IMPACT OF CLIMATE CHANGE ON AGRICULTURE IN THE MENA REGION: A SPATIAL PANEL ECONOMETRIC ANALYSIS

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Abstract

The Middle East and North Africa (MENA) region is highly dependent on agriculture, making it particularly susceptible to the effects of climate change. This study examines the impact of climate change on agriculture in the MENA region, using a weather-panel approach across 20 countries over the period $1991-2018$. Emphasizing the importance of accounting for spatial autocorrelation, we estimate a Fixed Effects Spatial Error Model (FE-SEM) taking into account spillover effects among neighboring countries. Our model improves the precision of estimates and reveals a non-linear relationship between the agricultural production function and weather, with different short-term marginal effects of temperature and precipitation across seasons. The simulation under the SSP5 8.5 scenario $(2020-2039)$ predicts predicts a negative impact on the MENA agricultural production index, with an average of -29.1%.. These findings call on policymakers to prioritize adaptation strategies, invest in sustainable resource management, and cooperate with international efforts to comprehensively address the impacts of climate change on agriculture in the MENA region.

Keywords: Climate change; agriculture; MENA region; spatial panel econometrics; short term adaptation.

JEL Codes: Q12, Q54, R12.

1 Introduction

"*End hunger, achieve food security and improved nutrition and promote sustainable agriculture*" is the second of the 17 sustainable development goals adopted by all United Nations Member States in 2015 for the 2030 Agenda for Sustainable Development [FAO et al., 2017]. This objective requires the widespread promotion of sustainable agriculture through equal access to land, technology, and markets, while ensuring resilience to the challenges of climate change [FAO, 2015]. This is particularly challenging in certain regions of the world, such as the Middle East and North Africa (MENA) region where agriculture is the primary source of food and income, as well as the main employer in many countries [OECD/FAO, 2018]. This dependency on agriculture makes the region even more vulnerable to climate change.

The MENA region has witnessed a consistent rise in temperatures and reduction in precipitation over the past century [IPCC, 2022]. Notably, the temperature increase has been pronounced, ranging between 0.2°C per decade and 0.4°C per decade, particularly robust since the 1970s in North Africa [Seneviratne et al., 2022]. Moreover, the Middle East is anticipated to experience the most significant warming on extremely hot days, accompanied by heightened aridity of the land [Atlas, 2021]. As to precipitation, there has been a reduction in mean annual precipitation across much of North Africa during the period 1971–2000 [Donat et al., 2014; Hertig et al., 2015; Nicholson et al., 2018; Zittis and Hadjinicolaou, 2017]. Simultaneously, in the Middle East, there is a discernible pattern of decreased precipitation and increased evapotranspiration, contributing to drought conditions and a decline in surface runoff [Ranasinghe et al., 2021]. More recently, Amouzay et al. [2023] identified a significant structural breaks in temperature and precipitation time series from 1901 to 2012, and suggest that climate change has indeed begun to occur in MENA Countries. Projections indicate that these trends will continue in the coming decades [Almazroui, 2020; Bucchignani et al., 2018; Collins et al., 2013; Driouech et al., 2020; ESCWA, 2017; Merlone et al., 2019; Ranasinghe et al., 2021].

The traditional nature of the sector, coupled with water scarcity and limited arable land, characterized by a high percentage of arid and semi-arid lands with low agricultural productivity [IPCC, 2022], exacerbates the risks of climate change and its impact on the region [Evans, 2009; Ferrise et al., 2013; Immerzeel et al., 2011; Marty et al., 2018; Nin-Pratt et al., 2017; Waha et al., 2017]. Furthermore, the rapid population growth in the region, from approximately 140 million in the early 1960s to over 500 million in 2020 [UN, 2019], induce an increase in agricultural import dependency of these countries, especially in a context increased climate change impacts [Le Mouël et al., 2023], would weaken this region' food security [Jobbins and Henley, 2015; Sadler and Magnan, 2011; Zolfaghari and Jariani, 2021].

In this regard, the current study aims to examine the impacts of climate change on agriculture in MENA countries using spatial panel data models [Anselin et al., 2008; Elhorst, 2014]. The objective is to demonstrate the importance of considering spatial autocorrelation and provide policy makers with more accurate quantitative insights on the adaptation of agriculture in MENA countries.

In our analysis, we adopt the profit function approach first proposed by [Deschênes and Greenstone, 2007], and consider spatial autocorrelation to control for the effect on agricultural activity in MENA countries. This paper contributes to the existing literature by using a recent spatial panel data model to examine the impact of climate change on agriculture in the MENA region, as well as by conducting a comparative analysis between non-spatial and spatial panel models. This approach is particularly appropriate for this study as our sample consists of countries that are geographically close and have interdependent climates. Thus, we use a gridded meteorological data set collected in the Climate Research Unit (CRU) database [Harris et al., 2020]. These data can be a source of significant spatial correlations [Auffhammer et al., 2013]. Therefore, our model includes variables that account for geographical disparities. Additionally, studies based on panel data can lead to biased inferences [Baylis et al., 2011; Fisher et al., 2012; Kumar, 2011], which can be misleading when formulating national policy for MENA countries. Therefore, we use specific estimation procedures that incorporate the effects of spatial autocorrelation and individual heterogeneity, following on the studies by Chen et al. [2016] and Vaitkeviciute et al. [2019]. To the best of our knowledge, this is one of the few empirical papers that use a spatial panel approach to study the impact of climate change on agriculture in MENA countries. Furthermore, using the most recent meteorological and agricultural production data (2018)[1], this paper contributes to the existing literature providing evidence of a significant contemporary relationship between climate change and agriculture in the MENA region, and we also use future projections of climate change covering the period 2020 to 2039 to simulate their projected impacts on the agricultural production index of MENA countries.

The literature review and the methodological framework is presented in the Sections 3 and 2. Section 4 presents the data and variables used for this study, while Section 5 presents the results describing the impact of climate change on agriculture. The last Section 6 distils the conclusions and policy implications of the study.

2 Literature review

There is a substantial body of literature that examines the impact of climate change on agriculture globally (see Ortiz-Bobea [2021] for a recent review of this literature). To understand the relationship between climate and agriculture, Blanc and Reilly [2017] note that economists often use statistical approaches, which are based on the actual experiences of farmers. In particular, the Ricardian approach and the profit approach as the most frequently used methods in the empirical literature

[1] Previous MENA studies such as Drine [2011] and Alboghdady and El-Hendawy [2016] use data up to 2007 and 2009.

[Auffhammer, 2018; Carter et al., 2018]. The Ricardian approach is a cross-sectional analysis of land price per hectare regressed on climate variables, and it assumes that land price reflects the future income stream that the farmer would receive from the best land allocation [Mendelsohn et al., 1994]. The profit approach, on the other hand, is a panel analysis of agricultral profit (revenue or production) as a function of weather, and is based on the annual behavior of producers to maximize their revenues [Deschênes and Greenstone, 2007]. This approach is short-term, in which revenues in the observed year are affected only by weather conditions in the same year [Dell et al., 2014]. This approach is widely used in developing countries due to data availability [Blanc and Reilly, 2017].

2.1 Climate change impacts on agriculture studies in MENA region

The literature on the impact of climate change on agriculture is relatively new in this region, but it is growing as the importance of the topic becomes increasingly clear. Studies have shown that climate change leads to shifts in cropland and vegetation [Evans, 2009; Ferrise et al., 2013], as well as shorter crop growing seasons [Ferrise et al., 2013; Gasmi et al., 2011; Mougou et al., 2011]. For example, the MENA region is projected to experience a decrease of about two weeks in the wheat growing season due to climate change. In addition, crop yields are also expected to be negatively impacted by climate change, with a decrease of nearly 60% in agricultural yields resulting from a 3-4°C warming [Al-Bakri et al., 2011; Alboghdady and El-Hendawy, 2016; Breisinger et al., 2011; Cline, 2007; Drine, 2011; Eyshi Rezaie and Bannayan, 2012; Gasmi et al., 2011; Giannakopoulos et al., 2009; Müller et al., 2010; Verner, 2013]. Leguminous and maize crops are expected to be the most affected due to the longer periods of drought projected during the summer period covering the period 2031-2060 [Giannakopoulos et al., 2009; Schilling et al., 2012]. On the other hand, IPCC WGI AR6 report, highlight the dual impact of climate change on cash crop yields in North Africa, revealing both positive and negative effects [IPCC, 2022]. Sugarcane yields, for instance, experienced an average decline of 5.1% between 1974 and 2008, while sorghum yields increased by 0.7%, and cassava yields saw an 18% rise during the same period due to climate change [Ray et al., 2019]. A meta-analysis of 56 studies predicts a 5% decline in economic welfare for the agriculture sector in North Africa under 2°C global warming and a more substantial 20% decline under 3°C global warming compared to the 1995–2005 period, indicating a more pessimistic outlook than previous economic estimates [Moore et al., 2017]. In the Middle East, specifically in Saudi Arabia and Yemen, the anticipated severe impact of increasing water scarcity, driven by rising temperatures, is expected to adversely affect agriculture and food production, posing a threat to food security [Al-Zahrani et al., 2019; Baig et al., 2019].

However, to the best of our knowledge, only two studies have considered the profit function approach [Alboghdady and El-Hendawy, 2016; Drine, 2011], which is widely used in relation to developing countries due to data availability. These studies suggest that decreased precipitation, increased heat waves and drought are the main causes of decreased agricultural productivity in the region, excluding the temperature effect which is not significant. They also confirm that the nonlinear effect of climate variables is significant on agricultural production in the MENA region.

In a study by Drine [2011], balanced panel data regarding the production function was used to analyze the impact of climate variability on agriculture in 11 countries in the MENA region over the period of 1980-2007. The findings suggest that decreased precipitation, increased heat waves and drought have a negative impact on agricultural productivity, while temperature had no significant impact. Another study by Alboghdady and El-Hendawy [2016] used a production function model to examine the impact of climate change on agricultural production in 20 MENA countries between 1961 and 2009. The results showed that a 1% increase in winter temperature led to a 1.12% decrease in agricultural production, and a 1% increase in temperature variability in winter and spring resulted in a 0.09% and 0.14% decrease in agricultural production, respectively. Additionally, increased precipitation in winter and fall, as well as variability in precipitation in winter and summer, had negative impacts on agricultural production. These findings indicate that climate variables have a non-linear impact on agricultural production in the MENA region.

2.2 Panel spatial models in climate change impacts on agriculture studies

In recent years, may studies dealing with the impact of climate change on agriculture have begun to incorporate spatial autocorrelation into their analysis [Chatzopoulos and Lippert, 2016; Polsky, 2004; Schlenker et al., 2006; Schmidtner et al., 2015]. According to Fisher et al. [2012], one limitation of the production function approach proposed by [Deschênes and Greenstone, 2007] is the biased standard error term due to the absence of spatial correlation. To address this limitation, an analysis using spatial econometric models is recommended as they allow for the consideration of spatial autocorrelation effects caused by agricultural and weather variables. Previous research Elhorst [2014] has identified three types of spillover effects, those caused by global spillover effects captured by the Spatial AutoRegressive (SAR) model or the Spatial Durbin Model (SDM) [Chatzopoulos and Lippert, 2015; Dall'Erba and Domínguez, 2016; Ortiz-Bobea, 2015; Polsky, 2004], and those caused by local spillover effects captured by the Spatial Lag on explanatory variables (SLX) model [Dall'Erba and Domínguez, 2016]. Additionally, a fourth case of spatial spillover effects caused by the global autocorrelation of spatial errors and captured by the Spatial Error Model (SEM) has also been estimated in this literature [Chen et al., 2016; Lippert et al., 2009; Schlenker et al., 2006; Vaitkeviciute et al., 2019].

The recent development of spatial econometrics applied to panel data allows for the consideration of not only individual heterogeneity, but also spatial dependencies between regions [Anselin et al., 2008; Baltagi et al., 2003; Piras, 2014]. Kumar [2011] discusses different spatial models used in an income approach of the study of Indian agriculture, and Baylis et al. [2011] proposed an extension to the study by Schlenker et al. [2006], based on the inclusion of a formal spatial panel framework. They applied spatial lag and spatial error models, using both fixed and random effects.

Other studies have delved into explanations for spatial interactions related to the spatial correlation of errors. Auffhammer and Schlenker [2014] have highlighted that this correlation could result from unaccounted variations in climatic variables, such as wind speed, solar radiation, and other factors. Meanwhile, Miao et al. [2016] suggest that agricultural yields in different countries could be spatially correlated due to similarities in their soil or geographical characteristics. Additionally, Auffhammer et al. [2013] demonstrated that this spatial correlation results from the underlying data generation process and the extrapolation methods used to create gridded meteorological data sets. In this regard, Harari and Ferrara [2018] propose that the use of gridded meteorological data can lead to significant repercussions among neighboring countries through prices, trade markets, or conflicts.

In our case study, the data consists of aggregated variables at the country level for the MENA region. Therefore, we choose to use a Panel SEM, as suggested by Chen et al. [2016] and Vaitkeviciute et al. [2019]. This model is the most appropriate for this type of aggregated data, as the SAR model and SLX model are not suitable for this case since the SAR model is interesting in the context of individual (farm)-level data, while the SLX model is excluded due to collinearity issues [Dall'Erba and Domínguez, 2016]. The SEM model captures global spatial autocorrelation, which can be caused by measurement errors, omitted variables, or unobserved shocks that follow a spatial pattern. Additionally, spatial autocorrelation can be a result of the different scales of the data and the aggregation process [Vaitkeviciute et al., 2019].

3 Methodology

In what follows, we begin firstly by examining in Section 3.1 the empirical model specification adopted in our case study, secondly, we specify the economic hypotheses presented in Section 3.2 that we empirically verify with the help of the developed model.

3.1 Empirical Model specification

The literature review indicates that the production function approach is dominant in many studies done for developing countries because of data availability. Indeed, Ricardian models are rarely appropriate for these countries, since they are based on land values for which data are not available due to lack of information on private land ownership [Mendelsohn and Dinar, 2009]. Thus, doubts about Ricardian analysis' inability to account for omitted variables [Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020] have led more recent studies to use panel econometrics [Blanc and Reilly, 2017]. Because our case study is made up of developing countries, we use the same specification as works of Barrios et al. [2008], Lee et al. [2012] and Belloumi [2014]. These studies analyze the link between agricultural production and annual weather fluctuations at different levels (countries, regions, etc.), using fixed-effects models which seem to be appropriate for assessing short-term relationships and should be preferred in the production function approach. Drawing on Barrios et al. [2008], we estimate the aggregate agricultural production function in the MENA countries while accounting for the effects of key weather variables on production changes.

As a baseline specification, we estimate the following individual and time fixed-effect panel model:

$$\begin{aligned} ln\left(Y_{it}\right) = \beta_0 + \beta_1 ln\left(L_{it}\right) + \beta_2 ln\left(Lst_{it}\right) + \beta_3 ln\left(Irrg_{it}\right) + \beta_4 ln\left(lab_{it}\right) + \\ \beta_5\left(T_{it}\right) + \beta_6\left(T_{it}^2\right) + \beta_7\left(P_{it}\right) + \beta_8\left(P_{it}^2\right) + \mu_i + \nu_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

Where Y_{it} is the of aggregate agricultural output for the i country in year t. The variables L_{it}, Lst_{it}, $Irrg_{it}$ and lab_{it} are measures of land, livestock, irrigation and labor inputs respectively. For the weather variables, both the linear and quadratic terms are included in the model in order to capture the non-linear relationship between the agricultural production and the weather variables. Therefore, we include temperature and precipitation and their squares $(T_{it}, P_{it}, T_{it}^2, P_{it}^2)$ as climatic factors that can affect agricultural production. Additionally, the time varying effects ν_t, common to all countries, proxies by a set of time dummies and intended to capture unobserved factors (such as soil quality, labor skills, technological progress…etc.), which can influence agricultural production. As of μ_i, it is intended to capture any unobserved country specific and time invariant effects as , that may be correlated with the other regressors and hence bias our estimates by using a fixed effects estimator. Finally, the term ε_{it} is the idiosyncratic error term and the β_k $(k = 0, ..., 8)$ are the coefficients to be estimated.

