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Agricultural Adaptation to Climate Change in Morocco: Between Vulnerability and Resilience.

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Abstract

This paper investigates the trajectory of agricultural revenues in Morocco between 1995 and 2021, with the aim of elucidating the intricate relationships among vulnerability and resilience to climate change and agricultural economic performance. Agricultural revenues are analysed in relation to two main sets of independent variables: vulnerability and resilience. The assessment of resilience is grounded in a range of indicators, encompassing economic, social, and governance aspects. Conversely, vulnerability is examined through key dimensions such as the sensitivity of health, food security, ecosystems, human habitation, water resources, and infrastructure. The methodological approach employs an ARDL (Autoregressive Distributed Lag) and vector error correction model (VECM) to capture the long-term interactions and dynamics among these variables. The results reveal that the effects of vulnerability are significantly more pronounced than those of resilience. The agricultural sector is more susceptible to vulnerability, with a relatively lower capacity for resilience. The insights derived from this research are expected to contribute to a deeper understanding of the factors affecting agricultural revenues in Morocco. Furthermore, the findings hold potential for informing policy recommendations aimed at enhancing the resilience of the agricultural sector within the unique context of the country.

Keywords: Climate change; Vulnerability; Resilience; Agricultural revenues; Morocco

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Introduction

In developing countries, the livelihoods of rural and poor households depend mainly on agriculture, which provides them with food, income and employment. Furthermore, in least developed countries, agriculture can be an engine of economic growth (Ravallion and Datt, 1996), also contributing to the development of other sectors (Tiffin and Irz, 2006; Kaya et al., 2013), and thus play a crucial role in poverty reduction (Christiaensen and Martin, 2018). In Morocco, agriculture occupies an undeniable economic and social place, representing approximately 38% of total employment at the national level and approximately 74% in rural areas. The agricultural sector also contributes about 13% to GDP, being considered essential, as Morocco’s economic growth rate is closely linked to agricultural production (Moroccan Ministry of Agriculture, 2018). Agriculture also provides essential inputs to other economic sectors such as industry and services and is an important source of foreign exchange through agricultural exports (World Bank, 2007; Christiaensen et al., 2011). Furthermore, by ensuring the availability of affordable food in urban areas, agriculture contributes to improving urban food security (Dethier and Effenberger, 2012). However, climate change, characterised by an increase in the frequency and intensity of extreme weather events, changes in precipitation patterns, and rising temperatures (Mbow et al., 2017), is expected to have a significant impact on agricultural production, particularly in developing countries (Mendelsohn, 2009; Chen et al., 2016; Zaveri et al., 2020). The expected decline in agricultural productivity due to climate change, coupled with the increasing difficulties for farmers to adapt to these new conditions (Thornton et al., 2018), could significantly affect overall economic growth and food security (Mbow et al., 2017; FAO, IFAD, UNICEF, WFP, and WHO, 2020). Thus, reducing vulnerability to climate change and strengthening the long-term adaptive capacities of rural and urban communities to its adverse effects have become urgent challenges for developing countries. These countries lack the means to cope with climate hazards, and their economies are heavily dependent on climate-sensitive sectors such as agriculture, water and coastal areas. The literature is rich in analyses of the impacts of climate change on agriculture, based mainly on projections of climate variables (Benkachchach et al., 2023). However, the study of the impacts of climate change on agriculture cannot be limited to climate projections alone; these effects must be analysed within the theoretical framework of vulnerability. In this context, our research aims to understand how climate change-related vulnerabilities and resilience capacities impact agricultural revenue by examining Morocco's agricultural sector and its vulnerability to climate change risks.

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Vulnerability theory states that climate change impacts depend on a system's exposure, sensitivity, and adaptive capacity (Fussel and Klein, 2006). The level of exposure depends on geographic conditions, while sensitivity is determined by dependence on climate resources. The strength of the agricultural sector's adaptive capacity depends on economic, social, and political resilience (Smit et al., 1999). Indeed, Malik et al. (2023) observed a negative effect of annual minimum temperature and declining landholdings on agricultural GDP in Iran. Similarly, Jamshidi et al. (2019) revealed that the majority of smallholder farmers in India were particularly vulnerable to climate change, with 13 factors contributing to this vulnerability, such as education, income, access to infrastructure, credit, and land size. While factors such as cropping intensity, rural literacy, and access to credit had positive impacts on Iranian agricultural GDP (Malik et al., 2023). Although systems may be exposed and sensitive to climate change, they have adaptive capacities that mitigate its severe impacts.

Existing studies focus on either the physical aspects of climate change or the social aspects. Anticipating, resisting, and recovering from climate change impacts depends on access to various forms of capital, including natural, economic, social, and political capital (Calgaro and Lloyd, 2008). Although the importance of vulnerability and resilience assessment has been widely recognised in the climate change literature (Downing and Patwardhan, 2004; Füssel, 2007; Kelly and Adger, 2000), assessing agricultural vulnerability and resilience to severe climate change impacts has not been widely studied. Our paper aims to bridge this gap by assessing the vulnerability and resilience of Moroccan agriculture to climate change. These two concepts are particularly important for studying the human dimensions of climate change, which include culture, society, economy, and environment (Brondizio and Moran, 2008; Janssen and Ostrom, 2006).

The objective of our paper is to evaluate the vulnerability and resilience of Moroccan agriculture to climate change, in addition to analysing the particular impacts on agricultural income from 1995 to 2021. This analysis aims to identify key factors affecting agricultural performance and provide avenues for developing effective adaptation policies. For Morocco to develop policies appropriate to the severe impacts of climate change on the agricultural sector, it is crucial to analyse and understand the distinct effects of vulnerability and resilience indicators on this sector. Therefore, we examined in detail the extent to which the vulnerability to climate change of sectors essential to life, such as food, infrastructure, human habitat, water, health, and ecosystems. As well as climate change resilience represented by freedom to do business, political stability and non-violence, anti-corruption, regulatory quality, rule of law, social

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inequalities, education, innovation and ICT infrastructure, impact the agricultural sector of Morocco. The hypotheses formulated will be detailed in the following section.

Specifically, our paper aims to analyse the impact of climate change vulnerability and economic, social, and governance resilience on Moroccan agricultural revenues. To address this objective, we exploit the annual numerical data of ND-GAIN (Notre Dame Global Adaptation Initiative) covering the period 1995-2021. ND-GAIN produces the ND-GAIN index, which assesses the concepts of climate change vulnerability and resilience in different countries. This dataset contains reliable and transparent indicators, collected and maintained by trustworthy organisations (Dogru et al., 2019). To our knowledge, this is the only dataset available at a macro level to examine vulnerability and resilience within the agricultural sector and other economic activities. Furthermore, Armstrong (2012) argued that complex regression models including many variables reduce the precision of estimates, even in the presence of large datasets. One solution to this problem is to develop an index based on "an a priori analysis that allows analysts to take into account existing knowledge on the ground" (Armstrong, 2012, p. 692).

