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MAPPING BUCHAREST: ANALYZING THE SIX SECTORS THROUGH GEOSPATIAL DATA AND SPATIAL AUTOCORRELATION

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Abstract

Connectivity at the level of basic services within a city is the basis for adopting an investment strategy, both at the level of public administration and in the private environment. In addition, based on the concept of connectivity to citizens' basic needs, individuals can make decisions about purchasing a home. Therefore, the paper aims to analyse Bucharest, at the level of the 6 administrative sectors, from the perspective of connectivity to basic services (health, education, culture, etc.). In order to achieve this objective, with the help of GIS technology, relevant data will be extracted on residential buildings, transport infrastructure, and variables characterizing basic services at city level, for all 6 sectors of the capital. At the level of the 6 sectors of the capital there are structural differences in terms of access to basic services, especially as a result of the expansionary residential trend in the peripheries of the 6 sectors of Bucharest.

Keywords: spatial analysis, GIS, urban development, city, social inclusion
JEL Classification: R41, R58, R52

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1. Introduction

Urban development planning must be based on robust analyzes of the spatial distribution of basic services for society. The study aims to identify structural differences in urban mobility across various levels (education, healthcare, and public transportation) within the six sectors of Bucharest. In addition, the paper aims to identify the relationship in spatial profile between the 6 sectors of Bucharest for each variable used in this research. In order to achieve these goals, geospatial data were extracted through processing carried out in RStudio, with the Online Street Map (OSM) platform as the data source. Later, based on the data extracted from the Online Street Map, using the dodgr package, the average, median and maximum distances from residential dwellings (blocks, houses) to the public transport station, to schools, kindergartens, high schools were calculated and up to hospitals, clinics/medical offices. Then, based on the variables computed from OSM, in order to achieve all objectives, global spatial autocorrelation and local spatial autocorrelation were used. Based on the analysis conducted, structural differences in urban mobility among the six sectors of Bucharest are expected. However, considering the administrative nature of these six sectors, no significant spatial autocorrelations are anticipated, neither at the global level nor at the local level.

In the Literature Review section, the territorial evolution of the Bucharest-Ilfov region is briefly presented, including the 6 sectors of the Municipality of Bucharest. Also, in this section, some directions for increasing the territorial resilience of large cities are presented. The data collection process used in this research, the description of the variables and the sample, and the main methods used to achieve the main objective of this investigation are described in the Data & Methodology section. Later, in the Results & Discussions section, the main results of the research are presented, with an emphasis on the structural differences between the 6 sectors of the City of Bucharest. Finally, in the section dedicated to the conclusions, the main conclusions of the research, the limits of the results, but also the future directions for the development of this research are presented.

2. Literature Review

The way Bucharest has changed and grown over time has had a significant impact on community life, particularly the desire for a tightly knit community that was strongly emphasized during the communist era. This has led to the creation of socially isolated areas or ghettos, described as such by their own residents (Mionel and Negut, 2011). Turcu (2017) affirms that the spatial distribution of the retrofit of apartment buildings is unequally distributed across Bucharest's six municipalities. Findings show an unequal and unfair spread of retrofit action within and between cities - raising wider implications for the potential shortcomings of European Union retrofit programmes in Central and Eastern Europe. Moreover, Armas and Gavris (2013) stated that social vulnerability is an urban process that increased in a post-communist Bucharest, raising the concern that the population at risk lacks the capacity to cope with disasters. The assessment of the indices indicates a significant and similar clustering pattern of the census administrative units, with an overlap between the clustering areas affected by high social vulnerability.

