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Long-Run Versus Short-Run Analysis of Climate Change Impacts on Agricultural Crops

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Abstract In this paper, we propose an original empirical investigation of the long-run versus short-run impacts of climate change on the Tunisian agricultural sector. Using an original regional database, we apply the panel cointegration tests and estimation of Pedroni (Oxford Bulletin of Economics and Statistics S1 61:653–670, 1999; Review of Economics and Statistics 89:727–731, 2001) to estimate the long-run effects. We find that an increased annual temperature decreases both cereal and date productions, with an exception in highland areas. In addition, the annual rainfall has a positive effect on cereals, but rain shortages in the south affect production negatively in this region. The short-run climate effects are smaller than the long-run effects. The rainfall has a weak positive effect that is counterbalanced by the threat of brutal temperature increases over the last decades. This paper calls for the implementation of a public policy privileging and subsidizing the threatened areas. Adaptation measures should include the implementation of a water demand management system that promotes using scarce water resources more efficiently. Moreover, policy makers should seriously consider encouraging the development of drought-tolerant crops, especially in the south of Tunisia where global warming has caused a severe drought. In the north of Tunisia, adaptation measures may include choosing tree species and forestry practices less vulnerable to storms and fires, especially in Jendouba, the forestry region of Tunisia.

Keywords Climate change impacts · Date and cereal crops · Panel cointegration · Error correction model

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1 Introduction

The climate and weather play a major role in agricultural productivity. They determine the types of crops grown by farmers and even the yield at harvest time; thus, they alter the patterns of rainfall, temperature, and radiation, among other weather elements. According to Mendelsohn et al. [27], analytical and empirical arguments hold that climate changes lead to declining agricultural productivity. Fischer et al. [15] predicted that 29 African countries faced an imminent aggregate loss of 35 million tons in their potential cereal production as a result of anticipated climate change. The impact of climate change on crop productivity could have multiplier effects. First, with increased temperature and evapotranspiration, more water will be required for crop production. If there is no corresponding increase in precipitation, the countries are likely to experience a serious crop failure in most parts. Second, rising temperatures have also been associated with increased disease incidence in many countries.

The Tunisian agricultural sector employs more than 20 % of the labor force. Moreover, it represents 11.5 % of the gross national product and contributes to an important part of the Tunisian exports as a source of foreign currency. Thus, the Tunisian agricultural sector should not be neglected in any development plan, and policy makers are invited to provide serious protection to this sector, given its vulnerability to climate change impacts. Policy makers should anticipate future climate change accurately, hence reduce its negative impacts and improve investment decisions (e.g., irrigation, precision of early warning systems). Cereal and date crops represent over 50 % of the Tunisian agricultural output. These crops are expected to be the most affected by climate change and weather conditions.

Tunisia, which belongs to both Mediterranean and sub-Saharan countries, has an attractive geographical position. The south of Tunisia experiences the joint effect of this geographical position and climate warming, given its Saharan nature. In contrast, the north of Tunisia benefits from a Mediterranean climate characterized by a hot and dry summer and a relatively rainy winter. Given this diverse climate, we first intuitively try to explain the long-run weather and climate impacts before confirmation by objective analysis based on empirical investigations. Temperature is expected to affect cereal and date yields negatively, at least in the southern regions that are characterized by a dry climate. However, rainfall and precipitations are expected to have positive impacts on the agricultural production. According to Fischer and Velthuizen [14], a plausible positive effect of temperature can be found in mountainous areas. Otherwise, a long-run negative rainfall effect can be found in the southern regions that have suffered from severe drought for the last three decades. Moreover, climate data on Tunisia gathered during the 20th century indicate heating, estimated at over 1 °C, with a pronounced trend in the past 30 years. At the beginning of the 20th century, the country experienced one drought every 10 years, in contrast with the current state of 5 or 6 years of drought per 10 years. Given the importance of agriculture to employment and livelihoods in Tunisia, the loss of agricultural productivity due to climate change will affect the country's entire economy.

Over the last three decades, the link between climate change and agricultural productivity has benefited from active research in applied econometrics on environmental and agricultural economics. Most of these studies have been carried out in developed countries, mainly in Europe and in the United States. We mention some of them for illustration purposes: Lang [21], Lippert et al. [23], Fischer et al. [16], Schlenker et al. [37], Adams et al. [2, 3], Rosenzweig and Parry[33]) Rosenberg and Scott[32]). The Middle East and North Africa (MENA) countries, however, have been the subject of relatively few studies.

In this context, this study is innovative: to the best of our knowledge, panel cointegration is used for the first time to study the climate change impacts on agricultural production using a rich panel data set from 1975 to 2011 in 24 Tunisian regions. Our database consists of annual panel data for cereal production, date production, temperature, and rainfall. The second innovation of this study is to analyze the long-run versus short-run impacts of climate change on agriculture in Tunisia. To the best of our knowledge, no published paper has examined the impacts of climate change on agriculture in Tunisia. Moreover, the Mediterranean region is potentially vulnerable to climatic changes induced by temperature and precipitation variations. Consequently, it is important to empirically investigate the interdependence between these two important factors and agricultural crops. We contribute empirically to the existing literature by the application of recent econometric techniques to the Tunisian regional database. This extension involves looking for the appropriate econometric tools and explicitly taking into account the deep Tunisian economic and political structural transformations that have taken place over the last four decades.

The first step of our study involved analyzing the data and carrying out the necessary tests to see whether the data are stationary. We then used the panel cointegration technique, which explicitly integrates the nonstationary character of our panel data, to derive the estimates of the long-run weather effects with the right properties. Our findings led us to propose relevant policy recommendations. Section 2 of this paper presents a brief constructive literature review, and Section 3 gives a description of the original climate database. The new econometric techniques, which have been extensively developed for a number of years and on which we rely, are briefly surveyed in Section 4. The empirical investigation and the analysis of the main results are provided in Section 5. Finally, a number of policy recommendations conclude the paper.

2 Overview of the Literature

It is expected that, globally, 20 % of all damages caused by climate change will occur in the agricultural sector; hence, understanding climate vulnerability and weather patterns is a crucial element in estimating future climate change impacts (Intergovernmental Panel on Climate Change [IPCC], [20]). These changes have been considered as a major source of consensus between researchers on environmental economics over the last three decades. The long-term change in mean temperature, rainfall, and precipitation has gradually been recognized as an additional factor which will have, in conjunction with other conventional constraints, a significant weight on the form and scale of spatial and temporal impacts on agricultural productivity. The general consensus to emerge from the growing body of literature in this domain is that, in the absence of adequate response strategies to long-term climate change as well as to climate variability, diverse and region-specific impacts will become more apparent.