Using the ARDL model, we assess the relationship between agricultural revenues, vulnerability and resilience to climate change. Another VECM model was adopted to assess the impact of climate change sensitivity and economic, social and governance resilience on the agricultural sector. The results of the ARDL model highlight that, in the long term, vulnerability to climate change negatively impacts agricultural revenues; this impact is estimated at nearly 23%. In other words, increased vulnerability in the food, water, health, ecosystem services, human habitat and infrastructure sectors leads to a reduction in agricultural revenues. This result highlights the high dependence between the agricultural sector and its vital sectors. Compared to the short-term impact, the negative impact on the agricultural sector in the long term, due to vulnerability to climate change, intensifies due to the absence of resilience impact on agricultural revenues. However, in the short term, resilience to climate change does not have a significant impact on agricultural revenues because adaptation measures require time to generate impacts. Moreover, in the long term, resilience to climate change has a negative impact, but not significant. This result is paradoxical. Even if this impact is insignificant, it can be referred to the high costs of adaptation measures. Thus, some approaches require an immediate decrease in production to ensure better sustainability. The results of the ARDL model corroborate our hypothesis that vulnerability to climate change (H1) has a negative

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impact. However, the results do not validate the hypothesis that resilience (H3) has a positive impact on agricultural revenues.

According to the VECM model, sensitivity has a negative impact on agricultural revenues. In other words, an increase in the sensitivity index reduces agricultural revenues by 19.025% in the short term and by 9.658% in the long term. On the other hand, an increase in the governance resilience index increases agricultural revenues by 5.591% in the short term and by 3.835% in the long term. At the same time, economic resilience has a positive impact on agricultural revenues (2.583%). On the other hand, social resilience has a negative impact on Moroccan agricultural revenues. This unexpected result is explained by the fact that a more socially resilient society normally has better solidarity networks, access to education, subsidies, innovation, institutions capable of promoting economic diversification, social security and also training and professional retraining. This leads to a shift in labour and investment from the agricultural sector to other sectors. This decreases the population's dependence on the agricultural sector and consequently destroys the share of the agricultural sector in GDP.

The results of the VECM model support our hypotheses that sensitivity (H2) has a negative effect and economic resilience (H4) and governance resilience (H6) have a positive effect on agricultural revenues. However, the results do not support the hypothesis that social resilience (H5) has a positive effect on agricultural revenues. In general, the results of the analyses suggest that vulnerability to climate change affects agricultural revenues in the long term as well as in the short term. Specifically, with increased sensitivity to climate change, agricultural revenues decrease. However, increased adaptive capacity, manifested by economic and governance resilience, leads to an increase in agricultural revenues in the long term.

This article is structured as follows: The **"Literature Review"** section discusses the literature on the vulnerability and resilience of agriculture to climate change. The **"Theoretical Framework and Hypothesis Development"** section presents the vulnerability theory and the hypotheses of our study; the **"Research Methodology and Data Sources"** section presents the data used and the empirical methods; the **"Results"** section presents the results, which are discussed in the **"Discussion and Conclusion"** section. The latter also includes concluding remarks to conclude.

1. Literature Review

Recent research on climate change vulnerability has demonstrated a diversity of variables and methodologies to assess vulnerability. In 2023, a study by Malik et al. focused on India using the Ricardian approach to examine the impact of socio-economic, demographic, and climatic indicators on agricultural growth. Their results highlighted the negative effect of annual minimum temperature and declining land holdings on agricultural GDP, while factors such as cropping intensity, rural literacy, and access to credit had positive effects. Some districts, such as Budgam, Ganderbal, and Bandipora, demonstrated higher vulnerability due to low literacy rates, high population density, and extensive rice cultivation. In contrast, Kargil, Rajouri, and Poonch districts showed lower vulnerability due to their low population density and level of institutional development.

In a study conducted by Jamshidi et al. (2019) in Iran, the analysis of the vulnerability of the agricultural sector to climate change was based on the perceptions of the participants surveyed about climate change, extreme weather occurrences, and factors contributing to vulnerability. Jamshidi et al. (2019) used 7, 12, and 23 indicators to measure exposure, sensitivity, and adaptive capacity, respectively. The results showed that the majority of the participants surveyed acknowledged the existence of climate change, with about one-third attributed to human activity. The assessment also revealed that the majority of smallholder farmers were relatively vulnerable to climate change, with 13 factors contributing significantly to this vulnerability, such as education, income, access to infrastructure, credit, and land size.

Furthermore, Halkos et al. (2020) used the Notre Dame Global Adaptation Initiative (ND-GAIN) Climate Change Vulnerability Index to analyse the relative impact of various macroeconomic characteristics on vulnerability. These macroeconomic factors include GDP, public debt, population, agricultural coverage, and socio-political and institutional conditions. Their results showed a significant correlation between climate change vulnerability and most of the explanatory variables examined, also highlighting increased vulnerability in less developed countries compared to developed and transition countries.

In 2020, Schilling et al. undertook a comparative review of climate change vulnerability in five North African countries: Algeria, Egypt, Libya, Morocco, and Tunisia, highlighting its social implications. Their vulnerability analysis focused on several aspects, including climate change exposure, water resources, sensitivity, and adaptive capacity. The results indicate that all these countries are exposed to substantial temperature increases and increased risk of drought due to climate change. Among these countries, Algeria emerges as the most vulnerable, mainly due to

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its high sensitivity to climate change. Schilling et al. (2020) considered Algeria to be the most vulnerable, a conclusion that differs from that of the previous study conducted by Schilling et al. (2012), where Morocco was identified as the most vulnerable.

2. Theoretical framework and hypothesis development

According to Fussel and Klein (2006), vulnerability refers to the degree to which a system is susceptible or unable to cope with the adverse effects of climate change, including climate variability and extremes. This vulnerability is composed of three elements: exposure to climate change, sensitivity to climate change, and the adaptive capacity of a system (Fussel and Klein, 2006; Ionescu et al., 2009; Smit et al., 1999).

Exposure to climate change refers to the nature and degree to which a system is exposed to climate variation (Fussel et al., 2006). Sensitivity is defined as "the degree to which a system is affected, either negatively or beneficially, by climate variability or change" (IPCC, 2007). More specifically, a sector is sensitive to climate change because of its dependence on climatic conditions (Füssel & Klein, 2006, p. 314). Adaptive capacity, on the other hand, refers to the ability of a system to adapt and cope with the impacts of climate change without direct intervention or policy implementation (Ionescu et al., 2009). According to the IPCC, a society's adaptive capacity can be divided into generic and impact-specific indicators. Generic indicators include factors such as education, income, and health. Indicators specific to a particular impact, such as drought or flooding, may relate to institutions, knowledge, and technology (Parry, 2007). Thus, while increased exposure and sensitivity negatively affect a system's vulnerability to climate change, increased adaptive capacity reduces that vulnerability. In other words, the exposure and sensitivity of systems to climate change, as well as their adaptive capacity, determine the level of vulnerability (Smit et al., 1999).

However, the exact impact of vulnerability to climate change on agriculture remains to be clarified. Based on the conceptual framework and relevant literature, the following hypotheses are proposed:

H1.Vulnerability to climate change negatively affects agricultural revenues.

