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CLIMATE CHANGE AND CLIMATE POVERTY IN TUNISIA: FRESH EVIDENCE FROM A SPATIAL ECONOMETRIC APPROACH

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Abstract:

The purpose of this paper aims to assess the implicit of climate poverty in Tunisia. Using a novel spatial econometric approach, this research presents the relationship between precipitation, temperature, and poverty of governorate and those of neighboring governorates. Our results of spatial modeling reveal that the climate change as well as precipitation and temperature have a direct and indirect impact on poverty, thus shows the presence of spatial autocorrelation and spillover effects between governorates. Results shows that the unemployment increase the poverty in the governorate i and neighboring governorate at i. Our results join empirical literature that find a negative direct and indirect effects of education and urbanization on poverty, while consumption expenditure and regional investment have a positive impact on poverty. The results of this paper call for policymakers to take urgent measures and appropriate policies to reduce climate poverty in Tunisia.

JEL codes : Q54, C21, I32, R11

Key words: Climate change, Climate poverty, Spatial econometrics, Spillover effects, SPDM, Tunisia.

1. INTRODUCTION

In the past few decades, climate change represents one of the most pressing challenges facing our planet. Unquestionable scientific evidence attests that human activities have led to substantial alterations in global climate patterns. These variations manifest as phenomena such as rising average temperatures, an increase in extreme weather events, the melting of glaciers, and rising sea levels (IPCC, 2014). However, it is crucial to recognize that the impacts of climate change extend beyond environmental alterations. They also have profound repercussions on human society, affecting multiple aspects of our lives, from food security to health, from the economy to political stability (Nivedha, 2022). Among these myriad consequences, the complex interaction between climate change and poverty has emerged as one of the most crucial areas of research (Leichenko and Silva, 2014). Nevertheless, it is essential to note that very few quantitative estimates of the impact of climate change on poverty have been put forth (IPCC, 2014; Olsson, L. et al., 2014). Existing studies tend to focus on the overall economic impact of climate change, primarily assessing macroeconomic aggregates such as Gross Domestic Product (GDP) or overall consumption at regional or national levels (Arent et al., 2014). While these analyses generally show that disadvantaged countries are more vulnerable than their wealthier counterparts, they do not necessarily reveal how impoverished populations within these countries are affected (Tol, 2002; Sterner and Persson, 2008). It is also worth noting that some studies delve into the implications of global impacts on households but often take a top-down approach, where macroeconomic impacts are assessed first, with household-level repercussions considered subsequently (Skoufias et al., 2011). In this context, it is imperative to begin by examining the impact of climate change on economic growth, as overall economic growth plays a fundamental role in poverty reduction. This is especially crucial since, over the past few decades, the majority of poverty reduction has been achieved through economic expansion rather than income redistribution (Dollar and Kraay, 2002). However, economic growth is one of the channels through which climate change can influence poverty, and global analyses alone are insufficient. It is essential to understand that climate impacts on overall economic indicators, such as GDP, and impacts on impoverished populations may not be strongly correlated. The poorest often represent a minuscule fraction of national income, meaning that the consequences of climate change on the poor may have little impact on national income. In a scenario where only the poorest are affected by climate change, GDP could remain virtually unchanged, yet poverty could still increase. Furthermore, the poor are often disproportionately affected by climate shocks, lose more in relation to their wealth when struck by such shocks, and receive less support after these events, whether it's assistance from family, financial institutions, or social safety nets (Ivanic and Martin, 2008; Hertel et al., 2010). Analysis of demographic data and risk maps demonstrates that the poor are more frequently exposed to floods, droughts, and heatwaves (Winsemius et al., 2015). For example, in Nigeria, 20% of the population are significantly more likely to be affected by climate disasters than the national average. Moreover, case studies in Bangladesh, India, and Honduras show that the poor experience two to three times more losses than the non-poor when hit by floods or storms. Climate shocks can also keep populations in poverty by complicating household asset accumulation, periodically destroying their stock of assets, and creating irreversible impacts on human capital, especially in terms of health and education (Heltberg et al., 2014).

