Climate variability impact on agricultural production in Morocco: New evidence from a spatial econometric analysis

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Abstract

This paper examines the impact of climate variability on agricultural production in 12 Moroccan regions, differentiating between rain-fed and irrigated crops. Using a spatial panel data model with a 21-year (1999-2019), we analyze the impact of climatic and economic variables on three main crops: cereals, market gardening and rosaceous plants, while taking into account spatial autocorrelation and regional heterogeneity. The results highlight the sensitivity of various crops to variations in temperature and precipitation, revealing significant spillover effects due to omitted variables or shocks not observed in a spatial pattern. Thus, rainfall has a positive impact on rain-fed cereals but a negative impact on irrigated crops, underlining the inefficiencies of irrigation techniques and the need for sustainable water management. Irrigated rosaceae crops show high temperature sensitivity, underlining the urgency of climate-resilient agricultural practices. This finding underscores the urgent need for targeted regional public policies rather than standardized national policies to mitigate the effects of climate variability on Moroccan agriculture and ensure its long-term sustainability.

Keywords: *Climate variability, Agriculture, Spatial panel data, Production function approach, Morocco.*

1. Introduction

The effects of climate change have been increasingly recognized. Observations of climate change in the Mediterranean region, presented in the sixth assessment report (AR6) of IPCC (2022), show a significant increase in temperature (from 0.9 to 5.6°C) and a decrease in precipitation (from 4% to 22%) over the last two decades of the 21st century.

Morocco, like other Mediterranean countries, has experienced a temperature increase of +0.42°C/ decade since 1990, accompanied by a decrease in precipitation of more than 20% between 1961 and 2005 (Driouech *et al*., 2010). More recently, Amouzay *et al*. (2023) identified a significant structural break in temperature in 1993 and another break related to precipitation in 1972. These breakpoints confirm the current trends in climate data. Indeed, a study by Driouech *et al*. (2021) based on data from 30 meteorological stations covering the period from 1960 to 2016 showed that the daily temperature in Morocco has risen at higher rates than the global scale. The depicted trend of

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0.33°C per decade corresponds to a warming of approximately 1.1°C for 1984-2016. However, the annual mean precipitation and standardized drought index showed less spatially consistent tendencies despite the predominance of negative trends. Furthermore, projections of climate trends indicate that this situation is likely to persist (Filahi *et al*., 2017).

The increasing variability in precipitation and high frequency of droughts will likely further reduce the availability of water resources (Woillez, 2019). This, in turn, negatively impacts potential agricultural yields, employment opportunities, and the purchasing power of rural populations (Abdelmajid *et al*., 2021). Indeed, the Moroccan agricultural sector plays a key role in the country's economic fabric given its contribution to gross domestic product (GDP) and its interaction with other economic sectors. According to report of Ministry of Economy (2019), the weight of the Agricultural Gross Domestic Product (AGDP) in GDP varied between 12% and 14% between 2008 and 2018, with an average of 12.8%. The agricultural sector also plays a vital social and territorial role, employing nearly 40% of the active population at the national level, and 74% in rural areas (Ministry of Agriculture, 2019). Agriculture's vital importance to the national economy makes a country vulnerable to climate risks that threaten its food security (Abdelmajid *et al*., 2021; Palatnik and Lourenço Dias Nunes, 2015; Toumi *et al*., 2021).

This study aims to shed further light on the impact of climate variability on Moroccan agriculture using regional data for key agricultural products in both rainfed and irrigated areas. Indeed, climate variability manifests itself heterogeneously in space, with its impact varying significantly across different regions of the globe (Desmet and Rossi-Hansberg, 2024). Consequently, regions whose economies are heavily reliant on agriculture, which is inherently sensitive to temperature variations and extreme weather events, are more likely to experience significant damage than those whose economies are focused on industry or services, which are generally less dependent on climatic conditions (IPCC, 2023). Analyzing the impacts of climate variability on agricultural production necessitates a spatial approach, as effects are not confined to the directly affected regions. Indeed, Chatzopoulos and Lippert (2016) identify five key motivations for this inclusion. First, it minimizes omitted variable bias by incorporating spatial information otherwise neglected. Second, it controls for spatial dependence that can emerge from data aggregation, as aggregated units can be artificially more homogeneous. Third, interactions between landowners, who inform each other about prices and valuations, create spatial dependence. Fourth, land use practices shared by neighboring farms reinforce this dependence. Finally, land investments create external benefits for adjacent plots, which can be modeled using spatial lags of the explanatory variables. Thus, our goal is to emphasize the importance of using spatial panel data models to calculate spatial autocorrelation and spillover effects across regions, thereby providing policymakers with more accurate quantitative information on how Moroccan agriculture adapts to climate risks. By integrating the spatial dimension into our analysis, we can better understand the complex mechanisms linking climate variability to agricultural production in Morocco, and thus develop more effective and sustainable adaptation strategies.

This study's originality lies in its use of recent disaggregated data (spanning three categories: regions, products, and production methods) while explicitly employing spatial econometric techniques applied to panel data to account for spatial effects. Specifically, this article makes three major contributions to the existing national-level literature on the impact of climate variability on agriculture. Firstly, it utilizes a spatial panel data approach, which captures spatial autocorrelation and regional heterogeneity, aspects often overlooked in previous analyses. Literature has demonstrated that the impact of climate variability varies significantly across regions (Auffhammer *et al*., 2013), creating spatial heterogeneity influenced by geographical and economic factors (Chen *et al*., 2016; Coulibaly *et al*., 2020; Karahasan and Pinar, 2023; Vaitkeviciute *et al*., 2019; Zouabi and Peridy, 2015), thus necessitating contextualized solutions adapted to local realities (Desmet and Rossi-Hansberg, 2024). This approach allows us to highlight the geographical spillover effects of climate variability on agricultural production across regions, an aspect ignored by most national studies. This contribution is all the more important as the literature emphasizes the spatial heterogeneity of climate variability impact (Desmet and Rossi-Hansberg, 2024), requiring solutions tailored to local specificities. Taking into account the spatial dimension allows for a better delineation of the areas affected by climate variability and directs adaptation policies towards regionalized solutions, in line with local priorities. To the best of our knowledge, this is the first time such an approach has been adopted to study the impact of climate variability on Moroccan agriculture. Secondly, the study addresses a gap by focusing on an analysis of disaggregated data up to 2019, both at the regional level and for specific crops (cereals, market gardening, and rosaceous crops), allowing for the distinction of differentiated impacts of climate variability on various productions. This multi-level approach, often neglected by national studies that primarily focus on rain-fed cereal crops, offers a finer perspective and provides updated evidence on the vulnerability of the Moroccan agricultural sector, enabling the identification of the most climate-sensitive crops. Finally, the study compares the impacts of climate variability on rain-fed and irrigated production systems, highlighting the limited effectiveness of current irrigation practices and emphasizing the importance of investing in more efficient adaptation strategies. This comparison is essential for developing agricultural policies that consider the specificities of each production system and promote sustainable water resource management.

The remainder of this paper is organized as follows: The literature review and the methodological framework is presented in the Sections 2 and 3. Section 4 describes the study's context, variables, and data sources. It also proposes a spatial exploratory analysis of agricultural production in Morocco using global and local spatial autocorrelation. Section 5. Section 6 concludes the study and provides policy proposals.

2. Literature Review

A large and active body of literature quantifies the impact of weather and climate change on agriculture worldwide (see Ortiz-Bobea [2021] for a recent review of the literature). Indeed, to properly understand existing relationships between climate and agriculture, some analysts (Blanc and Reilly, 2017) emphasize that economists favor statistical approaches based on farmers' experience. In particular, these authors distinguish the Ricardian approach (Mendelsohn *et al.*, 1994) and the agricultural production function approach (Deschênes and Greenstone, 2007) as those most frequently used in the empirical literature. On the one hand, the Ricardian approach is a cross-sectional analysis of land value per hectare that assumes that farmers behave optimally in the long term and that land value reflects the future income stream that the farmer would receive from the best land allocation (Mendelsohn *et al.*, 1994). On the other hand, the agricultural production function approach is a panel analysis of net revenue/profit/production as a function of weather, and is based on the annual behavior of producers seeking to maximize their revenues (Deschênes and Greenstone, 2007). This is a short-term approach where agricultural revenues in the observed year are affected only by climate variability as measured by weather conditions in the same year (Auffhammer *et al.*, 2013; Dell *et al.*, 2014). The latter approach is particularly used in developing countries because of insufficient availability of data for the Ricardian approach (Blanc and Reilly, 2017). African countries often find it difficult to apply Ricardian models because of the unavailability of information on private landowners in most countries. In addition, a proportion of agricultural land is held by village communities or the state, resulting in a lack of land transactions to assess land values (Mendelsohn and Dinar, 2009).

A great deal of other work on modeling the impacts of climate change on agriculture on a global or regional scale is available in scientific literature. However, specific studies on Morocco have been conducted (Balaghi *et al.*, 2016, 2008; Belcaid and El Ghini, 2019; Fader *et al.*, 2016; Giannakopoulos *et al.*, 2009; Gommes *et al.*, 2009; Ponti *et al.*, 2014; Rosenzweig *et al.*, 2014; Schilling *et al.*, 2012), as indicated in the synthesis and analysis of the literature by Woillez (2019). In particular, we point to a study by the MOSAICC project (Balaghi *et al*., 2016), which used projections from three different GCMs to simulate the impact of climate change on rain-fed wheat and barley (bour) yields using the Aqua Crop model. According to those authors, increasing temperatures and declining precipitation led to a decrease in simulated yields for the majority of Morocco's major agricultural regions by the mid-century in both the RCP4.5 and RCP8.5. Wheat and barley yields increase only in mountainous regions and in the north of the country, where warming creates more favorable conditions. The aggregation of these yield evolutions and their inclusion in a CGE-type economic model has a rather limited impact on Moroccan GDP. Other studies have focused on the role of public policies, particularly the Green Morocco Plan (GMP), as tools for adaptation to climate risks that can ensure food security for Moroccans (Abdelmajid *et al*., 2021; Akesbi, 2012; Oulhaj *et al*., 2013; Ouraich and Tyner, 2018; Sraïri, 2021). Indeed, Ouraich and Tyner (2018) studied the impact of climate change on productivity shocks in the agricultural sector. Using a regionalized computable general equilibrium model, the authors estimated the potential adaptation of Morocco's current agricultural development and investment strategy, the GPM. The results indicated no major differences between the impacts of climate change with and without the GPM. In the absence of GPM adaptation, the impact on GDP ranged from −3.1% to +0.4%. Including the GPM targets, the impact on the GDP ranges from −2.9% to +0.43%. Very recently, Abdelmajid *et al*. (2021) examined the constraints induced by climate change on natural resources and investigated the extent to which the agricultural sector and GMP can ensure food security in Moroccans under these constraints. These authors argue that the Moroccan agricultural policy pursued until now, and particularly the GMP, may well aggravate the consequences of climate change on natural resources, especially water, and, by extension, the food security of the country as a whole.

