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SPATIAL PATTERNS AND GEOGRAPHIC DETERMINANTS OF WELFARE AND POVERTY IN TUNISIA

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Abstract

Previous poverty analysis in Tunisia concluded that the poor population is concentrated in interior areas, especially in the northwest and center west. Thus more information on the spatial dimension of welfare and poverty may be of interest for any poverty alleviation programs as poverty may be associated to geographic locations. However, the analysis of the spatial dimension cannot be limited to the addition of some variables to our econometric model. We have to consider the neighborhood effects and the heterogeneity of households' behaviors in more disaggregated geographic units using specific tools of spatial and geographical analysis. First, we conduct an exploratory spatial data analysis (ESDA) based on a geographical information system (GIS), to visualize the "local" spatial structure of poverty. Second — to deal with spatial autocorrelations and unobserved spatial heterogeneity of the households' behaviors — we use a spatial autoregressive model (SAR) and a geographical weighted regression model (GWR) respectively. Spatial and non-spatial models are compared according to their prediction performances. SAR and GWR spatial models are found superior to the traditional non-spatial regression model, and give a better approximation of the Tunisian poverty map.

ملخص

خلصت تحليلات الفقر السابقة في تونس إلى تركز السكان الفقراء في المناطق الداخلية خاصة في المنطقة الشمالية الغربية والمنطقة الغربية الوسطى. ولذا فإن المزيد من المعلومات عن البعد المكاني للرفاهية و الفقر تتسم بالأهمية لأي برنامج يهدف إلى تخفيف حدة الفقر حيث يرتبط الفقر بأماكن جغرافية معينة. وبالرغم من ذلك فان تحليل البعد المكاني لا يمكن أن يقتصر على جمع بعض المتغيرات في نموذج دالة قياس اقتصادي. فيجب أن نضع في اعتبارنا تأثيرات المناطق المجاورة وتباين عناصر سلوكيات الأسر في وحدات جغرافية متفرقة باستخدام أدوات محددة لتحليل مكاني وجغرافي. أولاً: نقوم بعمل تحليل بيانات استكشافي للاماكن المتفرقة يعتمد على نظام معلومات جغرافي لتصوير هيكل مكاني "محلي" للفقر. ثانياً كي نتعامل مع ارتباطات ذاتية مكانية وتباين مكاني غير ملحوظ في عناصر السلوكيات لدى الأسر. نستخدم نموذجاً مكانياً ذاتي الانحدار ونموذج انحدار جغرافي مرجح على التوالي. ونقارن النموذج المكاني وغير المكاني تبعا للأداء المتوقع لكل منهما. ويفضل استخدام النموذج المكاني ذاتي الانحدار ونموذج الانحدار الجغرافي عن استخدام نموذج انحدار تقليدي غير مكاني حيث يعطيان اقترابا أفضل لخريطة الفقر في تونس.

1. Introduction

Nowadays regional development in Tunisia is one of the development program's main goals. The plan is the reduction of poverty and inequality in certain areas through modernizing the basic infrastructures, and valorizing human resources which may give better perspectives for the regions (Rallet, 1995). All studies on poverty analysis in Tunisia confirmed the need for these actions. [Ayadi et *al*., (2004, 2006); World Bank (2003); UNDP (2004)]. They concluded that although poverty had decreased in Tunisia (from 13% in 1980 to 4.2% in 2000), it remains concentrated in the north and center west regions. However, these studies used statistical and econometric tools considering each area as an isolated entity. The role of spatial dependence and/or spatial heterogeneity was completely neglected which may have generated some misspecification errors if some forms of spatial correlations or spatial heterogeneity had in fact existed. Thus the estimated measures and the statistical inferences of the previous poverty analyses may be questionable.

The analysis of the relation between the place of residence and the standard of living drew the attention of economists since the fifties. Two different issues may be considered. William Alonso (1964) advocated that households' standard of living determined their localities of residence. So, when socially deprived individuals or households live in the same neighborhood, this clustering of poverty and welfare dependency could create a local climate, generating attitudes and practices that would further deepen the social isolation of the local residents (Bolt et *al*., 1998). John Kain (1968) contemplated that it was not the standard of living which influenced the spatial location but rather the reverse. The area of residence presents physical barriers and spatial obstacles to wider social circles of interaction and communication. The relation between the place of residence and the standard of living is so complicated. The concentration of the underprivileged population results in "impoverishing" a district. In addition, because it cumulates the social and economic difficulties, an underprivileged district can become in itself a potential factor of poverty for its occupants.

In the last decade, several empirical studies on the household's standard of living have used new statistical and econometric tools that combined traditional spatial econometrics literature with a cartographic representation of data and a geographic information system (GIS). Elbers et al., (2000, 2003) used small area estimation techniques to analyze poverty and welfare at a more disaggregated level in Ecuador. Elbers et al., (2007) used "poverty maps" for three countries: Ecuador, Madagascar and Cambodia as tools for an *ex ante* evaluation of the distributional incidence of geographic targeting of public resources. They found large gains from targeting smaller administrative units, such as districts or villages.

The aim of this paper is to use some new spatial statistical tools for analyzing the determinants of welfare and poverty in Tunisia. We depict spatial variations in the relationships between per capita expenditure and socio-economic characteristics at the level of smaller administrative units — the delegation[2]. We use three sources of information: the dataset of the CGDR-INS (2005) which records some monetary and non-monetary welfare indicators by delegation. To supplement our information on non-monetary indicators we use the ONFP[3] 2001 survey which gives rather fine information on the characteristics of the households. Lastly, we use the GIS (*geographical information system*) which gives the precise location of the country's various delegations. For a more efficient analysis of spatial location effects we use specific tools for Exploratory Spatial Data Analysis (ESDA), and households' spatial correlation and spatial heterogeneity behavior are based on SAR and GWR models.

2 The finest administrative unit in Tunisia.

3 National Office of Family and Population.

This paper is organized as follows. Section 2 describes some indicators and cartographic representations of some variables used in our analysis on geographical disparity in Tunisia. Spatial disparity measures are used in Section 3 to confirm our reports on the existence of geographical disparities. In Section 4, using per capita expenditures as a proxy of household welfare, we estimate the effects of some demographic, economic and geographic variables on per capita income using an OLS model on the one hand. On the other hand we use SAR and GWR models to deal with spatial correlation and heterogeneity of households' behaviors. A spatial autoregressive model (SAR) is used to consider the spatial correlation structure and we use a local analysis with Geographically Weighted Regression (GWR) which helps to estimate the spatially varying impacts of some independent variables on per capita household expenditure. In Section 5, we discuss the econometric results and the conclusion is presented in Section 6.

2. The Tunisian Context

Since its independence in 1956, Tunisia has made several strategic decisions anchored on human development: increased enrolment in basic schooling, the provision of basic health services, and an active participation of women in the development process. Public policies simultaneously targeted growth and poverty reduction. Nowadays more integrated programs of rural development providing infrastructure necessary to regional development are being set up. However, except for agricultural areas, economic growth was concentrated in the coastal zones. This configuration can be explained by two reasons: The first one is that Tunisia inherited a considerable infrastructure for production and distribution facilities, concentrated on the coastal zones, set up by the French protectorate. The second reason is that the private capital investment has been characterized by a regional over-concentration, located exclusively along the coasts. Concentration of infrastructure and human capital in the coastal zones facilitated the development of industrial facilities and services, and consequently led to the rapid growth of the Tunisian economy. Ayadi et al. (2004) and Lahoual (2007) argue that if the government had invested a little more in the interior of the country rather than just in the coastal zones, rural poverty could have been reduced. However, growth would have suffered given the significant cost of laying down proper infrastructure in non-coastal zones, and the relative immobility of human capital from coastal to non-coastal zones. Table 1 gives an illustration of the geographic disparities of monetary and non-monetary indicators.

Figure (1.a) depicts the geographical distribution of per capita expenditure among governorates[4], where we see an obvious inequality. We also see that the households with access to drinking water and sanitation network are more concentrated in the country's coastal zones (Figure 5.a and 5.c in Appendix).