H2.Sensitivity to climate change has a negative impact on agricultural revenues.

Similar to a climate change vulnerability assessment, a climate change resilience assessment should be comprehensive and systematic. It should identify ways in which a country can successfully absorb additional private sector investments and effectively apply them to increase resilience to climate change and other global challenges (Ionescu et al., 2009; Füssel and Hildén, 2014; ND-GAIN, 2025). A country's resilience to climate change is determined by a

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country's economic environment, political stability, and social conditions. These factors influence the ability to take necessary actions and make investments to implement climate change adaptation and mitigation strategies. The assessment of economic, social, and governance resilience is based on quantifiable indicators such as government spending, business freedom, corruption, violence, education, and the rule of law (ND-GAIN, 2025). Therefore, economic conditions play a key role in the achievement of mitigation and adaptation strategies (Dogru et al., 2016). In particular, economic freedom represents a country's ability to withstand the dangers associated with climate change. This concept was introduced by Adam Smith in his iconic book The Wealth of Nations (Smith & McCulloch, 1776). While economic resilience is essential to respond to climate change, governance and social resilience also play a major role in the development of mitigation and adaptation policies. Social resilience refers to the ability of individuals and entities to effectively address local and international challenges (Füssel & Hildén, 2014). A country's social resilience is influenced by elements such as the level of disparities, the quality of education, communication systems, and the capacity for innovation (ND Gain, 2025). On the other hand, governance resilience is defined as "the power of government to effectively design and implement enforceable policies and the respect of citizens and the state for the institutions that govern economic and social relations between them" (Kaufmann et al., p. 2). Political instability, linked to mismanagement and corruption, discourages investment, thus complicating the development of strategies to reduce climate change. It is therefore important to examine the extent to which climate change resilience affects economic activities, particularly agricultural ones, in order to inform stakeholders on the key areas of intervention to develop mitigation and adaptation strategies (Ionescu et al., 2009). Thus, based on the literature, we posit that higher levels of economic, social and governance resilience suggest increased resilience to climate change. In other words, countries with better regulatory quality, greater economic freedom, higher education, political stability, control of corruption, rule of law, and increased innovation capacity are expected to cope better with the adverse effects of climate change. The following hypotheses are proposed to test these postulates:

H3.Climate change resilience positively affects agricultural revenues.

H4.Agricultural revenues are positively influenced by economic resilience.

H5.Social resilience positively affects agricultural revenues.

H6.Governance resilience has a positive impact on agricultural revenues.

Fussel (2007) specified four common dimensions to describe a vulnerability situation:

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i. The system: this can be a geographic region, a biological population, or an economic sector.
ii. The attribute of concern: this is the value of the vulnerable system, such as the gross domestic product (GDP) of an economy.
iii. The hazard: it represents the potential damage to the system, for example, the loss of potential income or profits.
iv. The temporal reference: it designates the time horizon of the vulnerability, for example, short-term or long-term.

In our paper, the system is the agricultural sector of Morocco. The attribute of concern relates to agricultural revenues. The hazard lies in the potential loss of agricultural revenues, and the temporal reference is both short and long-term.

3. Research Methodology and Data Sources

3.1 Research Methodology

In this paper, to respond to our hypotheses, we use two models: the ARDL model and the VECM model.

3.1.1 ARDL model

The ARDL (Autoregressive Distributed Lag) model was used to analyse the impact of vulnerability and resilience to climate change on Moroccan agriculture. ARDL is a cointegration testing model initially introduced by Pesaran and Shin in 1995 and later developed by Pesaran et al. in 2001. It is used to solve spurious regression problems that appear when time series of variables are non-stationary. In addition, ARDL is used to test cointegration, long-run and short-run equilibrium relationships, and levels and differences (Sarkodie & Owusu, 2020). This model has several advantages, including its adaptation and efficiency for small datasets and when the variables are integrated at the I(0) level or at first difference I(1), or both, but not I(2), without the presence of autocorrelation or heteroscedasticity (Shrestha & Bhatta, 2018). In our paper, we employed this model to estimate the relationships between the variables in the short run and the long run using the EViews 12 program. Where agricultural revenues is illustrated as a function of vulnerability and resilience. The empirical model is specified as follows:

$$\boldsymbol{AR_t = \alpha_0 + \alpha_1 VUL_t + \alpha_2 RES_t + \varepsilon_t} \qquad (1)$$

Where AR, VUL, RES and ε represent agricultural revenues, vulnerability to climate change, resilience to climate change and the error term, respectively.

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The main objective of the ARDL model is to examine the long-run cointegration relationship between agricultural revenues (AR), climate change vulnerability (VUL) and climate change resilience (RES). The following equations (2) and (3) express the relationship between these variables in the long run and short run by applying the ARDL-ECM model.

$$\Delta logRA_t = \lambda_0 + \sum_{k=1}^{p} \lambda_{1k}\,\Delta logRA_{t-k} + \sum_{k=0}^{p} \lambda_{2k}\,\Delta VUL_{t-k} + \sum_{k=0}^{p} \lambda_{3k}\,\Delta RES_{t-k} + \beta_1 logRA_{t-1} + \beta_2 VUL_{t-1} + \beta_3 RES_{t-1} + \varepsilon_t \quad (2)$$

$$\Delta logRA_t = \lambda_0 + \sum_{k=1}^{p} \lambda_{1k}\,\Delta logRA_{t-k} + \sum_{k=0}^{p} \lambda_{2k}\,\Delta VUL_{t-k} + \sum_{k=0}^{p} \lambda_{3k}\,\Delta RES_{t-k} + \delta ECT_{t-1} + \varepsilon_t \quad (3)$$

Where λ_0 represents the intercept, λ_1, λ_2 and λ_3 represent the short-term relationships, β_1, β_2 and β_3 represent the long-term relationships, ρ indicates the lag order, Δ denotes the first difference operator, $t-1$ represents the time lag, ε_t denotes the error term, and $\mathbf{k}$ is the optimal lag length determined by the Akaike information criterion (AIC).

3.1.2 VECM Model

Furthermore, for Morocco to develop appropriate policies to address the severe impacts of climate change, it is crucial to analyse and understand the distinct impacts of vulnerability and resilience indicators. Moreover, we also assessed the impact of the indicators composing the concepts of vulnerability and resilience on the Moroccan agricultural sector. In other words, agricultural revenues are modelled as a function of sensitivity, economic and social resilience, and governance. The empirical model is specified as follows:

$$AR_t = \beta_0 + \beta_1 SEN_t + \beta_2 ECO_t + \beta_3 SOC_T + \beta_4 GOV_T + \varepsilon_t \quad (4)$$

Where RA, SEN, ECO, SOC and GOV represent agricultural revenues, climate change sensitivity, economic, social and governance resilience and the error term, respectively.

