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The Symmetric and Asymmetric Effects of Climate Change and Carbon Dioxide Emissions on Crop Production in Tunisia

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ABSTRACT

Agriculture remains a cornerstone of the Tunisian economy, accounting for over 12% of the country's GDP and providing employment for more than 14% of the labor force in 2022 (WDI, 2023). However, the sector is increasingly vulnerable to climate change particularly variations in temperature and precipitation as well as environmental pressures such as air pollution, all of which can harm crops, vegetation, and forest resources. This study explored the influence of climate change and air pollution on Tunisia's agricultural sector, employing both the ARDL and NARDL models to examine the effects of temperature, precipitation, and CO_2 emissions on crop production over the period 1996-2022. The findings reveal significant short- and long-term relationships among the studied variables. In the short term, CO_2 emissions were associated with a reduction in agricultural productivity, though this relationship was not statistically significant. In contrast, the long-term results demonstrate a substantial negative impact of environmental degradation on the crop production index. The analysis further shows that water productivity, fertilizer usage, and male employment in agriculture contribute positively to long-term agricultural output. Conversely, female employment in agriculture appears to have a negative impact on crop production over the same period. Additionally, while variables such as arable land, average temperature, and precipitation exhibit positive effects on crop production, these relationships were not statistically significant. The study also highlights the asymmetric effects of climate change and CO_2 emissions, where positive and negative shocks exert varying degrees of influence on agricultural output in Tunisia. These results emphasize the crucial role of natural resources, particularly water productivity, as well as the importance of human capital in enhancing agricultural development. Notably, to the best of the author's knowledge, this research is the first to simultaneously investigate both the symmetrical and asymmetrical dynamic interactions between climate change, carbon emissions, and crop production in Tunisia using ARDL and NARDL cointegration frameworks.

Keywords: Climate Vulnerability, Carbon Emissions, Agricultural Productivity, Tunisia, NARDL Model
JEL Classifications: O13, Q10, Q15, Q53, Q54

1. INTRODUCTION

Tunisia is confronting a convergence of escalating climate risks, increasing carbon dioxide emissions, worsening water scarcity, and declining crop productivity. These interconnected environmental challenges pose serious threats to the country's agricultural sector a cornerstone of food security, rural livelihoods, and economic development. As climate change intensifies, Tunisia faces more frequent and severe droughts, unpredictable rainfall patterns, and rising temperatures, all of which amplify water scarcity and endanger agricultural yields in a region already marked by limited natural resources. Although Tunisia contributes minimally to global CO_2 emissions, it bears a disproportionate share of the impacts. Emissions from industrial activity, transportation, and energy production accelerate climate change, which in turn exacerbates local weather variability and ecological stress. While elevated CO_2 levels may sometimes stimulate crop growth, their overall effects are complex and often harmful, especially when coupled with heat stress, erratic precipitation, and limited access to water. Agriculture in Tunisia is highly sensitive to climate variables and consumes a significant share of the country's water resources. The overexploitation of groundwater and decreasing rainfall levels, driven by climate change, are rapidly depleting water reserves. This places severe constraints on irrigation-dependent farming, threatening food production and the sustainability of rural livelihoods. Moreover, environmental degradation such as air pollution and biodiversity loss compound these threats, as shifting temperatures and rainfall patterns alter the spread of pests, diseases, and pollinator activity, all of which influence agricultural productivity. Recent climate data underscore the urgency of the problem: June 2022 was the hottest on record, with a +3.4°C temperature anomaly, while June 2023 saw an increase of +0.3°C compared to the norm. Average temperatures ranged from 21.2°C in Tala to 31°C in Tozeur, illustrating the spatial variability and widespread nature of heat stress. Climate models forecast an increase in the frequency and severity of extreme weather events including droughts, heatwaves, and floods placing further pressure on Tunisia's fragile agricultural system. Despite its modest economic contribution accounting for just over 16% of GDP and 17% of employment in 2022 the agricultural sector remains critical to national stability and food sovereignty. National initiatives like the Promotion of Agricultural Economic Development (PEAD) and the Market Access for Typical Agrofood Products (PAMPAT) seek to support farmers and stimulate rural development. However, the sector continues to face major structural barriers, including inadequate infrastructure, limited access to technology and inputs, weak market integration, and climate-induced production volatility. The novelty of this study lies in its integrated approach to analyzing the dynamic and asymmetric effects of climate risk, CO_2 emissions, and water scarcity on crop production in Tunisia using both ARDL and NARDL models. While previous studies have investigated these elements separately, this paper presents a comprehensive and nuanced exploration of their combined impacts. It fills a critical gap in the literature by offering empirical insights into how environmental stressors interact over time and affect agricultural outcomes in a climate-vulnerable economy. Given the urgency of building climate resilience, this research contributes timely and actionable findings that can inform policymakers, development agencies, and agricultural stakeholders. By identifying key risk factors and mitigation pathways, the study aims to support the formulation of sustainable agricultural strategies that ensure food security and long-term rural development in Tunisia. The paper is organized as follows: after the introduction, we review relevant literature and previous findings. We then outline our research methods, data, and model before discussing our results and conclusions.

