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Asymmetric Effects of Climate Change on Agricultural Production in Algeria: An Econometric Analysis Using the Nonlinear Autoregressive Distributed Lag (NARDL) Model over the Period 1960–2023

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Abstract:

This study aims to analyze the impact of climate change on agricultural production in Algeria over the period 1960–2023 using the Nonlinear Autoregressive Distributed Lag (NARDL) model. The results reveal the presence of nonlinear dependencies among the variables, The findings also confirm the existence of a long-run equilibrium relationship. Furthermore, the study identifies asymmetric long-run effects of temperature and rainfall on agricultural production. In contrast, the results indicate symmetric effects of both positive and negative changes in carbon dioxide (CO_2) emissions. Additionally, the expansion of agricultural land exerts a positive and statistically significant effect on agricultural production.

Keywords: Climate change; Agricultural production; NARDL model.

Jel Classification Codes: Q54, Q18, C22.

1. INTRODUCTION

The agricultural sector is considered one of the strategic sectors of the Algerian economy due to its pivotal role in ensuring food security, diversifying the economic base, creating employment opportunities, supporting rural development, and reducing dependence on the hydrocarbon sector. Agricultural production also constitutes a fundamental pillar for maintaining stable food supplies and reducing reliance on imports, particularly in light of recurring global crises and the growing demand for food driven by population growth. In recent years, Algeria has devoted increasing attention to the development of this sector by implementing programs and strategies aimed at enhancing productivity through the expansion of irrigated agricultural land and the promotion of agricultural investment, thereby contributing to sustainable economic development and strengthening national food security.

Meanwhile, the world has witnessed accelerating climate change over recent decades, which has become one of the most significant challenges facing economies worldwide. This is largely attributable to the continuous increase in greenhouse gas emissions, particularly carbon dioxide (CO_2), leading to rising global average temperatures, more frequent extreme weather events, disrupted precipitation patterns, and recurrent droughts and floods. Reports issued by the Intergovernmental Panel on Climate Change (IPCC) confirm that these changes are no longer merely future projections but have become a tangible reality imposing growing challenges on economic and social sectors, particularly in the Mediterranean region, of which Algeria is an integral part.

Climate change is closely linked to the agricultural sector, as agriculture is among the most climate-sensitive sectors owing to its direct dependence on environmental conditions. Rising temperatures, fluctuations in rainfall,. Moreover, the recent literature suggests that the effects of these climate variables may be asymmetric, as the impacts of increases in climate variables may differ from those of decreases. Consequently, conventional linear models may be inadequate for capturing these complex relationships,

highlighting the importance of employing nonlinear approaches such as the Nonlinear Autoregressive Distributed Lag (NARDL) model.

Against this background, examining the impact of climate change on agricultural production in Algeria is of considerable importance, given that the country faces increasing climate-related challenges that may threaten the sustainability of its agricultural sector. Furthermore, understanding whether this relationship is symmetric or asymmetric can provide valuable empirical evidence to support policymakers in designing more effective agricultural and environmental policies that balance environmental protection, agricultural productivity, and national food security.

1.1 Research Problem

Based on the foregoing discussion, the research problem can be formulated as follows:

To what extent do climate change variables affect agricultural production in Algeria over the period 1960–2023, and is this relationship symmetric or asymmetric in both the short run and the long run?

1.2 Research Objectives

The objective of this study is to analyze the impact of climate change on agricultural production in Algeria and to examine the symmetric and asymmetric relationships between climate variables and agricultural production using the Nonlinear Autoregressive Distributed Lag model (NARDL).

1.3 Research Methodology

This study adopts a descriptive-analytical approach through a comprehensive review of the theoretical literature and previous empirical studies related to climate change and agricultural production. In addition, econometric techniques are employed to examine the relationship between the study variables using the Nonlinear Autoregressive Distributed Lag (NARDL) model, which enables the simultaneous analysis of short-run and long-run dynamics, as well as the estimation of the symmetric and asymmetric effects of positive and negative shocks in the explanatory variables on agricultural production.

1.4 Literature Review

Recent literature has shown growing interest in examining the impact of climate change on the agricultural sector, particularly with the development of nonlinear models, most notably the Nonlinear Autoregressive Distributed Lag (NARDL) model, which has enabled the analysis of both symmetric and asymmetric effects of climate shocks on agricultural production. Most empirical studies have identified a long-run relationship between climate variables and agricultural production, although the response of the agricultural sector varies according to the nature and direction of climate shocks.

In this context, (SAMUEL & al, 2022) found asymmetric effects of climate change on crop production in Nigeria. Their findings revealed that changes in rainfall enhanced agricultural production in the short run, whereas changes in both temperature and rainfall reduced production in the long run. Similarly, (Zhang & al, 2023) demonstrated an asymmetric relationship between climate change and rice productivity in Malaysia, showing that increases in temperature and rainfall reduced rice productivity, while decreases in these variables improved productivity, highlighting the heterogeneous response of crops to the direction of climate shocks.

In Algeria, (Benmehaia, 2023) reported that the expansion of cultivated land and increased rainfall contributed positively to cereal productivity, whereas higher temperatures and carbon dioxide (CO_2) emissions reduced productivity. The study also confirmed the stability of the estimated model and identified causal relationships among the variables. By contrast, (Choudhary & al, 2024) employed the Panel ARDL model to examine crop production in India and concluded that rising temperatures exert a negative long-run effect on agricultural production, whereas carbon dioxide emissions and cultivated land improve agricultural output.

Several studies have also focused on specific crops. (Miah & al, 2025) showed that rising temperatures adversely affect rice productivity in Bangladesh in the long run, whereas rainfall and fertilizer application positively enhance productivity, while carbon dioxide emissions reduce rice productivity. Likewise, (Khalifa, 2025) found both symmetric and asymmetric effects of climate change in Tunisia, revealing that

environmental degradation decreases crop production, whereas water productivity and fertilizer use play a positive role in supporting agricultural production.