Even though urban areas have played a role in poverty reduction, it is important to note that upward mobility of poor populations can be hindered by climate shocks and risks. Urban households can quickly fall into poverty due to increased exposure to shocks, vulnerability of their assets, and a lack of socio-economic resilience (Hallegatte et al., 2017). The poorest urban areas can be more exposed to climate risks due to population density, overcrowded buildings, and inadequate infrastructure. As an area becomes more urbanized, the scarcity and high cost of land push disadvantaged populations toward often less secure locations on the outskirts of cities. Additionally, as consumers of food rather than producers, urban households are vulnerable to food price shocks resulting from abnormal weather conditions (Nakamura et al., 2023). Studies reveal that urban households are more vulnerable to flood and drought shocks in different countries. For example, a major tropical storm in Guatemala in 2020, characterized by record rainfall, led to a more significant decrease (12.6%) in per capita consumption in urban areas, significantly increasing urban poverty while affecting rural areas less severely. Furthermore, the increase in food prices due to these disasters reduced the consumption of urban households, while a social safety net program primarily protected rural households (Nakamura et al., 2023). However, (Arouri et al, 2016) shows that the urbanization process in Vietnam stimulates the transition from farm to non-farm activities in rural areas. More specifically, urbanization tends to reduce farm income and increase wages and non-farm income in rural households. This suggests that total income and consumption expenditure of rural households are more likely to increase with urbanization. Indeed, Urban areas tend to be less poor, and consequently, poverty levels of the whole country tend to decline as the part of urban population increases (Ravallion et al., 2007). Recognizing the magnitude of the challenges posed by climate change, it is important to emphasize that this issue is now globally recognized as one of the most urgent of the 21st century. Mediterranean countries, including Tunisia, are facing increasing threats from the adverse effects of climate change (Cramer et al., 2018). Tunisia, with its diverse geography and historical ties to natural resources, is particularly vulnerable to these complex challenges (Radhouane, 2013). The impact of climate change in Tunisia is becoming increasingly tangible, significantly affecting poverty in the country. Rising temperatures, more frequent periods of drought, and sudden floods have devastating consequences for Tunisian agriculture, a crucial economic pillar for many rural communities. Decreased agricultural yields and water scarcity often push farmers into poverty (Frija et al., 2021). The issue of poverty in Tunisia has sparked intense debates, particularly regarding measurement methods and the extent of the phenomenon. Indeed, two main approaches, one official defined by the National Institute of Statistics (INS) and the other advocated and used by the World Bank since 1995, are distinguished based on five-year household surveys and poverty reports in Tunisia. While both approaches define poverty based on the monetary estimation of minimum energy needs per person per year and a common definition of fundamental nutritional and caloric needs, they differ in terms of food poverty thresholds and non-food expenditures, depending on rural/ or urban areas (Ayadi et al., 2007). In rural areas, many cases of social disadvantage can go unnoticed due to a lack of information or adequate means of transportation. In contrast, in urban areas, the high cost of living and family issues can push many citizens into the category of vulnerable people. It is essential to note that poverty goes well beyond mere income insufficiency (Betti, 2008); it also manifests as poor health or education conditions, lack of access to knowledge and communication opportunities, the inability to exercise human and political rights, and damage to dignity, self-confidence, and self-respect (Human Development Report, 1997). The aim of this study is to explore in-depth the impact of climate change on poverty in Tunisia, recognizing that poverty is a multidimensional issue affecting large segments of the Tunisian population. The effects of climate change, such as rising temperatures and decreased/or increased precipitation, interact in complex ways with existing socio-economic factors to shape the well-being of Tunisians. The originality of our work lies in the use of spatial econometric approaches on panel data to explicitly take into account the spatial effects of spatial associations as well as the spillover effects between governorates. The importance of this technique is that it allows, on the one hand, giving a clear idea of the direct and indirect effects of temperature and precipitation on climate poverty of the governorate i and that of neighboring governorates. On the other hand, it is benefits technique to solve the problem of the lack of a model linking the four factors simultaneously: climate, climate poverty, demographic and socioeconomic factors. The results of this study can aid policymakers to intrude and act efficiently in the different governorates influenced by climate change.

This paper is structured in six sections. Section 2 presents the global and local spatial autocorrelation tests. Section 3 presents the data used and model specification. Section 4 and 5 introduce our empirical methodology and discuss our findings on the effect of climate factors, demographic and socioeconomic factors on the regional poverty in Tunisia. Section 6 offers some conclusions.

2. STATISTICS OF GLOBAL SPATIAL AUTOCORRELATION

These statistics tests allow us to detect the spatial autocorrelation maps and analyze the spatial distribution, in order to examine the spatial dynamics in the 24 governorates of Tunisia. Indeed, these statistics measure spatial dependence come mainly from geography (Cliff et Ord, 1973; Cliff and al., 1981) and provide information on the different autocorrelation patterns through global and local spatial association. However, the detection of spatial autocorrelation is based on two specifics tests, such as ‘Moran’s I index’ and ‘Geary Coefficient’s c’.

2.1. Moran’s Index

Moran’s I statistic (1950) is the most well known and most often used in various studies to detect spatial autocorrelation. This test can be applied to measuring climate poverty and other explanatory variables. On the other hand, the Geary (1954) coefficients index is used to see if the variability of the climate poverty and other explanatory variable are significantly smaller than the one expected theoretically of a spatial distribution and to confirm the existence of spatial association. To examine this phenomenon, Moran’s I statistic and Geary coefficients index of spatial association are defined as:

$$M_i^G = \frac{N}{S_0} \times \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \qquad \textbf{(1)}$$

$$G_c^G = \frac{N-1}{2S_0} \times \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}(y_i - y_j)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \qquad \textbf{(2)}$$

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Where Y_i represents the variable showed in the governorate i, $\bar{y}$ is the mean average of this variable at the national level. M_i^G and G_c^G represents the global Moran index and global Geary coefficient. W is the element located on line i and column j of the spatial weight's matrix W_{ij}, and N is 24 governorates. S_0 is the sum of spatial weights matrix of dimension (N × N) while the values of variable y appear in the vector y of dimension (N × 1). The values of Moran's I is vary between [-1 and 1]. A positive spatial autocorrelation corresponds to a value of the I statistic that is 1 and, inversely, a negative autocorrelation is represented by a value -1. Table 1 provides the results of the global spatial autocorrelation of Moran and Geary for poverty during the period 1999-2004 and 2009-2014 respectively. Both statistics tests are significant at 1% level. These findings indicate the existence of positive association at the level of the poverty rates and can be represented in the form of a Moran map. Nevertheless, the results are schematized in Fig. 1, which indicate the presence of a positive autocorrelation between each variable and its spatial shift as well as the impact of neighborhood and concentration of poverty. However, Moran and Geary tests do not allow us to evaluate the local structure of the spatial association. To tests the local structure, we use in this study the local spatial autocorrelation.

