationships between daily temperature extremes and global crop yields. Nature Communications. 15: 221–234.

Iizumi, T., Yokozawa, M., Nishimori, M. and Nishimura, C. 2025. Assessing the capacity of agricultural R&D to increase the stability of global crop yields under climate change. PNAS Nexus. 4: 205–219.

Islam, M., Barman, A., Kumar, G., Kabir, A. and Paul, B. 2019. Vulnerability of inland and coastal aquaculture to climate change : Evidence from a developing country. Aquaculture and Fisheries. 4: 183–189.

Kadanali, E. and Yalcinkaya, O. 2020. Effects of Climate Change on Economic Growth: Evidence from 20 Biggest Economies of The World. Romanian Journal of Economic Forecasting. 23: 93–118.

Kalkuhl, M. and Wenz, L. 2020. The impact of climate conditions on economic production. Evidence from a global panel of regions. Journal of Environmental Economics and Management. 103: 1-20.

Khan, M. T. I., Anwar, S., Yaseen, M. R., and Nadeem, A. M. 2022. The Impact of Natural Disasters and Climate Change on Agriculture: An Empirical Analysis. Journal of Economic Impact. 4: 28–38.

Kuznets, S. S. 1955. Economic growth and income inequality. The American Economic Review. 45: 1–28.

Li, C., Zhang, Y., Wang, Q. and Chen, S. 2025. Predicting changes in agricultural yields under climate change: A statistical meta-analysis. Scientific Reports. 15: 3345–3358.

Mursyid, H., Daulay, M. H., Pratama, A. A., Laraswati, D., Novita, N., Malik, A. and A. Maryudi. 2021. Governance issues related to the management and conservation of mangrove ecosystems to support climate change mitigation actions in Indonesia. Forest Policy and Economics. 133: 1–6.

Raihan, A., Ibrahim, S. and D.A. Muhtasim. 2023. Dynamic impacts of economic growth, energy use, tourism, and agricultural productivity on carbon dioxide emissions in Egypt. World Development Sustainability. 2: 1-14.

Raihan, A., Muhtasim, D. A., Farhana, S., Hasan, M. A. U., Pavel, M. I., Faruk, O., Rahman, M. and A. Mahmood. 2022. Nexus between economic growth, energy use, urbanization, agricultural productivity, and carbon dioxide emissions: New insights from Bangladesh. Energy Nexus. 8: 1-16.

Raihan, A., Muhtasim, D. A., Pavel, M. I., Faruk, O. and M. Rahman. 2022. An econometric analysis of the potential emission reduction components in Indonesia. Cleaner Production Letters. 3: 1-9.

Ruane, A. C., Jägermeyr, J., Müller, C., Elliott, J. and C. Rosenzweig. 2024. Non-linear climate change impacts on crop yields may intensify with warming level. Earth's Future. 12: 872–889.

Saptutyningsih, E., Diswandi, D. and W. Jaung. 2020. Does social capital matter in climate change adaptation? A lesson from agricultural sector in Yogyakarta, Indonesia. Land Use Policy. 95: 1-5.

Sarkodie, S. A., Strezov, V., Weldekidan, H., Asamoah, E. F., Owusu, P. A. and I. N. Y. Doyi. 2019. Environmental sustainability assessment using dynamic Autoregressive-Distributed Lag simulations—Nexus between greenhouse gas emissions, biomass energy, food and economic growth. Science of the Total Environment. 668: 318–332.

Timmer, C.P., 1988. The agricultural transformation. *Handbook of development economics*, *1*, pp.275-331.

Wade, K. and M. Jennings. 2016. The impact of climate change on the global economy. Schroders Talking Point. 1–12.

Xue, G., Niu, W., Chen, C., Wu, Y. and X. Zhu. 2024. Research on the cost allocation method of deep sea wind power considering carbon trading and green certificate trading. Frontiers in Energy Research. 12: 1374524.

Yousaf Raza, M., Hasan, M. M. and Y. Chen. 2023. Role of economic growth, urbanization and energy consumption on climate change in Bangladesh. Energy Strategy Reviews. 47: 101088

Zhang, H., Xiong, P., Yang, S. and J. Yu. 2023. Renewable energy utilization, green finance and agricultural land expansion in China. Resources Policy. 80: 1-16.

Zhang, Q., Akhtar, R., Saif, A. N. M., Akhter, H., Hossan, D., Alam, S. M. A. and M.F. Bari. 2023. The symmetric and asymmetric effects of climate change on rice productivity in Malaysia. Heliyon. 9: 1-16.

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