Despite the remarkable proliferation of empirical work over the past two decades, econometric models incorporating the spatial dimension have rarely been used to study the impact of climate change on Moroccan agriculture. Indeed, these studies fail to account for the spatial interaction of data, which could potentially introduce estimation biases (Chen *et al*., 2016; Schlenker *et al*., 2006; Vaitkeviciute *et al*., 2019). Thus, our intention is to account for spatial interaction in our modeling, resulting from both the geographical proximity of Moroccan regions and our gridded meteorological data (Auffhammer *et al*., 2013), by utilizing the production function approach initially suggested by Deschênes and Greenstone (2007).

3. Methodology

Our methodology for assessing the potential impacts of climate change on Moroccan agricultural production relies on observing the evolution of meteorological and socioeconomic variables over a defined period. First, we examine the empirical model specification adopted in our case study (3.1), then introduce linear models with spatial interaction on panel data and specify the testing procedures employed (3.2).

3.1. *Empirical Model Specification*

The literature review indicates that the production function approach is dominant in many studies on developing countries owing to data availability. We use specifications similar to those in Zouabi and Peridy (2015). This study analyzes the link between agricultural production and annual weather fluctuations in Tunisian regions using fixed-effects models, which would appear to be appropriate for assessing short-term relationships and should thus be preferred in the production function approach. The latter is based on the Cobb-Douglas type production function assumption (Jones *et al*., 2017). We can estimate the aggregate agricultural production function in Morocco while accounting for the effects of key weather variables on the changes in agricultural production. The basic Cobb-Douglas production function can be written as

$$Y_{it} = F\left(K_{it}, L_{it}, T_{it}, P_{it}\right) = A_{it} K_{it}^{\alpha} L_{it}^{\beta} T_{it}^{\theta} P_{it}^{\gamma}, \quad (1)$$

where Y_{it} denotes the given production in country i and in year t, K_{it} and L_{it} reflect respectively the capital and labor used in agriculture. Capital was represented by three variables: land, irrigation area, and livestock (or Draught animals). Labor is represented by the agricultural labor force. T_{it} and P_{it} correspond to average temperature and precipitation, respectively. α, β, θ, and γ are the coefficients to be estimated and can be interpreted as elasticities. A_{it} includes unobserved variables (such as soil quality, labor skills, and technical progress) that can influence agricultural production. These unobserved effects can be evaluated using the following equation:

$$A_{it} = Ae^{u_i+\nu_t+\varepsilon_{it}} \tag{2}$$

where u_i, ν_t and ε_{it} represent the specific effects at the regional level, time-specific effects, and idiosyncratic error terms, respectively.

Substituting (2) into (1) yields:

$$Y_{it} = Ae^{\mu_i+\nu_t+\varepsilon_{it}} K_{it}^{\alpha} L_{it}^{\beta} T_{it}^{\theta} P_{it}^{\gamma} \tag{3}$$

After log transformation, the fixed effects model of this study is as follows:

$$\begin{aligned} log\,(Y_{it}) &= log(A) + \alpha log\,(K_{it}) + \beta log\,(L_{it}) + \\ &+ \theta log\,(T_{it}) + \gamma log\,(P_{it}) + \mu_i + \nu_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

This panel-data model can be used to account for irrigated crops. Agronomic research suggests that irrigated crops respond differently to climate than rain-fed crops do (Mendelsohn and Dinar, 2009). Schlenker *et al*. (2006) tests different model specifications by including an irrigation variable in a model for all counties and then separating the sample into irrigated and non-irrigated counties. Deschênes and Greenstone (2007) and Wang *et al*. (2009) build on these results and offer regression analyses on separate samples as well as on the full sample, covering both irrigated and non-irrigated countries. Drawing on these studies, we substitute agricultural production and total land area for irrigated crops in Equation 4 when estimating these types of crops.

3.2. *Panel Spatial Models used in Climate Change impact on Agriculture Studies*

Most empirical studies based on production function use panel data. However, over the past decade, spatial autocorrelation has begun to feature prominently in econometric studies of the impacts of climate change on agriculture (Chatzopoulos and Lippert, 2016; Chen *et al*., 2016; Ortiz-Bobea, 2016; Polsky, 2004; Schlenker *et al*., 2006; Schmidtner *et al*., 2015; Vaitkeviciute *et al*., 2019). Indeed, the inclusion of state-fixed effects could amplify the omitted-variable bias if they operate more strongly within states than across states, as shown in Ortiz-Bobea (2021). Nonetheless, the introduction of the spatial panel model addresses this issue and allows for convincing control of time-invariant confounders. Because our sample is composed of regions that are part of the same country and have common characteristics (in terms of climate, infrastructure, production systems, etc.), it is necessary to consider the interactions caused by geographical proximity, also called spatial interaction, in the modeling. Consequently, we follow Vaitkeviciute *et al*. (2019) and Karahasan and Pinar (2023) in our analysis and adopt a panel Spatial Error Model (SEM), which is the most suitable specification for this type of aggregated data. Indeed, according to Vaitkeviciute *et al*. (2019), a Spatial AutoRegressive (SAR) model and a Spatial Lag to the explanatory X variables (SLX model) are not suitable for our case because the SAR model is interesting in the context of individual (farm)-level data, whereas the SLX model is excluded because of collinearity issues. This leads us to work with an SEM that captures the global spatial autocorrelation. In other words, the spatial autocorrelation of errors implies the possible presence of measurement errors that tend to propagate across aggregated unit boundaries, omitted variables, or unobserved shocks that follow a spatial pattern. In addition, the existence of spatial autocorrelation can be explained by different data as well as by the aggregation process scales.

The SEM model is better suited for aggregated data, mainly because of the possible existence of spatial autocorrelation in the residuals, which in turn can be attributed to the construction of weather data (Vaitkeviciute *et al*., 2019). Therefore, we used an SEM panel model that implies the following residual term:

$$\begin{aligned} log\,(Y_{it}) &= log(A) + \alpha log\,(K_{it}) + \beta log\,(L_{it}) + \\ &+ \theta log\,(T_{it}) + \gamma log\,(P_{it}) + \mu_i + \nu_t + \varepsilon_{it}, \end{aligned} \tag{5}$$

such that $\varepsilon_{it} = \rho \sum_{k=1}^{N} \omega_{ik}\eta_{ik} + \epsilon_{it},$

where ε_{it} correspond to the residual term which is composed of the spatially autocorrelated error term, ω_{ik} is the generic element of a nonnegative, $N \times N$ spatial-weight matrix W_N in which neighborhood relationships between regions are defined, ρ is the spatial autocorrelation coefficient that captures a correlated effect of unobservable characteristics, η_{ik} is the spatially correlated error term, and ϵ_{it} is the error term.

The choice between these models is made through specification tests described in the practical bottom-up approach (see Le Gallo [2002] for a summary), which begins with the non-spatial model. We then use Lagrange Multiplier tests (LMLAG and LMERR) and their robustness (Robust-LMLAG and Robust-LMERR) to determine the SAR, SEM, or non-spatial model (Anselin, 1988; Anselin *et al*., 1996).

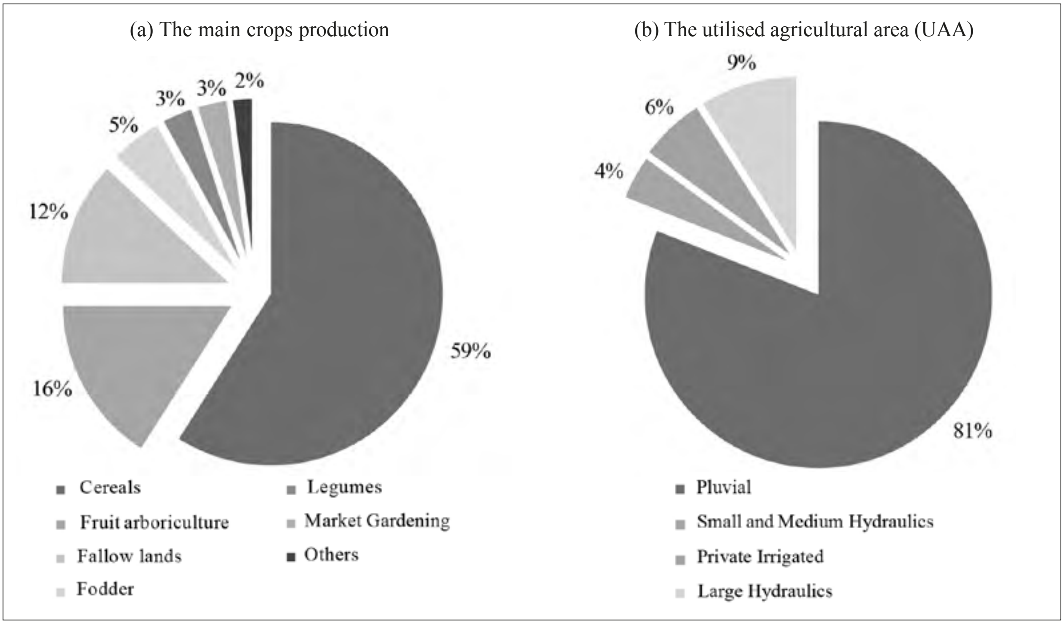
4. Context, Data and Exploratory Analysis

This study leverages panel data collected from a sample of 12 regions within Morocco spanning the period from 1999 to 2019. Our selection of variables and regions was constrained by the availability of consistent data on both climate and agriculture. In this section, we first provide context (4.1) by outlining the Moroccan agricultural landscape, highlighting the predominance of rainfed areas and the importance of cereal production. It also emphasizes the spatial and temporal variability in agricultural production, and underscores the impact of spatial concentration of crops on regional economic performance. The second sub-section (4.2) details the data sources used in the analysis, explaining the origin and measurement of economic and meteorological variables, and emphasizing the importance of accounting for crop-specific growing seasons. Finally, the third sub-section (4.3) focuses on spatial exploratory analysis, using the Moran's I test to identify the spatial autocorrelation of agricultural production across Moroccan regions and exploring potential explanations for this spatial dependence.

4.1. *Contextualizing the Moroccan Agricultural Landscape*

With an area of nearly 8.7 million hectares, Morocco's Useful Agricultural Area (UAA) is rich in agro-climatic systems that allow it to produce a very wide range of crops in Morocco, both irrigated and non-irrigated. These are mainly cereals, fruit crops (generally composed of rosacea,

Figure 1 - Breakdown of the main crops and UAA in Morocco.