The large literature regarding the impacts of climate change on agricultural production cannot be exhaustively reviewed in this paper. Thus, we review a few selected studies that reflect a good mix of the overall literature trends. Over the last three decades, the literature on climate change impacts on agriculture has been dominated by two different methodologies. One method applies econometric models to time series, cross-sectional, or panel data, whereas the second one uses the

Ricardian or hedonic method as theoretical background. We review a few selected studies based on these two approaches.

Deschênes et al. [10, 11] examined the economic impacts of climate change on agricultural output. Using U.S. data on agricultural production and weather variables, they found that climate change increases annual profits by $1.3 billion. Deschênes et al. [11] indicated that the predicted impacts of climate change on farm profits are heavily dependent on the functional form assumed for the climatic and control variables. However, Fisher et al. [17] explained the divergence between results by the difficulties experienced in calculating the profit measure, the use of older climate change projections, and missing and incorrect weather and climate data.

Empirical findings on 60 crops in Taiwan showed that the two climate variables (temperature and precipitation) have significant implications on many crop yields [6]. A negative impact of temperature on yield was observed for several rice- and maize-producing countries [24]. However, differences in simulated yield increases due to doubling CO_2 among models were small in comparison to the differences between simulated and observed yields for ambient conditions [13]. Crop adaptability to particular years as well as yield increment and yield stability was found to be crucial factors for the future [7].

According to Rosenzweig et al. [34], climate change is expected to result in long-term water and other resource shortages, drought and desertification, disease and pest outbreaks on crops and livestock, and the rise of sea levels. Consequently, vulnerable areas are expected to experience losses in agricultural productivity, primarily due to reductions in crop yields. The global welfare changes in the agricultural sector are approximated between losses of US$61.2 billion and gains of US$0.1 billion [31]. Under the most severe scenarios of climate change, losses are expected to be omnipresent (see studies by; [33, 9, 4]). Experts predict a spatial shift of crops and agriculture production, and estimation results indicate 24 % of production losses in developed countries and 16 % in developing countries.

Lobell et al. [25] derived the nonlinear effect of heat on African maize. Using a data set of over 20,000 historical maize trials in Africa, combined with daily weather data, they found that each degree day spent above 30 °C reduced the final yield by 1 to 1.7 %. In addition, Schlenker and Roberts [35] examined the effect of nonlinear temperature on crop yield in the United States. Using data in temperature distribution within each day and across all days in the growing season, they showed that yields increase with a temperature up to 29 °C for corn, 30 °C for soybeans, and 32 °C for cotton. The authors showed that temperature is very harmful above these thresholds.

Welch et al. [39] estimated the effects of daily minimum and maximum temperatures on rice yields in tropical Asia. Using data on rice yields in six important rice-producing countries and daily temperature values, they found statistically significant impacts of temperature and radiation during both the vegetative and ripening phases of the rice plant. Findings showed that the rice yields decrease with a higher minimum temperature and increase with a higher maximum temperature. The authors concluded that temperature variation must be considered when investigating the impacts of climate change on irrigated rice in Asia. When examining the climate change impact on Kenya, Fischer and Velthuizen [14] found that higher temperatures have a positive impact in highland areas. Similarly, Downing [12] showed that in western Kenya an increase in temperature by 2.5 °C would lead to an increase of 67 % in high-potential land.

The Ricardian method has been applied to various countries, including the United States, Brazil, and Germany, and to the African continent. Schlenker et al. [36] derived the effects of climate change on U.S. agriculture. Using the hedonic approach, they found that changes in long-run weather patterns might have a smaller effect on commodity prices, especially on crops produced in California and Florida. The hedonic approach was used as a theoretical background by Lang [21], who found that land prices are determined by climatic factors. Lang also showed that German farmers are winners of climate change in the short run, with maximum gains occurring at a temperature increase of +0.6 °C against current levels. In the long run, there may be losses from global warming. Seo et al. [38] applied the Ricardian approach to analyze the distribution of climate change impacts on agriculture across agro-ecological zones in Africa and found that the effects of climate change will be quite different across Africa, and the humid forests will become more productive in the future.

Quantitative studies on the impacts of climate change have been based mainly on experimental and cross-sectional research. The experimental technique that includes agro-economic simulation models was applied by Parry et al. [28] and Adams et al. [1]. The agronomic approach was criticized by Mendelsohn et al. [27] and Mendelsohn and Dinar [26], who argued that this approach overestimates damage. This method (controlled experiments), which is characterized by higher implementation costs, was primarily used to estimate the impacts on grains [3]. The main focus of these studies was the identification of adaptation mechanisms to climate change scenarios.

Many results are derived from several crop simulation studies. These results show that an evolution in mean temperature or rainfall will be accompanied by an evolution in agricultural production or productivity. For instance, an increase by 2 °C in the minimum temperature will reduce rice yield in India at the rate of 0.71 ton/ha while a 1 °C rise in the mean temperature would have no significant effect on wheat yields [5]. Hulme et al. [18] argued that in 100 years' time, Africa could be 2–6 °C warmer on average, which will certainly affect the overall agricultural production. Developing countries, and particularly the poorest countries, will not be able to avoid the impacts of climate change, which are evident in several scenarios that include higher temperatures, drought, and main rainfall decrease. In the light of these findings, we used desegregated data covering 24 regions in Tunisia to study the case of Tunisia and compared results with those of other studies. To the best of our knowledge, this paper is the first to present a long-run versus short-run analysis of climate change impacts on agricultural production using the nonstationary panel data technique.

3 Data Description and Analysis

The empirical analysis is based on 24 regions in Tunisia, namely Tunis, Ariana, Ben Arous, Manouba, El Kef, Kasserine, Béja, Siliana, Medenine, Tataouine, Kebili, Nabeul, Tozeur, Gafsa, Gabés, Kairouan, Sidi Bouzid, Bizerte, Zaghouan, Sousse, Monastir, Mahdia, Jendouba, and Sfax. The time dimension of the panel data covers the period 1979–2011.