2. LITERATURE REVIEW

This review consolidates recent research findings to offer a thorough understanding of how these factors interact and impact agricultural systems, with a particular focus on Tunisia. Khalifa (2025) examines the impact of climate change, agricultural productivity, and food security on Tunisia's economic growth from 1990 to 2022. Utilizing the autoregressive distributed lag (ARDL) model, the study finds that past agricultural productivity plays a crucial role in driving economic growth. Additionally, Granger causality tests indicate a unidirectional influence of temperature variations on crop production. Mahdavian et al. (2024) utilize the nonlinear autoregressive distributed lag (NARDL) model and Granger causality analysis to examine the relationship between climate variables and food security in Iran from 1990 to 2020. Their findings indicate that a 1% increase in temperature leads to an 8.06% decline in livestock production, while a 1% decrease in temperature results in a 3.85% rise in livestock output. Precipitation positively affects food security, with a 1% increase in rainfall boosting livestock production by 0.8% and a 1% decrease reducing it by 1.02%. In the long run, positive methane (CH4) shocks show no significant impact on food security, whereas negative CH4 shocks enhance food security by 7.5%. Furthermore, the Granger causality test confirms a bidirectional causal link between CH4 emissions and livestock production, alongside a unidirectional causality running from production to temperature. Amin et al. (2024) highlights that extreme weather events, including intense heatwaves and irregular rainfall, have become more frequent and severe. These conditions are adversely affecting crop yields and overall agricultural stability. Nabil et al. (2024) demonstrates that rising temperatures and shifting precipitation patterns are significantly impacting agricultural productivity. The study specifically notes that heat stress has a detrimental effect on key crops such as wheat and barley, resulting in reduced yields and heightened food security concerns. Houssine et al. (2024) examines how reduced water availability is affecting irrigation practices and crop productivity. The research finds that increased evaporation rates and decreased precipitation are leading to significant water shortages, which are negatively impacting crop yields and agricultural sustainability. Fawzi et al. (2024) suggests that the effects of elevated CO_2 on crop yields are complex. While some crops may benefit from higher CO_2 levels, these potential gains are often offset by adverse temperature effects and water scarcity. Mushtaq et al. (2024) studied the influence of global climate change on crop production, noting that greenhouse gas emissions increase temperatures, enhancing plant growth and productivity. However, elevated temperatures also accelerate vegetation migration, disrupt crop maturation, intensify insect infestations, and augment evapotranspiration. Khurshid et al. (2023) explored the asymmetric effects of climatic and non-climatic factors on livestock productivity in Pakistan. Their findings reveal that carbon emissions, mean temperature, and precipitation exert contrasting influences on livestock productivity in both the short and long run. Similarly, Benmehaia (2023) analyzed the impact of climate change on cereal crop yields in Algeria using time series data from 1961 to 2021. Applying the nonlinear autoregressive distributed lag (NARDL) model with an asymmetric error correction component and the Granger causality approach, the study found that, in the long run, increases in cultivated area and positive precipitation shocks enhance cereal crop yields. Conversely, temperature shocks, carbon emissions, and negative precipitation shocks negatively affect yields. In the short run, fluctuations in cultivated area, temperature, and precipitation contribute positively to crop yield, while carbon emission shocks significantly reduce it. The results of the pairwise Granger causality test indicate the existence of both unidirectional and bidirectional causal relationships among the variables. Asfew et al. (2023) examined the effects of climate change on crop production in Sub-Saharan African countries using a dynamic panel model (GMM) from 2002 to 2020. They found that a percentage change in precipitation leads to a 0.62% increase in crop production on average, while carbon emissions and temperature negatively impact agricultural output. Amaefule et al. (2023) investigated the impact of climate change and carbon emissions on agricultural productivity in Nigeria using the ARDL model covering the period from 1960 to 2019. They identified a long-term relationship between carbon emissions and agricultural productivity, noting that carbon emissions and carbon intensity negatively impact food production. Saidmamatov et al. (2023) explored the nexus between agriculture, water, energy, and environmental degradation in Central Asia using panel FMOLS, DOLS, and ARDL-PMG models. They found that water productivity, economic growth, energy consumption, and electricity production positively impact CO_2 emissions in the long run, with energy consumption being the main driver of CO_2 emissions in the short term. Oyelami et al. (2023) examined the link between climate change and food security in Sub-Saharan Africa during the period from 1996 to 2020 using ordinary least squares (OLS) and cross-sectional autoregressive distributed lag (CS-ARDL) models. Noorunnahar et al. (2023) studied the effects of climatic and non-climatic parameters (CO_2 emissions, average temperature, average rainfall, population, agricultural technology, and energy consumption) on maize yield in Bangladesh from 1980 to 2020 using the ARDL model. They found that all climate parameters negatively impact maize yield in both the short and long run, while agricultural technology positively affects yield. Population growth had a negative impact, and energy consumption had a positive short-term but negative long-term effect on maize yield. Hamada (2023) tested the impact of climate change on Egyptian agriculture, noting negative effects on agriculture, hydropower, and biodiversity. Karadavut et al. (2023) analyzed the importance of agricultural sustainability in Turkey from 1995 to 2020 using the ARDL model. They found that increased irrigation led to higher crop production, but excessive use of clean and groundwater resources negatively affected crop value. They highlighted the importance of water sources and economic stability for sustainable agriculture. Ditta et al. (2023) measured the impact of climate change on food security in selected developing economies from 2004 to 2021, finding that climatic variations positively impact food security in the long run due to extended growing seasons and fertilization effects, though urbanization and energy consumption deteriorate food security. Atoyebi et al. (2023) examined changes in food supply in Nigeria from 1980 to 2021 using the ARDL model, discovering that carbon dioxide emissions from fossil fuels impact food production, while emissions from liquid and solid fuels do not. Said (2023) used quantitative and qualitative methods to explore the impact of climate change on food security in Somalia, concluding that changes in precipitation and temperature lead to land degradation and reduced crop production. Teklu et al. (2023) estimated the determinants of multiple adoptions of climate-smart agriculture innovations in Ethiopia, noting the influence of farm size and financial services on crop rotation and agroforestry adoption. Zeleke et al. (2023) studied the relationship between farmers and climate risks in North Wello Zone, Ethiopia, finding that smallholder farmers face varying degrees of climate change vulnerability. They identified locust outbreaks and irregular rainfall as major contributors to vulnerability. Caleb et al. (2023) examined the nexus between agricultural output growth and bank credit in Nigeria, revealing a long-term relationship between the two. Abrar and Maryam (2023) examined the impact of climate change on food security in Pakistan from 1990 to 2022 using the ARDL model. They found that temperature increases negatively affect wheat yield during the sowing phase but positively impact it during the maturity phase. Tampubolon (2023) analyzed the effect of the COVID-19 pandemic on the food and agricultural sector in Indonesia, concluding that the pandemic did not negatively influence agricultural production but had a slight negative impact on economic growth. Uddin and AlMamun (2023) analyzed the effect of climate change on agricultural employment in South Asia from 1992 to 2021 using panel ARDL. They found that past year temperature positively affected agricultural employment in the short run but negatively in the long run. Ansari et al. (2023) examined agricultural financing and technological advances on climate change mitigation in India, noting that increased rainfall decreases temperature and boosts sugarcane output. Sargani et al. (2023) studied the impact of farmers' risk attitudes on livelihood adaptation strategies in China and Pakistan, highlighting differences in how farmers cope with risks. Thi Hien et al. (2023) analyzed the influence of agricultural expansion, technological innovation, and forest cover on Vietnam's economic development, finding that forest cover and technological innovations positively impact economic development. Balasundram et al. (2023) studied the impact of digital agriculture technologies on climate change and food security, emphasizing the necessity of digital technology to mitigate climate change effects and ensure food security. Jiang et al. (2023) investigated the mediating role of agricultural insurance and low-carbon technology innovation on agricultural carbon emissions in China, concluding that insurance can indirectly suppress emissions through technological innovation. Asfew and Bedemo (2022) examined the impact of climate change on cereal crops in Ethiopia, finding that precipitation positively impacts cereal production in both the short and long run, while temperature negatively affects it. Aluwani (2022) studied the impacts of climate change, CO_2 emissions, and renewable energy consumption on agricultural economic growth in South Africa, finding that climate change reduces growth while carbon emissions increase it in the short run. Alehile et al. (2022) analyzed the effects of climate change on Nigeria's agricultural sector and concluded that increasing temperatures and irregular rainfall patterns have a detrimental impact on crop output. Chandio et al. (2021) examined the effects of climatic and non-climatic factors on Indian agriculture from 1965 to 2015, noting that CO_2 emissions and temperature adversely affect agricultural output, while rainfall positively impacts it. Non-climatic factors such as energy use, financial development, and labor force positively impact agricultural production and yield in the long run.