Table 1 : spatial autocorrelation tests

		Moran's, I index		**Geary's C index**	
Variables	**Weight Matrix**	I	P-value	C	P-value
Poverty 1999-2004	W (1)	0.323 *** (0.133)	0.003	0.647 *** (0.138)	0.005
Poverty 2009-2014	W (1)	0.409 *** (0.135)	0.000	0.520 *** (0.136)	0.000

Note: standards errors are in parentheses. ***, ** and * are significant levels at 0.01, 0.05 and 0.1

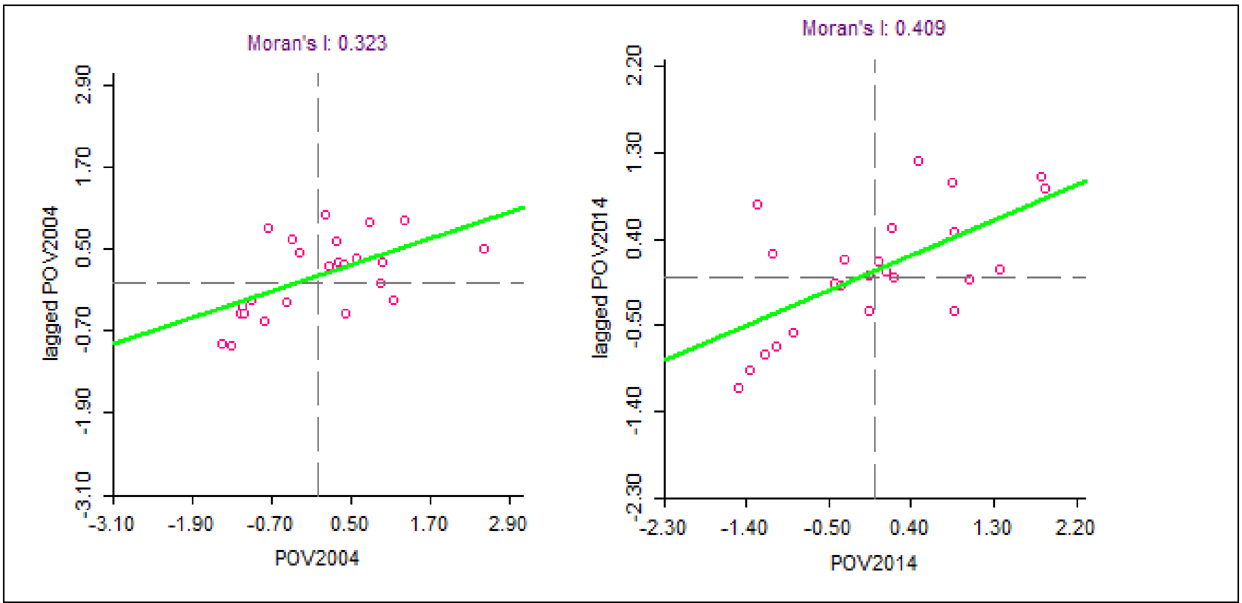

Fig. 1: Moran chart: Poverty 1999-2004 and 2009-2014

2.2. Local statistics tests of spatial autocorrelation 'LISA'

The local spatial autocorrelation allows us to evaluate the individual concentrations to the global spatial autocorrelation. The main of this statistic tests are to validate and verify the weather, for a given variables i it is surrounded by similar values to its own value, y_i or if, on the contrary, it is surrounded by value of the observation y_j that are far from its own value. We note that the LISA index gives us complete and accurate information about the presence of a spatial concentration of homologous value between governorates. The local spatial statistic autocorrelation tests proposed by Anselin (1995) is defined as:

$$M_i^L = (y_i - \bar{y}) \sum_{j=1}^{N} w_{ij}(y_j - \bar{y}) \quad for\ i \neq j \qquad \textbf{(3)}$$

Where; M_i^L is local Moran index.

The LISA tests are dividing the space into four types of local spatial association. Two types (High-High and Low-Low) of the LISA indicate the presence of positive spatial local autocorrelation. While the High-Low and Low-High indicates a global negative spatial autocorrelation schema.

Fig 2 shows Moran's two maps (map A and B) of total poverty during the period 1999-2004 and 2009-2014 in Tunisia. These maps of global poverty for 2009-2014 shows that there is a change in the governorates of northeastern Tunisia, Manouba and Ben Arous are insignificant in 2004 which became significant, and it benefited from a Low-Low type of spatial dynamics in 2014. Sid-Bouzid and Gafsa also changed spatial structures were High-High type in 2004, which became insignificant in 2014.