However if we consider Figures (1.b) and (1.c), which present the per capita expenditure map at the delegation level, we depict more heterogeneities within governorates. Figure 5.b and 5.d in the Appendix, represent respectively the geographic distribution of access to drinking water and improved sanitation by delegations. They also depict some intra-governorate heterogeneities.

Those figures show that the geographical position of the household is important. Two phenomena can be detected. The welfare level of each delegation is affected by the welfare levels of its neighbors — there is a kind of spatial autocorrelation. On the other hand, geographic, climatic and historical conditions may have an influence on the welfare level of each delegation. Thus for any efficient analysis of welfare and poverty, we must consider the spatial effects —spatial autocorrelation and spatial heterogeneity — by using the appropriate techniques.

4 Tunisia is divided administratively into 24 governorates.

3. Spatial Data Analysis

3.1 Global Autocorrelation

We use ESDA[5] for our spatial data analysis, referring to global and local investigations of spatial autocorrelation. The first stage of ESDA consists of evaluating the global spatial autocorrelation, where the presence of spatial correlation can be defined as the coincidence of value similarity with location similarity (Anselin, 2001). We have a positive spatial autocorrelation if nearby or neighboring areas are more alike (spatial clustering) and a negative spatial autocorrelation when neighboring areas are unalike (spatial outliers). In order to test this assumption, we use two statistics: statistic I of Moran and the statistic c of Geary defined respectively as follows (Anselin, 1995):

$$I = \frac{N\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S_0 \sum (y_i - \bar{y})^2}$$

And

$$c = \frac{(N-1)\sum_i \sum_j w_{ij}(y_i - y_j)^2}{2S_0 \sum_i (y_i - \bar{y})^2}$$

Where y_i is the value of the y variable at location i, $\bar{y}$ is the sample mean, w_{ij} is the corresponding element of the spatial weight matrix W and $S_o = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$. N is the total number of areas or observations.

Table 2 reports the results of both tests for the variables: logarithm of per capita expenditure (ldpa); level of education (nivsc) and the average size of household by delegation (size). The two tests accepted the hypothesis of positive spatial correlation with a significance level of 99%, indicating the presence of a positive spatial autocorrelation in the geographical distribution of these variables[6].

Spatial correlation may also be summarized using a Moran scatter plot which gives us more details about the kind of spatial autocorrelation. This scatter plot, suggested by Anselin (1996), plots the variable of interest on the horizontal axis against a spatial lag (the standardized spatial weighted average) on the vertical axis. The Moran scatter plot is presented by four different quadrants corresponding to the four types of local spatial association between each delegation and its neighbors (see Rupasingha et al., 2007).

- Quadrant High-High (H-H) displays the localities with a high value of the variable surrounded by localities with high values.

- Quadrant Low-Low (L-L) shows the localities with a low value surrounded by localities with low values.

- Quadrant Low-High (L-H) shows the localities with low value surrounded by localities with high values.

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5 ESDA is a subset of exploratory data analysis (EDA) that focuses on the distinguishing characteristics of spatial data— specifically on spatial autocorrelation and spatial heterogeneity (Anselin et al., 2007).

6 Values of I larger (but resp. smaller) than the expected value E (I) =-1/n-1 indicate positive (resp. negative) spatial autocorrelation.

- Quadrant High-Low (H-L) shows the localities with high value surrounded by localities with low values.

Figure (2.a) plots the logarithm of per capita expenditure (ldpa) against its spatial lags (Wldpa), and figure (2.b) plots the level of schooling (nivsc) against its spatial lags (Wnivsc). The first and second quadrant (H-H and L-L) points in Figures 2.a and 2.b suggest positive spatial autocorrelation. The first quadrant (H-H) shows that delegations with high per capita expenditure and high levels of education are surrounded by delegations with similar value for the two variables. However delegations with low per capita expenditure and low levels of education are neighbors of delegations with low per capita expenditure and low levels of education (quadrant (L-L)).

3.2 Local Spatial Autocorrelation

Previously defined global indicators cannot help us analyze the spatial heterogeneity at the local level as they are incapable of identifying the local association and differences or the kind of spatial correlation of each district. The local Moran statistics (***I_i*),** also referred to as Local Indicator of Spatial Association (LISA), are more often used to measure the local spatial concentration (clustering) (Anselin, 1995; Le Gallo and Ertur, 2003). The local Moran statistic for an observation *i* may be defined as (Anselin, 1995, 1998):

$$I_i = (z_i / m_2) \times \sum_j w_{ij} z_j$$

Where z_i and z_j are deviations from the mean of a specific indicator and $m_2 = \sum_i z_i^{\ 2} / N$, such that the summation considers only areas close to *i*.

LISA satisfies two conditions: (i) for each observation *i*, LISA gives an indication on the significant clustering of similar value of type **H-H** (high-high) or **L-L** (low-low). (ii) the sum of LISA associated to all the observations is proportional to the global indicator of spatial association defined previously (Anselin, 1995; Longley and Tobon, 2004).

Figures 6.a, 6.b, 6.c and 6.d in the Appendix present the LISA map, which is the significant local Moran statistic ***I_i*** (with a significance level of 5%)[7] for the variables logarithm of per capita expenditure, level of education, average size of household, and connection to the sanitation network. It is clear that almost all L-L type associations are in the interior region while the H-H type associations are along the coastal regions.

Table 3 gives the number of significant spatial associations of type H-H or L-L between delegations of the same governorate. We notice a clear regional disparity between the coastal areas (Great Tunis and the middle-east) and the interior areas — more particularly the center-west. Thus 77% of Great Tunis' delegations and 43% of the center-east's delegations are of type H-H when we consider per capita expenditure. Conversely, 83% of center-west delegations have a low level of expenditure (type L-L).

As a conclusion we can say that the results of ESDA on the global and local levels confirm the existence of some spatial autocorrelation and geographical heterogeneity. The aim of the next section is to integrate these phenomena into our econometric model specification.

7 We use the SpaceStat package to calculate the local Moran statistics and the Arcview GIS 3.2 to represent the significant map.

4. Econometric Estimations

4.1 Data

We use three databases: the 2005 CGDR-INS database, the 2001 HDS survey conducted by the Tunisian National Office of Population and Family (ONPF), and the GIS dataset.

The CGDR-INS dataset provides information on the economic and social indicators for the 261 Tunisian delegations. The variables selected for each delegation are: per capita expenditure, education, average size of household, rate of unemployment and the number inhabitants per house.

The HDS database provides precise information on some 6,083 households on aspects such as living conditions (the possession of durable goods as car, television or radio) and housing conditions (standard of housing, quality of the ground etc,) for 2001[8]. The survey identifies the geographical position of each household in the sample, which helps us arrange the data according to various spatial scales (governorates and delegations).

We use the GIS tools to identify the near neighbor delegation and to compute the Euclidean distance separating each delegation to the main CBD[9] (Tunis and Sfax).

4.2 Econometric Models

We start with Wilson's 1987 proposition indicating that "…a person's patterns and norms of behavior tend to be shared by those with which he or she has the most frequent or sustained contact and interaction."

Minot and Baulch (2005) examine the geographic distribution of poverty in Vietnam by applying small area estimation methods to household budget data and population census data. They show that poverty varies across districts. In some districts, more than 90% of the population lives below the poverty line. In others districts, particularly those located in or near the large urban centers, less than 5% of the population is poor.

Benson et al. (2005) use spatial econometric methods on rural Malawi data to show the existence of a strong positive spatial autocorrelation of poverty and then they use the non-parametric method of GWR to show that the relation between poverty and its determinants is not stable over space.

The classic regression techniques are not appropriate if we want to consider spatial dependency. They do not respect the hypothesis of spatial autocorrelation of model variables. In addition, they do not allow for the space instability of the estimated coefficients (Anselin, 1988; Anselin and Griffith, 1988; Bailey and Gatrell, 1995; Fotheringham et al., 1996). Therefore, we must specify an econometric model considering spatial correlations and spatial coefficients instability.

4.2.1 Global Spatial Model Specification: Spatial Autoregressive Model

We start with a non-spatial model which can be formulated as (Elbers et *al*., 2005):

$$ldpa_i = X_i \beta + \varepsilon_i \quad (1)$$

Where $ldpa_i$ is the logarithm of the average expenditure, X_i is the matrix of the explanatory variables and ε_i is the error term of the household's resident at delegation i. The β vector of coefficients is estimated using the Ordinary Least Squares (OLS) method.