3. DATA AND METHODOLOGY

3.1. Data Description

This study investigates the relationship between climate change, air pollution, and the agricultural sector in Tunisia, employing both the ARDL and NARDL methodologies. We use annual time series data spanning from 1996 to 2022, sourced from the World Development Indicators (World Bank, 2024), and conduct our econometric analysis using E-Views 13 software. The selected study period is based on data availability across all variables included in the model. In this analysis, the crop production index is utilized as the dependent variable, while climate risk, carbon dioxide emissions, water productivity, fertilizer consumption, and employment in agriculture serve as the key explanatory variables. More specifically, the agricultural sector is represented by the crop production index; climate risk is captured through mean annual temperature and precipitation levels; carbon dioxide emissions are measured in metric tons per capita; fertilizer consumption is expressed in kilograms per hectare of arable land; water productivity is assessed by the constant 2015 US$ GDP generated per cubic meter of total freshwater withdrawal; employment in agriculture is represented by the share of male and female employment in the sector; and arable land is measured as a percentage of the total land area. To achieve normality and stabilize variance, all variables are converted into their natural logarithmic forms. The detailed descriptions of the variables, along with their logarithmic transformations, are provided in Table 1.

3.2. Model Method

Despite the critical importance of these factors, empirical research exploring the relationships between crop production, water productivity, fertilizer consumption, precipitation, temperature fluctuations, arable land, carbon dioxide emissions, and agricultural employment in Tunisia remains limited. This study is inspired by the contributions of Noorunnahar et al. (2023), Asfaw et al. (2023), and Amaefule et al. (2023), who have examined similar dynamics in other regional contexts. Building on these prior investigations, we construct the following model to explore these complex interrelationships within Tunisia's agricultural sector, as presented in Equation (1):

$$CPI_t = f\,(AGL_t;\ CO2_t;\ MNT_t;\ PR_t;\ FERT_t;\ WAT_t;\ EM_t;\ EF_t) \tag{1}$$

Where CPI_t is the agricultural production for each year in Tunisia, AGL_t is the arable land for each year in Tunisia, $CO2_t$ emission is the carbon dioxide emission for each year in Tunisia, MNT_t is the Mean temperature for each year in Tunisia, PR_t is the precipitation for each year in Tunisia, $FERT_t$ is the fertilizer consumption for each year in Tunisia, WAT_t is water productivity for each year in Tunisia, EM_t is the male employment in agriculturefor each year in Tunisia, and EF_t is the female employment in agriculture for each year in Tunisia.

Following the logarithmic transformation of the variables, the empirical model is specified as follows (Equation [2]):

$$LCPI_t = \alpha_0 + \alpha_1\, LAGL_t + \alpha_2\, LCO2_t + \alpha_3\, LMNT_t + \alpha_4\, LPR_t + \alpha_5\, LFERT_t + \alpha_6\, LWAT_t + \alpha_7\, LEM_t + \alpha_8\, LEF_t + \varepsilon_t \tag{2}$$

Note: ε is the error term; (α_0, α_1, α_2, α_3, α_4, α_5, α_6, α_7, α_8) are the coefficients.

3.3. Stationary Techniques for Data

To assess the stationarity of the variables included in the model, it is essential to apply various unit root tests, as these tests help determine whether the time series data exhibit a unit root. Commonly employed methods include the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, the Andrews and Zivot (AZ) test, the Ng-Perron test, the KPSS test, the Ouliaris-Park-Perron test, and the Elliott-Rothenberg-Stock test, among others. The selection of multiple tests is crucial, given that their effectiveness can vary based on sample size and data characteristics (Raihan et al., 2022). In this study, we adopt the ADF test developed by Dickey and Fuller (1979), the PP test by Phillips and Perron (1988), and the AZ test by Zivot and Andrews (2002) to identify potential autoregressive unit roots in the series. The testing framework operates under the null hypothesis that the series contains a unit root, while the alternative hypothesis suggests stationarity. To address issues of endogeneity and autocorrelation, the model includes both explanatory variables and the leads and lags of their first-differenced terms (Raihan et al., 2022). A key advantage of this approach lies in its flexibility to accommodate variables integrated at different orders. Upon establishing cointegration among the variables, the study advances to the ARDL estimation to derive the long-run coefficients, as specified in Equation (3).

$$\begin{aligned}\Delta LCPI_t &= \beta_0 + \beta_1 LCPI_{t-1} + \beta_2 LAGL_{t-1} + \beta_3 LCO2_{t-1} \\ &+ \beta_4 LMNT_{t-1} + \beta_5 LPR_{t-1} + \beta_6 LFERT_{t-1} + \beta_7 LWAT_{t-1} \\ &+ \beta_8 LEM_{t-1} + \beta_9 LEF_{t-1} + \sum\nolimits_{p=1}^{q} \gamma_1 \Delta LCPI_{t-p} + \sum\nolimits_{p=1}^{q} \gamma_2 \Delta LAGI_{t-p} \\ &+ \sum\nolimits_{p=1}^{q} \gamma_3 \Delta LCO2_{t-p} + \sum\nolimits_{p=1}^{q} \gamma_4 \Delta LMNT_{t-p} + \sum\nolimits_{p=1}^{q} \gamma_5 \Delta LPR_{t-p} \\ &+ \sum\nolimits_{p=1}^{q} \gamma_6 \Delta LFERT_{t-p} + \sum\nolimits_{p=1}^{q} \gamma_7 \Delta LWAT_{t-p} + \\ &\sum\nolimits_{p=1}^{q} \gamma_8 \Delta LEM_{t-p} + \sum\nolimits_{p=1}^{q} \gamma_9 \Delta LEF_{t-p} + \varepsilon_t\end{aligned} \tag{3}$$

Table 1: Source and description of variables

Variables	Description	Logarithmic forms	Units	Sources
CPI	Crop production (agricultural production for each year	LCPI	Index	WDI
AGL	Arable land	LAGL	% of land area	WDI
CO_2	Carbon dioxide emission	LCO_2	Metric tons per capita	WDI
MNT	Annual mean temperature	LMNT	°C	CHKP
PR	Annual precipitation	LPR	Millimeter	CHKP
FERT	Fertilizer consumption	LFERT	Kilograms per hectare of arable land	WDI
WAT	Water productivity	LWAT	Constant 2015 US$ GDP per cubic meter of total freshwater withdrawal)	WDI
EM	Employment in agriculture male	LEM	% of male employment	WDI
EF	Employment in agriculture female	LEF	% of female employment	WDI

WDI: World development indicators, CHKP: Climate change knowledge portal

Note: Δ is the first difference; q is the optimum lag length; β_0 is the constant; $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9$ are the short-run impact; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7, \gamma_8, \gamma_9$ are the long-run impact; $\varepsilon_t \simeq$ iid(0,Ɣ) is the error term.

3.4. Cointegration and Causality Analysis

To investigate the causal dynamics among the nine variables. Crop production, Arable land, Carbon emissions, Mean temperature, Precipitation, Fertilizer consumption, Water productivity, Male employment, and Female employment. This study employs the NARDL-ARDL methodology. This approach enables the identification of both short- and long-term relationships between the variables in the model. Following this, we advance to the second stage by applying the bounds testing procedure developed by Pesaran et al. (2001), along with the Toda and Yamamoto causality framework. The causality analysis rests on two fundamental assumptions: (i) future events cannot influence the past, and causality flows from the past and present toward the future; and (ii) causality can only be assessed between stochastic variables. The Toda and Yamamoto test is particularly valuable for determining whether 1 time series can effectively forecast another, provided the series are stationary. In essence, if we consider two stationary time series, X and Y, X is said to cause Y if it provides statistically significant information about the future values of Y. In this study, the Toda and Yamamoto method is employed to detect causal relationships among the variables, as represented in Equation (4).

$$X_t = \delta_0 + \sum_{k=1}^{K} \delta_k X_{(t-k)} + \sum_{j=1}^{J} \alpha_j Y_{(t-j)} + \varepsilon_t \tag{4}$$

Note: t → (1996-2022); X represents Crop production; Y is the explanatory variables, δ_k(k=1.,K) and α_j (j=1,….J) are the model unknown parameters considering K and J as the maximum delays number of the selected variables (we rely on the Akaike information criterion [AIC]). ε_t are the models' errors.