However, the governorate of Kef and Jendouba also changed dynamics structures were insignificant in 2004, which are benefited from a High-High type of spatial association in 2014. On the other hand, the governorate of Sfax also experiencing a change in its spatial structures, were insignificant in 2004 and which benefit from a negative spatial dynamic of Hight-Low type in 2014. These findings show that these governorates are benefiting from a positive poverty structure. However, the significance map levels (fig.2, right), shown that the presence of spatial autocorrelation is statistically significant at 1%, 5% and 10% levels. We conclude that the spatial dynamics of the highest overall poverty during 1999 and 2014 are registered in the governorate of North-West, Center and South Tunisia, such as Seliana, Kasserine, Kairouan, Sidi-Bouzid and Gafsa.

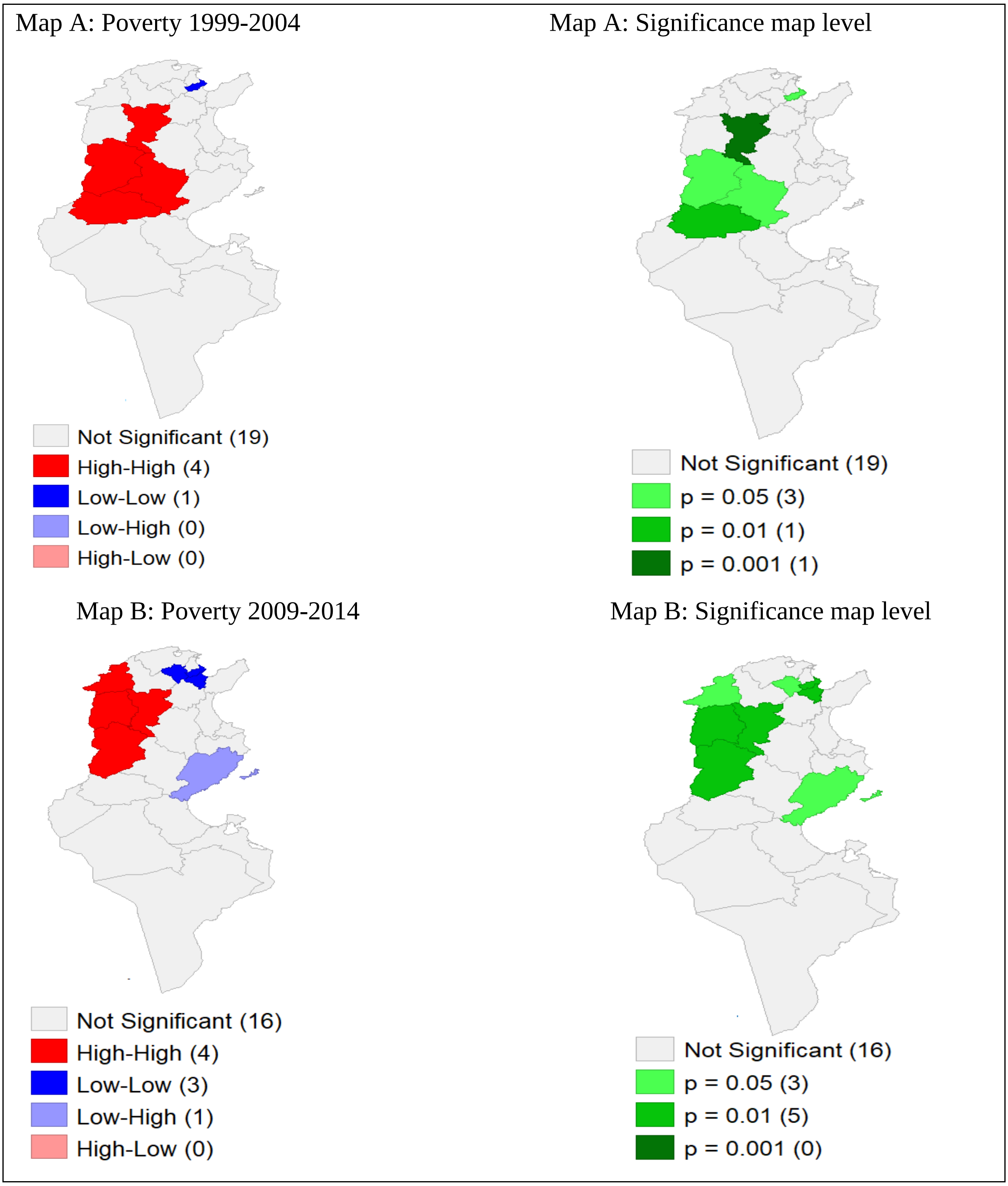

Fig.2: Moran's map of poverty in 2004 and 2014: Map A and Map B (left): Poverty rate in 1999-2004 and 2009-2014. Map A and Map B (right): the significance level of poverty.