Other studies have expanded the scope of analysis to include agricultural indicators beyond production. (Özkan & Miçooğullari, 2026) found that climate change exerts asymmetric effects on agricultural employment in Türkiye, with agricultural mechanization and trade significantly influencing employment levels. Similarly, (Yuhuan & Thann, 2026) identified asymmetric responses of Myanmar's agricultural sector, where the adverse effects of increases in rainfall and carbon dioxide emissions exceeded those associated with their decreases, while declines in temperature generated stronger positive effects than temperature increases.

Furthermore, some studies extended the analysis to the macroeconomic level. (Ishag, 2026) demonstrated that climate change affects not only agricultural production but also livestock production and economic growth in Sudan, emphasizing that drought shocks are more severe than equivalent increases in rainfall. Likewise, (Oo, 2026) found that the Italian agricultural sector possesses a strong capacity to correct short-run disequilibria; however, the long-run adverse effects of extreme climate shocks outweigh the benefits associated with improved climatic conditions.

Overall, the existing literature consistently supports the existence of a long-run relationship between climate change and agricultural production and highlights the superiority of the NARDL model over conventional linear models in capturing nonlinear relationships. Nevertheless, the literature remains inconclusive regarding the effect of carbon dioxide emissions. While some studies report a negative impact, others document a positive effect attributable to the Carbon Fertilisation Effect. Moreover, the nature of asymmetry differs across countries owing to variations in climatic conditions, water resources, and the structural characteristics of the agricultural sector. Against this background, the present study seeks to investigate the symmetric and asymmetric effects of climate change on agricultural production in Algeria using the NARDL model, thereby

contributing to filling an empirical gap in the literature on the Algerian agricultural economy.

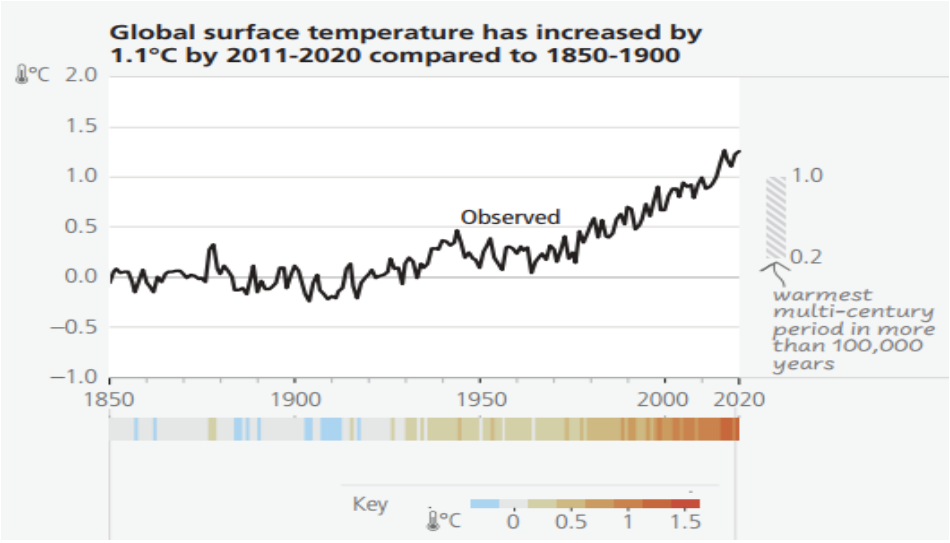
2. Climate Change

2.1 Concept of Climate Change, Its Impacts, and Attribution

Climate change refers to long-term changes in temperature, precipitation patterns, and other climatic variables. According to the Intergovernmental Panel on Climate Change (IPCC), human activities—particularly greenhouse gas emissions resulting from fossil fuel use, deforestation, and land-use change—are the primary drivers of global warming. Consequently, climate change has increased the frequency and intensity of extreme weather events, such as heatwaves, droughts, and floods, adversely affecting food and water security, human health, economic activities, and biodiversity, with the most vulnerable communities being disproportionately impacted (IPCC, 2023, p. 42).

Figure1 shows a clear upward trend in global mean surface temperature between 1850-2020 relative to the 1850–1900 baseline. Global temperatures remained relatively stable until the early twentieth century, before gradually increasing from the 1940s and accelerating rapidly after the 1970s due to intensified human activities and greenhouse gas emissions.

Figure 1. Changes in Global Mean Surface Temperature.



Source: (IPCC, 2023, p. 43)

During 2011-2020, the global average temperature reached approximately 1.1°C above the pre-industrial level, representing the highest value in the historical record. The figure also highlights a shift from cooler to warmer temperature anomalies and indicates that current warming is approaching the warmest multi-century period in more than 100,000 years, emphasizing the unprecedented nature of modern climate change. (IPCC, 2023, pp. 43-44)

2.2 The Current State of Climate Change Worldwide

International reports indicate that the world is experiencing an unprecedented escalation in the impacts of climate change, reflected in the continuous rise in global average temperatures, the increasing frequency and intensity of heatwaves, droughts, and floods, as well as the sustained increase in atmospheric carbon dioxide concentrations. As a result, economic sectors have become increasingly exposed to climate-related risks, particularly the agricultural sector, which is among the most vulnerable to climate variability. These developments demonstrate that climate change has become a major threat to the sustainability of agricultural production and global food security, highlighting the urgent need for effective adaptation policies to strengthen the resilience of agricultural systems (WMO, 2025, pp. 19-20) .

North Africa, including Algeria, is among the regions most vulnerable to the impacts of climate change. The region has experienced a persistent increase in average temperatures, a decline in precipitation, and a higher frequency of drought events. These changes have resulted in reduced water resources, accelerated desertification, and lower agricultural productivity, particularly in rainfed farming systems (IPCC, 2022, p. Chapter 9).

