

USING GIS FOR DETECTING SPATIAL CHANGES IN THE HEALTH SYSTEM ADMINISTRATION DOMAIN

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Abstract. În ultimul timp s-a pus accentul pe posibilitatea de a putea analiza, folosind sisteme precum GIS -ul, activitatea unor instituții de importanță majoră care prin rezultatul activității au o influență asupra populației din anumite regiuni. Instituții precum cea sanitară au sau pot găsi în acest instrument de analiză o privire de ansamblu asupra schimbărilor care se produc la nivel administrativ și pot detecta schimbările ce pot surveni de-a lungul timpului într-o regiune, județ etc. Un rol important în acest sens îl joacă autocorelarea spațială, care presupune că două elemente învecinate se corelează mult mai bine decât două elemente îndepărtate, și asupra gradului de corelație intervine efectul decalajului sau poziționării în spațiu sau în timp.

Key words: Administrative changes, GIS, Health, Space, Spatial autocorrelation.

INTRODUCTION

This study is based on few projects which already studied the spatial autocorrelation in specific domains, even sanitary. One of the projects was the analysing of epidemiology disease in Thailand, where the GIS system provide the possibility to integrate data in space and time. Another project was the one from China. Here the GIS system highlighted the region development in the Greater Beijing.

The purpose of the current study is to identify the spatial changes happened after the 90's in the Bihor county using an GIS system based on spatial autocorrelation indices analyse. In this case the system refers to the numbers of the doctors and to other employees from the sanitary system, like the social assistance personal.

The Minister of Health and Family have the control over the public sanitary units activity at a county or local level and also the control over the law application methodology used in the sanitary domain (Ordonanța nr. 70 din 29 august 2002).

In the application of the ordonance no. 70 from 29 august 2002 the Minister of Health and Family, like an principal in the sanitary domain have more attributions. One of them is to ensure that the repartition and redistribution of doctors in the public sanitary units is equilibrated and it's made based on informations regarding the exceed of doctors and the unoccupied working places received from the local authorities. The administration manage also the others sanitary domain employees, like the social assistance.

MATERIALS AND METHODS

The spatial pattern of geographic objects are often the results of physical or cultural processes taking place on the surface of the earth. Spatial pattern is a static concept since these patterns only show how geographic objects distribute at one

given time. However, spatial processes is a dynamic concept because these processes show how the distribution of geographic objects changed over time. For any given geographic phenomenon, we often need to study both its spatial patterns and the spatial processes associated with these patterns. Understanding the spatial patterns allows us to understand how the geographic phenomenon distributes and how it can be compared with others. Spatial statistics are the most useful tools for describing and analyzing how various geographic objects (or events) occur or change across the study area.

We can use spatial statistics to describe the spatial patterns formed by a set of geographic objects so what we can compare them with patterns found in other study areas. For the spatial processes associated with these patterns, we can use spatial statistics to describe their forms, to detect changes, and to analyze how some spatial patterns change over time.

To realise the purpose of this project we chose to study the Bihor county, divided by villages. For this, it has been obtained a database with data and specific parameters for the sanitary domain for the years 1992, 1998 and 2004. The shapefile used for analysis is polygon based, where each polygon represents a village. For attributes we take in consideration the number of doctors from the villages, and the number of employees used in social assistance.

The method was spatial autocorrelation based. Spatial autocorrelation means that the attribute values being studied are self-correlated and the correlation is attributable to the geographic ordering of the object.

To make a spatial autocorrelation measurement in an geographic object dataset, first we have to discuss the methods that are used to capture spatial relationship among the areal units (between the villages). These methods can be found in a GIS software. In the next few rows we will describe the algorithms that are used to calculate the matrix used in finding the spatial relationship.

