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RESEARCH ARTICLE

Climate Change and Its Impact on Agriculture in Morocco: An Analysis Using the ARDL Model

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ABSTRACT

Climate change is an increasingly pressing global threat, with variations in temperature, shifts in precipitation patterns, and the intensification of extreme weather events directly impacting agricultural productivity. This is particularly evident in African countries like Morocco, where the agricultural sector is heavily dependent on climatic conditions. The primary objective of this research is to assess the repercussions of climate change on Moroccan agriculture through an econometric analysis utilizing an ARDL model. This model is applied to data covering the period from 1990 to 2022, comprising 32 observations. By examining the effects of climatic variations on agricultural performance, the study also provides forward-looking projections based on two IPCC scenarios extending to the year 2100. The findings highlight the significant negative impacts of climate change on the productivity and resilience of Morocco's agricultural sector.

INTRODUCTION

Today, international organizations, expert groups, policymakers, and ordinary citizens are all increasingly concerned about the harmful effects of climate change. According to the World Health Organization (WHO), the impacts of climate change on human health are manifold, ranging from deaths and illnesses caused by extreme weather events such as heatwaves, storms, and floods to the rise in zoonotic diseases and those transmitted through water and food.

The Intergovernmental Panel on Climate Change (IPCC, 2007) highlights that climate change is likely to impact developing countries earlier and more severely. These nations rely heavily on climate-sensitive sectors such as agriculture, forestry, fisheries, and tourism, while also grappling with poorer public health and fewer, often lower-quality public services. Africa is among the most affected regions, with Morocco standing out as a particularly vulnerable case.

In another context, industries play a critical role in global greenhouse gas (GHG) emissions, primarily in the form of carbon dioxide, methane, and nitrous oxide. According to the IPCC, direct industrial emissions accounted for approximately 21% of global emissions in 2010. These emissions mainly arise from fossil fuel combustion to power factories and chemical processes such as cement and petrochemical production. Industries also contribute indirectly to emissions due to their high demand for electricity and transportation (IPCC, 2014).

Greenhouse gas (GHG) emissions from industrial activities amplify the natural greenhouse effect, leading to a rise in global temperatures. According to the United Nations Framework Convention on Climate Change (UNFCCC), industrial emissions, combined with those from other sectors, are major drivers of the increase in average global temperatures. This warming has severe consequences, including rising sea levels, more frequent and intense heatwaves, and disruptions to climatic patterns (UNFCCC, 2021).

These impacts disproportionately affect low-income countries and vulnerable populations, as they often face extreme environmental conditions and have fewer resources to adapt to climate change (Céline Guivarch, 2021). Within these communities, the poorest individuals and women are frequently the hardest hit. They suffer the most from declining agricultural productivity, rising food prices, and extreme weather events, which exacerbate their economic and social vulnerabilities (Goar, 2024).

In African countries, climate change significantly undermines livelihoods by reducing income levels and worsening food security. In Morocco, agriculture plays a pivotal role in the nation's economic and social development, contributing substantially to GDP, employment, and efforts to combat poverty and food insecurity (Tazigh, 2020). However, the sector remains highly vulnerable to climate variability. Factors such as droughts, rising temperatures, and unpredictable rainfall patterns have led to a decline in agricultural productivity, highlighting the sector's fragility in the face of climate change.

In this complex and uncertain context, the present study seeks to address the following question: What is the impact of climate change on Morocco's agricultural sector*?* To answer this, the study adopts a methodological approach that begins with the formulation of hypotheses, which are subsequently tested using econometric techniques. Specifically, two hypotheses are proposed:

Hypothesis 1: Climate change significantly reduces agricultural productivity in Morocco, primarily due to rising temperatures and precipitation variability.

Hypothesis 2: The industrial sector in Morocco negatively impacts the agricultural sector.

This article is structured as follows. First, it provides a theoretical review by defining the concept of climate change and exploring its causes. Next, it examines existing studies that have investigated the effects of climate change on Moroccan agriculture. Finally, an empirical analysis is conducted using the ARDL (AutoRegressive Distributed Lag) model to assess the impact of climate change on agricultural productivity.

LITERATURE REVIEW

2.1 Definition and Causes of Climate Change

According to the Intergovernmental Panel on Climate Change (IPCC), climate change is defined as "a change in the state of the climate that can be identified through changes in the mean and/or variability of its properties, and which persists over an extended period." Climate, in turn, refers to the distribution of various meteorological variables over a defined period. Thus, climate change represents a sustained shift in both the average and variability of climatic properties (Nicolas Lancesseur, 2020).

This phenomenon can arise from natural causes, such as variations in solar activity or Earth's orbital cycles. However, it is now primarily attributed to human activities, particularly the emission of greenhouse gases (GHGs) from fossil fuel combustion, deforestation, and intensive agriculture (IPCC, 2021).

GHG emissions are the main driver of current global warming. These gases—primarily carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) enhance the natural greenhouse effect by trapping heat radiated from Earth's surface. Fossil fuel combustion for energy production, transportation, and industry constitutes the primary source of these emissions. For example, in 2020, fossil fuels accounted for 75% of global CO_2 emissions (International Energy Agency, 2021).

In this context, the study by Kerfal et al. (2024) highlights the role of greenhouse gas (GHG) emissions, which remain a significant driver of climate change, in the degradation of environmental quality. This deterioration is expected to have harmful effects on the agricultural sector, further exacerbating its vulnerabilities to climatic variability and environmental stress.

Deforestation is another significant contributor to climate change as it diminishes the ability of forests to absorb CO_2. Trees act as natural carbon sinks, storing large amounts of CO_2. When they are cut down or burned, this stored carbon is released into the atmosphere. Deforestation, often driven by agricultural expansion, logging, or urbanization, substantially contributes to global emissions. According to FAO (2020) report, deforestation and land-use changes are responsible for about 10% of global CO_2 emissions.