8 For more details see Ayadi et al., 2006.

9 Central Business District.

We extend the structure of the above non-spatial models with a spatial lag of the dependent variable ($Wldpa_i$) which allows us to consider relations between people who are geographically close. The spatial lag model can be formalized by adding the spatially weighted variable on the right-hand side of equation (1)[10]:

$$ldpa_i = \rho Wldpa_i + X_i \beta + \varepsilon_i \tag{2}$$

Where W is a ($N \times N$) "weights" matrix defining the neighborhood structure and ρ is the spatial auto-regressive parameter. This model is appropriate in the case of spatial dependence between the dependent variable of near localities giving rise to spatial auto-regressive problems.

The spatial weights matrices (W) may take different forms. Getis and Aldstadt (2004) identify different types of W. The simplest form is the contiguity-type matrix, where the *(i,j)*th element noted w_{ij} is equal to 1 when the regions i and j are contiguous of order 1, and zero otherwise. Several other matrices are defined; such as the k-nearest neighbor weight matrices, the general distance weight matrices, and the inverse distance weight matrices. More complex spatial weight matrices based on additional assumptions such as those based on economic distance can be created (Case et al., 1993).

4.2.2 Local Spatial Model Specification: Geographically Weighted Regression

The explanatory variables effects may differ from a geographical area to another. We should use a model that can incorporate the non-stationarity of the coefficients. For this, the GWR may be useful. The GWR procedure, suggested by Fotheringhan et al. (1998), is based on the following econometric specification:

$$ldpa_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{3}$$

Where (u_i, v_i) denotes the geographical coordinates of the i^{th} point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function $\beta_k(u, v)$ at point i (Fotheringham et al., 2002).

A continuous surface of parameter values is estimated under the assumption that locations nearer to region i will have more influence on the estimation of the parameter of equation (3) for that location (Fortheringham et al., 2000). Algebraically, the GWR estimator is:

$$\hat{\beta}(u_i, v_i) = (X'W(u_i, v_i)X)^{-1} X'W(u_i, v_i)Y$$

With $\hat{\beta}(u_i, v_i)$ = $(\hat{\beta}_0(u_i, v_i), \hat{\beta}_1(u_i, v_i), ..., \hat{\beta}_k(u_i, v_i))'$ and $W(u_i, v_i)$ is an N by N matrix whose off-diagonal elements are zero and whose diagonal elements $(w_{i1}, w_{i2}, ..., w_{iN})$ denote the weights of observed data for point i.

5. Econometric Results

5.1 Global Analysis

A first comparison of the estimated coefficients of OLS non-spatial model and SAR model (Table 4) shows that the variables (nivsc), (eau_rob), (onas), (dtunis), and (dsfax) are all significant in the two specifications, but the estimated impact is smaller when we consider the spatial effect (SAR model). The statistical significance of the spatial coefficient ρ and the increase of the value of $\overline{R}^2$ ($\overline{R}^2_{SAR} > \overline{R}^2_{OLS}$), make us realize that SAR is more appropriate than OLS.

10 See Anselin 1988 for more details of the spatial models.

If we consider the GWR estimation results, we see that most effects of exploratory variables are similar except for the housing conditions (sol1, sol2) which have a significant effect only for the SAR model.

However, although the signs of OLS estimated coefficients may be similar to those of SAR or GWR, we have an inconsistency problem (Anselin, 1988). The non-spatial specification has misspecification errors as it ignores the spatial dependence problem previously detected using Geary and Moran global tests.

5.2 Local Analysis

Table 5 gives details of GWR estimation results. The F statistic (Brunsdon et al., 1999) ANOVA tests for spatial stationarity and AIC criteria values reported at the bottom of the table indicate that the GWR model is better than OLS. It also provides detailed statistics of the GWR parameters across the entire sample (261 delegations). The parameter estimates for the four independent variables (nivs, onas, dtunis, and dsfax) vary widely over space (Figure 3). The *p*-value from a Monte Carlo significance test indicates that the spatial variation in these variables is significant. This provides strong evidence that the marginal effects of these variables are not constant, but vary over space within the Tunisian areas. Thus "nivs" have greater marginal effects on per capita expenditures in the north–eastern regions but a negative effect in the Centre. Sanitations (Onas) will have greater marginal effects in the north-western regions but no effects on the southern ones.

5 .3 Regional and Income Levels Analysis

GWR estimators stipulate that the marginal effects of explanatory variables on per capita expenditure are not constant within the Tunisian areas. In what follows we focus on variations by region and decile. Table 6 shows that "schooling level" and "household size" have more significant effects in coastal regions (Great Tunis, north-east, middle-east and south-east) compared to non-coastal regions. The "rate of good housing status" (sol2) has a more significant effect in central and southern areas.

In Table 7 the results of GWR are aggregated into four different income classes: a) the lowest 10% in terms of income; b) the lowest 25%; c) the lowest median household income; and d) upper median income. The effect of the variable (nivsc) increases as income levels increase, it is about 0,0138 for upper median income classes, but only about 0,0058 for the households in the first decile. Household size has a positive effect on upper median income classes, but a negative effect on the other classes. The effect of the "rate of good housing status" (sol2) decreases with higher income class; it is about 14% for the lowest income deciles but it decreases by 50 % in the above median income class.

5.4 Model Predictive Capacity

SAR and GWR models estimates provide better prediction then OLS as we consider three indicators: Root Mean Squared Error magnitude (RMSE)[11], Spearman rank correlation coefficient, and the kernel smoothed non-parametric function. For each of the three models we compare their respective predicted values with the actual ones. We calculated the RMSE as well as the Spearman rank correlation coefficient associated with each of the three models (see Tables 8 and 9). We depict a clear superiority of SAR and GWR models compared to the non-spatial model estimated by OLS. This is indicated by the lowest RMSE value, 108 for the GWR model against 150.6 for OLS estimation and about 136 for the SAR models (Table

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11 $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\varepsilon_i^2}$

8). GWR yields the largest Spearman rank correlation coefficient value (0,94), whereas OLS and SAR yield smaller coefficient values (0,89 and 0,9 respectively) (Table 8). These results are consolidated in Figure 4 which illustrates the kernel-smoothed non-parametric density function from the observed and predicted values for the three models.

When we consider RMSE and the Spearman rank correlation coefficient by region, we can see that the SAR model is most appropriate for analyzing the household welfare in Great Tunis and middle-west. Those areas are characterized by neighbor effects and homogeneity on per capita expenditure. In the other regions, the GWR model is more appropriate as it produces smaller RMSE across income classes and the biggest Spearman rank correlation coefficient compared to OLS and SAR.

5.5 Policy Implications

One of the striking aspects of welfare maps generated by this study is the wide variation in welfare levels and the relationships between geographic factors and the welfare level approximated by per capita expenditure, sanitation conditions and housing conditions. The spatial welfare analysis and the welfare mapping were necessary steps for any poverty analysis and poverty maps identifications. Both poverty and standard of living appear to be highly heterogeneous phenomena showing a wide spatial variability. Spatial heterogeneity between areas can be explained by the initial endowments (education, sanitations access, housing conditions) and their market access facilities (access to main CBDs). The correlation between market access and poverty is strongest in disadvantaged areas. Generally, areas with more difficult geographic conditions achieved a better fit in our spatial models, suggesting that access to the main urban centers (Tunis and Sfax) has a stronger influence on human welfare than in areas where environmental conditions are less difficult.

The most obvious application for these results may be in improving information on the spatial distribution of poverty for the purpose of targeted poverty alleviation programs. Small area estimation analyses and the resulting maps may help to refine programs at the national and the sub-national levels. Welfare maps help identify regions which may benefit most from additional resources. Targeting poor areas is an intuitively appealing solution to the budget constraint faced by poverty reduction programs. Elbers et al. (2007) show that the use of more highly disaggregated poverty data in targeting cuts the cost of reducing poverty significantly.