3. Methodology and Data

3.1 Variables and Data

Based on the theoretical literature and previous empirical studies, this study examines the impact of climate change on agricultural production in Algeria over the period 1960–2023. The study variables were selected in accordance with production theory and the findings of previous research.

To ensure the reliability and credibility of the empirical results, annual time-series data were obtained from recognized official international

sources. The use of a relatively long time span makes it possible to investigate both the short-run and long-run relationships among the variables. Furthermore, all variables were transformed into their natural logarithms to facilitate the interpretation of the estimated coefficients as elasticities and to mitigate potential heteroskedasticity.

The dependent variable is the Agricultural Production Index (API). The main explanatory variables are average temperature and precipitation, which serve as indicators of climate change and climatic variability.

The model also incorporates carbon dioxide (CO_2) emissions to capture environmental pressure and to examine the potential carbon fertilization effect on agricultural productivity. In addition, agricultural land is included as a control variable representing a conventional agricultural production input.

Accordingly, based on economic theory and the existing empirical literature, the following log-linear relationship is specified for estimation:

$$LCPI = f(LTEMP, LRAIN, LPCO2, LL)$$

Table 1. Data Sources and Variables

Variable	Symbol	Definition and Unit	Data Source
Agricultural Production Index	LCPI	Natural logarithm of the Agricultural Production Index (2014–2016 = 100), which includes all agricultural crops.	World Development Indicators (WDI), World Bank
Average Temperature	LTEMP	Natural logarithm of the annual average surface air temperature (°C).	Climate Change Knowledge Portal (CCKP), World Bank
Precipitation	LRAIN	Natural logarithm of annual precipitation (mm).	Climate Change Knowledge Portal (CCKP), World Bank
Carbon Dioxide Emissions	LPCO2	Natural logarithm of per capita CO_2 emissions (metric tons per capita).	World Development Indicators (WDI), World Bank
Agricultural Land	LL	Natural logarithm of agricultural land (% of total land area).	FAOSTAT

Source: Prepared by the author

3.2 Estimation Method and Econometric Framework

The conventional Autoregressive Distributed Lag (ARDL) model assumes that explanatory variables exert symmetric effects, implying that it cannot

distinguish between the impacts of positive and negative changes in the explanatory variables. To overcome this limitation, this study adopts the nonlinear approach proposed by (Shin & al, 2014), namely the Nonlinear Autoregressive Distributed Lag (NARDL) model, which relaxes the linearity assumption and allows the identification of asymmetric relationships among variables. The core feature of the NARDL methodology is the decomposition of explanatory variables into the cumulative sums of positive and negative partial changes. Unlike the conventional linear ARDL model, the NARDL framework enables the separate estimation of the effects of positive shocks (increases) and negative shocks (decreases).

Let x denote an explanatory variable to be decomposed. Its first difference is defined as:

$$\Delta x_t = x_t - x_{t-1}$$

The positive and negative changes are then obtained as follows:

$$\Delta {x_t}^+ = \max(\Delta x_t, 0)$$
$$\Delta {x_t}^- = \min(\Delta x_t, 0)$$

The corresponding cumulative partial sums are constructed as:

$${x_t}^+ = \sum_{i=1}^{t} \Delta {x_t}^+ = \sum_{i=1}^{t} \max(\Delta x_t, 0) \ , \ {x_t}^- = \sum_{i=1}^{t} \Delta {x_t}^- = \sum_{i=1}^{t} \min(\Delta x_t, 0)$$

To examine the asymmetric relationship between climate change and agricultural production, the variables temperature, precipitation, and carbon dioxide (CO_2) emissions were decomposed into their positive and negative partial sums, denoted by $LTEMP^+$, $LTEMP^-$, $LRAIN^+$, $LRAIN^-$, $LPCO2^+$, and $LPCO2^-$, respectively. The nonlinear long-run specification is expressed as follows:

$$LCPI = f(LTEMP^+, LTEMP^-, LRAIN^+, LRAIN^-, LPCO2^+, LPCO2^-, LL)$$

4. Results and Discussion

4.1 Unit Root Test Results

The unit root test was conducted to examine the time-series properties of the study variables, verify their stationarity, and determine their order of integration. To assess the stationarity of each variable, the study employed the Augmented Dickey–Fuller (ADF) unit root test, the results of which are reported in Table 2. The findings indicate that all variables are integrated of order one, I(1), with the exception of the logarithm of average annual

rainfall (LRAIN), which is integrated of order zero, I(0).

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

Variables	Model	None		Trend & intercept		Intercept		Degree of Integration
		Statistic	prob	statistic	prob	statistic	prob	
LCPI	Level	1.40	0.958	-3.19	0.096	-0.13	0.940	
	1st deff	-7.59	0.000	-7.95	0.000	-7.85	0.000	I(1)
LTEMP	Level	1.09	0.926	-5.47	0.000	-2.10	0.245	
	1st deff	-11.00	0.000	-10.96	0.000	-11.08	0.000	I(1)
LRAIN	Level	-0.43	0.522	-6.87	0.000	-6.48	0.000	
	1st deff	-12.56	0.000	-12.36	0.000	-12.45	0.000	I(0)
LPCO2	Level	0.94	0.907	-4.68	0.002	-4.18	0.001	
	1st deff	-5.33	0.000	-5.43	0.000	-5.41	0.000	I(1)
LL	Level	-0.55	0.471	-1.54	0.802	-1.83	0.361	
	1st deff	-7.09	0.000	-7.17	0.000	-7.05	0.000	I(1)

Source: Prepared by the author based on EViews 12.

4.2 Results of the Nonlinearity Test

To verify the presence of nonlinearity in the data, the BDS test, developed by (Brock & al, 1996), was employed. The BDS test is widely used to detect nonlinear and non-random patterns in time-series data. It also helps distinguish chaotic behavior from nonlinear stochastic processes and is capable of identifying various forms of nonlinearity. The results of the BDS test (Table 3) reject the null hypothesis of linear dependence for most of the study variables, providing strong evidence of nonlinear dynamics in the data. The rainfall variable was the only exception, as its BDS statistic was not statistically significant across all embedding dimensions. In contrast, the remaining variables exhibited significant nonlinear behavior. Furthermore, the BDS statistics increased with higher embedding dimensions, indicating a stronger degree of nonlinearity, particularly at larger dimensions.