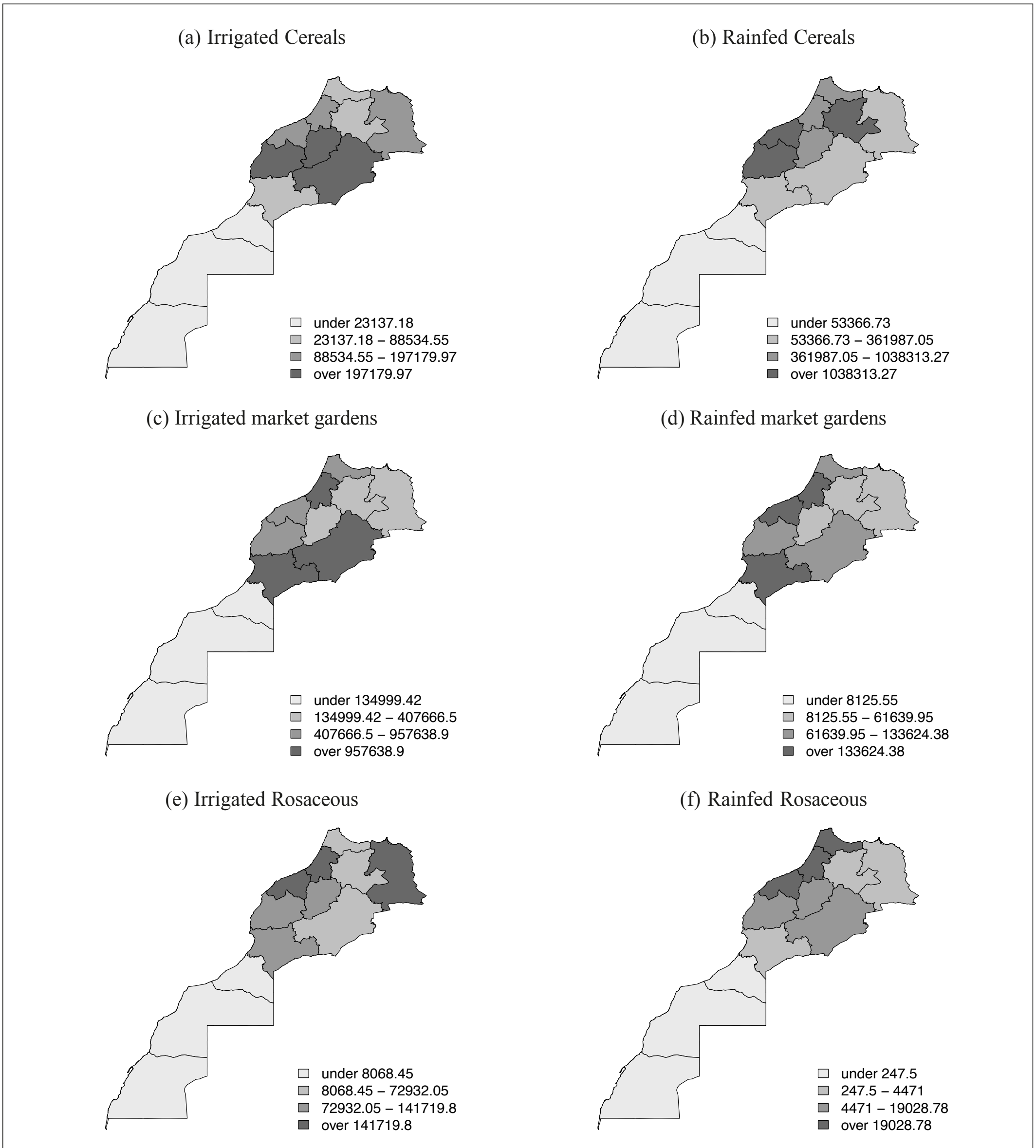


Source: Ministry of Agriculture, 2019.

olives, and almonds), fallow land, fodder crops, market gardens, leguminous, and others (Ministry of Agriculture, 2019). However, this UAA is characterized by the dominance of rain-fed areas (Bour) (up to 80% of the total UAA) and the consequent weight of cereals (nearly 59% of the total UAA, that is, 79% of the UAA in rain-fed areas, as shown in Figure 1).

Analysis of inter-regional variability over the period 1999-2019 shows that production instability is not only temporal but also spatial. Indeed, the distribution by regional zone shows that most crops are spatially concentrated (Figure 2 below). For example, cereals and tree crops are located in the northwest (Tangier-Tetouan-Al-Hoceima, Rabat-Salé-Kenitra, Casablanca-Settat, Marrakech-Safi, Béni Mellal-Khénifra) and northeast (Fez-Meknes and Oriental) regions, re-

Figure 2 - Agricultural production in Morocco: spatial patterns of irrigated and rainfed crops (1999-2019).



spectively. This explains the differentiation in the performance of the agricultural sector according to these regions in terms of their weight in the national AGDP. Indeed, according to report of Ministry of Economy (2019), during the period 2001-2016, the region of Fez-Meknes recorded the largest share in the national agricultural value-added, with an average share of 16.5%, followed by the region of Marrakech-Safi (14.2%), Rabat-Salé-Kénitra (13.4%), and Casablanca-Settat (12%).

4.2. *Data Sources and Measurement*

As previously mentioned, we use regional panel data describing the annual production of three types of crops: Cereals (aggregation for cereal products: wheat, barley, and corn), Market Gardening (aggregation for products: Tomatoes, Potato and Onion), and Rosaceous (aggregation of products: Almond, Apricot, Plum, Apple and Pear) as a function of meteorological variables (Precipitation and Temperature) and agricultural inputs (Total Area of Rain-fed and Irrigated Land, Livestock and Labor) in the twelve Moroccan regions, namely Tangier-Tetouan-Al Hoceima, Oriental, Fez-Meknes, Rabat-Salé-Kénitra, Béni Mellal-Khénifra, Casablanca-Settat, Marrakesh-Safi, Drâa-Tafilalet, Souss-Massa, Guelmim-Oued Noun, Laâyoune-Sakia El Hamra, Dakhla-Oued Ed-Dahab. The time dimension of the panel data covers a period of twenty-one years (1999-2019).

The data concerning economic variables (Production, Labor, Capital) is drawn from the database built with the help of Geographic Information Systems (GIS) existing since the 1990s at the level of the Haut Commissariat au Plan (HCP)[1]. Production is measured in tons. The contribution of capital is represented by livestock (in this context, refers to draught animals) and land inputs. Indeed, the capital requirements of traditional agriculture are low, and Moroccan agriculture relies mainly on animal traction. Therefore, we use the number of donkeys, horses, and mules as an indicator of this livestock input, as it was done in many other studies (Antle, 1983; Barrios *et al*., 2008; Frisvold and Ingram, 1995; Hayami *et al*., 1971; Nguyen, 1979). Land supply is represented by the total area of rain-fed agricultural land measured in hectares. Irrigation can be crucial for production under drought conditions, so it is important to account for changes in the proportion of irrigated land per hectare over time when estimating irrigated crop production function (Ward *et al*., 2014). Labor is also a key determinant of the agricultural production function. We employ the regional agricultural labor data drawn from the HCP database to account for this factor in our production function specifications.

Finally, meteorological data at the regional level, including average monthly temperature and total monthly precipitation, are gridded data extracted from the Global Climate Monitor (GCMon) Web Viewer database. This tool, which is both a data model and a visualization platform, provides access to global climate data (Camarillo-Naranjo *et al*., 2019). The data available are based on the CRU TS3.21 version of the University of East Anglia Climate Research Unit database, covering the period from January 1901 to December 2012, with a spatial resolution of half a degree in latitude and longitude (Harris *et al*., 2014; 2020). From January 2013 until the present, data supplying the GCMon system have come from the Global Precipitation Climatology Centre (GPCC) for precipitation (Fan and Van den Dool, 2008), and the Global Historical Climatology Network-Monthly (GHCN-M) version 3.2.1 for global mean temperature (Ziese *et al*., 2011). The collected monthly weather data were then used to aggregate the annual weather variables (mean temperature and total cumulative precipitation), to account for the effects of weather fluctuations at the specific periods of the year when climate is critical to the growth of rain-fed crops. Indeed, according to Blanc and Reilly (2017) the use of variables from specific periods of the year in the estimates makes it possible to capture discrete parts of the response function. For this reason, and using information on the normal agricultural growth cycle in Morocco by year provided by Balaghi *et al*. (2008),

[1] *Annuaire Statistique des Régions from 1999 to 2019*, available at the library of HCP.

Table 1 - Descriptive statistics.

Statistic	*Notation*	*N*	*Mean*	*St. Dev.*	*Min*	*Max*
Log_Rainfed_Cereals	LogRainf_Cer	210	17.338	3.515	5.132	21.298
Log_Irrigated_Cereals	LogIrrg_Cer	210	15.876	2.650	2.322	19.004
Log_Rainfed_Rosaceous	LogRainf_Ros	210	13.755	2.426	7.622	17.462
Log_Irrigated_Rosaceous	LogIrrg_Ros	210	16.572	2.365	7.868	19.865
Log_Rainfed_Market_Gardening	LogRainf_MarkG	210	14.238	2.486	4.907	18.378
Log_Irrigated_Market_Gardening	LogIrrg_MarkG	210	18.664	1.640	13.694	20.906
Log_Labor	Loglabor	210	18.430	1.123	15.009	19.692
Log_Land	LogLand	210	17.675	2.696	9.155	20.341
Log_Livestock	LogLivestock	210	6.752	1.647	0.848	8.583
Log_Mean_Temperature	LogTmean	210	3.782	0.233	2.911	4.147
Log_Total_precipitation	LogRainf	210	10.194	0.981	7.460	12.563

we calculated the weather variables for the growing season for each of the three crops examined in our case study[2].

However, since irrigation is technically practiced throughout the year, we aggregate the meteorological variables annually (from January to December) without taking into consideration the growing seasons of the irrigated crops. Table 1 presents the descriptive statistics of our economic data.

4.3. *Exploratory Spatial Analysis*

This section examines the spatial dimension of agricultural production and climate variability in Morocco through spatial autocorrelation analysis. Building on the global spatial correlation identified by Moran's I (4.3.1), we utilize the Local Indicator of Spatial Association (LISA) to explore the localized patterns of crop production and meteorological variable clustering (4.3.2).

4.3.1. *Exploring Spatial Dependence: Evidence from Moran's I Statistic*

The spatial dimension of the geographic location of agricultural production and meteorological variables can be further explored using global correlation statistics, such as the Moran's I test, which identifies spatial correlation between Moroccan regions. This test, first introduced by Moran (1948), determines whether regions with similar values for agricultural production and meteorological variables tend to cluster together spatially.

The Moran's I statistic is defined as follows:

$$I_W = \frac{n}{\sum_i \sum_j W_{ij}} . \frac{\sum_i \sum_j W_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_i (y_i - \overline{y})^2} \quad (6)$$

Table 2 presents the results of Moran's I test, its standard deviations (Sd(I)) and p-value, allowing for assessment of the significance of its results for agricultural production and meteorological variables. Moran's I statistic is calculated using the neighborhood matrix W and the values of the variable under study. To analyze the spatial relationships between the data, we employed spatial weight matrices, which represent the neighborhood relationships between data points. Inspired by the work of Le Gallo and Ndiaye (2021), these matrices are commonly used in spatial econometrics and allow for quantifying the influence of neighboring points on a given point. We consid-

[2] According to Balaghi *et al*. (2008), the cropping-practices are adapted to the bimodal rainfall distribution in the country. The first peak in autumn–winter fills the soil moisture reserves and allows the establishment of the crop. The second peak in the spring months is used for dry matter accumulation. Sowing takes place between September and December, depending on the precocity of first precipitations in autumn. Harvest starts around June in the South and continues until July for the Northern regions, as temperatures rise first in the South.

Table 2 - Global spatial correlation test Moran's I.