The data on cereal production, annual rainfall, and temperatures were collected for the entire sample. However, data on date production were collected for the southern region only (Gabés, Gafsa, Tataouine, Tozeur, and Kebili), which monopolizes date production owing to its Saharan climate, and for a longer period, beginning in 1976. This novel and rich database was provided by the Tunisian Ministry of Agriculture and Water Resources and the National Institute of Meteorology. Annual values of rainfall and temperature data for 35 years were collected from all the meteorological stations in the entire country. Data regarding the annual production of cereals in each region were collected by the Statistics Department of the Ministry of Agriculture and Water Resources.

Drought conditions may also be brought on by lower amounts of precipitation. In arid regions, drought may reduce subsequent river discharge and irrigation water supplies during the growing period. Episodes of high relative humidity, frost, and hail can also affect yield and the quality of fruits and vegetables (especially corn and other grains). Crop yields are most likely to suffer if dry periods occur during critical developmental stages such as reproduction. In most grain crops, flowering, pollination, and grain filling are especially sensitive to water stress. Moreover, above a certain temperature threshold, crops respond negatively, and agricultural productivity will be significantly reduced.

Cereal crops are vulnerable to daily periods of high temperature. In arid regions, air temperatures between 45 and 50 °C that occur for at least 30 min directly damage crop leaves. Lower temperatures between 30 and 40 °C can also be damaging if they persist for longer periods of time. The vulnerability of crops to higher temperatures is also determined by differences in altitude. In highland areas, crops respond positively to temperature increases [14] whereas, in low-lying areas, higher temperatures might damage crops. Moreover, heat accentuation, caused by drought stress for a long period, is often accompanied by high solar irradiance and high winds. Such irradiance reduces transpiration and consequently raises plant temperatures.

Table 1 shows some aggregate statistics about annual fluctuations of the variables and thus gives a preliminary description of the variables in the long run. For both cereal and date production, we observe a significant difference between the maximum annual production and the mean value over the last 35 years. This can be primarily explained by the profound structural transformation that the Tunisian economy went through. After independence from France in 1956, Tunisia encouraged agricultural investment and developed financial institutions that subsidized farmers. Indeed, in 1960, the national agricultural bank was created to promote agricultural activities and increase production. This bank was restructured in 1989 to facilitate accessibility of farmers to loans with reduced interest rate. These actions have transformed the economy and augmented the share of the agricultural sector in the GDP. The agricultural sector represented only 5 % of the

Table 1 Descriptive statistics of the variables

Variable	Description	Mean	Min	Max
Rainfall in mm (RL)	Average annual level of precipitations (mm)	52.83	1	296
Temperature (TM)	Average annual level of temperature (°C)	11.78	5	21
Cereals in tons (*Y*)	Cereal annual production by region (tons)	361,473.3	0.5	5,398,880
T=33 (1979–2011) and n=24				
Descriptive statistics of the second subsample				
Rainfall in mm (RL)	Average annual level of precipitations (mm)	22.7	1	168
Temperature (TM)	Average annual level of temperature (°C)	12.23	8	21
Dates in tons (*Y*)	Date annual production by region (tons)	21,161.26	1,089	91,000
T=36 (1976–2011) and n=5				

GDP in 1970 whereas it currently represents 11.5 %, which is explained by the structural transformation of this sector within the Tunisian economy over the last four decades.

We used these data to examine the relationship between the yields of the two most important agricultural crops (cereals and dates) and annual weather fluctuations measured by temperature and rainfall. Moreover, when there is an interaction term, the effect of one variable that forms the interaction depends on the level of the other variable in the interaction. The interaction effect between the two climate variables was also tested. The effect of precipitation on agricultural crops is linked to the effect of temperature: for a given level of temperature $temp_0$ in a region, the effect of precipitation is the effect of rainfall+the effect of interaction × $temp_0$. This means that the total effect of precipitation depends on the level of temperature in the region. Hence, there is really no unique effect of precipitation on agricultural crops; it is different for each level of temperature. Finally, the variables were converted into natural logarithmic form before the empirical analysis.

4 Empirical Methodology

As there was a very important time dimension, the existence of a panel long-run relationship between the variables was not excluded from our assumptions. Consequently, the econometric method involved three steps: we began by testing the panel unit roots using two first generation tests proposed by Levin et al. [22] and Im et al. [19]. Then, we carried out the seven tests proposed by Pedroni [29] to obtain the long-term relationship between all variables. Finally, we used the fully modified ordinary least squares (FMOLS) technique to estimate the cointegration vector for heterogeneous cointegrated panels, which corrects the standard OLS bias induced by the endogeneity and serial correlation of the regressors. The use of standard OLS could bias results and overestimates the long-run impact of rainfall and temperature on agricultural crops.

Following Pedroni [30], we employed estimation techniques taking into account the heterogeneity of long-run coefficients. The FMOLS group mean estimator can be used to obtain panel data estimates of the long-run impacts of climate variables on agricultural crops. These estimators correct the standard pooled OLS for serial correlation and endogeneity of regressors that are normally present in a long-run relationship. In our empirical analysis, we put emphasis on between-dimension panel estimators. It is worth noting that the between-dimension approach allows for greater flexibility in the presence of heterogeneity across the cointegrating vectors where rainfall and temperature coefficients are allowed to vary. Additionally, the point estimates of the between-dimension estimator can be interpreted as the mean value of the cointegrating vectors, while this is not the case for the within-dimension estimates.

4.1 Panel Unit Root Test

The Levin, Lin, and Chu test (LLC hereafter) is the founding work in the nonstationary panel data literature. Like the augmented Dickey-Fuller (ADF) test in time series, the LLC tests the null hypothesis of $\delta = 0$, for all i, against the alternative of $^{\delta}$<0 in the following equation:

$$\Delta y_{it} = \delta y_{i,t-1} + \sum_{l=1}^{Pi} \theta ip \Delta yi, t-1 + uit \tag{1}$$

where $d_{1t}=\varnothing$, $d_{2t}=\{1\}$, and $d_{3t}=\{1,t\}$ are used to define the three ADF cases.