During the period under examination, the development region of Bucharest-Ilfov experienced significant growth compared to other regions in Romania. Over a span of 30 years, the urban area encompassing Bucharest and Ilfov County doubled in size, with the year 2007 marking a particularly rapid expansion in new developments. In terms of Bucharest city specifically, District 1 saw the most remarkable urban growth (Lazar et al., 2022). Ioja et al. (2014) has analyzed land use conflict in Bucharest Metropolitan Area. Their findings indicated that the overall scores identified local administrative areas defined by a significant or high prevalence of conflicts related to spatial-land use, primarily situated within the Bucharest Metropolitan Area. Following this, Bacau et al. (2020) examined the coherence among planning tools in Bucharest. The primary findings suggest that Bucharest's plans exhibit high temporal consistency concerning issues and general measures, but low consistency in spatial planning intentions on both vertical and horizontal levels. To address spatial resilience, Lu et al. (2021) argue that resilience offers an adaptive strategy for managing environmental changes, natural hazards, and public health emergencies.

Thus, urban mobility could be one of the key factor which can improve the resilience of the cities. In order to build a sustainable urban mobility model, it is mandatory to make an economic spatial analysis of a city. For example, Tsiotas et. al (2017) have assessed the urban mobility of Volos (Greece). The main findings of their study have shown the main economic acitivity sector is tourism, observing a dominance of hotels, banking and gas station. Also, the have observed that the bus routing is primarly oriented to serving the urban economic activity and secondarily residence.

An interesting solution that can lead to a smart ubran mobility model is the concept of polycentric city. Most of the cities from Eastern Europe has a simillar model like Ostrava where creative industries are highly concentrated into the historical city centre and the inner city (Slach et al., 2015). Granqvist et al. (2019) have identified three interpretations of polycentricity: (city-)regional spatial balance, city-regional sustainable transport, and urban attractiveness and sustainability. This idea is also supported by Wen et al. (2023), who concluded that applying the polycentric city concept could improve the air quality index.

3. Data & Methodology

In order to achieve all the objectives of the research, as presented in the introduction, data were extracted and processed for the 6 sectors of the Municipality of Bucharest. Thus, using the osmdata software package, developed in the R working environment, data were extracted in geospatial coordinates at the level of each sector. In a first phase, 3 dimensions of basic services for society were defined: education, transport and medicine. For the first dimension, education, geospatial data were extracted from the amenity module of the Open Street Map (OSM), kindergartens, schools and colleges. For the second dimension, transport, from the OSM public_transport module, the geographical coordinates for all public transport stations (stops) were extracted. Geospatial data for medical offices (medical centers) and hospitals were extracted from the amenity module of OSM. The next step involved extracting the coordinates in multipolygon format for residential buildings. Thus, from the building module of OSM, the coordinates for apartment blocks (apartments), houses, or other residential buildings (residential) were obtained. The third step in calculating the distances from residential buildings to the three dimensions defined in this research was to extract all road categories from OSM using Euclidean distance. Finally, using the dodgr package developed in the R environment, distances from residential buildings to each of the three basic service dimensions (education, medicine, transport) were calculated based on the previously extracted road network. In cases where the resulting distance was "Inf," indicating that some roads starting from a residential building did not directly reach one of the points of interest (kindergarten, school, high school, doctor's office, hospital, public transport station), the value was corrected by calculating the areal distance from the residential buildings to the points of interest.

Table no. 1: The description of variables

Acronym	Definition	Type of distance	Unit of measure
Average_education	The average distance from residential buildings to education units (kindergarten, school, college).	By foot	Meters
Median_education	The median value of distances from buildings to education units (kindergarten, school, college).	By foot	Meters
Max_education	The maximal distance from residential buildings to education units (kindergarten, school, college).	By foot	Meters
Average_medicine	The average distance from residential buildings to medical units (medical centre, hospital).	By motorcar	Meters
Median_medicine	The median value of distances from residential buildings to medical units (medical centre, hospital).	By motorcar	Meters
Max_medicine	The maximal distance from residential buildings to medical units (medical centre, hospital).	By motorcar	Meters
Average_transport	The average distance from residential buildings to public transport station.	By foot	Meters
Median_transport	The median value of distances from residential buildings to public transport station.	By foot	Meters
Max_transport	The maximal distance from residential buildings to public transport station.	By foot	Meters

Source: Authors' own work

For the transport and education dimensions, the distance was calculated as being traveled on foot, while for the medicine dimension, the distance was calculated using motorized transport. These approaches were chosen because it is important for residents of a sector to access schools, kindergartens, high schools, and bus stations without needing other means of locomotion, which also helps to reduce traffic congestion. Conversely, since visits to medical facilities are infrequent and emergencies typically involve ambulance transport, it is more relevant to analyze the distance traveled by a motorized vehicle (Table no. 1).

