Impacts of climate change on Tunisian olive oil output and adaptation strategies

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Abstract:

This paper proposes to model the long run impact of climate change on olive output in Tunisia, the third largest olive-oil producing country in the world, using panel cointegration techniques. The methodology is applied to annual panel data for Tunisia (1980-2012). First, a long run analysis of the impact of climate variables on olive production reveals that temperature increase reduces olive output in semi arid areas. Second, the use of inappropriate working tools and method during the harvesting process affects negatively production in some regions. Therefore, we propose an appropriate training for workers in Tunisia to develop their skills and public policy subsidizing the innovation of used capital stock at least in the southern regions. We also propose encouraging the development of drought tolerant olive trees, especially in the south of Tunisia where global warming has caused a severe drought.

Key words: Olive output, Tunisia, Panel cointegration, climate change, adaptation.

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I) Introduction:

The main purpose of this paper is to adequately model the long run climate change effects in regional annual olive output using recent development in econometric techniques. We thus use annual panel data from 1980 to 2012 in twenty four regions in Tunisia. Indeed, Tunisia is a suitable case study for regional data as its climate is highly diversified with extremes ranging from Saharan climate in the south to European climate in the north. The average annual temperature ranges from 35 °C in the south to 20°C in the north. The center of the country seems to have a Mediterranean weather. Therefore, useful recommendations in terms of adaptation policy can deal with the regional level to take into account regional disparities.

In the literature, the use of suitable econometric method that can investigate the long run impacts of climate change during the last three decades has often been neglected. Indeed, the literature on climate change impacts on agriculture has been dominated by two different methodologies. One method applies static econometric models to time series, cross-sectional, or panel data, whereas the second one uses the Ricardian or hedonic method derived from Ricardo (1817) as theoretical background. We mention some of them for illustration purposes: Lang (2007), Lippert et al. (2009), Fisher et al. (2002), Deschênes and Greenstone (2007, 2012), Schlenker et al. (2006), Adams et al. (1995), Adams et al. (1998), Rosenzweig (1993), Rosenzweig et al. (1994) Rosenberg et al. (1994).

Our study takes an innovative approach by implementing rigorous second generation panel unit roots tests to fully describe the cross-sectional dependence induced by the common factor of the panel data series included in the olive production function. In our study, empirical results reveal the presence of common stochastic components, enabling us to develop a panel cointegration analysis. We then use the second generation panel cointegration tests developed by Westerlund (2007) to test if the olive production function forms a long run equilibrium system.

Panel cointegration and error correction model techniques allow short-run and long-run regional climate change effects on olive production to be calculated and compared. A short run analysis of the economic impacts of climate change on olive production aims to calculate the impact in the short-run before taken mitigation actions. Indeed, Climate mitigation is any action taken to permanently eliminate or reduce the long-term risk and hazards of climate to human life and food security. However, a long-run analysis of climate change impacts on olive production emphasizes the role of adaptation measures that can reduce losses and promote benefits from climate change. For example, using data from Kenya, Fischer and Velthuizen (1996) found that higher temperatures have a positive impact in highland areas. Similarly, Downing (1992) showed that in western Kenya an increase in temperature by 2.5 °C would lead to an increase of 67 % in high-potential land. Distinguishing short-run climate change impact on olive production from long-run impact is relevant in Tunisia, which is the third world olive oil producer by 279000 tons in 2013. Tunisia has an olive growing tradition that dates back 1000 years. Phoenicians and Carthaginians are the first civilizations that have introduced olive growing in the country. According to an estimation of the international olive council, the global olive oil production was about 3.2 million tons in 2013. The main olive producer's countries are Spain, Italy, Greece and Tunisia. Indeed, Spain produces 1.6 million tons, Italy produces 0.5 million tons and Greece produces 230000 tons. In 2015, Tunisia is expected to be the second world olive oil producer after Spain.

Sustainable development, initially introduced by Brundtland report (1997) during the earth summit, is defined as development that strives to meet present generation needs without compromising the ability to meet future generation's needs. Sustainable agriculture and food systems that better address future generation needs should be considered seriously in government development plan. For the Tunisian case, olive oil contributes to an important part of the Tunisian exports as a source of foreign currency and represents a key factor for food security.

To the best of our knowledge, we are the first to develop empirical analysis using panel cointegration to analyze the economic impacts of climate change on olive production. As seen before, this paper raises two issues such as development economic and environmental and resource economics. We use a rich panel data set from 1980 to 2012 in twenty four Tunisian regions. The data, obtained from the Tunisian ministry of agriculture, include aggregated regional data for olive production, used capital stock, labor, rainfall and temperature. The economic background of our model is a cobb Douglass production function augmented by climate variables.