Agriculture also plays a significant role in GHG emissions, particularly through intensive livestock farming, which generates high levels of methane and nitrous oxide—both potent greenhouse gases. Methane is largely emitted from the digestive systems of ruminants (enteric fermentation) and from the decomposition of organic matter in rice paddies. Nitrous oxide is released from the excessive use of chemical fertilizers. According to the Food and Agriculture Organization (FAO), the agricultural sector contributes approximately 18% of global GHG emissions, making it one of the most polluting sectors globally.

The Impact of Climate Change on Agriculture in Morocco

Agriculture remains a critical pillar of Morocco's social and economic structure. However, the sector's reliance on climatic stability makes it highly vulnerable to climate change. Predominantly focused on cereal cultivation, Moroccan agriculture depends heavily on rainfall, and its fragility is evident in both its social implications for rural and mountainous populations and its broader economic impact. Climate change is expected to directly and indirectly affect economic growth and employment through declining agricultural yields.

Using the Cropwat model to assess rainfed winter cereals, projections indicate a significant drop in yields. More frequent droughts could lead to a 30% decline in domestic production. Additionally, vegetable yields are projected to decrease by as much as 40% by 2030 (Arrus, 2006).

El Mourid et al. (2014) highlight the potentially severe consequences of climate change on Moroccan agriculture, particularly for staple crops like wheat and barley. Their estimates suggest that yields may decrease by 15–25% by 2050 due to rising temperatures, reduced precipitation, and increased climatic variability. They also predict an intensification of drought periods, particularly in semi-arid regions of the country where water resources are already scarce.

Rainfed crops, such as cereals and legumes, are especially vulnerable as they directly depend on rainfall. Research by Karrou (2016) indicates that precipitation variability significantly reduces the yields of rainfed crops, with agricultural losses reaching up to 30% during drought years. This underscores the pressing need for adaptive strategies to mitigate the impact of climate change on Morocco's agricultural sector.

The combination of higher temperatures and reduced rainfall has significantly diminished water availability for irrigation, exacerbating water stress in agricultural regions. These climatic conditions not only restrict crop growth but also increase the risk of diseases and pest infestations. According to Bouazzama (2018), yields of water-intensive crops such as maize and citrus could decrease by 20–35% in a warming scenario without adaptive measures.

Driouech (2019) highlights the growing frequency of heatwaves, which impose thermal stress on crops. Key cereal crops like wheat and barley, which are staples of Moroccan agriculture, are particularly vulnerable to rising temperatures. These heatwaves accelerate the crops' growth cycles, reducing yields, especially in major agricultural zones such as the Saïss plains and the Souss-Massa regions.

Woillez (2019) forecasts that unmitigated declines in precipitation will cause a significant drop in cereal yields by 2050. While irrigation could potentially boost yields even in increasingly arid conditions, Morocco may face challenges in offsetting rainfall deficits through irrigation alone. This limitation is likely to be accompanied by a marked increase in the frequency of heat and drought periods. Non-irrigated agriculture is expected to experience severe impacts, with wheat and barley yields potentially falling by up to 40% in some areas. Additionally, water demands for crops are projected to rise substantially, necessitating more intensive irrigation. However, river flows may decrease by over 30%, further straining water resources.

Soil erosion presents another major challenge to Moroccan agriculture. Over 8.7 million hectares of arable land are affected by erosion, with losses ranging from 500 tons of soil per square kilometer in the Middle Atlas to over 5,000 tons in the Rif. This degradation significantly undermines agricultural productivity. The causes of erosion are multifaceted, including a combination of natural and human factors such as irregular rainfall, overgrazing, sparse vegetation, excessive wood harvesting, and inadequate agricultural practices (FAO, 2017).

3. RESEARCH METHODOLOGY

This study employs an econometric approach using the ARDL (AutoRegressive Distributed Lag) model to assess the impact of climate change on Morocco's agricultural sector. The choice of this model is driven by two key considerations. First, it allows for the analysis of the relationship between the dependent variable and independent variables over a period from 1990 to 2022, encompassing 32 observations. This timeframe was selected based on the availability of historical data for several variables used in the study. Second, the ARDL model enables forecasting based on the Representative Concentration Pathway (RCP) scenarios developed by the IPCC.

The ARDL Model

The ARDL model is an econometric estimation method widely used to analyze both long-term and short-term relationships between variables. It is particularly effective when the variables are a mix of stationary and non-stationary series, provided they are integrated at order 0 or 1 (Pesaran, M. H., & Shin, Y., 1997).

The general form of an ARDL model is expressed as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \varepsilon_t$$

Where:Y_t:The dependent variable at time t; X_{t-j} : Lagged explanatory variables; α_0 : Constant term ; $\beta_i$et γ_j : Coefficients of the lagged terms ; p, q : Lag orders for the dependent and independent variables, andε_t : Error term

Implementing an ARDL model involves several key steps to ensure the validity of the results, whether analyzing short-term effects or the long-term relationships between variables.

The first step is to determine the order of integration of the variables using stationarity tests such as the Augmented Dickey-Fuller (ADF) test or the Phillips-Perron (PP) test. These tests identify whether the variables are stationary at level I(0)or integrated of order I(1). This step is crucial, as the ARDL model requires variables to be either I(0), I(1), or a mix of both, but not I(2).

Once stationarity is confirmed, the optimal lag orders (p and q) for the dependent and explanatory variables must be determined. This step typically relies on information criteria such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), or the Hannan-Quinn Criterion (HQC). Selecting the correct lags ensures that the model captures the dynamic relationships effectively.