The results presented in this study have several applications for potential policy options. The identification of poverty traps using the local indicator of spatial association provides policy makers with an opportunity to improve targeted development programs directed towards the most deprived areas. Poor areas may also be selected to receive some form of direct transfer payments, for example in the form of subsidized credit or direct local administrative budget subsidies. Poverty maps, deduced from welfare maps, represent an efficient tool in identifying priorities within the national development strategy, narrowing the regional and social disparities regarding basic development indicators, and adopting efficient pro-poor macroeconomic policies.

6. Conclusion

This paper analyzes the patterns of households' welfare, approximated by per capita expenditures at the level of small administrative units in Tunisia (the delegation). Three models are used for predicting log of average per capita household expenditure: the OLS model; the spatial autoregressive model (SAR); and the geographically weighted regression model (GWR). We confirm the presence of some spatial autocorrelations and spatial heterogeneity of the different variables of our models. All statistical tests confirm the existence of a significant spatial correlation between the units. Thus ignoring this spatial component in a regression analysis could lead to misleading estimates of parameters.

In addition, based on the AIC criteria, the Root Mean Square Error (RMSE) and the Spearman rank correlation coefficient, we deduce that GWR and SAR estimators give us better predictions than does the non-spatial OLS.

The ANOVA test for spatial stationarity proved the superiority of GWR over global OLS and SAR models in analyzing the households' welfare except for Great Tunis where more homogeneity is depicted. This suggests that the major determinants of welfare are not stationary over space. So, taking the spatial variability into consideration could be important for designing and evaluating poverty reduction strategies in Tunisia.

References

Amarasinghe, U., Samad, M., and Anputhas, M., 2005. "Spatial Clustering of Rural Poverty and Food Insecurity in Sri Lanka", *Food Policy*, 30, 493-509.

Anselin, L., 1988a. "Lagrange Multiplier Diagnostics for Spatial Dependence and Heterogeneity", *Geographical Analysis*, 20, 1-17.

Anselin, L., 1988b. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic.

Anselin, L., 1995. "Local Indicator of Spatial Association LISA", *Geographical Analysis*, 27, 93-115.

Anselin, L., and Artur, G., 1992. "Spatial Statistical Analysis and Geographic information Systems", *The Annals of Regional Science*, 26, 19-33.

Anselin, L., and Griffith, D. A., 1988. "Do Spatial Effects Really Matter in Regression Analysis", *Regional Science Association,* 65, 11-34.

Anselin, L., and Hudak, S., 1992. "Spatial Econometrics in Practice: A Review of Software Options", *Regional science and urban economics*, 22, 509-536.

Anselin, L., Florax, R.J.G.M., and Rey, S.J., 2004. *Advances in Spatial Econometrics Methodology, Tools and Applications*. Springer-Verlag, Berlin.

Anselin, L., Rey, S., 1991. "The Performance of Tests for Spatial Dependence in Linear Regression", Technical report 91-13, National Center for Geographic Information and Analysis, University of California, Santa Barbara.

Ayadi, M., Boulila, G., Lahouel, M., and Montigny, P., 2004. "Pro-Poor Growth in Tunisia", International Development & Strategies.

Ayadi, M., and El Lahga, A., 2006. "Pauvreté et inégalités en Tunisie : une approche non-monétaire", 10ème rencontres Euro-Mediterranneennes, université de Caire 4-5, Novembre.

Bailey, T. C., and Gatrall, A. C., 1995. "Interactive Spatial Data Analysis", Essex: Longman Scientific and Technical.

Benson, T., Chamberlin, J., and Rhinehart, I., 2005. "An Investigation of the Spatial Determinants of the Local Prevalence of Poverty in Rural Malawi". *Food Policy*, 30, 532-550.

Brunsdon C., A.S. Fotheringham and M.E. Charlton. 1996. "Geographically Weighted Regression: A Method for Exploring Spatial Non-stationarity", *Geographical Analysis* 28, 281-98.

Brunsdon C., Fotheringham, A.S., and Charlton, M., 1998. "Geographically Weighted Regression-modelling: Spatial Non-stationarity", *The Statistician*, 47, 431-443.

Brunsdon, C., Fotheringham, A.S., and Charlton, M., 2002. "Geographically Weighted Summary Statistics: A Framework for Localized Exploratory Data Analysis", *Computers, Environment and Urban Systems*, 26, 501-524.

Case, A.C., 1991. "Spatial Patterns of Household Demand", *Econometrica*, 59(4): 953-965.

Daimon., T. 2001. "The Spatial Dimension of Welfare and Poverty: Lessons from a Regional Targeting Program in Indonesia", *Asian Economic Journal*, 15(4).

Doreian, P., 1980. "Linear Models with Spatially Distributed Data: Spatial Disturbances or Spatial Effects? ", *Sociological Methods & Research*, 9(1): 29.

Elbers, C., Fujii, T., Lanjouw, P., Özler, B., and Yin, W., 2007. "Poverty Alleviation through Geographic Targeting: How Much Does Disaggregation Help?", *Journal of Development Economics*, 83, 198-213.

Elbers, C., Jean, L., and Peter, L., 2003. "Micro-level Estimation of Poverty and Inequality", *Econometrica*, 71, 355-364.

Elbers, C., Jean, L., and Peter, L., 2005. "Imputed Welfare Estimates in Regression Analysis", *Journal of Economic Geography*, 5, 101-118.

Elbers, C., Lanjouw, J.O., Lanjouw, P., 2000. "Micro-level Estimation of Welfare", Policy Research Working Papers, vol. 2911. Development Research Group, the World Bank, Washington, DC.

Farrow, A., Larrea, C., Hyman, G., and Lema, G., 2005. "Exploring the Spatial Variation of Food Poverty in Ecuador", *Food Policy*, 30, 510-531.

Fotheringhan, S. A., Brunsdon, C., and Charlton, M. 1996. "The Geography of Parameter Space: An Investigation of Spatial Non-stationary", *International Journal of Geographical Information Systems* 10(5), 605-628.

Gideon B., Jack Burgers and Ronald van Kempen, 1998. "On the Social Significance of Spatial Location; Spatial Segregation and Social Inclusion", *Netherlands Journal of Housing and Built Environment*, 13 (1).

Getis, A., and J. Aldstadt., 2004. "Constructing the Spatial Weights Matrix Using a Local Statistic", Geographical Analysis 36(2), 90-104.

Hauret, L., 2005. "Analyse économique de la dimension géographique de la pauvreté une application à la région Lorraine", *Recherches et Prévisions*, n°79 March 2005.

Le Gallo, J., and Ertur, C., 2003. "Exploratory Spatial Data Analysis of the Distribution of Regional per capita GDP in Europe, 1980-1995", *Paper in Regional Science*, 82. 175-201.

Leung, Y., Chang-Lin Mei, and Wen-Xiu Zhang. 2000a. "Statistical Tests for Spatial Non-stationarity Based on the Geographically Weighted Regression Model", *Environment and Planning* , 32, 9-32.

Longley, P.A., and Tobon, C., 2004. "Spatial Dependence and Heterogeneity in Patterns of Hardship: An Intra-Urban Analysis", *Annals of the American Geographers*, 94(3): 503-519.

Minot, N., Baulch, B., 2005. "Spatial Patterns of Poverty in Vietnam and their Implications for Policy", *Food Policy,* 30, 461-475.

PNUD 2004. "Stratégie de réduction de la pauvreté. Etude du phénomène de la en Tunisie".