The studies by Baylis et al. [2011]; Dall'Erba and Domínguez [2016]; Massetti and Mendelsohn [2011]; Ortiz-Bobea [2015] underscores the impact of agricultural practices and climatic conditions in adjacent regions on agricultural production, resulting in spillover effects that elude capture by conventional non-spatial panel models or ex-post adjustments for spatial error correlation. Consequently, incorporating these effects and spatial autocorrelation within the error terms yields more precise estimations of climate change's influence on agriculture. Chen et al. [2016] exemplify this approach by employing a panel Spatial Error Model (SEM) with diverse spatial weight matrices. This model effectively addresses the endogeneity of socioeconomic variables, estimates spatial correlation, and accounts for heteroscedasticity and autocorrelation within the error terms. The rationale for selecting the SEM model lies in its capacity to model individual and temporal heterogeneity through fixed effects, and its suitability for aggregated data, such as meteorological data, often characterized by spatial autocorrelation in the residuals [Auffhammer et al., 2013; Chen et al., 2016; Vaitkeviciute et al., 2019; Ward et al., 2014].

In order to investigate spatial autocorrelation and to model spillover effects among MENA countries, we estimate the model (1) incorporating a spatially correlated error term. Specifically, we estimate the following specification of panel SEM with individual and time fixed effects:

$$\varepsilon_{it} = \rho \sum_{k=1}^{N} \omega_{ik} \eta_{ik} + \epsilon_{it} \tag{2}$$

The term ϵ_{it} corresponds to the residual which is composed of the spatially autocorrelated error term, ω_{ik} is the generic element of a non negative spatial-weight matrix W_N $(N \times N)$ in which neighborhood relationships between countries are defined, ρ is the spatial autocorrelation coefficient that captures a correlated effect of unobservable characteristics, η_{ik} is the spatially correlated error term.
We then examine the total marginal values of aggregate agricultural output in order to evaluate the weather change marginal impacts on the MENA countries agriculture. The marginal values appraised at the mean are calculated as derivatives of equation (1) according to a weather variable and can be written as:

$$\begin{aligned} \frac{\partial Y}{\partial T} &= (\beta_5 + 2\beta_6 T) \times Y, \\ \frac{\partial Y}{\partial P} &= (\beta_7 + 2\beta_8 P) \times Y, \end{aligned} \tag{3}$$

where β_5, β_6, β_7 and β_8 are coefficients of weather variables and dependent on the estimated model specifications, T and P are sets of explanatory weather variables (temperature and precipitations for four seasons) and their squares and Y is the of aggregate agricultural output.
Finally, we compare the near-future impacts of climate change on the overall agricultural production of MENA countries based on Shared Socioeconomic Pathways (SSPs) scenarios developed by the research community [Riahi et al., 2017]. These are part of a new scenario framework developed by the climate change research community with the aim of facilitating integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation [Riahi et al., 2017]. Based on five narratives describing alternative socio-economic evolutions, including sustainable development, regional rivalry, inequality, fossil-fuel-driven development and intermediate development, these trajectories enable their future use and integration into new assessments and research projects [O'Neill et al., 2017].

3.2 Research hypotheses

In this case study, we test the following research hypotheses that provide a framework for investigating the intricate relationship between weather change and agricultural dynamics in the MENA region, facilitating a comprehensive evaluation of the marginal impacts on the agricultural sector:

- H1: The SEM fixed-effects model would be the most appropriate for estimating the short-term relationship between weather and the agricultural production function in MENA countries.

Despite the clear evidence that neighboring countries share geographical and environmental similarities impacting agriculture (such as climate, soil type, and pest presence), Ricardian studies have often overlooked or inadequately addressed spatial autocorrelation [Chen et al., 2016]. This regional similarity contributes to spatial error correlation and creates spillover effects. These effects can manifest through frequent contact between neighboring farmers leading to similar agricultural practices [Polsky, 2004], public spending on agricultural R&D that benefits neighboring countries [McCunn and Huffman, 2000], or shared resources like irrigation water and the evapotranspiration-rain cycle [Dominguez et al., 2009]. Consequently, omitting spatially correlated explanatory variables can induce spatial correlation in the error terms, as highlighted by [Chen et al., 2016]. Ultimately, neglecting these spatial factors can bias estimations of climate change's impact on crop agricultural production.
To test this hypothesis H1 and select the most appropriate specification for our data, we perform spatial specification tests. We start by estimating the model with no spatial autocorrelation, and implement the classic and robust Lagrange multiplier (LM) tests. These tests allow us to choose between the model whose dependent variable is spatially lagged, the model whose error term is spatially autocorrelated and the model with no spatial autocorrelation.

- H2: The spatial panel specification would be more accurate than the classical panel specification in a production function model to capture the short-term effect of weather changes on MENA agriculture.

Indeed, Schlenker et al. [2006] emphasized the importance of incorporating spatial characteristics for accurate estimations. Ricardian models often exhibited high t-statistic values, indicating potential spatial error correlation due to the neglect of spatial heterogeneity. To address this, Schlenker et al. [2006] analyzed land value sensitivity while correcting for spatially correlated errors. Similarly, Seoa and Mendelsohnb [2008] demonstrated that spatial models, which integrate spatial correlation, offer more precise impact estimations than traditional a-spatial models. Furthermore, Baylis et al. [2011] provided strong evidence of spatial effects in estimations, demonstrating the influence of integrating spatial panel methods on results. Ortiz-Bobea [2015] addressed the vulnerability of the Hedonic approach to omitted spatially dependent variables, such as the option value of agricultural land.

By comparing three spatial and a-spatial models, Ortiz-Bobea [2015] demonstrated that traditional panel models overestimate the potential damages of climate change by amplifying biases related to unaccounted factors, such as development pressure on agricultural land. The use of the more robust spatial model reveals that the actual impact of climate change on the US agricultural sector is likely less significant than previously estimated, even statistically insignificant [Ortiz-Bobea, 2015].
To test this hypothesis H2, we estimate the following econometric models of non-spatial and spatial panel data: model with individual and time-fixed effects without spatial error autocorrelation (cf. equation 1), and model with individual and time-fixed effects with spatial error autocorrelation (cf. equation 2). We then carry out a comparative analysis between these models, testing the significance of the spatial error autocorrelation coefficient, which captures the effect of unobservable factors, suggesting the possibility of a strong diffusion effect between neighboring countries.

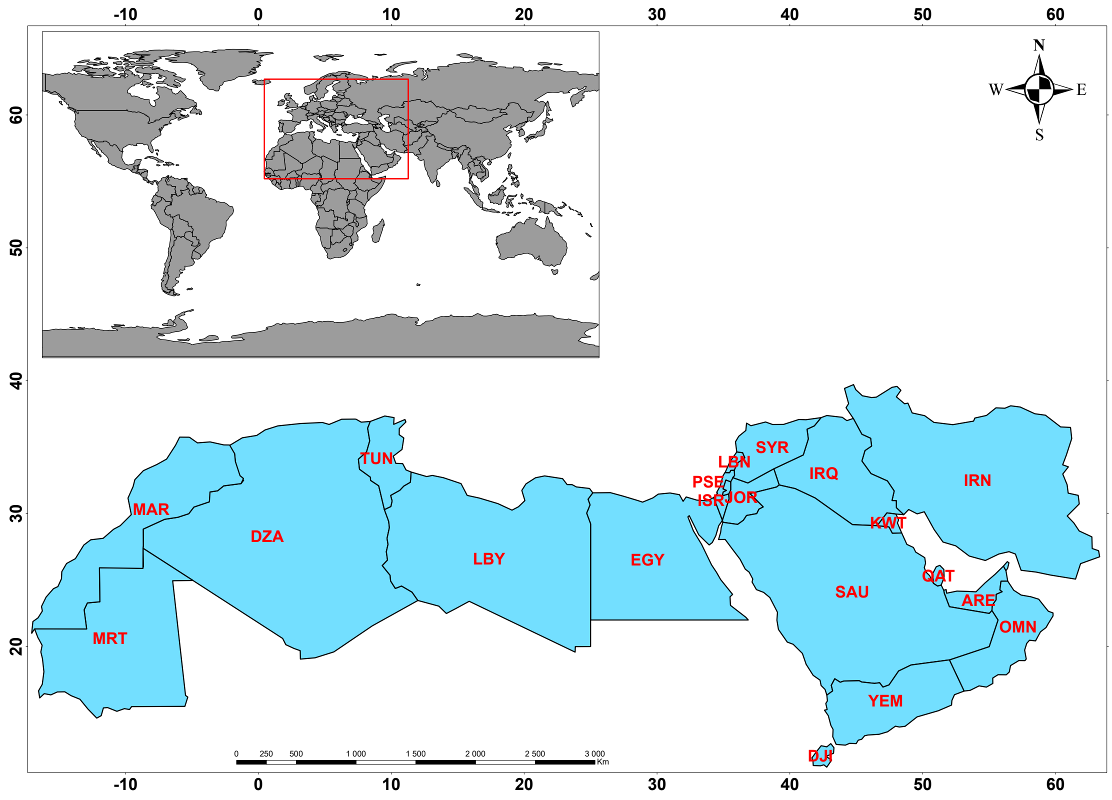
- H3: The weather variables could have a nonlinear relationship with respect to the agricultural production index in MENA countries.

Indeed, the analysis of the relationship between meteorological variables and crop yields is often limited by the use of simplified measures, such as monthly averages of temperature and precipitation. This approach ignores the distribution of weather events around these averages and the non-linear nature of plant growth in response to temperature [Schlenker and Roberts, 2009]. This omission is important in light of the agronomic literature that describes plant growth as a highly non-linear function of temperature. If temperatures are averaged over time or space, and the true underlying relationship is non-linear (e.g., increasing then decreasing as a function of temperature), standard regression techniques dilute the true underlying curvature of the relationship [Schlenker and Roberts, 2009]. The use of averages "flattens" the actual relationship, masking the negative impact of extreme temperatures. Additionally, including data from multiple months in models creates multicollinearity, making results unstable and unreliable. These statistical limitations obscure the true complexity of the relationship between climate and agricultural yields. These problems are exacerbated when squared averages are included in regressions to try to capture the possible non-linearities described in the previous paragraph [Schlenker and Roberts, 2009].
To test this hypothesis H3, we check the statistical significance of the coefficients of the squared weather variables in the model that include individual and temporal effects with spatial autocorrelation of the errors (cf. equation 2). The quadratic term of the weather variables represents the non-linear relationship and captures the second-order effect of these variables on agricultural production in MENA countries.

4 Data and exploratory analyses

This study uses panel data from a sample that covers 20 countries within the MENA region (Algeria, Djibouti, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, and Yemen), for the period 1991-2018 (for study area Map see **Figure** 1 below). Our choice of indicators and countries was limited by the availability of consistent data on both climate and agriculture. In this section we first specify the variables and their data sources (Section 4.1), and then present an exploratory analysis of the dependent variable in order to highlight the existence of spatial dependence between MENA countries (Section 4.2).

Figure 1: Perimeter of study



4.1 Weather and agriculture variables

Weather Data: Country-level weather data (monthly mean temperature, monthly total precipitation) were collected from the Global Climate Monitor (GCMon) Web Viewer database wich is a data model and a geovisualization tool that provides access to global climate data [Camarillo-Naranjo et al., 2019]. The data currently available correspond to the CRU TS3.21 version of the Climate Research Unit (University of East Anglia) database –a product that provides data at a spatial resolution of half of a degree in latitude and longitude, spanning January 1901 to December 2012, on a monthly basis [Harris et al., 2014, 2020]. Since January 2013, the datasets feeding the system have been the GHCN–CAMS temperature dataset [Ziese et al., 2011], the Global Precipitation Climatology Centre (GPCC) and First Guess precipitation dataset [Fan and Van den Dool, 2008]. These monthly data were then used to aggregate the weather variables–average temperature and total accumulated precipitation–in order to account for the effects of weather fluctuations in the particular periods of the year when climate is critical to the growth of the region's crops. For this reason, and because we do not have county–level information on agricultural planting and harvest dates per year, we calculated weather variables for the four seasons (see Figures frome 19 to 26 in Appendix 9). Indeed, Massetti et al. [2016] study the US case using cross-sectional data. They found that while the growing season degree-day indicator is a more compact alternative to the seasonal temperature and precipitation traditionally used to quantify farmland values, the four-season model is more accurate. Massetti et al. [2016] add that climate effects outside the growing season are also significant. Their cross-sectional evidence suggests that seasonal temperature and precipitation are very important in the United States. These aspects may be even more important in the case of the MENA region because of the importance of Autumn and winter crops. According to OECD/FAO [2018], between 1961 and 2016, the MENA region's harvested area was predominantly devoted to cereals, which cover about 60% of the total harvested area, with wheat remaining the main crop [OECD/FAO, 2018].

Agricultural Data: Our source of agricultural data is the AGROSTAT system of the statistical division FAOSTAT [2022]. As a dependent variable in the weighted equation (1), and to address the problem of unavailability of accurate data, we use the FAO agricultural production index, where net production quantities of each commodity are weighted by the 2014-2016 average international commodity prices and summed for each year, and the aggregate for a given year, measured as international United States dollars (*US$*), is divided by the average aggregate for the base period 2014-2016. FAO explains that the international commodity prices, expressed in "international dollars", are used in order to avoid the use of exchange rates for obtaining continental and world aggregates, and also to improve and facilitate international comparative analysis of productivity at the national level[2]. The level of this indicator shows significant variations over time and greatly across countries (see Figure 12 in Appendix 9), as shown in Figure 2, above. In order to proxy the capital factor in

[2]FAO using a Geary-Khamis formula for derive the international prices for the agricultural sector. This method assigns a single price to each commodity. For example, one metric ton of wheat has the same price regardless of the country where it was produced.

Figure 2: Observed Agricultural Production Index (API) in the MENA countries from 1991 to 2018

the production function we use the livestock, land and Irrigation area inputs as it is done in many other studies [Antle, 1983; Barrios et al., 2008; Belloumi, 2014; Frisvold and Ingram, 1995; Lee et al., 2012]. Indeed, the capital requirements of traditional agriculture are low [Belcaid and El Ghini, 2019] and MENA agriculture relies mainly on animal traction. Therefore, mechanization is also not considered, and we use FAO's the total head count of cattle, sheep, and goats as a proxy indicator of livestock input. Land supply is represented by the FAO's measure of total agricultural area, which includes arable land and the area used for permanent crops and permanent pastures and is given in 1000's of hectars. In addition, Irrigation can be crucial for production under drought conditions, so it is important to account for changes in the proportion of land irrigated over time when estimating our production function (Ward et al. [2014]). Agricultural labor is also a key determinant of the agricultural production function. We exploit the labor data for MENA countries available in the International Labor Organization's [ILOSTAT, 2022] database, so that this factor can be taken into account in our production function specifications. The Table 1, below, presents the descriptive statistics of our economic data.