Variables	*Moran's I statistic*	*Standard deviation*	*p-value*
Rainfed Crops			
Log_Rainfed_Cereals	0.269***	3.385	0.00035
Log_Rainfed_Market_Gardening	0.241**	2.0859	0.01849
Log_Rainfed_Rosaceous	0.318***	1.5486	$6.002e^{-05}$
Irrigated Crops			
Log_Irrigated_Cereals	0.225***	2.9762	0.0014
Log_Irrigated_Market_Gardening	0.257**	2.1866	0.0143
Log_Irrigated_Rosaceous	0.157***	2.3386	0.0096
Meteorological Variables			
Average Precipitation	0.434***	3.296	0.00049
Average Temperature	0.306***	2.4901	0.0063

ered three types of matrices: a Gabriel's neighbor-based adjacency matrix (W_{cont}), a 5-nearest neighbor matrix (W_{nn5}), and an inverse distance matrix ($W_{dinverse}$). Graphical representations of these matrices are provided in Figures 6, 7, and 8 of Appendix A.

Since we are using gridded meteorological data which can lead to spatial correlation resulting in significant impacts between neighboring regions (Auffhammer *et al.*, 2013), we only present here the results associated with the $W_{dinverse}$ matrix, as it has the strongest explanatory power and promotes the most intuitive economic interpretation. The Moran's I test reveals a significant positive spatial autocorrelation for all agricultural crops, both rainfed and irrigated. This indicates that agricultural production in Morocco exhibits a strong spatial correlation, with regions of high or low agricultural production tending to cluster together. Furthermore, a significant positive spatial autocorrelation is found for both temperature and precipitation, confirming the spatial variability of Morocco's climate. This correlation can be attributed to various factors, including land quality suitability for specific crops, shared climatic characteristics with neighboring regions, effective farmer organization, and economies of scale.

4.3.2. *Spatial Clustering Analysis: Evidence from LISA*

While Moran's I test effectively identifies global spatial autocorrelation, its limitation lies in its inability to provide insight into the local structure of this correlation. As Anselin (1995) points out, Moran's I test offers a global perspective, neglecting to reveal the intricacies of localized spatial dependencies. To overcome this limitation, we employ the Local Indicator of Spatial Association (LISA) a technique that goes beyond global analysis.

The most commonly used LISA is the local Moran's I, defined as follows:

$$I_i = (y_i - \overline{y}) \sum_j W_{ij}(y_j - \overline{y}) \tag{7}$$

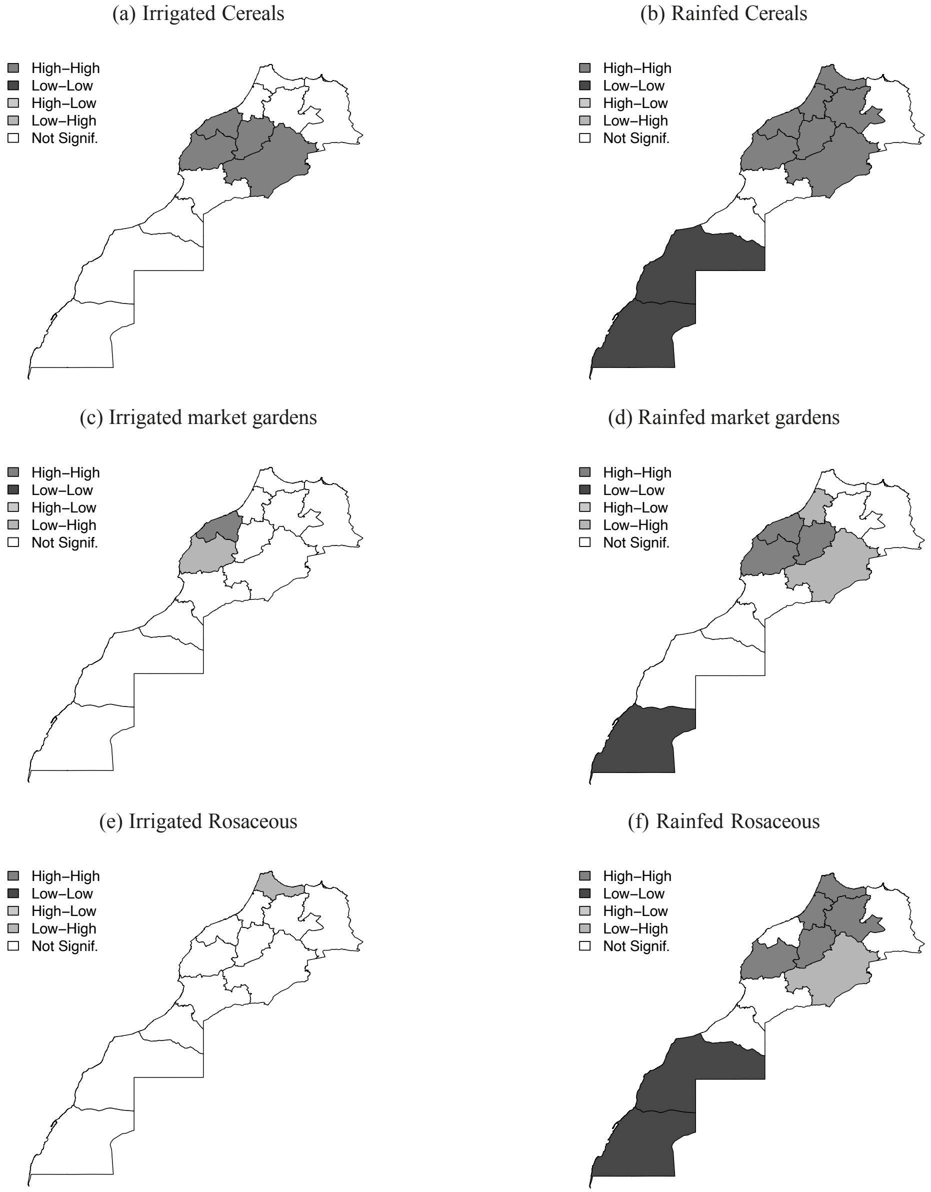
LISA pinpoints significant clusters of similar values surrounding a specific location and also identifies areas of spatial non-stationarity (Anselin, 1995), which deviate from the overall global pattern. In our case study, LISA allows us to discern four distinct scenarios:

- *HH*: a *H*igh production region is surrounded by other *H*igh-production regions
- *LL*: a *L*ow production region is surrounded by other *L*ow-production regions
- *HL*: a *H*igh production region is surrounded by *L*ow-production regions
- *LH*: a *L*ow production region is surrounded by *H*igh-production regions

In the first two cases (*HH* and *LL*), local autocorrelation is positive while in the other cases (*HL* and *LH*), local correlation is negative.

Figure 3 provides spatial clustering patterns corresponding to the LISA index of each agricultural production for the three rain-fed and irrigated crops respectively. The local test, using

Figure 3 - Spatial clustering patterns of irrigated and rainfed crops using LISA in Moroccan regions (1999-2019).



HH, *HL* indicate *H*igh production patterns with *H*igh and *L*ow clustering characteristics; *LL*, *LH* indicate *L*ow production patterns with *L*ow and *H*igh clustering characteristics, respectively. *Not Signif.* indicates no clustering significance.

the LISA index, reveals a positive local spatial autocorrelation for both irrigated and rainfed cereals (Figures 3a and 3b below). This means that regions with high cereal production tend to be surrounded by other regions with high production levels, which corresponds to the *HH* scenario identified by LISA. In other words, we observe a spatial clustering in the northern regions of Morocco, which exhibit high cereal production, in contrast to the southern regions that display a negative

Figure 4 - Spatial patterns of average precipitation and temperature in Morocco (1999-2019).

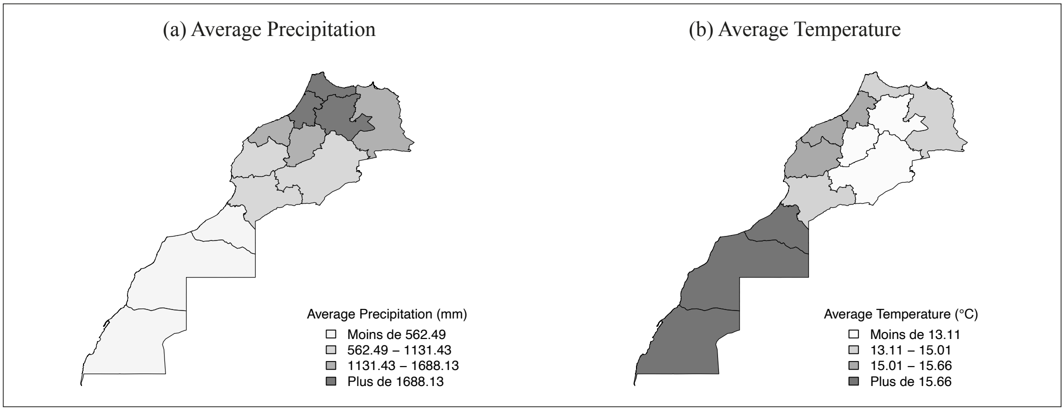
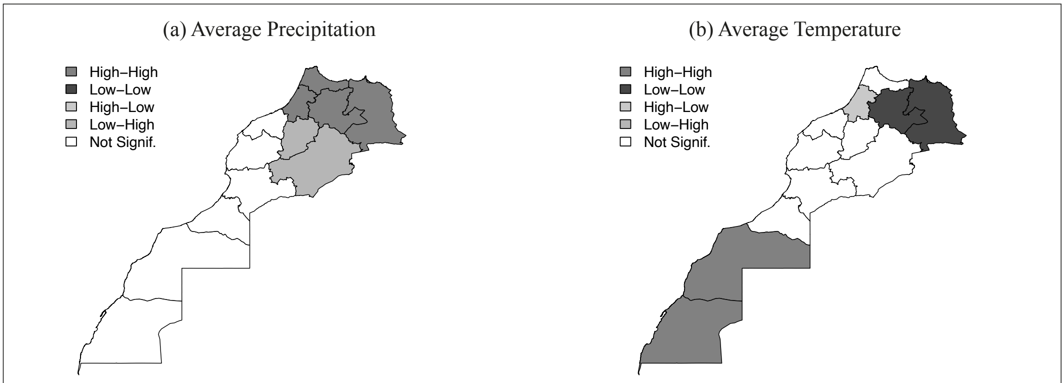


Figure 5 - Spatial Clustering Patterns of average precipitation and temperature using LISA in Moroccan Regions (1999-2019).



HH, HL indicate *H*igh production patterns with *H*igh and *L*ow clustering characteristics; *LL, LH* indicate *L*ow production patterns with *L*ow and *H*igh clustering characteristics, respectively. *Not Signif* indicates no clustering significance.

local spatial autocorrelation. The latter indicates a spatial clustering of regions with low cereal production, which tend to be surrounded by other regions with low production. This result confirms the idea that favorable conditions for cereal production, such as water availability, irrigation infrastructure, and suitable agricultural practices, are concentrated in the northern regions of the country.

The same observation is made for market gardening and rosaceous crops (Figures 3c, 3d, 3e and 3f), but with a less marked intensity than for cereals.