In our methodology, the first step is to conduct the Pesearan (2007) panel unit roots tests. We then study panel cointegration using Westerlund (2007) methodology which explicitly integrates the non-stationary character of our panel data to derive the estimates of the long-run weather effects with the right properties. Panel cointegration can be interpreted as an indication of parallel long-run movement in the non stationary series. Finally, we investigate error correction model to estimate the short-run effects.

Applied to the Tunisian panel data, we observe panel cointegration relationship which means that olive production function forms a long-run equilibrium system. Our results confirm that, in the long-run, annual olive crop is more likely to react sharply to temperature and rainfall fluctuations than others agricultural crops. We also observe heterogeneity in the long-run effects of climate change between northern, central and southern regions. 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 paper is organized as follows. Section II presents a brief overview of the climate change and agricultural crops modeling literature. Section III describes the context and the regional panel data used in our study. Section IV develops the economic model and the methodology we use to estimate short-run and long-run climate impacts on olive production. Section V presents and discusses the results of our empirical analyses. It outlines recommendations for innovative adaptation policies to reduce losses from climate change and promote benefits.

II) Modeling the economic impacts of climate change on agricultural crops: Empirical results

The impact of climate change and weather variability on agricultural productivity was the subject of many research papers in environmental and resource economics during the last three decades. These studies of 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 derived from Ricardo (1817) as theoretical background. We review a few selected studies based on these two approaches.

Using U.S data describing agricultural output and climate variables, Deschênes and Greenstone (2007, 2012) examine the economic impacts of climate change on agricultural output. The authors conclude that climate change increases annual profits by $1.3 billion. They also 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. (2012) show that the difficulties experienced in calculating the profit measure, the use of older climate change projections, and missing and incorrect weather and climate data, are the main sources of divergence between results and conclusion regarding climate impacts on agriculture.

Chang (2001) uses data describing production in 60 crops in Taiwan to empirically study the impacts of climate change on agricultural crops. He shows that the two climate variables (temperature and precipitation) have significant implications on many crop yields. Moreover, Lobell (2007) finds that a negative impact of temperature on yield was observed for several rice and maize producing countries. 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 (Ewert et al., 2002). Crop adaptability to particular years as well as yield increment and yield stability were found to be crucial factors for the future (Chloupek and Hrstkova, 2004).

Reilly et al (1994) advocate that global welfare changes in the agricultural sector will be between losses of US \$ 61.2 billion and gains of US \$ 0.1 billion. It is also advocated by Rosenzweig et al (1993); Rosenzweig and Parry (1994) and Darwin et al (1995) that losses are expected to be omnipresent. These experts estimate losses in agriculture production by 24 % in developed countries and 16 % in developing countries; such difference is certainly due to adaptation measures and mitigation actions to reduce several climate change impacts. Furthermore, long-term water and other resource shortages, drought and desertification, disease and pest outbreaks on crops and livestock, and the rise of sea levels are the expected results of climate change.

For the African case, Lobell et al (2011) use a data set of over 20,000 historical maize trials and daily weather data to derive the nonlinear effect of heat on African maize. The authors show that each degree day spent above 30°C reduced the final yield by 1.7%. However, for the United States case, Schlenker and Roberts (2009) 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.

For the Asian case, Welch et al. (2010) use data set describing rice yields in six important rice-producing countries and daily temperature values. They found significant impacts of temperature and radiation during the vegetative and ripening phases of the rice plant. They thus showed that the rice yields decrease with a higher minimum temperature and increase with a higher maximum temperature. Moreover, the same positive effect of temperature in agricultural crops was demonstrated by Fisher and Velthuizen (1996) and Downing (1992) in studying the case of Kenya.

The Ricardian method has been applied to various countries, including the United States, Brazil, and Germany, and to the African continent. Schlenker et al. (2005) 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 (2007), 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. (2009) 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. (1988) and Adams et al. (1988). The agronomic approach was criticized by Mendelsohn et al. (1994) and Mendelsohn and Dinar (1999), 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 (Adams et al., 1998). 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 per hectare while a 1°C rise in the mean temperature would have no significant effect on wheat yields (Aggarawal and Sinha, 1993). Hulme et al. (1999) 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 analysis of climate change impacts on olive output using the non-stationary panel data technique.

