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Exploring local income inequalities by using spatial statistics. Emphasis on Romanian metropolitan areas

Cosmina-Daniela Ursu [a], **József Benedek** [a;b]
[a] Babeş-Bolyai University, Cluj-Napoca, Romania; [b] University of Miskolc, Hungary

Abstract
Following the collapse of the communist regime, Romania underwent significant economic, territorial, and social transformations that exacerbated inequality. To help policymakers create effective economic strategies, it is necessary to pinpoint the areas with the largest disparities. Thus, using spatial statistics available in ArcGIS, the primary goal of this study is to identify spatial clusters/outliers of income per capita. The findings indicate a strong concentration of high incomes at the regional level in Bucharest-Ilfov, West, Centre, and North-West regions. Conversely, low-income groups are concentrated in every other region, and their circumstances do not appear to improve over the course of the analysis period (2007–2021). At the metropolitan level, large cities are particularly home to high-value clusters and their influence within metropolitan areas is outlined.

Keywords: spatial inequalities, income per capita, cluster and outlier analysis, Romania

Introduction

Income inequalities is a widely studied subject, which encompasses various dimensions. In Europe, and especially in Central and Eastern countries (CEE), it is generally acknowledged that the inequalities have risen during the last decades, the drivers being not only economic, but also social and political (Camagni et al., 2020; Peters et al., 2010; Rose & Viju, 2014). Some researchers agree that the European Union's enlargement towards Central and Eastern Europe increased the existing disparities and the economic crisis of 2009 amplified the regional disparities (Camagni et al., 2020; Pascariu & Ţigănaşu, 2017; Smętkowski, 2013). Moreover, to overcome the negative effects of economic inequalities after the EU integration, CEE countries have designed policies to attract Foreign Direct Investments (FDI) for large urban centres, growth poles and capital, but the consequences were only the increases in regional disparities (Pascariu & Ţigănaşu, 2017; Smętkowski, 2017). Nonetheless, the European funds generated a catching-up process between 2000-2008 disparities (Pascariu & Ţigănaşu, 2017). Camagni et al. (2020) also approve that, even with the help of EU funds, some regions would benefit more than others, leading to territorial

✉ Cosmina-Daniela Ursu, PhD student, Doctoral School of Geography, Babeş-Bolyai University, Cluj-Napoca, Romania; e-mail: cosmina.ursu@ubbcluj.ro.

inequalities. Other authors assumed that the construction of infrastructure led to increases in regional disparities (Buckwalter, 2003; Smętkowski, 2017). At the EU level, the Cohesion Policy aims to reduce the disparities between regions and provide financial support through multiple channels.

The most frequently used index for measuring global inequalities is Gini, which ranges from 0 (or 0%) to 1 (or 100%), 0 representing perfect equality and 1 representing perfect inequality. In Eastern Europe, after the fall of the communist regime, the Gini coefficient had an abrupt rise (Ezcurra et al., 2007; Kalwij & Verschoor, 2007; Török & Benedek, 2018). Ezcurra et al. (2007) studied the evolution of territorial imbalances in the per capita income in the Central and Eastern Europe regions between 1990 and 2001, using Gini and Teil Index. The results show an intensification of the existing territorial inequalities and the creation of new spatial patterns. Glaeser et al. (2008) observed the impact of inequalities on metropolitan areas, assuming that inequalities in skills are directly correlated to income inequalities. The Gini coefficient was used as a measure for inequalities.

Rodríguez-Pose & Tselios (2009) analysed regional personal income distribution in Western Europe for 1995-2000 by using Exploratory Spatial Data Analysis. The authors managed to represent the evolution of income per capita and Gini coefficient through cluster maps at regional level in Europe. This is one of the first studies that encompassed both income per capita and its spatial representation in a cluster analysis. The results emphasize the importance of spatial statistics in mapping the evolution of income inequality within European regions.

Although the Gini index is widely used and has a certain importance, inequalities could also be spatially represented on maps. In this sense, Global Moran's Index and Anselin Local Moran's Index were frequently used for spatial clustering analysis, for various purposes (Andrews et al., 2020; Hughey et al., 2018; Panzera & Postiglione, 2020; Rodríguez-Pose & Tselios, 2009).

