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Tunisian Coastal Cities Attractiveness and Amenities

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Abstract

The aim of this paper is to explain the density variation among coastal cities by the availability of amenities inside cities. A spatial index of cities attractiveness is computed using the Kulldorff scan statistic technique. Spatial pattern of density clusters revealed that north delegations are more attractive than south delegations and historical business centers of big cities become less attractive for residential population. To assess the spatial interdependence between delegations and the impact of amenities on spatial density pattern we use a spatial Durbin model. Estimation results show delegations with high level of basic amenities like health and educational amenities are the more attractive. Delegations with high level of luxury amenities like clinics kids clubs and post offices exert a positive spillover effect on surrounding delegations. The lack of hospitals in a typical delegation exerted a negative indirect effect on population density inside surrounding delegations.

Keywords: urban population density, amenities, coastal cities, spatial Durbin model, scan statistic.

JEL Classification: C21, J11, O18, R21.

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1. Introduction

The urban spreading of Tunisian littoral cities has been considered as the significant feature of the last three decades. Recent data on population density reveals that in Tunis the capitals of Tunisia, 100% of households live in urban area, the population density is about 2814 habitant per km^2. The rate of urbanization in the other big coastal cities like Sfax and Sousse is more than 73% and the population density is about 200 habitants per km^2.

With 51 % of the total population of the country, the littoral fringe consumed 89 % of the production of the electricity. It concentrated almost all of the industrial production, 84 % of the beds of hospitals, 84 % of the doctors and 70 % of the pupils of primary schools according to the general census of the population and the housing environment published in 1966. These disparities already characterized the Tunisian landscape since the independence, Signole (1985). Urban planners were confronted with this strong regional disparities perceived as an obstacle to development and to reduce the disparities in economic activity and population, they adopted a "voluntarist" policy of pole industrial creation in disadvantaged regions, by the promotion of investment incentive policies. A major achievement of this policy was the decentralization of economic activity by stimulating growth in the interior, but it also fail to reduce people migration towards the littoral cities, Belhadi (1990) et Ben Letaeif(2008). During the last three decades, Tunisian authorities adopted a structural reform plan in 1986, removed its trade barriers after signing the General Agreement on Trade and Tariffs in 1990, joined the World Trade Organization in 1994 and created a Free trade area with the European Union in 1996. This world open economic orientation aroused urban planners to opt for choices strengthening these tendencies of selective and differentiated development by recommending a strong politics of métropolisation, centered on three big cities of the littoral band of the country, Dhaher (2013). The consequence of this urban politics is the increasing of urban population density more quickly than expected in coastal cities; this fast increase is underlain by the developments of transport networks; touristic and industrial big projects in coastal band. The resulting urban structure of the country is characterized by the dominance of the capital Tunis witch inhabit more than 22%, its dominance is connected to the concentration of public investments responsible for national space polarization and for the attractiveness of migratory flows to the capital; and the concentration of the most large and medium size cities in the coastal band, Chabbi (2005)[1].

[1] Most urban cities are located in the costal band, 142 delegations among 264 are located in this zone.

The analysis of the factors that explain these density disparities among urban Tunisian areas constituted the aim of several recent empirical studies. Amara et al (2010) found that the urban decentralization in Tunis cities in caused by the emergence suburban employment sub-centers. Ayadi and Ben Said (2012) explained the increasingly density trend in suburban area by the expansion of irregular and non planned settlement. The limitation of these studies is the use of the distance from historical CBD, in an exponential density function, as the only factor explaining spatial distribution of population density.

The purpose of this paper is to further enhance the research by explaining the spatial variation of urban density among Tunisian littoral cities by the differentiation in urban amenities. Literature on the effect of amenities on city growth is developed in section 2, spatial statistic tools and spatial econometric model used to detect the impact of amenities on population density are presented in section 3. Section 4 describes the study area and the data used to analyze the amenities impacts. Section 5 presents the density cluster maps and empirical results that highlight the relationship between density variation and amenities availability. Section 6 concludes the study findings.

2. Literature review

Amenities can be defined as non-marketed qualities of a locality that make it an attractive place to live and work (Power 1988). In a very wide sense, urban amenities can be defined as the positive externalities generated from agglomerations of people, firms, private and public goods and services, transportation facilities and physical infrastructure (Andersson and Andersson, 2006; Quigley, 1998; Pia 2014). Deller et al. (2001) used a measurement of amenities that include the flowing five different variables: the climate of the particular area, the land itself, water, winter recreation, and developed recreational infrastructure[2].

The choice of a particular location depends on a level of these amenities that is in accordance with this particular location. . The consumer localization choice among localities is a trade off both higher transportation costs and housing space against a better quality of non-marketable amenity goods, Alperovich (1980a). In this way, the positive assessment of amenities makes some communities more attractive than others and can explain the disparities between urban areas, consumer preference for particular county amenity, determine the magnitude of the positive effect exerted by such amenity on the local economy, both in terms of attracting

[2] For a pertinent literature review on concepts, measures and measures of amenities, readers can see the published PH.D dissertation of Harry Landis Vogel (2006).

people to that county and its economic development (Rudzitis, 1999; Vias, 1999; Delbert et al., 2001).

In their work Kemper and Schmenner (1974) concluded that "declining exponential density function" based on the land-use Muth-Alonso (1969) model fail to explain much of the spatial variation of manufacturing density". Building on this finding, Alperovich (1980b) demonstrated that amenity variables, added to an econometric model designed to explain density variation, increase the explanatory power of this model, this results indicate that amenity variables account for a much higher proportion of the locational variability of population and housing densities.

Studies that focus on the impact of amenities on firm location and employment growth (Gottlieb, 1994; Kusmin, 1994; McGranahan, 1999; Deller et al, 2001; Kahsai et al, 2013) contend that there is a weak relationship between amenities and business location and economic growth.