Table (3). BDS Nonlinearity Test Results

BDS statistic	**m=2**	**m=3**	**m=4**	**m=5**	**m=6**
LCPI	16.33***	16.69***	17.18***	17.96***	19.11***
LTEMP	13.15***	14.96***	15.95***	17.54***	19.69***
LRAIN	1.76*	1.38	1.10	0.81	0.37
LPCO2	9.54***	9.77***	9.94***	10.55***	11.26***
LL	20.53***	22.23***	24.46***	27.65***	31.88***

Source: Prepared by the author based on the Stata 17.

4.3 Cointegration Test Results

After confirming the presence of nonlinear relationships in the data, the parameters of the Nonlinear Autoregressive Distributed Lag (NARDL) model were estimated. To examine whether a long-run equilibrium relationship exists among the model variables, the Bounds Testing approach within the NARDL framework was employed. This procedure is based on the F-statistic, which tests the null hypothesis (H_0) of no cointegration against the alternative hypothesis (H_1) that a long-run cointegrating relationship exists among the estimated variables.

The results of the Bounds Test, reported in Table 4, indicate that the calculated F-statistic is 5.91, which exceeds the corresponding upper critical bound at the 1%, 5%, and 10% significance levels, given the sample size and degrees of freedom. Accordingly, the null hypothesis of no cointegration is rejected in favor of the alternative hypothesis, confirming the existence of a long-run equilibrium (cointegrating) relationship among the variables included in the estimated NARDL model.

Table 4. Summary of Cointegration Test Results (Bound Tests)

F-statistic	**Critical F-values**	**Significance level**		
5.91		**1%**	**5%**	**10%**
	I(0)	2.73	2.17	1.92
	I(1)	3.9	3.21	2.89

Source: Prepared by the author based on outputs from EViews 12**.**

4.4 Diagnostic Tests

The unit root tests confirmed that the study variables are stationary at levels and first differences, while the cointegration test indicated the existence of a long-run equilibrium relationship among the variables. Accordingly, the Nonlinear Autoregressive Distributed Lag (NARDL) model was estimated to examine both the long-run and short-run relationships among the study variables.

The NARDL model was estimated. Based on the Akaike Information Criterion (AIC), which automatically selects the optimal lag structure, the model was found to be jointly statistically significant, as indicated by the F-statistic (p-value = 0.000). Furthermore, the adjusted coefficient of determination (Adjusted R^2) was 0.970, indicating that the model has a high

explanatory power.

Table (5) presents the diagnostic test results for the estimated model. The findings confirm that the model satisfies the standard econometric assumptions and is free from specification problems that could bias the estimation results. Specifically, the Breusch–Godfrey Serial Correlation LM Test and the corresponding F-test indicate the absence of serial correlation, with p-values of 0.404 and 0.467, respectively, both exceeding the 5% significance level. Likewise, the Breusch–Pagan heteroskedasticity test confirms the absence of heteroskedasticity, as the p-values of both the LM and F-statistics are 0.567 and 0.616, respectively.

Furthermore, the Jarque–Bera test yields a p-value of 0.358, indicating that the residuals are normally distributed. Finally, the Ramsey RESET test confirms that the model is correctly specified, as the p-value associated with the F-statistic is 0.252, which exceeds the 5% significance level. Therefore, the estimated NARDL model can be considered statistically valid and appropriate for analyzing the asymmetric long-run and short-run effects of climate change on agricultural production in Algeria.

Table 5. Model Diagnostic Test Results

Test	Test Statistic	p-value	Statistical Decision
LM Test	0.69	0.404	No autocorrelation in the residuals
F Test	0.53	0.467	No autocorrelation in the residuals
LM Test	8.63	0.567	Homoscedasticity of residuals
F Test	0.81	0.616	Homoscedasticity of residuals
Jarque-Bera Test	2.05	0.358	Residuals are normally distributed
Ramesy Test	1.35	0.252	The model is correctly specified

Source: Prepared by the authors based on outputs from EViews 12**.**

4.5 Estimation of the Error Correction Term and Short-Run Dynamics

Table 6 presents the estimated Error Correction Model (ECM) and the short-run coefficients of the variables included in the study. The results indicate that the coefficients associated with the negative changes in carbon dioxide (CO_2) emissions were negative in both the current and the lagged periods, implying a positive relationship between CO_2 emissions and agricultural production. Specifically, the estimated coefficients were −0.39 in the current period, which was statistically insignificant (p-value = 0.283),

and −1.18 in the lagged period, which was statistically significant (p-value = 0.000) at the 5% significance level. These findings imply that a 1% decrease in CO_2 emissions leads to a decline in agricultural production of approximately 0.39% in the current period and 1.18% in the subsequent period.

This negative relationship between declining CO_2 emissions and agricultural production in the short run may be explained by the reduction in the physiological benefits associated with the CO_2 fertilization effect, whereby higher atmospheric CO_2 concentrations enhance photosynthetic activity and improve water-use efficiency, particularly for C3 crops such as wheat and barley. Consequently, a reduction in atmospheric CO_2 concentrations may temporarily lower agricultural output before the long-run benefits of emission reductions through mitigating climate change begin to materialize.

Furthermore, the estimated error correction coefficient, denoted by ECT_{t-1} (λ), was −0.88 and statistically significant (p-value = 0.000). The negative and significant coefficient confirms the existence of a stable long-run equilibrium relationship among the variables. The magnitude of the coefficient indicates that approximately 88% of the short-run disequilibrium in agricultural production from the previous period (t–1) is corrected in the current period (t), following any short-run shock to the explanatory variables. Hence, the estimated adjustment speed is relatively high, suggesting a rapid convergence of agricultural production toward its long-run equilibrium path.