We estimate an ARDL model for each variable as specified in Equation (5)

$$\begin{aligned} \Delta X_t &= \alpha_0 + \sum_{k=1}^{K} \alpha_k \Delta X_{(t-k)} + \sum_{j=1}^{J} \alpha_j \Delta AGL_{(t-j)} \\ &+ \sum_{l=1}^{L} \theta_l \Delta CO2_{(t-l)} + \sum_{m}^{M} \vartheta_m \Delta MNT_{(t-m)} + \sum_{n}^{N} \mu_n \Delta PR_{(t-n)} \\ &+ \sum_{p}^{P} \rho_p \Delta FERT_{(t-p)} + \sum_{q}^{Q} \beta_q \Delta WAT_{(t-q)} + \sum_{v}^{V} \delta_v \Delta EM_{(t-v)} \\ &+ \sum_{f}^{F} \omega_f \Delta EF_{(t-f)} + ECT_{(t-1)} + \gamma_t \end{aligned} \tag{5}$$

Note: Δ is the first difference operator; α_k, α_j, θ_1, ϑ_m, μ_n, ρ_p, β_q, δ_v, and ω_f are the model unknown parameters with lags level k, j, m, n, p, q, v, and f; ECT is the lagged error correction term; γ are the models' errors.

3.5. Empirical Finding

3.5.1. Summary statistics

The Table 2 indicates that Arable land, Carbon emissions, and Precipitation exhibit greater volatility compared to the other variables. Additionally, the variables are normally distributed at the 1% significance level. The high standard deviation observed for most variables suggests substantial variability. To address this issue, a logarithmic transformation has been applied.

Figure 1 illustrates the trends of various variables from 1996 to 2022. The data reveals notable fluctuations, particularly in Crop Production, Mean Temperature, and Precipitation in Tunisia. For instance, in 2020, Precipitation experienced a significant decrease, while Mean Temperature steadily increased, and Crop Production also declined. These observations highlight that the variables exhibit considerable variability over time. The graphical representations of these variables are shown in the figures above, underscoring the dynamic nature of the data.

3.5.2. Unit root tests

In this study, we utilize three tests to detect autoregressive unit roots: the Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979), the Phillips-Perron (P-P) test by Phillips and Perron (1988), and the Andrews-Zivot (A&Z) test by Zivot and Andrews (2002). The results of these stationarity tests are summarized in Table 3.

Our data exhibit a unit root at the level, but become stationary after first differencing. This observation indicates that many variables are stationary at I(1) rather than I(0), thus satisfying the conditions for causality analysis. Specifically, the Mean Temperature, Precipitation, and Water Productivity were stationary at the level, while Crop Production, Arable Land, CO_2 Emissions, Fertilizer Consumption, and Employment in Agriculture (both male and female) were non-stationary at the level but became stationary after first differencing. To select the optimal ARDL model, we employed the Akaike information criterion (AIC), which helps identify the model with the best balance between goodness-of-fit and parsimony. The AIC indicated that the optimal lag length is 1. Therefore, the ARDL (1, 0, 1, 0, 0, 0, 0, 1, 0) model is preferred, as it provides the lowest AIC value. The choice of lags is based on the AIC criterion, as follows in Figure 2:

3.5.3. ARDL model estimation results

After verifying that the variables are cointegrated at different orders, the study advances to the ARDL estimation to determine the long-run coefficients.

Table 4 summarizes the results of the ARDL model estimation, which shows that lagged carbon emissions have a significant negative impact on crop production in Tunisia. On the other hand, factors such as fertilizer consumption, water availability, and male employment in agriculture all have a positive effect on crop yields. These findings align with the work of Ahmed et al. (2023) and Lee et al. (2024), who found that increased fertilizer use boosts crop productivity by correcting nutrient deficiencies and fostering plant growth. Similarly, studies by Khairallah et al. (2023) and Sidi et al. (2024) indicate that improved water availability achieved through effective irrigation and water management strategies positively influences crop yields by providing sufficient moisture for crops. Additionally, Bouraoui et al. (2023) and Haddad et al. (2024) show a positive relationship

Figure 1: Historical trend of variables

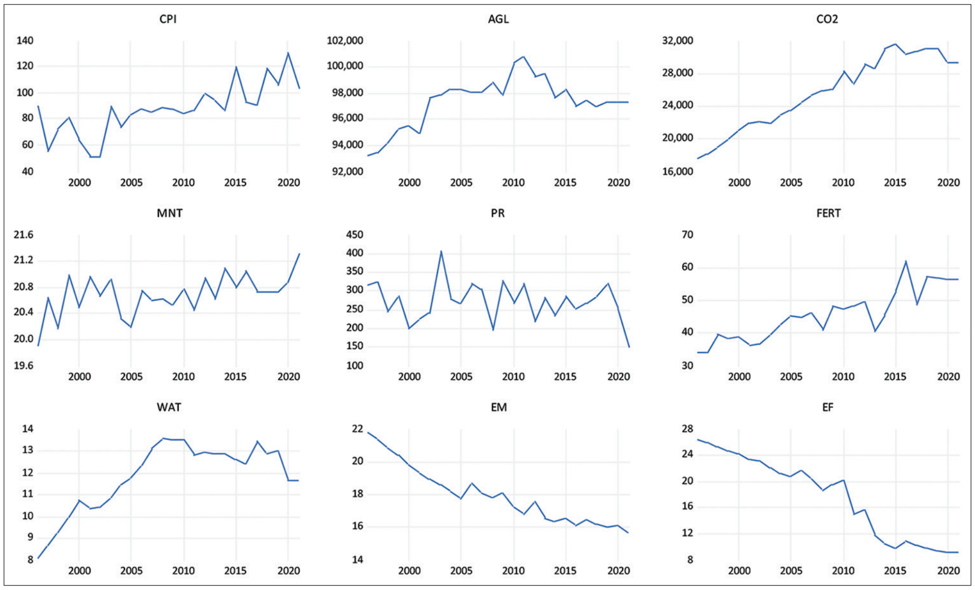


Table 2: Descriptive statistics for variables

Variables	CPI	AGL	CO_2	MNT	PR	FERT	WAT	EM	EF
Mean	87.646	97330.19	25660.49	20.689	272.053	45.699	11.806	17.968	17.653
Median	87.840	97620.00	25972.45	20.720	274.765	45.603	12.390	17.774	19.868
Maximum	131.120	100720.0	31627.40	21.330	407.420	61.973	13.603	21.793	26.358
Minimum	50.840	93240.00	17572.00	19.910	145.530	33.926	8.128	15.648	9.154
Std. Dev.	19.469	1900.041	4462.031	0.312	53.308	7.819	1.561	1.761	6.227
Skewness	0.045	−0.559	−0.287	−0.459	−0.002	0.342	−0.840	0.666	−0.186
Kurtosis	3.152	2.924263	1.795089	3.329	3.652	2.164	2.686	2.433	1.463
Jarque-Bera	0.034	1.360822	1.931363	1.031	0.461	1.264	3.166	2.272	2.709
Probability	0.982	0.506409	0.380724	0.597	0.794	0.531	0.205	0.321	0.257
Sum	2278.820	2530585.	667172.7	537.920	7073.390	1188.188	306.963	467.191	458.998
Sum Sq. Dev.	9476.211	90253924	4.98E+08	2.438	71045.21	1528.526	60.940	77.600	969.529
Observations	27	27	27	27	27	27	27	27	27