This means that there is a significant spatial clustering in the northern regions, where market gardening and rosaceous crops show high production. These regions tend to be surrounded by other regions with high production of the same crops, which corresponds to the *HH* scenario identified by LISA. However, there are also regions with low production of these crops that tend to be surrounded by other regions with high production, which corresponds to the *LH* scenario identified by LISA. If we take, for example, rainfed market gardening (Figure 3d), we find that the regions "Casablanca-Settat, Marrakech-Safi and Béni Mellal-Khénifra" exhibit high production of rainfed market gardening and tend to be surrounded by other regions with high production of rainfed market gardening. In contrast, the

"Drâa-Tafilalet" region is a region with low production of rainfed market gardening, and it tends to be surrounded by other regions with high production of rainfed market gardening.

However, for irrigated rosaceous crops (Figure 3e), the local test reveals a negative spatial autocorrelation. This means that regions with low production of irrigated rosaceous crops are surrounded by regions with high production of irrigated rosaceous crops, which corresponds to the *LH* scenario identified by LISA. This particular spatial dynamic could be explained by the influence of specific restrictive conditions associated with these crops, such as water availability for rainfed market gardening or temperature and light requirements for irrigated rosaceous crops. Moreover, market pressures and competition could also play a role, with low-producing regions potentially facing challenges in market access and profitability, while high-producing regions benefit from organizational advantages and expertise.

The geographic concentration of crops in northern Morocco is primarily driven by a well-defined climatic boundary separating a wetter north from a drier south. Figure 4 above illustrates the spatial clustering patterns corresponding to the LISA index of temperature and precipitation variables, respectively. This climatic boundary is evident in the spatial variability of precipitation, which is more pronounced in the north (Figure 4a). In contrast, the south is characterized by an arid climate (Figure 4b). Spatial analysis confirms this climatic variability. The Moran's I test reveals a significant positive spatial autocorrelation for both temperature and precipitation (Table 2), which is further supported by the local LISA test (Figure 5b and 5a). Regions in the south with high average temperatures tend to be surrounded by other regions with similar high temperatures (*HH* scenario), while the opposite is true for precipitation in the north. This positive local spatial autocorrelation for temperature in the south and precipitation in the north highlights the climatic differences that explain the concentration of crops in the north. Indeed, according to Ezzine *et al*. (2017) the northern part of Morocco is characterized by a sub-humid Mediterranean-type climate, with an average annual rainfall of 1200 mm, which is favorable for agriculture, while, the southern part is characterized by a Saharan (dry) climate, with average annual rainfall of less than 100 mm, which is not suitable for agricultural production. This diversity is due to the combination of several factors, namely its latitudinal location, the influence of the Atlantic Ocean and the Mediterranean Sea, and the influence of elevation through Atlas and Rif mountains (Ezzine *et al*., 2017). The northern regions benefit from several favorable conditions for the development of agricultural production. Indeed, in the Tangier-Tetouan-Al-Hoceima region, for example, the useful agricultural area represents nearly 38% of the total area. Thus this region, thanks to the large hydraulic basin of Loukkous, is endowed with a significant irrigated agricultural perimeter, whose proportion of irrigated land represents 10% of the Tangier-Tetouan region and 6% of the Taza-Al Hoceima-Taounate[3] region. These physical characteristics combined with the Mediterranean-type climate and oceanic influence, with a rainy season that lasts from October to March, are favorable to the production of this type of crops and explain why the northern regions, with high production of such crops, are surrounded by similar region with high production.

5. Estimation Results and Discussions

This section presents the results of estimating the impact of climate variability on agricultural production across 12 Moroccan regions (5.1). We then delve into a comprehensive discussion of these results, exploring their implications and highlighting the limitations of our study (5.2).

5.1. *Interpreting Estimation Results*

This section delves into a detailed interpretation of the estimation results, examining the influence of both climatic and economic factors on agricultural production in Morocco. We begin by discussing the specification tests and model selection

[3] http://www.apdn.ma/index.php?option=com_content&view=article&id=233&Itemid=227&lang=fr.

process employed to ensure the robustness and validity of our findings. Subsequently, we analyze the impact of climatic variables, particularly temperature and precipitation, on the production of both rainfed and irrigated crops, emphasizing the significance of spatial autocorrelation in shaping these effects. We then explore the role of economic variables, including labor, capital, and land area, in influencing agricultural production and reveal any disparities across different crop types

5.1.1. *Specification Tests and Selection of the Appropriate Model*

Following the practical bottom-up approach, we begin our specification with a non-spatial ordinary least squares (OLS) regression model as a reference (Elhorst, 2003). We performed a few specification tests tailored to the spatial panel data shown in Table 3 below. First, we used the classical Lagrange Multiplier (LM) and Robust Lagrange Multiplier (RLM) tests applied on the

Table 3 - Pooled OLS estimation and tests for spatial autocorrelation.

	Dependent variable					
	LogRainf_Cer (1)	*LogIrrg_Cer* (2)	*LogRainf_Ros* (3)	*LogIrrg_Ros* (4)	*LogRainf_MarkG* (5)	*LogIrrg_MarkG* (6)
LogLabor	−1.275*** (0.375)	0.059 (0.389)	−0.019 (0.393)	−0.056 (0.420)	−0.689 (0.565)	1.167*** (0.241)
LogLand	1.054*** (0.080)	0.085 (0.083)	0.364*** (0.084)	0.077 (0.090)	−0.033 (0.121)	0.037 (0.052)
LogLivestock	1.013*** (0.306)	1.206*** (0.317)	0.201 (0.320)	0.865** (0.342)	1.117** (0.460)	−0.065 (0.196)
LogTmean	−0.928* (0.550)	−2.355*** (0.571)	3.059*** (0.576)	−4.045*** (0.616)	1.851** (0.829)	1.240*** (0.353)
LogRainf	0.231* (0.125)	−0.291** (0.130)	0.588*** (0.131)	−0.244* (0.140)	0.292 (0.189)	0.091 (0.081)
Constant	16.529*** (5.251)	17.013*** (5.444)	−11.247** (5.495)	28.192*** (5.874)	10.009 (7.910)	−8.669** (3.370)
Observations	210	210	210	210	210	210
R^2	0.835	0.689	0.621	0.545	0.253	0.689
Adjusted R^2	0.831	0.681	0.612	0.534	0.234	0.681
F Statistic (df = 5; 204)	206.876***	90.198***	66.985***	48.842***	13.799***	90.208***
Hausman test:	14.697**	9.608*	749.47***	17.482***	16.064***	14.378**
Spatial test	*Tests for spatial dependence on residuals*					
LM test: lml	0.626	15.219***	6.022**	0.956	3.590**	52.266***
LM test: lme	20.33***	3.962**	7.492***	25.907***	3.485*	2.108
RLM test: Rlml	2.987*	23.3***	14.702***	1.134	10.248***	55.349***
RLM test: Rlme	22.691***	12.044***	16.173***	26.085***	10.143***	5.191**
Spatial Hausman test:	10.847**	12.345**	14.136**	16.274***	19.402***	23.188***

*Note: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.*

error terms (LM_{ρ}) and spatial lags (LM_{δ}) to decide between the SEM, SAR, and the non-spatial model (Anselin *et al*., 1996). Generally, these tests reject the hypothesis of no spatial correlation for the error terms and spatial offsets.

Indeed, the classical LME_{ρ} and $RLME_{\rho}$ tests showed that the null hypothesis of no spatially auto-correlated error term is strongly rejected at the 1% and 5% significance level while suggesting that the SEM specification is the most appropriate for all the crops studied. Next, the spatial Hausman test (SHT) was used to test the effectiveness of the spatial random effects estimator. The coefficients related to the SHT test were highly significant and showed that the fixed effect model is the most appropriate. Finally, all of these tests suggested that the specification that considers both spatial error autocorrelation and individual heterogeneity in a fixed-effect model (FE-SEM) is the most appropriate for our case study.

5.1.2. *Impact of Climate Variability on Agricultural Production*

The results of the FE-SEM model estimation for rainfed and irrigated crops are presented in Table 4. Moreover, for robustness, the results of the SAR estimator are also presented in Table 5 in Appendix B. Examining the coefficients of the meteorological variables in the FE-SEM model, we observe a more significant impact of meteorological variables on agricultural production in Morocco. Furthermore, the FE-SEM model demonstrates that cereal production is highly sensitive to temperature and precipitation. Indeed, the temperature coefficients exhibit a negative sign on the production of this crop. These coefficients indicate that, ceteris paribus, a 1% change in temperature generates a decrease of 1.149% and 2.469% in rainfed and irrigated production, respectively. The negative sign of the temperature variable coefficients is not surprising and signifies that high temperatures have detrimental effects on cereal production in Morocco. It is noteworthy that this sector still occupies nearly 60% of the total useful agricultural area, of which 90% is cultivated in rainfed areas (Ministry of Economy, 2019). This concentration of cereals, particularly in unfavorable rainfed areas, makes it more vulnerable to climatic hazards, explaining the negative sign of the temperature coefficient. Consequently, this vulnerability will persist.

Regarding precipitation coefficients, they exhibit a positive sign for rainfed production and a negative sign for irrigated production. These

Table 4 - Estimation results of spatial error model (SEM).

	Dependent variables					
	LogRainf_ Cer	*LogIrrg_Cer*	*LogRainf_ Ros*	*LogIrrg_Ros*	*LogRainf_ MarkG*	*LogIrrg_ MarkG*
LogLabor	−0.232*	1.330***	−1.030***	2.080***	−0.182	0.591***
	(0.067)	(0.135)	(0.258)	(0.285)	(0.195)	(0.170)
LogLand	1.011***	0.180***	0.339***	−0.119	−0.070	0.044
	(0.068)	(0.069)	(0.077)	(0.082)	(0.104)	(0.050)
LogLivestock	0.257	0.352**	0.728***	−0.359	0.761***	0.2952*
	(0.157)	(0.178)	(0.249)	(0.253)	(0.251)	(0.161)
LogTmean	−1.149**	−2.469***	2.911***	−4.346***	2.505***	1.208*
	(0.487)	(0.535)	(1.063)	(1.081)	(0.764)	(0.671)
LogRainf	0.578***	−0.434***	0.866***	0.064	0.376**	−0.002
	(0.117)	(0.123)	(0.149)	(0.143)	(0.182)	(0.101)
ρ	−0.257***	−0.593***	−0.368***	−0.266***	−0.255***	−0.193**
	(0.092)	(0.093)	(0.089)	(0.062)	(0.091)	(0.092)
Observations	210	210	210	210	210	210

*Note: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.*

coefficients indicate that, ceteris paribus, a 1% change in precipitation generates an increase of 0.578% in rainfed production and a decrease of 0.434% in irrigated production, suggesting low efficiency of irrigation techniques. This inefficiency is partly linked to the issue of water reallocation. While drip irrigation is considered an efficient technology, it does not guarantee water savings at the watershed level, as it can affect return flows and therefore water availability for other users. Climate change, by accentuating the decrease in precipitation and increasing evaporation, risks exacerbating this situation, creating increased competition for water and enhancing the risk of groundwater overexploitation. This overexploitation aggravates inequalities in access to groundwater, as more affluent farmers can continue to irrigate while others are forced to reduce or abandon their production. Furthermore, the lowering of groundwater levels makes drilling more expensive and pumps less efficient, reducing farmers' profitability.