For solving inequality problems, one must primarily know the location of the highest inequalities in order to help policy makers design better strategies for economic revival. Thus, the main purpose of this study is to identify spatial clusters in Romania where low/high local incomes are received. Although there are several studies employing different measures for income inequalities, only few of them have encompassed the local spatial dimension (Benedek, 2015; Török & Benedek, 2018). The major minus of the inequalities studies is the use of indicators only at macro-level (such as GDP per capita), ignoring the local level of inter- and intraregional disparities, mostly because of lack of data (Rodríguez-Pose & Tselios, 2009). In this context, the present study aims to cover this gap by using income data for each territorial administrative unit (TAU) in Romania.

The study also updates the spatial distribution of income inequalities, setting the emphasis on metropolitan areas. The main assumption is that, around the most important urban centres, spatial clusters will be established, naturally indicating the influence that the urban centre has for its neighbouring localities. Geographic

Information System softwares are useful, not only for data representation but also for applying clustering measures. In this case, Cluster and Outlier Analysis will be performed. Moreover, through the evolution of Moran's Index, the pattern of clustering could be analysed between 2007 and 2021.

The remainder of this paper is organized as follows. Section 1 introduces the existing studies about inequalities in Romania, whereas section 2 describes the study area, the data and methods used. The results section firstly presents the context of income inequalities at the CEE level and, in particular, for Romania, by using the Gini Index. Secondly, the distribution of income in Romania is analysed, and the results of the Moran's Index are presented. Cluster and Outliers results are mapped and explained further, both at regional and metropolitan level. In the Discussion section, the results are correlated with previous studies. The study ends with concluding remarks and further research directions.

1. Literature review

After the fall of the communist regime, Romania has gone through various transformations in economics, development and social life. Many regions were affected by depopulation, poverty, social exclusion (Militaru & Stanila, 2015). Income inequalities have grown since 2000 (Gavriluţă et al., 2020; Goschin, 2017; Precupeţu, 2013; Török, 2019) and a social polarization could be observed. There is a large gap between the majority of people belonging to the middle class and with low wages and only a small part of rich people who earn more (Istrate & Horia-Şerban, 2018; Precupeţu, 2013). In addition, globalization is considered one cause for the spread of inequalities. Even if some inequality degree is unavoidable, fighting its consequences is desirable for a healthy economic growth (Militaru & Stanila, 2015). Furthermore, policies and inequality are closely related in that certain policy choices may either contribute to or worsen inequality (Rose & Viju, 2014).

Income inequalities are still a subject of concern for policy makers, but also for economists and researchers. Chilian (2012) used Gross Value Added and employment to analyse the inter-regional disparities for 2000-2008 and noticed large development gaps between the capital region and the rest of the country. Precupeţu (2013) described the inequalities by using three dimensions: income, labour market and education and observed that the inequalities are deeply rooted and will probably maintain in the following years. The results show that Romania has a high level of income inequalities, in the context of the lowest median equivalised income in the EU. Goschin (2015) analysed the evolution of inequalities in Romania for 1995-2012 by using a synthetic index that includes GDP/capita, labour productivity and life expectancy. The results show that existing inequalities before EU accession were deepened. Istrate & Horea-Şerban (2018) focused on the link between poverty and income inequalities and concluded that there is a bidirectional relationship between these indicators. Makreshanska-Mladenovska & Petrevski (2018) remarked that, in the case of

Romania, income distribution has become equal, ranging from 31% in 1998 to 28% in 2014 (according to World Bank's World Development Indicator Database). Benedek et al. (2019) evaluated the growth poles programme from the perspective of regional inequalities by using local income data from the Department for Fiscal Policy and Local Budgeting within the Ministry of Regional Development, Public Administration and European Funds. Török (2019) has analysed regional inequalities in Romania before and after the EU accession, comparing the GDP per capita and the Local Human Development Index for each county. Ivan et al. (2020a) used night-time lights to measure regional inequalities at the county level in Romania. In another study, Ivan et al. (2020b) projected local income based on Earth Observation for the cities over 50 000 inhabitants. Mitrică et al. (2020) performed an analysis at the local rural level in Romania by using the Social Disadvantage Index (SDI) and observed that most territorial inequalities are located in the north-eastern, south-eastern, south and south-western parts of the country.