The ARDL model is estimated using the Ordinary Least Squares (OLS) method. The estimation involves deriving coefficients for the lagged terms of the dependent and explanatory variables. These coefficients provide insights into the short-term effects of changes in the explanatory variables on the dependent variable.

To examine the existence of a long-term relationship between variables, the bounds testing approach for cointegration is performed. This test evaluates the null hypothesis that no cointegration exists (H0: no cointegration). The F-statistic is compared against two critical bounds:

A lower bound assumes all variables are I(0).

An upper bound assumes all variables are I(1).

If the F-statistic exceeds the upper bound, the null hypothesis is rejected, confirming the presence of cointegration.

Once cointegration is established, long-term coefficients are derived from the estimated parameters of the model. These coefficients represent the permanent effects of changes in explanatory variables on the dependent variable. In contrast, short-term effects are directly observed from the model as coefficients associated with the differenced terms of the variables.

The final step is to evaluate the model's quality using diagnostic tests:

Breusch-Godfrey Test: Checks for the absence of residual autocorrelation.

Jarque-Bera Test: Assesses the normality of residuals.

Stability Tests (CUSUM and CUSUMSQ): Ensures that the estimated coefficients remain stable over time.

These diagnostic checks validate the reliability of the results and help identify potential weaknesses in the model. By following these steps, the ARDL model provides robust insights into both the short-term and long-term dynamics of the variables under study.

Data Used

In this study, the agricultural value added serves as the dependent variable to be explained through climate changerelated variables.

To analyze the impact of climate change, three key explanatory variables were selected: temperature, precipitation, and industrial value added. Temperature plays a crucial role in climate dynamics, as rising average temperatures trigger cascading effects such as glacier melt and sea-level rise. Precipitation, on the other hand, serves as an indicator of shifts in hydrological patterns, which can result in droughts or floods. Lastly, industrial value added represents the intensity of economic activity, which is often closely linked to greenhouse gas emissions. Together, these variables enable a comprehensive exploration of the intricate interactions between human activities and global environmental changes.

The selected indicators and their respective data sources are presented in the table below, providing a clear overview of the variables and their origins for further analysis.

Table 1: Indicators Used

Indicators	Description	Sources
AGRI	Agricultural Value Added as a Percentage of GDP	World Bank
PRECIP	Average Annual Precipitation (in mm)	World Bank
TEMP	Average Annual Surface Air Temperature in Morocco (in Degrees Celsius)	World Bank
INDUS	Industrial Value Added as a Percentage of GDP	World Bank

Source : Authors

The following analysis presents the trends of the variables during the study period from 1990 to 2022.

Figure 1 illustrates the evolution of agricultural value added (AGRI) from 1990 to 2022, showing an overall downward trend. In the early 1990s, agricultural value added reached high levels, averaging around 18%. However, it gradually declined throughout the late 1990s, stabilizing around 12%. From this point onward, fluctuations became more moderate, ranging between 10% and 12%, with occasional slight increases, particularly in 2015 and 2020.

This decline can be attributed to various factors, including deteriorating climatic conditions, reduced agricultural productivity, and structural changes within the sector. These findings emphasize the need to invest in sustainable agricultural practices and adaptive strategies to enhance the sector's contribution to the economy and its resilience to environmental challenges.

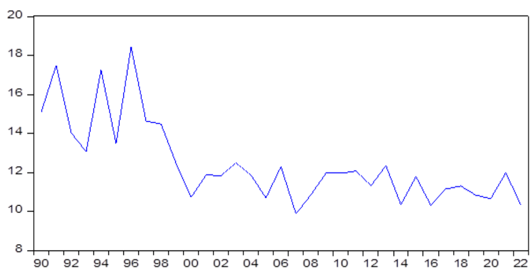


Figure 1: Evolution of the AGRI variable between 1990 and 2022 as a % of GDP

Source: Developed using World Bank data, Eviews 10.0 output

Figure 2 depicts the annual precipitation (PRECIP) trends between 1990 and 2022, characterized by significant variability. Certain years, such as 1996, 2008, and 2017, recorded high levels of precipitation, exceeding 500 mm, 460 mm, and 400 mm respectively. In contrast, other years experienced substantial declines, with precipitation dropping to approximately 200–240 mm, indicative of drought periods.

This alternating pattern of wet and dry years highlights considerable fluctuations, likely influenced by climatic factors such as natural cycles and the broader impacts of climate change. These findings underscore the importance of understanding precipitation variability to inform water management strategies and agricultural planning.

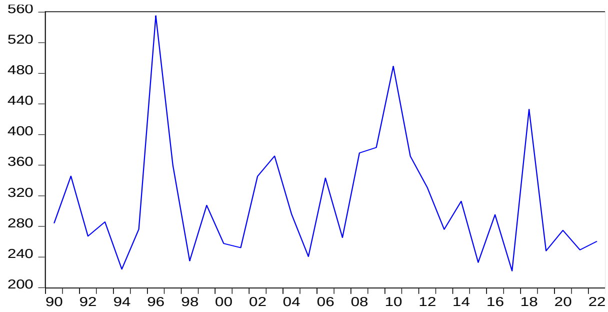


Figure 2: Evolution of the PRECIP variable between 1990 and 2022 in mm

Source: Developed using World Bank data, Eviews 10.0 output

Figure 3 illustrates the trend in annual average temperatures (TEMP) from 1990 to 2022, showing a general upward trajectory. In the early 1990s, temperatures hovered around 17°C, with occasional fluctuations. However, from the late 1990s onward, a noticeable progressive increase is observed, culminating in significant peaks in 2016 and 2022, where temperatures reached nearly 19.2°C.