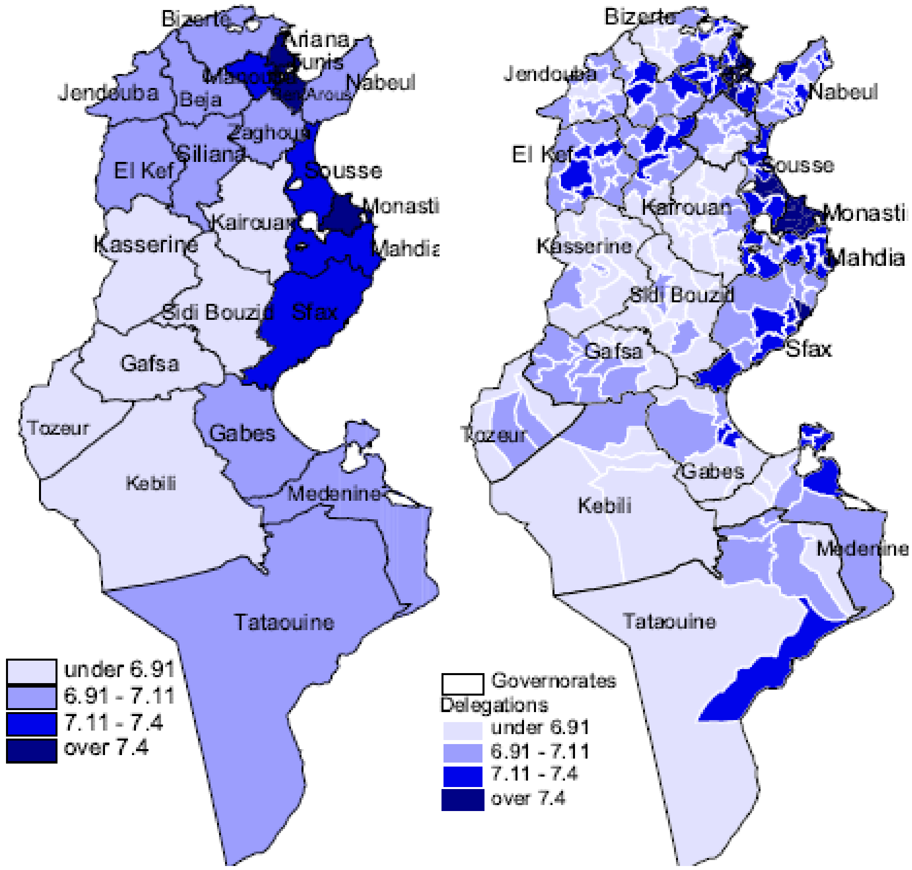
Rallet, A., 1995. "Libéralisation de l'économie, problématique de développement régional et routines institutionnelles: le cas de la Tunisie", *Revue Région & Développement*, 2.

Rupasingha, A., Goetz, S.J., 2007. "Social and Political Forces as Determinants of Poverty: A Spatial Analysis", *The Journal of Socioeconomics*, 36 (4), 650-671

Wilson, W.J. 1987. "The Truly Disadvantaged: The Inner City, the Underclass, and Policy", Chicago: The University of Chicago Press.

World Bank, 2003. "Republic of Tunisia, Poverty Update", Volumes I, IIA and IIB, MENA, World Bank August 2003.

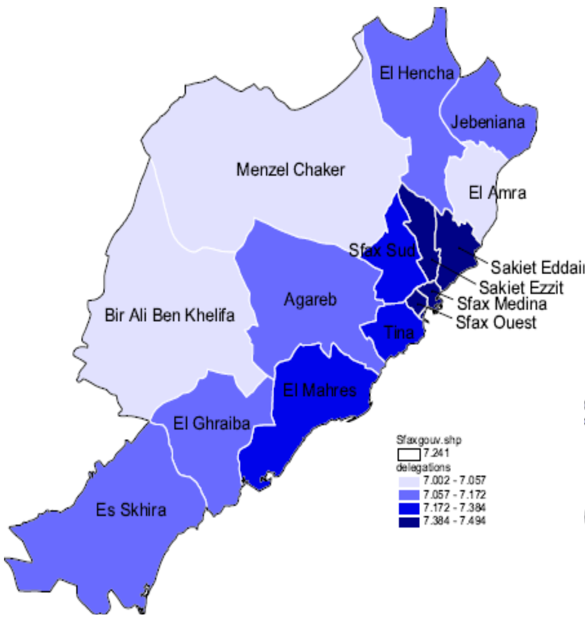
Figure 1.b: Logarithm of Per Capita Expenditure Distribution (TND)[1]



a b

[1] Tunisian Dinar.

Figure 1.c: Spatial Distribution of Log of Per Capita Expenditure by Governorates



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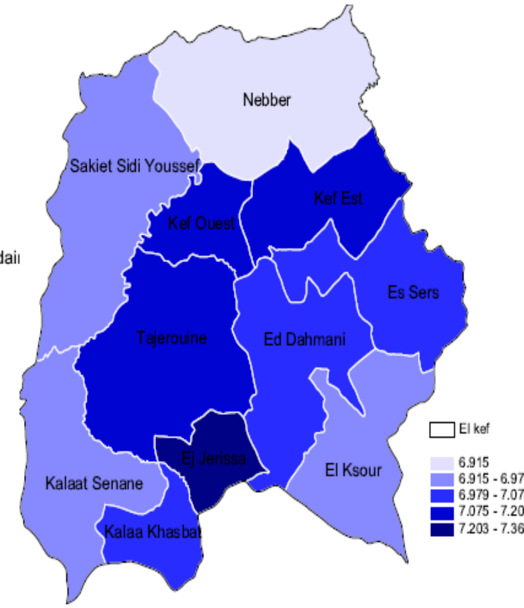

Gafsa

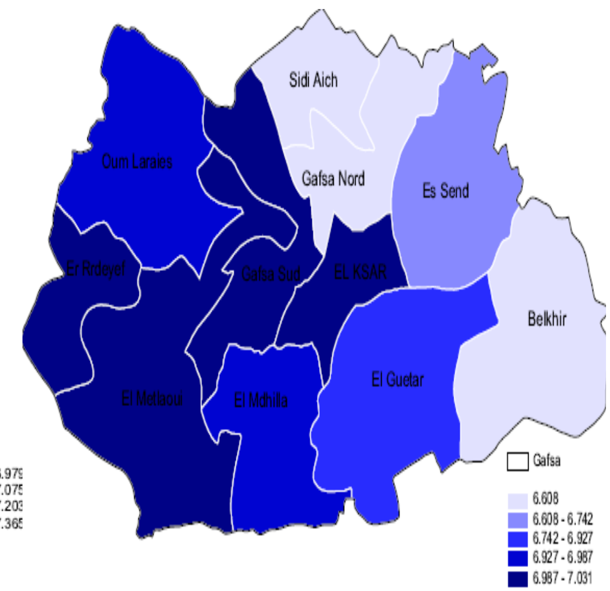

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Figure 2.a: Moran Scatter Plot for Logarithm

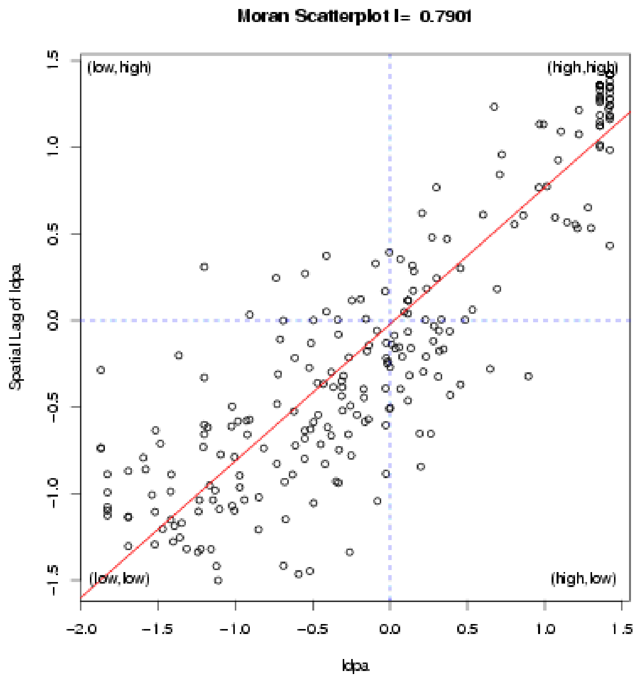


Figure 2.b: Moran Scatter Plot for the Level of the Per Capita Expenditure per Delegation of Education per Delegation