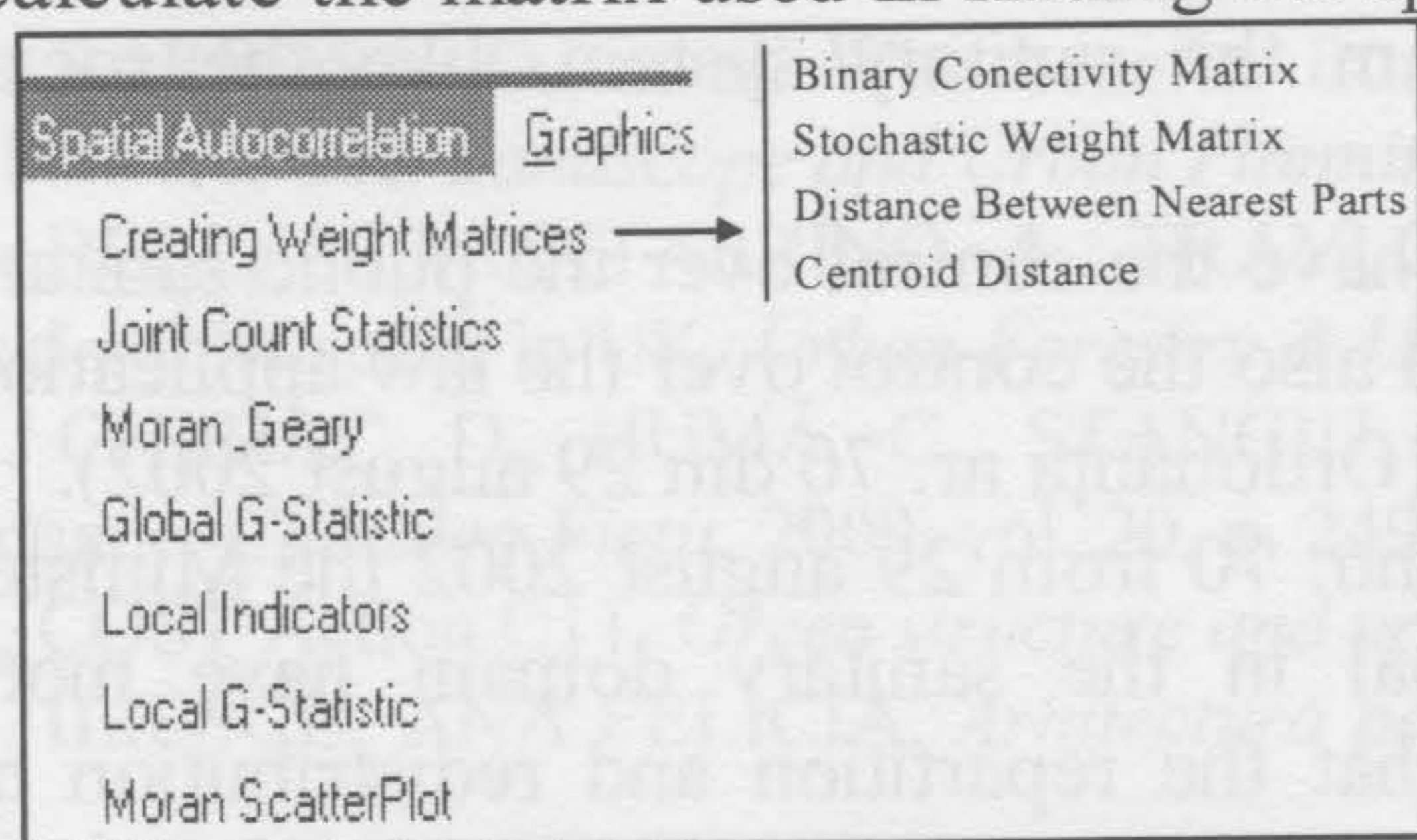


Fig. 1. Spatial Autocorrelation script - list of functions

The GIS software used is ArcView 3.2 and the script „Spatial Autocorrelation”. This tool allows statistics and matrix calculations. (Fig. 1.).