III. Context and Data Set Description

Olive is the most important agricultural export commodity in Tunisia. Currently these exports account for about 20% of total export earnings of Tunisia. The country is the largest olive producer in North Africa and the Middle East. It is the most important olive –growing country of the southern Mediterranean region. Olive growing occupies 1.68 Million ha which represents 30 % of the Tunisian cultivated land. Tunisia's olive resources are estimated at over 65 million olive trees. It is an important source of employment for 269000 or 57% of the country's farmers. The Châal region, located in Sfax, has the biggest state-owned olive farms by around 300000 olive trees and is the biggest olive farm in the MENA (Middle East and North Africa) region.

Considering the adaptability of the olive tree to the climate and soil conditions of Tunisia, olive culture is expected to maintain its importance in Tunisian agriculture. However, at the beginning of the 20th century, the country experienced one drought every 10 years, in contrast with the current state of five or six 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. 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), 2007a).

The main purpose of this innovative empirical research paper is to adequately model the climate impacts on regional olive production using tools available in advanced panel data field. We thus use annual data from 1980 to 2012 for twenty four regions in Tunisia. Indeed, Tunisia is a suitable case study for data disaggregated at the regional level as the same political decision is taken in the whole country. Therefore, useful recommendations in terms of adaptation policy to climate change should deal with the regional level.

We use panel regional data describing annual olive output in twenty four regions namely Tunis, Ariana, Benarous, Manouba, Elkef, Kesrine, Béja, Seliana, Mednine, Tataouine, Kebili, Nabeul, Tozeur, Gafsa, Gabes, Kairouan, Sidibouzid, Bizerte, Zaghouan, Sousse, Monastir, Mahdia, Jendouba, and Sfax. The time dimension of the panel data covers the period 1980-2012. We present the Tunisian map in the appendix to show the localization of each region in the north, the south or the center of Tunisia.

The data on olive production, annual rainfall, and temperature were collected for the entire sample and 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 33 years were collected from all the meteorological stations in the entire country. Data regarding the annual labor and used capital stock, as the inputted production factors in each region, were collected by the Statistics Department of the Ministry of Agriculture and Water Resources. The following table provides some descriptive statistics of the variables used to estimate the Cobb Douglass production function in log-log form. 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 olive output, we observe a significant difference between the maximum annual production and the mean value over the last 33 years. This can be primarily explained by climate variability and the structural transformation of the Tunisian economy after independence from France in 1956 and especially during the last three decades. During this period Tunisian agriculture sector was extremely developed by creating financial institutions encouraging agricultural activity, like the national bank of agriculture (BNA) created in 1968 and the national agency to promote agricultural investments. Tunisia produces an average of 100000 tons of olive oil per year. In 1996, production averaged 35000 tons and reached a peak level of 280000 tons in 2004. Because of the three consecutive seasons of drought from 2000 to 2003, production was stabilized at 129000 tons in 2008. This interannual variability of production can primarily explain the non stationary character of olive production in Tunisia. However, average annual level of climatic factors shows important dispersion indicating higher fluctuations of these two weather variables during the last three decades.

Table 1

Descriptive Statistics of the Variables

Variable	Description	Mean	Min	Max
Rainfall in mm (RL)	Average annual level of precipitations (mm)	345,36	14	1230
Temperature (TM)	Average annual level of temperature (°C)	19.5	13.5	24
Olive in tons (Y)	Olive annual production by region (tons)	32655,78	2000	523342
Labor (L)	Annual labor (worker)	2083	466	13848
Capital stock (K)	Annual used capital stock (unit)	13605	8868	19320
*T=33 (**1980-2012**) and n=24 (Panel: T*N = 792)*				

In arid regions like the south of Tunisia, drought may reduce subsequent river discharge and irrigation water supplies during the growing period. Crop yields are most likely to suffer if dry periods occur during critical developmental stages such as reproduction. Many crop yields are especially sensitive to water stress. Moreover, above a certain temperature threshold, crops respond negatively, and agricultural productivity will be significantly reduced.

The last twenty years were characterized by an imminent heating and rainfall shortages. According to the IPPC (2007), the Mediterranean region is one of the most affected regions by climate change. Moreover, when we look to the spatial distribution of rainfall and temperature in Tunisia, which is located in the southern Mediterranean region, we see that some regions experienced a significant change in its climate conditions. We observe also a concentration of precipitation in the extreme north and especially the North-West (Bizerte, Jendouba and Béja). However, the southern regions are characterized by a Saharan climate with higher temperature level without precipitations between May and October.