The relationship between amenities and population constituted an important stream in amenity literature. Clark and Cosgrove (1991) and McGranahan (1999) presume that population change patterns are affected by climatic amenities. Glaeser et al (2001) found that natural amenities such as climate and coastal proximity are dominant predictors of population density inside US cities, they notes that high amenity cities have grown faster than low amenity cities. Large differences in American and European cities are strongly caused by differences in consumption amenities; recent empirical results suggest that physical infrastructures, such as cultural institutions, architecture and other historical amenities are key factors that determine the localization choice of people (Rappaport 2008; Albouy 2012).

For the purpose of exploring spatial variability of density among cities and the detection of high and low density clusters we use a scan statistic technique (Kulldorff and Nagarwall, 1995; Kulldorff, 1997; 2010) for cluster detection. In urban economic literature spatial autocorrelation indices are used to detect population or employment centers and sub-centers, this wide range of literature used the LISA[3] (Anselin 1985). The shortcoming of this statistic test is its incapacity to make inference for detected clusters. The Scan Statistic test overcomes the problems of inference, selection bias and the population heterogeneity. Many recent empirical studies in urban economic literature used the scan statistic; Tuia et al (2007) used the scan statistic to describe urban space in terms of density of service types; they said "Such a

[3] Local Indicator of Spatial Association.

method could be used in urban studies and planning to detect areas where a lack of services could lead to forced trips or to a loss in the quality of life"[4]. Helbich (2011) used the scan statistic technique to analyze the spatial distribution of "postsuburban" services[5] and to evaluate the polycentric form of Vienna city.

Past empirical studies that attempted to inspect the role of space in regional growth ignored to address the spatial dependence between regions, the "aspatial" models used leads to inefficient standard errors which in turn affect the significance levels of the variables, Wooldridge (2002). Predictions made based on this can be misleading and may have undesired policy implications. Nzaku and Bukenya (2005) introduced a spatial lag of the dependent variables to capture spatial dependence and extended these models. Recent works of Deller et al. (2005), Monchuk and Miranowski (2007), Carruthers et al. (2008) and Royuela et al. (2010) also used a spatial model to control for the unobserved spatial distribution of amenities in the region. With the exception of Monchuk and Miranowski (2007), all these empirical studies never consider the spatial impacts of surrounding county amenities on regional economic growth. Thus, their studies reflect only the direct effects of local amenities on the regional growth indicators, ignoring the spillover effects coming from surrounding counties. Kahsai et al (2013) extends previous studies by estimating a simultaneous spatial Durbin model SDM thus model allow capturing the total effects of amenities (direct and indirect) by explicitly evaluating the role of own and surrounding county amenities in regional economic growth using the SDM. They found that historical and cultural amenities exert a positive effect on population and employment densities growth of surrounding counties.

3. Spatial econometric tool

3.1 Scan statistic tool

One of the most important statistical tools for cluster detection is Kulldorff's spatial scan statistic. This method searches over a given set of spatial zones, finding those zones which maximize a likelihood ratio statistic and thus are most likely to be generated under the alternative hypothesis of clustering rather than the null hypothesis of no clustering. Randomization testing is used to compute the p-value of each detected zone, correctly

[4] Tuia et al 2007 page 5.

[5] According to Helbich (2011), the advantage of the Scan statistic technique, compared to earlier procedure for employment and population urban subcenters detection (Giuliano & Small 1991; Baumont et al 2004), is that it avoid the problem of the threshold.

adjusting for multiple hypotheses testing, and thus we can both identify potential clusters and determine whether they are significant. Then the goal of the scan statistic is to find zones where the incidence rate of a phenomenon is higher inside the zone than outside.

Let n_z and $\mu(z)$ be the population size and case count, respectively, in zone z. Define p and q as the probability of being a case inside and outside zone z, respectively. Based on the null hypothesis of clusters in zone z $H_0 : p = q$ versus the alternative of the existence of a cluster in zone z $H_1 : : p > q$.

The propabilité of n_G the number of events in the study area is:

$$\frac{e^{-p\mu(z)-q(\mu(G)-\mu(z))}[p\mu(z)+q(\mu(G)-\mu(z)]^{n_G}}{n_G!} \tag{1}$$

The density function $f(x)$ of a specific point being observed at location x is:

$$\begin{cases} \frac{p\mu(x)}{p\mu(z)+q(\mu(G)-\mu(z))} & if\ x\ \in z \\ \frac{p\mu(x)}{p\mu(z)+q(\mu(G)-\mu(z))} & if\ x\ \notin z \end{cases} \tag{2}$$

Kulldorff (1997) defines a likelihood ratio statistic as:

$$L(Z,p,q) =$$

$$\frac{e^{-p\mu(z)-q(\mu(G)-\mu(z))}[p\mu(z)+q(\mu(G)-\mu(z)]^{n_G}}{n_G!} \times \prod_{x_i \in z} \frac{p\mu(x_i)}{p\mu(z)+q(\mu(G)-\mu(z))} \times \prod_{x_i \in z} \frac{q\mu(x_i)}{p\mu(z)+q(\mu(G)-\mu(z))}$$

$$= \frac{e^{-p\mu(z)-q(\mu(G)-\mu(z))}}{n_G!}\ p^{n_z} q^{n_G-n_z} \prod_{x_i \in z} \mu(x_i) \tag{3}$$

This equation take its maximum when $p = n_z/\mu(z)$ and $q = (n_G - n_z)/(\mu(G) - \mu(z))$, so

$$\begin{cases} \frac{e^{-n_G}}{n_G!} \left(\frac{(n_G - n_z)}{(\mu(G) - \mu(z))}\right)^{n_G - n_z} \prod_{x_i \in z} \mu(x_i) & if\ n_z/\mu(z) > (n_G - n_z)/(\mu(G) - \mu(z) \\ \frac{e^{-n_G}}{n_G!} \left(\frac{(n_G)}{\mu(G)}\right)^{n_G} \prod_{x_i \in z} \mu(x_i) & otherwise \end{cases}$$