Binary connectivity matrix making is based on giving binary attributes to the polygons, 0 or 1. So, the algorithm will give value 1 if the polygons are next to each other and 0 if they are not adjacent. This matrix also shows

how the polygons are connected between them, that's why we can call her the *connectivity matrix*.

The matrix can be obtained using the next formula:

$$c_i = \sum_j c_{ij} \quad (1)$$

- where i - row,
 j - column,

c_i – can be only 1 or 0.

To find out how much a neighbor has influence on the value of the study area it is necessary to realise the *stochastic matrix*. The matrix takes in consideration the number of neighbors that each village have and give numeric values in a proportional way with the neighbor weight. If for example one village have six neighbors that the value given in the matrix for each of the six neighbors will be 1:6 , means 0.17.

Besides using adjacency as a measure to describe the spatial among a set of geographic features and to define a neighborhood among them, another common measure is *centroids distance*. One of the first rules of geography is saying that all the objects have a connection, but the closer have the better connection. This algorithm it's using the distance between the center of the polygons that are defining the villages.

For the GIS software this is an easy job, but the methods that are applying are different because some of them are applying the centroid outside the polygon area. Because the distance is used for the weight, the matrix of spatial matrix is noted with „D”, and it has values like d_{ij} , wich is representing the distance between centroids.

In modeling spatial processes, the distance weight is often used in an inverse manner, as the strenghts of most spatial relationships diminish when distances increases. Therefore, when the distance matrix is used, the weight is an inverse of the distance between polygon i and polygon j.

$$w_{ij} = c_{ij} / c_i \quad (2)$$

- where w_{ij} is the weight.

With the advances in GIS software algorithms, features other than the distance between centroids can be easily determined. It is also relatively easy to determine the distance between any of two geographic features based on the distance of their nearest parts. A value of 0, means that polygons are adjacent.

In the next phase, based on the calculated matrix, we will make the study of the spatial autocorrelation using global and locals indices. In Fig. 2 there is an schematic representation of the algorithms.