This rising trend likely reflects the effects of global warming, marked by a steady increase in average global temperatures. While year-to-year variations suggest the influence of natural climatic fluctuations, the overall upward trend underscores potential impacts on the environment, agriculture, and local ecosystems. These findings highlight the need for strategies to mitigate and adapt to the long-term consequences of rising temperatures.

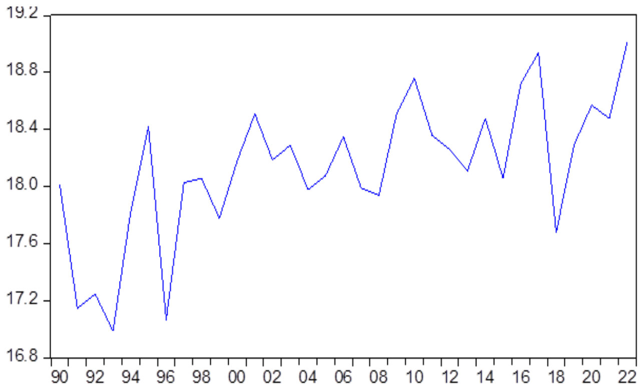


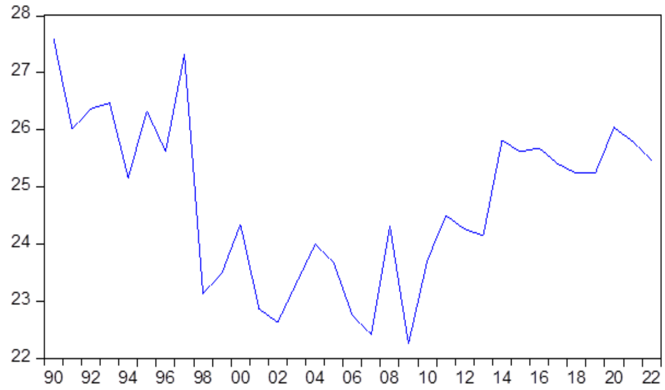
Figure 3: Evolution of the TEMP variable between 1990 and 2022, in degrees Celsius

Source: Developed using World Bank data, Eviews 10.0 output

Figure 4 illustrates the trend in industrial value added (INDUS) as a percentage of GDP over the period 1990–2022. In the early 1990s, the industrial sector's share was relatively high, fluctuating around 26–27%. However, a significant decline occurred toward the late 1990s, dropping to approximately 23%.

Following this dip, the industrial sector experienced moderate fluctuations, with sporadic decreases, such as during the global financial crisis in 2008. A gradual recovery began after 2010, peaking near 26% in the mid-2010s. Nevertheless, a slight decline was observed toward the end of the study period.

This pattern may be attributed to economic factors such as structural shifts, economic crises, or the gradual diversification of the economy away from industry. Understanding these underlying dynamics is essential to address the challenges and leverage the opportunities faced by the industrial sector in a rapidly evolving global economy.



Source: Developed using World Bank data, Eviews 10.0 output

Figure 4: Evolution of the INDUS variable between 1990 and 2022, as a % of GDP

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 provides an overview of the key descriptive statistics for the variables studied during the period 1990 to 2022. These statistics include the mean, median, standard deviation, coefficient of variation, and the maximum and minimum values for each variable.

This summary offers a comprehensive snapshot of the data's distribution and variability, providing a foundation for further analysis and interpretation of the relationships between the variables under investigation.

Table 2: Descriptive Statistics

Variables	AGRI	INDUS	PRECIP	TEMP
Mean	12.47020	24.76128	311.2236	18.13091
Median	11.96208	25.16400	285.9900	18.18000
Maximum	18.43998	27.59814	555.0500	19.01000
Minimum	9.875247	22.25957	221.9800	16.99000
Std. Dev.	2.130989	1.435634	76.55975	0.495507
Skewness	1.353860	-0.037519	1.363575	-0.649508
Kurtosis	4.199965	2.083776	4.806499	3.197983
Jarque-Bera	12.06104	1.162009	14.71358	2.374132
Probability	0.002404	0.559336	0.000638	0.305115
Sum	411.5165	817.1223	10270.38	598.3200
Sum Sq. Dev.	145.3156	65.95344	187564.7	7.856873

Source: Authors' Calculations, Eviews 10.0 Output

The table presents descriptive statistics for four variables: AGRI (agricultural value added), INDUS (industrial value added), PRECIP (precipitation), and TEMP (temperature), based on a dataset comprising 33 observations. The average precipitation (PRECIP) is 311.22 mm, while the mean temperature (TEMP) is 18.13°C. However, the standard deviations highlight varying levels of dispersion: PRECIP exhibits the highest variability (76.56), whereas TEMP is the most stable (0.49). The medians, which are close to the means for certain variables, suggest a relatively balanced distribution. Nonetheless, the large difference between the minimum (221.98) and maximum (555.05) values for PRECIP reflects significant variability.

In terms of distribution, skewness coefficients indicate that AGRI and PRECIP have positive skewness, suggesting that their values are concentrated toward the lower end of the range, while TEMP displays slight negative skewness. The kurtosis coefficient reveals that AGRI (4.20) and

PRECIP (4.81) have distributions that are more peaked than normal, indicating the presence of extreme values.

Correlation Analysis

The following table illustrates the correlation between the variables in the model. This analysis helps identify the relationships and potential dependencies between the key variables, providing a basis for further econometric analysis.