To identify the spatial relationship among the six sectors of the capital across the three dimensions, global and local Moran autocorrelation indices were tested and calculated. Spatial autocorrelation is a statistical measure used to assess the similarity or differences between attribute values that are geographically close to each other. Positive spatial autocorrelation indicates that high or low attribute values tend to cluster in space, while negative spatial autocorrelation suggests that neighboring locations exhibit contrasting attribute values.

The spatial autocorrelation function is described by the following relation:

$$R(k) = \frac{\sum_{i=k+1}^{n}[(c_i - \bar{c})(c_{i-k} - \bar{c})]}{\sum_{i=1}^{n}(c_i - \bar{c})^2} \quad (1)$$

where:

- k represents the spatial gap;
- c_i is a sample for a space series of volume n;
- $\bar{c} = \frac{\sum_{i=1}^{n} c_i}{n}$ represents the average of the values c_i (Baumont et al., 2002).

Global spatial autocorrelation provides an overall summary of the relationships between each territorial unit and its neighbors, while local spatial autocorrelation highlights the specific relationships between individual territorial units and their neighbors (Baumont et al., 2022). The Moran statistic measures the strength of the linear association between an attribute (y) at a given location and the weighted average of the same attribute at neighboring locations (Wy), and can be interpreted as the slope of the regression of (y) on (Wy). The Moran index quantifies the degree of similarity between the geographical structures analyzed, with values ranging from -1 to 1.

Moran's I statistic is described by the following calculation formula:

$$I = \frac{n}{S_O} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (2)$$

where

- z_i represents the deviation of an attribute from its mean, $(x_i - \bar{x})$;
- $w_{i,j}$ is the spatial gap between territorial units *i* and *j*;
- n represents the number of territorial statistical units;
- $S_O = \sum_i^n \sum_j^n w_{ij}$ indicates the aggregate measure of all spatial weights (Anselin,1995)

The statistical hypotheses tested for Moran's I statistic are as follows:
Null hypothesis (H0): There is no spatial autocorrelation (random spatial variation).
Alternative hypothesis (H1): There is spatial autocorrelation (spatial dependence).

$$z_I = \frac{I - E(I)}{S_{error\ I}} \quad (3)$$

where $E(I) = \frac{-1}{n-1}$.

If $z_I > Z_{\alpha/2}$, then there is spatial autocorrelation.

Anselin (1995) argues that the local Moran Index assesses the statistical significance of each indicator specific to a particular location. Local statistics can be defined as follows:

$$I_i = z_i \sum_j w_{ij} z_j \tag{4}$$

where

- z_i, z_i represents the deviations from the mean;
- w_{ij} is the weighting factor;
- sum for j values indicates that only neighbouring values are included.

It establishes a proportional relationship between the sum of the local statistics and the corresponding global statistic, the global Moran Index being obtained as the average of the local indices:

$$I = \frac{\sum_{i=1}^{n} I_i}{n} \tag{5}$$

The local index identifies clusters as four types of spatial associations, corresponding to the quadrants of the Moran diagram. Quadrant I consists of regions with above-average levels of the variable of interest, with neighbours also showing above-average values (High-High). Quadrant II includes regions with below-average values, surrounded by neighbours with above-average values (Low-High). Quadrant III contains regions with below-average levels of the variable, with neighbours also having below-average values (Low-Low). Quadrant IV consists of regions with above-average values, but with neighbours exhibiting below-average values (High-Low).

4. Results and discussions

The first step in analyzing the performance of the 6 sectors on the 3 main pillars (education, medicine, transport) was the spyder chart analysis. This type of chart is best suited to analyze the performance of the 6 statistical units on each individual statistical indicator.