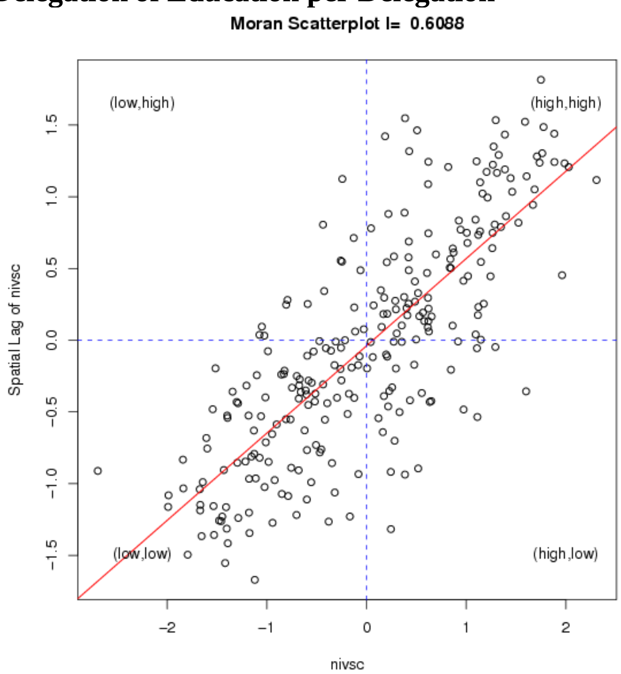
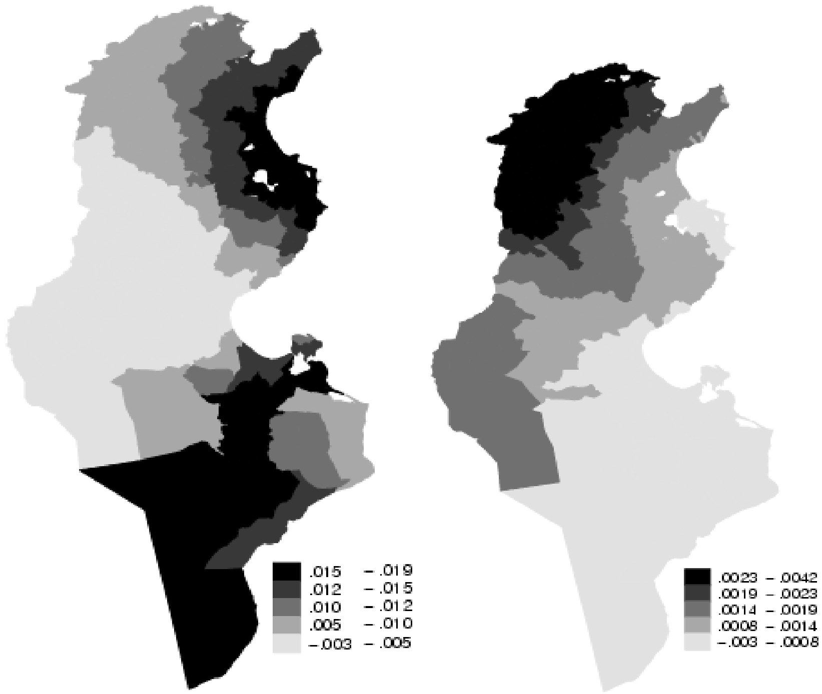


Figure 3: Spatial Variation in the GWR Parameters



"nivsc" parameters "onas" parameters

Figure 4: Kernel-Smoothed Non-Parametric Density Function

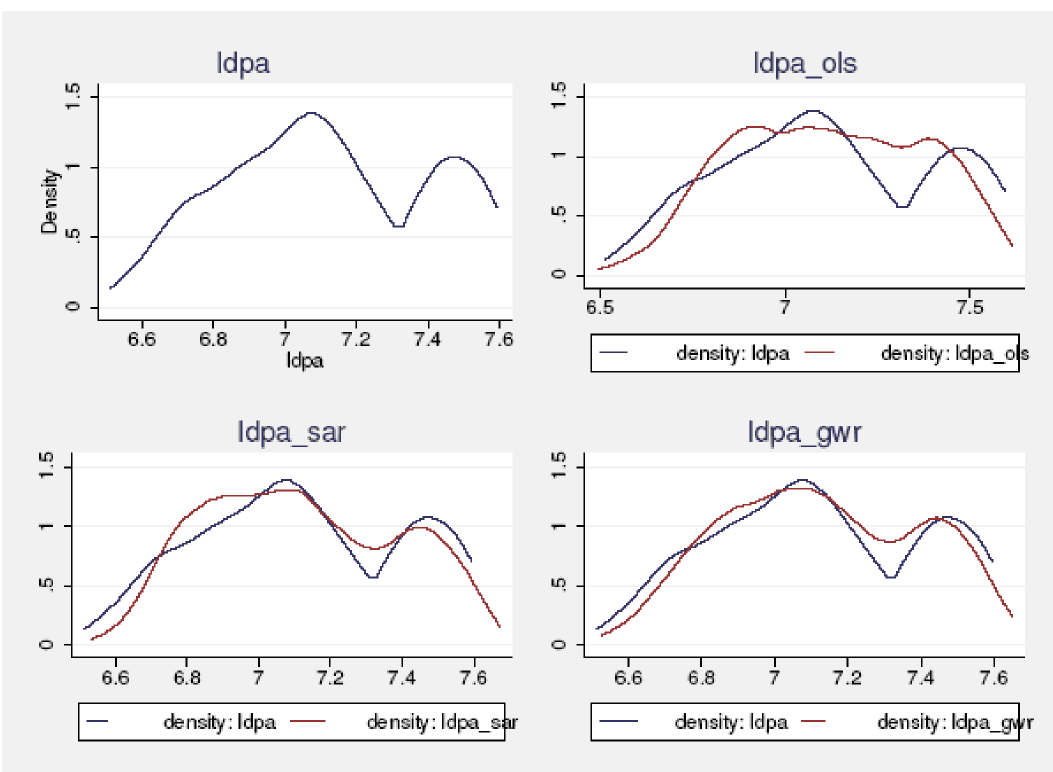


Table 1: Indicators of the Standard of Living

Variables	Great Tunis	Coastal zones (littoral)	Non-coastal zones (interior)
Per capita expenditure (DT)	1737	1323	999
Rate of uneployment (%)	13,9	13,1	18,5
Bad housing status (%)	0,7	1,3	4,1
Good housing status (%)	79,8	60,8	32,9
Education level (secondary level) (%)	38,3	30,6	26,8
Education level (higher level) (%)	12,6	6	4,2
Drinking water (%)	98	83,5	63,3
Size of the household	4,2	4,7	4,9
Total number of delegations	48	117	96

Table 2: Global Test for Spatial Autocorrelation

	Moran's I		Geary c	
Variable	I	**p-value**	c	**p-value**
Ldpa	0,802	0,000	0,213	0,000
Nivsc	0,604	0,000	0,407	0,000
Size	0,590	0,000	0,422	0,000

Table 3: Significant LISA by Governorates

Governorates	Number of delegations	ldpa H-H	ldpa L-L	nivsc H-H	nivsc L-L	onas H-H	onas L-L	size H-H	size L-L
Ariana	7	5	-	2	-	4	-	-	2
Ben Arous	12	8	-	8	-	7	-	-	5
Manouba	8	3	-	1	-	2	-	-	-
Tunis	21	21	-	17	-	20	-	-	15
Great Tunis	48	37	-	28	-	33	-	-	22
Bizerte	14	-	-	-	3	2	1	-	-
Nabeul	16	-	-	-	-	-	-	-	-
Zaghouan	6	-	-	-	2	-	-	-	-
Northeast	36	-	-	-	5	2	1	-	-
Beja	9	-	-	-	1	-	-	-	-
El kef	11	-	-	-	1	-	-	-	-
Jendouba	9	-	-	-	2	-	-	-	-
Siliana	11	-	2	-	2	-	-	1	-
Northwest	40	-	2	-	6	-	-	1	-
Mahdia	11	-	-	-	5	-	9	1	-
Monastir	13	13	-	4	-	6	-	-	-
Sfax	15	2	-	1	5	-	6	2	2
Sousse	15	8	-	4	-	5	-	-	3
Middle east	54	23	-	9	10	11	15	3	5
Kairouan	11	-	9	-	9	-	2	6	-
Kasserine	13	-	9	-	6	-	4	8	-
Sidi bouzid	12	-	12	-	5	-	9	6	-
Middle west	36	-	30	-	20	-	15	20	-
Gabes	10	-	3	-	-	-	2	2	-
Medenine	9	-	2	-	-	-	2	1	-
Tataouine	7	-	-	-	-	-	4	5	-
Southeast	26	-	5	-	-	-	8	8	-
Gafsa	11	-	4	1	-	-	2	2	-
Kebili	5	-	4	-	-	-	-	4	-
Tozeur	5	-	2	-	-	-	-	1	-
Southwest	21	-	12	1	-	-	2	7	-