Table 3: Correlation Coefficient Between the Variables Studied

	AGRI	INDUS	PRECIP	TEMP
AGRI	1.000000			
INDUS	0.327587	1.000000		
	(0.0627)	-----		
PRECIP	0.272139	-0.092849	1.000000	
	(0.1255)	(0.6073)	-----	
TEMP	-0.623629	-0.224272	-0.226858	1.000000
	(0.0001)	(0.2096)	(0.2042)	-----

Source: Authors' Calculations, Eviews 10.0 Output
Note: (.) Probability Value

The results indicate that the most notable correlation is between AGRI (agricultural value added) and TEMP (temperature), with a negative and significant coefficient of -0.623629 (p = 0.0001). This strong inverse relationship suggests that higher temperatures negatively affect agricultural performance, a trend commonly observed in unfavorable climatic conditions.

In contrast, the correlations between AGRI and INDUS (industrial value added) at 0.327587 (p = 0.0627) and AGRI and PRECIP (precipitation) at 0.272139 (p = 0.1255) are weak and statistically insignificant. These findings indicate that, within this sample, these variables have a less direct influence on agricultural outcomes.

Stationarity Analysis

Table 4 presents the results of the stationarity tests conducted on the variables included in the model. These tests are essential to determine the integration order of the variables and to ensure the appropriateness of the econometric techniques applied in the analysis.

Table 4: Order of Integration of the Variables Studied

Variables	**t_statistic I(0)**	**t_statistic I(1)**	**Décision**
AGRI	0.1503	0.0000	I(1)
TEMP	0.9318	0.0000	I(1)
PRECIP	0.0004	----	I(0)
INDUS	0.0386	----	I(0)

Source: Authors' Calculations, Eviews 10.0 Output

The unit root test results indicate that the variables PRECIP and INDUS are stationary at the level of integration order 0 (I(0)). In contrast, the other variables, AGRI and TEMP, become stationary only after first differencing, implying they are integrated of order 1 (I(1)).

Optimal ARDL Model and Its Estimation

To identify the most appropriate ARDL model, one that yields statistically significant results with a minimal number of parameters, the Akaike Information Criterion (AIC) was employed. Figure 5 illustrates the optimal model selected based on this criterion, ensuring the balance between model complexity and explanatory power.

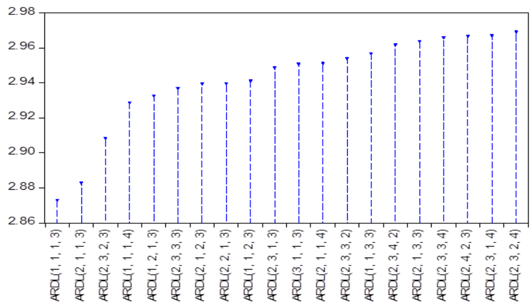


Figure 5: Graphical AIC Values, Top 20 Models

Source: Authors' Analysis Using Eviews 10.0

Based on the data in Figure 5 and the AIC criterion, the optimal ARDL model is identified as ARDL (1, 1, 1, 3), as it achieves the lowest AIC value. This model is considered statistically significant and provides the most reliable results. The estimation of the selected ARDL (1, 1, 1, 3) model, deemed the most suitable for the analysis, is presented in the table below.

Table 5: Estimation Results of the Coefficients

Variables	Coefficients	Std. Error	t-Statistic	Prob.*
AGRI(-1)	-0.108020	0.156159	-0.691732	0.4971
INDUS	-0.242088	0.197273	-1.227176	0.2340
INDUS(-1)	0.719844	0.195231	3.687152	0.0015
PRECIP	0.008487	0.003030	2.801023	0.0110
PRECIP(-1)	0.006871	0.003124	2.199024	0.0398
TEMP	-0.531623	0.503435	-1.055990	0.3036
TEMP(-1)	-0.669103	0.564753	-1.184772	0.2500
TEMP(-2)	-1.119820	0.540325	-2.072493	0.0514
TEMP(-3)	-1.704468	0.540579	-3.153041	0.0050
C	69.81049	16.44614	4.244796	0.0004
R-squared	0.813601	Mean dependent var		12.16264
Adjusted R-squared	0.729722	S.D. dependent var		1.928204
S.E. of regression	1.002440	Akaike info criterion		3.103953
Sum squared resid	20.09772	Schwarz criterion		3.571018
Log likelihood	-36.55929	Hannan-Quinn criter.		3.253371
F-statistic	9.699660	Durbin-Watson stat		1.943888
Prob(F-statistic)	0.000014			

Source: Authors' Calculations Using Eviews 10.0

Cointegration Test

The cointegration test developed by Pesaran et al. (2001) requires the prior estimation of the ARDL model. The calculated statistic, corresponding to Fisher's F-value, is then compared to the critical bounds to determine the presence of a long-term relationship between the variables.

Table 6: Cointegration Test Results

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	10.52238	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

Source: Authors' Calculations Using Eviews 10.0

The analysis of the table above indicates that the results of the bounds cointegration test confirm the existence of a cointegrated relationship. Specifically, the calculated F-statistic of 10.52238 exceeds the upper critical bound at all significance levels (10%, 5%, 2.5%, and 1%). This provides strong evidence of a long-term relationship between the variables.

Short-Term Dynamics, Adjustment Coefficient, and Long-Term Coefficients

Table 7 presents the estimation results for the short-term relationship. The adjustment coefficient, also referred to as the error correction term, is negative and statistically significant (-1.108020). This finding indicates the presence of an error correction mechanism, confirming the existence of a long-term (cointegrated) relationship between the studied variables. This mechanism ensures that short-term deviations are corrected over time, aligning with the established long-term equilibrium.