3. DATA SOURCE AND MODEL SPECIFICATION

The data used in our study were extracted from the annual reports of the different national books that span the period between 1999-2004 and 2009–2014. Annual weather data (precipitation and temperature) are provided in the National Meteorological Institute (NIM) database. The data of investment are collected from the Agency for the Promotion of Agricultural Investments (APIA). The value of life expectancy, education, electricity consumption, water consumption, urbanization, unemployment, and population collected from the various yearly books published by National Institute of Statistics (NIS). The data of average expenditure consumption per capita is come from the General Census of Population and Housing (RGCPH) 2004 and 2014. These data cover Tunisia's 24 governorates (Ariana, Manouba, Ben Arous, Tunis, Nabeul, Bizerte, Béja, Jendouba, Siliana, El Kef, Zaghouane, Kairouan, Sousse, Mounastir, Mahdia, Sid Bouzid, Kasserine, Sfax, Gafsa, Gabes, Kebili, Tozeur, Médenine, and Tataouine). In order to our research the effect of climate change on climate poverty, we estimate the micro-spatial model as follows:

$$Poverty_{\,ij} = \beta_0 + \beta_1 P + \beta_2 T + \beta_4 UNE + \beta_5 ACEPC + \beta_6 I + \beta_7 EDU + \beta_8 EC + \beta_9 WC + \beta_{10} LE + \beta_{11} URB + \beta_{12} POP + \mu_{ij} \qquad \textbf{(4)}$$

- Poverty (i, j) represents the two-way poverty rate between governorate i and governorate j.
- P and T represent the precipitation in mm and the average temperature in degrees Celsius, respectively.
- Unemployment variable is a measure of the unemployment rate in each governorate.
- ACEPC variable represents the average consumption expenditure per capita in each governorate.
- I variable is a measure of the total of investment in each governorate.
- EDU variable is a measure of the education rate in each governorate.
- EC and WC variables are a measure of the electricity consumption (percentage of household access to electricity) and water consumption (percentage of household access to water) in each governorate.
- LE variable is a measure of the life expectancy at birth (represents the current health mortality conditions) in each governorate.

- URB variable is a measure of the urbanization rate (percentage of urban population) in each governorate.
- POP represents the number of persons is living in each governorate and measure the population growth.

4. METHODOLOGY AND ECONOMETRIC APPROACH

In the last few years, the development of estimation and specialized software (GeoDa, R and Stata) has largely simplified the use of spatial econometrics models and the techniques of this method are increasingly diverse, Anselin (2000, 2004, 2006) Le Sage (2009). In this section of our study, we present the main econometrics models used, such as spatial econometrics models to examine the impact of climate change on climate poverty in Tunisia.

4.1. Spatial weights matrices

The spatial weights matrix is traditionally used to examine the spatial proximity between to governorates i and j and is designed by W. The weights matrices are of dimension (N × N). However, for a set of N governorates, the spatial weights matrix expresses, in an exogenous specification, the relationship and the proximity between each of the governorates. The general specification of the weight's matrix W, $w_{ij}\ \forall\ i,j\ =\ 1, \ldots\ldots, 24$, are non-negative and finite. For governorates i, a particular observation of the weight's matrix, w_{ij} acquire a value 1 when governorate j is located at a distance equal or smaller than governorate i. If this not the case, the value is equal zero. The weights matrix is defined by:

$$w_{ij} = \begin{cases} 1\ if\ governorates\ i\ and\ j\ are\ neighboring, \\ \quad 0\ otherwise, \forall\ i,j\ =\ 1,\ldots,24;\ i \neq j \end{cases} \qquad \textbf{(5)}$$

In this paper, we retain the first order of weights matrix (W (1)) to analyze the global and local spatial autocorrelation. In our study, the impact of climate change on poverty decreases when the distance between governorates i and j increases.

4.2. Spillover effect model

In the spatial econometrics approach, the spillover effect normally occurs rather than the dynamic effect. This means that for a particular area (governorates), the data used in this paper is generating process and influenced by the nature of the dependent variables related to nearby governorates. This is the case, when the increase in climate poverty rate in a governorate result

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in climate poverty in the neighboring governorates. This type of specification model called the spatial autoregressive model (SPARM). The specific model is as follows:

SPARM: $$y_{it} = \lambda y_{it} + \alpha + \beta_1 x_{i1} + \cdots + \beta_K x_{iK} + \mu_i \; \forall\, i = 1,\ldots,24 \qquad \textbf{(6)}$$

In addition, the SPARM can be written in matrix as follows:

$$y = Wy\lambda + X\beta + \mu \qquad \textbf{(7)}$$

where y_{it} is the poverty rate into to the governorate i at the time t. x_{it} is the matrix of exogenous variables. W_{ij} is the weights matrices. The parameter λ is a scalar and measures the spillover effect of neighboring governorates and range from 0 to 1. On the other hand, if the SPARM fails to control for the problem of residual spatial association, several alternatives' models are existed. One of the most model used in the spatial estimation is the spatial Durbin model, SPDM. This type of spatial model included both endogenous and exogenous variables. The SPDM is as follows:

SPDM: $$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \gamma \sum_{j=1}^{N} w_{ij} x_{jt} + \mu_i + \tau_i + \varepsilon_{it} \qquad \textbf{(8)}$$

Where: y_{it} represents the climate poverty from the governorate i at the period t.