When it comes to using spatial statistics for representing inequalities at different levels in Romania, to the authors' knowledge, only a few studies approached this method. Benedek (2015) differentiated core and periphery structures at county level based on the GDP per capita and Human Development Index. Goschin (2017) used Moran's I statistic to test spatial dependence in economic convergence. Török & Benedek (2018) analysed the spatial patterns of local income inequalities using data from 2013.

Considering that there are few studies at the local level, the present paper aims to contribute to the research field of inequality studies in Romania by analysing the evolution of local incomes for three years (2007, 2014 and 2021). The spatial patterns derived could indicate the areas affected by poverty and the ones that have a good economic performance. Policy recommendations reducing inequality and poverty overall should be implemented according to each case.

2. Data and methods

2.1. Study area

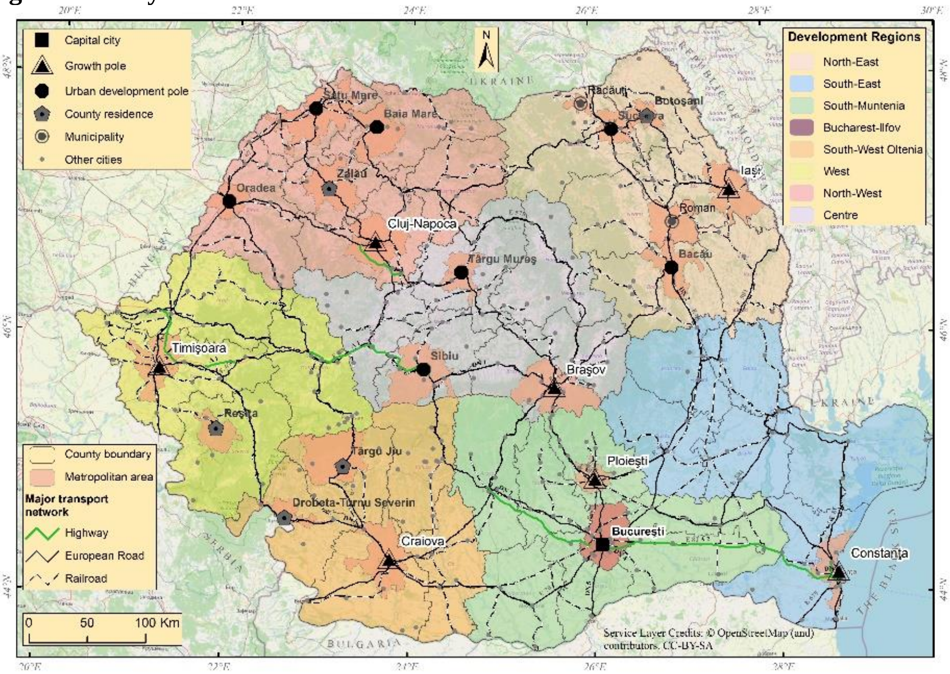
The study focuses on the Territorial Administrative Units (TAUs) of Romania, both urban and rural (3181 in total). According to Law 315/2004, there are 8 Development Regions corresponding to NUTS 2 level (Figure 1). Their aim is to reduce existing regional disparities by stimulating a balanced development and encouraging interregional cooperation (Romanian Parliament, 2004). In this study, even if the analysis is performed at the local level, spatial patterns will be also observed at the regional level. According to the national laws, there are 7 growth poles (Cluj-Napoca, Iaşi, Timişoara, Braşov, Craiova, Ploieşti and Constanţa) and other 13 urban development poles established through Government Decision no. 1149/2008 (Romanian Government, 2008). They were designed to receive priority investments from community and national funding in order to generate spillover effects for the surrounding areas. In this case, the study aims to evaluate the income inequalities for 22 metropolitan areas (MAs), which were selected according to the availability of their official documents (table 1). All growth poles have established metropolitan areas, while only 7 urban development poles (Oradea, Târgu-Mureş, Suceava, Satu-Mare, Baia-Mare, Sibiu and Bacău) have an active metropolitan association. There are also other municipalities, which have formed metropolitan areas. The most populated metropolitan area according to 2021 Census data is Bucharest, which encompasses the capital city and Ilfov County (table 1).