First, checking the stationarity of integer variables is essential. The stationarity of a time series is important because it can influence its behaviour (Frenkel et al., 1978). According to Granger (1969), using non-stationary variables in a regression can lead to consequences such as invalid significance tests, inefficient coefficients and suboptimal forecasts. Time series stationarity refers to statistical characteristics that are constant over time, such as the mean and variance. If these characteristics are constant over time, the series is said to be stationary. Otherwise, the series is non-stationary. To convert a stationary series from a non-stationary series, one can apply differentiation operations, thus producing sets of observations such as the first differentiated values and the second differentiated values. We used the Augmented Dickey-Fuller (Dickey and Fuller, 1979), Phillips-Perron (Phillips and Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski, Phillips, Schmidt and Shin, 1992) tests to test the stationarity of the variables. Once stationarity is established, we move on to the analysis of cointegration, which is defined as a systematic long-term simultaneous movement between two or more economic variables (Yoo, 2006). In our paper, this analysis will rely on the Johansen (1988) cointegration testing procedure, which is more efficient than the two-phase approach of Engle and Granger (1987) when dealing with a small sample and a large number of variables. The Johansen procedure uses two tests to determine the number of cointegrating vectors: the trace test and the maximum eigenvalue test.

- The trace statistic examines the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations, where n is the number of variables in the system, for r = 0, 1, 2, …, n-1.
- The maximum eigenvalue statistic tests the null hypothesis of r cointegrating relations against the alternative of r+1 cointegrating relations, for r = 0, 1, 2, …, n-1.

If cointegration is detected between the series, this indicates the existence of a long-term equilibrium relationship between them. To analyse the long-term adjustment between the variables, we exploit the vector error correction model (VECM). The VECM is a restriction of the VAR (vector autoregressive) model. It allows not only to indicate the speed of long-term adjustment, but also to determine the direction and intensity of the short-term relationships. Equation (4) presents the VECM model.

$$\Delta LnAR_t = C_1 + \Sigma_{i=1}^{p}\gamma_{11i}\Delta logAR_{t-i} + \Sigma_{i=1}^{p}\gamma_{12i}\Delta SEN_{t-i} + \Sigma_{i=1}^{p}\gamma_{13i}\Delta ECO_{t-i} + \Sigma_{i=1}^{p}\gamma_{14i}\Delta SOC_{t-i} + \Sigma_{i=1}^{p}\gamma_{15i}\Delta GOV_{t-i} + \rho_1 ECT_{t-1} + \epsilon_{1t} \quad (5)$$

Where:

Δ **:** First difference.

C_1 **:** represents the constant.

$\gamma_{11i}, \gamma_{12i}, \gamma_{13i}, \gamma_{14i}$ et γ_{15i} **:** correspond to the coefficients of the error correction model.

ρ_1 **:** Adjustment coefficients.

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$\boldsymbol{ECT_{t-1}}$ **:** Error correction term that represents the deviation from the long-term equilibrium.

Thus, we validate the model using standard tests, including tests of normality of residuals, absence of autocorrelation and homoscedasticity of residuals. This entire process is carried out using the EVIEWS 12 software.

3.2 Data Sources

In this paper, we used secondary data of annual time series covering almost three decades, from 1995 to 2021. In the first model, vulnerability and resilience to climate change are considered as independent variables, while in the second model, their components are considered as independent variables. Table 1 presents the indicators composing the concepts of vulnerability and resilience to climate change.

Table 1: indicators composing the concepts of vulnerability and resilience to climate change

Vulnerability				**Resilience**		
Sector	**Exposure**	**Sensitivity**	**Adaptive Capacity**	**Economic**	**Governance**	**Social**
Ecosystem Services	Projected change of biome distribution	Natural capital dependency	Protected biome	Doing business	Political stability and nonviolence	Social inequality
	P.C of marine biodiversity	Ecological footprint	Engagement in international environmental conventions		Control of corruption	ICT infrastructure
Food	P.C of cereal yields	Food import dependency	Agricultural capacity		Regulatory quality	Education
	Projected population change	Rural population	Child malnutrition		Rule of law	Innovation
Human Habitat	P.C of warm periods	Urban concentration	Quality of trade and transport			

			infrastructure			
	P.C of flood hazard	Age dependency ratio	Paved roads			
Health	P.C of deaths from climate change induced diseases	Dependency on external resource for health services	Medical staff			
	P.C in vector-borne diseases	Slum population	Access to improved sanitation facilities			
Infrastructure	P.C of hydropower generation capacity	Dependency on imported energy	Electricity access			
	P.C of sea level rise impacts	Population living under 5 m above sea level	Disaster preparedness			
Water	P.C of annual runoff	Fresh water withdrawal rate	Dam capacity			
	P.C of annual groundwater recharge	Water dependency ratio	Access to reliable drinking water			

Source: Developed by the authors using ND-GAIN data

The Moroccan agricultural revenues (AR) data were extracted from the Food and Agriculture Organisation's digital database (FAO, 2025). Information on the concepts of vulnerability and resilience within the Moroccan territory, as well as the variables constituting these concepts, were collected online from the Notre Dame Global Adaptation Initiative (ND-GAIN), a program of the University of Notre Dame dedicated to climate change adaptation (ND-GAIN, 2025). The ND-GAIN produces the ND-GAIN index, which assesses the concepts of vulnerability and resilience to climate change in different countries.

The ND-GAIN dataset is particularly suited to this study for four main reasons. First, ND-GAIN is a non-profit institution that constructs this dataset by "reviewing the most recent climate change literature and consulting with academics, adaptation practitioners, and global development experts" (Chen et al., 2015, p. 5). Second, ND-GAIN's vulnerability and resilience measures represent the most comprehensive dataset available, composed of indicators that are freely available to the public and available for the majority of countries in the world. Third, this dataset contains reliable and transparent indicators, collected and maintained by trustworthy organisations. Finally, it is presented in time series format, going back to 1995 and extending to the most recent year available, which allows for tracking trends over time and for sophisticated analyses, such as time series and panel data analysis. Furthermore, to our knowledge, this is the only dataset available at a macro level to examine vulnerabilities and resilience within the agricultural sector and other economic activities. Furthermore, Armstrong (2012) argued that complex regression models that include many variables reduce the precision of estimates, even in the presence of large datasets. One solution to this problem is to develop an index based on "an a priori analysis that allows analysts to take into account knowledge present on the ground" (Armstrong, 2012, p. 692).

4. Results

4.1 Descriptive analysis

The basic statistics of the variables used in models 1 and 2 are presented in the table and figure below. Table 2 presents the descriptive statistics for vulnerability (VUL), resilience (RES), sensitivity (SEN) to climate change, as well as economic (ECO), social (SOC) and governance (GOV) resilience, and also agricultural revenues (logAR) in Morocco from 1995 to 2021. Table 2 shows the mean, standard deviation, highest and lowest values of these variables. Exposure and adaptive capacity are major components of vulnerability to climate change. We excluded the exposure variable from our study because it remains constant throughout the study period. Similarly, we omitted the adaptive capacity variable because of its collinearity with the other variables. Figure shows the time series of the study variables. They were not stable during the study period, as shown in Figure 1.