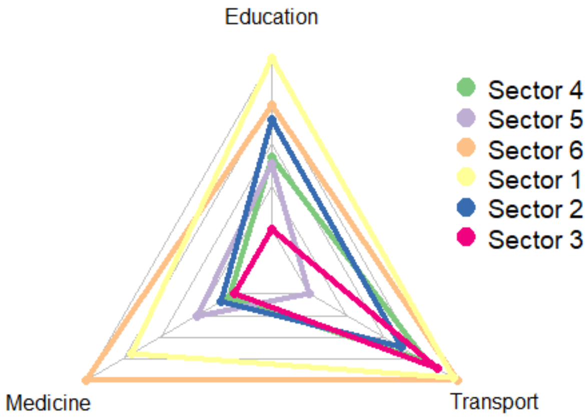

Figure no. 1: The average distance from residential building to each dimension

Source: Authors' own work using RStudio

District 6 records the highest value for the average distance traveled by citizens from residential buildings to the hospital/doctor's office (2498 m) and to the bus stop (455 m). Instead, Sector 1 records the highest average distance on the Education dimension with a value of approximately 706 m (Figure no. 1). Also, Sector 1 is the second sector, after Sector 6 when we talk about the average distance to the bus stop with a value of about 450 meters. On the Medicine and Education dimensions, the best performing sector is Sector 3, recording the lowest values (446- Education and 775- Medicine). Conversely, Sector 3 is the third sector in terms of average distance to the bus stop (430 m), being overtaken by Sector 1 and Sector 6. The other 3 sectors (Sector 4, Sector 5 and Sector 2) seem to have a balanced distribution, Sector 5 being the best performer in terms of the average distance to the bus stop (272 m).

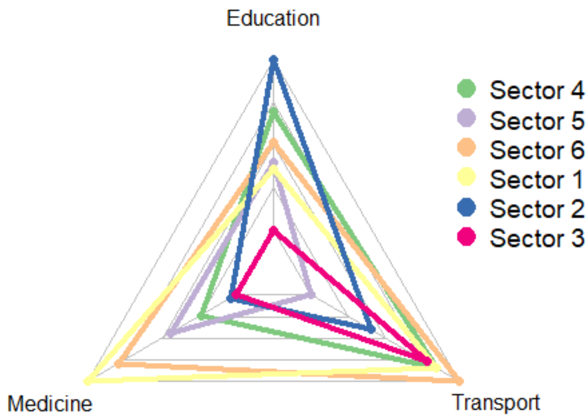

Figure no. 2: The median distance from residential building to each dimension

Source: Authors' own work using RStudio

As in the previous case, Sector 3 is the best performing sector in terms of Education (393 m) and Medicine (513 m) (Figure no. 2). Sector 1 registers the highest median value on the Medicine dimension (1776 m), while on the transport dimension (it is surpassed only by Sector 6 (367 m)). On the Transport dimension, it performs best, as in the case of average distance, Sector 5, with a median value of approximately 245 m. Sector 4 records high median values on the Education (553 m) and Transport (348) dimensions. Sector 2 is characterized by the highest value on the Education dimension (623), but also reduced values on the dimension Medicine (560 m) and Transport (294 m).