Table 1. Data on metropolitan areas

No.	**Metropolitan area**	**Population (2021)**	**Number of members**	**Surface (sq.km.)**
1	Bucharest	2.259.665	41	1802,87
2	Iaşi	452.732	27	1557,99
3	Braşov	426.379	22	2130,56
4	Cluj	425.130	20	1740,56
5	Constanţa	423.994	16	1110,28
6	Timişoara	369.891	22	1589,38
7	Craiova	344.848	29	1887,58
8	Ploieşti	285.323	14	611,771
9	Bacău	250.602	24	1220,38
10	Sibiu	246.513	21	2079,67
11	Oradea	244.920	12	753,961
12	Târgu Mureş	213.918	15	922,814
13	Baia Mare	207.077	20	1490,47
14	Satu-Mare	205.581	26	1937,31
15	Suceava	179.269	16	734,215
16	Roman	147.134	29	1333,03
17	Târgu Jiu	140.659	20	2057,55
18	Zalău	135.873	23	1431,59
19	Botoşani	130.552	9	526,607
20	Drobeta	128.563	7	524,509
21	Reşiţa	81.599	10	865,876
22	Rădăuţi	54.918	8	267,796

Source: the authors, based on data from the National Institute of Statistics (2021)

Figure 1. Study area



Source: authors' representation

On the other hand, the smallest MAs (Reşiţa and Rădăuţi) had under 90.000 inhabitants. In terms of surface, Braşov, Sibiu and Târgu Jiu cover over 2000 sq. km., while almost a third of the MAs cover less than 1000 sq. km. The number of members for each MA represents the current situation, but it may change in time according to the decision makers' will of association. Excluding Bucharest, other 2 MAs only reach 29 members while Drobeta and Rădăuţi have fewer than 10 members. Overall, the analysis will show which members of the metropolitan areas are the most dynamic in terms of their local income performance.

2.2. Data

For representing spatial clusters at the local level in Romania, the average local income per capita was calculated for 2007, 2014 and 2021. The Department for Fiscal Policy and Local Budgeting within the Ministry of Public Works, Development and Administration collects yearly income data for each TAU. They include taxes, fees and income tax payable by residents, economic agents, legal entities and public institutions of local importance (Benedek et al., 2019). Furthermore, the local income was reported to the population by domicile data, obtained from the National Institute of Statistics. The choice of the years selected for analysis was made based on equal periods, as well as specific key moments, 2007 being the year of Romania's EU accession.

2.3. Methods

For analysing the local income inequalities at the local level in Romania, two methods were employed by using ArcMap 10.6 software.

First, local income inequalities were assessed by using Moran's Index, which is a global clustering measure that explores the relationship between features situated nearby (Getis, 2010). In this way, the evolution of Moran's Index shows how the overall income patterns evolved in time and whether the values were clustered, dispersed or having a random distribution (Moran, 1948; Scott & Janikas, 2009). The formula incorporated in the ArcGIS Spatial Autocorrelation tool (Moran's I) is the following (Eq. 1):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{j=1}^{n} (X_i - \overline{X})^2} \tag{1}$$

where I = Global Moran's I statistic for spatial autocorrelation, n = sample size (n = 3181), i = individual observation and j = observations at other locations, $w_{i,j}$ is spatial weight matrix between feature i and j (distance threshold), X_i=individual income per capita z-score value, $\overline{X}$ mean income per capita z-score value and S_0 = aggregate of all spatial weights defined by the Eq. 2 (Moran, 1950):

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

The statistical analysis starts, in our case, with a null hypothesis that the local income per capita for each TAU is randomly distributed across the country. The goal of Spatial Autocorrelation (Moran's I) tool is to reject this hypothesis (Getis, 2010). When the p value is 0, it means that the cluster is statistically significant and that the null hypothesis can be rejected. A positive value for Moran's Index indicates a tendency towards clustering, while the negative values express the dispersion tendency. Thus, Moran's I does not only show the existence of spatial autocorrelation (which could be positive or negative), but also its strength (Fischer & Getis, 2010).