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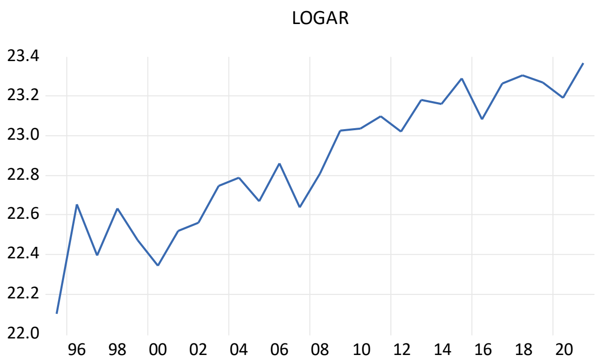
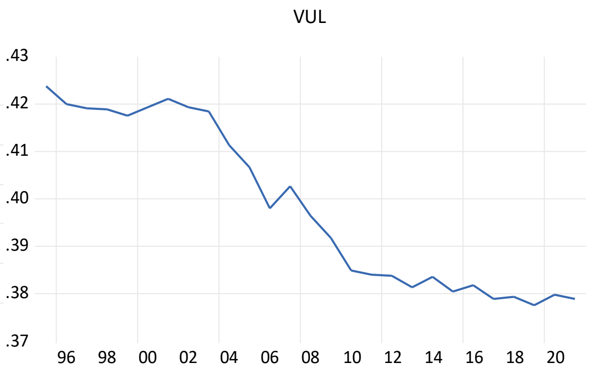
Table 2: Descriptive statistics of the variables

	LogAR	VUL	RES	SEN	ECO	SOC	GOV
Mean	22.86975	0.398492	0.375329	0.313242	0.423542	0.242430	0.460016
Median	22.86231	0.396553	0.362062	0.307363	0.405742	0.238495	0.455990
Maximum	23.36644	0.423626	0.428941	0.337249	0.514551	0.328295	0.528918
Minimum	22.10315	0.377697	0.340017	0.294086	0.382228	0.189038	0.418884
standard deviation	0.343618	0.017539	0.028300	0.015034	0.049134	0.045743	0.028325
Skewness	-0.347808	0.181023	0.738143	0.435897	0.771237	0.367971	0.795770
Kurtosis	2.127799	1.305935	1.997499	1.612184	1.914291	1.793120	2.828253
Jarque-Bera	1.400195	3.376051	3.582485	3.021817	4.002740	2.247944	2.882811
Probability	0.495637	0.184884	0.166753	0.220709	0.135150	0.324986	0.236595
Sum	617.4834	10.759229	10.13389	8.457536	11.43562	6.545614	12.42042
Sum. Standard Deviation	3.069913	0.007998	0.020824	0.005876	0.062767	0.054403	0.020860
Observations	27	27	27	27	27	27	27

Source: prepared by the authors





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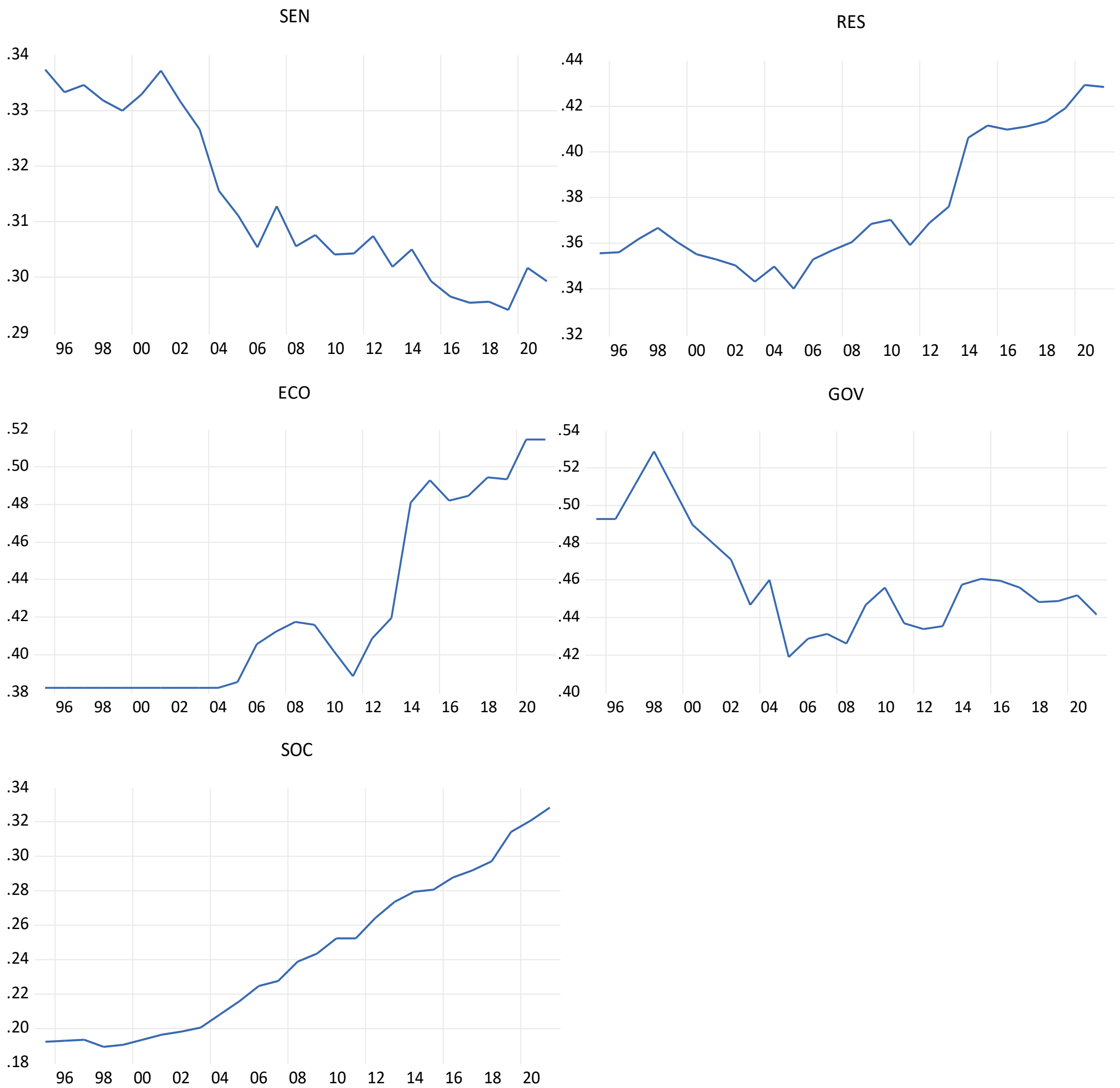

Figure 1: Eviews outputs

4.2 Stationarity Analysis: Unit Root Test

We first examine the stationarity of all variables, which is essential to avoid spurious regression. In this paper, the unit root tests, namely Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979), Phillips-Perron (PP) test (Perron, 1988) and Kwiatkowski-Phillips-Schmidt-and-Shin (KPSS) test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), were used to determine the stationarity of the variables. Table 3 presents the results of the unit root tests.