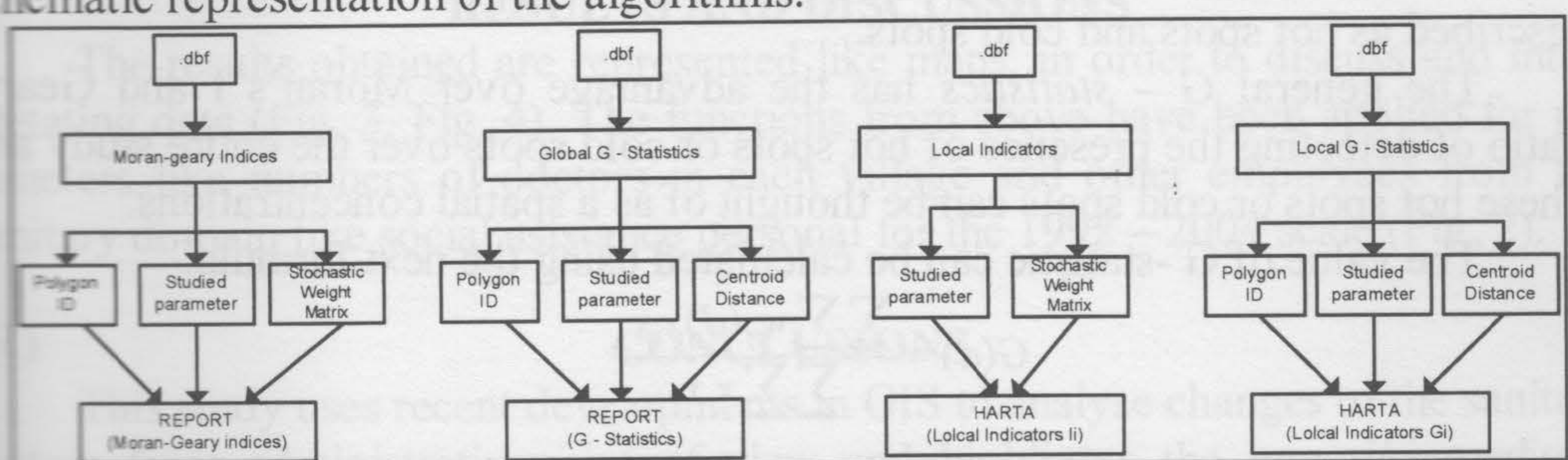


Fig. 2. Spatial autocorrelation indices calculations – schematic representation

Spatial autocorrelation global indices

The use of *joint count statistics* provides a simple and quick way of quantitatively measuring the degree of clustering or dispersion among a set of spatially adjacent polygons. This method is applicable to nominal data only. In this case the spatial autocorrelation can be positive or negative. This situation is quite restrictive,

as most real-worlds cases deal with variables at interval or ratio measurement scales. In these cases, Morans'I and Geary Ratio C can be used.

Morans'I and *Geary's Ratio* have some common characteristic, but their statistical properties are different. Still, both statistics are based on a comparasion of the values of neighboring areal units. If neighboring areal units over the entire study area have similar values, then the statistics should indicate a strong positive spatial autocorrelation. If neighboring areal units have very dissimilar values, then the statistics should show a strong negative spatial autocorrelation. The two statistics, however, use different approaches to compare neighboring values.

$$I = \frac{n \sum \sum w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum (x_i - \bar{x})^2} \quad (3)$$

- where: I – is Moran's I and values between -1 and +1 (I = -1, negative autocorrelation; I = +1, positive autocorrelation).

w_{ij} - weight distance

x_i - scale

W - sum of the values from weigth matrix.

$$c = \frac{(n-1) \sum \sum w_{ij} (x_i - x_j)^2}{2W \sum (x_i - \bar{x})^2} \quad (4)$$

- where:

c – Geary ratio, scale is between 0 and 2 (c = 0, perfect positive spatial autocorrelation; c = 2, perfect negatice spatial autocorrelation).

n – studied village numbers.

The difference between them is that Moran's I is comparing neighbors values with the average and Geary Ratio is comparing neighbors values directly, each one with other.

Moran's I and Geary's Ratio have well-established statistical properties to describe spatial autocorrelation globally. They are, however, not effective in identifying different types of clustering spatial patterns. These patterns are sometimes described as hot spots and cold spots.

The general *G – statistics* has the advantage over Moran's I and Geary's Ratio of detecting the presence of hot spots or cold spots over the entire study area. These hot spots or cold spots can be thought of as a spatial concentrations.

The value of G -statistic can be calculated using the next formula:

$$G(d) = \frac{\sum \sum w_{ij}(d) x_i x_j}{\sum \sum x_i x_j} \quad (5)$$

- where $i \neq j$,

d – is the distance within wich areal units will be regarded as neighbors.

The value of G – statistics can be interpreted like the follow: a moderate level of G(d) reflects spatial association of high and moderate values, and a low level of G(d) indicates spatial association of low and below – averages values.

Spatial autocorrelation locals indices

All the spatial autocorrelation statistics discussed so far share a common characteristic: they are global statistics because they are summary values for the entire study region. It is reasonable to suspect that the magnitude of spatial autocorrelation does not have to be uniform over the region (spatial homogeneity), but rather varies according to the location. In other words, it is likely that the magnitude of spatial autocorrelation is high in some subregions but low in other subregions within the study area. It may even be possible to find positive autocorrelation in one part of the region and negative autocorrelation in another part. This phenomenon is called spatial heterogeneity.

In order to capture the spatial heterogeneity of spatial autocorrelation, we have to rely on another set of measures. All these measures are based upon their global counterparts discussed above but are modified to detect spatial autocorrelation at local scale. These indicators are local Moran and local G – statistic.

The *local Moran* statistic for areal unit i is defined as:

$$I_i = z_i \sum_j w_{ij} z_j \quad (6)$$

- where z_i and z_j are the deviations from the mean.