Levin et al. [22] proposed a three-step procedure to implement their test. The adjusted statistic used in our study is:

$$\frac{t^*_\delta = t_\delta - N \times \text{std}(\delta) \times \mu^*_{\underset{mT}{\sim}} \times \widehat{\sigma}\widetilde{\varepsilon}^{-2} \times \widehat{S}_N \times \widetilde{T}}{\sigma_{mT}{}^{\sim *} \sim N(0,1)}$$

with $\frac{\sqrt{N}}{T} \to 0$, where $\hat{S}_N$, $\mu^*_{\underset{mT}{\sim}}$, and $\sigma^*_{\underset{mT}{\sim}}$ are, respectively, the average standard deviation ratio calculated in the second step and the mean and standard deviation adjustments simulated by the authors for a different order of m and time series dimension $\widetilde{T}$ [22].

The Im, Pesaran, and Shin test (IPS thereafter) is formulated by the LLC equation when m=2 and δ_i varies across individual cross-sectional units.

Thus, the IPS tests the null hypothesis of δ_i=0 for all I, against the alternative of δ_i<0 for i=1,…,N_1 and δ_i=0 for i= N_1 +1,…,N.

With $N_1 \in (0, N)$, such as $\lim_{N\to\infty} \left({}^{N_1}/_N\right) = \delta$ where $0 \le \delta \le 1$.

If N_1=0, we find the null hypothesis.

Im et al. [19] proposed to use the average of the individual ADF-statistics defined as follows:

$$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^{N} t_{iT}\,(P_i, \beta_i)$$

t_{iT}=(P_i,β_i) is the individual student statistic associated to the null hypothesis for a given lag order P_i and a vector of ADF coefficients.

$$\beta_i = \left(\beta_{i,1}, \beta_{i,2}, \ldots, \beta_{i,pi}\right)$$

Im et al. [19] used the standard normal statistic Z.

$$\overline{Z} = \left[\sqrt{N}\frac{\left(\overline{t}_{NT} - E(t_{iT})\right)}{\sqrt{\mathrm{var}(t_{iT})}}\right] \underset{N\to\infty}{\to} N(0,1)$$

where the terms $E(t_{iT})$ and $\mathrm{var}(t_{iT})$ are, respectively, the mean and variance of each statistic, and they are generated by simulations and are tabulated in Im et al. [19].

4.2 Pedroni's Panel Cointegration Tests

After testing for stationarity of the variables, we turned to testing for the existence of a long-run relationship among the variables. We applied the residual-based method developed by Pedroni [29] where the cointegration rank is a priori known and equal to one. Thus, to test for the null of no cointegration in heterogeneous panels with multiple regressors, the starting point for this cointegration test is the estimation of the following panel regression:

$$\begin{aligned} \ln Y_{it} &= \alpha_{0i} + \alpha_{1i}\ln \mathrm{RL}_{it} + \alpha_{2i}\ln \mathrm{TM}_{it} \\ &\quad + \alpha_{3i}(\ln\mathrm{RL}\times\ln\mathrm{TM})_{it} + \varepsilon_{it} \end{aligned} \quad (2)$$

for i=1,…..,N,t=1,…..,T; where T refers to the number of observations over time and N refers to the number of individual members in the panel. Y, RL, TM, and RL × TM are, respectively, date or cereal production, rainfall, temperature, and an interaction variable between rainfall and temperature. The following steps were followed. First, after estimation, we stored the residuals $\widehat{\varepsilon}_{it}$. Second, we differentiated the original data series for each member and computed the residuals for the differentiated regression:

$$\begin{aligned} \Delta \ln Y_{it} &= \alpha_{1i}\Delta \ln \mathrm{RL}_{it} + \alpha_{2i}\Delta \ln\mathrm{TM}_{it} \\ &\quad + \alpha_{3i}\Delta(\ln\mathrm{RL}\times\ln\mathrm{TM})_{it} + \eta_{it} \end{aligned} \quad (3)$$

Third, we calculated $\widehat{L}^2_{11i}$ as the long-run variance of $\widehat{\eta}_{it}$. Fourth, using the residual $\widehat{\varepsilon}_{it}$ of the original cointegrating equation, we estimated the appropriate autoregressive model. To compute the nonparametric statistics, we estimated $\widehat{\varepsilon}_{it} = \widehat{\psi}_i \widehat{\varepsilon}_{i,t-1} + \widehat{\kappa}_i$ and used the residuals to compute the long-run variance of $\widehat{\kappa}_i$, denoted $\widehat{\sigma}_i^2$. The term λ_i was computed as $\widehat{\lambda}_i = 1/2\left(\widehat{\sigma}_i^2 - \widehat{s}_i^2\right)$, where s_i^2 is just the simple variance of $\widehat{\kappa}_i$. On the other hand, for the parametric statistics, we estimated $\widehat{\varepsilon}_{it} = \widehat{\psi}_i\widehat{\varepsilon}_{i,t-1} + \sum_{k=1}^{ki}\widehat{\psi}_{i,k}\Delta\widehat{\varepsilon}_{i,t-k} + \widehat{\mu}_{i,t}$ and used the residuals to compute the variance of $\widehat{\mu}_{i,t}$, denoted $\widehat{s}_i^{*2}$. Using each of these steps, we constructed the statistics that follow and then applied the appropriate mean and variance adjustment terms reported in Pedroni [29].

Following Pedroni [29], the heterogeneous panel and heterogeneous group mean panel cointegration statistics were calculated as follows:

Panel V-statistic:

$$Z_{N,T,\widehat{v}} \equiv T^2 N^{3/2}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{\varepsilon}_{i,t-1}^{2}\right)^{-1}$$

Panel ρ-statistic:

$$\begin{aligned} Z_{N,T^{-1}\widehat{\rho}} &\equiv T N^{1/2}\left(\left(\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{\varepsilon}_{i,t-1}^{2}\right)\right)\right)^{-1} \\ &\quad \times\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11\boldsymbol{i}}^{-2}\left(\widehat{\varepsilon}_{i,t-1}\Delta\widehat{\varepsilon}_{it} - \widehat{\lambda}_{\boldsymbol{i}}\right)\right) \end{aligned}$$

Panel t-statistic (nonparametric):

$$Z_{tN,T} \equiv \left(\widetilde{\sigma}_{N,T}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{\varepsilon}_{i,t-1}^{2}\right)\Bigg)^{-1/2}\times\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\boldsymbol{L}}_{11\boldsymbol{i}}^{-2}\left(\widehat{\varepsilon}_{i,t-1}\Delta\widehat{\varepsilon}_{it} - \widehat{\lambda}_i\right)\right)$$