As seen before, climate change and weather fluctuations have a diverse impact which can be positive or negative. Thus, policy makers may adopt adaptation strategy that can reduce losses which are expected to be omnipresent, and increase benefits (Fisher and al (2005)). Highland areas in the North West seem to have benefit from temperature change in the last twenty years, as we see from the average level of temperature change. Moreover, climate Tunisian data gathered during the 20th century indicate heating, estimated at over 1°C, with a pronounced trend in the past 30 years.

IV. ECONOMIC MODEL AND ECONOMETRIC METHODOLOGY

IV. 1. Economic model: Cobb Douglass production function

The economic background of the estimated model was inspired from the Cobb Douglass production function. The latter was augmented by two climatic factors (precipitations and temperature) to capture the economic impacts of climate change on Tunisian olive output. In the following model (1), we present this production function in its exponential form.

$$Y_{it}= \text{F (L, K, RL, TM)} = L^{\alpha_{1i}} K^{\alpha_{2i}} RL^{\alpha_{3i}} TM^{\alpha_{4i}} \quad (1)$$

In model (1), Y, L, K, RL and TM represent respectively olive production, labor, inputted capital stock, precipitation and temperature. Transforming the model (1) using logarithm (ln), we obtain equation (2) augmented by a residual term to take care for specific unobserved factors:

$$ln\ Y_{it}=\alpha_{1i}\ ln\ L_{it}++\alpha_{2i}\ ln\ K_{it}+\alpha_{3i}\ ln\ TM_{it}+\alpha_{4i}\ ln\ RL_{it}+\varepsilon_{it} \quad (2)$$

To estimate equation (2), we use annual data in olive, labor and capital stock. However, annual data in temperature and precipitations are collected during the critical period within the year. This period generally represented by three consecutive months (February, March and April).

As we have an 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 second generation test proposed by Pesaran (2007). Then, we carried out the tests proposed by Westerlund (2007) to obtain the long-term relationship between all variables. Finally, we used the fully modified OLS (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 may overestimate the true long-run impacts of climate change on olive output.

IV.2. Panel unit root test of Pesaran (2007):

To test for panel unit root, Pesaran (2007) consider the following simple dynamic linear heterogeneous panel data model:

$$y_{it}=(1-\rho_i)\mu_i+\rho_i y_{i,t-1}+u_{it}\ ,\ i=1,..,N;\ t=1,\ldots\ldots,T \qquad (3)$$

Where the error term u_{it} follows a single common-factor structure

$$u_{it}=\gamma_i f_t+e_{it} \qquad (4)$$

where f_t is an unobserved common factor, γ_i is the corresponding factor loading and e_{it} is an idiosyncratic error term independent across i and independent of the common factor. It is convenient to re-write (3) as

$$\Delta y_{it}=\alpha_i+\beta_i y_{i,t-1}+\gamma_i f_t+e_{it} \qquad (5)$$

Where $\alpha_i=(1-\rho_i)\mu_i$, $\beta_i=-(1-\rho_i)$ and $\Delta y_{it}=y_{it}-y_{i,t-1}$. The unit root hypothesis of interest, $\rho_i=1$, can now be expressed as

$$H_0\colon \beta_i=0,\ \forall\ i$$

Against the possibly heterogeneous alternatives

$$H_1\colon\begin{cases}\beta_i<0 & for\ \ i=1,2,\ldots \mathrm{N}_1\\ \beta_i=0 & \text{for } \mathrm{i}=\mathrm{N}_1+1,\ldots,\mathrm{N}\end{cases}\quad \text{With } 0<\mathrm{N}_1\leq N$$

To account for the cross-sectional dependence induced by the common factor, Pesaran (2007) suggest to cross-sectionally augmenting the test equation (5) with cross-sectional averages of the first differences and the lagged levels. The cross-sectionally augmented Dickey-Fuller regression is then given by

$$\Delta y_{it}=\alpha_i+\mathrm{b_i}\ y_{i,t-1}+c_i\bar{y}_{t-1}+d_i\Delta\bar{y}_t+\varepsilon_{it}\ , \qquad (6)$$

Where $\bar{y}_{t-1}=\sum_{i=1}^{N} y_{i,t-1}$, $\Delta\bar{y}_t=\sum_{i=1}^{N}\Delta y_{it}$ and ε_{it} is the regression error. The individual specific test statistic for the hypothesis $H_{0i}\colon \beta_i=0$ for a given i is now the t-statistic of $\mathrm{b_i}$ in (6). The statistic is called cross-sectionally augmented Dickey-Fuller *($CADF_i$)*. The panel unit root for the hypothesis $H_0\colon \beta_i=0$ for all i against the heterogeneous alternative $H_1 : \beta_i<0$ for some i is given by the cross-sectional average of the $CADF_i$ tests, such that

$$CIPS=\frac{1}{N}\sum_{i=1}^{N} CADFi$$

It is called CIPS, since it resembles the IPS statistic (IM et al., 2003). The critical values for the test statistics based on stochastic simulations are provided in Pesaran (2007).