In this study, Spatial Autocorrelation was analysed for each year by using Inverse distance as the conceptualization of spatial relationships, which shows that nearby features have a larger influence on the target feature than the ones situated far away (Environmental Systems Research Institute [ESRI], 2019). Since the studied indicator (the revenues per inhabitant) does not causally depend on the location of the TAU as it does in other scenarios (such as the spread of pollutants from an industrial platform to the surrounding areas which would require taking into account the contiguity issue), the inverse distance was deemed to be the most relevant measure when it came to metropolitan areas. Other conceptualizations of spatial relationships are used for modelling contagious processes or for dealing with continuous data, based on the idea that the spatial interaction between two polygons increases if they share a boundary (ESRI, 2019). In the case of MAs, the members may have a diversity of revenues. Thus, the objective is to ascertain the degree of disparity and to highlight the TAUs that differ significantly from the surrounding members. The distance method used is Euclidian, row standardization and for the threshold distance, 30 km were assigned. The distance was chosen based on the legislative documents regarding the metropolitan areas in Romania, which confirm that the extent of metropolitan areas is up to 30 km (Romanian Parliament, 2001). Given the extension of the study area, the tests have proven that any threshold under 24 km would mean that some TAUs would not have any neighbour, which generally invalidates the significance of the corresponding results.

Nevertheless, Moran's I does not specifically locate the clusters (Hughey et al., 2018; Török & Benedek, 2018), so another cluster detection method was used. Cluster and Outlier Analysis (Anselin Local Moran's I) is based on Luc Anselin (1995) method for creating spatial clusters and identifying the outliers. In this respect, the formula is detailed in Eq. 3:

$$I_i = \frac{(X_i - \bar{X})}{\sigma^2} \sum_{j=1}^{n} w_{ij}(X_j - \bar{X}) \tag{3}$$

I_i = Local Moran's I statistic for localized spatial autocorrelation, n = sample size (n=3181), i = individual observation and j = observations in another location, X_i = individual income per capita z-score value, X mean income per capita z-score value, σ^2 = variance of income per capita z-score, w_{ij} is spatial weighting (distance threshold) (Anselin, 1995).

The spatial pattern of the distribution of income per capita can be seen by employing Cluster and Outlier analysis. In order to identify the most competitive regions and metropolitan areas and to determine how they changed in 2007, 2014, and 2021, an analysis was conducted both at the regional and metropolitan levels.

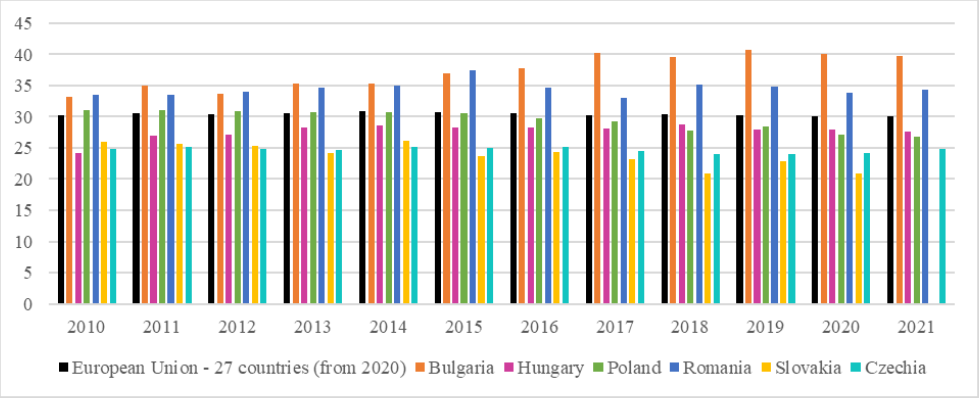
3. Results

The first part of this section presents the inequality in the CEE countries (including Romania) using data from EUROSTAT. The primary goal is to use official reports to bolster the study's later findings. Secondly, data from EUROSTAT, the National Institute of Statistics and the Ministry of Public Works, Development and Administration database are used to present inequalities in Romania at the national and regional levels. The clustering analysis, which began with the interpretation of the Global Moran's Index and proceeded with the Cluster and Outlier analysis, is credited to the following subsection. This was carried out on a metropolitan and regional scale. Also, a comparison between the metropolitan areas was made, along with the evolution of the number of clusters and outliers for each level.