Table 4: Estimation Results of Equation 1, 2 and 3

Variables	OLS Model	SAR Model	GWR Model
Nivsc	0,0074**	0,0019*	0,0107**
Eau_rob	0,0026**	0,0005**	0,0025**
Onas	0,0013**	0,0004**	0,0015*
Size	-0,0261	-0,0179	0,0206
Dtunis	-0,0006**	-0,0001**	-0,0007**
Dsfax	-0,0008**	-0,0001**	-0,0012**
Car	0,1236*	0,0494	0,0374
Sol1	-0,3745*	-0,1422**	-0,3959
Sol2	0,1462**	0,0363**	0,0863
Txchom	0,0014	0,0011**	0,0018
Txmasc	0,002	0,0013	0,0004
Mglog	-0,0744	-0,105	0,0186
ρ		0,547**	
$\overline{R}^2$	0,79	0,87	
Number of Observations	261	261	261

Table 5: GWR Results : Stationarity Test

		OLS	Gaussian GWR		Stationarity Test
		Global	Min	Max	*p*-value
$\hat{\beta}_0(u_i, v_i)$	constant	6,753	4,423	7,891	0,253
$\hat{\beta}_1(u_i, v_i)$	nivsc	0,007	-0,004	0,0195	0,094*
$\hat{\beta}_2(u_i, v_i)$	eau_rob	0,003	-0,0004	0,0095	0,238
$\hat{\beta}_3(u_i, v_i)$	onas	0,0013	-0,0032	0,0044	0,038**
$\hat{\beta}_4(u_i, v_i)$	size	-0,026	-0,102	0,132	0,28
$\hat{\beta}_5(u_i, v_i)$	dtunis	-0,0006	-0,002	0,0072	0,000***
$\hat{\beta}_6(u_i, v_i)$	dsfax	-0,0008	-0,007	0,0055	0,000***
$\hat{\beta}_7(u_i, v_i)$	car	0,124	-0,928	0,15	0,248
$\hat{\beta}_8(u_i, v_i)$	sol1	-0,375	-1,415	0,428	0,721
$\hat{\beta}_9(u_i, v_i)$	sol2	0,146	-0,048	0,373	0,833
$\hat{\beta}_{10}(u_i, v_i)$	txchom	0,001	-0,007	0,0115	0,416
$\hat{\beta}_{11}(u_i, v_i)$	txmasc	0,002	-0,007	0,0103	0,855
$\hat{\beta}_{12}(u_i, v_i)$	mglog	-0,074	-0,485	0,324	0,933
Residual Sum of Aquares		3,989	1,861		
σ^2_{ML}		0,015	0,007		
AIC		-324,545	-487,32		
F-test		3,142***			

Note: Variables with * are significant at the 90% level; ** at the 95% level; and *** at the 99% level.

Table 6: Exploratory Variables Effects by Regions

Variables	Great Tunis	Northeast	Northwest	Middle east	Middle west	Southeast	Southwest
nivsc	0,013	0,013	0,009	0,016	0,006	0,011	-0,001
Eau_rob	0,003	0,003	0,001	0,002	0,002	0,004	0,004
onas	0,002	0,002	0,003	0,001	0,002	-0,002	0,001
size	0,048	0,048	0,003	0,063	-0,056	0,003	-0,013
dtunis	-0,001	-0,001	-0,001	-0,001	-0,001	-0,001	-0,00
dsfax	-0,001	-0,001	-0,00	-0,002	-0,001	-0,003	-0,001
car	0,118	0,12	0,059	0,034	0,034	-0,197	-0,015
sol1	-0,207	-0,21	-0,261	-0,661	-0,387	-0,855	-0,134
sol2	0,034	0,026	0,049	0,139	0,145	0,097	0,133
txchom	0,003	0,003	0,002	-0,003	0,001	0,005	0,006
txmasc	0,000	0,000	-0,001	-0,001	0,002	0,003	0,003
mglog	0,128	0,116	-0,152	-0,023	0,133	-0,021	-0,117
Number of Observations	48	36	40	54	36	27	20

Table 7: Exploratory Variables Effects by Income Classes

Income Classes **Variables**	**10%**	**25%**	**<50%**	**>50%**
nivsc	0,0058	0,0067	0,0076	0,0138
eau_rob	0,0025	0,0024	0,0025	0,0026
onas	0,0012	0,0014	0,0015	0,0015
size	-0,0376	-0,021	-0,0053	0,0462
dtunis	-0,0004	-0,0004	-0,0004	-0,0009
dsfax	-0,0012	-0,0011	-0,0011	-0,0013
car	-0,0079	0,0071	0,0025	0,0721
sol1	-0,4101	-0,3723	-0,3825	-0,4093
sol2	0,1409	0,1146	0,1034	0,0692
txchom	0,0021	0,0027	0,0027	0,001
txmasc	0,0016	0,0013	0,001	-0,0002
mglog	0,0742	0,0327	-0,0089	0,0458
Income (DT)	<844,147	<1005,307	<1222,92	>1222,92
Number of Observations	26	65	130	131

Table 8: RMSE for the Three Models by Region and Income Classes

	RMSE_OLS	**RMSE_SAR**	**RMSE_GWR**
Global RMSE	150,6	136	108
		RMSE by region	
Great Tunis	147,6	106,2	117,1
Northeast	172,8	158,7	140,8
Northwest	103,3	114,1	80,9
Middle East	168,2	165,9	113,5
Middle West	152,6	99	121,2
Southeast	164,9	164,6	68,7
Southwest	117	120,6	54,4
		RMSE by income classes	
<10%	145,7	113,8	98,7
<25%	145,4	121,6	100,3
<50%	141,4	127,7	96,8
>=50%	156	138,5	112,9

Table 9: Spearman Rank Correlation Coefficient

	OLS	**SAR**	**GWR**
Spearman rank correlation coefficient	0,89	0,9	0,94
	Spearman rank correlation coefficient by region		
Great Tunis	0,74	0,78	0,76
Northeast	0,79	0,73	0,73
Northwest	0,85	0,82	0,92
Middle East	0,86	0,89	0,89
Middle West	0,53	0,47	0,61
Southeast	0,6	0,6	0,9
Southwest	0,88	0,9	0,89
	Spearman rank correlation coefficient by income classes		
<10%	0,24	0,08	0,48
<25%	0,35	0,27	0,61
<50%	0,71	0,68	0,85
>=50%	0,83	0,86	0,86

Appendix 1

Figure 5: Spatial Distribution of Wellbeing in Tunisia

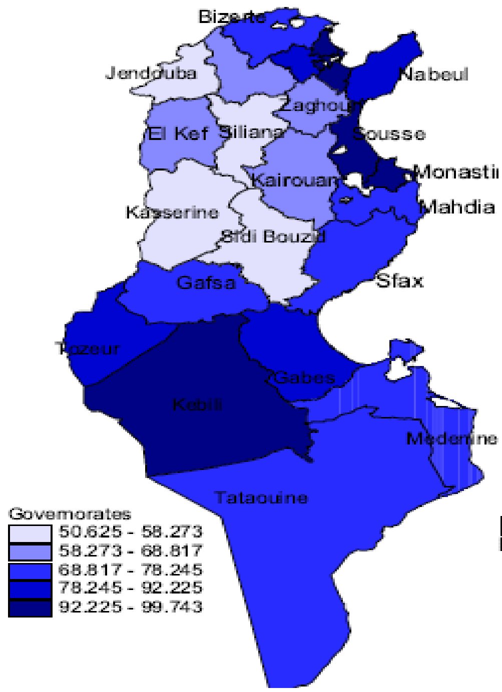


Figure 5.a: Access to Drinking Water per Governorate (percentage)