The results for irrigated rosaceous crops are not significantly different concerning climatic variables. For instance, irrigated rosaceous crop production is highly sensitive to temperature, showing a negative coefficient indicating that, ceteris paribus, each 1% increase in temperature causes a decrease of 4.346% in irrigated rosaceous crop production. Conversely, the coefficient for the precipitation variable is not significant. This result highlights that irrigated rosaceous crops are more sensitive to thermal conditions than to precipitation. Temperature directly affects crop growth and development, and a rise in temperatures can lead to water stress, decreased pollination, and an increase in diseases and pests. Moreover, a rise in temperatures causes an increase in plant transpiration as they seek to cool themselves by releasing water as vapor (Molle and Tanouti, 2017). Drip irrigation, while optimizing water input, is not always sufficient to compensate for this increase in transpiration, especially under water stress conditions. The dependence of these crops on irrigation therefore makes them more vulnerable to temperature variations, as water availability is insufficient to offset negative effects, particularly increased transpiration (Molle and Tanouti, 2017).

On the other hand, the FE-SEM model shows that rainfed rosaceous crop production and market gardening (rainfed and irrigated) are less vulnerable to climate change. Indeed, the coefficients of the "temperature" variable exhibit a positive sign for the agricultural production of these crops. The positive sign indicates that, ceteris paribus, each 1% increase in temperature generates an increase of 2.911%, 2.505%, and 1.208% in the agricultural production of rainfed rosaceous crops and market gardening (rainfed and irrigated), respectively. This result can be explained by the fact that the positive effect of the temperature variable coefficient depends on other parameters specific to the crop and its environment, and that higher temperatures during the growing season could have a positive effect on the growth of certain crops. This suggests that these crops thrive in warm weather conditions and are therefore not highly sensitive to global warming.

This result is partially explained by the adaptation of crops and agricultural practices following the GMP. This program has encouraged the adoption of more resistant and profitable crops, such as rosaceous crops and market gardening, and has promoted the use of drip irrigation. Drip irrigation can contribute to crop growth despite higher temperatures by ensuring optimal water supply. Additionally, rainfed rosaceous crops and rainfed market gardening naturally benefit from a certain resilience to the semi-arid climatic conditions of Morocco. However, it is important to highlight that groundwater overexploitation and rising temperatures can eventually negatively affect these crops. It is crucial to continue research and monitor the evolution of these crops in the face of climate variability to anticipate risks and adapt agricultural practices.

5.1.3. *Spatial Error Autocorrelation and Spillover Effects*

The spatial error autocorrelation coefficient, ρ, is negative and highly significant for all agricultural productions, indicating the presence of spillover effects between Moroccan regions. This result supports the argument that unobserved factors are spatially correlated, even after controlling for factors such as weather and agricultural inputs. These unobserved factors include insufficient cohesion of agricultural public policies at the regional level, creating disparities. The GMP has had a significant impact on Moroccan agriculture by encouraging drip irrigation and easing access to land. However, this policy, while aiming to modernize and develop agriculture, has generated significant negative effects on water resource management. Take the example of the Gharb region. The GMP has facilitated access to land owned by the state and the privatization of collective lands, attracting investors eager to develop intensive agricultural projects based on drip irrigation. At the same time, generous subsidies offered for drip irrigation have encouraged many farmers to exploit wells without authorization, increasing pressure on groundwater and exacerbating the overexploitation of the Gharb aquifer. This situation highlights a crucial problem of the impact of agricultural policies favorable to one region on neighboring regions. Indeed, the concentration of investments and subsidies in the Gharb has led to increased competition for water resources, negatively affecting neighboring regions such as Loukkos and Doukkala. These regions, already facing problems of groundwater overexploitation, are seeing their situation deteriorate due to the decrease in return flows in aquifers, originating from areas where drip irrigation is practiced intensively.

Furthermore, poor farmer organization can exclude smallholders, who lack resources and have unequal access to markets and modern agricultural adaptation technologies. Certain unsustainable agricultural practices, such as overgrazing and deforestation, contribute to soil erosion and fertility loss. Moreover, excessive use of inputs, such as pesticides and fertilizers, exacerbates these problems. Furthermore, monoculture (cereals) over vast areas reduces plant biodiversity, while excessive irrigation and lack of drainage lead to soil salinization. Recurrent periods of drought put significant pressure on groundwater resources, making Moroccan agriculture more vulnerable to climate change. In other words, spatial error autocorrelation implies the possible presence of measurement errors that tend to propagate across aggregation unit boundaries, omitted variables, or unobserved shocks following a spatial pattern. Moreover, the existence of spatial autocorrelation could be explained by the different data scales and the aggregation process.

5.1.4. *Impact of Economic Variables on Agricultural Production*

Concerning economic variables, capital and labor factors have a statistically significant impact on Moroccan agricultural production. The FE-SEM model shows that regional agricultural production is highly dependent on agricultural labor in Morocco. Indeed, the coefficients of this production factor exhibit a positive sign indicating that, ceteris paribus, each 1% increase in agricultural labor generates an increase of 1.330%, 2.080%, and 0.591% in the production of cereal, rosaceous, and irrigated market gardening, respectively. Unexpectedly, however, labor seems to have a detrimental effect on some rainfed crops. Indeed, ceteris paribus, each 1% increase in agricultural labor generates a decrease of 0.232% and 1.030% in the production of rainfed cereals and rosaceous crops, respectively. This result appears unexpected at first glance.

The unexpected impact of labor on the production of some rainfed crops can be explained by several factors. First, the structure of agricultural employment in Morocco is dominated by self-employed workers and family businesses, often involving unpaid and unskilled labor. This situation is reinforced by the fact that the agricultural sector faces an aging workforce, with a gradual decline in the working-age population in rural areas. Moreover, the harvest of these crops requires specific skills that workers do not always possess, leading to low productivity. Finally, the use of inadequate or poor-quality tools contributes to a decrease in production. It is therefore crucial to invest in worker training and improve the quality of tools used to increase labor productivity in the agricultural sector. The model predicts a significant positive impact for livestock (Draught animals), indicating that, ceteris paribus, each 1% increase in this production factor generates an increase of 0.352%, 0.728%, 0.761%, and 0.295% in the production of irrigated cereals, rainfed rosaceous crops, and rainfed market gardening and irrigated market gardening, respectively. This demonstrates the crucial role of livestock in agriculture, explaining its traditional aspect in Moroccan regions. While for irrigated rosaceous crops, the model predicts a negative but non-significant impact for livestock, indicating that, ceteris paribus, each 1% increase in this production factor generates a decrease of 0.359% in irrigated rosaceous crop production. Several factors can explain this negative impact. First, the trampling of livestock can compact the soil, reducing water infiltration and increasing runoff. This can create waterlogged conditions around the roots of rosaceous crops, promoting the development of diseases and rot. Moreover, soil compaction can degrade its structure, making rosaceous crops more vulnerable to erosion and water stress. Second, while animal manure provides nutrients to the soil, compaction can limit their availability for rosaceous crops. Excessive manure can also create a nutrient imbalance, increasing competition between rosaceous crops and other plant species, and promoting the development of diseases. Finally, animal manure can contaminate irrigation water, impacting water quality and the health of rosaceous crops.

As for the contribution of the total useful agricultural area of Morocco, it has a positive impact, showing that, ceteris paribus, each 1% increase in this factor implies an increase of 1.011%, 0.180%, and 0.339% in the agricultural production of rainfed cereals, irrigated cereals and rainfed rosaceous crops, respectively. This result is explained by the policies of the GMP, which aimed to stimulate agricultural production by promoting the expansion of cultivated areas. The GMP has facilitated access to land, particularly by encouraging the privatization of collective lands and allowing the purchase of public lands, thus attracting investors eager to develop intensive agricultural projects. Cereals and rosaceous crops, being important crops in Morocco, have benefited from this expansion of cultivated areas. On the other hand, this result can be explained by the use of new technologies, selected seeds, and fertilizers, as well as the cultivation of virgin and fertile land such as forested areas and pastures, in addition to the cultivation of certain species intended for rainfed production in irrigated areas, such as cereals (Oulhaj *et al*., 2013). This expansion is directly linked to the adoption of drip irrigation, and the National Program for Irrigation Water Savings (PNEEI) has played a crucial role in this process. The ambitious goal of converting 550,000 hectares of gravity or sprinkler-irrigated land to drip irrigation in 15 years, accompanied by massive subsidies and technical support, has accelerated the transformation of Moroccan irrigated agriculture.

However, the coefficients for market gardening (rainfed and irrigated) and irrigated rosaceous crops are not significant. This result can be explained by several factors related to the adoption of drip irrigation. First, drip irrigation, while allowing for better water use, does not necessarily translate into a reduction in the amount of water consumed at the field level. Indeed, crop intensification, increased tree density, and the adoption of more water-demanding crops, often associated with this technology, can offset water savings achieved. Second, field evapotranspiration is not always affected by drip irrigation. The reduction of soil evaporation may be limited, and the increase in crop transpiration due to more frequent irrigation may even lead to an overall increase in evapotranspiration. Finally, the expansion of vegetable cultivation towards rainfed areas, where water remains the main limiting factor, can also play a role. Indeed, the area dedicated to early market gardening, an essential component of market gardening, has increased by 42% between 2003-2007 and 2019, reaching 40,000 hectares. Vegetable cultivation is mainly concentrated in the regions of Souss-Massa, Rabat-Salé-Kénitra, Casablanca-Settat, and Tangier-Tetouan-Al Hoceima. Access to water in these regions is often a major obstacle, explaining why an increase in area is not always synonymous with an increase in production.

5.2. *Discussion of Results*

This section delves deeper into the discussion of our study's findings, analyzing the key factors that determine agricultural production in Morocco. We begin by examining the spatial interdependence of agricultural production, highlighting the presence of significant spillover effects between Moroccan regions (5.2.1). Next, we explore the sensitivity of different crops to climate variability (5.2.2). Subsequently, we examine the role of production factors and explore their impacts (5.2.3). Finally, we discuss the limitations of our study and identify avenues for future research (5.2.4).

5.2.1. *Spatial Interdependence and Spillover Effects*

Our findings highlight the presence of strong spatial interdependencies within the Moroccan agricultural sector, suggesting the need to consider spatial spillover effects when analyzing the impact of climate variability on agricultural production in Morocco. Indeed, a geographical concentration of agricultural production in the northern regions, confirmed by positive spatial autocorrelation (Moran's I test) and the use of a FE-SEM model, which accounts for both spatial error autocorrelation and heterogeneity between regions, shows that integrating the spatial dimension into econometric models and considering unobserved factors and regional disparities are crucial for a complete understanding of the Moroccan agricultural sector and for developing more relevant policies. These conclusions are consistent with those obtained by other researchers (Chen *et al*., 2016; Karahasan and Pinar, 2023; Schlenker *et al*., 2006; Vaitkeviciute *et al*., 2019). For example, Chen *et al*. (2016) analyzed the impact of climate variability on agriculture in China using a spatial panel data model on crop yields, planted areas of major crops (corn and soybeans), and meteorological data for the years 2000 to 2009. Chen *et al*. (2016) showed that the presence of spatial correlation between counties can be explained by the existence of several factors, such as agricultural policies, production practices, and local characteristics, that have influenced yields similarly in neighboring counties.