Panel ADF-statistic (parametric):

$$\widehat{Z}_{tN,T}^{*} \equiv \left(\left(\widetilde{s}_{\boldsymbol{N,T}}^{*2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11\boldsymbol{i}}^{-2}\widehat{\varepsilon}_{i,t-1}^{*2}\right)\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{\varepsilon}_{i,t-1}^{*}\Delta\widehat{\varepsilon}_{i,t}^{*}$$

Group ρ-statistic:

$$\widetilde{Z}_{N,T^{-1},\widehat{\rho}} \equiv T N^{-1/2}\left(\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\widehat{\varepsilon}_{\boldsymbol{i,t}-1}^{2}\right)\right)^{-1}\times\left(\sum_{t=1}^{T}\widehat{\left(\varepsilon_{i,t-1}\Delta\widehat{\varepsilon}_{it} - \lambda_i\right)}\right)$$

Group t-statistic (nonparametric):

$$\widetilde{Z}_{N,T,t} \equiv N^{-1/2}\left(\sum_{i=1}^{N}\left(\widehat{\sigma}_i^{2}\sum_{t=1}^{T}\widehat{\varepsilon}_{i,t-1}^{2}\right)\right)^{-1/2}\times\left(\sum_{t=1}^{T}\left(\widehat{\varepsilon}_{i,t-1}\Delta\widehat{\varepsilon}_{it} - \widehat{\lambda}_i\right)\right)$$

Group ADF-statistic (parametric):

$$\widetilde{Z}_{tN,T}^{*} \equiv N^{-1/2}\left(\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\boldsymbol{s}}_{\boldsymbol{i}}^{*2}\widehat{\boldsymbol{\varepsilon}}_{\boldsymbol{i,t}-1}^{*2}\right)\right)^{-1/2}\times\left(\sum_{t=1}^{T}\widehat{\varepsilon}_{i,t-1}^{*}\Delta\widehat{\varepsilon}_{i,t}^{*}\right)$$

where $\widehat{\sigma}_i^2$ and $\widehat{S}_i^{*2}\left(\widehat{s}_{N,T}^{*2}\right)$ are, respectively, the long-run and contemporaneous variance for individual i. The other terms are properly defined in Pedroni [29] with the appropriate lag length determined by the Newey-West method. All seven tests are distributed as being standard normal asymptotically. This requires standardization based on the moments of the underlying Brownian motion function. The panel V-statistic is a one-sided test where large positive values reject the null of no cointegration. The remaining statistics diverge to negative infinitely, which means that large negative values reject the null. The critical values are also tabulated by Pedroni [29]. After testing for panel cointegration and estimation of long-run coefficients, we specified and estimated short-run effects, as indicated in the last section.

4.3 FMOLS Mean Group Panel Estimator [30]

The FMOLS group panel estimator was developed by Pedroni [30]. To present the method, we consider the following fixed-effect panel cointegration system:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + \mu_{1,it}, \quad t = 1, \ldots, T \text{ and } i = 1, \ldots, N \tag{4}$$

$x_{it}^{'}$ can in general be m-dimensional vectors of regressors which are integrated of order one, that is:

$$x_{it} = x_{i,t-1} + u_{2,it}, \forall\, i, T \tag{5}$$

where the vector error process $w_{it}=(u_{1,it};u_{2,it})$ is stationary with the asymptotic covariance matrix $\Omega_i, \forall i=1,\ldots,N$,

$\Omega_i=\Omega_i^0+\Gamma_i+\Gamma_i^{'}$, Ω_i^0 is the contemporaneous covariance and Γ_i is a weighted sum of autocovariances.

The long-run covariance matrix is constructed as follow: $\begin{bmatrix} \Omega_{11i} & \Omega_{21i}^{'} \\ \Omega_{21i} & \Omega_{22i} \end{bmatrix}$, where Ω_{11i} is the scalar long-run variance of the residual ε_{it}, Ω_{22i} is the long-run covariance among the $u_{2,it}$, and Ω_{21i} is the vector that gives the long-run covariance between the residual $u_{1,it}$ and each of the $u_{2,it}$.

The FMOLS estimator is given by:

$$\widehat{\beta}_{\text{FMOLS}} = \left(\sum_{i=1}^{N}\widehat{L}_{22i}^{-2}\sum_{t=1}^{T}\left(x_{it}-\overline{x}_i\right)^2\right)^{-1} \sum_{i=1}^{N}\widehat{\boldsymbol{L}}_{11i}^{-1}\widehat{\boldsymbol{L}}_{22i}^{-1}\left(\sum_{t=1}^{T}\left(x_{it}-\overline{x}_i\right)y_{it}^{*}-T\widehat{\gamma}_i\right)$$

where $y_{it}^{*} = (y_{it}-\overline{y}_i) - \frac{\widehat{L}_{21i}}{\widehat{L}_{22i}}\Delta x_{it} + \frac{\widehat{L}_{11i}-\widehat{L}_{22i}}{\widehat{L}_{22i}}\beta(x_{it}-\overline{x}_i)$ and

$$\widehat{\gamma}_i = \widehat{\Gamma}_{21i} + \widehat{\Omega}_{21i}^{0} - \frac{\widehat{\Gamma}_{21i}}{\widehat{\Gamma}_{22i}}\left(\widehat{\Gamma}_{22i} + \widehat{\Omega}_{22i}^{0}\right)$$

The panel group FMOLS estimator is the average of the FMOLS estimator computed for each individual:

$$\widehat{\beta}_{\text{FMOLSG}} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}_{\text{FMOLS}}$$

The last section indicates the empirical results and comments, interpretations, and policy recommendations.

5 Empirical Results

Our empirical investigations began with two different panel unit root tests. Testing for stationarity is the first step of the panel cointegration procedure. The proof of the same order of integration, for all the variables, allows testing for panel long-run relationships between the variables integrated in the same order, and the long-run relationships can be estimated by FMOLS without ambiguity [30]. Given the results obtained, we used the appropriate method (FMOLS) to estimate the long-run impacts of climate variables on agricultural crops. Finally, a panel error correction model is estimated in the last subsection to evaluate the short-run impacts.