Table 6. the Error Correction Model and Short-Run Dynamics.

Variables	Coefficients	t-statistic	p-value
$\Delta(\boldsymbol{LPCO2_NEG_t})$	-0.39	-1.08	0.283
$\Delta(\boldsymbol{LPCO2_NEG_{t-1}})$	-1.18	-2.85	0.000
$\boldsymbol{EC_{t-1}}$	-0.88	-7.99	0.000

Source: Prepared by the authors based on outputs from EViews 12**.**

4.6 Estimation of the Long-Run Coefficient:

To provide a more comprehensive assessment of the nonlinear characteristics of the Algerian agricultural sector and to reinforce the nonlinear autoregressive distributed lag (NARDL) framework, the Wald test

was employed to examine long-run asymmetry. This test evaluates whether the effects of positive climate shocks differ significantly from those of negative climate shocks.

The results reported in Table 7 indicate the presence of long-run asymmetry for both temperature and rainfall. Specifically, the p-values were 0.048 for temperature and 0.020 for rainfall, both of which are below the conventional 5% significance level. Accordingly, the null hypothesis of symmetry is rejected, confirming that positive and negative shocks in these two climate variables have significantly different long-run effects on agricultural production. In contrast, the p-value for carbon dioxide (CO_2) emissions was 0.100, which exceeds the 5% significance level. Therefore, the null hypothesis of symmetry cannot be rejected, indicating that positive and negative changes in CO_2 emissions exert symmetric long-run effects on agricultural production.

Table 7. Results of the Wald Test for Long-Run Symmetry (Wald Test)

variable	Null Hypothesis (H0)	F-statistic	P-value	Decision
Temperature (+/-)	$LTEMP^{+}=LTEMP^{-}$	4.14	0.048	Asymmetric
Rainfall (+/-)	$LRAIN^{+}=LRAIN^{-}$	5.85	0.020	Asymmetric
CO2 Emissions (+/-)	$LPCO2^{+}=LPCO2^{-}$	2.82	0.100	Symmetric

Source: Prepared by the author based on outputs from EViews 12**.**

Table 8 reports the estimated long-run coefficients of the NARDL model. The results indicate that the coefficient of positive temperature shocks is negative (−1.68) but statistically insignificant (p-value = 0.544), exceeding the 5% significance level. This suggests that a 1% increase in average temperature is associated with a 1.68% decline in agricultural production; however, this effect is not statistically significant.

By contrast, the coefficient of negative temperature shocks is negative (−7.42) and statistically significant (p-value = 0.004), indicating that a 1% decrease in average temperature reduces agricultural production by 7.42%. This finding can be attributed to the fact that agricultural production in Algeria depends on an optimal thermal range for crop growth and relies heavily on winter crops, particularly cereals, which require moderate temperatures throughout their growth cycle. When temperatures fall below

the optimal threshold, the risks of frost damage, delayed germination, and reduced plant development increase, resulting in production losses that are greater than those associated with moderate increases in temperature, which mainly accelerate evapotranspiration, shorten the grain-filling period, and intensify heat stress.

The results further show that the coefficient of positive rainfall shocks is positive (0.41) and statistically significant (p-value = 0.001). This implies that a 1% increase in average rainfall raises agricultural production by approximately 0.41%. In contrast, the coefficient of negative rainfall shocks is positive (0.10) but statistically insignificant (p-value = 0.421), indicating that a 1% decrease in average rainfall has no statistically significant effect on agricultural production.

This result suggests that higher rainfall enhances soil moisture, replenishes groundwater resources, increases reservoir storage, and alleviates water stress on crops, thereby improving agricultural productivity. Conversely, the weaker effect of declining rainfall may reflect the increasing reliance of Algerian agriculture on alternative water sources, including center-pivot irrigation, deep groundwater wells, dams, and supplementary irrigation systems, which mitigate the adverse consequences of reduced precipitation. Moreover, the expansion of irrigation projects and groundwater exploitation, particularly in the Sahara and the High Plateaus, has reduced the sector's dependence on rainfall alone. Consequently, decreases in rainfall do not produce proportionate declines in agricultural output, whereas increases in rainfall generate larger productivity gains by providing additional water resources, reducing irrigation costs, improving soil moisture, enhancing fertilizer-use efficiency, and increasing the productivity of rain-fed crops.

The estimated coefficients for both positive and negative changes in carbon dioxide (CO_2) emissions are positive, with values of 0.93 and 1.79, respectively, and both are statistically significant (p-values = 0.001 and 0.000, respectively). These findings indicate the existence of a long-run relationship between CO_2 emissions and agricultural production. However, the Wald test fails to reject the null hypothesis of symmetry, implying that the effects of increases and decreases in CO_2 emissions are not statistically

different. Therefore, the relationship between CO_2 emissions and agricultural production is symmetric in the long run.

These findings suggest that the relationship between CO_2 emissions and agricultural production reflects the combined influence of two opposing mechanisms. On the one hand, higher atmospheric CO_2 concentrations may stimulate photosynthesis and improve water-use efficiency through the CO_2 fertilization effect. On the other hand, reductions in CO_2 emissions mitigate the adverse consequences of climate change, including rising temperatures and water stress. The Wald test indicates that these two mechanisms generate statistically equivalent responses, explaining the absence of a significant difference between the effects of positive and negative CO_2 emission shocks on agricultural production.

Finally, the coefficient of agricultural land is positive (1.93) and statistically significant (p-value = 0.002) at the 5% significance level. This indicates that a 1% increase in agricultural land is associated with a 1.93% increase in agricultural production. This result may reflect agricultural policies aimed at expanding cultivated land through land reclamation programs, as well as promoting agricultural development in the Sahara and the High Plateaus by expanding irrigation infrastructure and exploiting groundwater resources, thereby enhancing the productive capacity of the agricultural sector.