The test statistic λ of the likelihood ratio test can be written as:

$$\lambda = \underset{z \in Z}{sup} \frac{\left(\frac{(n_Z)}{\mu(z)}\right)^{n_Z} \left(\frac{(n_G - n_Z)}{(\mu(G) - \mu(z))}\right)^{n_G - n_Z}}{\left(\frac{(n_G)}{\mu(G)}\right)^{n_G}} \; I\left(\frac{(n_Z)}{\mu(z)} > \frac{(n_G - n_Z)}{(\mu(G) - \mu(z))}\right) \tag{4}$$

where λ is the estimated baseline incidence rate, and I( ) is an indicator function equal to 1 when the number of observed cases in zone *z* exceeds that expected under H_0, and is equal to 0 otherwise.

The most likely cluster is defined by the zone $\check{z}$, maximizing L_z over all possible zones considered. The statistical significance of $L_{max} = L_{\check{z}}$ is obtained via Monte Carlo simulation. Specifically, the n_z cases are distributed uniformly among the $\mu(z)$ individuals according under the null hypotesis, and the maximum value of L_z is calculated for each simulated data set. The *p*-value associated with the most likely cluster is the proportion of observed and simulated statistics greater than or equal to the value of $L_{\max}$ observed in the data. Note that the Monte Carlo inference ranks the observed maximum likelihood ratio statistic $L_{\max}$ from the data among a set comprised of the maximum likelihood ratio statistic from each simulated data set, and not among the statistics observed at the same zone as the maximum in the data set. As a result, inference is not based on the distribution of a likelihood ratio for a particular zone, but rather the on the distribution of the maximized likelihood ratio under the null hypothesis, regardless of which zone contains the maximum.

3.2 The spatial Durbin model

The occurrence of significant clusters in the study area means that there is a spatial dependence between zones. Under this spatial dependence problem the OLS estimators become biased and inconsistent and inference drawn from OLS are misleading (Lesage 1999 ; Baumont et al 2001). In cluster zones a spillover effect can be exerted from each zone on surrounding zones, the SDM[6] ((Pace and LeSage, 2006; Lesage 2008) allow accounting for dependence between zones and permit to assess the spillover effect on the study zones. The model employed in this study is:

$$y = \rho W y + \alpha \iota + X\beta + WX\theta + \varepsilon \tag{5}$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

This model specification will allow the explanatory variables contained in the matrix X from neighboring regions to exert an influence on y value of region *i*. This is accomplished by

[6] The Spatial Durbin Model

entering an average of the explanatory variables from neighboring regions, created using the matrix product W X. in this model the constant term vector ι_n is eliminated from the explanatory variables matrix X.

If ρ ≠ 0, then the interpretation of the parameter vectors β (and θ) in the spatial Durbin model is different from a conventional least squares interpretation, (Pace and LeSage, 2006). In least-squares the r^{th} parameter, β_r, from the vector β, is interpreted as representing the partial derivative of y with respect to a change in the r^{th} explanatory variable from the matrix X, which we write as x_r.

Specifically, in standard least-squares regression where the dependent variable vector contains independent observations, the partial derivatives of y_i with respect to x_{ir} have a simple form : $\partial y_i/\partial x_{ir} = \beta_r$ for all i, r ; and $\partial y_i/\partial x_{jr} = 0$, for $j \neq i$ and all variables r.

It follows from (6) that the derivative of y_i with respect to x_{jr} takes a much more complicated form:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \qquad (6)$$

In contrast to the least-squares case, the derivative of y_i with respect to x_{ir} usually does not equal β_r, and the derivative of y_i with respect to x_{jr} for $j \neq i$ usually does not equal 0. Therefore, any change to an explanatory variable in a single zone can affect the dependent variable in all zones. This is of course a logical consequence of our simultaneous spatial dependence model since it takes into account other regions' dependant variable, and these are determined by the characteristics of those regions. Any change in the characteristics of neighboring regions that set in motion changes in dependant variable will impact the dependant variable of neighboring regions, and so on.

In the case of the own derivative for the i^{th} region,

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \qquad (7)$$

$S_r(W)_{ii}$ expresses the impact on the dependent variable observation i from a change in x_{ir} as a combination of direct and indirect (neighborhood) influences. These spatial spillovers arise as a result of impacts passing through neighboring regions and back to the region itself.

Since the impact of changes in an explanatory variable differs over all regions, it seems desirable to find a summary measure of these varying impacts. Pace and LeSage (2006) set forth the following scalar summary measures that can be used to average these impacts across all institutions.

The Average Direct effect = averaged over all n regions/observations providing a summary measure of the impact arising from changes in the i^{th} observation of variable *r*.

The Average Total effect = Average Direct effect + Average Indirect effect. This scalar summary measure has two interpretations. First it includes the average direct impact plus the average indirect impact of a raise in one explanatory variable in all regions on the dependant variable of the typical region. Second the total average effect measures the total average impact of one explanatory variable raise in a region *j* on the dependant variable of all other regions[7].

Finally, the *Average Indirect effect* = Average Total effect – Average Direct effect by definition. This effect measure the impact of an explanatory variable raise in all other regions on the dependant variable of an individual region.

4. Study Area and data

Located between 37° 20 ' 35 ' 'and 30° 14' 58' 'of northern latitude, Tunisia belongs to the subtropical zone. Its coasts extend on more than 1,300 km Tunisia is considered as the most urbanized African country with urbanization rate more than 65% and annual urban population growth of about 1,6%, urban density is equal to 860 habitant per km^2 against 65 habitant per km^2 at the country level. In 2011, the rate of urban households connected to the STEG electricity system is more than 99%, potable water is supplied to more than 99,5% and the connection to The ONAS sewerage service is about 91%. Despite these urban indicators the Tunisian urban system is characterized by an unbalanced population repartition between littoral and interior regions, among 264 Tunisian delegations[8], 142 are located in the littoral regions and 122 in the internal regions and 75 % of the total urban population lives in the littoral regions, the zone of concentration of big and medium size cities.