Table 7: Estimation Results of the Short-Term Coefficients

Variables	Coefficients	Std. Error	t-Statistic	Prob.
D(INDUS)	-0.242088	0.165859	-1.459607	0.1599
D(PRECIP)	0.008487	0.002090	4.061879	0.0006
D(TEMP)	-0.531623	0.406710	-1.307130	0.2060
D(TEMP(-1))	2.824288	0.617703	4.572241	0.0002
D(TEMP(-2))	1.704468	0.465259	3.663479	0.0015
CointEq(-1)*	-1.108020	0.139449	-7.945708	0.0000
R-squared	0.813743	Mean dependent var		-0.123707
Adjusted R-squared	0.774940	S.D. dependent var		1.928938
S.E. of regression	0.915098	Akaike info criterion		2.837286
Sum squared resid	20.09772	Schwarz criterion		3.117525
Log likelihood	-36.55929	Hannan-Quinn criter.		2.926937
Durbin-Watson stat	1.943888			

Source: Authors' Calculations Using Eviews 10.0

Meanwhile, Table 8 presents the estimation results of the long-term model. These results provide insights into the persistent effects of the explanatory variables on the dependent variable, highlighting the dynamics of the long-term relationships within the study.

Table 8: Estimation Results of the Long-Term Coefficients

Variables	Coefficients	Std. Error	t-Statistic	Prob.
INDUS	0.431180	0.147317	2.926881	0.0083
PRECIP	0.013861	0.003209	4.319437	0.0003
TEMP	-3.632619	0.540068	-6.726231	0.0000
C	63.00472	11.44477	5.505109	0.0000

Source: Authors' Calculations Using Eviews 10.0

The analysis reveals several key insights into the long-term relationships between the variables:

Precipitation, with a coefficient of 0.013861 and a p-value of 0.0003, has a positive and statistically significant effect on agricultural value added, although the magnitude of its impact remains moderate. Water plays a critical role in agricultural productivity, especially in regions where farming and livestock rely on natural rainfall. Increased precipitation enhances crop yields and overall sector performance. However, the extent of this effect can vary depending on the availability of irrigation infrastructure, agricultural practices, and the adaptability of systems to climatic variability.

Conversely, the temperature variable (TEMP) exhibits a strong and highly significant negative relationship with agricultural value added, with a coefficient of -3.632619 and a significant p-value. Elevated temperatures induce thermal stress on crops and livestock, reducing agricultural yields and intensifying water shortages. Additionally, high temperatures contribute to extreme climatic events such as droughts, further exacerbating the sector's vulnerability. These findings underscore the urgent need for adaptive strategies, such as introducing heat-resistant crops and improving irrigation systems, to mitigate the adverse effects of climate change on agriculture.

The industrial value-added variable (INDUS) shows a positive and statistically significant relationship with agricultural value added, with a coefficient of 0.431180 and a p-value of 0.0083.

This indicates that industrial development indirectly supports agriculture. By supplying improved equipment, inputs, and infrastructure, industrial activities enhance the efficiency and productivity of agricultural operations. This synergy between the industrial and agricultural sectors is particularly advantageous in contexts where they are closely linked, promoting sustainable and balanced economic growth.

These results highlight the multifaceted nature of the relationships between climatic and economic factors and the agricultural sector, emphasizing the need for targeted interventions to ensure resilience and growth.

Model Validation

The model validation phase aims to assess the reliability of the estimated model using the following diagnostic tests: the autocorrelation test for errors, the heteroscedasticity test, the normality test for residuals, and the model stability test. These tests are described below.

The ARCH test was applied to examine the homoscedasticity of residuals. Acceptance of the null hypothesis indicates that the residuals are homoscedastic. Table 9 presents the results of this test, which confirm that the null hypothesis of homoscedastic residuals is accepted at the 5% significance level. The p-value, being greater than 5% (0.677 > 5%), supports this conclusion.

These results ensure that the residuals do not exhibit heteroscedasticity, reinforcing the model's validity for further analysis.

Table 9: ARCH Test on Residuals

F-statistic	0.161852	Prob. F(1,27)	0.6906
Obs*R-squared	0.172805	Prob. Chi-Square(1)	0.6776

Source: Authors' Calculations Using Eviews 10.0

To check whether the residuals follow a normal distribution, the Jarque-Bera test was conducted. The p-value for this test is 0.850, which is significantly higher than the 0.05 threshold. Consequently, the null hypothesis of normality in the residuals is accepted at the 5% significance level (Figure 10).

This result confirms that the residuals are normally distributed, further validating the robustness of the estimated model.

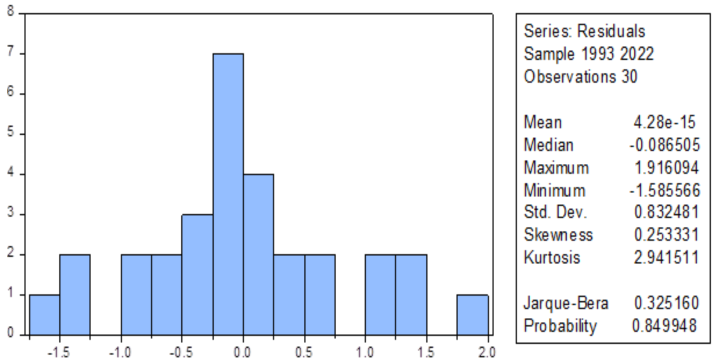


Figure 6: Jarque-Bera Test on Residuals

Source: Authors' Calculations Using Eviews 10.0

To assess the absence of error autocorrelation, the Breusch-Godfrey test was applied. The results indicate that the p-value associated with the test is greater than the critical threshold of 5%. Therefore, it can be concluded that the residuals do not exhibit autocorrelation (Table 10).

This finding reinforces the validity of the model and its assumptions, ensuring that the error terms are independent and do not compromise the reliability of the estimates.