Table 8. Estimation Results of the Long-Run Model

Variable	Coefficient	t-Statistic	p-value
LTEMP_POS	-1.68	-0.61	0.544
LTEMP_NEG	-7.42	-2.98	0.004
LRAIN_POS	0.41	3.44	0.001
LRAIN_NEG	0.10	0.81	0.421
LPCO2_POS	0.93	3.44	0.001
LPCO2_NEG	1.79	4.82	0.000
LL	1.93	3.17	0.002

Source: Prepared by the author based on outputs from EViews 12**.**

4.7 Structural Stability Test of the Estimated NARDL Model To assess the structural stability of the estimated NARDL model in both the short run and the long run, the CUSUM (Cumulative Sum of Recursive Residuals) test and the CUSUMSQ (Cumulative Sum of Squares of Recursive Residuals) test were employed. If the plotted statistics remain within the 5%

confidence bounds, the null hypothesis of parameter stability cannot be rejected, indicating that the estimated coefficients are structurally stable over the sample period. As illustrated in Figures 2 and 3, the CUSUM and CUSUMSQ plots remain entirely within the 5% critical bounds, confirming the stability of both the short-run and long-run coefficients of the estimated NARDL model throughout the study period.

Figure 2. CUSUM Test

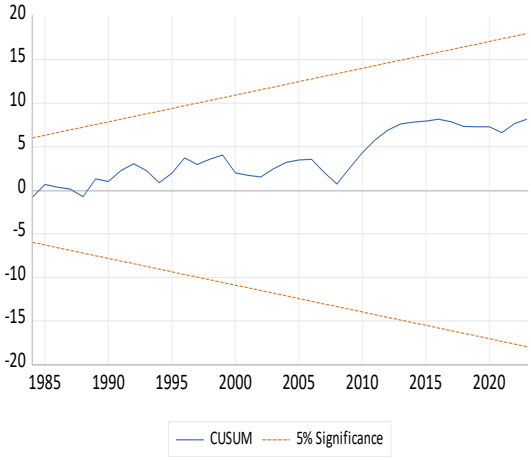
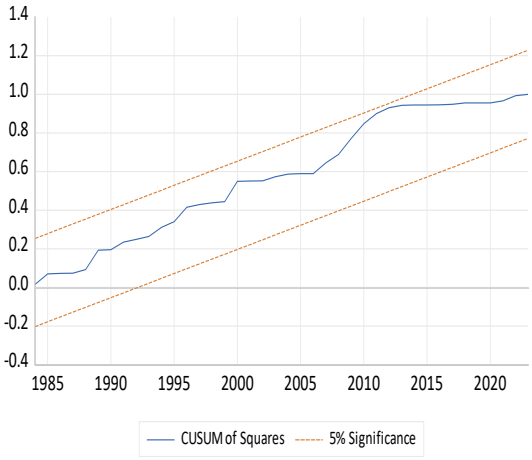