SD: Standard deviation

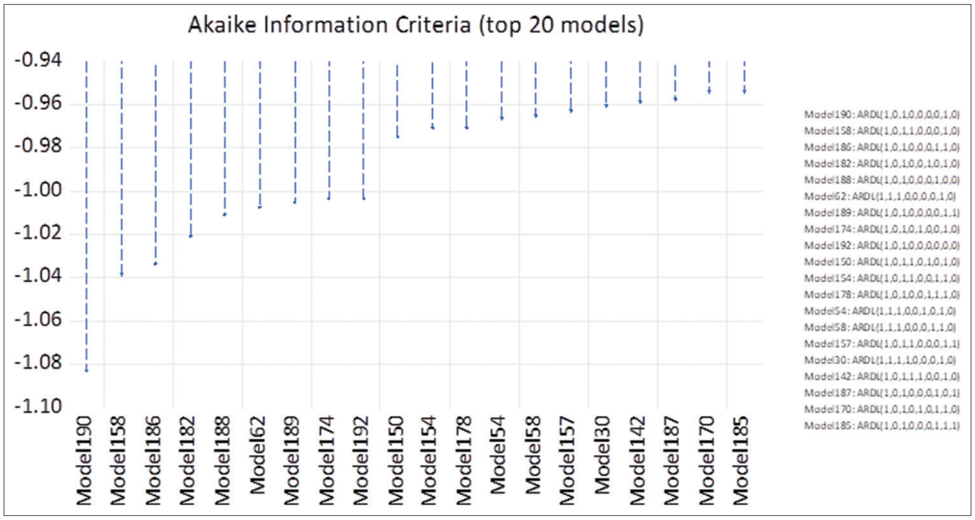
Table 3: Unit root test results

Variables	Level			1st difference		
	ADF	PP	AZ	ADF	PP	AZ
LCPI	−2.455 (0.137)	−2.393 (0.153)	−5.810 (0.336) 2005	−4.963***	−23.639***	−5.289*** 2010
LAGL	−2.411 (0.148)	−2.411 (0.144)	−3.649 *** 2002	−6.199***	−6.108***	−8.177** 2012
LCO_2	−2.462 (0.136)	−2.588 (0.108)	1.465 (0.557) 2018	−4.8***	−4.875***	−7.857** 2016
LMNT	−5.188***	−5.167***	−8.189*** 2004	−12.456***	−12.461***	-
LPR	−4.386***	−4.277***	−5.357*** 2003	−7.546***	−8.79***	-
LFERT	−1.779 (0.381)	−1.582 (0.476)	−4.824 (0.166) 2015	−6.938***	−13.74***	−3.819** 2016
LWAT	−3.270**	−12.326***	−5.985*** 2013	-	-	-
LEM	−2.881*	−2.651*	−3.640 (0.111) 2016	−5.636***	−7.323***	−8.277** 2006
LEF	−0.164 (0.931)	−0.043 (0.945)	−5.89*** 2013	−5.959***	−5.91***	-

***,**, and* denote significance respectively at the 1%, 5%, and 10%

between male employment in agriculture and crop productivity. This correlation is likely driven by factors such as the availability of labor, specialized agricultural knowledge, and the capacity to apply advanced farming techniques. The presence of skilled

Figure 2: The optimal model of the AIC information criterion



labor not only enhances farm operations but also improves productivity and contributes to greater agricultural efficiency. The R-squared value of 0.863 suggests that 86.3% of the variation in crop production is explained by both climatic and non-climatic variables considered in this study. Furthermore, the Bounds test was conducted to explore the short-term relationships among the variables, and the results confirm the presence of both long-term and short-term causality at the 5% significance level.

The diagnostic tests presented in Table 5 reveal that the ARDL model does not exhibit autocorrelation, heteroscedasticity, or departures from normality in the error terms, suggesting that the model is appropriately specified. Furthermore, the stability of the model's coefficients is confirmed, as the stability curves consistently stay within the acceptable range at the 5% significance level.

Figure 3 illustrates the results of the Cusum and Cusum squared tests, which confirm the stability of the model coefficients at the 5% significance level, as the curves remain within the acceptable corridor. The null hypothesis is not rejected for all tests, indicating that the model is stable. Therefore, the model is validated as static. The estimated ARDL (1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0) model is robust and effectively explains 75% of the dynamics of crop production index (CPI) in Tunisia over the period from 1996 to 2022.

3.5.4. ARDL bounds test

The results of the cointegration test, as shown in Table 6, confirm the presence of a cointegrating relationship between the variables, with the F-statistic exceeding the upper bound value. This indicates the existence of a long-term equilibrium relationship, allowing for the estimation of the long-run effects among the series. Specifically, arable land, carbon dioxide emissions, annual mean temperature, annual precipitation, fertilizer consumption, water productivity, male employment in agriculture, and female employment in agriculture all exhibit long-term cointegration with crop production in Tunisia.

Additionally, we applied the Johansen and Juselius cointegration (JJC) approach, presented in Table 7, to further validate the long-term cointegration relationships between crop production and both climatic and non-climatic variables.

Table 7 provides evidence of long-term cointegration among arable land, carbon dioxide emissions, annual mean temperature, annual precipitation, fertilizer consumption, water productivity, male and female employment in agriculture, and crop production

Table 4: The ARDL estimation

LCPI				
ARDL (1, 0, 1, 0, 0, 0, 0, 1, 0)				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.***
LCPI (−1)	−0.222	0.180	−1.227	0.241
LAGL	5.720	3.836	1.491	0.159
LCO_2	−0.695	0.855	−0.813	0.430
LCO_2 (−1)	−2.062	1.111	−1.855	0.086
LMNT	0.605	2.284	0.265	0.794
LPR	0.173	0.141	1.229	0.240
LFERT	1.136	0.365	3.111	0.008
LWAT	6.967	2.922	2.383	0.033
LEM	3.719	1.676	2.218	0.044
LEM (−1)	2.448	1.632	1.499	0.157
LEF	−1.039	0.311	−3.341	0.005
C	−164.421	51.787	−3.174	0.007
R-squared	0.863			
Adjusted R-squared	0.748			
F-statistic	7.479	Durbin-Watson stat		2.363
Prob (F-statistic)	0.000			

Table 5: Estimated ARDL diagnostic test results

The test hypothesis	Tests	Values (probalility)
Autocorrelation	Breusch-Godfrey	1.160 (0.348)
Heteroskedasticity	Breusch-Pagan-Godfrey	1.353 (0.298)
Normality	Jarque-Bera	0.169 (0.918)
Specification	Ramsey (Fisher)	0.954 (0.343)