Table 10: Test for Absence of Error Autocorrelation

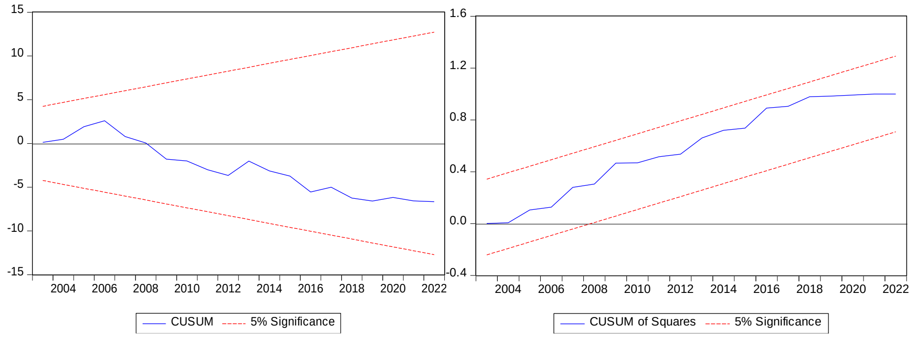
F-statistic	0.579636	**Prob. F(2,18)**	0.5702
Obs*R-squared	1.815212	**Prob. Chi-Square(2)**	0.4035

Source: Authors' Calculations Using Eviews 10.0

To evaluate the stability of the model, the CUSUM of squares test is particularly relevant. This test, based on the cumulative sum of the squares of recursive residuals, operates under the null hypothesis that the relationship is stable. The results fall within two boundary lines representing the confidence interval, indicating that the estimated model is stable, as the curve remains within the dashed corridor (Figure 7).

This outcome confirms that the coefficients are consistent over time, reinforcing the reliability of the model's estimations.

Figure 7: CUSUM and CUSUMSQ Stability Test



Source: Authors' Calculations Using Eviews 10.0

Impact Projections

Forecasting Accuracy

After confirming the absence of structural changes in the data used for the study, the Theil statistic was employed to evaluate the forecasting capability of the model during the analysis period. The results of this evaluation are illustrated in Figure 8.

This assessment ensures the model's reliability in projecting the impacts of the studied variables, providing a solid basis for informed decision-making.

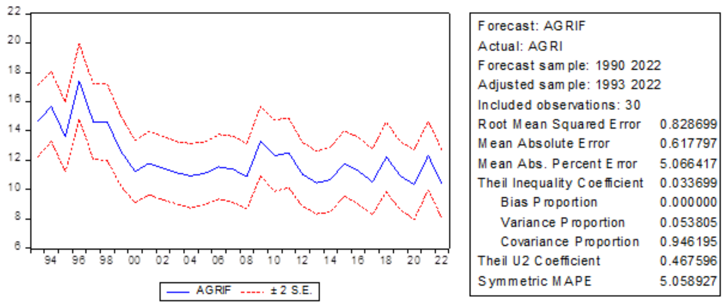


Figure 8: Theil Forecast Test

Source: Authors' Calculations Using Eviews 10.0

The Theil coefficient is 0.0336, which is less than 1 and close to zero, while the bias proportion (BP) equals 0. Additionally, the variance proportion, at 0.0538, is near zero, and the covariance proportion, at 0.9461, is close to 1. These results indicate that the model demonstrates strong predictive accuracy during the study period. Consequently, the model's results can be confidently used for policy analysis, future evaluations, and achieving set objectives.

Projections Based on RCP Scenarios

The table below presents the various Representative Concentration Pathways (RCP**)** scenarios developed by the IPCC. These pathways illustrate different assumptions about greenhouse gas emissions, their atmospheric concentrations, and their impacts on global climate through temperature variations.

By integrating these scenarios into this study, we aim to analyze climatic dynamics under different conditions and better understand the potential implications of future climate change. These insights provide a foundation for informed decision-making and strategic planning in response to diverse climate scenarios.

Table 11: Climate Change Scenarios (IPCC, 2014)

	The RCP2.6 Scenario	The RCP8.5 Scenario
Temperature Variation	+2°C	+4,5°C

Source: Authors based on the IPCC 2014 Report

The graph below illustrates a decline in agricultural value added up to 2100 under both scenarios, RCP2.6 and RCP8.5.

In the RCP2.6 scenario, which assumes significant efforts to reduce greenhouse gas emissions, the decline in agricultural value added is noticeable, reflecting the substantial impact of climate change. Conversely, under the RCP8.5 scenario, characterized by high emissions with no mitigation actions, the decrease is significantly more pronounced.

This stark contrast highlights the exacerbated effects of climate change in a context of inaction, posing a greater threat to the sustainability of the agricultural sector. These findings emphasize the critical importance of implementing mitigation strategies to safeguard agricultural resilience and productivity in the face of a changing climate.

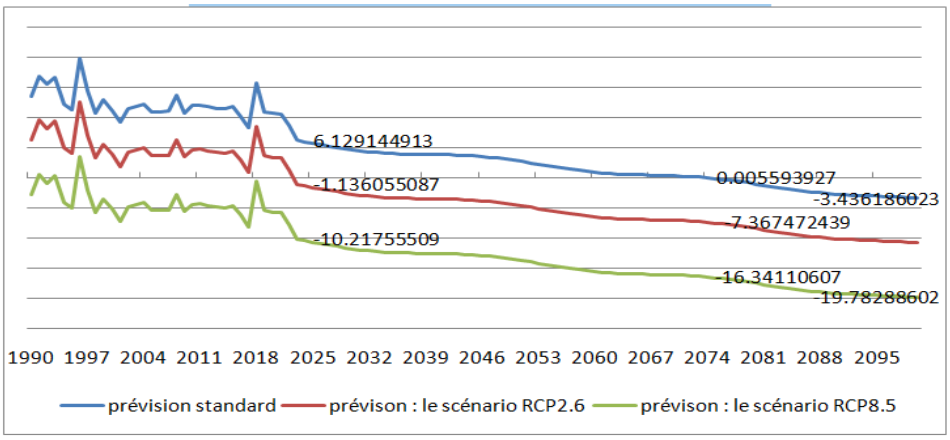


Figure 9: Forecast of Agricultural Value Added (AGRI)

Source: Authors' Calculations Using Eviews 10.0

CONCLUSION

Climate has a profound impact on agriculture, widely recognized as the human activity most dependent on climatic variations. The effects of climate on agriculture vary globally, with particularly significant socio-economic consequences in developing countries (Sultan Benjamin, 2015).