Table 1: Descriptive statistics

Variable	Units	Mean	S.D.	Source	Time period
agricultural production index	US$	85.75	25.88	FAOSTAT	1991-2018
Winter Temperature	°C	18.63	4.757	CRU TS	1991-2018
Spring Temperature	°C	14.52	5.038	CRU TS	1991-2018
Summer Temperature	°C	28.40	4.332	CRU TS	1991-2018
Autumn Temperature	°C	23.58	4.913	CRU TS	1991-2018
Winter Precipitation	mm	124.50	123.71	CRU TS	1991-2018
Spring Precipitation	mm	150.23	143.302	CRU TS	1991-2018
Summer Precipitation	mm	23.57	40.681	CRU TS	1991-2018
Autumn Precipitation	mm	55.60	61.769	CRU TS	1991-2018
Labor	% of total labor force	20.253	16.721	LABORSTA	1991-2018
Irrigation Area	1000 hectares	1076.3	1997.006	FAOSTAT	1991-2018
Land	1000 hectares	20543.3	37025.34	FAOSTAT	1991-2018
Livestock	head	11379437	16277361	FAOSTAT	1991-2018

4.2 Exploratory analysis of dependent variable

The study of spatial autocorrelation is an essential step before considering any specification of spatial interactions in an appropriate model. The spatial dimension of the geographical location of the agricultural production index can be studied in more detail using the global spatial autocorrelation indices and tests : Moran's I statistic and Geary's C statistic (see Appendix 7 for more details). These tests are exploratory statistical tools that may highlight the existence of a spatial dependence between the values of the agricultural production index in the MENA countries and to test the significance of the identified spatial structure. Table 2, below, shows the results of the autocorrelation test, its standard deviation (Sd) and its p-value. Concerning the weight matrices, and inspired by Le Gallo and Ndiaye [2021], we build simple spatial matrices commonly used in spatial econometrics, namely the contiguity matrix based on Gabriel's neighbors, denoted W_contGW (Figure 14 in Appendix 9), a matrix of k closest with $k = 5$: $w_{ij} = 1$ if j is one of $i's$ five nearest neighbors of i and 0 otherwise. denoted W_nn5 (Figure 15 in Appendix 9) and an inverse distance matrix, denoted $W\_dinverse$ (Figure 16 in Appendix 9). We see in Table 2, below, that the different spatial autocorrelation matrices are positive and significant. Since the analytical approach to the global spatial autocorrelation indices analysis may be sensitive to irregularly distributed polygons, a safer approach to hypothesis testing is to run an Monte-Carlo (MC) simulation. Thise last confirmed the availability of a global spatial autocorrelation (see the Table 3 below), this means that the index of agricultural production in the MENA region is positively correlated spatially. In other words, neighboring countries with high production surround countries that also have high production. This correlation may have several explanations such as the quality of the land and its suitability for specific types of production, common climatic characteristics with neighboring countries, appropriate organisation of farmers and economies of scale.

Table 2: Global spatial correlation test

Matrix W	Moran's I statistic	Sd(I)	p-value	Geary's C statistic	Sd(C)	p-value
W_contGW	0.356^{**}	2.139	0.016	0.605^{*}	2.047	0.053
W_nn5	0.224^{***}	2.478	0.006	0.744^{**}	2.165	0.015
W_dinverse	0.082^{**}	2.266	0.011	0.870^{**}	2.012	0.022

Table 3: Monte-Carlo Simulation of Moran and Geary Tests

Matrix W	MC of Moran I	p-value	MC of Geary C	p-value
W_contGW	0.356^{**}	0.01	0.605^{**}	0.02
W_nn5	0.224^{*}	0.06	0.744^{**}	0.02
W_dinverse	0.082^{*}	0.06	0.870^{**}	0.04

5 Empirical estimation results and discussions

This section delves into the empirical estimation results and subsequent discussions, commencing with a benchmark analyses to determine the most suitable model for assessing the impact of climate change on agricultural production within the MENA region (Section 5.1). We then proceed to examine Short-term change impacts of weather fluctuations on agricultural output, taking into account spatial autocorrelation and individual and temporal heterogeneities (Section 5.2). Finally, utilizing the preceding results, we conduct simulations to evaluate the potential impacts of short-term climate change on agricultural production in the MENA region, providing valuable insights for the planning and implementation of adaptation and mitigation strategies (Section 5.3).

5.1 Benchmark analyses

The first research hypothesis of this study aims to verify if the SEM fixed-effects model is the most appropriate for estimating the short-term relationship between weather and agricultural production function in the MENA region. We estimate the classical four-season model to test this hypothesis. In order to determine which model is best suited to the data, this article begins by conducting an analysis of the non-spatial panel model, then examines whether there is spatial correlation between spatial units. To check the robustness of our results, we first examine two estimators for the non-spatial Model presented in Table 5: Column (1) presents the results of the Fixed-Effects model estimation (FE-OLS (1)) that ignores spatial autocorrelation but considers individual heterogeneity (FEi-OLS), while the results of the FE-OLS model estimation, which ignores spatial autocorrelation but considers temporal heterogeneity (FEt-OLS), are presented in column (2). Following the same logic, we also consider two estimators for the spatial model: The results [3] of the Fixed-Effects spatial error model estimation (FE-SEM (2)) that considers spatial autocorrelation and individual heterogeneity (FEi-SEM)), as well as those of the FE-SEM model that considers spatial autocorrelation and temporal heterogeneity (FEt-SEM), are presented in columns (3) and (4) of Table 5, respectively. To confirm our model choice, we conducted specification tests. First, to select the most appropriate specification, we start with the model without spatial autocorrelation and implement the Lagrange Multiplier (LM) tests. The results of these tests are presented in Table 4. The results of these tests lead us to choose a SEM specification. Indeed, classical and robust LM tests are performed to study spatial dependency [Anselin et al., 2008; Elhorst, 2003]. The conventional LM tests show that the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially auto-correlated error

[3]Given the presence of a country (Djibouti) that has no common border with other countries in our sample, we adopt the Gabriel neighbor-based contiguity matrix in our analysis. This is done to avoid a block-diagonal structure in the weight matrix on one hand and to ensure a connection between the countries in the MENA region on the other hand.

Table 4: Specification tests

Hypotheses	Model (??)
LM spatial lag:	
lml $H_0 : \lambda = 0$	103.32***
$H_1 : \lambda \neq 0$	(p$< 2.2e^{-16}$)
LM spatial error:	
lme $H_0 : \rho = 0$	54.599***
$H_1 : \rho \neq 0$	(p$= 1.478e^{-13}$)
Robust LM spatial lag:	
rlml $H_0 : \lambda = 0$	88.007***
$H_1 : \lambda \neq 0$	(p$< 2.2e^{-16}$)
Robust LM spatial error:	
rlme $H_0 : \rho = 0$	39.29***
$H_1 : \rho \neq 0$	(p$= 3.654e^{-10}$)
Spatial Hausman test (SHT)	
H_0 : SEM-RE is efficient	33.403**
H_1 : One model is inconsistent	(p= 0.030)

term are strongly rejected at the 1% significance level. With the robust LM tests[4], both hypotheses are also rejected at the 1% significance level. Furthermore, since the value of robust RLMlag tests is higher than that of robust RLMerr tests, the SEM model appears to be the most suitable for our study. This result is in line with the existing literature [Chen et al., 2016; Kumar, 2011; Schlenker et al., 2006; Vaitkeviciute et al., 2019]. This supports the choice of a model that considers both spatial autocorrelation of errors and individual heterogeneity (FE-SEM (2)) to measure the impact of weather variables on the agricultural production index in the MENA region.

[4]To check the robustness of our results. Spatial AutoRegressive (SAR) model was also estimated (see the equation (4) in Appendix 7 for SAR model specification and Table 8 in Appendix 8 for its estimation results).

5.2 Short-term weather change impacts

While many papers have examined the relationship between weather and agricultural production function, few have considered the effects of spatial autocorrelation. In order to achieve better adjustment effects, a comparative analysis between the FE-SEM model and the FE-OLS model of non-spatial panel data is conducted. By comparing these two specifications, improvements in the values, significance, and sign of the estimated coefficients are observed in the case of the spatial model. These results are consistent with existing findings in other regions of the world [Chen et al., 2016; Kumar, 2011; Lippert et al., 2009; Schlenker et al., 2006; Ward et al., 2014]. Schlenker et al. [2006] suggest that neglecting the spatial correlation of error terms can lead to an underestimation of the true variance-covariance matrix and consequently overestimate the t-values, as it is incorrectly assumed that error terms are independent. Moreover, Dall'Erba and Domínguez [2016] demonstrate that this difference is primarily attributed to the omission of the spatial diffusion effect of the data. The choice of an FEi-SEM model (Column (3) of Table 5) could be considered since it has the lowest AIC (1580.003). This model shows a positive and statistically highly significant spatial correlation between the unobserved error terms. Indeed, the spatial correlation coefficient (ρ) is positive and highly significant in any regression, supporting the argument that there are unobservable factors that are spatially correlated, even after controlling for elements such as weather conditions and agricultural inputs. Unobservable factors for us, such as technology, agricultural policies or regulations, and the use of the same production practices, are potentially included in these spatially correlated error terms, suggesting the possibility of a strong diffusion effect among neighboring countries. These results have allowed us to confirm the second hypothesis of this study. namely that the specification of spatial panel data is more accurate than the conventional panel in a production function model to capture the short-term effect of climate change on agriculture in the MENA region.

Weather change impacts: By examining the coefficients of weather variables in the FEi-SEM model, we observe a more significant impact of on the agricultural production index in MENA countries. Indeed, the FEi-SEM model shows a statistically significant impact at the 5% level for the coefficients of the "temperature" variables in the spring and autumn seasons, respectively, while the coefficients for the winter and summer seasons are not significant. These coefficients have a positive sign for autumn and a negative sign for spring. The positive sign indicates that an increase of one unit in temperature during the autumn generates, ceteris paribus, a 10% increase in the agricultural production index in the MENA region. This result can be explained by the fact that higher temperatures could have a positive effect on the growth of some crops [Hatfield and Prueger, 2015]. Indeed, the surface temperature has increased in the past century all over MENA region, resulted in an increasing trend of growing-season length [IPCC, 2022]. Thus, Hatfield et al. [2011] show higher temperatures at the reproductive stage will impact the ability of pollen to thrive, the

Table 5: Estimation results of a-spatial and spatial panel model with fixed effects

	Dependent variable: log(InPrd)			
	Non-Spatial model: OLS (1)		Spatial model: SEM(2)	
	FEi_OLS	FEt_OLS	FEi_SEM	FEt_SEM
Winter Temperature	0.006	0.028	0.007	0.022
	(0.029)	(0.024)	(0.028)	(0.023)
Spring Temperature	−0.051**	−0.083***	−0.040**	−0.080***
	(0.020)	(0.018)	(0.018)	(0.017)
Summer Temperature	−0.002	0.316***	−0.062	0.304***
	(0.072)	(0.070)	(0.067)	(0.066)
Autumn Temperature	0.081	−0.019	0.100**	−0.019
	(0.049)	(0.052)	(0.046)	(0.048)
Winter Temperature.square	−0.0003	−0.0001	−0.0003	0.0001
	(0.001)	(0.001)	(0.0006)	(0.0006)
Spring Temperature.square	0.002***	0.002***	0.001**	0.001***
	(0.001)	(0.001)	(0.0006)	(0.0006)
Summer Temperature.square	0.0003	−0.005***	0.001	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Autumn Temperature.square	−0.002	0.001	−0.002**	0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
Winter Precipitations	0.0001	0.0004	0.00005	0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Spring Precipitations	0.00000	0.001***	−0.00005	0.0008***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Summer Precipitations	−0.001*	−0.001*	−0.001**	−0.001*
	(0.001)	(0.001)	(0.0006)	(0.0005)
Autumn Precipitations	−0.0004	−0.001	−0.0003	−0.0008
	(0.001)	(0.001)	(0.0005)	(0.0005)
Winter Precipitations.square	$-2.056e^{-08}$	$-6.403e^{-07}$	$-3.021e^{-08}$	$-6.620e^{-07}$
	$(5.156e^{-08})$	$(6.066e^{-07})$	$(4.948e^{-07})$	$(5.773e^{-07})$
Spring Precipitations.square	$1.922e^{-07}$	$-9.286e^{-07**}$	$1.979e^{-07}$	$-9.845e^{-07**}$
	$(3.782e^{-07})$	$(4.027e^{-07})$	$(3.591e^{-07})$	$(3.833e^{-07})$
Summer Precipitations.square	$5.092e^{-06**}$	$6.196e^{-06***}$	$5.897e^{-06***}$	$5.895e^{-06***}$
	$(2.288e^{-06})$	$(2.390e^{-06})$	$(2.173e^{-06})$	$(2.280e^{-06})$
Autumn Precipitations.square	$1.692e^{-06}$	$3.643e^{-06}$	$1.540e^{-06}$	$3.693e^{-06*}$
	$(2.096e^{-06})$	$(2.274e^{-06})$	$(1.973e^{-06})$	$(2.153e^{-06})$
log(Irrigation)	0.229***	0.020**	0.193***	0.192**
	(0.029)	(0.009)	(0.027)	(0.008)
log(labor)	−0.289***	0.099***	−0.247***	0.102***
	(0.040)	(0.016)	(0.040)	(0.015)
log(Land)	0.450***	−0.019**	0.541***	−0.020**
	(0.095)	(0.009)	(0.092)	(0.008)
log(Livestock)	0.157***	0.003	0.146***	0.004
	(0.022)	(0.013)	(0.020)	(0.012)
ρ			0.191***	0.077*
			(0.044)	(0.045)
Observations	560	560	560	560
AIC			1580.003	1771.94
Adjusted R^2	0.489	0.296		

Note: *p<0.1; **p<0.05; ***p<0.01

fertilization process, and the development of grains or fruits. This result is similar to that of Verner and Breisinger [2013], who argue that some countries could benefit from higher temperatures, which would extend the growing season and increase crop productivity. The negative sign of the coefficients for the "temperature" variable in spring is not surprising and means that high temperatures during this time of the year have negative effects on agriculture in the MENA region. Indeed, for every increase of one unit in the "temperature" variable during spring, the model predicts a -4% decrease in the agricultural production index ceteris paribus. This decline in agricultural production in the MENA region could be attributed to several reasons. Firstly, the increase in temperature during spring may promote water evaporation, leading to increased drought [Hare et al., 2011; IPCC, 2019]. Secondly, when temperatures exceed a certain threshold, it can damage plant tissues and reduce plant growth, increasing thermal stress on crops [Waha et al., 2017]. Finally, high temperatures can also contribute to soil degradation, reducing fertility and increasing salinity, compromising the soil's ability to support crop growth [Bucchignani et al., 2018; Iglesias et al., 2011; IPCC, 2019; Namdar et al., 2021]. As for the variable precipitation we observe that the coefficient for the summer season is significant at the 5% level. While the coefficient for precipitation in the winter, spring, and autumn seasons is not significant. The lack of significance in the coefficients of other seasons could be explained by the significant warming trends that the MENA region has experienced in recent decades [Almazroui, 2020; Driouech et al., 2020; Merlone et al., 2019]. This warming trend may intensify the evaporation phenomenon, subsequently nullifying the effect of precipitation. Thus, the irregularity and seasonality of precipitation in this region could be a determining factor. Indeed, according to Amouzay et al. [2023], precipitation in MENA countries is uneven throughout the year, varying from seasonality to extreme seasonality with a long dry season. The sign of the precipitation variable for summer is negative, resulting in a -0.2% decrease in the agricultural production index, ceteris paribus, for each increase of one unit of precipitation. Indeed, excessive precipitation during this season can lead to floods, damaging crops and agricultural infrastructure. These trends have already been observed in Oman, Saudi Arabia, and Yemen Verner and Breisinger [2013]. Furthermore, increased precipitation during the summer can elevate the risk of soil salinization for irrigated crops, as rainfall can dissolve salts in the soil and bring them to the surface [Namdar et al., 2021].