The advantage of this indicator is the fact that he can provide values for each areal unit (village), and the results can be mapped. The local Moran reflects how neighboring values are associated with each other.

The *local G – statistic* is derived for each areal unit (village) to indicate how the value of the areal unit on concern is associated with the values of surrounding areal units defined by a distance threshold, d . Formally, the local G – statistic is defined as:

$$G_i(d) = \frac{\sum_j w_{ij}(d) x_j}{\sum_j x_j} \quad (7)$$

- where $i \neq j$.

RESULTS AND DISCUSSIONS

The results obtained are represented like maps, in order to discuss and interpret data (Fig. 3, Fig. 4). The functions from above have been applied for parameters like numbers of doctors in each village and other employees from the sanitary domain like social assistance personal for the 1992 – 2004 scale (Fig. 2).

CONCLUSIONS

This study uses recent developments in GIS to analyse changes of the sanitary system from administrative point of view and highlights the importance of the spatial effects over the studied area, the Bihor county. We demonstrate also that the GIS and the analyse of spatial data can discover the finest spatial characteristics of Bihor county, regarding the evolution of sanitary system in this area.

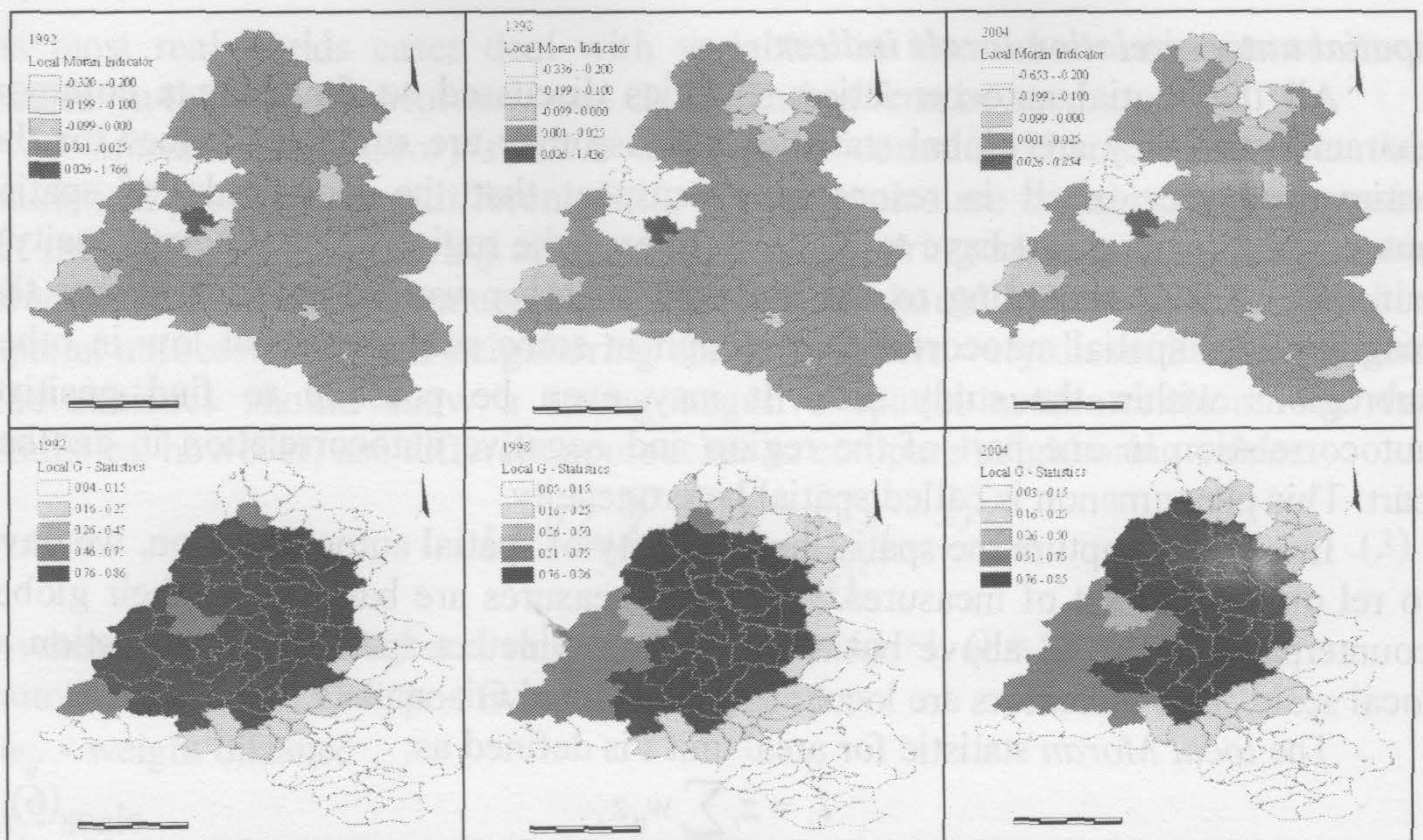


Fig. 3. Spatial autocorrelation indicators for representing the numbers of *doctors* parameter