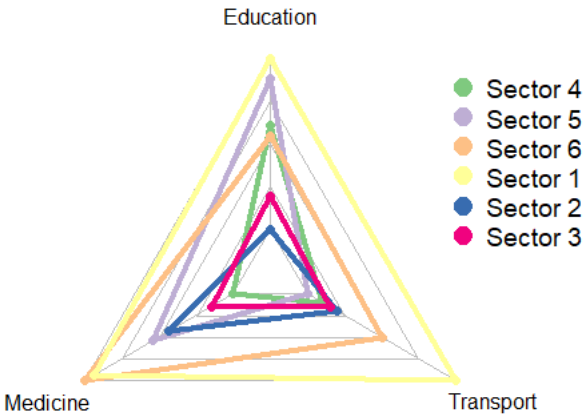

Figure no. 3: The maximal distance from residential building to each dimension

Source: Authors' own work using RStudio

Sector 1 records the maximum average distance (4531 m) from residential buildings to schools, kindergartens, high schools (Education dimension), but also the highest value on the Transport dimension (3841 m). Sector 6 shows a high value on the Transport dimension (2646 m), and on the Medicine dimension, it shows the highest value (7830 m). At the opposite pole, Sector 2 is the most resilient sector on the Education dimension (645 m), while Sector 4 presents the lowest value for the Medicine dimension (3041 m) and Sector 5 is the most resilient on the Transport dimension (1910 m). However, although Sector 5, on average, presents a low value for the 3 social dimensions, in this case, on the Education dimension, it presents a high value (4081 m), being surpassed only by Sector 1. Sector 3 presents balanced values on all 3 dimensions, showing relatively small differences between these dimensions (Figure no. 3).

Starting from the principle of subsidiarity, the 6 sectors are developed through government policies, but also through the local public policies of the general mayor's office of the capital. That is why it is important to identify if there is autocorrelation between the 6 sectors of the Municipality of Bucharest on the 3 indicators analyzed in this paper. To identify possible autocorrelation, Moran's global and local autocorrelation indices were calculated using a queen neighborhood matrix.

Table no. 2: P-value of Global Moran test

Variable	p-value
Average_education	0.2
Median_education	0.915
Max_education	0.38
Average_medicine	0.0313
Median_medicine	0.11
Max_medicine	0.020
Average_transport	0.91
Median_transport	0.94
Max_transport	0.26

Source: Authors' own work using RStudio

With a probability of 90%, it can be stated that there is spatial autocorrelation at the level of two variables Average_medicine(0.26) and Max_medicine (0.2). The results of global local autocorrelation indicate that the values are clustering in spatial profile in the case of variables Average_medicine and Max_medicine. Thus, the values of Global Moran index show a poor spatial autocorrelation. Therefore, it can be stated that only for one dimension out of the 3 analyzed in this research there is significant autocorrelation, the transport and education dimensions do not show significant autocorrelation between the 6 sectors of the capital (Table no. 2). Also, for the most variables analyzed, the global spatial autocorrelation coefficient is not significant which could be a direct effect of the individual strategy development at the level of local public administration of each sector.

Afterwards, for the two variables where the spatial autocorrelation is statistically significant, the local autocorrelation is analyzed through the Moran-LISA index (Local Index Spatial Autocorrelation).

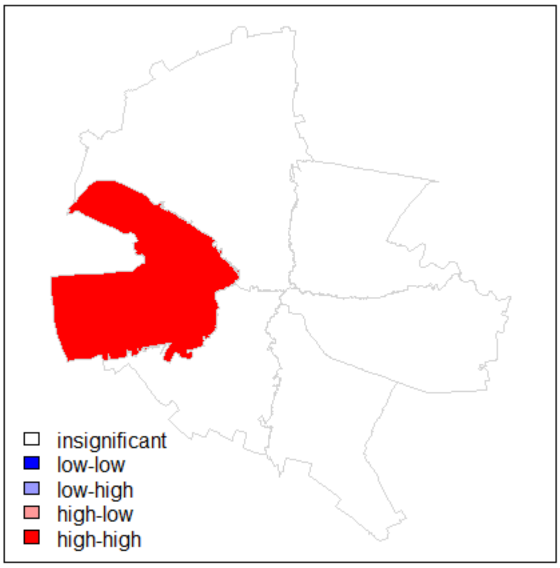

Figure no. 4: LISA map of Average_medicine

Source: Authors' own work using RStudio

With a probability of 90%, a significant autocorrelation is identified, specific to Sector 6 of the capital. This correlation is the high-high type, which means that for this variable, Sector 6 is adjacent to two sectors that present high values from the perspective of this indicator, Sector 1 and Sector 6 (Figure no. 4).