Table 6: The cointegration Bounds test

CPI=f (AGL, CO2, MNT, PR, FERT, WAT, EM, EF)			
F-statistic	**6.467**		
Critical threshold	**1%**	**5%**	**10%**
I (0)	2.62	2.11	1.85
I (1)	3.77	3.15	2.85

Figure 3: Cumulative sum test

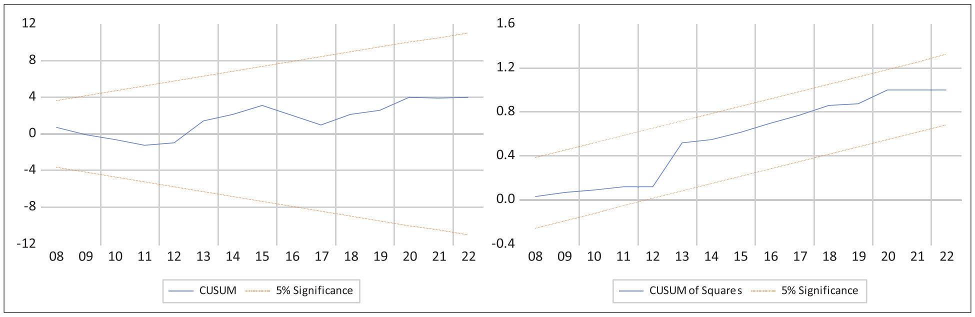


Table 7: The Johansen and Juselius cointegration

Dependent variable LCPI				
Hypothesis	**Trace statistic**	**Eigenvalue**	**Statistic critical value at 5%**	**Probability****
None*	313.5221	0.992712	197.3709	0.0000
At most 1*	190.4852	0.871565	159.5297	0.0003
At most 2*	139.1769	0.799529	125.6154	0.0057
At most 3*	98.99978	0.748441	95.75366	0.0293
At most 4	64.49788	0.603313	69.81889	0.1235
At most 5	41.38266	0.532770	47.85613	0.1768
At most 6	22.35931	0.493891	29.79707	0.2789
At most 7	5.334254	0.148518	15.49471	0.7723
At most 8	1.314835	0.051234	3.841465	0.2515

in Tunisia. This table offers a comprehensive analysis of the long-term relationships between these variables, highlighting their interconnectedness and the sustained influence of each on crop production.

3.5.4.1. Short run and long run cointegration test

Table 8 presents the results from the ARDL model, showcasing both short-term and long-term effects on crop production. The findings reveal that carbon emissions have a negative impact on crop production in Tunisia across both time frames, though the short-term effect is not statistically significant. Specifically, a 1-unit increase in carbon emissions leads to a 2.25-unit decrease in crop production in the long term, in line with the findings of Amaefule et al. (2023). This negative relationship is likely driven by factors such as urbanization, transportation, non-renewable energy consumption, and deforestation. This result contrasts with the study by Asfew and Bedemo (2022), who found that a 1% rise in carbon dioxide emissions contributed to a 0.23% increase in cereal crop production. The study also observes that an increase in female employment in agriculture negatively affects crop production in the long run. A 1% rise in female agricultural employment is associated with a 0.85% decrease in crop production. This negative impact could be attributed to inequalities in access to resources, training, and decision-making power compared to their male counterparts. Women in agriculture often face lower wages, poor working conditions, and limited access to benefits, all of which can hinder productivity. These findings align with the FAO and ILO (2010) report, which emphasized that restricted access to agricultural extension services and climate adaptation tools limits women's ability to enhance crop production and respond to climate shocks. Empowering women in agriculture is essential for improving food security, reducing poverty, fostering economic development, and advancing climate resilience (UN Women, 2017). Addressing these disparities is vital for optimizing agricultural productivity and ensuring that all labor contributions are fully utilized. Furthermore, the results highlight the significant positive effects of fertilizer consumption, water productivity, and male employment in agriculture on crop production over the long term. Specifically, a 1% increase in fertilizer consumption, water productivity, and male employment leads to increases in crop production of 0.93%, 4.7%, and 5.05%, respectively. These results are consistent with Li et al. (2024), who found that nitrogen and organic fertilizers improve crop yield stability and water use efficiency. Similarly, Asfew and Bedemo (2022) reported that a 1% increase in fertilizer consumption per hectare enhances cereal crop production by around 0.34%. In contrast to the negative impact of increased female employment, this study emphasizes the positive contributions of higher fertilizer use, better water management, and increased male employment on crop yields. Balancing the challenges related to female employment while leveraging these positive factors is key to optimizing agricultural productivity and achieving sustainable agricultural development.

3.5.4.2. Pairwise granger causality tests

The results of the pairwise Granger causality tests, presented in Table 9, reveal the following:

- Unidirectional causality: A one-way causal relationship was identified from arable land (AGL), carbon dioxide emissions (CO_2), fertilizer consumption (FERT), and both male (EM) and female (EF) employment in agriculture to crop production. This finding is consistent with Ghosh et al. (2023), who observed a unidirectional causality from CO_2 emissions to agricultural value-added (LnAVA) in Bangladesh using ARDL and ECM techniques from 1980 to 2014. Similarly, Ali et al. (2021) reported a one-way causality from CO_2 emissions to cereal production in India. A unidirectional causality was also found

Table 8: The short and the long run cointegration test

Dependent variable: (LCPI)				
Short run dynamics				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
CointEq (−1)	−1.222	0.180	−6.756	0.000
D (LCO_2)	−0.695	0.855	−0.813	0.430
D (LEM)	3.719	1.676	2.218	0.044
Long run estimates				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
LAGL	4.680	3.340	1.401	0.184
LCO_2	−2.257	0.896	−2.519	0.025
LMNT	0.495	1.868	0.265	0.794
LPR	0.141	0.118	1.194	0.253
LFERT	0.930	0.295	3.142	0.007
LWAT	5.700	2.147	2.655	0.019
LEM	5.046	1.864	2.706	0.018
LEF	−0.850	0.259	−3.274	0.006
C	−134.539	42.947	−3.132	0.007

EC = LCPI – (4.6808*LAGL − 2.2572*LCO_2 + 0.4958*LMNT + 0.1420*LPR + 0.9301*LFERT + 5.7010*LWAT + 5.0468*LEM − 0.8507*LEF − 134.5391)

Table 9: The granger causality test

Variables	LCPI	LAGL	LCO_2	LMNT	LPR	LFERT	LWAT	LEM	LEF
LCPI	-								
LAGL	→	-							
LCO_2	→	≠	-						
LMNT	←	≠	←	-					
LPR	≠	≠	≠	≠	-				
LFERT	→	≠	←	→	≠	-			
LWAT	↔	←	↔	→	≠	→	-		
LEM	→	≠	←	↔	≠	→	←	-	
LEF	→	≠	←	→	≠	→	↔	≠	-

Left to right (→), right to left (←), and bidirectional causality (↔)

from CO_2 emissions to annual mean temperature (MNT). This contrasts with the findings of Abdi et al. (2023), who documented bidirectional causality between temperature, carbon emissions, and cultivated area in East Africa. Additionally, a unidirectional causality from water productivity (WAT) to fertilizer consumption (FERT) was observed, suggesting that improvements in water management practices enable farmers to optimize fertilizer use, thereby reducing waste and improving crop yields. This result aligns with the findings of Raza and Ali (2024) and Singh and Kumar (2024).