IV.3. Panel cointegration test:

After testing for stationarity of the variables, we then test for the existence of a long-run relationship among the variables. As discussed in BANERJEE, MARCELLINO, and OSBAT (2004), panel cointegration tests can be largely oversized in the presence of cross-unit long-run relationships. Not accounting for such relationships makes it more likely to obtain a finding in favor of cointegration, which may be false. An alternative panel cointegration test was proposed by WESTERLUND (2007). The tests are general enough to allow for a large degree of heterogeneity, both in the long-run cointegrating relationship and in the short-run dynamics, and dependence within as well as across the cross-sectional units. Also, WESTERLUND's (2007) tests have good small-sample properties with small size distortions and high power relative to other popular residual-based panel cointegration tests, such as PEDRONI (1999, 2004). WESTERLUND (2007) developed four error-correction-based panel cointegration tests. Two tests are designed to test the alternative hypothesis that the panel is cointegrated as a whole, while the other two tests the alternative that at least one unit is cointegrated. The author considers the following error correction model where all variables in level are assumed to be integrated of order 1:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i(y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij}\Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij}\Delta x_{i,t-j} + \varepsilon_{it}, \quad (7)$$

Where $d_t = (1,t)'$ holds the deterministic components, $\delta_i' = (\delta_{1i}, \delta_{2i})$ being the associated vector of parameters. In order to allow for the estimation of the error correction parameter, α_i, by least squares, (7) can be rewritten as

$$\Delta y_{it} = \delta_i' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij}\Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij}\Delta x_{i,t-j} + \varepsilon_{it}, \quad (8)$$

Where $\lambda_i' = -\alpha_i\beta_i'$. The parameter α_i corresponds to the speed at which the system corrects back to the long-run equilibrium relationship. WESTERLUND (2007) proposes four tests that are based on least squares estimate of α_i. The tests are designed to test the null hypothesis of no cointegration by testing whether the error correction term in a conditional error correction model is equal to zero. The alternative hypothesis depends on what is being assumed about the homogeneity of α_i.

Two of the four tests are called *group-mean statistics*, do not require the α_i to be equal, and given as

$$G_\tau=\frac{1}{N}\sum_{j=1}^{N}\frac{\hat{\alpha}_i}{SE(\hat{\alpha})} \quad , \qquad G_\alpha=\frac{1}{N}\sum_{j=1}^{N}\frac{T\hat{\alpha}_i}{\hat{\alpha}(1)}$$

Where $SE(\hat{\alpha})$ is the standard error of $\hat{\alpha}$ and $\hat{\alpha}(1)=\frac{\hat{\omega}_{ui}}{\hat{\omega}_{yi}}$, with $\hat{\omega}_{ui}$ and $\hat{\omega}_{yi}$ are the usual NEWEY and WEST (1994) long-run variance estimators based on $\hat{u}_{it}=\sum_{j=-q_i}^{p_i}\hat{\gamma}_{ij}\,\Delta x_{i,t-j}+\hat{\varepsilon}_{it}$ and Δy_{it}. The G_τ and G_α statistics test the null hypothesis of no cointegration for all cross-sectional units (H_0: $\alpha_i = 0$ *for all* i) against the alternative that there is cointegration for at least one cross-sectional unit (H_1^G : $\alpha_i < 0$ *for at least one* i). The rejection of null indicates the presence of cointegration for at least one cross-sectional unit in the panel.

The other two tests are called *panel statistics,* assume that α_i is equal for all *i,* and can be given as follows

$$P_\tau=\frac{\hat{\alpha}_i}{SE(\hat{\alpha})} \quad , \qquad P_\alpha= \mathrm{T}\,\hat{\alpha}_i$$

The P_τ and P_α statistics pool information over all the cross-sectional units to test the null of no cointegration for all cross-sectional units (H_0: $\alpha_i= 0$ for all *i*) against the alternative of cointegration for all cross-sectional units ($H_1^P\!:\alpha_i = \alpha$ for all i). The rejection of null should therefore be taken as the rejection of no cointegration for the panel as a whole.