Nonlinear weather variables impacts: In practical terms, the coefficients of the quadratic terms of meteorological variables reflect the second-order effect of these variables on the agricultural production index [Mendelsohn et al., 1994]. Thus, over the entire period, the quadratic coefficients for temperature in the spring and autumn seasons are significant at the 5% level, respectively. However, the quadratic coefficients for the winter and summer seasons are not significant. The significant coefficient for temperature during the spring season has a positive sign, predicting a convex relationship between the temperature variable and the agricultural production index. In contrast, the negative sign of the coefficient for the autumn season predicts that this index is a concave function of temperature. Ceteris paribus, higher temperatures during autumn would be detrimental to agricultural production, while the same increase would be beneficial during spring. These results are consistent with those of Giannakopoulos et al. [2009], who showed that crops cultivated during the autumn and winter seasons (legumes and corn) are expected to be most affected in the Western Maghreb and some parts of the Mashreq. Furthermore, the coefficients of the quadratic terms for precipitation variables reflect the second-order effect of these variables on the agricultural production index. Thus, the quadratic coefficient for precipitation in the summer season is significant at the 1% level, but those for the winter, spring, and autumn seasons are not significant. The significant coefficient for precipitation during the summer season has a positive sign, predicting a convex relationship between the precipitation variable and the agricultural production index. Ceteris paribus, an increase in precipitation during the summer season would be beneficial, contributing to better water availability, vital for crop irrigation, leading to improved agricultural yields and promoting crop diversification. Overall, these results allow us to confirm our second hypothesis that meteorological variables exhibit a non-linear relationship with the agricultural production function in the MENA region, in line with existing literature [Chen et al., 2016; Dell et al., 2014; Mendelsohn et al., 1994; Schlenker and Roberts, 2009].

Weather change marginal impacts: To provide a more detailed understanding of how climate affects the agricultural production index, we calculate the total short-term marginal impacts of temperature and precipitation for the spatial model (FEi-SEM) using Equation (3). The average marginal values of the agricultural production index for each season are presented in Table 6, below. From these results, we observe that the FEi-SEM model shows significant negative short-term marginal impacts of winter temperature, resulting in an average decrease in the agricultural production index in the MENA region of $-0.528\,US\$$. In contrast, the FEi-SEM model suggests significant positive short-term impacts of spring, summer, and autumn temperatures, leading to an average increase in the agricultural production index in the MENA region of $0.363\,US\$$, $1.358\,US\$$ and $0.148\,US\$$ respectively. These results, except for the summer, are consistent with findings from empirical literature worldwide, demonstrating beneficial effects of warmer temperatures in spring and autumn but adverse effects in summer and winter [Massetti and Mendelsohn, 2011; Mendelsohn and Massetti, 2017; Van Passel et al., 2017]. Regarding the short-term marginal impacts of precipitation, the FEi-SEM model shows that winter precipitation has a non-significant positive short-term impact, resulting in an average increase in the agricultural production index in the MENA region of $0.0052\,US\$$. In contrast, spring, summer and autumn precipitation has a non-significant negative short-term impact, leading to an average decrease in the agricultural production index in the MENA region of $-0.0001\,US\$$, $-0.078\,US\$$ and $-0.027\,US\$$ respectively. Thus, our results confirm,

Table 6: Marginal weather change impacts on agricultural production

Climatic variables	FEt_SEM	FEi_SEM
Temperature		
Winter	2.257 *US$*	−0.528 *US$*
	[2.182 ; 2.333]	[−0.599 ; −0.457]
Spring	−2.701 *US$*	0.363 *US$*
	[−2.759 ; −2.642]	[0.308 ; 0.418]
Summer	0.497 *US$*	1.358 *US$*
	[0.382 ; 0.612]	[1.250 ; 1.465]
Autumn	2.004 *US$*	0.148 *US$*
	[1.908 ; 2.099]	[0.058 ; 0.237]
Precipitation		
Winter	0.257 *US$*	0.0052 *US$*
	[−0.483 ; 0.527]	[−0.467 ; 0.477]
Spring	0.049 *US$*	−0.0001 *US$*
	[−0.560; 0.659]	[−0.570 ; 0.570]
Summer	−0.058 *US$*	−0.078 *US$*
	[−0.155 ; 0.038]	[−0.168 ; 0.012]
Autumn	−0.033 *US$*	−0.017 *US$*
	[−0.259 ; 0.192]	[−0.228 ; 0.193]

Note: Confidence interval at 95% is presented in parentheses.

as shown in previous studies in the MENA region [Alboghdady and El-Hendawy, 2016; Drine, 2011; Waha et al., 2017], that countries in the region will be more adversely affected by a decrease in precipitation than an increase in temperatures. Indeed, according to Waha et al. [2017], most of the land area in the MENA region receives less than 300 mm of annual precipitation, and the lower limit for rainfed agriculture is between 200 and 300 mm of annual precipitation. These results may support decisions regarding effective and efficient policy measures, especially for irrigation. In fact, Belghazi [2013] emphasized the crucial role of irrigation and capital intensification as key factors for productivity growth in the agriculture of MENA countries, compensating for the structural scarcity of precipitation in the region and the effects of climate change. Thus, Yuan et al. [2022] showed that the use of drip irrigation underneath plastic mulch enables better water utilization by reducing evaporation losses and providing targeted irrigation to plants.

Economic variables impacts: Regarding the economic control variables in the FEi-SEM model, we observe that the coefficients representing the contribution of capital and labor factors are all significant at the 1% level. Indeed, the model predicts a positive impact for livestock, indicating that a 1% increase in this production factor generates, ceteris paribus, a 0.146% increase in the agricultural production index. According to Dixon et al. [2001], the livestock population (21 million heads in 2000) increased at a rate of nearly 0.8% between 1971 and 2000, explaining the primary role of this factor in the growth of agricultural productivity and the sustainability of traditional farming practices in the MENA region. As for the contribution of the total areas of rainfed and irrigated agricultural land, both have a positive impact, showing that a 1% increase in these areas generates, ceteris paribus, an increase of 0.541% and 0.193%, respectively, in the agricultural production index of MENA countries. Indeed, according to the OECD/FAO [2018] report, the production of horticultural and cereal products increased during the period 1971-2016, due to the expansion of cultivated areas and improved yields. Moreover, the analysis of the total area variable of irrigated agricultural land allows us to demonstrate that public policy interventions, such as the improvement or expansion of irrigation infrastructure (especially groundwater), have a positive impact on agricultural production in MENA countries, mitigating the adverse effects of decreased agricultural production due to rising temperatures Ward et al. [2014]. According to Belghazi [2013], the share of irrigated land in arable permanent crops slowly increased from 17.3% in 1994-1996 to 18.5% in 2007. Moreover, irrigation enabled countries like Egypt, Kuwait, Saudi Arabia, the UAE, Oman, and Lebanon to achieve yields exceeding three tons per hectare in 2010-2016 for wheat [OECD/FAO, 2018]. Conversely, the contribution of agricultural labor is negative and significant. Indeed, a 1% increase in this factor leads, ceteris paribus, to a decrease of -0.247% in the agricultural production index. This decline in agricultural production could be attributed to social factors. Firstly, farms are relatively small in most countries in the MENA region, and they have a significant family workforce. However, their ability to adopt new technologies and access investment is limited, resulting in a shortage of skilled labor in the agricultural sector. This can impact agricultural productivity due to a lack of technical knowledge and skills needed to maximize crop yields. As a result, many agricultural workers may choose to migrate to other sectors or leave the MENA region in search of better economic opportunities. According to Belghazi [2013], limited access to education and illiteracy primarily affect rural areas, especially agricultural workers and women. Illiteracy is responsible for the marginalization of the rural workforce as it leads to low productivity growth in much of the agricultural sector, mainly in small poor households that are the first to migrate to urban areas. Consequently, the agricultural workforce in MENA countries was about 25 million in 1994-96, decreasing to 24.5 million in 2007. Over the past decades, the agricultural workforce in MENA countries has been slowly declining at a rate of 0.2% per year, compared to the annual growth of 0.7% in the rural population worldwide [Belghazi, 2013].

5.3 Simulation of short term climate change impacts

Marginal impacts can be complemented by the impacts of future climate scenarios on the agricultural production index of MENA region countries. For this purpose, simulations were conducted using the Shared Socioeconomic Pathways (SSP) climate change scenarios rather than the Representative Concentration Pathways (RCP). The climate research community has demonstrated that RCPs must cover various aspects, describing different climate futures, and ideally encompassing internal and consistent socioeconomic developments [Moss et al., 2010; Van Vuuren et al., 2011, 2014]. Furthermore, the conceptual framework for the design and use of SSP scenarios calls for the development of global pathways describing the future evolution of key societal aspects that, together, would pose a series of challenges for climate change mitigation and adaptation [O'Neill et al., 2017]. Thus, SSPs are considered more suitable for local and regional needs, allowing for the exploration of the impact of various greenhouse gas emission reduction policies on the agricultural sector [O'Neill et al., 2017].

Climate projections scenario: The climate change scenarios play an essential role in assessing the impact of climate change. They help understand the long-term consequences of short-term decisions and offer the opportunity to explore different future developments in the context of fundamental uncertainties Riahi et al. [2017]. In our study, we use SSP1 2.6 and SSP5 8.5 scenarios for the period 2020-2039. Indeed, SSP1 2.6 scenario is the most optimistic, assuming relatively low temperatures and significant efforts to reduce greenhouse gas emissions. It aims to limit global warming, targeting to keep the overall increase below 2°C compared to pre-industrial levels Riahi et al. [2017]. While SSP5-8.5 scenario is a pessimistic scenario predicting higher temperatures among the scenarios. It assumes continued dependence on fossil fuels, rapid economic growth, and population increase, lead-

Table 7: Summary Statistics of Projected Climate Change for 2020–2039

	Observations 1991-2018	SSP1 2.6 2020-2039	Relative Variation	SSP5 8.5 2020-2039	Relative Variation
Average Temperature	21.28	24.12	+13%	24.29	+14%
Average Precipitation	353.89	135.59	−61%	133.50	−62%

ing to very high greenhouse gas emissions and significant global warming Riahi et al. [2017]. Climate projection data of SSP1 2.6 and SSP5 8.5 scenarios for the period 2020-2039 are collected from the World Bank Group's Climate Change Knowledge Portal (CCKP).

The portal provides climate projection data from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) global climate model compilations. Indeed, Moore et al. [2017] as well as Auffhammer and Schlenker [2014] recommended the use of the CMIP6 average rather than a individual model. This preference is justified by systematic demonstrations indicating that predictions resulting from this multimodel approach outperform those from individual models. Thus, Knutti [2010] highlights that this method can mitigate significant heterogeneity present in individual models, resulting in a loss of crucial information. We utilize the monthly data presented on the portal as projected averages for the period 2020-2039, spatially presented by country with a resolution of $25km \times 25km$.

We calculate the relative variation in future climate change by differentiating the average meteorological variables projected by the SSP1 2.6 and SSP5 8.5 scenarios over the period 2020 to 2039, compared with that of our study period (1991-2018). Tables 11–12 in Appendix 8 and Figures 17–18 in Appendix 9, show the spatial distributions of these projected changes in weather variables for MENA countries. The summary statistics for the projected values of our meteorological variables are shown in Table 7 above, showing that the SSP5 8.5, e.g., scenario seems to suggest future global warming in the MENA region by 2039, predicting a 14% increase in Average temperature and a −62% decrease in Average precipitation.

Predicted impact from scenarios projections: The results of the FEi-SEM model's predicted impacts from the SSP1 2.6 and SSP5 8.5 scenarios covering the period 2020-2039 provide an overview of the expected impacts on the agricultural production index of MENA countries. Tables 9 and 10 in Appendix 8 presents the values of anticipated impacts by country, and their spatial distribution maps are presented in Figures 10–11 in Appendix 9. For a visual representation of these results, Figures 3,4, 5 and 6 above, illustrate the predicted impacts of temperature and precipitation

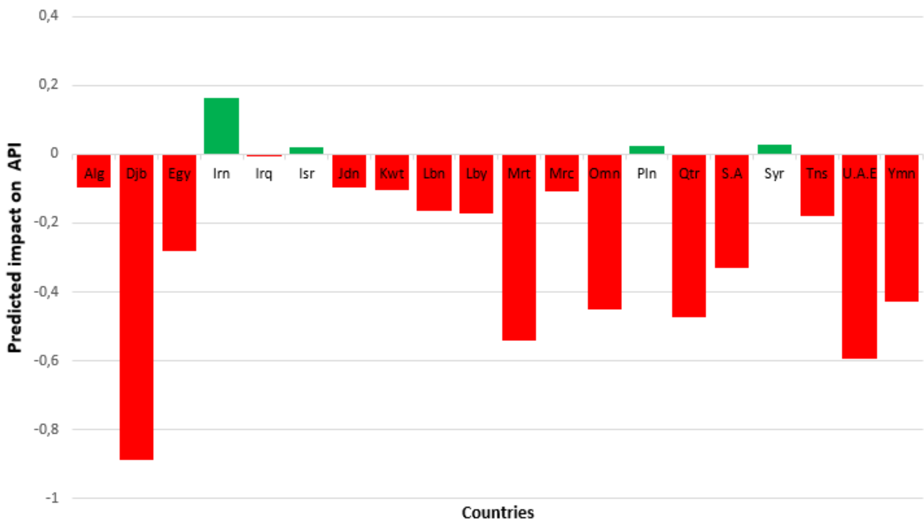


Figure 3: Predicted temperature impact on API by country: Scenario SSP1 2.6

for both scenarios, SSP1 2.6 and SSP5 8.5. For total impacts, see figures 7 and 8 in Appendix 9. Overall, these results reveal a negative trend on agricultural production in MENA countries. Indeed, the FEi-SEM model, under SSP5 8.5 scenario for exemple, reveals that the average predicted impact on the agricultural production index is -29.1%. However, we note that the predicted impact of temperature change is much greater than that of precipitation. When we look at the predicted impact of temperature increase, we see that most MENA countries are expected to experience negative effects on their agricultural production index, with an average predicted impact of -27%. However, there are notable exceptions, such as Iran, Israel, Palestine, and Syria, which could benefit from climate change under SSP1 2.6 scenario, and Iran, Iraq, and Syria under SSP5 8.5 scenario. One point to note is the great heterogeneity of the expected negative impacts of rising temperatures between countries in the MENA region. For example, the countries of the Arabian Peninsula (Saudi Arabia, Qatar, United Arab Emirates, Oman, Yemen) are likely to suffer significant losses, particularly in Djibouti, which is in a particularly vulnerable situation. In contrast, the countries of North Africa (Algeria, Egypt, Libya, Morocco, Tunisia) and the Mashreq (Iraq, Kuwait, Syria, Lebanon, Jordan, Israel and Palestine) appear to be less affected, although variations remain within these geographical groups. With regard to the expected impact of reduced rainfall, we find a predicted average impact of -2.1% on the agricultural production index in the MENA region under SSP1 2.6 and SSP5 8.5 scenarios conditions covering the period 2020-2039. In fact, the FEi-SEM model predicts a generalized negative effect on agricultural production in all MENA countries, with the exception of Djibouti, for which the model anticipates a positive impact.