Figure 3.CUSUMSQ Test

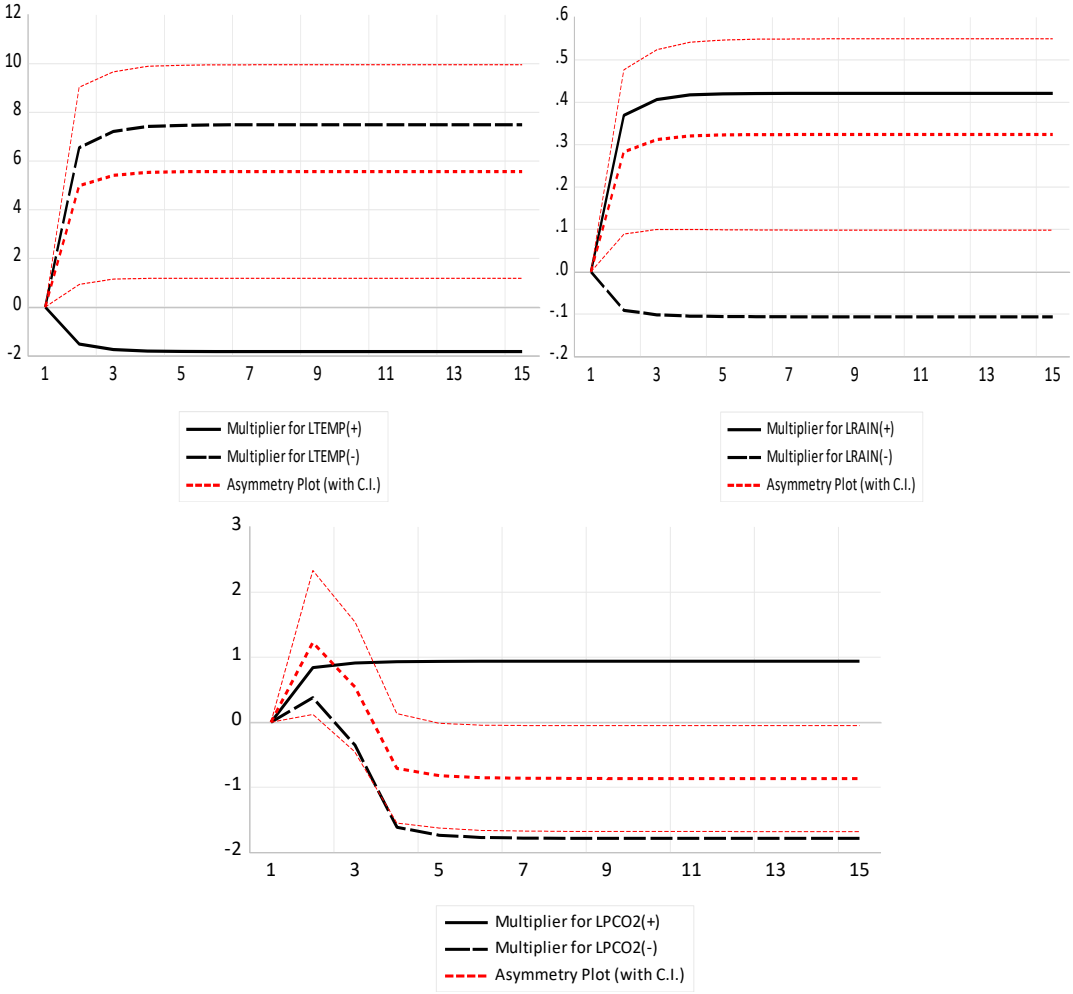


Source: Prepared by the author based on outputs from EViews 12**.**

4.8 Dynamic Multipliers:

The NARDL model enables the estimation of dynamic multiplier effects, which illustrate how agricultural production (LCPI) adjusts over time in response to positive and negative shocks in each explanatory variable. Figure4 shows that the response of agricultural production to positive and negative shocks in temperature and rainfall differs markedly over time. The gap between the positive and negative shock trajectories persists even after the system converges to its long-run equilibrium, thereby confirming the Wald test results, which indicate the presence of long-run asymmetry. In contrast, the dynamic multipliers associated with carbon dioxide (CO_2) emissions reveal a gradual convergence between the positive and negative shock trajectories until they become nearly identical in the long run. This finding is consistent with the Wald test, which indicates that positive and negative changes in CO_2 emissions exert symmetric long-run effects on agricultural production.

Figure 4. Dynamic Multipliers of the Estimated NARDL Model



Source: Prepared by the author based on outputs from EViews 12**.**

4. CONCLUSION

This study employed the Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the impact of climate change on agricultural production in Algeria over the period 1960–2023. The empirical analysis was based on a series of rigorous diagnostic and econometric tests.

4.1 Main Findings

The analysis began with the BDS test, which confirmed the existence of significant nonlinear dependencies among the main variables, thereby

justifying the use of the NARDL framework instead of conventional linear models.

Furthermore, the ARDL Bounds Test confirmed the existence of a stable long-run cointegration relationship among the variables. The calculated F-statistic (5.91) exceeded the upper critical bounds, indicating that climate variables and agricultural production move together within a stable long-run equilibrium relationship.

The estimated error correction model also confirmed the existence of long-run equilibrium despite short-run disequilibrium. The estimated error correction term (ECT = –0.88) was negative and statistically significant, implying that approximately 88% of any short-run disequilibrium is corrected within one period, reflecting a rapid adjustment toward the long-run equilibrium.

The empirical results further indicate that approximately 79% of the variation in agricultural production is explained by changes in temperature, rainfall, carbon dioxide (CO_2) emissions, and agricultural land, while the remaining variation is attributable to other factors not included in the model. Moreover, the model successfully passed all diagnostic tests, confirming its adequacy, stability, and high explanatory power.

The most important finding of the study is the identification of long-run structural asymmetry in the response of Algeria's agricultural sector to climate change. Although the NARDL model was specifically designed to distinguish between the effects of positive and negative shocks, the Wald test rejected the null hypothesis of symmetry for temperature and rainfall, indicating asymmetric long-run effects. In contrast, the null hypothesis could not be rejected for carbon dioxide emissions, implying that positive and negative changes in CO_2 emissions exert symmetric long-run effects on agricultural production.

These findings suggest that the Algerian agricultural sector is highly sensitive to climatic conditions, particularly because it relies heavily on winter crops, especially cereals, which require moderate temperatures throughout their growth cycle. When temperatures fall below the optimal threshold, frost damage, delayed germination, and reduced crop growth

become more severe than the adverse effects associated with moderate temperature increases.

The results also indicate that the agricultural sector benefits more from periods of abundant rainfall, as increases in precipitation improve soil moisture and water availability, thereby enhancing agricultural production to a greater extent than the adverse effects caused by rainfall shortages. This finding may be explained by the fact that part of the negative impact of reduced rainfall is mitigated through irrigation systems, whereas abundant precipitation provides an additional natural water source that benefits both rain-fed and irrigated agriculture.

Regarding carbon dioxide emissions, higher atmospheric CO_2 concentrations may enhance agricultural productivity through the carbon fertilization effect, which stimulates photosynthesis and improves water-use efficiency. Conversely, the positive effect associated with reductions in CO_2 emissions can be attributed to the mitigation of climate-related stresses, such as heat stress and water imbalance, thereby creating more favorable conditions for crop growth. The symmetry identified by the Wald test suggests that these two opposing mechanisms ultimately generate statistically similar long-run responses.

Finally, the results demonstrate that agricultural land is not merely a quantitative production factor but also serves as a platform for implementing agricultural technologies and investments. Consequently, expanding agricultural land, when combined with efficient resource management, contributes significantly to increasing agricultural production.

4.2 Policy Recommendations

Based on the empirical findings, the study proposes the following policy recommendations:

- Develop and disseminate crop varieties that are more resilient to temperature fluctuations while adjusting planting calendars to accommodate changing climatic conditions and reduce production losses.

-Establish effective early warning systems capable of forecasting heatwaves, droughts, and abnormal rainfall events, enabling farmers to implement timely adaptation measures.

-Expand investment in irrigation infrastructure through the modernization of irrigation networks and more efficient utilization of dam and groundwater resources to reduce the adverse effects of rainfall variability and stabilize agricultural production.

- Protect agricultural land from conversion to urban and industrial uses while continuing land reclamation programs and expanding cultivated areas, particularly in regions with adequate water resources.

- Promote water-saving irrigation technologies, such as drip and center-pivot irrigation, together with the widespread adoption of climate-smart agricultural practices to improve water-use efficiency.

- Given the symmetric relationship between CO_2 emissions and agricultural production, implement gradual emission reduction policies while maintaining agricultural productivity through greater reliance on renewable energy, improved fertilizer and machinery efficiency, and the adoption of low-carbon agricultural practices.