IV.4. FM-OLS Mean Group Panel Estimator (Pedroni, 2001)

The FM-OLS group panel estimator was developed by Pedroni (2001). To present the method, we consider the following fixed effect panel cointegration system:

$$y_{it} = \alpha_i + x_{it}'\beta + u_{1,it}, \qquad t = 1....T \text{ and } i = 1,..., N \quad (9)$$

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

$x_{it}= x_{i,t-1} + u_{2,it}$, $\forall\ i, T$ (10)

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

$\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$, 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} and 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 FM-OLS estimator is given by:

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

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

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

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

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

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

V. Empirical results and economic interpretations

Panel unit root tests results are shown in Table 2, for both in level and in first differences variables and with two specifications of the deterministic component, namely with an intercept only and with an intercept and a linear trend. We use the Akaike information criterion to choose the appropriate lag-length. We can clearly see that not all the variables are stationary, for the two consumption blocks. All the variables become stationary, as can be seen from table 1, when we test for panel unit-root in first difference. Therefore, the variables in first difference are stationary or integrated of order zero *(I (0)),* which means their levels are integrated of order one (*I (1)).*

Table 2: **Panel unit root test following Pesaran (2007)**

Variables	Level		First difference	
	Intercept only	Intercept & trend	Intercept only	Intercept & trend
LnY_{it}	-0.94 (0.24)	1.09 (0.65)	-5.23 (0.00)	-7.81 (0.00)
LnL_{it}	-0.04 (0.39)	-0.86 (0.56)	-6.18 (0.00)	-8.71 (0.00)
LnK_{it}	-0.56 (0.67)	-0.71 (0.53)	-9.56 (0.00)	-8.07 (0.00)
$LnRl_{it}$	-0.67 (0.23)	-0.92 (0.63)	-5.67 (0.00)	-4.96 (0.00)
$LnTM_{it}$	-0.98 (0.19)	1.23 (0.14)	-7.25 (0.00)	-7.01 (0.00)

Note: p-values for the null hypothesis of non stationarity are reported between parentheses. Individual lag lengths are based on Akaike Information Criteria (AIC).

In Table 3, we present the Westerlund (2007) test results. We compute both asymptotic and robust bootstrapped p-values. The latter is making inference possible under very general forms of cross-sectional dependence. According to the group-mean and panel test statistics, we can strongly reject the null of no cointegration. This provides strong evidence of the presence of error correction for individual panel members and for the panel as a whole. We find that equation (2) forms a long run equilibrium model resulting from long run cross sectional dependencies among the twenty four Tunisian regions.

Statistic			
	Value	*p-value*	*Robust p-value*
Group-mean stat			
G_τ	*-5.76*	*0.00*	*0.00*
G_α	*-12.67*	*0.003*	*0.001*
Panel statistics			
P_τ	*-11.88*	*0.002*	*0.00*
P_α	*-13.03*	*0.012*	*0.00*
Note*: Optimal lag and lead lengths are determined by Akaike Information Criterion.*			

Table 3: **WESTERLUND's (2007) PANEL COINTEGRATION TEST**

Empirical results from the first and the second step show that the integrated variables in the same order (I(1)) are cointegrated. Thus, equation (2) forms a long run equilibrium model. However, as noted before, the estimation method should be different from classic method (OLS and ML) usually used to estimate model with stationary variables. According to Pedroni (2001), the use of OLS may over estimate the coefficients and lead to erroneous interpretations and then incorrect policy recommendations. Consequently, we will use method recommended to estimate panel cointegration relationship. The FMOLS estimator is super-consistent, asymptotically unbiased, and normally distributed, even in the presence of endogenous regressors.

As argued throughout the paper, important heterogeneity, both climatic and economic, exist between northern regions with Mediterranean rainy climate and southern regions characterized by Saharan weather. The results presented, in table 4, confirm the character of the Tunisian climate which is highly diversified with extremes ranging from Saharan climate in the south to European climate in the north. The average annual temperature ranges from 35 °C in the south to 20°C in the north. The center of the country seems to have a Mediterranean weather.

Table 4: FMOLS estimation of long run relationship, equation (2)