These findings align with those of Lobell and Asseng [2017], who demonstrated that temperature

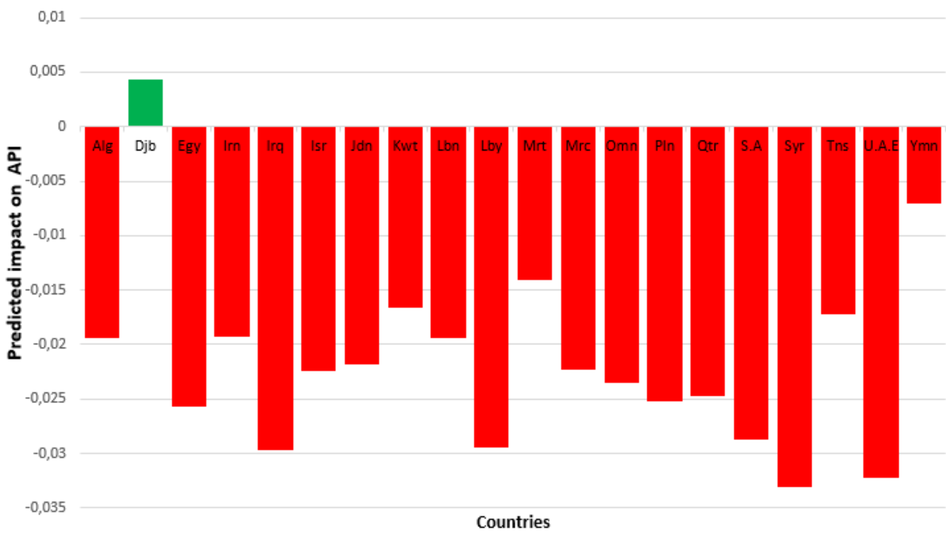


Figure 4: Predicted precipitations impact on API by country: Scenario SSP1 2.6

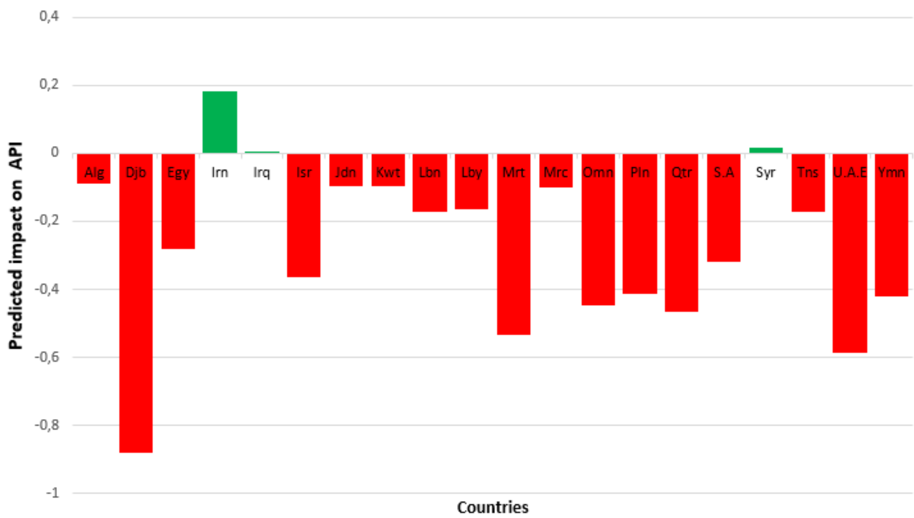


Figure 5: Predicted temperature impact on API by country: Scenario SSP5 8.5

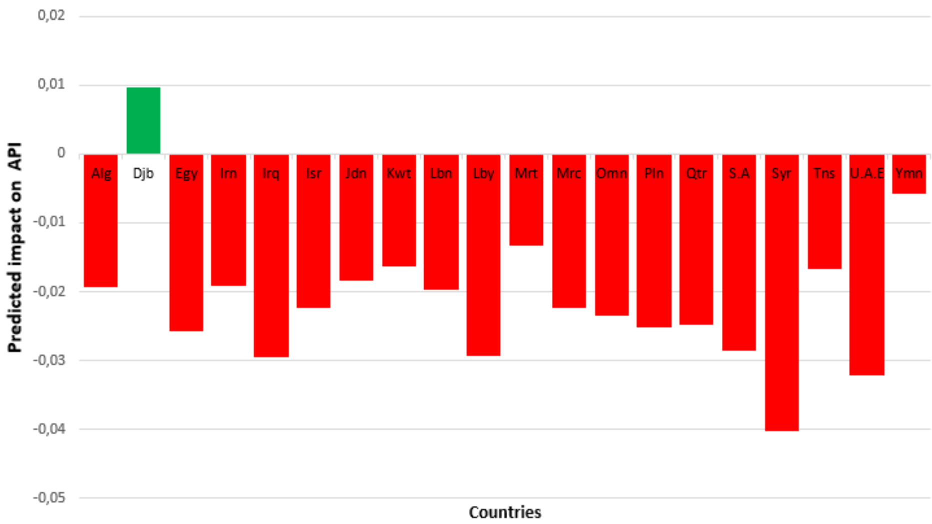


Figure 6: Predicted precipitations impact on API by country: Scenario SSP5 8.5

changes are expected to overshadow precipitation changes. The results from Lobell and Burke [2010] also emphasized that studies examining the sensitivity of simulated yields to precipitation changes reported reduced sensitivity when aggregated across various soil types. Schlenker and Roberts [2009] estimated a relatively weak effect of changes in the growing season precipitation, indicating that a 50% reduction in precipitation would result in a predicted yield loss of only 10%. Thus, the work of Lobell and Burke [2008] highlighted that warming is expected to be the primary driver of both anticipated impacts related to climate trends and associated uncertainties, especially at regional and global scales. However, they also underscored that the impacts of precipitation trends may be significant in certain locations and time scales [Lobell and Burke, 2008].

These results highlight the vulnerability of the MENA region's agricultural sector to global warming and reduced rainfall in the near future (2020-2039). These predicted negative impacts on agricultural production could lead to a reduction in the availability of locally produced food. This could affect the food security of countries in the region, by increasing dependence on imported food. According to Le Mouël et al. [2023], current trends in food consumption and agricultural production in the MENA region will result in a growing reliance on food imports until 2050. This dependence will further increase due to the impacts of climate change, especially in the sub-regions of the Middle East, Near East, and Maghreb, where net imports could represent up to 70% of national food requirements Le Mouël et al. [2023].

6 Conclusion

The aim of this study was to assess the impacts of climate change on agriculture in the MENA region using the profit function approach. Our study takes into consideration both spatial autocorrelation and individual heterogeneity among different countries. We compared the results of spatial and non-spatial models to determine the short-term effects of weather variations on agricultural production. Our models are based on balanced panel data for 20 countries over a 28-year period (1991-2018). We found that taking into account the spatial auto-correlation among data of MENA countries is crucial to accurately assess the impacts of weather variations on agriculture. The profit function approach initially proposed by Deschênes and Greenstone [2007], commonly used to assess the short-term impacts of climate on agriculture, has faced criticism for neglecting spatial autocorrelation [Fisher et al., 2012]. In our research, we address this limitation by incorporating spatial autocorrelation in our estimates, employing the Fixed Effects Spatial Error Model (FE-SEM). Statistical specification tests were conducted to confirm the presence of spatial autocorrelation in our models.

Our findings affirm that disregarding the spatial dimension in production function models results in less accurate estimates of the benefits and losses to agriculture due to weather changes. By integrating spatial autocorrelation into our analysis, we account for spillover effects between neighboring countries, highlighting the existence of spatially correlated unobservable factors. These factors exhibit a significant degree of spillover among neighboring countries, underscoring that failure to control for spatially correlated errors leads to less precise estimates of specific climate impacts. The spatial model (FEi-SEM) also demonstrates enhancements in the values, significance, and direction of the coefficients of meteorological variables, indicating an improved ability to quantify the impact of these variables on agricultural production in MENA countries. Additionally, our analysis uncovers a non-linear relationship between the agricultural production function and weather in the MENA region. It reveals negative short-term marginal impacts of higher temperatures in winter, while for other seasons, these impacts are positive on MENA agricultural production. Regarding precipitation, winter precipitation is beneficial and nonsignificant, whereas precipitation in other seasons has a nonsignificant negative impact on agricultural production in this region. Finally, we simulate the short-term future climate change impact on MENA agriculture, utilising projected changes in meteorological variables under the SSP5 8.5 scenario for the period 2020-2039. The results indicate a predicted negative impact on the agricultural production index of -25.5% in MENA countries. In light of this, policies for the sustainable management of natural resources, particularly water and soil, are imperative to ensure the long-term sustainability of agriculture in these countries.

While our study offers valuable insights into the impact of climate change on agriculture in the MENA region, it is crucial to acknowledge certain limitations that warrant consideration for future research, aiming to bolster the robustness of our findings. Firstly, our reliance on aggregated FAO data for agricultural production poses a limitation. Future research should explore methods to acquire more precise data at a finer spatial scale, allowing for a more detailed analysis of agricultural production. Additionally, considering the diverse nature of the MENA region, where climate change effects may differ among sub-regions, future studies could investigate regional variations in climate-agriculture relationships, taking into account local characteristics and vulnerabilities. Secondly, our analysis employs the profit function approach, focusing solely on short-term interactions between weather and agriculture. To provide a more comprehensive understanding, future research could delve into the long-term dynamics of climate-agriculture relationships. Thirdly, while our study simulates future climate change impacts under the SSP5 8.5 scenario, a more thorough assessment would involve exploring alternative scenarios and their potential implications on agricultural outcomes. This could include an examination of different emission pathways and their diverse effects on agriculture in the MENA region.

In conclusion, our study advances our understanding of the short-term impacts of climate change on agriculture in the MENA region, especially by addressing the issue of spatial autocorrelation. However, recognizing the outlined limitations, future research efforts should aim to refine and expand our findings to provide a more comprehensive and nuanced understanding of the dynamic relationship between climate change and agriculture in the region.

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7 Appendix: Model and test specifications

The Spatial AutoRegressive (SAR) panel model: 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.

$$\begin{aligned} ln\left(Y_{it}\right) = \lambda \sum_{j=1}^{N} \omega_{ij} ln\left(Y_{it}\right) + \beta_1 ln\left(L_{it}\right) + \beta_2 ln\left(Lst_{it}\right) + \beta_3 ln\left(Irrg_{it}\right) + \beta_4 ln\left(lab_{it}\right) + \\ \beta_5\left(T_{it}\right) + \beta_6\left(T_{it}^2\right) + \beta_7\left(P_{it}\right) + \beta_8\left(P_{it}^2\right) + \beta_0 + \mu_i + \nu_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

where: Y_{it} is the dependent variable for cross-sectional i at time t ($i = 1.....N$; $t = 1.....T$). $\sum_{j=1}^{N} \omega_{ij} Y_{kt}$ is the interaction effect of the dependent variable Y_{it} with the dependent variables Y_{it} in neighboring units, where ω_{ij} is the i, j^{th} 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. β is matching $1 \times K$ vector of fixed but unknown parameters. μ_i is individual fixed effect, ν_t terme is time fixed effect and ε_{it} is vector of the idiosyncratic error term.

Global spatial correlation test: To do the correlation spatial we have applied two most popular global spatial correlation tests in spatial econometric :

- The Moran index is represented as follows [Moran, 1948] :

$$I_W = \frac{n}{\sum_i \sum_j W_{ij}} . \frac{\sum_i \sum_j W_{ij}(y_i - \overline{y})(y_j - \overline{y_j})}{\sum_i (y_i - \overline{y})^2} \tag{5}$$

The Moran test follows the following hypotheses:

- H_0: No spatial auto-correlation.
- H_1: $I_W > 0$ (positive spatial auto-correlation).
- The Geary index can be formulated as follows [Geary, 1954]:

$$C_w = \frac{n-1}{2\sum_i \sum_j W_{ij}} . \frac{\sum_i \sum_j W_{ij}(y_i - y_j)^2}{\sum_i (y_i - \overline{y})^2} \tag{6}$$

Geary's test hypotheses can be written as follows:

- H_0: The differences between neighbors have no particular structure.
- H_1: $C_W < 1$ (positive spatial autocorrelation).

8 Appendix: Tables

Table 8: Estimation results of Fixed Effects Spatial AutoRegressive panel model (FE_SAR 4)

	Dependent variable: log(InPrd)	
	FEi_SAR	FEt_SAR
Winter Temperature	0.001	0.022
	(0.025)	(0.023)
Spring Temperature	-0.045^{**}	-0.076^{***}
	(0.017)	(0.017)
Summer Temperature	-0.036	0.302^{***}
	(0.067)	(0.066)
Autumn Temperature	0.072^{**}	-0.019
	(0.043)	(0.049)
Winter Temperature.square	-0.0001	0.0001
	(0.0006)	(0.0006)
Spring Temperature.square	0.001^{**}	0.001^{***}
	(0.0006)	(0.0005)
Summer Temperature.square	0.0008	-0.005^{***}
	(0.001)	(0.001)
Autumn Temperature.square	-0.001^{**}	0.0009
	(0.001)	(0.001)
Winter Precipitations	-0.00003	0.0004
	(0.0002)	(0.0003)
Spring Precipitations	0.00003	0.0009^{***}
	(0.0002)	(0.0002)
Summer Precipitations	-0.001^{**}	-0.001^{*}
	(0.0005)	(0.0005)
Autumn Precipitations	-0.0003	-0.0008
	(0.0005)	(0.0005)
Winter Precipitations.square	$-3.021e^{-08}$	$-6.469e^{-07}$
	$(4.948e^{-07})$	$(5.749e^{-07})$
Spring Precipitations.square	$7.504e^{-08}$	$-1.033e^{-06**}$
	$(3.323e^{-07})$	$(3.822e^{-07})$
Summer Precipitations.square	$5.656e^{-06***}$	$6.107e^{-06***}$
	$(2.009e^{-06})$	$(2.266e^{-06})$
Autumn Precipitations.square	$1.540e^{-06}$	$3.769e^{-06*}$
	$(1.973e^{-06})$	$(2.153e^{-06})$
log(Irrigation)	0.189^{***}	0.021^{**}
	(0.025)	(0.008)
log(Land)	0.40^{***}	-0.020^{**}
	(0.084)	(0.008)
log(Livestock)	0.129^{***}	0.004
	(0.019)	(0.012)
log(labor)	-0.168^{***}	0.106^{***}
	(0.036)	(0.015)
λ	0.339^{***}	0.117^{***}
	(0.034)	(0.042)
Observations	560	560
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9: Predicted climate change impact on agricultural production index (API)

	Scenario SSP5 8.5		Scenario SSP1 2.6	
Country	Temperature	Precipitations	Temperature	Precipitations
Algeria	−0.095	−0.019	−0.088	−0.019
Saudi Arabia	−0.331	−0.025	−0.320	−0.028
Djibouti	−0.886	0.004	−0.880	0.009
Egypt	−0.281	−0.019	−0.282	−0.025
U.A. Emirates	−0.595	−0.029	−0.588	−0.032
Iran	0.164	−0.022	0.182	−0.019
Iraq	−0.007	−0.021	0.002	−0.029
Israel	0.019	−0.016	−0.365	−0.022
Kuwait	−0.104	−0.029	−0.096	−0.0163
Lebanon	−0.162	−0.014	−0.171	−0.019
Libya	−0.171	−0.022	−0.164	−0.029
Mauritania	−0.539	−0.023	−0.533	−0.013
Morocco	−0.109	−0.025	−0.101	−0.022
Oman	−0.452	−0.024	−0.447	−0.023
Jordan	−0.096	−0.019	−0.097	−0.018
Palestine	0.022	−0.028	−0.411	−0.025
Qatar	−0.473	−0.033	−0.465	−0.024
Syria	0.029	−0.017	0.015	−0.040
Tunisia	−0.181	−0.032	−0.172	−0.016
Yemen	−0.427	−0.007	−0.421	−0.005
Predicted impact Average	−0.270	−0.021	−0.234	−0.021

Table 10: Total predicted climate change impact on API in MENA region

Country	Scenario SSP5 8.5	Scenario SSP1 2.6
Algeria	−0.107	−0.114
Saudi Arabia	−0.349	−0.359
Djibouti	−0.875	−0.877
Egypt	−0.308	−0.307
U.A. Emirates	−0.620	−0.627
Iran	0.163	0.145
Iraq	−0.027	−0.037
Israel	−0.388	−0.002
Kuwait	−0.113	−0.121
Lebanon	−0.191	−0.182
Libya	−0.193	−0.200
Mauritania	−0.547	−0.552
Morocco	−0.123	−0.131
Oman	−0.470	−0.475
Jordan	−0.119	−0.114
Palestine	−0.436	−0.002
Qatar	−0.489	−0.498
Syria	−0.017	−0.011
Tunisia	−0.189	−0.198
Yemen	−0.428	−0.433
Predicted impact Average	−0,291	−0,255