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Table 3: Results of Unit Root Tests

Variables	ADF	PP	KPSS	Unit Root
LogAR	-11.095***	-17.057***	0.123***	I(1)
VUL	-2.732***	-2.593***	0.112***	I(0)
RES	-4.534***	-4.534***	0.289***	I(1)
SEN	-5.773***	-5.719***	0.133***	I(1)
ECO	-4.014***	-4.014 ***	0.184***	I(1)
SOC	-3.978***	-3.941***	0.104***	I(1)
GOV	-5.179***	-5.179***	0.105***	I(1)

Notes: The selection of the lag order is according to the Schwarz Information Criterion (SIC).

***, ** and *** indicate the statistical significance levels of 10%, 5% and 1%.**

According to the results of the ADF, PP and KPSS tests, the variables logAR, RES, SEN, ECO, SOC and GOV are stationary at first difference I(1). On the other hand, VUL is stationary at level. This means that for model 1, a combination of I(0) and I(1) at the 1% significance level, all variables are stationary. Therefore, the ARDL model is adequate to establish a significant long-run relationship between the variables in the model.

Table 3 shows that the variables in the second model, namely logAR, SEN, ECO, SOC and GOV, exhibit stability at first difference. The first order integration is a prerequisite for establishing a cointegration relationship between these variables.

4.3 First model: ARDL model

4.3.1 Bounds Tests

As the series have different degrees of stationarity according to the unit root tests, it is possible to estimate the short- and long-run relationships using bounds tests. Based on the F value to confirm the existence of cointegration between the variables for the long-run relationship. The optimal number of lags in the model is determined using the Akaike Information Criterion (AIC), with a maximum of 4 lags. The results of the related F statistics are reported in Table 4.

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Table 4: ARDL Bounds Tests

	Value	Signification	Lower Bound I(0)	Upper Bound I(1)
F Statistics	5.165	10%	2.63	3.35
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

Source: made by the authors

The results showed that the calculated value of the F-statistic exceeds the upper critical bound at the 1% and 5% significance levels, suggesting the rejection of the null hypothesis of no cointegration. In other words, the results of the bounds test using the selected ARDL (1, 4, 0) model exceed the critical values at the 1% significance level. After testing the F-value, the results confirm the cointegration between the variables. The results of the estimation of the short- and long-term relationship between vulnerability and resilience to climate change and agricultural revenues are discussed in the following paragraphs.

4.3.2 Long-term and short-term dynamics

According to the results in Table 5, the error correction term (CointEq (-1)) was negative and statistically significant at 1%. This confirmed the cointegration between the variables, and the model is corrected from the short-term equilibrium to the long-term equilibrium of -1.021. In the short term, vulnerability to climate change is statistically negative and significant at the 1% level. An increase in the vulnerability index leads to a decrease of 14.213% in agricultural revenues. In other words, increased vulnerability of the food, water, health, ecosystem services, human habitat and infrastructure sectors leads to a reduction in agricultural revenues. This result illustrates the significant dependence between the agricultural sector and its vital sectors. However, in the short term, climate change resilience does not have a significant impact on agricultural revenues, as adaptation measures require time to take effect.

In the long term, vulnerability to climate change negatively impacts agricultural revenues; this impact is estimated at nearly 23%. Compared to the short-term impact, the negative impact of vulnerability to climate change on the agricultural sector becomes more pronounced. This result stems from the absence of a resilience effect on agricultural revenues. In addition, resilience to climate change has a negative, but not significant, impact. This result is paradoxical. Even if

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this impact is insignificant, it can be referred to the high costs of adaptation measures. Thus, some strategies require an immediate reduction in production to ensure better sustainability.

Table 5: Long-term and short-term results

Variable indépendante : logRA			
Variables	Coefficient	Ecart type	T-Statistique
A long terme			
VUL	-22.970***	5.438	-4.223
RES	-3.149	2.267	-1.389
Constante	33.780***	8.016	4.213
A court terme			
△VUL	-14.213***	4.535	-3.133
CointEq(-1)*	-1.021***	0.206	-4.953

***, ** and *** indicate the statistical significance levels of 10%, 5% and 1%.**

After estimating Model 1, we move on to the second model, which estimates the cointegration relationship between logRA, SEN, ECO SOC and GOV.

4.4 Second model: VECM

4.4.1 Johansen cointegration test

Before performing the Johansen cointegration test, it is essential to determine the optimal number of lags. For this, we use the following criteria: FPE (Final Prediction Error), AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion) and HQ (Hannan-Quinn Information Criterion). According to the results presented in the table below, all criteria, except AIC and HQ, recommend retaining an optimal number of lags equal to 1.

Table 6: Determination of the optimal number of lags

Lag	LogL	LR	FPE	AIC	SC	HQ
0	278.2711	NA	8.87e-17	-22.77259	-22.52716	-22.70748
1	381.4510	154.7699*	1.39e-19*	-29.28758	-27.81502*	-28.89691
2	402.7253	23.04717	2.59e-19	-28.97711	-26.27740	-28.26088
3	445.8948	28.77968	1.57e-19	-30.49124*	-26.56439	-29.44944*

Source: made by the authors

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When the variables are integrated of the same order, it is possible that they exhibit a joint movement. Cointegration tests, considered as an extension of stationarity tests, allow us to detect whether the integrated variables of the same order follow the same stochastic trend and therefore have a cointegration relationship.

Thus, the estimation of the cointegration rank, which corresponds to the rank of the matrix, is carried out by applying Johansen cointegration. The rank (r) can be formally tested using the trace and maximum eigenvalue statistics. The results are presented in Table 7.

Table 7: Tests based on the trace statistic and the maximum eigenvalue statistic

Rang	Stat de la trace	Stat valeur propre max
0*	121.632	45.526
	{69.818}	{33.876}
1*	76.105	42.841
	{47.856}	{27.584}
2*	33.263	21.296
	{29.797}	{21.131}
3	11.966	11.942
	{15.494}	{14.264}
4	0.024	0.024
	{3.841}	{3.841}

Notes: r: indicates the number of hypotheses of cointegrating relationships ; * indicates significance at 5% ; {}: indicates the critical value

The tests are conducted sequentially to determine the potential number (r) of cointegration relationships. We first test the null hypothesis that there is no cointegration relationship between the variables. In this regard, the trace statistic for (r = 0) reports a value of 121.632, greater than the critical value of 69.818 for a significance level of 5%. These results lead us to reject the null hypothesis. On the other hand, the hypotheses postulating the existence of at most one or two cointegration relationships respectively cannot be rejected. For the maximum eigenvalue statistic (r = 0), a value of 45.526 greater than the critical value of 33.876 at the 5% significance level, leads us to reject the hypothesis of no cointegration between the variables. However, the hypotheses postulating the existence of at most one or two cointegration relationships

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respectively were accepted. According to the results of the Johansen cointegration test, the trace test indicates the existence of 3 cointegrations. Thus, the maximum eigenvalue test indicates the existence of 3 cointegrations between the corresponding variables. For reasons of facilitating interpretations, we will consider only one cointegration in the estimation of the VECM model.