[7] Pace and LeSage (2006) show that the numerical magnitudes arising from calculation of the average total effect summary measure using these two interpretations are equal

[8] The delegation is an administrative unity that constitutes the four digit code of the population census cutting. The two digit code is the governorate, and Tunisia is divided in 24 governorates and 264 delegations. The sector constitutes the sex digit code.

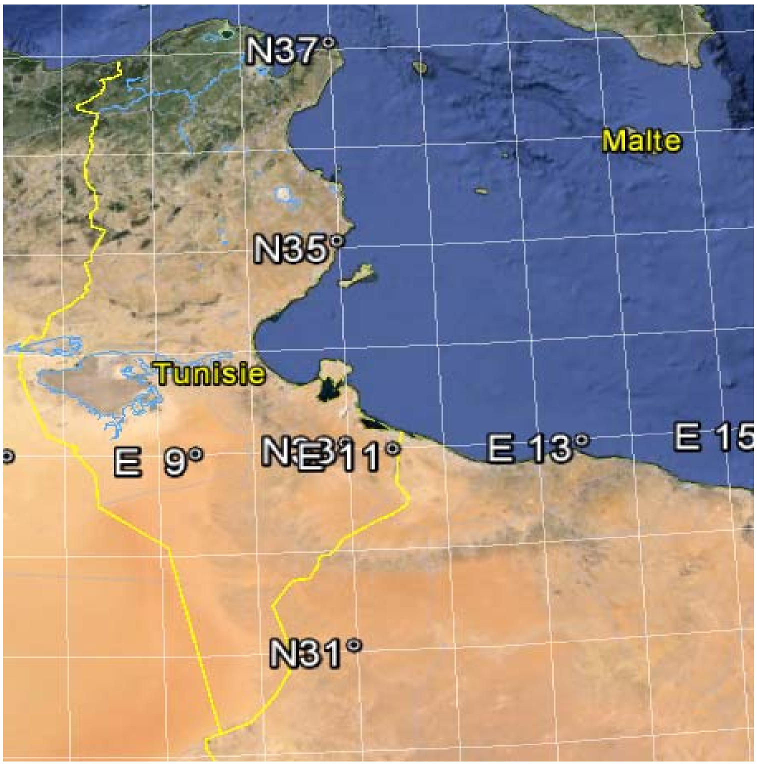

Figure 1. Geographic location of Tunisia

The scale of the process of péri-urbanisation became more marked only after the independence of the country in 1956, in particular in the main littoral cities (Tunis, Sfax and Sousse). The possibilities of jobs offered by various sectors (tourism industry and tertiary sector), the concentration of universities, the improvement of the environment, the closeness of the leisure activities, are the main factors that affect the urban concentration in coastal cities

With more than 65 % of the total population of the Country, the big cities of littoral (Bizerte, "Grand Tunis", Nabeul, The Sahel Kairouan Sfax Sidi Bouzid and Gabes) consumed 89 % of the of electricity production. It concentrated 75.8 % of the working population, 84 % of the hospital beds, 84 % of the doctors and 72.7 % of the pupils at the primary schools and 74.6% of the pupils at the prep and secondary school, according to the general census of the population and housing published in 2004.

The study area is the coastal band and nearby big cities of Tunisia, it contain the 173 most urbanized delegations of the country, the urbanization rate inside this delegations is more than 66% .

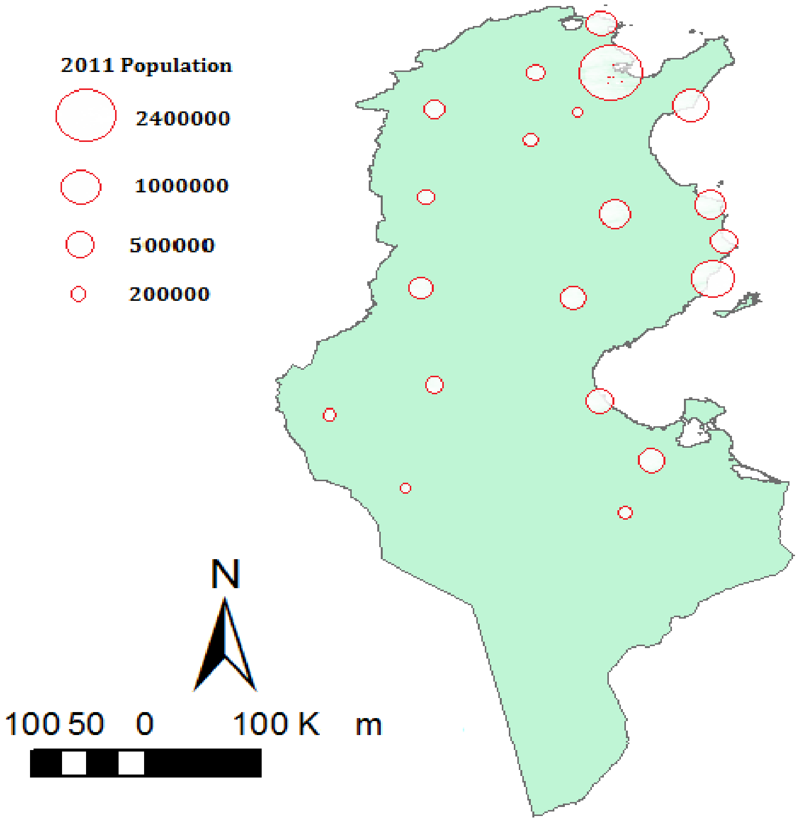

Figure 2. Tunisian populations repartition by governorate in 2011.