Table 11: Average variations between the SSP5 8.5 scenarios and the period (1991-2018)

	Period : 1991-2018		Scenario SSP5 8.5		Variation	
Country	Temperature	Prcipitation	Temperature	Prcipitation	Var_Temp	Var_Pricip
Algeria	18.30	558.28	24.54	48.07	0.34	−0.91
Saudi Arabia	21.052	413.01	26.64	47.38	0.26	−0.88
Djibouti	28.90	209.70	29.50	255.35	0.02	0.22
Egypt	20.45	98.00	24.01	3.37	0.17	−0.96
U.A.Emirates	27.62	75.51	28.86	31.17	0.04	−0.58
Iran	10.98	340.64	19.12	269.43	0.74	−0.21
Iraq	18.16	447.49	24.05	206.24	0.32	−0.53
Israel	19.61	654.90	20.20	216.84	0.02	−0.66
Kuwait	25.67	102.02	27.30	123.98	0.06	0.21
Lebanon	18.38	602.27	16.53	530.41	−0.10	−0.11
Libya	21.60	127.25	23.24	8.2	0.07	−0.93
Mauritania	22.30	57.87	28.69	54.85	0.28	−0.05
Morocco	17.44	662.41	24.54	48.07	0.40	−0.92
Oman	28.22	60.15	28.76	12.97	0.01	−0.78
Jordan	19.61	654.90	20.45	216.84	0.04	−0.66
Palestine	21.40	221.81	20.20	216.84	−0.05	−0.02
Qatar	27.62	75.51	28.45	50.26	0.02	−0.33
Syria	19.81	814.85	20.20	12.97	0.01	−0.98
Tunisia	18.87	625.46	21.32	182.46	0.13	−0.70
Yemen	19.57	275.83	26.30	134.21	0.34	−0.51
Average	21.28	353.89	24.29	133.50	0.14	−0.62

Table 12: Average variations between the SSP1 2.6 scenarios and the period (1991-2018)

	Period : 1991-2018		SSP1 2.6		Variation	
Country	Temperature	Prcipitation	Temperature	Prcipitation	Var_Temp	Var_Pricip
Algeria	18.30	558.28	24.34	48.17	0.33	−0.91
Saudi Arabia	21.052	413.01	26.46	47.17	0.25	−0.88
Djibouti	28.90	209.70	29.45	237.41	0.01	0.13
Egypt	20.45	98.00	23.89	3.28	0.16	−0.96
U.A.Emirates	27.62	75.51	28.69	33.04	0.03	−0.56
Iran	10.98	340.64	18.94	273.85	0.72	−0.19
Iraq	18.16	447.49	23.84	208.18	0.31	−0.53
Israel	19.61	654.90	21.416	219.48	0.09	−0.66
Kuwait	25.67	102.02	27.09	124.91	0.05	0.22
Lebanon	18.38	602.27	16.43	540.12	−0.10	−0.10
Libya	21.60	127.25	23.09	8.18	0.06	−0.93
Mauritania	22.30	57.87	28.50	51.05	0.27	−0.12
Morocco	17.44	662.41	24.34	48.17	0.39	−0.93
Oman	28.22	60.15	28.64	13.73	0.01	−0.77
Jordan	19.61	654.90	20.32	53.31	0.03	−0.92
Palestine	21.40	221.81	21.41	219.48	0.0004	−0.01
Qatar	27.62	75.51	28.28	51.62	0.02	−0.31
Syria	19.81	814.85	20.05	219.48	0.01	−0.73
Tunisia	18.87	625.46	21.13	182.98	0.12	−0.70
Yemen	19.57	275.83	26.15	128.28	0.33	−0.53
Average	21.28	353.89	24.12	135.59	0.13	−0.61

9 Appendix: Figures

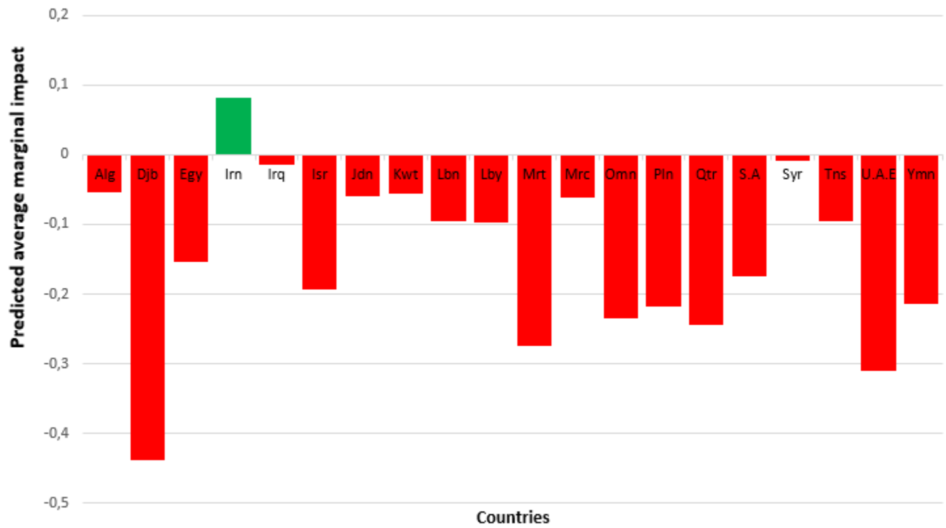

Figure 7: Total Predicted impact on API by country: Scenario SSP 2.6

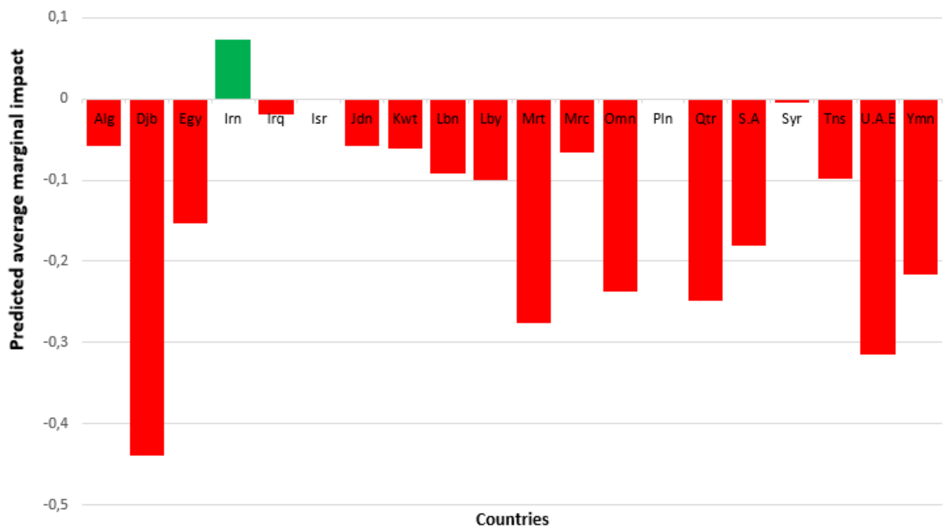

Figure 8: Total Predicted impact on API by country: Scenario SSP 8.5

(a) Temperature impacts (b) Precipitations impacts

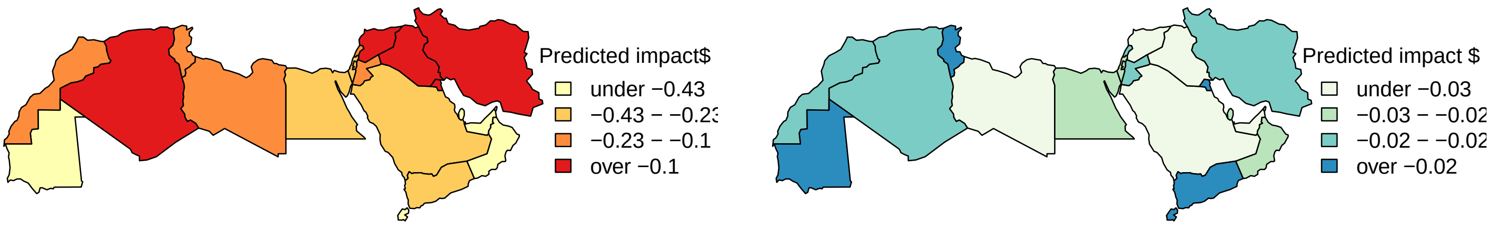

Figure 9: Predicted climate change impacts on API by country: Scenario SSP 2.6

(a) Temperature impacts (b) Precipitations impacts

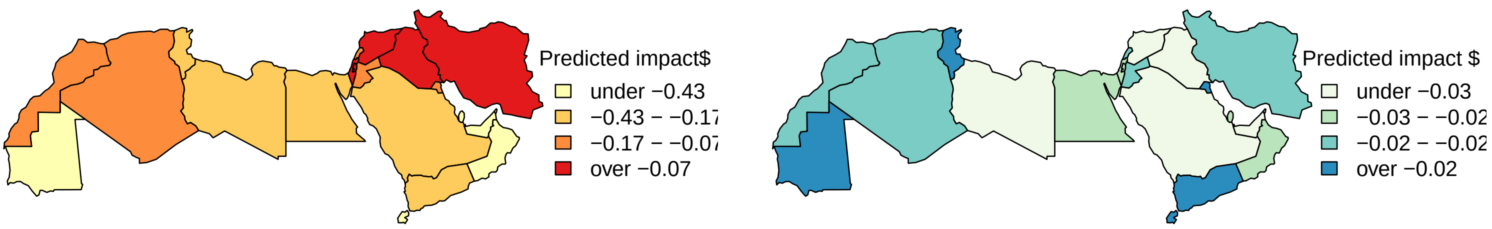

Figure 10: Predicted climate change impacts on API by country : Scenario SSP 8.5

(a) Scenario SSP 2.6 (b) Scenario SSP 8.5

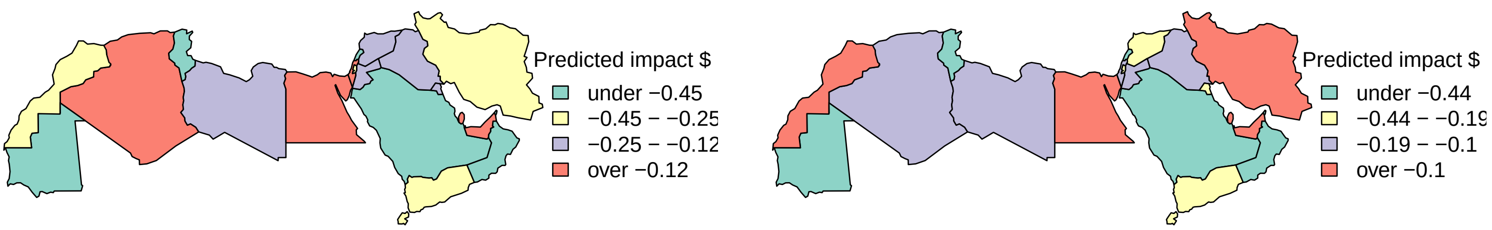

Figure 11: Total predicted climate change impacts on API by country

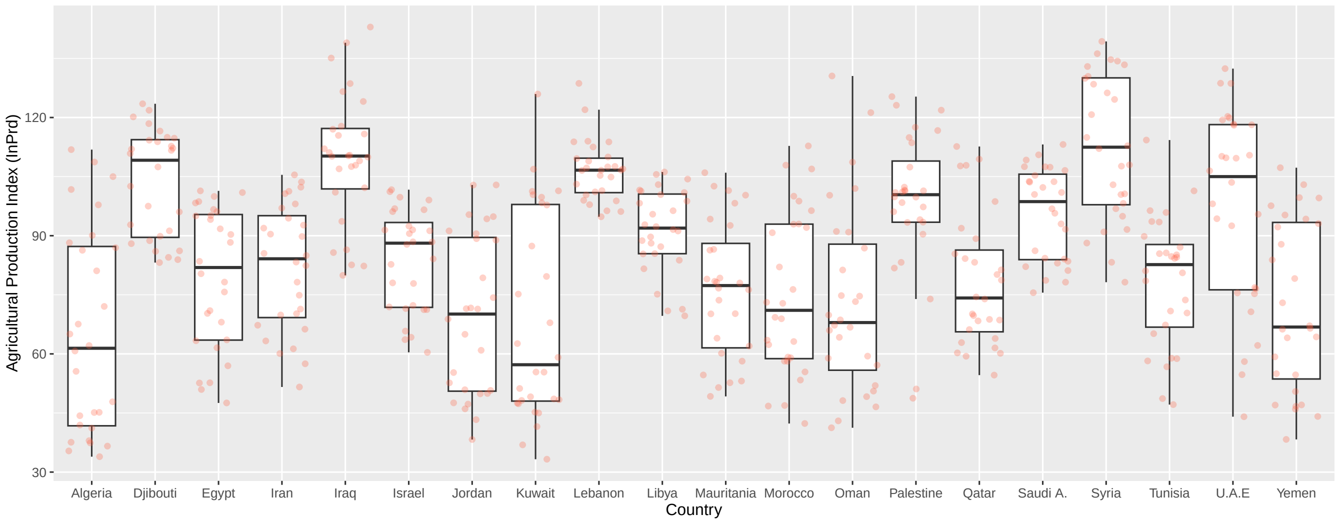

Figure 12: Boxplots of agricultural production index by country over 1991-2018

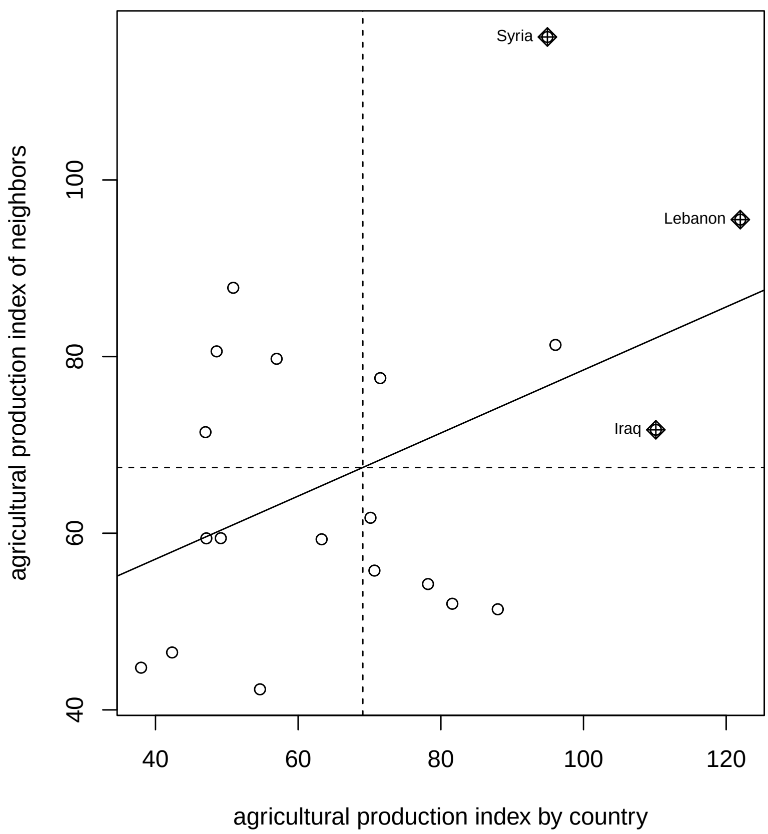

Figure 13: Moran Scatter-plots for agricultural production index (API)

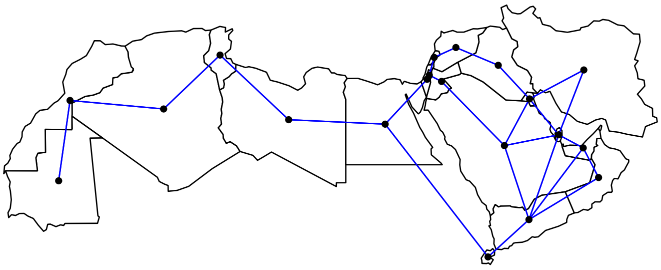

Figure 14: Gabriel contiguity weight matrix (W_cont)