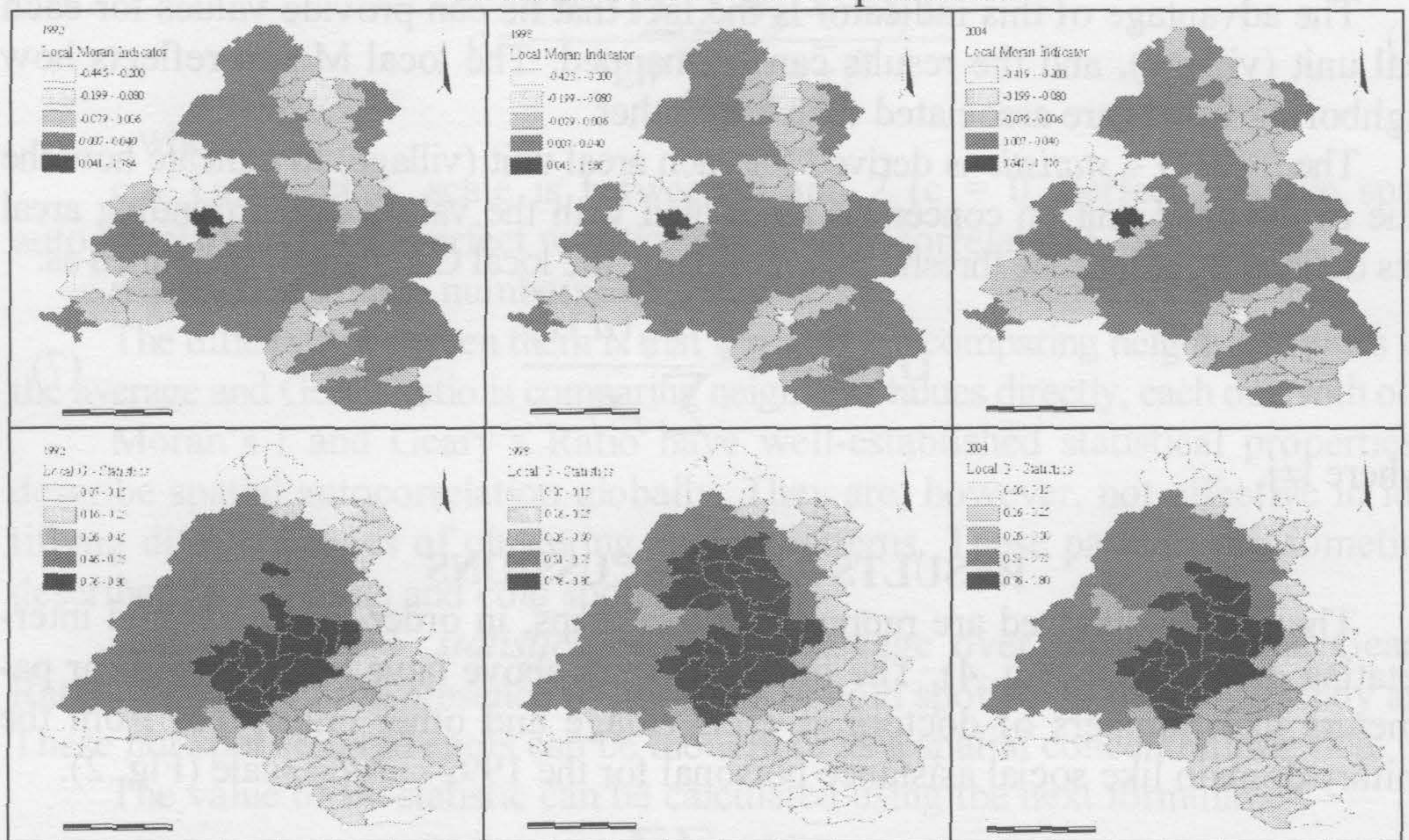


Fig. 4. Spatial autocorrelation indicators for representing the numbers of *social assistance employees* parameter

The local analyse also reveals that the territory of Bihor county is divided in parts regarding the number of doctors and social assistance employees. From the maps we can observe that in 1992 the spatial autocorrelation was positive with a clustered grouping aspect of the values. However we can observe that the sanitary system is suffering a few modification, the spatial autocorrelation has become a little randomized, and the changes are made in an negative direction (Fig. 5).