5.1 Unit Root and Panel Cointegration Tests

We began with a panel unit root test for all the series. Table 2 presents the results we obtained. As indicated in Section 4.1, both LLC and IPS tests are normally distributed. Consequently, we compared the calculated statistic of each test with 1.96. Table 2 shows clearly that not all the variables are stationary in the two subsamples. All the variables become stationary, as can be seen from the large negative values of LLC and IPS statistics, when we carried out a panel unit root test in the first difference. Therefore, the variables in the first difference are stationary or integrated of order zero ($I(0)$), which means their levels are integrated of order one ($I(1)$).

The presence of a panel unit root is sensitive to the inclusion of a trend. Indeed, there is a unit root in the dynamic of temperature only when a trend is included in Eq. (1). This implies that the cyclical components of annual temperature are deterministic rather than stochastic. In contrast, rainfall, date production, and cereal production exhibit a panel unit root with and without time trend inclusion in Eq. (1).

The results illustrated in Table 2 led us to test the relationships between the cereal production or date production (Y) and the climate variables (RL and TM) for both the first and the second subsamples. The seven tests proposed by Pedroni [29] were carried out. In practice, the calculated statistic of each test is compared to the normal critical value −1.64. The panel V-test has a critical value of 1.64; hence, if the test statistic is

Table 2 Panel unit root tests

	LLC test		IPS test	
	Trend	No trend	Trend	No trend
First subsample: T=33, n=24				
TM	−1.07	−4.51[a]	−1.19	−0.81
ΔTM	−10.5[a]	−11.2[a]	−17.9[a]	−12.8[a]
RL	1.61	0.59	1.66	0.71
ΔRL	−4.48[a]	−5.04[a]	−6.01[a]	−9.16[a]
Y	1.94	−0.49	4.17	−3.67[a]
ΔY	−16.06[a]	−19.2[a]	−26.7[a]	−25.6[a]
Second subsample: T=36, n=5				
TM	−1.06	−2.1[a]	−1.2	−4.7[a]
ΔTM	−1.06	−2.1[a]	−1.2	−4.7[a]
RL	−0.48	−1.04	−0.01	1.16
ΔRL	−6.7[a]	−7.3[a]	−11.9[a]	−13.4[a]
Y	−0.48	1.04	−0.01	1.16
ΔY	−16.5[a]	−13.2[a]	−18.9[a]	−22.8[a]

[a] Indicates that we reject unit root at 5 %

greater than 1.64, we reject the null of no cointegration. The main results are shown in Table 3.

The majority of these tests reject the null of no cointegration, which indicates the existence of long-run equilibrium between the variables that are $I(1)$. Indeed, in the long run, annual cereal and date productions are determined by climate variables (rainfall and temperature).

The first step of the panel cointegration test method was to estimate Eq. (2); then, the estimated residuals from this equation were used to implement the seven statistics. Consequently, the interaction effect of rainfall and temperature was clearly considered in testing the long-run relationship through the additional variable (lnRL×lnTM). We then conducted the individual and group FMOLS estimations. The results of climate change impacts on cereal production are summarized in Table 4 while the long-run estimations of climate change impacts on date production are summarized in Table 5.

Table 3 Panel cointegration tests results

	First subsample: T=33, n=24		Second subsample	
	Trend	No trend	Trend	No trend
Pedroni [29] panel cointegration tests				
Panel V	1.81	3.2	3.8[a]	5.04[a]
Panel ρ	−11.6[a]	−13.2[a]	−21.1[a]	−21.5[a]
Panel t	−15.8[a]	−16.9[a]	−21.8[a]	−18.7[a]
Panel ADF	1.7	0.9	−16.6[a]	−11.2[a]
Group ρ	−17.1[a]	−16.1[a]	−20.01[a]	−22.2[a]
Group t	−18.9[a]	−17.2[a]	−23.7[a]	−21.8[a]
Group ADF	2.6	1.5	−18.4[a]	−16.1[a]

[a] Rejects the null hypothesis at the 5 % significance level. Except for the V-stat, all test statistics have a critical value of –1.64 (if the test statistic is less than –1.64, we reject the null of no cointegration). The V-stat has a critical value of 1.64 (if the test statistic is greater than 1.64, we reject the null of no cointegration)

5.2 Climate Change Impacts on Cereal Production

As we had collected data on cereal production for all regions in Tunisia, we were able to interpret differences in long-run climate effect between the heterogeneous 24 regions. We used the FMOLS estimator developed by Pedroni [30] to estimate the long-run relationship between cereal production, rainfall, and temperature. The combination of the two effects of rainfall and temperature was examined through an interaction term between these two climatic variables. The FMOLS estimator is super-consistent, asymptotically unbiased, and normally distributed, even in the presence of endogenous regressors. Beginning with the long-run results (see Table 4), our main findings can be summarized as follows.

From the FMOLS individual results, we can conclude that the long-run impact of temperature is statistically significant for almost all the regions. The long-run effect of temperature on cereal production is combined with the effect of the interaction variable. For a given level of annual rainfall (rainfall$_0$), the long-run effect of temperature is given by $(\widehat{\alpha}_{2i} + \widehat{\alpha}_{3i} \times \text{rainfall}_0)$, where $\widehat{\alpha}_{2i}$ and $\widehat{\alpha}_{3i}$ are the long-run coefficients estimated by FMOLS from Eq. (2). Moreover, the long-run effect of precipitations on cereal production is also given by ($\widehat{\alpha}_{1i} + \widehat{\alpha}_{3i}*$ temperature$_0$), where $\widehat{\alpha}_{1i}$ is the unique effect of rainfall estimated from Eq. (2). The negative effect of temperature for instance will be canceled by the effect of rainfall through the interaction term when the coefficient $\widehat{\alpha}_{3i}$ is positive (the case of Nabeul), while the positive effect of rainfall can be canceled by the effect of temperature when $\widehat{\alpha}_{3i}$ is negative (the case of Béja). Table 4 shows clearly the heterogeneity of both long-run rainfall and temperature impacts between mountainous, costal, and southern regions.

In the long run, an increase in annual temperatures decreases cereal production, in accordance with other results in the literature. Welch et al. [39] estimated the same negative impact of temperature on rice yields in tropical Asia. However, the long-run positive effect of higher temperatures in four mountainous regions (Kasserine, El Kef, Jendouba, and Béja) depends on the effect of the interaction variable, which was negative and significant in these regions, namely −0.25 and −0.56 in El Kef and Kasserine, respectively. Any benefit from climate variability in mountainous region is canceled by the interaction term for a given level of precipitation.