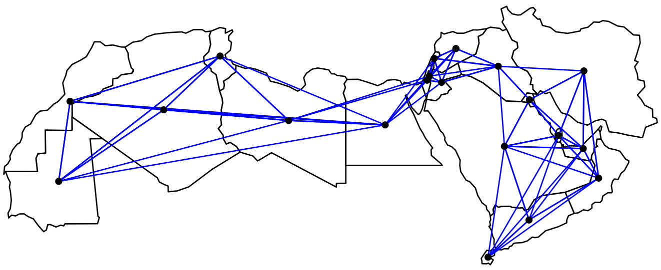

Figure 15: Nearest neighbors weight matrix (W_nn5)

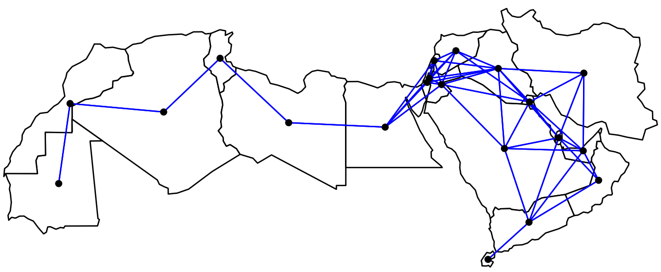

Figure 16: Inverse distance matrix (W_dinverse)

(a) Temperature variations

(b) Precipitations variations

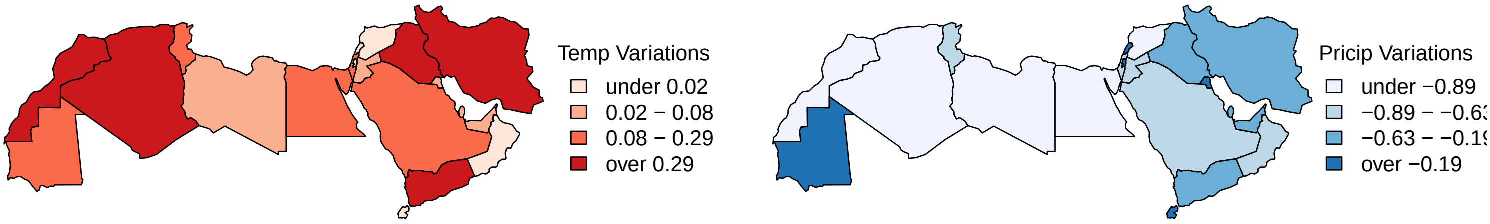

Figure 17: Average variations between the SSP 2.6 scenario and the period (1991-2018) in MENA countries

(a) Temperature variations

(b) Precipitations variations

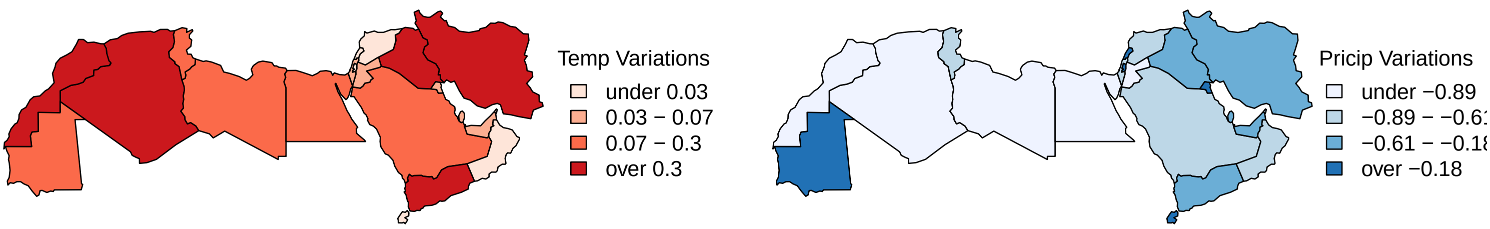

Figure 18: Average variations between the SSP 8.5 scenario and the period (1991-2018) in MENA countries

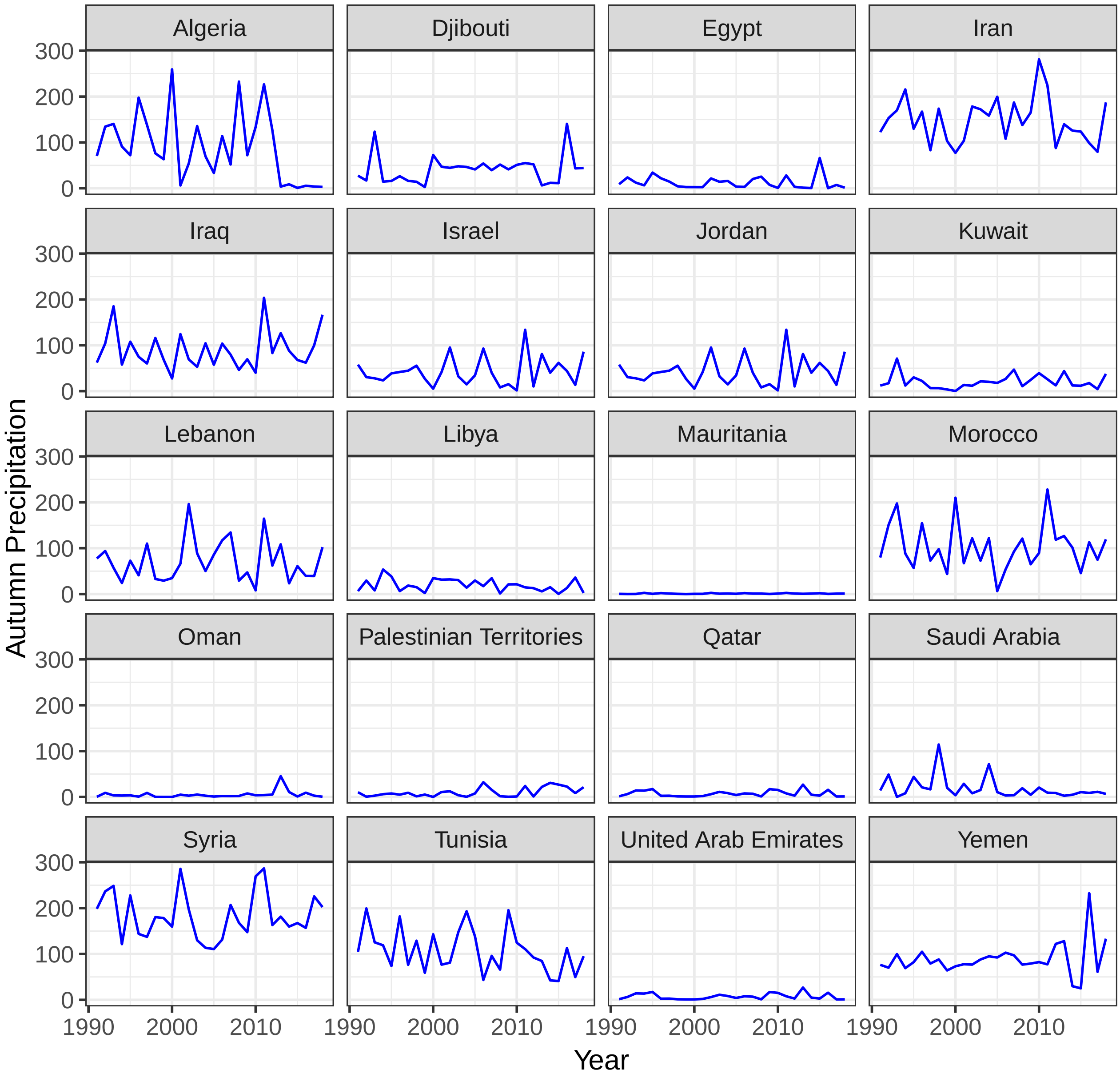

Figure 19: Annual Precipitation in the MENA countries during the Autumn season from 1991 to 2018

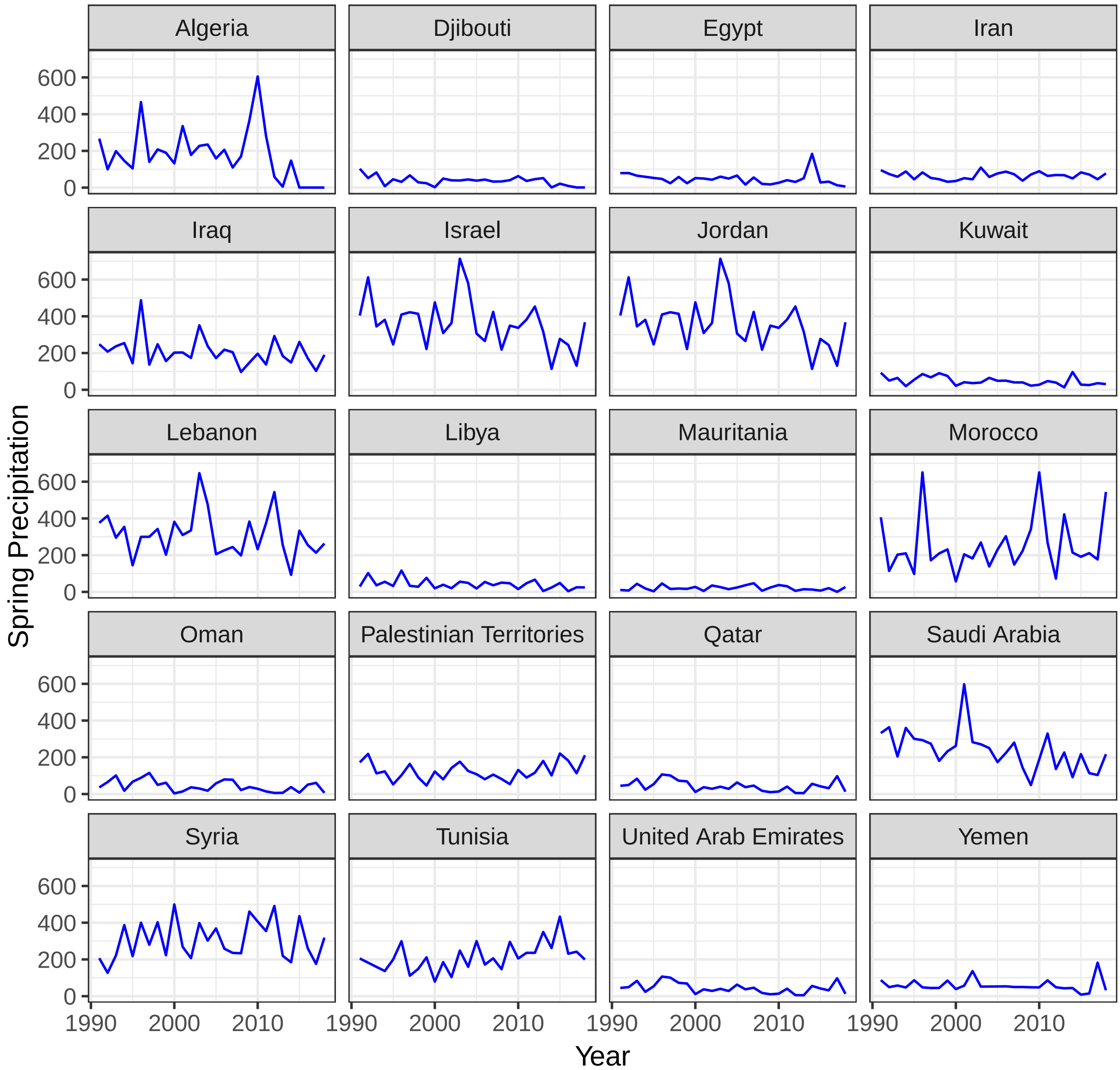

Figure 20: Annual Precipitation in the MENA countries during the Spring season from 1991 to 2018

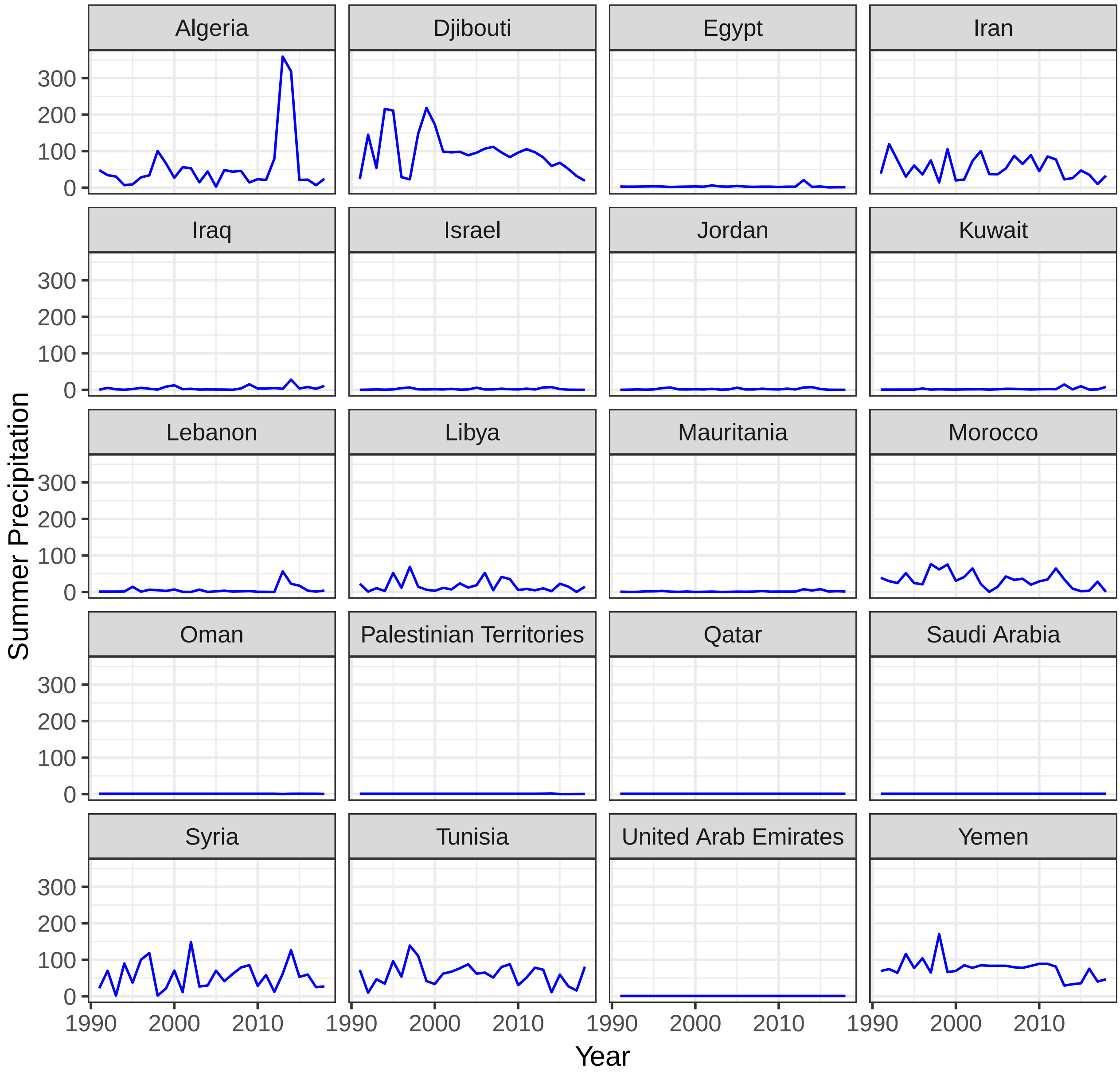

Figure 21: Annual Precipitation in the MENA countries during the Summer season from 1991 to 2018