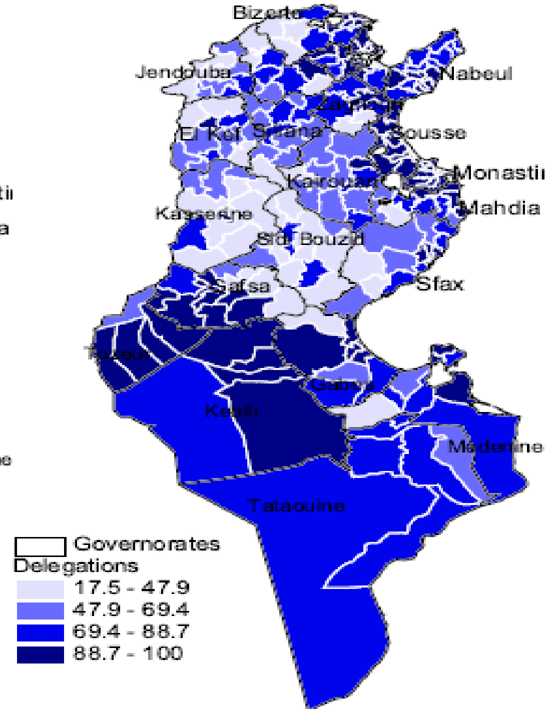


Figure 5.b: Access to Drinking Water per Delegation (percentage)

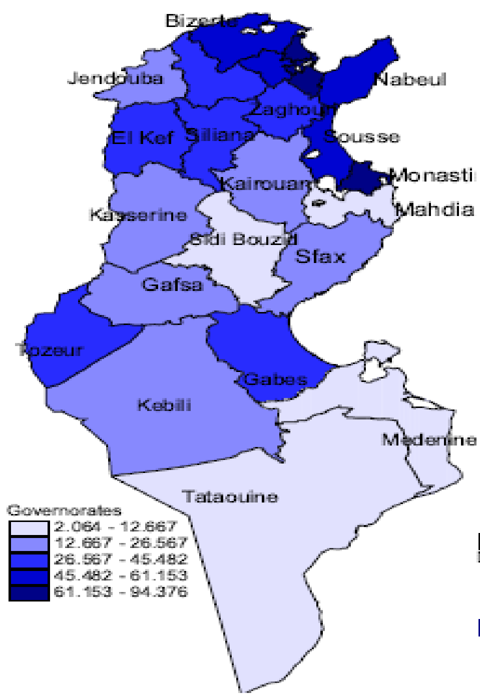


Figure 5.c: Access to Improved Sanitation per Governorate

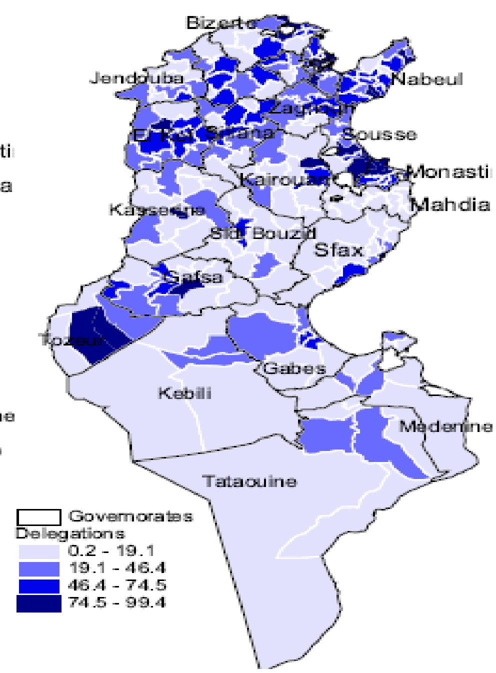


Figure 5.d: Access to Improved Sanitation per Delegation

Appendix 2
Figure 6: LISA Clusters

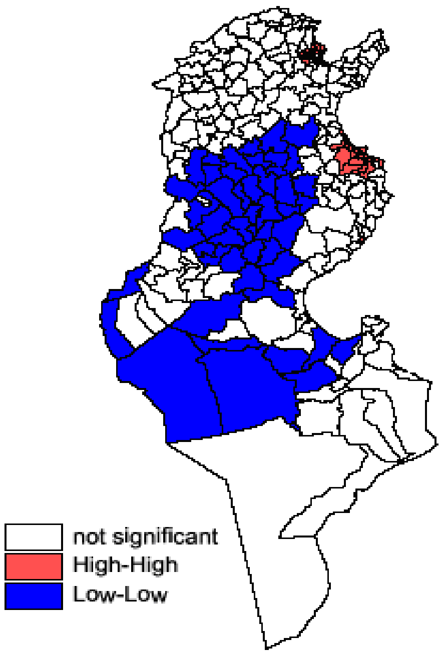


Fig 6.a: LISA Per Capita Expenditure

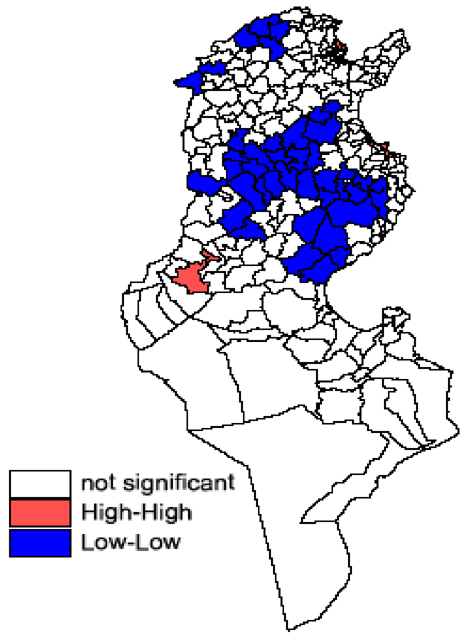


Fig 6.b: LISA Education Level

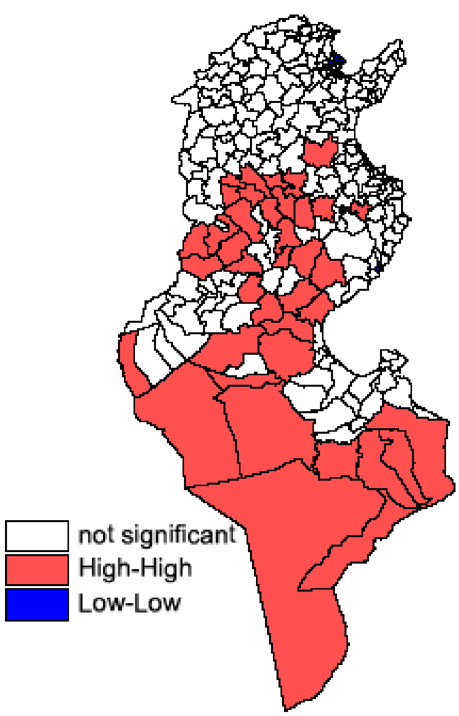


Fig 6.c: LISA Size of Household

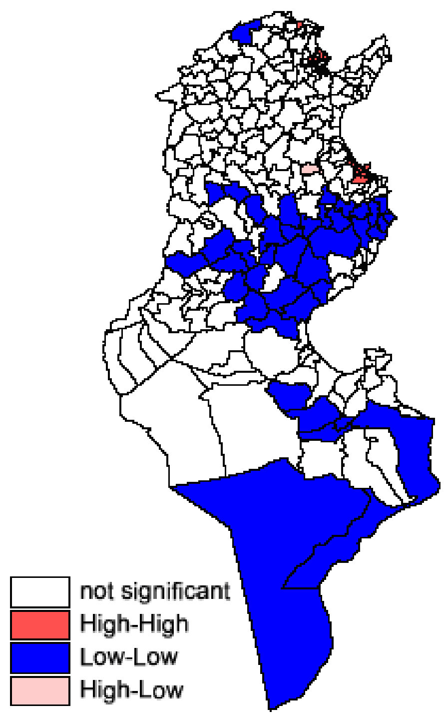


Fig 6.d: LISA Access to Sanitation