Population and amenities data used in this study are obtained from the General Commissariat of Regional Development (CGDR) and the population projection data from the National Institute of Statistics (INS). The data set contain information on educational, health, cultural and industrial equipments available in each delegation in 2011[9]. Population data used in this study comes from the 2011 census population projection published by the INS[10].

5. Estimation and results

5.1 Scan statistic detection of density clusters:

We apply the spatial stat scan technique to detect density clusters among coastal Tunisian delegations[11]. Number of habitant in a delegation is considered as events and the delegation area as population. The area vary considerably among delegations it range from 1,5 km^2 in Medina the historical center of the capital, to 2530 km^2 in EL Hamma in the south (Table 1).

[9] Data on 2011 are the recent database available.
[10] The INS measures of population by governorates and delegations are based on the 2004 census data adjusted by birth and death registration in municipalities.
[11] Here the scan test is conducted with SatScan by specifying the threshold distance of 30 Km which represent the mean distance from centroid delegations to administrative chef delegation.

The stat scan technique permits to avoid these problems of area distortion and population heterogeneity (Kosfeld 2012).

	N	Minimum	Maximum	Mean	Std. Deviation
population	173	5176	118929	44820,25	25864,623
area	173	1,52	2530,05	265,0033	341,34281
density	173	4,03	24401,79	1939,1291	3875,02650

Table 1. Descriptive statistics of density variables

Figure (3) show the most likely density clusters detected in coastal delegations.

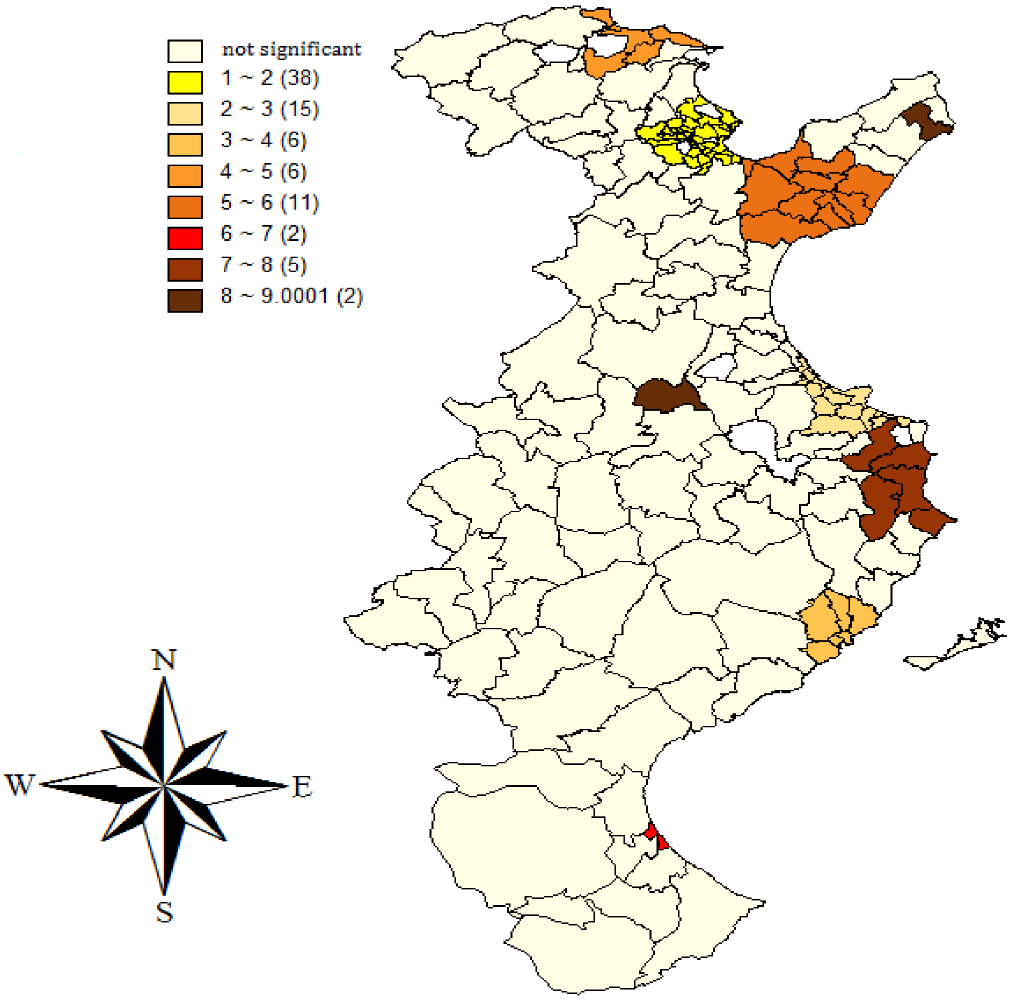

Figure 3. Map of the most likely significant clusters of population density

The most likely cluster is detected in delegations inside the Grand Tunis (log LR=4622848, 7266 and p=0,000000)[12], with more than 1/3 of the littoral population concentrated in this cluster, this cluster includes the historical and the modern business centers of Tunis the capital and the delegations surrounding them.

The second likely cluster is detected in delegations surrounding the historical business center of Sousse (log LR=767199, 1989 and p=0,000000), this cluster contain more than 666349 habitants. Delegations surrounding the historical business center of Sfax constitute the third likely cluster (LLR= 651683,6678; p=0,00000), it contain 599085 habitants.

The weak significant LLR is detected in Kelibia (log LR=21625, 14031 and p=0, 000000).

The scan statistic technique computes the cluster risk for each detected significant likely cluster; figure (4) present global cluster risk in most likely clusters map.