Figure 22: Annual Precipitation in the MENA countries during the Winter season from 1991 to 2018

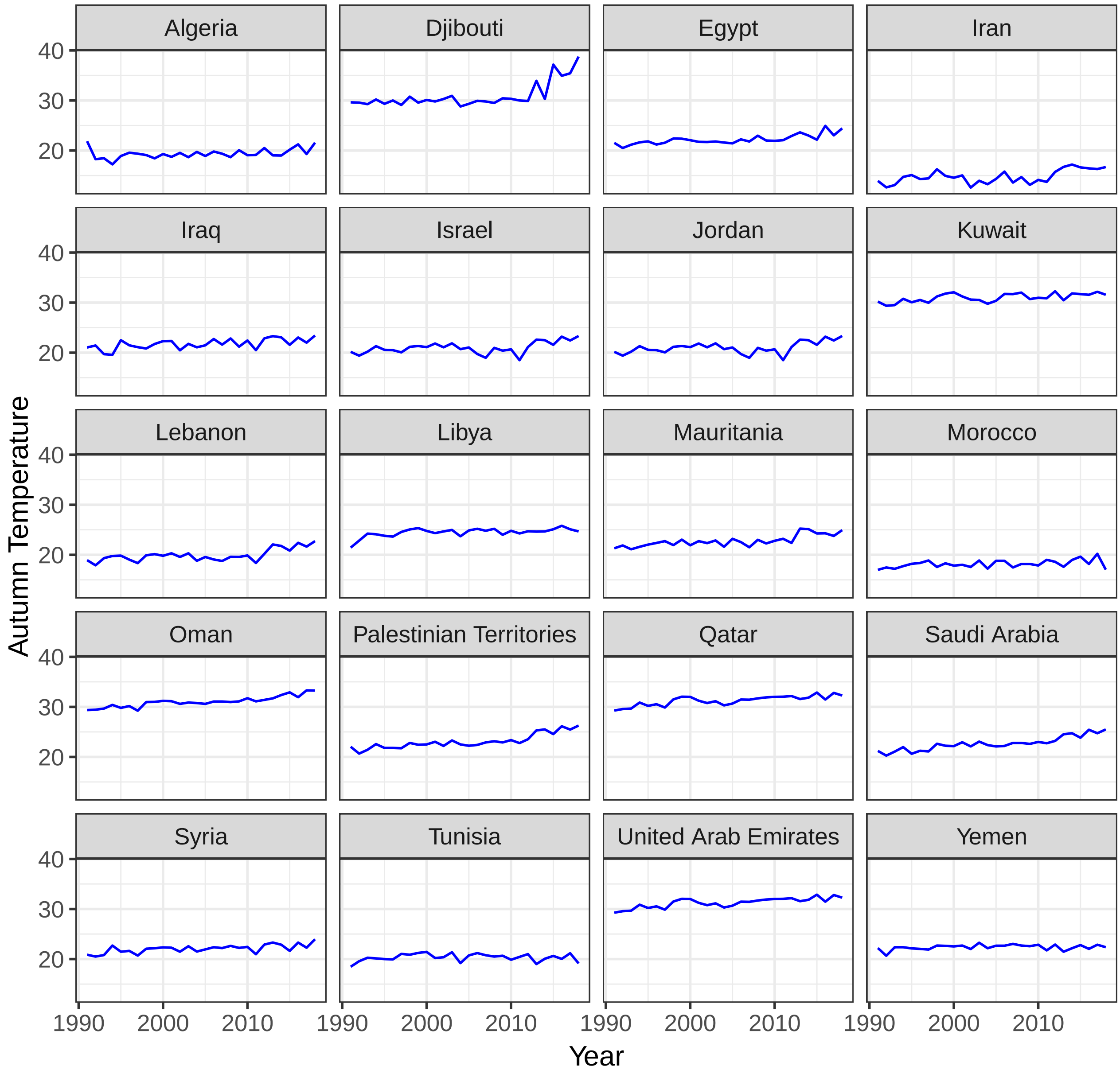

Figure 23: Annual Temperature in the MENA countries during the Autumn season from 1991 to 2018

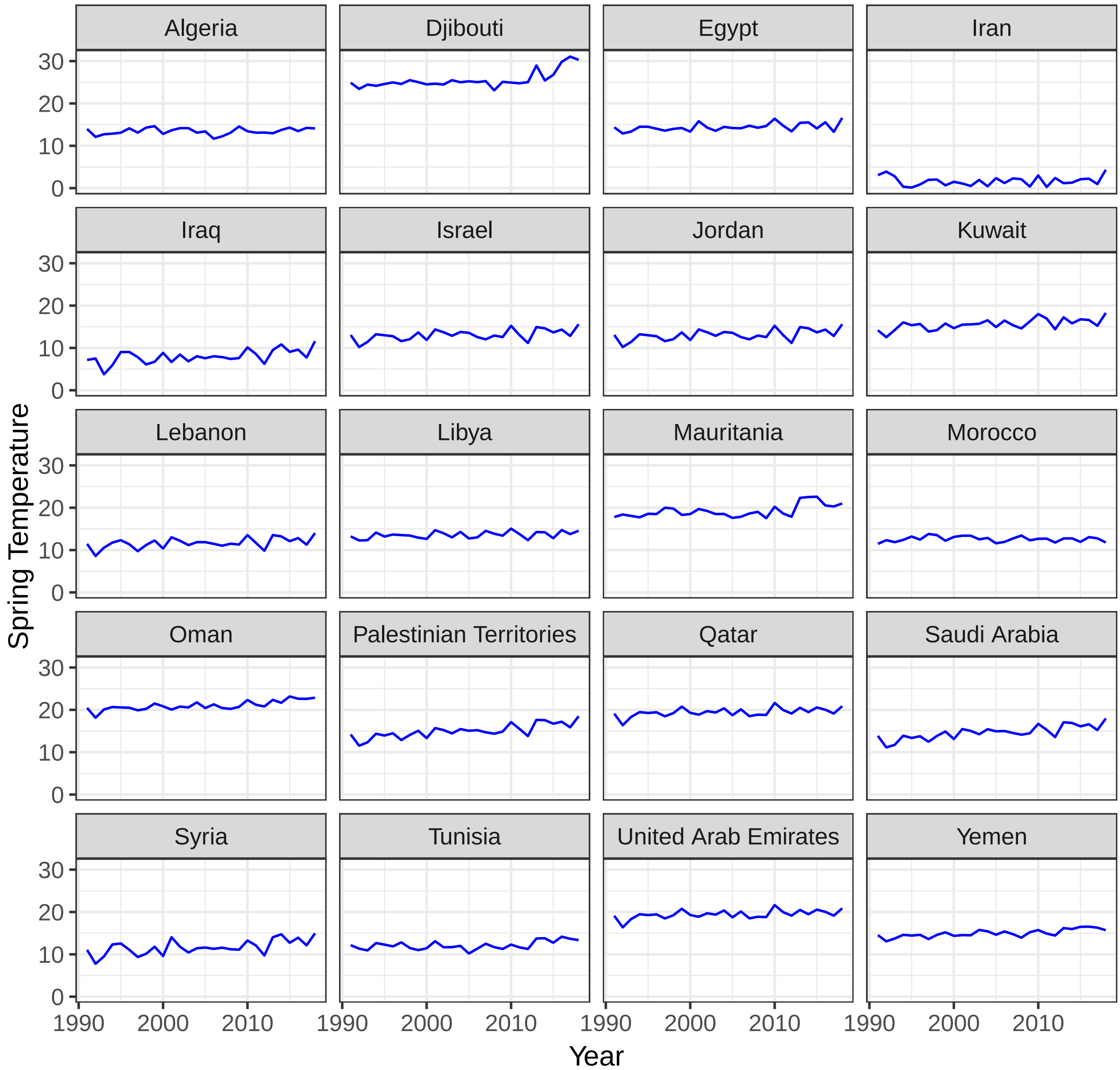

Figure 24: Annual Temperature in the MENA countries during the Spring season from 1991 to 2018

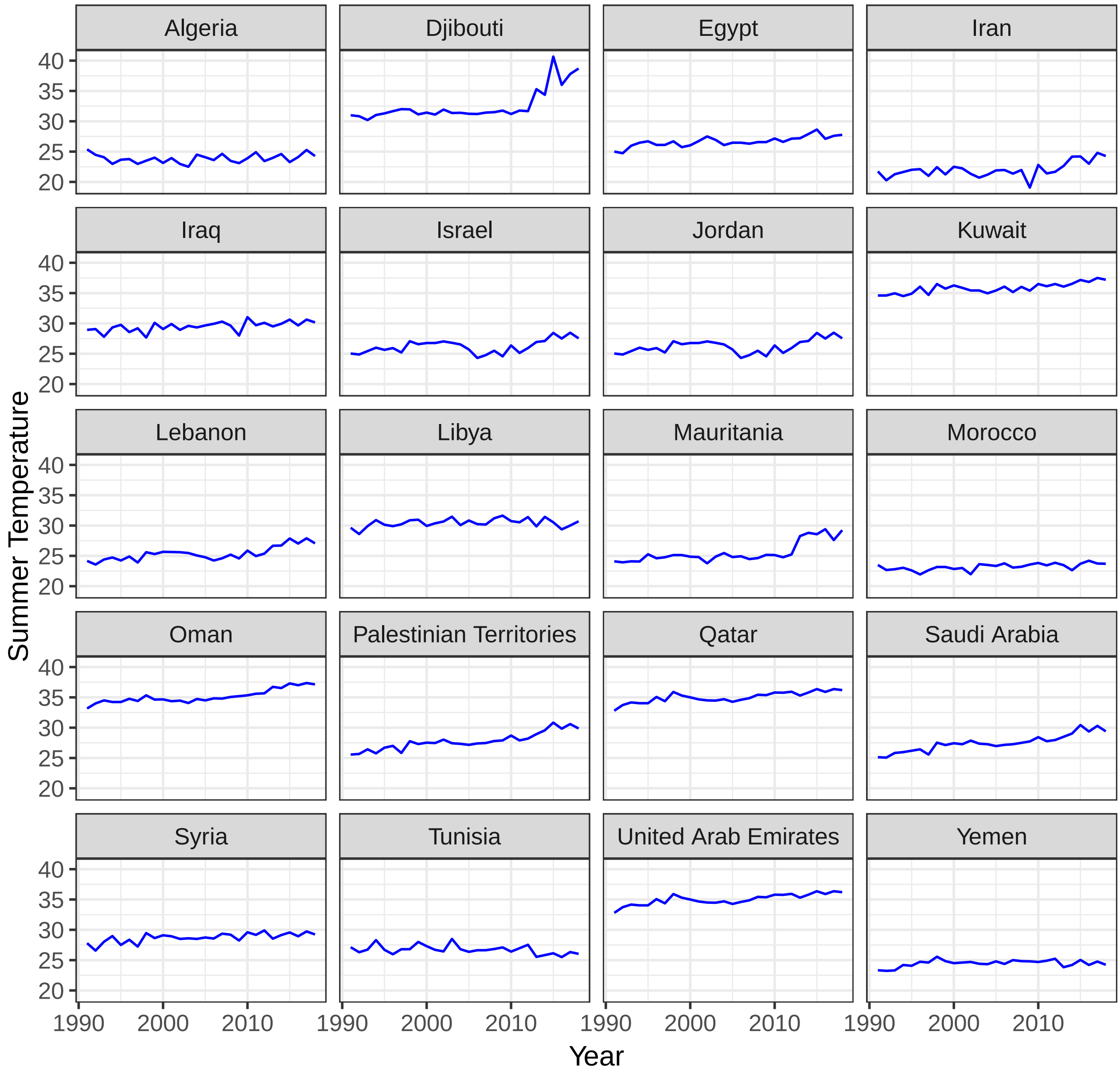

Figure 25: Annual Temperature in the MENA countries during the Summer season from 1991 to 2018

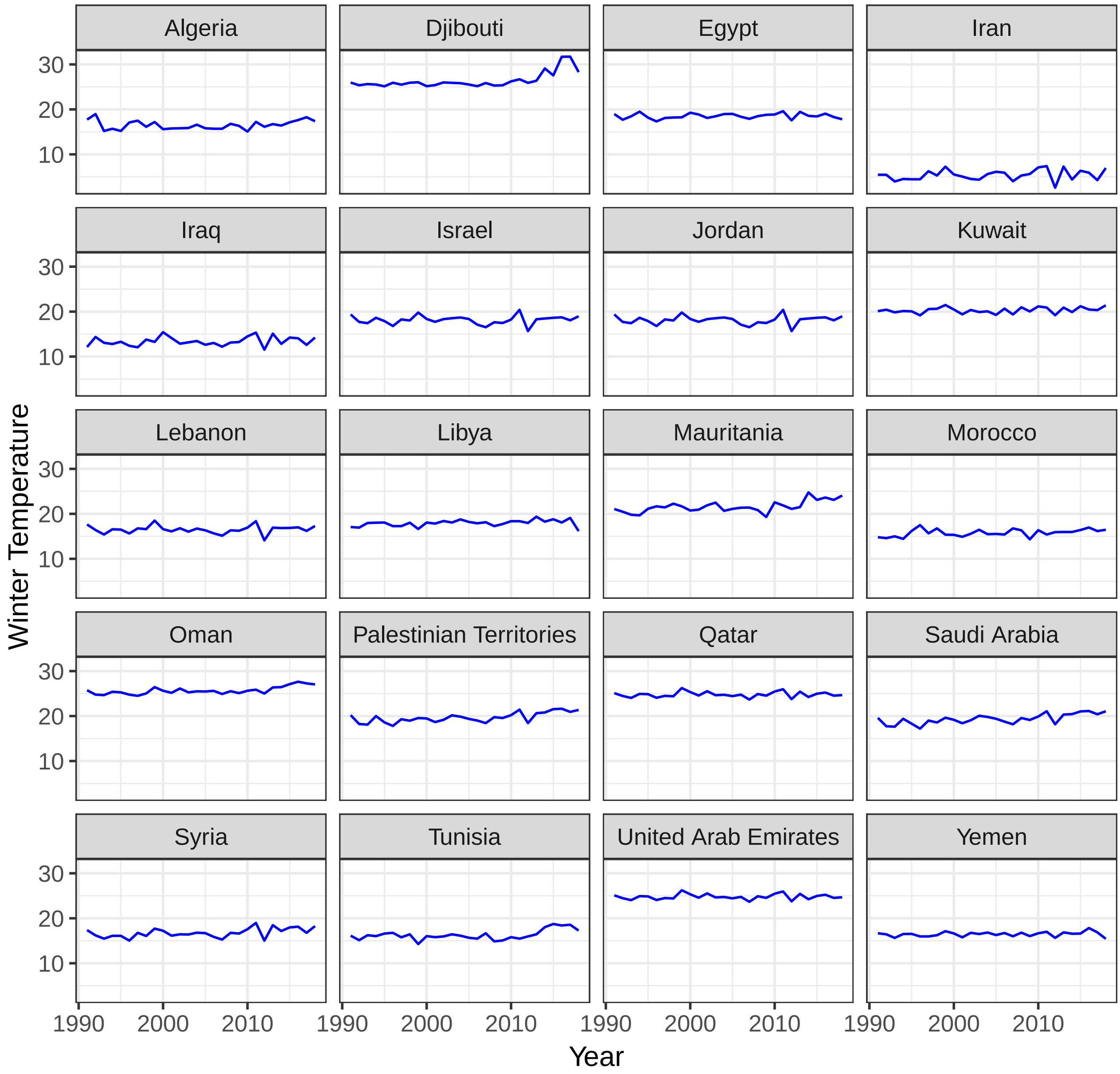

Figure 26: Annual Temperature in the MENA countries during the Winter season from 1991 to 2018