regions	Capital	Labor	Temperature	Rainfall

FMOLS individual result				
Northern regions				
Tunis	0.02* (3.00)	-0.05* (-2.93)	-0.05* (-2.24)	-0.001 (-0.29)
Ariana	0.02 (1.05)	-0.05 (-1.18)	-0.06 (-0.96)	-0.002 (-0.22)
Manouba	0.08* (2.64)	-0.10 (-1.49)	-0.24* (-2.74)	0.005 (0.34)
BenArous	0.13 (0.72)	0.02 (1.13)	0.14 (0.20)	-0.08 (-0.92)
Nabeul	0.11 (1.68)	-0.27 (-1.47)	0.01 (0.06)	-0.006 (-0.18)
Bizerte	-0.01 (-0.34)	0.12 (0.89)	0.15 (0.68)	0.002 (0.09)
Béja	0.02 (0.34)	0.002 (0.01)	0.14 (1.08)	0.009 (0.24)
Jendouba	0.18* (3.35)	0.01* (2.91)	-0.44* (-2.41)	0.03** (1.92)
El-Kef	-0.45* (-2.62)	0.006 (0.0013)	0.39 (0.78)	0.71* (4.79)
Seliana	-0.04 (-0.54)	-0.16 (-0.73)	0.37 (1.32)	0.09** (1.97)
Zaghouan	-0.09 (-0.69)	-0.007 (-0.02)	0.18 (0.33)	0.09 (1.09)
Central regions				
Sousse	0.62* (1.99)	0.15* (3.37)	-5.84* (-4.14)	0.14 (0.72)
Monastir	-0.05 (-0.45)	0.33 (0.96)	0.51 (0.98)	0.26* (2.92)
Mahdia	0.008 (0.05)	0.21 (0.46)	0.78 (1.39)	0.32* (2.63)
Kairouan	0.45* (2.07)	-0.51 (-0.96)	-1.21 (-1.40)	0.02 (0.51)
Kasserine	0.43* (3.76)	0.04* (3.56)	-0.22 (-0.62)	0.04 (0.52)
Sidibouzid	0.58* (4.71)	-0.35 (-1.11)	-1.35* (-2.37)	0.13 (1.29)
Southern regions				
Sfax	0.02 (0.06)	-0.21 (-0.16)	0.91 (0.46)	0.19 (0.37)
Gafsa	0.12* (2.46)	-0.28* (-2.11)	-0.02 (-0.17)	-0.02 (-0.38)
Gabes	0.11* (4.04)	0.01* (4.12)	-0.27* (-2.1)	-0.01 (-0.55)
Medenin	0.22** (1.73)	-0.85* (-2.19)	-0.52 (-0.93)	-0.01 (-0.10)
Tozeur	-0.29* (-2.08)	1.03* (2.76)	0.18 (0.32)	0.02 (0.08)
Kebeli	-0.13 (-0.84)	0.08 (0.19)	0.06 (0.13)	0.05 (0.17)
Tataouine	0.002 (0.09)	0.0004 (0.17)	-0.12 (-1.49)	-0.01 (-0.61)
FMOLS group estimation result				
Panel Group estimation	0.08* (5.32)	0.03 (1.26)	-0.27* (-2.83)	0.07* (-2.5)

Note: ** and * indicate significance at 5 and 1% respectively.

Potential precipitations, which can reduce negative impact of warming , are mainly concentrated in September, October and Mars and range from 50 mm in the south to more than 700 mm in the north. In the long-run, the impact of annual temperature on olive output is negative and statistically significant, with a 1% increase in temperature leading to more than a 0,27 % decrease in olive production for all the twenty four regions. However, at the regional level, temperature effect ranges from 0,05 % in Tunis (a northern region) to more than 5 % in Sousse (central region). Thus, the temperature effect reveals that central and southern regions are more affected by heating than other regions in the north. In the literature, using data in rice yields and climate variables, Welch et al (2010) show that temperature reduces production in tropical Asia.

Obviously, nowadays the adverse effect of climate change on agricultural productivity is a common issue. Global warming is expected to cause a significant increase in temperature, and in extreme events, with very low precipitation. This would have implications essentially on agricultural production, including changes in crop yield, variations in plant tolerance and prevalence of crop disease.

The weather factors (rainfall and temperature), which are widely considered as the principal indicator of climate change, have a diverse effects in the long run. Precipitations during the critical period have a positive impact in the long run but its shortages in some regions (like Sousse and Jendouba) may reduce olive production in these regions. However, for the rest of Tunisia, an important positive and significant impact of precipitations in the long run was estimated in the center and in some southern regions (Sfax, Sidibouzid and Monastir).

Moreover, the estimated impact of inputted capital stock and labor on olive production indicates that these factors could reduce productivity in some regions. If we look to the impact of the used capital stock, we conclude that its coefficient is positive and significant in many regions and is globally significant and affect positively the output in the long run (table 4). The positive effect of used capital stock means that technical innovation is important in the olive production process. However, its negative coefficient (in some regions like Tozeur and Elkef) indicates that, in the long run, the used capital stock may affect negatively olive output in these regions. If we look deeply to the historical characteristics of agriculture activities in these two regions, we see that are known by the production of date and cereals more than olive. Indeed, given its Saharan climate, the region of Tozeur monopolizes date production with good quality. However, the region of Elkef produces more than 50% of Tunisian cereals output thanks to its mountainous climate. Consequently, used capital stock, in these regions, has not been innovated which can affect negatively production and quality of olive.