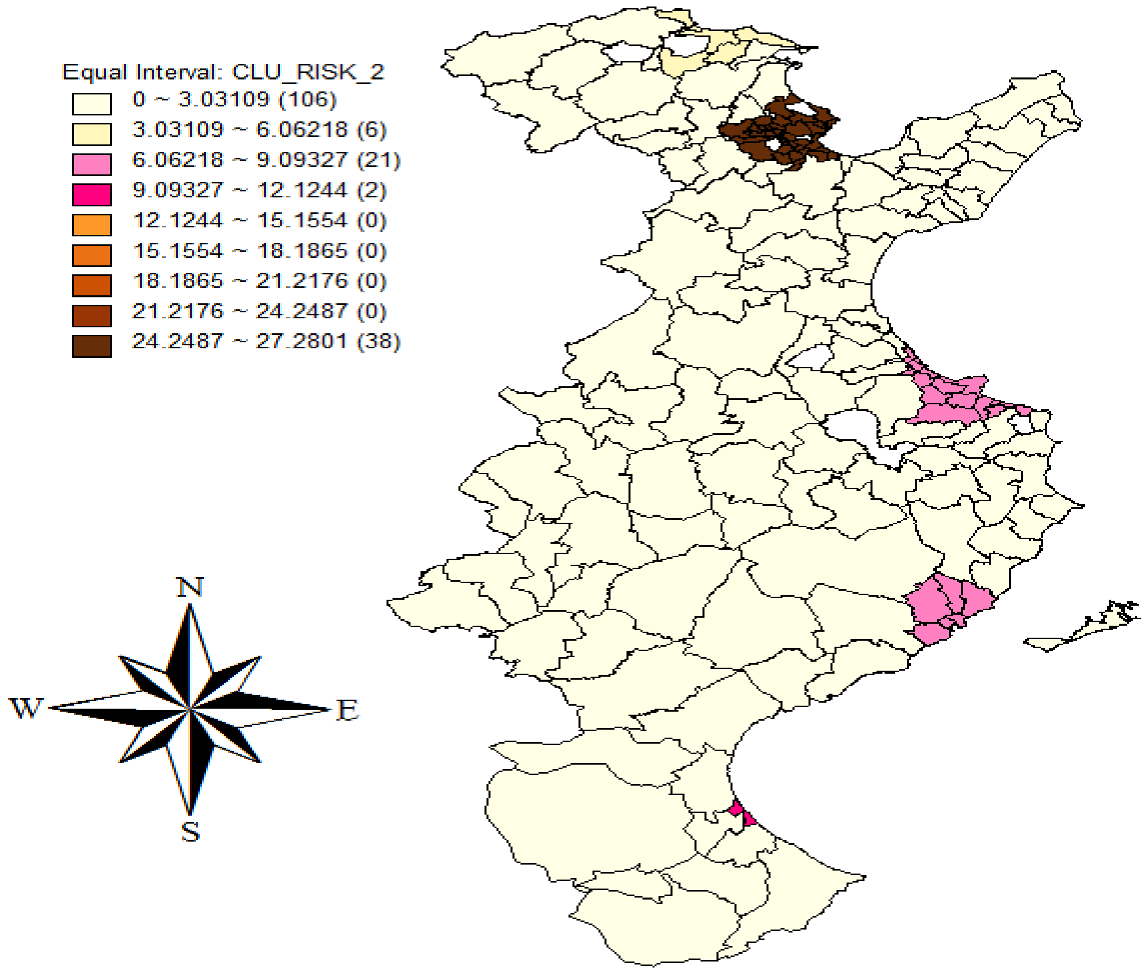

Figure 4. Map of the density global cluster risk

[12]Significance is determined by simulated Monte Carlo test of 999 replicates.

relative risk in the most likely cluster is: 27,208, indicates that the likelihood of density risk inside this area is about twenty seven times higher than outside, The second high relative risk is detected in Gabes center delegations, the density risk in this south regions in most important then the density risk in the metropolis cities like Sousse and Sfax. The weak significant cluster risk is detected in the “Cap Bon” delegations.

The Scan Statistic technique computes an index of local density risk, which permits to detect the delegations with the highest density risk inside the cluster. Table presents the repartition of delegations by the local density risk.

delegation	local density risk
CITE ETTADHAMEN	145,838029
OMRANE SUPERIEUR	121,49082
SEJOUMI	103,016641
TUNIS MEDINA	100,141357
BAB SOUIKA	85,6596944
EZZOUHOUR	81,8583829
TAHRIR	80,2811308
LE BARDO	60,3017866
SIDI EL BECHIR	58,8538729
DOUAR HICHER	55,1684239
EL OMRAN	49,7613161
EL OUARDIA	47,7020966
EL MOUROUJ	44,2233875
SFAX OUEST	42,2082464
EL KRAM	37,3867061
ARIANA VILLE	35,3509827
EL KABARIA	35,0371783
SOUSSE JAWHARA	34,0267087
LA NOUVELLE MEDINA	33,571012
SOUSSE RIADH	30,9145112
JEBEL JELLOUD	28,9917717
EZZAHRA	28,5174715
SFAX VILLE	28,0819035

Table 2. Top 23 delegations in density local cluster risk.

The analysis of table 2 show that historical centers of Tunis; Sousse and Sfax became less attractive for residential population and the local risk density inside other suburban centers is higher than density in these centers[13]. “Cité Ettadhamen” delegation located in the Ouest part of the metropolis of Tunis is the more attractive coastal city, local density risk inside this delegation is 145 time higher than outside. In regions outside the capital, “Sfax Ouest” delegation has a local density risk twice higher than the local density risk in the historical

[13] The red color highlights the historical centers and the blue color highlight the recent attractive sub centers.

business center of Sfax. “Sousse Jawhra” and “Sousse Erriadh” delegations are more attractive than Sousse historical business center. In the south area, the historical center of Gabes is still dominant with the highest local density risk inside the region.

The scan statistic results chow that coastal big cities like Tunis; Sfax; Sousse; Nabeul and Bizert are becoming more decentralized.