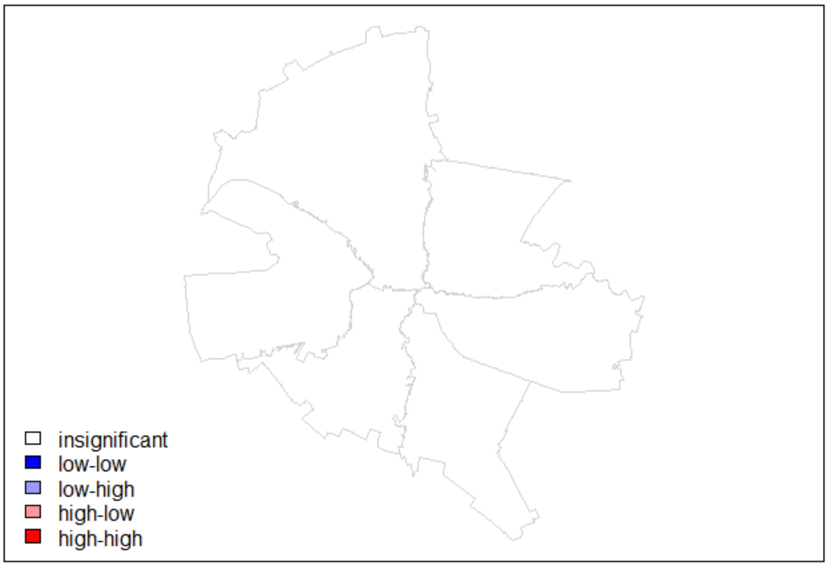

Figure no. 5: LISA Map of Max_medicine

Source: Authors' own work using RStudio

Despite the existence of a significant spatial autocorrelation at the global level for the Max_medicine variable, at the local level, with 90% probability, it cannot be stated that it is statistically significant (Figure no. 5). The situation presents itself as a result of the administrative structure of the Municipality of Bucharest. In the city center, Sectors 1,2,3,4 and 5 can be seen to meet and therefore adjoin each other in the city center, the only Sector that does not share a common border with all other sectors is Sector 6, which adjoins only with Sector 1 and Sector 5. Therefore, the spatial autocorrelation at the local level is not significant due to the concentration of medical offices and hospitals around the center of the capitals, the center area being divided between 5 of the 6 sectors of the capital (Sector 1, Sector 2, Sector 3, Sector 4, Sector 5).

Conclusions

On all the dimensions analyzed in this research, the amplitude of the series at the level of the 6 sectors of the Municipality of Bucharest is relatively small, which means that the mode of urban development at the level of the 6 sectors is somewhat similar. However, it is found that the highest distance on all 3 dimensions is registered at the level of sectors 1 and 6, a sign that the residential expansion of these two sectors was not accompanied by the increase in resilience and sustainability of the 3 dimensions, access to the 3 services, structurally remaining the same. At the opposite pole, Sector 5 presents one of the lowest values, mainly as a result of relatively low residential expansion, being one of the sectors with the most vacant, unused land, especially in the Ferentari-Rahova-Humulești area. A balanced strategy seems to have Sectors 4, 3 and 2 which show moderate values on all 3 dimensions.

As a general conclusion, it can be observed that the lowest values are on the transport dimension, a sign that the road infrastructure is the only one that has kept pace with the real estate expansion on the periphery of the 6 sectors, while the Medicine and Education dimensions have remained concentrated around the center of these 6 sectors. Furthermore, analyzing the spatial autocorrelation, it is observed that there is high-high spatial autocorrelation between Sector 1 and Sector 6 on the Medicine dimension, recording the greatest distances from residential buildings to medical facilities. Therefore, the two sectors can develop a joint strategy to ensure easier access to medical services for all citizens of these sectors.

The limits of the research are represented by the small number of variables and the lack of inclusion in the analysis of the localities bordering the 6 sectors (Chiajna, Bragadiru, Berceni, Pantelimon, Popești-Leordeni, Otopeni, etc.). Therefore, the main development directions of the research are represented by the inclusion of several variables in the analysis and the inclusion in the sample of localities bordering the City of Bucharest.

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