Our econometric model results reveal that climate change has a significant negative effect on Moroccan agricultural activity. Climatic variations, such as rising temperatures and changing precipitation patterns, reduce crop productivity and undermine the resilience of agricultural systems.

In the short term, our study demonstrates that precipitation has a positive and statistically significant impact, indicating that increased rainfall boosts agricultural value added. Conversely, temperature negatively influences agricultural value added, but this relationship is not statistically significant, suggesting that its short-term impact is limited. Similarly, industrial variation has a negative effect on agricultural value added, though this impact is also not statistically significant.

In the long term, precipitation continues to have a positive impact due to its essential role in agricultural productivity, particularly in regions dependent on natural rainfall. In contrast, rising temperatures exert a significant and pronounced negative effect, reducing agricultural yields due to thermal stress, water shortages, and extreme weather conditions. Industrial activities, however, have a positive and statistically significant influence on agricultural value added, contributing through improved infrastructure, equipment, and inputs. These findings highlight the importance of fostering intersectoral synergies and adopting climate adaptation strategies to sustain the agricultural sector.

The forecasts suggest a downward trend in agricultural value added under all scenarios, underscoring the need for Morocco to adopt modern methods and techniques to enhance profitability and address the challenges of climate change. This calls for a shift toward climate-resilient crops less dependent on weather variability.

The unfavorable climatic conditions of recent decades may progressively become the norm in Morocco, placing the agricultural sector at risk. This highlights the urgency for specific interventions. Low precipitation and high temperatures, largely driven by greenhouse gas emissions, must be considered when formulating agricultural development policies.

- Integrating climate concerns into development processes requires strategic actions by policymakers, local authorities, and socio-economic stakeholders. Key measures include:
- Encouraging research to identify new climate-resilient agricultural technologies.
- Diversifying crop types and varieties to adapt to changing climatic conditions.
- Optimizing planting schedules to align with climate evolution.

By addressing these challenges, Morocco can build a more resilient agricultural sector, capable of sustaining economic growth and ensuring food security in the face of ongoing climate change.

BIBLIOGRAPHY

Arrus, N. R. (2006). L'agriculture du Maghreb au défi du changement climatique : quelles stratégies d'adaptation face à la raréfaction des ressources hydriques ?

Bouazzama, B. B. (2018). Assessing the vulnerability of irrigated agriculture to climate change in Morocco. Agricultural Water Management, 120-130.

Céline Guivarch, N. T. (2021). Inégalités mondiales et changement climatique. Revue de l'OFCE.

Driouech, F. D.-G. (2019). Weather extremes in a changing climate in Morocco: Impacts and adaptation strategies. International Journal of Climatology, 2565-2577.

El Mourid, M. K. (2014). Climate change and agricultural water management in Morocco. Regional Environmental Change, 15-26.

FAO (2017). Morocco in the face of climate change.

FAO (2020). Global Forest Resources Assessment 2020.

Goar, M. (2024). Le dérèglement climatique va accélérer les inégalités entre sexes, entre catégories sociales et entre générations, alertent les experts de la FAO. LE MONDE.

International Energy Agency (2021). World Energy Outlook 2021.

IPCC (2007) Climate Change 2007 Synthesis Report

IPCC (2014). Climate Change 2014: Mitigation of Climate Change. Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change

IPCC (2014). *Climate Change 2014: Synthesis Report.*

IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Karrou, M. E. (2016). Water and land productivities under rainfed conditions in Morocco: Implications for climate change adaptation. Agricultural Systems, 110-118.

Kerfal Wafa, EL ALAOUI Aicha, JAOUHAR Jinane. (2024). Relationship between Environmental Performance and Socio-Economic Development in MENA. Pakistan Journal of Life and Social Sciences, 17756-17769.

MOKADDEM, A. B. (2019). l'impact du changement climatique sur l'agriculture et la croissance économique de la tunisie.

Nicolas LANCESSEUR, C. L. (2020 , Juillet). Documents de Travail de la DG Trésor . impact économique du changement climatique : revue des méthodologies d'estimation, résultats et limites.

Pesaran, M. H., & Shin, Y. (1997). "An autoregressive distributed lag modelling approach to cointegration analysis.

Pesaran, M. H., Y. Shin, and R. Smith, 2001, Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16, pp. 289-326.

Sultan Benjamin, R. P. (2015). Les sociétés rurales face aux changements climatiques et environnementaux en Afrique de l'Ouest. Les impacts du changement climatique sur les rendements agricoles en Afrique de l'Ouest.

Tazigh, F. (2020). l'impact du changement climatique sur l'agriculture au maroc: une étude. Journal of Environmental and Agricultural Studies.

UNFCCC (2021). The Role of Industry in Global GHG Emissions.

WHO website consulted on 11/09/2024. « https://www.who.int/teams/environment-climate-change-and-health/call-for-climate-action »

WOILLEZ, M.-N. (2019, Juillet). Revue de littérature sur le changement climatique au Maroc : observations, projections et impacts.