4.4.2 Long-term and short-term dynamics

The presence of cointegration between the variables indicates a long-term relationship between them, thus allowing the application of the VECM model. The long-term relationship between logRA, SEN, ECO, SOC and GOV is presented below. This analysis concerns Morocco over the period from 1995 to 2021 and is based on a cointegration vector.

Table 8: Long-term and short-term results

Variable indépendante: logRA			
Variables	Coefficient	Ecart type	T-Statistique
A long terme			
SEN	-9.658**	2.180	-4.428
ECO	2.583**	0.442	6.448
SOC	-12.778**	0.829	-15.405
GOV	3.835**	0.622	6.156
Constante	-19.735	_	_
A court terme			
ECT	-1.962**	0.458	-4.277
△SEN	-19.025**	8.119	-2.343
△ECO	2.382	1.609	1.480
△SOC	-25.999**	8.410	-3.091
△GOV	5.591**	2.255	2.478

***, ** and *** indicate the statistical significance levels of 10%, 5% and 1%.**

Table 8 presents the long-run, short-run, and error correction coefficients obtained through the VECM approach. Before interpreting the long-run coefficients, it is essential to check the significance of the error correction coefficients in order to determine the existence of a cointegration relationship in the models. Therefore, the ECT coefficient represents the speed of adjustment; it measures how quickly the dependent variables return to equilibrium after a disturbance in the explanatory variables (Engle et al., 1987). In our model, the coefficient is

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negative and significant at the 5% level, indicating the speed of adjustment of the ECT to return to equilibrium. Negative and statistically significant coefficients indicate that the error correction mechanisms are effective, thus demonstrating the existence of cointegration between the variables. Therefore, we can proceed to interpret the long-run coefficients of the variables.

In the long run, the coefficients of the sensitivity, economic resilience, social resilience and governance resilience variables are significant at the 5% level. Sensitivity has a negative impact on agricultural revenues. In other words, an increase in the sensitivity index reduces agricultural revenues by 9.658%. On the other hand, an increase in the economic resilience index and the governance resilience index increases agricultural revenues by 2.583% and 3.835%, respectively. On the other hand, social resilience negatively impacts Moroccan agricultural revenues. The results of the VECM model corroborate our hypotheses that sensitivity (H2) has a negative effect, and economic resilience (H4) and governance resilience (H6) have a positive effect on agricultural revenues in the long run. However, the results do not support the hypothesis that social resilience (H5) has a positive effect on agricultural revenues in the long run.

In the short term, the coefficients of the sensitivity, social resilience and governance variables are statistically significant, while economic resilience is insignificant. According to the results in Table 8, sensitivity negatively impacts agricultural revenues; this impact is estimated at 19.025%, while resilience to governance has a positive impact on agricultural revenues of 5.591%. Although most of the coefficients in the long term and in the short term are statistically significant with the expected signs, social resilience surprised us with its negative impact on agricultural revenues.

Sensitivity to climate change affects agricultural revenues in the short term as well as in the long term. This impact goes from 19.025% in the short term to 9.658% in the long term. This result means that adaptation measures play an important role in reducing the sensitivity to climate change of several sectors, namely: food, water, health, ecosystem services, human habitat and infrastructure. Overall, the results of the analyses suggest that vulnerability to climate change affects agricultural revenues in the long term as well as in the short term. Specifically, with increased sensitivity to climate change, agricultural revenues decrease. However, increased adaptive capacity, manifested in economic resilience and governance, leads to increased agricultural revenues in the long term.

4.5 Diagnostics and stability test

To finalise this article, we use several diagnostic tests to ensure the stability of the ARDL and VECM models. The results are reported in Tables 9 and 10. The results of the Jarque-Bera test show that the residuals follow a normal distribution. In addition, the models do not display autocorrelation of errors, and the heteroscedasticity test confirms the absence of heteroscedasticity. In addition, the value of R^2 for the model indicates the quality of the fit. The results of the analyses show that the coefficient of determination R^2 in model 2 indicates that nearly 77% of the variability of agricultural revenues can be attributed to sensitivity, economic, social and governance resilience. In addition, 92% of the variability of agricultural revenues is attributed to vulnerability and resilience to climate change. Finally, to examine the stability of the selected ARDL and VECM model parameters, we use the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests for the ARDL model. In addition, we use the inverses of the roots of the AR characteristic polynomial to validate the long-term stability of the VECM model variable parameters. The results of the two plots, CUSUM and CUSUMQ, are in Figures 2 and 3. The two lines plotted inside the two straight lines, which are limited by a 5% significance level. The plots of both statistics are within the limits, which establishes that the model does not violate any assumption. Therefore, the ARDL model is stable and the estimated results are reliable and well considered for policy practices. From Figure 4 of the plot of the inverses of the roots of the characteristic polynomial AR, all the points are inside the unit circle, thus confirming the stability of the selected VECM model and indicating that the estimated coefficients of the variables remain stable throughout the study period.

Table 9: Residual diagnostics for the ARDL model (1, 4, 0)

Test de normalité (Jarque-Bera)	0.840 (0.656)	**R^2**	0.922
Test LM de Breusch Godfrey	1.388 (0.281)	**R^2ajustée**	0.888
Test de Breusch Pagan Godfrey	0.554 (0.781)	**F- Statistique**	27.284 (0.000)

Source: made by the authors

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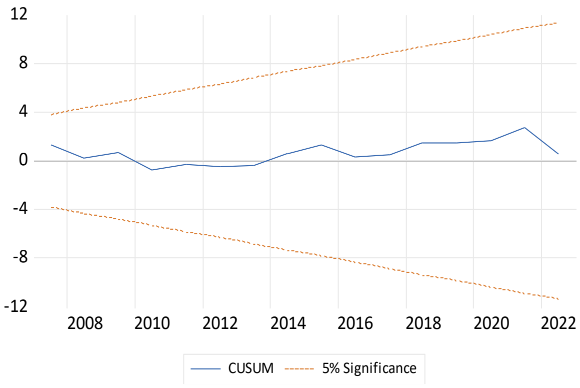
Tableau 10 : Residual diagnostics for the VECM model

Test	F-statistique	Probabilité
Test de normalité (Jarque-Bera)	11.146	0.34
Test LM de Breusch Godfrey	0.545	0.905
Test de Breusch Pagan Godfrey	348.92	0.227
R^2	_	0.772
R^2ajustée	_	0.564