$\sum_{j=1}^{N} w_{ij} y_{jt}$ is climate poverty from neighboring governorate to i.

x_{it} is the control variables of the governorate i.

$\sum_{j=1}^{N} w_{ij} x_{jt}$ is the control variables of the governorates j.

4.3. Lagrange Multiplier tests (LM-test)

The LM test proposed by Anselin (2001) is used to verify the existence of the spatial dependence between areas. This approach is based on two errors tests, such as LM_γ and LM_λ which are as follows:

$$LM_\lambda = \frac{[\tau\prime\, TR \otimes W)\, Y/\hat{\sigma}^2]^2}{Z} \qquad \textbf{(9)}$$

$$LM_\gamma = \frac{[\tau\prime\, TR \otimes W)\, \tau/\hat{\sigma}^2]^2}{T \times Tw} \qquad \textbf{(10)}$$

Where; τ is the vector of residuals without spatial effects ε_i, $\otimes$ is the vector of Kronecker product.

More recently, Elhorst (2010) proposed the robust LM test of the error's tests. These tests are presented as follows:

$$LM_{\lambda\ robust} = \frac{[\tau\prime\ (TR \otimes W)\ Y/\hat{\sigma}^2 - \tau\prime\ (TR \otimes W)\ \tau/\hat{\sigma}^2]^2}{Z-TTw} \quad \textbf{(11)}$$

$$LM_{\gamma\ robust} = \frac{[\tau\prime\ (TR \otimes W)\tau/\hat{\sigma}^2 - \frac{TTw}{Z} \times \tau\prime(TR \otimes W)\ Y/\hat{\sigma}^2]^2}{T \times Tw\ [1 - TTW/Z]} \quad \textbf{(12)}$$

Where LM lag and LM lag robust are under the hypothesis tests: $H_0: \gamma\ and\ \lambda = 0$ and $H_1: \gamma\ and\ \lambda \neq 0$

If we accept H_0, that indicates the absence of the autocorrelation of the endogenous variable and absence serial correlation of the error's terms, and otherwise of H_1. The finding of the LM lagged and LM robust are presented in Table 2 as bellow. The results of this tow tests confirm that the H_0 is rejected and enhance the absence of serial correlation at the level of the dependent variables and the absence of the spatial autocorrelation. However, the LM$_\lambda$, LM$_{\lambda\ \mathrm{robust}}$, LM SAC$_\gamma$ and LM SAC$_\lambda$, with coefficients equal to 36.451, 36.415 and 36.469 for the period 1999-2004 and 9.114, 9.495 and 9.556 for the period 2009-2014, leads us to reject the hypothesis test of the absence of a global autocorrelation. All these tests indicate that the SPDM signification is the most appropriate, as they suggest that the spatial correlation not only concerns the dependent variable, but also the independent variables.

Table 2: Results of Lagrange multiplier.

Periods / Models / Tests	Survey 1999-2004		Survey 2009-2014	
	SPARM (1)	SPDM (2)	SPARM (2)	SPDM (3)
LM_{γ}	1.072 (0.282)	0.054 (0.816)	0.037 (0.847)	0.060 (0.805)
LM_{λ}	1.585 (0.208)	36.451 *** (0.000)	0.031 (0.859)	9.114 *** (0.002)
$LM_{\gamma\ robust}$	0.000 (0.975)	0.018 (0.893))	0.264 (0.607)	0.442 (0.506)
$LM_{\lambda\ robust}$	0.513 (0.473)	36.415 *** (0.000)	0.258 (0.611)	9.495 *** (0.002)
LM SAC_{γ}	1.586 (0.452)	36.469 *** (0.000)	0.295 (0.862)	9.556 *** 0.008
LM SAC_{λ}	1.586 (0.452)	36.469 *** (0.000)	0.295 (0.862)	9.556 *** 0.008

Note: p-value in parentheses: * Significant at the error threshold 1%, ** Significant at the error threshold 5%, and * Significant at the error threshold 10%.**

5. RESULTS AND DISCUSSION

In our analysis the classical econometrics approach (for example, ordinary least squares method (OLS)) do not provide an unbiased efficient estimator to examine climate poverty (eq. 4). However, we explore alternative estimation methods that highlight the interdependence of the variables. Indeed, Baltagi and Liu (2008) had used the Generalized Least Squares (GLS) method. Additionally, Lesage and Pace (2009) and Elhorst (2010) had used the Maximum Likelihood Estimator (MLE). In this study, we use the MLE estimators proposed by Lesage and Pace (2009) and Elhorst (2010) to estimate spatial effect of climate poverty in Tunisia. Our findings indicates that there is a significant correlation between poverty and climate change, such as temperature and precipitation, with a largely less pronounced effect during the period 2009-2014. The analysis of the impact of temperature on poverty show a negative and direct impact on the governorate j and that of neighboring regions at j. In other terms, if the average temperature increases by one degree Celsius, the poverty rate increases from the governorates j by 3.090 points to the neighboring governorates at j during the period 1999-2004. However, the effect of temperature on poverty during 2009-2014 is less than period during 1999-2004, with a coefficient equal -2.180. Similarly, our results show that precipitation has direct and indirect impacts on the poverty of governorates j and neighboring governorates to j. On the

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other words, if average rainfall increases by one millimeter, the poverty rate increases from the governorates j to neighboring governorates to j by 0.023 points during the period 1999-2004 and by 0.021 points during the period 2009-2014. We can therefore conclude that there is a spillover effects on this explanatory variable.