More recently, Karahasan and Pinar (2023) analyzed the impact of climate change on the spatial distribution of agricultural production in Turkey between 2004 and 2019, using fixed-effects panel models while taking spatial aspects into account (SAR and SEM models). Karahasan and Pinar (2023) showed that including spatial effects significantly improves the understanding of agricultural dynamics, highlighting the spatial heterogeneity of the impact between regions. Indeed, their results indicated that climate change has a variable effect depending on the region, with a greater impact in the northern and central areas dominated by agriculture. This finding highlights the inefficiency of "one-size-fits-all" policies in mitigating the negative effects of climate change in topographies exhibiting significant spatial dissimilarities. Thus, they suggested that climate change will significantly threaten the evolution of agricultural activities essential to regional development. Moreover, Karahasan and Pinar (2023) demonstrated that spatial spillover effects and heterogeneity will be crucial for designing climate change policies for rural and agricultural development. Therefore, local model analysis is essential for understanding these regional variations and implementing targeted and effective solutions.

5.2.2. *Sensitivity of Different Crops to Climate Variability*

The FE-SEM model highlights the high sensitivity of rainfed cereal production to temperature variations. These results align with the findings of several studies that shed light on the challenges associated with climate change and water resource management. Simulation studies on the evolution of agricultural yields by Balaghi *et al*. (2016) have indeed shown that climate change will affect wheat and barley, which could experience a projected yield decrease of over 50% in many provinces by 2050. In light of these challenges, the approach employed by the CALESA project (Developing Promising Strategies Using Analogue Sites in Eastern and Southern Africa) proves particularly relevant (Leal Filho and Mannke, 2011). This project, conducted in sub-Saharan Africa, where, like Morocco, nearly 90% of basic food production comes from small rainfed agricultural systems, offers an innovative approach to agricultural adaptation to climate change. Using analogue sites, defined as areas exhibiting the projected future climate conditions, the project has successfully identified promising adaptation strategies for rainfed agriculture in semi-arid and subhumid areas. Ex ante analyses coupled with field research have enabled the evaluation of the effectiveness of these strategies under real conditions, providing tangible solutions for farmers grappling with the challenges of climate change (Leal Filho and Mannke, 2011). The lessons learned from the CALESA project present significant potential for Morocco, particularly in terms of developing adaptation strategies for future climate conditions and strengthening the resilience of agricultural systems against droughts and extreme temperatures.

Irrigated cereal and rosaceous crops are extremely vulnerable to climate variability, as they have experienced a significant decrease in production due to variations in temperature and precipitation. According to Abdelmajid *et al*. (2021), this decrease is explained by the increase in groundwater pumping and the risk of aquifer salinization. Additionally, the High Commission for Water, Forests, and the Fight Against Desertification estimates that soil salinization in Morocco affects almost all major irrigated areas. Oulhaj *et al.* (2013) estimate that 22,000 hectares of irrigated land in the provinces of Zagora and Errachidia are affected by salinization, which combines its effects with those of wind erosion. Thus, Fader *et al.* (2016) confirmed that Morocco could face difficulties in mitigating precipitation deficits through irrigation due to the projected decrease in water resources. Moreover, Moutawakkil (2009) highlighted that irrigation presents certain management shortcomings: dangerous exploitation of groundwater, alarming degradation of water and soil resources, a pricing system that does not guarantee the balance of recurring water service costs, and a still low water fee recovery rate. Thus, these results can be explained on the one hand by the under-irrigation of nearly 63% of irrigated areas, mainly those based on the gravity irrigation system that uses large amounts of water, especially since a large part is lost through evaporation, and on the other hand, by the low efficiency of irrigation techniques in nearly 50% of irrigated areas (Ministry of Economy, 2019). Moreover, Schyns and Hoekstra (2014) show that evaporation from storage reservoirs is the second most important form of surface or groundwater consumption in Morocco, after irrigated crop production. Thus, the scarcity of surface or groundwater on a monthly basis is severe in all river basins, and pressure on groundwater resources from abstractions and nitrate pollution is considerable in most basins (Schyns and Hoekstra, 2014). This suggests the rationalization of water resources and the adoption of water-saving irrigation techniques, which is a vital option to accompany the climate variability adaptation efforts undertaken as part of the GPM in Morocco. Indeed, Yuan *et al*. (2022) showed that the use of plastic mulch drip irrigation in the mountain-oasis-desert system of northwestern China has positive climate impacts. This technique enables better water use by reducing evaporation losses and providing targeted irrigation to plants. This leads to increased crop productivity and more efficient use of water resources. Moreover, Schyns and Hoekstra (2014) showed that the most significant potential water savings can be achieved through the partial relocation of crops to basins where they consume less water and through the reduction of the water footprint of crops.

Contrary to cereal production, the FE-SEM model indicates that rainfed rosaceous crops and market gardening (both rainfed and irrigated) are less affected by climate change. These results can be explained by the efforts made by policymakers within the framework of the GPM to contain the negative influence of the cereal sector on agricultural growth. Indeed, according to report of Ministry of Economy (2019), the transformation of the agricultural sector structure originates from the reorientation of agricultural strategies, since the early 2000s, towards better adaptation of agricultural production to the agro-climatic context. This evolution was further consolidated within the framework of the GPM, which reinforced support for crops more resilient to climate hazards, such as market gardening and rosaceous crops. For example, land-use projections for the Gharb indicate a shift from 127,000 hectares of cereals to crops such as olives, citrus fruits, fruits, sugar beets, and fodder, which require more water (ABH-Sebou, 2015). Thus, water conservation policies, to combat water shortages and groundwater overexploitation, have led to a significant increase in the drip irrigation conversion rate, from 10,000 hectares per year to 50,000 hectares per year (El Gueddari and Arrifi, 2009). Indeed, this trend is reinforced by the fact that drip irrigation is often integrated into intensification strategies, leading to an increase in plantation density and a conversion to crops requiring more water. Studies conducted in Tadla (Kuper *et al*., 2012), Souss (BRLi et Agroconcept, 2013), Haouz (Molle and Tanouti, 2017), and Saïss (Kuper *et al*., 2017) have confirmed this link between drip irrigation, intensification, and crop diversification, promoting the expansion of market gardening and fruit trees.

5.2.3. *Economic Variables Analysis's and Their Impact on Moroccan Agriculture*

Regarding economic variables, the FE-SEM model analysis reveals a strong dependence of regional agricultural production in Morocco on agricultural labor, with a positive effect observed for irrigated crops and a negative effect observed for rainfed crops. These results align with the findings of other studies, which highlight the strong dependence of farms on labor. Sraïri *et al.* (2018) distinguished two types of situations: small rainfed farms often favor livestock raising, which requires little land and capital but with limited gross margins, which could hinder the sector's attractiveness for younger generations. Large irrigated farms, on the other hand, can diversify their activities towards cash crops (market gardening, fruit trees), which requires increased reliance on external labor, positively impacting production and profitability. However, this dependence on labor faces an underlying trend: the constant decline in agricultural employment since 1991, from 42.98% in 1991 to 32.36% in 2019, with an acceleration of the decline in recent years (Ministry of Economy, 2019). This situation can be partially explained by the demographic evolution of rural areas. According to Harbouze *et al.* (2019), the agricultural sector represented 72.9% of jobs in rural areas in 2016. The working-age population is expected to remain stable and then decline in rural areas until 2030, while the number of people over 65 will increase, which could weigh on the labor force available for agriculture. Moreover, employment in the Moroccan agricultural sector is dominated by self-employed workers or family businesses, with over 85% of them employing no or few employees. Additionally, unpaid employment, consisting of family helpers, accounts for over 50% of agricultural labor, highlighting the informal nature of work in the agricultural sector and the blurred distinction between the family environment and employment. Finally, the harvesting of certain types of crops requires skills that workers do not typically possess, highlighting the need for appropriate training. Furthermore, the use of inappropriate or poor-quality tools can affect production, highlighting the low labor productivity in certain crops and the need to improve tools and worker skills.

Moreover, our FE-SEM model confirms the significant contribution of the capital represented by livestock (or draught animals) and the useful agricultural area of rainfed and irrigated crops to Moroccan agricultural production. The model highlights the importance of livestock for the production of irrigated cereals, rainfed rosaceous crops, and market gardening in Morocco, but suggests a negative but non-significant impact on irrigated rosaceous crops. These results align with other studies conducted in Morocco, such as those by Elhimdy and Chiche (1988) and Bansal *et al.* (1992), which both evaluated the performance of local animal breeds in single and double hitching. These studies highlight the dependence of the performance of livestock on several factors such as age, genetics, diet, health status, and handling during work (Elhimdy and Chiche, 1988). It is important to note that the results of these studies, as well as our FE-SEM model, suggest that the use of livestock can present challenges. For example, the adaptation of smaller and slower animals to faster and larger animals can lead to stress and reduced efficiency (Bansal *et al.*, 1992). This could explain the negative (non-significant) impact observed in our model for irrigated rosaceous crops. Further research could explore the economic and environmental implications of using livestock based on their types and agricultural techniques used, taking into account these key factors that influence their performance.

Regarding the useful agricultural area in Morocco, the FE-SEM model shows a positive impact on the production of cereals and rainfed rosaceous crops but not on market gardening and irrigated rosaceous crops. This result, although seemingly positive, is actually complex and can be explained by several factors. The increase in UAA in Morocco has mainly occurred on marginal lands previously used for livestock or forest (Oulhaj *et al.*, 2013), which has contributed to land degradation and a decrease in yields on these lands brought into cultivation (El Jazouli *et al.*, 2019; Ghanam, 2003; Harbouze *et al.*, 2019; Simonneaux *et al.*, 2015). The low productivity of irrigated crops, despite the increase in UAA, is due to poor water management, deficient production techniques, and farm fragmentation (Kusi *et al.*, 2023; Oulhaj *et al.*, 2013). The majority of farms located on marginal lands practice subsistence agriculture and are highly vulnerable to drought (Harbouze *et al*., 2019). Despite an increase in UAA, Moroccan agriculture faces significant challenges related to land degradation, low yields, and farm fragmentation, highlighting the need for mitigation strategies focused on land and soil conservation, improving production techniques, and consolidating farms.