5.2 Spatial econometric analysis

To detect factors that affect this spatial reparation of density clusters among Tunisian coastal delegations we estimate a spatial Durbin model presented in equation (4). This model allows assessing the spatial dependence between delegations and the spillover effect exerted by a delegation on surrounding delegations.

5.2.1 The estimated equation

$Y = \rho WY + X\beta + WX\Theta + \varepsilon$

$\varepsilon \sim N(0,\sigma^2 I)$

W represents a spatial contiguity matrix with elements characterized by:

$w_{ij} = 1$, *if i and j are contiguous*

$w_{ij} = 0$, *if i and j are not contiguous*

$w_{ii} = 0$

where w_{ij} *is the i, jth element of W*

The spatial Durbin model (SDM) allows density local Risk for each region to depend on own-region factors from the matrix X that influence the density risk, plus the same factors averaged over the m neighboring regions, $W X$. According to Kirby and LeSage (2009), in SDM, changes in the independent variable x_i leads to a direct impact (effect) on a county’s marginal local density risk as well as a spatial spillover (indirect) impact on neighboring counties’ marginal density risk

5.2.2 Estimation results

As dependant variable in our SDM regression model we use the spatial index of local density risk, the explanatory variables used in this study are presented in appendix A. The SDM introduce as explanatory variables the surrounding average of each explanatory variable which we label as $W.X_i$ ·

Table 3 contains descriptive statistics of the amenity variables for delegations with not significant cluster risk, delegations with significant cluster risk and for all delegations.

	Not signifiant cluster risk			Signifiant cluster risk			all		
	Mean	N	Std. Deviation	Mean	N	Std. Deviation	Mean	N	Std. Deviation
chef-dist	70,2306	88	40,38940	24,3407	85	24,87143	47,6836	173	40,70148
hosp-nb	,51	88	,503	,54	85	,628	,53	173	,566
clinic-nb	,10	88	,305	,82	85	1,115	,46	173	,886
youthclub-nb	1,28	88	,922	1,27	85	1,148	1,28	173	1,036
kidsclub-nb	,58	88	,827	3,01	85	4,524	1,77	173	3,439
cultureclub-nb	,74	88	,536	,85	85	,880	,79	173	,725
bib-nb	1,36	88	,776	1,75	85	1,318	1,55	173	1,091
bank-nb	1,91	88	2,843	11,19	85	16,636	6,47	173	12,684
hotel-nb	,68	88	2,549	5,51	85	15,400	3,05	173	11,178
post-nb	7,41	88	4,680	13,58	85	10,863	10,44	173	8,847
primsch-nb	18,48	88	10,318	12,34	85	6,275	15,46	173	9,085
prepsch-nb	4,65	88	2,528	6,07	85	3,043	5,35	173	2,874
pharm-nb	4,51	88	2,775	12,95	85	10,689	8,66	173	8,810
infirm-nb	,35	88	,845	4,06	85	5,153	2,17	173	4,097
nurs-nb	,16	88	,523	2,54	85	3,917	1,33	173	3,010
kindgard-nb	9,90	88	10,191	24,12	85	14,759	16,88	173	14,482
terrsport-nb	1,61	88	1,853	4,15	85	4,846	2,86	173	3,851
firme-nb	17,02	88	20,925	43,33	85	39,727	29,95	173	34,150

Table3. Descriptive statistics of amenity variables

These descriptive statistics show that the high cluster delegations are more equipped than low cluster risk delegation[14].

[14] A one way ANOVA test applied on these data show that the differences in means between high and low clusters delegations are significant, except for hospitals, youth clubs and culture clubs.

The estimation results of the impact of availability of these amenity variables on local density risk are presented in the flowing table:

	coefficient	p-value	direct	p-value	indirect	p-value	total	p-value
(Intercept)	13,5509*	0,0844						
chef-dist	-0,1835	0,0196	-0,1846**	0,0108	-0,0216	0,8224	-0,2062**	0,0136
hosp-nb	4,4578*	0,0803	3,6374	0,1516	-16,6945***	0,0082	-13,0571*	0,0777
clinic-nb	-1,0000	0,6538	-0,3816	0,8318	12,5831**	0,0455	12,201*5	0,0979
youthclub-nb	-2,1200*	0,0969	-2,1623*	0,0976	-0,8600	0,7417	-3,0223	0,3785
kidsclub-nb	0,3228	0,4888	0,4606	0,3202	2,8036**	0,0151	3,2642**	0,0123
cultureclub-nb	2,0057	0,3203	2,3639	0,2566	7,2893	0,1800	9,6532	0,1206
bib-nb	-1,7819	0,2521	-2,1212	0,2082	-6,9041	0,1833	-9,0253	0,1511
bank-nb	-0,5328**	0,0443	-0,5352*	0,0638	-0,0486	0,9345	-0,5838	0,5941
hotel-nb	-0,1978	0,2088	-0,2093	0,2034	-0,2342	0,5801	-0,4435	0,3778
post-nb	0,4396**	0,0448	0,5072**	0,0245	1,3753**	0,0258	1,8825***	0,0059
primsch-nb	-0,7478***	0,0001	-0,7351***	0,0002	0,2573	0,4954	-0,4779	0,2102
prepsch-nb	2,0393**	0,0296	2,1367**	0,0263	1,9829	0,4046	4,1196	0,1492
pharm-nb	1,0549***	0,0093	0,9314**	0,0301	-2,5127*	0,0553	-1,5812	0,3156
infirm-nb	1,0908**	0,0211	1,1108**	0,0213	0,4061	0,7663	1,5168	0,3075
nurs-nb	0,0451	0,9482	0,0127	0,9934	-0,6576	0,7199	-0,6448	0,7412
kindgard-nb	-0,2660*	0,0972	-0,2786*	0,0973	-0,2554	0,5516	-0,5339	0,2955
terrsport-nb	-1,1516**	0,0175	-1,0628**	0,0256	1,8078	0,1567	0,7450	0,6061
firme-nb	-2,5354*	0,0444	-2,6052**	0,0422	-1,4205	0,6772	-4,0257	0,3111
w.chef-dist	0,0296	0,7609						
w.hosp-nb	-14,2060***	0,0030						
w.clinic-nb	10,1094**	0,0368						
w.youthclub-nb	-0,1364	0,9542						
w.kidsclub-nb	2,1142**	0,0174						
w.culturclub-nb	5,2012	0,2079						
w.bib-nb	-4,9562	0,1831						
w.bank-nb	0,0969	0,8933						
w.hotel-nb	-0,1333	0,6734						
w.post-nb	0,9658**	0,0402						
w.primsch-nb	0,3910	0,1967						
w.prepsch-nb	1,0363	0,5911						
w.pharm-nb	-2,2354**	0,0183						
w.infirm-nb	0,0416	0,9674						
w.nurs-nb	-0,5265	0,7045						
w.kindgard-nb	-0,1326	0,7014						
w.terrsport-nb	1,7079*	0,0868						
w.firme-nb	-0,4702	0,8531						