Table 5: Panel ECM estimation

Variables	$\Delta lnrl$	$\Delta lnrl_{t-1}$	$\Delta lntm$	$\Delta lntm_{t-1}$	Δlnk	Δlnk_{t-1}	Δlnl	Δlnl_{t-1}	ECT_{t-1}
Short run coefficients	0.03 (1,76)	-0.09* (-2,02)	0.04 (1,02)	-0.13** (-1,9)	0,07 (1,8)	0,1 (1,41)	-0,02 (2,6*)	(-0,04) (0,54)	-0,17 (-2,7)
Note: ** and * indicate significance at 5 and 1% respectively.									

The labor factor is also an important economic determinant of production. Its long run effect was significant and affects negatively production, in some regions, but its macro effect was not significant. In contrast, the results presented in table 4 clearly reveal a negative impact in the long-run of the inputted labor factor on olive output. This negative impact is mainly in the northern regions. In the north of Tunisia, naturally, olive is not the first agriculture commodity. These mountainous regions produce mainly circus and cereals. Thus, the method of olive collection may affect negatively output quality and quantity. For the rest of Tunisia, the impact of labor on olive production was estimated significant and equal to 1.03 in the region of Tozeur located in the south.

If we go toward a sound analysis of all the estimations presented in table 4 and 5, we can put forward the idea that all the short run coefficients are smaller, in absolute value, than the long-run coefficients. This implies that over the short run, the impact of temperature and rainfall on the olive production is smaller, but as time goes by, these variables tend to impact seriously olive output. However, the lagged error correction term, which is estimated significant and equal to -0.17, means that after a common shock on olive production and climate variables we need 6 years (1/0.17) to return to equilibrium.

Following these empirical results, government action should focus in mitigation and adaptation strategy to climate change. Any optimal policy, to avoid the negative impact of climate change on agricultural crops and promote benefits, must be inspired from quantitative analysis and modeling of the long-run relationship between agricultural crops and climate conditions. Thus, Tunisia is invited to maintain its position as the third world olive oil producer. This paper calls for the implementation of a specific action of mitigation and adaptation to climate change. Any actions may, at least, maintain production in its actual level and avoid the negative impact of heating and water shortages on Tunisian olive oil production.

Conclusion and policy Implications:

The main purpose of this paper is to adequately model the long run impact of climate change on olive output in Tunisia. As the second world olive oil producer this year and a diversified climate country, Tunisia is a suitable case study. Using a panel of annual date covering the last three decades and for all the Tunisian regions, we test the presence of panel unit root and then panel cointegration through a Cobb Douglass production function framework.

In the first step, we show that olive output and its determinants following the Cobb Douglass production function (Equation 2) exhibit a panel unit root. Advanced panel second generation tests of Pesaran (2007) and Westerlund (2007) lead us to conclude that equation (2) forms a panel long run equilibrium system. This long run relationship was estimated by FMOLS which is recognized as the adequate method to estimate such model, Pedroni (2001).

Our results show that the climate and weather variability effects on food production must be considered as a serious threat in Tunisia. Since we estimate relatively higher negative and variable long-run effects of temperature increase and rainfall shortages across regions, on olive production 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.

In addition, to ameliorate olive oil quality, government should subsidize innovation of used capital stock in harvesting process, especially in some northern and southern regions in which olive production is a minor activity. We recommend also appropriate training for workers in Tunisia to develop their skills. Moreover, Tunisian workers, in southern regions, use inappropriate working tools which certainly affect negatively olive production. This can explain the negative coefficient of capital variable in Tozeur (-0.29) and ELkef (-0.45).

This innovative empirical analysis is useful to assess the impact of climate change and variability on developing countries agricultural activities. North African countries are exposed to Mediterranean and Saharan climate change and weather variability. Africa is already a continent under pressure from climate stresses and is highly vulnerable to the impacts of climate change. Many areas in Africa are recognized as having climates that are among the most variable in the world on seasonal and decadal time scales. Floods and droughts can occur in the same area within months of each other. These events can lead to famine and widespread disruption of socio-economic well-being. Finally, Subsidies would enable farmers to develop water irrigation systems by drilling for groundwater. The adverse effects of climate change should be seriously anticipated in Africa, and appropriate action should be taken to minimize the damage they can cause.

Appendix:

The Tunisian map.

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