- Bidirectional causality between water productivity and crop production: There is bidirectional causality between water productivity (WAT) and crop production, indicating that changes in water productivity can affect crop production, and vice versa. This is supported by Jin and Li (2023) and Zhang and Cai (2022).
- No causal relationship: No causal relationship was found between fertilizer consumption (FERT) and crop production. This result is consistent with Singh and Bansal (2023) and Khan and Zahid (2023), who highlighted that the relationship is not always causal and may be influenced by other economic factors.

3.5.5. NARDL model estimation results

In this study, we employ the recently developed and advanced technique, the nonlinear autoregressive distributed lag (NARDL) model, to assess the asymmetric and non-linear impacts of temperature and rainfall on rice productivity. The traditional ARDL model overlooks the possibility of non-linearity and asymmetry in the relationships among the variables. To address this limitation, the ARDL model is extended to an asymmetric ARDL or NARDL model, as introduced by Shin et al. (2014), which allows for the exploration of dynamic adjustment patterns and asymmetries in both the short and long-run relationships between the variables. The following model is specified to investigate the relationships between these variables (Equation (6)):

$$CPI_t = f\,(CO2_t;\, MNT_t;\, PR_t) \tag{6}$$

To examine the asymmetric effects, we decompose carbon emissions, rainfall, and temperature into their positive and negative changes, represented by $LCO2^+$, $LCO2^-$, LPR^+, LPR^-, and $LMNT^+$, $LMNT^-$, respectively. This allows us to capture the differential impacts of increases and decreases in these variables on crop productivity. The modified model is outlined in Equation (7):

$$LCPI_t = \beta_0 + \beta_1\, LCO2^+_t + \beta_2\, LCO2^-_t + \beta_3\, LMNT^+_t + \beta_4\, LMNT^-_t + \beta_5\, LPR^+_t + \beta_6\, \mathrm{LPR}^-_t + \varepsilon_t \tag{7}$$

Therefore, the NARDL model for the underlying variables is expressed as follows in Equation (8):

$$\Delta LCPI_t = \beta_0 + \beta_1 LCPI_{t-1} + \beta_2^{+} LCO2^{+}_{t-1} + \beta_2^{-} LCO2^{-}_{t-1} + \beta_3^{+} LMNT^{+}_{t-1} + \beta_3^{-} LMNT^{-}_{t-1} + \beta_4^{-} LPR^{-}_{t-1} + \beta_4^{+} LPR^{+}_{t-1} + \sum_{p=1}^{q} \gamma_1 \Delta LCPI_{t-p} + \sum_{p=1}^{q} (\gamma_2^{-} \Delta LCO2^{-}_{t-p} + \gamma_2^{+} \Delta LCO2^{+}_{t-p}) + \sum_{p=1}^{q} (\gamma_3^{-} \Delta LMNT^{-}_{t-p} + \gamma_3^{+} \Delta LMNT^{+}_{t-p}) + \sum_{p=1}^{q} (\gamma_4^{-} \Delta LPR^{-}_{t-p} + \gamma_4^{+} \Delta LPR^{+}_{t-p}) + \varepsilon_t \tag{8}$$

Where $LCO2^{+}_{t}$, $LCO2^{-}_{t}$, $LMNT^{+}_{t}$ + $LMNT^{-}_{t}$ + LPR^{+}_{t} + and LPR^{-}_{t} represent the partial sum processes of positive and negative shocks in carbon emissions, annual mean temperature, and annual average rainfall, respectively. These decompositions allow for the analysis of the asymmetric effects of increases and decreases in these variables on the crop production index. The adequacy and stability of the specified NARDL models are further evaluated using various diagnostic tests, as shown in Table 10.

The negative and positive changes in Carbon emissions ($LCO2^{+}$, $LCO2^{-}$), Rainfall (LPR^{+}, LPR^{-}), and Temperature (MNT^{+}, MNT^{-}) are already presented in Equation (7). The cumulative total of both positive and negative changes is defined as follows in Equations 9-11).

$$\text{üüüüü}2^{+}_{t}\text{üüü} = \sum_{i=1}^{t} \Delta \quad 2^{+}_{i} = \sum_{i=1}^{t} \quad (\Delta \quad 2_{i}, 0); \quad 2^{-}_{t} = \sum_{i=1}^{t} \Delta LCO2^{-}_{i} = \sum_{i=1}^{t} min(\Delta LCO2_{i}, 0) \tag{9}$$

$$LCO2^{+}_{t} = \sum_{i=1}^{t} \Delta LCO2^{+}_{i} = \sum_{i=1}^{t} max(\Delta LCO2^{-}_{i}, 0); \quad LCO2^{-}_{t} = \sum_{i=1}^{t} \Delta LCO2^{-}_{i} = \sum_{i=1}^{t} min(\Delta LCO2^{-}_{i}, 0) \tag{10}$$

$$LPR^{+}_{t} = \sum_{i=1}^{t} \Delta LPR^{+}_{i} = \sum_{i=1}^{t} \max1(aLPR^{-}_{i}, 0); \quad LPR^{-}_{t} = \sum_{i=1}^{t} \Delta LPR^{-}_{i} = \sum_{i=1}^{t} \min(\Delta LPR^{-}_{i}, 0) \tag{11}$$

The empirical findings from our analysis are summarized and discussed in Table 10.

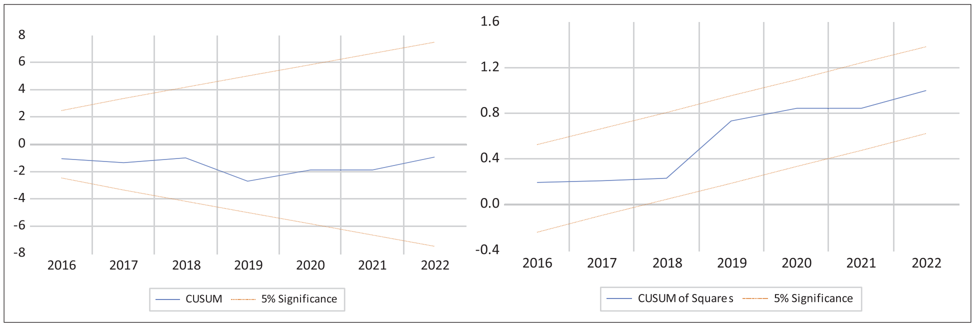
The cointegration test results within the NARDL framework indicate that the bound F-statistic is 3.8, surpassing the critical upper bound value at the 5% significance level. This confirms the presence of a nonlinear long-run equilibrium relationship among the model variables. Following this confirmation, the next step involves examining the short-run and long-run asymmetries in carbon emissions, rainfall, and temperature. To assess these asymmetries, the Wald test is conducted, and the results are