This result is in agreement with Fischer and Velthuizen [14] who showed, when examining the climate change impact on Kenya, that higher temperatures would have a positive impact

Table 4 FMOLS estimation of climate change impacts on cereal production

Regions	Rainfall	*t*-stat	Temperature	*t*-stat	RL × TM	*t*-stat
Individual FMOLS results (within dimension)						
Northern areas						
Tunis	0.91	(0.62)	−2.38	(−1.88)	0.03	(0.06)
Ariana	2.02[a]	(2.24)	3.65[a]	(2.13)	1.55[a]	(2.34)
Manouba	0.53[a]	(1.93)	−3.9[b]	(−1.72)	−0.91[a]	(2.76)
Ben Arous	0.49	(0.35)	−5.4	(−1.59)	−0.45	(1.23)
Nabeul	0.57	(0.5)	−2.07[a]	(−2.62)	1.05[a]	(2.56)
Bizerte	−0.08	(-0.04)	−2.66	(−0.47)	1.02	(1.29)
Béja	2.26	(1.37)	1.59[b]	(1.95)	−1.02[a]	(2.31)
Jendouba	0.84	(0.51)	1.89[a]	(2.52)	−0.85[a]	(1.97)
El Kef	0.05[a]	(2.03)	0.026[a]	(2.13)	−0.25[a]	(2.01)
Siliana	−1.01	(−0.91)	−2.56[a]	(−3.13)	−0.21[a]	(2.06)
Zaghouan	−2.39[a]	(−2.32)	−1.7[a]	(−2.29)	1.16[b]	(1.95)
Central and coastal areas						
Sousse	0.69	(0.69)	−0.40	(−1.15)	0.87	(1.46)
Monastir	−0.06	(−0.07)	−2.24[a]	(−3.5)	−1.07[a]	(2.05)
Mahdia	0.95	(1.50)	−7.04	(−1.77)	−0.82	(1.67)
Kairouan	1.64	(1.35)	1.31[a]	(2.14)	1.05[a]	(2.02)
Kasserine	1.96[b]	(1.90)	1.09[a]	(2.62)	−0.56[a]	(3.17)
Sidi Bouzid	−0.68	(−0.92)	−6.19[a]	(−2.53)	1.37[a]	(3.54)
Sfax	0.04[a]	(2.03)	−1.29[a]	(−7.78)	1.21[a]	(2.65)
Southern areas						
Gafsa	1.1	(2.05)	−2.45[a]	(−3.57)	0.44[a]	(2.09)
Gabés	−0.61	(−2.19)	−1.06[a]	(2.36)	−0.2[b]	(1.95)
Medenine	−0.36	(−0.35)	2.05	(1.39)	−0.25	(1.54)
Tozeur	−0.38[a]	(−2.08)	−2.19[a]	(−2.91)	1.21[a]	(2.07)
Kebili	−1.65[a]	(−2.12)	−0.63[a]	(−2.68)	1.02	(1.06)
Tataouine	−0.15[a]	(−1.94)	−8.5[a]	(−3.42)	0.9	(1.12)
Panel group FMOLS results (between-dimension)						
Between with trend	0.35[a]	(3.84)	−1.63[a]	(−3.25)	0.44[a]	(2.79)

[a], [b] Indicate significance at 1 and 5 %, respectively

Table 5 FMOLS estimation of climate change impacts on date production

Regions	Rainfall	*t*-stat	Temperature	*t*-stat	RL × TM	*t*-stat
Gabés	0.17	(1.17)	0.83	(0.66)	−0.56	(1.03)
Kebili	−0.21[a]	(−1.92)	2.16[a]	(1.96)	−0.23	(1.91)
Tozeur	0.14	(1.86)	0.65	(0.63)	0.15	(0.87)
Medenine	−0.01	(−0.15)	−2.12[b]	(−2.3)	0.9[b]	(2.3)
Gafsa	0.20	(0.90)	−4.33[b]	(−2.65)	1.2	(1.29)
Between with trend	−0.13	(−1.87)	−2.4[b]	(−2.74)	0.75	(1.04)

[a, b] Indicate significance at 5 and 1 %, respectively

in highland areas. The average altitude in the Béja area is 1,058 m, and its latitude and longitude are 3644°N and 911°E, respectively. El Kef has an altitude of 1,518 m above sea level and a latitude and longitude of 3608°N and 842°E, respectively. The positive effect of high temperatures on some agricultural crops has also been demonstrated by Lobell et al. [25] and Schlenker and Roberts [35] but only below some threshold of temperature.

Moreover, the regions most affected by the temperature increase over the last three decades are the southern regions. For instance, in Tataouine, which is located in the extreme south of Tunisia with a Saharan climate, a 1 % increase in temperature decreases annual cereal production by 8.5 % against only a 1.29 % decrease in a coastal region like Sfax. As the coefficient of the interaction term is positive and significant, the negative effect of temperature in Sfax is reduced by the annual precipitation increase.

With a current average of 5 or 6 years of drought every 10 years in a sub-Saharan climate, it is reasonable to detect this long-run negative effect of temperature on cereal production. The annual rainfall has a positive and statistically significant impact on the annual cereal production, as the panel group FMOLS estimation shows. Despite the poor significance of individual FMOLS long-run coefficients, we obtain a negative and statistically significant impact of rainfall in Zaghouan, Tozeur, and Kebili. This is certainly due to drought and a decrease of annual precipitations in these regions. The long-run negative effect of temperature on cereal production, shown in the panel group estimation, is more important in magnitude than the positive effect of rainfall. In contrast, the significant effect of the interaction variable (0.44) means that regular annual precipitation can reduce the negative effect of warming.

We now turn to the short-run results, as shown in Table 6. These reveal that the average annual rainfall and temperature figures are statistically significant for the panel of 24 regions and show that the short-run impacts of these two variables are smaller in magnitude than their long-run effect. This implies that over the short run, the impact of temperature and rainfall on the cereal production is smaller, but as time goes by, these variables tend to impact more on annual cereal crops and become a serious threat. Finally, the lagged error correction term is statistically significant. Its negative sign implies that after a common shock on cereal crop and climate variables, the cereal crop variable reverts to equilibrium. It is crucial to note that the coefficient of 0.15 precisely means that it takes 6 years (1/0.15) for cereal crops to return to equilibrium following a shock. The estimated coefficient (ECT_{t-1}) indicates also that about 15 % of this disequilibrium is corrected in between 1 year.