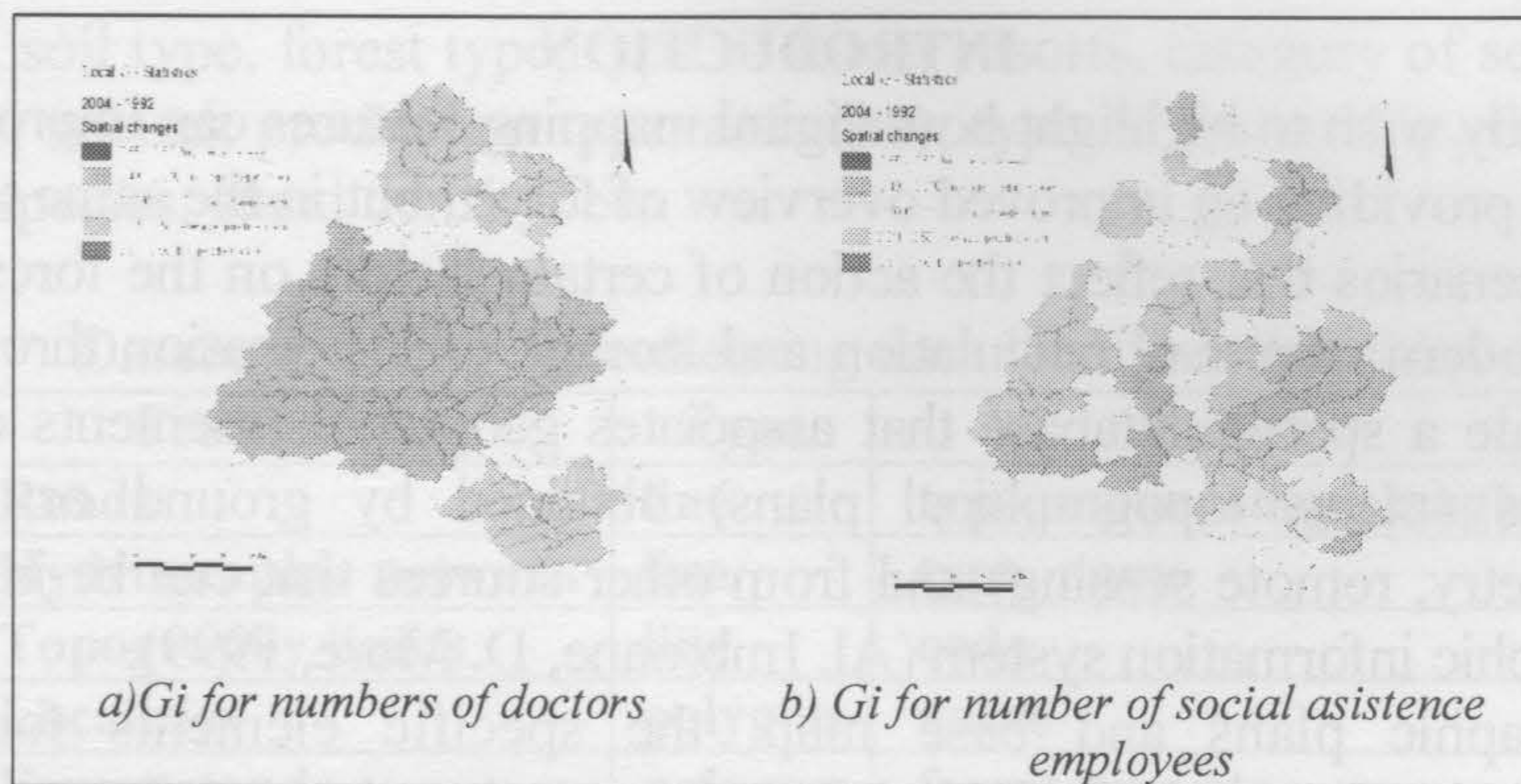


Fig. 5. Difference between 2004 -1992 looking at Gi indices for the studied parameters

Spatial autocorrelation can be a valuable tool to study how spatial patterns change over time. Results of this type of analysis lead to further understanding of how spatial patterns change from the past to present, or to estimations of how spatial patterns will change from the present to the future (H. Nakhapakorn et al., 2006).

REFERENCES

1. DANLIN Yu, YEHUA Dennis Wei, Spatial data analysis of regional development in Greater Beijing, China, in a GIS environment, Papers in regional Science vol. 87, Malden, 2008, USA.
2. HANCHANA Nakhapakorn, SUPET Jirakajohnkool, Temporal and Spatial Autocorrelation Statistics of Dengue Fever, Dengue Bulletin vol. 30, New Delhi, 2006, India.
3. LEE J., WONG David W. S., Statistical Analysis with ArcView GIS, John Wiley & Sons INC., 2001, pp. 192.
4. MUREȘAN F., DAINA Lucia, The buildings management in the sanitary public system of Bihor district - detailed research, Geographi tehnică 1/2008, Cluj-Napoca.
5. ***Ordonanța nr. 70 din 29 august 2002 privind administrarea unităților sanitare publice de interes județean și local.

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APPLIED GIS FOR DESIGNING THE DATABASE AND MAPPING SPECIFIC TO FORESTRY

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Abstract. Gestionarea pădurilor, în lumea, zilelor de azi, care se schimbă de la zi la zi, a devenit o provocare mult mai complexă și dificilă. Hărțile, luarea în calcul a diferiților factori, precum și deciziile care se impun pentru valorificarea produselor forestiere, se iau sub o notă de conflict des întâlnită, care totodată are și o doză de incertitudine. Specific amenajării pădurilor, în ultimul timp s-a dezvoltat o nouă tehnologie de informatizare a cartografiei, integrată într-un sistem informatic geografic (gis) prin care elemente ale spațiului geografic sunt completate cu informații tematice specifice amenajării pădurilor. În acest sistem se realizează modelul digital al terenului, ca expresie a stocării și prelucrării informației cartografice exprimată prin caracteristicile topografice de planimetrie și nivelment ale suprafeței terestre.

Key words: Cartography, Forest management, Forest planning, GIS, Maps.