As for irrigated crops (market gardening and rosaceous), the productivity per hectare of irrigation is low, and the cubic meter (m^3) of water is poorly valued (40% of the area of large irrigation perimeters is cultivated in cereals). The comparison of the productivity level per hectare remains one of the lowest compared to other countries (Oulhaj *et al*., 2013). In addition to this are deficient production techniques, the non-generalized use of selected seeds, and fertilization and phytosanitary treatments that are not always used optimally. Furthermore, this low productivity is due to the predominance of small farms (nearly 70% of UAA has an area of less than 2.1 hectares), which often coexist with large, modern, more productive, and professionally organized farms. This significant fragmentation is the result of the multiplicity of legal regimes governing agricultural land ownership (customary law, Islamic law, and positive law) and inheritance (Oulhaj *et al*., 2013). For its part, Ghanam (2003) highlights that in Morocco, the desertification process affects vast areas (over 90% of the territory) and is all the more pronounced as the climate is arid and the soils are vulnerable to erosion. Simonneaux *et al*. (2015) showed that even though precipitation is expected to decrease by 10% by the end of the 21st century, the change in temporal distribution would induce an increase in erosion of about 5 to 10%, assuming similar precipitation intensities. El Jazouli *et al*. (2019) showed that the annual soil loss varied from 0 to 400 per pixel, with an average of 58, 66, and 142 t/ha/an in 2003, 2013, and 2017, respectively. It is therefore very important for watershed managers to implement mitigation strategies focused on land and soil conservation, including their maintenance. Recent research by El Bakali *et al*. (2023) highlights the crucial role of financial incentives in promoting sustainable agricultural practices. Their systematic review demonstrated that financial incentives, such as subsidies for inputs and conservation practices, have a significant positive impact on the adoption of conservation agriculture (CA). These incentives contribute to improving crop yields and nutritional quality. Furthermore, Toumi *et al*. (2021) studied the influence of good governance on food security in Morocco. Their study revealed that effective governance in the agricultural sector is crucial to ensure access to legumes. However, challenges related to coordination and communication between stakeholders hinder the full realization of its potential.

5.2.4. *Study Limitations and Perspectives*

The analysis of the impact of climate variability on Moroccan agriculture is limited by a lack of accurate and detailed data. The availability of complete long-term historical data, particularly at the regional level, is restricted. This lack of data has forced us to focus on the production function approach developed by Deschênes and Greenstone (2007), which studies the short-term impact of climate variability rather than the long-term impact of climate change on Moroccan agriculture.

Moreover, data on key factors such as agricultural land prices, growing degree days, agricultural technical progress, fertilizer use, and soil fertility are uneven, limiting our ability to isolate their impacts from exogenous shocks, thus complicating a thorough analysis. Furthermore, future projections of temperature and precipitation rely on climate change scenarios developed at the national level, lacking regional specificity. This lack of detailed local data makes it difficult to simulate the impacts of climate change and plan for effective long-term adaptation in the Moroccan agricultural sector. Future research using data over a longer period to analyze the long-term impacts of climate change (Lobell *et al*., 2011; Nelson *et al*., 2010; Tao *et al*., 2006; Zhao *et al*., 2017) would be valuable to better understand and anticipate the challenges and opportunities that the Moroccan agricultural sector will face in the decades to come.

On the other hand, the use of a spatial econometric model based on a Cobb-Douglas function, which is limited by its rigidity of substitution and its specific form, raises questions about its ability to capture the complexity of the agro-climatic system. The limitations of the Cobb-Douglas function, notably its restriction in terms of flexibility, lead us to consider exploring more complex functions, such as the CES or Translog, in future research. While it offers a useful analytical framework for quantifying the effects of key variables, the current model does not capture the complexity of the agro-climatic system in its entirety. For instance, our model does not take into account the direct influence of temperature on water availability in the soil, evapotranspiration, plant growth, and sensitivity to diseases, interactions often exacerbated by periods of water deficit. Future research could explore bio-economic models, integrating explicit biological dynamics and a decision-making process stemming from economic theory, as well as a link between these two elements. These models would allow for a better understanding of the complex interactions between water use, agricultural production, and socioeconomic factors (Lokonon *et al*., 2019; Mouysset, 2023).

Finally, given that climate variability adaptation in agriculture is a complex process, it requires a combination of actions at the farm, market, institutional, and technological levels. Regional-level data masks significant variations at the farm level, which limits our analysis of the implementation of effective adaptation strategies, including crop diversification, water conservation, and access to credit and other resources. Jeder *et al*. (2021) showed, using a bottom-up approach, that socio-economic factors such as education level, land ownership, and membership in agricultural development groups influence farmers' perception and adaptation strategies. Future research could explore the bottom-up approach in the study of effective and sustainable adaptation strategies to climate variability, considering the needs and perspectives of farmers for the internal and external environment of their activities.

6. Conclusion

This paper analyzes the impact of climate variability on agricultural production in Morocco between 1999 and 2019 using a production function approach based on spatial panel data. This study is the first of its kind to employ recent and disaggregated data, both at the regional level (12 Moroccan regions) and by major agricultural products (cereals, market-gardening crops, and rosaceous fruits), as well as by production mode (rain-fed and irrigated). To better understand the impacts of climate variability on Moroccan agriculture and its regional variations, preliminary spatial autocorrelation analyses were conducted. This initial step was followed by an in-depth spatial panel data analysis, enabling the identification of specific climate and agricultural effects on irrigated and rain-fed crops for all three agricultural products. This approach allows for capturing the spatial heterogeneity of climate variability impacts on Moroccan agriculture across regions and crop types.

Spatial clustering analysis, encompassing mapping and both global and local Moran's I tests, reveals a concentration of agricultural production and rainfall in the northern regions of Morocco. The Moran's I tests consistently yielded positive and significant results for all agricultural products, indicating a strong positive spatial autocorrelation. This signifies that regions with high agricultural production are spatially clustered together, with neighboring areas also exhibiting high production levels.

Spatial panel data specifications suggest that a model considering both spatial error autocorrelation and individual heterogeneity in a fixed effects framework (FE-SEM) is most appropriate for this case study. Results from our FE-SEM model show at the regional level that Moroccan agriculture is heavily dependent on the direct effects of temperature and precipitation for all goods considered. Notably, these results confirm that the impact of climate variability on agricultural production differs across crops. Cereal production (rain-fed and irrigated) is highly sensitive to climate variability compared to other rosaceous and market gardening (rain-fed and irrigated). Additionally, these findings confirm that the impact of climate variability on irrigated crops differs from that on rain-fed crops. The latter are less vulnerable to climate change, suggesting limited effectiveness of irrigation techniques. This challenges the efforts made in the context of public agricultural policies (GMP) in Morocco towards climate variability adaptation in irrigation.

Furthermore, spatial analysis offers novel insights. It reveals the significance of explicitly accounting for spatial effects between Moroccan regions. The analysis demonstrates the presence of significant spatial heterogeneity, indicating the existence of unobservable factors that are negatively spatially correlated, even after controlling for variables such as weather and agricultural inputs. These unobservable factors, such as technology, agricultural policies, use of similar production practices, existence of dams, organized farmers, and economies of scale, may contribute to spatial correlation.

In other words, spatial error autocorrelation implies the possibility of measurement errors that tend to spread across aggregation unit boundaries, omitted variables, or unobserved shocks following a spatial pattern. Additionally, the existence of spatial autocorrelation might be explained by varying data scales and the aggregation process.

The findings of this paper raise concerns about the sustainability of agricultural production growth in Morocco and question the interdependencies between food availability and the policies adopted within the GMP framework. To mitigate the impact of climate on agriculture, appropriate measures should be implemented, such as implementing water conservation policies by encouraging investments from the public and private sectors targeting support for smallholder farmers, specializing in high-yielding, water-efficient, and drought-resistant crop varieties. Improving workforce skills and capital efficiency through the promotion of agricultural research and development, and implementing appropriate fiscal and environmental policies, as well as developing regional policies to enhance the benefits of dams and groundwater.

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Appendix A - Spatial-weight matrix

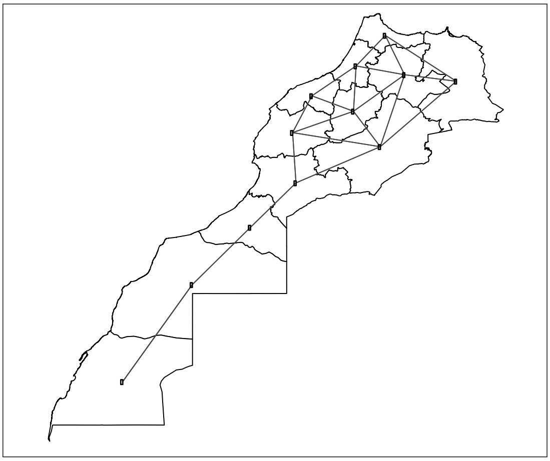

Figure 6 - Gabriel contiguity weight matrix (W_cont)

Figure 7 - Nearest neighbors weight matrix (W_nn5)

Figure 8 - Inverse distance matrix (W_dinverse)

Appendix B - SAR Model's specification and results

Spatial Autoregressive Model (SAR): This model is developed by Anselin *et al*. (2008) and improved by Elhorst *et al*. (2010) to consider directly the spatial dependence of the explained variable on the explanatory variables and the error term for the case of panel data.

$$Y_{it} = \lambda \sum_{j=1}^{N} \omega_{ij} Y_{jt} + X_{it}\beta + \mu_i + \nu_t + \varepsilon_{it}, \quad (8)$$

where Y_{it} is the dependent variable for cross-sectional i at time t (i = 1, ..., N ; t = 1, ..., T). $\sum_{k=1}^{N} \omega_{ik} Y_{kt}$ is the interaction effect of the dependent variable Y_{it} with the dependent variables Y_{it} in neighboring units, where ω_{ik} is the i, jth element of a prespecified non negative $N \times N$ spatial weights matrix W describing the arrangement of the spatial units in the sample, the response parameter of these endogenous interaction effects, and λ: the spatial autoregressive coefficient. X_{it}: $1 \times K$ is the vector of exogenous variables. β is matching $1 \times K$ vector of fixed but unknown parameters. μ_g is individual fixed effect, λ_t is time fixed effect and ε_{it} is vector of the idiosyncratic error term.

Table 5 - Estimation results of spatial autoregressive model (SAR).

	Dependent variables					
	LogRainf_Cer (1)	*LogIrrg_Cer* (2)	*LogRainf_Ros* (3)	*LogIrrg_Ros* (4)	*LogRainf_MarkG* (5)	*LogIrrg_MarkG* (6)
LogLabor	−1.259***	1.330***	−0.526*	2.080***	−1.628***	1.183***
	(0.317)	(0.135)	(0.393)	(0.285)	(0.405)	(0.236)
LogLand	0.921***	0.180***	0.131*	0.040	−0.033	0.0014
	(0.070)	(0.069)	(0.070)	(0.084)	(0.087)	(0.053)
LogLivestock	1.055***	0.352**	0.615**	1.281***	1.738***	−0.082
	(0.263)	(0.178)	(0.251)	(0.302)	(0.332)	(0.191)
LogTmean	−0.888*	−2.469***	7.746***	−7.650***	2.897***	2.630***
	(0.468)	(0.535)	(1.0009)	(1.257)	(0.602)	(0.775)
LogRainf	0.444***	−0.434***	0.687***	−0.332**	−0.037	0.107
	(0.124)	(0.123)	(0.134)	(0.157)	(0.156)	(0.099)
Constant	19.298***	15.348***	−15.959**	52.456***	36.077***	−11.586***
	(4.313)	(5.152)	(4.757)	(5.872)	(5.614)	(3.681)
λ	−0.191***	0.028	−0.492***	−0.139***	−0.864***	−0.163***
	(0.059)	(0.028)	(0.071)	(0.106)	(0.079)	(0.070)
Observations	210	210	210	210	210	210

*Note: * significant at 10% level, ** significant at 5% level, *** significant at 1% level*