Table 10: NARDL short- and long-term estimation

Dependent variable: LCPI			
Selected model: NARDL (1, 1, 1, 1)			
Bound test			
F.statistic			3.8
Critical values (%)	Lower bound		Upper bound
1	2.6		3.7
5	2.1		3.1
10	1.8		2.8
Short-run and long-run asymmetry statistics			
LCO_2	5.16***		
LMNT	1.08**		
LPR	3.08**		
Variables		**Coefficient**	
Short run estimation			
ECM		−0.58***	
D (LCO_2_POS)		8.5**	
D (LCO_2_NEG)		−3.4	
D (LMNT_POS)		−1.25	
D (LMNT_NEG)		−9.8*	
D (LPR_POS)		6.6**	
D (LPR_NEG)		−4.9*	
Long run estimation			
LCO_2_POS		4.8**	
LCO_2_NEG		−3.9***	
LMNT_POS		−1.4**	
LMNT_NEG		−1.9**	
LPR_POS		6.7	
LPR_NEG		−6.8*	
Adjusted R-squared			0.7
Durbin-Watson stat			1.87
Diagnostic test			**Prob.***
The normality test (Jarque-Bera)	0.45		0.79
Heteroskedasticity test: Breusch-Pagan-Godfrey	0.222		0.8
Breusch-godfrey serial correlation LM test	0.86		0.624
Ramsey RESET	0.56		0.48

*, **, and *** denote 1%, 5%, and 10% level of signifcance, respectively

Figure 4: NARDL CUSUM and CUSUMQ



Source: Author

presented in Table 10. Given that the probability values for both the short-run and long-run F-statistics in Table 10 are below 0.1, we reject the null hypothesis of symmetric effects. This enables a detailed analysis of how positive and negative shocks in these variables influence crop production in Tunisia.

Table 10 summarizes the findings from the NARDL model, where carbon emissions, rainfall, and temperature variables are decomposed into positive and negative partial sums. First, the error correction term (ECT) meets the necessary conditions, confirming that the speed of adjustment from short-term disequilibrium to long-term equilibrium is approximately 58%.

The long-term effects of temperature changes, both optimistic (MNT^{+}) and destructive (MNT^{-}), on crop production are estimated to be −1.4 and −1.9, respectively. This indicates that negative temperature variations have a more substantial impact on crop production. Specifically, a 1% increase in positive temperature shocks results in a 1.4% decline in crop production, whereas a 1% rise in negative temperature shocks leads to a 1.9% reduction in crop production in Tunisia. Interestingly, positive temperature shocks do not have a short-term impact on crop production. However, negative temperature shocks show a favorable short-term effect on crop production, with a 1% increase in negative temperature shocks resulting in a 9.8% increase in crop production. This finding aligns with the results of Zhang et al. (2023), who observed similar effects in Malaysia.

For rainfall, the long-term impacts of positive (LPR^{+}) and negative (LPR^{-}) variations on crop production are estimated to be 6.7 and −6.8, respectively. This indicates that the negative impact of rainfall is more pronounced. Specifically, crop production decreases by 6.8% for every 1% decrease in rainfall, while a 1% increase in rainfall leads to a 6.7% rise in crop production. This suggests an asymmetric relationship between rainfall and crop production in Tunisia. In the short term, the coefficients for the effects of positive and negative rainfall changes on crop production are 6.6 and 4.9, respectively. This means that a 1% change in rainfall results in a 6.6% and 4.9% increase in crop production for positive and negative shocks, respectively. These results are consistent with Baig et al. (2021), who found that negative rainfall and temperature components have a dominant effect on rice productivity in India. The results from the NARDL approach are consistent with those derived from the symmetric ARDL model, providing robust evidence of the impact of negative shocks in carbon emissions on crop production in Tunisia, both in the short and long run. Specifically, a 1% negative shock in carbon emissions leads to a 3.9% reduction in crop production in the long term, while positive shocks in carbon emissions lead to an increase in crop production. A 1% rise in positive carbon emissions shocks results in a 4.8% increase in crop production. This finding is in line with Otim et al. (2023), but contrasts with the findings of Wahyono et al. (2022), Khurshid et al. (2023), and Mahdavian et al. (2024).

To ensure the robustness of our findings, a series of diagnostic tests were conducted. The Adjusted R-squared value of 0.77 indicates that approximately 70% of the variation in crop production is explained by the independent variables in the model. Additionally, the diagnostic tests confirm the absence of serial correlation. The probability value of the Jarque-Bera (J-B) test exceeds 0.05, suggesting that the residuals follow a normal distribution. Furthermore, the RESET test confirms that the empirical model is correctly specified.

Figure 4 illustrates the evolution of the CUSUM and squared CUSUM tests for the NARDL model. These stability diagnostics are crucial for evaluating the robustness and reliability of the estimated model. The graphical representation shows that the estimated parameters remain stable at the 5% significance level, confirming the model's validity and consistency throughout the study period.

4. CONCLUSION AND POLICY RECOMMENDATIONS:

This study investigates the influence of climate and economic factors on crop production in Tunisia from 1996 to 2022, focusing on variables such as annual mean temperature, annual precipitation, water productivity, arable land, CO_2 emissions, fertilizer consumption, and agricultural employment (both male and female). Using the autoregressive distributed lag (ARDL) model and the Johansen-Juselius cointegration technique, the study explores both short- and long-term relationships among these variables. The results reveal that carbon emissions negatively affect crop production, particularly over the long term, while male agricultural employment positively contributes to crop production in both the short and long run. Moreover, fertilizer consumption, water productivity, and both male and female agricultural employment significantly influence long-term agricultural output. Arable land, fertilizer use, water efficiency, and agricultural employment are identified as key drivers of crop production in Tunisia. Further analysis using the Nonlinear ARDL (NARDL) model uncovers a notable and dynamic asymmetric relationship between climate change, carbon emissions, and crop production. The findings show that both positive and negative shocks in climate variables and CO_2 emissions affect crop production to different extents. However, the traditional linear ARDL model fails to capture these asymmetries, which could lead to biased or misleading conclusions. Specifically, the asymmetric long-run results indicate that increases and decreases in annual mean temperature both negatively impact crop production. Rainfall exhibits a mixed effect: Positive shocks enhance crop yields, while negative shocks reduce them. In the short run, fluctuations in rainfall (both positive and negative) significantly improve rice productivity. Carbon emissions also show asymmetric effects, with positive shocks promoting crop growth, while negative shocks hinder production.

Despite these valuable insights, there are some limitations to this study. First, the scope of the analysis is confined to Tunisia, and while the findings provide meaningful insights for this context, their applicability to other regions may be limited. Additionally, the study primarily focuses on annual data, which may obscure more immediate, seasonal variations in climate and economic factors that influence crop production. Future research could benefit from incorporating higher-frequency data, such as monthly or quarterly, to capture these fluctuations more accurately. Furthermore, while the study addresses key variables, other factors like soil quality, pest outbreaks, and technological advancements in agriculture were not considered, which may also have significant impacts on crop production. Finally, the study assumes that the relationships between variables remain constant over time, but it is possible that evolving agricultural practices, climate conditions, and policy interventions could alter these dynamics. To address the adverse effects of climate change on Tunisia's agricultural sector, policymakers should prioritize sustainable water management, promote climate-resilient farming techniques, and invest in renewable energy to mitigate carbon emissions. Strengthening research and development in agricultural innovation will be crucial to enhancing productivity and adaptability to climate variability. Moreover, incorporating gender considerations into agricultural policies such as improving data on women's contributions and fostering collaboration across ministries will ensure more inclusive decision-making. Regional assessments of climate change's impact on agricultural livelihoods can also support targeted interventions, ultimately fostering a more resilient and sustainable agricultural sector.

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