- Strengthen scientific research programs aimed at developing crop varieties resistant to heat and drought stress and assessing the projected impacts of climate change on Algeria's strategic crops to support evidence-based agricultural policymaking.

- Promote the broader adoption of climate-smart agriculture, including improved soil management, crop rotation, conservation agriculture, and digital technologies for irrigation and fertilizer management, thereby enhancing the resilience of Algeria's agricultural sector to climate change.

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5. Appendices:

Appendix (1): Stationarity Test

UNIT ROOT TEST RESULTS TABLE (ADF)
Null Hypothesis: the variable has a unit root

At Level

		LCPI	LTEMP	LRAIN	LPCO2	LL
With Constant	t-Statistic	-0.1328	-2.1004	-6.4824	-4.1814	-1.8314
	Prob.	*0.9401*	*0.2454*	*0.0000*	*0.0017*	*0.3616*
		n0	n0	***	***	n0
With Constant & Trend	t-Statistic	-3.1952	-5.4743	-6.8746	-4.6869	-1.5412
	Prob.	*0.0964*	*0.0002*	*0.0000*	*0.0021*	*0.8024*
		*	***	***	***	n0
Without Constant & Trend	t-Statistic	1.4059	1.0928	-0.4318	0.9499	-0.5564
	Prob.	*0.9585*	*0.9266*	*0.5224*	*0.9070*	*0.4715*
		n0	n0	n0	n0	n0

At First Difference

		d(LCPI)	d(LTEMP)	d(LRAIN)	d(LPCO2)	d(LL)
With Constant	t-Statistic	-7.8501	-11.0849	-12.4574	-5.4173	-7.0591
	Prob.	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
		***	***	***	***	***
With Constant & Trend	t-Statistic	-7.9513	-10.9614	-12.3676	-5.4329	-7.1724
	Prob.	*0.0000*	*0.0000*	*0.0000*	*0.0002*	*0.0000*
		***	***	***	***	***
Without Constant & Trend	t-Statistic	-7.5997	-11.0091	-12.5652	-5.3323	-7.0906
	Prob.	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
		***	***	***	***	***

Appendix (2): Results of the Cointegration Test Using the Bounds Testing Approach

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.912282	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Appendix (3): Diagnostic Tests

Results of the Autocorrelation Tests

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

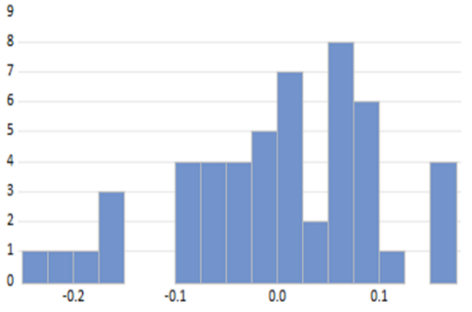
F-statistic	0.538054	Prob. F(1,39)	0.4676
Obs*R-squared	0.694034	Prob. Chi-Square(1)	0.4048

Results of the Heteroskedasticity Tests

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.814940	Prob. F(10,40)	0.6161
Obs*R-squared	8.631874	Prob. Chi-Square(10)	0.5674
Scaled explained SS	5.033865	Prob. Chi-Square(10)	0.8889

Results of the Normality Test of the Residuals



Series: Residuals
Sample 1973 2023
Observations 51

Mean	-9.52e-16
Median	0.012025
Maximum	0.174235
Minimum	-0.232857
Std. Dev.	0.096098
Skewness	-0.488745
Kurtosis	2.896037
Jarque-Bera	2.053379
Probability	0.358191

Results of the model is correctly specified

Ramsey RESET Test
Equation: NARDL
Omitted Variables: Squares of fitted values
Specification: LCPI LCPI(-1) LTEMP_POS LTEMP_NEG LRAIN_POS LRAIN_NEG LPCO2_POS LPCO2_NEG LPCO2_NEG(-1) LPCO2_NEG(-2) LL C

	Value	df	Probability
t-statistic	1.162472	39	0.2521
F-statistic	1.351340	(1, 39)	0.2521
Likelihood ratio	1.737211	1	0.1875

Appendix (4): Estimation of the Error Correction Model and the Short/Long-Run Relationship

ARDL Error Correction Regression
Dependent Variable: D(LGDP)
Selected Model: ARDL(2, 0, 0, 2, 2, 2, 0)
Case 2: Restricted Constant and No Trend
Date: 06/01/26 Time: 11:46
Sample: 1 34
Included observations: 32

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LGDP(-1))	0.278488	0.081797	3.404629	0.0034
D(LFDI)	0.002588	0.000766	3.381058	0.0036
D(LFDI(-1))	-0.001819	0.000758	-2.398139	0.0282
D(LSYM)	0.164472	0.139427	1.179628	0.2544
D(LSYM(-1))	-0.511245	0.158006	-3.235615	0.0049
D(LCR)	-0.010904	0.004180	-2.608320	0.0184
D(LCR(-1))	0.017573	0.004470	3.931674	0.0011
CointEq(-1)*	-0.495224	0.054363	-9.109669	0.0000

R-squared	0.770432	Mean dependent var	0.027096
Adjusted R-squared	0.703475	S.D. dependent var	0.022644
S.E. of regression	0.012331	Akaike info criterion	-5.741141
Sum squared resid	0.003649	Schwarz criterion	-5.374707
Log likelihood	99.85826	Hannan-Quinn criter.	-5.619678
Durbin-Watson stat	2.017637		

* p-value incompatible with t-Bounds distribution.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV	0.139686	0.058176	2.401083	0.0281
LOUV	0.342437	0.085597	4.000565	0.0009
LFDI	0.009487	0.002727	3.479166	0.0029
LSYM	0.523116	0.145788	3.588194	0.0023
LCR	-0.056841	0.032454	-1.751452	0.0979
LCO2	0.432061	0.134746	3.206492	0.0052
C	15.28167	2.308736	6.619065	0.0000