The level of poverty is also influenced by the unemployment in Tunisia. In general, high unemployment rate tends to increase the rate of poverty. The negative impact of this variable is much more pronounced in internal governorates whose main activity is agriculture, such as Jendouba, EL Kef, Siliana and Beja. Besides, in Tunisia there exist large regional disparities. In this context, the highest unemployment rates are found in the internal governorates of Tunisia, such as Gafsa and Kasserine, and in the northwestern, in particular Jendouba and EL Kef. While the lowest rates are recorded in the governorates of Ariana, Sfax and Monastir. The impact of the variable is more significant during the period 1999-2004 than in 2009-2014. In other words, an increase in the employment rate of region i accelerates climate poverty in that region but also in neighboring regions. We can therefore conclude that there is a negative spillover effect for this explanatory variable. We also note that the poverty is also a factor of high unemployment in Tunisia.

Table 3: Results of spatial Durbin Model (SPDM)

	Periods	Survey 1999-2004		Survey 2009-2014	
	Models	Coefficients	Std. Err.	Coefficients	Std. Err.
Variables					
Directs effects	Precipitation	0.025 ***	0.001	0.035 **	0.014
	Temperature	-3.090 ***	0.165	-2.180 ***	0.481
	Unemployment	0.160 **	0.024	0.235 **	0.094
	ACEPC	0.015 **	0.000	0.001 **	0.000
	Investment	0.706	0.018	-0.187 **	0.095
	Education	-0.470 ***	0.025	-0.799 ***	0.086
	Electricity Consumption	0.607	0.031	14.429 **	3.435
	Water Consumption	-0.934 ***	0.031	-0.889	0.726
	Life Expectancy	-0.050 ***	0.001	0.0005 **	0.000
	Urbanization	-0.132 **	0.008	-0.234 ***	0.111
	Population	-0.008	0.000	-0.018	0.003
Spillov	W*Precipitation	0.023***	0.000	0.021 ***	0.001
	W*Temperature	-2.813 ***	0.062	-1.184 **	0.500
	W*Unemployment	-0.216 **	0.020	-0.139 ***	0.090

W*ACEPC	-0.001 ***	0.000	-0.005 *	0.000
W*Investment	0.380 ***	0.013	-0.023	0.073
W*Education	-0.405 ***	0.030	0.081	0.100
W*Electricity Consumption	1.148	0.025	1.523 ***	0.529
W*Water Consumption	-1.277 ***	0.025	-1.176 ***	0.447
W*Life Expectancy	-0.025 **	0.000	-0.0005 **	0.000
W*Urbanization	-0.042 ***	0.001	-0.0277	0.068
W*Population	-0.007 ***	0.000	-0.004	0.003

Moreover, the results of the impact (W*ACEPC) of average expenditure of consumption per capita is negative and significant on the climate poverty. There are a direct and indirect relationships between poverty and the volume of expenditure of consumption. The high household spending leads to decrease the rate of climate poverty. This effects also reveals that there is an implicit strong association between, poverty, farmer's income, and the expenditure of consumption per capita. On the other words, if the average expenditure consumption per capita increase by one Dinars Tunisian leads to decrease poverty rate by 0.001 points during the period 1999-2004 and 0.005 points in 2009-2014. We also conclude that there is a negative spillover effect for this variable on the poverty of governorate i and neighboring governorates to i.

The variable (W*Investment) has a significant and positive effect on poverty, thus a positive spillover effect. This result may be explained by the regional disparities and inequality between the coastal and coastal regions. The 1% increase of investment leads to increases poverty rate from the internal governorates to north governorates and between neighboring regions to i by 0.380 during the period 1999-2004, while this link is insignificant during 2009-2014 period. We can therefore conclude there is a direct and indirect link between poverty rate and the volume of investments. This links is more pronounced in rural regions whose main activity is agriculture production, such as northwestern and south Tunisia.

The SPDM estimate for the direct and indirect impact of education (W*Education) on climate poverty shown in Table 3 also negative and statistically significant. It indicates that an increase of education reduces the risk of poverty and unemployment difficulties. This corresponds to 40% decreases in poverty risks between 1999-2004. A significant decline in poverty risks was observed as a result of high investment, job creation and the economic growth. While the empirical results shown in Table 3 (column 3), indicate that the effect of education on poverty afterwards the Tunisian revolution in 2011 is insignificant.

The estimated coefficient for the electricity consumption variable (the percentage of population access to electricity) has the expected sign. According to the estimated coefficient value (1.523), poverty in Tunisia is positively associated with electricity consumption during the period 2009-2014. While the correlation between two this variable is insignificant during 1999-2004 period. In fact, the electricity consumption aids the establishment and growth of activities, and entrepreneurship in the poorest governorates. Its strengths several activities such as trade, agriculture, industries, and service sectors, increase job creation and income of households. This, in turn, improves to reduces poverty by offering employment opportunities and increase the economic conditions of the internal governorates. In addition, the access to electricity facilitates social network and communication, such as mobile phones and internet, and enhance the individuals to access information, and participate in social and economics networks. These, improve to create opportunities, share knowledge, and leading to reduce poverty rate in governorate i and neighboring governorate to i. We can note that there is a positive spillover effect for this variable on the poverty of governorate i and neighboring governorates to i.