Rbar-squared = 0.8144

R-squared = 0.8511

Rho: 0.25342,
LR test: 5.235,
p-value: 0.022137**

AIC: 1486.2, (AIC for lm: 1489.4)

LM test for residual autocorrelation
test value: 0.22396, p-value: 0.63604

Note: ∗, ∗∗, and ∗∗∗ indicate a coefficient is significant at 10%, 5%, and 1% level, respectively

Table 4. SDM estimation results

The estimation results indicate that the model explains 81.4% of the spatial variation of the population risk density among delegations. The statistically significant value of the spatial dependence measure of ρ shows a strong spatial interdependence among regions.

The coefficients of the SDM model cannot be interpreted as partial derivatives (Lesage 2009). Direct, indirect and total impacts presented in Table permit to assess the signs and magnitudes of impacts arising from changes in the explanatory variables. We can see from the colon of direct impact that the local density cluster risk decrease with the distance from coastal big cities. The distance from administrative centers is considered as proxy to public establishment services. The administrative centers are coastal delegations so we can consider the distance from these centers a proxy for coastal proximity.

The positive and statistically significant direct impacts of health amenities like pharmacies and infirmaries and educational amenities like preparatory schools and crèches implies that the abundance of these amenities in a delegation make it more attractive for population searching the nearness to this basic amenities.

Youth clubs; primary schools; kinder gardens; sports fields, firms and banks have a statistically significant negative direct impacts, this implies that the abundance of this amenities in a delegation increase its housing value and make it less attractive for population and detract from its local density risk. Kahsai et al (2013) found that the availability of parks and recreation departments, private and public tennis courts, recreational centers, and golf courses have negative direct impacts on population growth in all counties of the Northeast region of the US. They explain this result by the fact that laying out lands for these projects reduces the availability of housing lands.

Private clinics, child clubs have positive indirect impacts, this implies that the availability of this luxury amenities in nearby delegations, leads to a local density risk increase inside such delegation. This result reveals the spillover impact from the availability of such luxury amenities in surrounding delegations.

Negative indirect and total impacts of public hospitals suggest that delegations surrounded by delegations that lack public hospitals are less attractive, and thus the density local risk in these delegations is low.

Post offices amenities exert positive direct, indirect and total impacts on population growth inside and surrounding delegations.

Previous studies on the impact of amenities on cities population growth concluded that climatic amenities and natural features are dominant factors in explaining this growth, Gleaser et al (2001). Berry-Cullen and Levitt found that the relationship between crime and population growth is strongly negative. Rappaport (1999) found that spending on schools predicts city growth. Andersson and Andersson (2006) show that physical infrastructures, such as cultural institutions, architecture and other historical amenities are key factors explaining the difference in attractiveness among European capital cities. Kahsai et al (2013 show that historical and cultural amenity have a positive effect on population density growth inside US counties. Spatial pattern of population density in Tunisian coastal cities is affected by basic amenities; hotels that represent the proxy for leisure amenities in cities have no effect on density pattern.

6. Conclusion

Tunisian coastal cities are characterized by a huge variability of population density and urbanization rates. This study tries to explain the density variation by the availability of amenities inside cities. Applying the Kulldorff scan statistic technique for cluster detection allowed detecting recent most attractive delegations. Spatial density clusters revealed that north delegations are more attractive than south delegations and historical business centers of big cities become less attractive for residential population. A Spatial Durbin model is used in order to assess the spatial interdependence between delegations with high and low local density risk and the impact of amenities on spatial density pattern. Estimation results found that people are more attracted to delegation with high level of basic amenities like health and educational amenities. Delegations with high level of luxury amenities like clinics kids clubs and post offices exert a positive spillover effect on surrounding delegations. A direct negative effect on density risk is exerted by Youth clubs; primary schools; kinder gardens; sports fields, firms and banks. The lack of hospitals in a typical delegation exerted a negative indirect effect on population density inside surrounding delegations.

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Appendix A

variable	Variable definition	source
chef-dist	The distance from delegation centroid to the chef administrative delegation	CGDR
hosp-nb	Number of public equipped hospitals	
clinic-nb	Number of clinics	
youthclub-nb	Number of public youth clubs	
kidsclub-nb	Number of public kids clubs	
cultureclub-nb	Number of public culture clubs	
bib-nb	Number of public libraries	
bank-nb	Number of banks	
hotel-nb	Number of hotels	
post-nb	Number of post offices	
primsch-nb	Number of primary schools	
prepsch-nb	Number of preparatory schools	
pharm-nb	Number of pharmacies	
infirm-nb	Number of infirmaries	
nurs-nb	Number of nurseries	
kindgard-nb	Number of kids gardens	
terrsport-nb	Number of sport fields	
firme-nb	Number of firms	