5.3 Climate Change Impacts on Date Production

The south of Tunisia, which is characterized by a Saharan climate, produces the totality of the country's date production. The estimation of long-run relationships between date production and climate variables was conducted with the FMOLS method, and results are reported in Table 5.

The results show the long-run negative effect of both temperature and rainfall on the date production. The FMOLS individual estimation indicates that the effect of the interaction term is significant only in Medenine, indicating a positive interaction effect. The negative impact of temperature is more important in magnitude than rainfall. In addition, as with the cereal production, some regions are more influenced than others. For instance, in Gafsa, a 1 % increase in annual

Table 6 Panel ECM estimation

	Δlrl	Δlrl$_{t-1}$	Δltm	Δltm$_{t-1}$	ECT_{t-1}
First subsample (impacts on cereal production)					
Short-run coefficients	0.034[a]	0.023[a]	−0.93[a]	−0.34	−0.15[a]
	(1.94)	(2.31)	(3.28)	(0.39)	(−2.6)
Second subsample (impacts on date production)					
Short-run coefficients	−0.09[b]	0.001	0.22	−0.19	−0.1[b]
	(−2.17)	(0.03)	(0.75)	(−0.66)	(−1.97)

T-statistics are in parenthesis

[a, b] Indicate significance at 1 and 5 %, respectively

temperature decreases the date production by 4.33 % while a 1 % increase in annual temperature increases the date production by 2.16 % in Kebili, which is located in the extreme southeast of Tunisia. Rainfall appears to decrease the date production in the long run, and this is certainly due to the increase of drought seasons over the last three decades.

The short-run results reveal that only rainfall figures are statistically significant for the panel of five southern regions. While rainfall has an effect of 0.13 in the long run, the effect falls to 0.09 in the short run. This implies that over the short run, the impact of rainfall on the date production is smaller; over time, however, rainfall has a greater impact on the date production. The one period lagged error correction term sign is negative and statistically significant at the 5 % level. This result implies that after a shock to the date production and climate variable caused by any extreme natural events, the date production reverts to equilibrium. The negative coefficient (−0.1) means that it takes slightly over 10 years (1/0.1) for the date production to return to equilibrium following a shock. The ECT_{t-1} indicates also that about 10 % of this disequilibrium is corrected in between 1 year.

6 Conclusion and Policy Recommendations

The main purpose of this paper was to identify the long-run relationships between agricultural crops and climate variables. Using a regional annual database, our contribution is twofold. First, tests for panel unit root and then panel cointegration between cereal and date production and climate variables show the presence of a long-run relationship between these variables. Second, the long-run coefficients estimation reveals variability in climate change impacts between regions. The southern regions, characterized by a Saharan climate, are the most affected by the temperature increase and water shortages that have taken place over the last three decades. However, the highland and coastal areas, located in the north, are only weakly influenced by climate change.

The short-run coefficients indicate that the impact of rainfall shortages on the date production is small; over time, however, these shortages tend to have a greater impact on the date production. In addition, over the short run, the impact of temperature and rainfall on the cereal production is small; over time, they tend to have a greater impact on annual cereal crops and become a serious threat. The time length between extremely good crops and shortages is estimated to be 6 years for cereal production and 10 years for date production.

Our results show that the climate and weather variability effects on food production must be considered as a serious threat in Tunisia as well as in the other neighbor countries in the Mediterranean region. Since we estimate relatively higher negative and variable long-run effects of temperature increase across regions on cereal and date yields over the last three decades, an appropriate public policy subsidizing farmers in the most affected regions that are characterized by an arid climate will lead to a significant reduction of the negative climate change impact on both agriculture unemployment and wealth creation. However, the rainfall variable has a weakly positive effect that is compensated by the threat resulting from the brutal temperature increase over the last few decades. Our results are in line with other empirical studies in the literature; the effects of temperature increases have been demonstrated by Fischer and Velthuizen [14] in the case of Kenya, Lobell et al. [25] in Africa, and Schlenker and Roberts [35] in the United States.

Following these findings, we advocate adaptation strategies that can reduce losses and promote benefits from climate change. Highland areas like Béja and El Kef seem to have benefited from climate change; policy makers are thus invited to develop more agricultural activities in these regions. Policy makers in Tunisia and its neighboring countries in the Mediterranean region should seriously respond to climate change impacts on agriculture. Temperature and rainfall are naturally linked through a physical mechanism. The rainfall variation may affect soil moisture which may in turn affect surface temperature by controlling the partitioning between the sensible and latent heat fluxes. Some studies found that temperature and rainfall are positively correlated during January but negatively correlated during July.

Finally, we believe that it is essential to design a public policy privileging and subsidizing the threatened areas in the south of Tunisia; for example, subsidies would enable farmers to develop water irrigation systems by drilling for groundwater. The adverse effects of climate change should be seriously anticipated in Tunisia, and appropriate action should be taken to minimize the damage they can cause. Given the long-run negative effect of rainfall shortage in the south, adaptation measures should include the implementation of a water demand management system that promotes using scarce water resources more efficiently. In addition, policy makers should seriously consider encouraging the development of drought-tolerant crops, especially in the south of Tunisia where global warming has caused a severe drought. In the north of Tunisia, adaptation measures may include choosing tree species and forestry practices less vulnerable to storms and fires, especially in Jendouba, the forestry region of Tunisia. Although many trees are resilient to some degree of drought, increases in temperature could make future droughts more damaging than those experienced in the past. Adaptation strategies are required and needed to avoid the negative effect of warming at regional and national level. Policy makers should consider that the climate change impacts vary considerably across regions. They should take decisions that promote the most affected regions, particularly Tataouine, Kebili, and Tozeur. Government efforts should turn to enhancing solidarity among regions and ensuring that disadvantaged regions and those most affected by climate change are able to take the necessary measures to adapt. It is important to connect this analysis with crop production planning and agricultural economics. The relationship among rainfall, temperature, and crop yield could be used in developing risk-reducing strategies.

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