Moreover, the analysis of the direct and indirect effect of the variable (W*water consumption) on poverty has a negative and statistically significant impact on climate poverty during the 1999-2004 and 2009-2014 period. We also note that the results reveals that there is an implicit strong relationship between population and water consumption. This impact can be explained by the insufficient access to clean water and sanitation facilities increases the prevalence of waterborne diseases. We also note that the increase of access to water and sanitation, increases healthcare cost and increase the poverty. We conclude that the rising of water consumption takes away valuable time and energy that could be utilized for health, education and income generating activities and enhance the poverty by limiting economic opportunities. The negative influence of this variable is much more pronounced in internal governorate whose affected by climate change, such as an increases temperature and decrease in the level of precipitation. These results reveals that there is a negative spillover effect on the governorate i and that neighboring governorates at i.

The analysis of the direct and indirect effect of the variable (W*life expectancy) has a negative and statistically significant impact of climate poverty during the period 1999-2004 and 2009-2014. The same impact can be observed in neighboring governorates i. We can therefore conclude there exist a direct and indirect relationships between poverty and health in Tunisia. This result also reveals a negative spillover effect between governorates.

The results of the SPDM estimation show that the direct and indirect impact between poverty and urbanization. This result is highly significant with a value (-0.042) during 1999-2004, while become insignificant during 2009-2014 period. We can also note that there is a negative spillover effect for this explanatory variable. Tunisia is one of the most urbanized countries in the Middle East and North African (MENA) region. Rural poverty increased and migrated to the urban region and increased from 40% in the 1960s to nearly 70 % today, thus is result of the regional disparities and inequal investment between coastal and non-coastal governorates. This finding can be explained by the decentralization, the climate-resilient and the iniquitous investments. We conclude that the effects of urbanization on the poverty tend to be smaller over time since the poverty rate decrease over time. Between 1999-2004, a 1 percentage point increase in the proportion of urban population in the governorate i results in a 4.2 percentage point reduction in the poverty rate. While between 2009-2014, the impact of urbanization on poverty is negative but insignificant. This result is in line with the finding of (Dollar and Kraay, 2000; Arouri, M., Ben Youssef, A., & Nguyen, C. (2017)).

6. CONCLUSION

An extensive empirical study that investigates climate change impact on poverty is important for policymakers to address and mitigate the adverse effects of climate shocks. In this paper, we conducted an empirical analysis on the effects of climate and non-climate variables such as average precipitation, average temperature, average annual expenditure consumption, regional investment, unemployment, water consumption, electricity, urbanization, education, life expectancy and population growth in Tunisia between 1999-2004 and 2009-2014. We utilized a spatial econometric technique to examine the direct and indirect economic impacts of climate change on poverty. Moreover, we employed the Moran's I and Geary's coefficient tests to examine the presence/ or absence of global spatial autocorrelation. LISA's test were employed to check the validity of global spatial association. SPDM approach were employed to examine the direct and indirect links of economic impact of climatic shocks on poverty. The limitation of this research is that it failed to include other important factors in the model that affect poverty. Specifically, the crucial variables that our study failed to introduce in the model are Gross Domestic Product (GDP) per governorate and inflation. These variables were left out because of issues with data availability and over decadal data limitation for Tunisia.

The results of the study reported the existence of direct and indirect impact of climate and non-climate variables on poverty. First, a rise in annual average precipitation is observed to increase poverty rate in Tunisia. But average temperature decreases the poverty rate. One-degree Celsius rise in temperature reduces poverty by 2.83 points in the governorate i and neighboring governorate at i. The sensitivity can be explained that Tunisian households are more dependent on agriculture production, when the climate change affect agriculture sector and reduce the productivity in governorate increases unemployment and rise the poverty. Thus shows the presence of spatial autocorrelation and spillover effects between governorates. Indeed, the impact of climate change is therefore a direct and indirect effects. On the other hand, the findings of the study join empirical literature that find a negative spillover effects of education and urbanization on poverty, while consumption expenditure and regional investment have a positive impact on poverty.

The findings of the study provide several policymakers. First, the government should formulate a coherent strategy to alleviate poverty. Secondly, the government can focus on creating jobs opportunities by promoting regional economic growth and entrepreneurship and can invest in infrastructure development. However, the government can prioritize investments in service sectors, such as education and health to ensure access for all and to improving the quality of education, access to primary healthcare services, and health insurance schemes for the internal governorates. The policymakers can employ programs that forward inclusive economic growth, regulations on minimum wages, and reforms in the labor market. Furthermore, they can also tackle issues of income inequality and promote fair distribution of assets. Moreover, there is the need to develop new strategies that can survive under harsh temperatures and droughts and support institutional research to reform resilient and sustainable development to reduce regional poverty in Tunisia.

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