Source: made by the authors



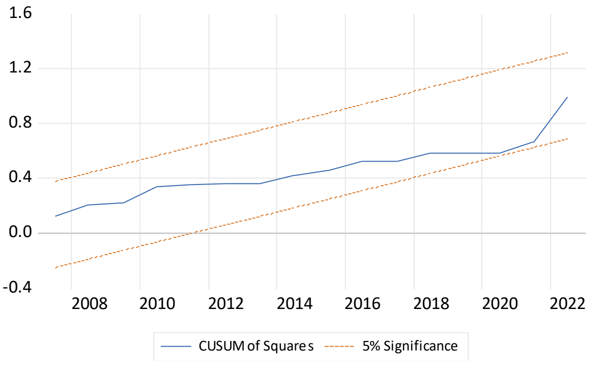


Figure 2: CUSUM test **Figure 3: CUSUMQ test**

Inverse Roots of AR Characteristic Polynomial

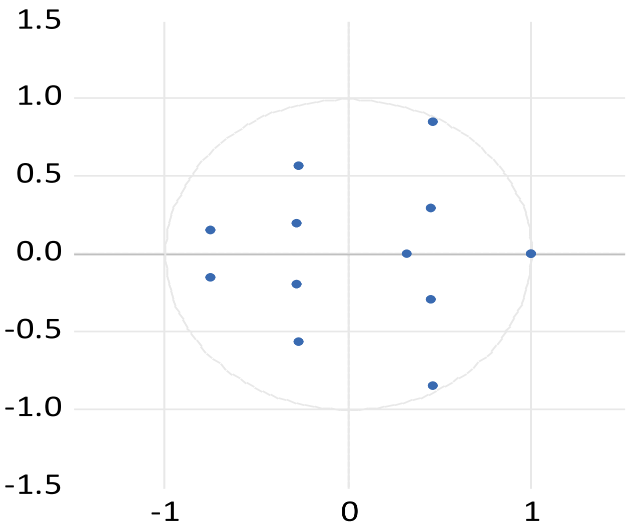


Figure 4: graph of the inverses of the roots of the characteristic polynomial AR

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Discussion and conclusion

Agricultural growth is particularly desired by countries whose economies heavily depend on this sector. However, sustainable agricultural development cannot be achieved without natural resources, whose availability and abundance vary worldwide. Climate change unilaterally affects essential natural resources such as food, water, forestry, and other vital sectors. By extension, this impacts the industries that depend on them, including agriculture. Thus, the analysis of the negative impacts of climate change on these vital sectors has been at the heart of the agricultural literature in recent decades (Benkachchach and El Issaoui, 2023; El-Khalifa et al., 2022), as the degradation of natural capital due to climate change could have adverse consequences on agricultural growth and sustainable development. Existing studies have focused mainly on climate change forecasts based on simulations and the development of adaptation and mitigation strategies (Bayraç and Doğan, 2016; Xu et al., 2019). However, these climate change scenarios overlook nonclimatic factors such as quality of life indicators; agricultural capacity; urban and rural populations; longevity; endangered species; dependence on natural capital; and economic, social, and political factors. This gap in the literature necessitates a comprehensive assessment of vulnerability and resilience.

Our study explores the impact of climate change vulnerability of critical sectors such as food, infrastructure, human habitat, health, water and ecosystems as well as climate change resilience represented by freedom to do business, political stability and non-violence, fight against corruption, regulatory quality, rule of law, social inequalities, education, innovation and ICT infrastructure on agricultural revenues in Morocco. Based on annual digital ND-GAIN data covering the period 1995-2021. The ARDL model was used to assess the relationship between agricultural revenues, vulnerability and resilience to climate change. Another VECM model was adopted to assess climate change sensitivity, economic, social and governance resilience and their impact on the agricultural sector. The tests conducted confirmed the existence of a cointegration relationship. Our empirical examinations affirm that climate change vulnerability significantly affects agricultural revenues. In particular, vulnerability and its component, climate change sensitivity, have a negative impact on agricultural revenues. The ARDL model results highlight that in the absence of resilience impact on agricultural revenues, vulnerability to climate change has a significant effect on the agricultural sector. This impact is accentuated over time. On the other hand, in the presence of economic resilience and governance impact, model 2, climate change sensitivity remains, although it tends to decrease as time passes. In other words, economic resilience and governance have a positive impact in the long term as

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well as in the short term on agricultural revenues, while social resilience has a negative impact. Regarding the unexpected negative impact of social resilience on the agricultural sector, this result is nothing short of an achievement. A more resilient society benefits from education, subsidies, innovation, institutions capable of supporting economic diversification, social security, training and professional retraining. This leads to a shift in labour and investment from the agricultural sector to other sectors. This reduces the population's dependence on the agricultural sector and consequently detriments the share of the agricultural sector in GDP.

Although Moroccan agriculture is highly vulnerable to climate change, it also shows adequate resilience to cope with severe impacts. However, the impacts of climate change vulnerability of the agricultural sector far exceed those associated with resilience. These findings disagree with those of ND-GAIN, which highlights a low vulnerability score for vital sectors including food, water, health, ecosystem services, human habitat and infrastructure, compared to a high preparedness score for Morocco that places it in the lower right quadrant of the ND-GAIN matrix. Adaptation challenges still exist, but Morocco is well placed to adapt (ND-GAIN, 2025). According to ND-GAIN, in 2025, Morocco will be ranked 132nd in terms of vulnerability and the 87th most ready country (ND-GAIN, 2025). These results highlight the need for adaptation policies to reduce the increased vulnerability of the agricultural sector compared to other sectors.

Additional adaptation policies increase a country's resilience to climate change; however, these results highlight the level of risk reached under current circumstances, namely, that the climate has already changed and that vulnerability requires immediate attention. Sectors with better social, economic, and political infrastructures are better prepared to cope with the impacts of climate change than are those with low-resilience indicators. Therefore, the vulnerability and resilience of agriculture, as well as the consequences of climate change, are likely to vary depending on a country's economic development. For example, less developed countries, small island nations, and hot, arid African countries are more sensitive to climate change because of their heavy dependence on agriculture and tourism (Kilungu and al., 2017; Schneider and Haller, 2017; Ofoegbu and al., 2017; Schmutter and al., 2017).

From a theoretical standpoint, this study makes a key contribution to the limited empirical literature on the effects of vulnerability and resilience to climate change on agriculture. We have argued that a systematic and comprehensive assessment of vulnerability and resilience, including both climatic and nonclimatic factors, is necessary to develop effective climate change mitigation and adaptation strategies. Vulnerability and resilience determine the

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foundations and extent of the mitigation and adaptation policies needed to address the impacts of climate change in a given country (Füssel and Hildén, 2014). While mitigation aims to reduce the current and future impacts of climate change, adaptation restructures economic models within the framework of a "new normal" (Dogru et al., 2019). Implementing mitigation and adaptation policies will help increase the resilience of various economic activities, including tourism (Adger, 2009; Cheer and Lew, 2018; Hashemi, Bagheri, and Marshall, 2017). Although analysing projected changes in climatic variables is essential for developing mitigation strategies (Ionescu et al., 2009), current assessments of the vulnerability and resilience of nonclimatic factors are also necessary for developing appropriate adaptation strategies.

Therefore, mitigation policies should be prioritised globally through international agreements to reduce greenhouse gas emissions. While mitigation strategies decrease vulnerability, adaptation strategies increase resilience, enabling the economy to withstand the effects of climate change (Cheer and Lew, 2018; Hashemi, Bagheri, and Marshall, 2017; Ofoegbu et al., 2017).

In addition to reducing sensitivity to climate change, Morocco needs to focus more on improving their adaptive capacities in terms of economic, social and political conditions. However, strengthening adaptive capacity requires a level of cooperation that goes beyond the agriculture sector. Therefore, government officials need to develop strategies and policies to increase the elements of business and investment freedom and education.

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