3.1. Inequalities in CEE countries

The Eurostat database's Gini coefficient of equivalised disposable income for the years 2010–2021 was used to evaluate the situation of income inequality in the CEE countries (Figure 2). There were noticeable variations for each state, even if the average EU of the Gini coefficient was nearly constant during the chosen time. Nonetheless, Romania and Bulgaria consistently had the highest Gini coefficient values, indicating the presence of severe regional disparities. Starting in 2015, Romania's Gini stayed around 35%, while Bulgaria's Gini surpassed 40%.

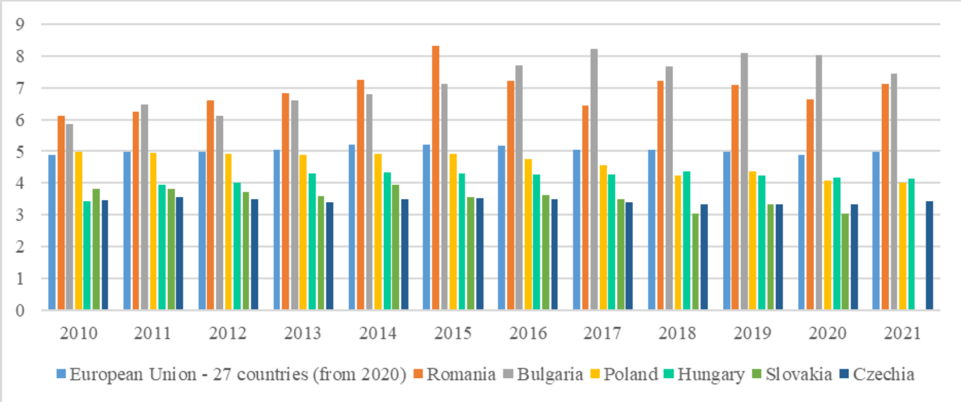
Figure 2. Gini coefficient of equivalised disposable income for 2010-2021 in CEE countries



Source: authors' representation based on Eurostat data (2022)

Eurostat measures the inequality of income distribution defined as the ratio of total equivalised disposable income received by 20% of the population with the highest income (top quintile) to that received by 20% of the population with the lowest income (lowest quintile) (Eurostat, 2023c). The comparison between CEE countries shows that Romania and Bulgaria are still the countries with the highest values recorded for the entire period (2010-2021) (Figure 3).

Figure 3. Inequality of income distribution among CEE countries for 2010-2021

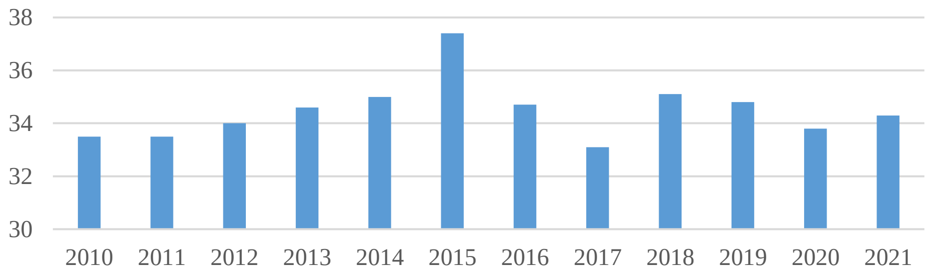


Source: authors' representation based on Eurostat data (2023a)

3.2. Inequalities in Romania

With a closer look at Romania's situation in particular (Figure 4), it is evident that the Gini values climbed gradually until 2015, when the highest value ever was recorded (37.4%), following which they varied. Based on the data on equivalised disposable income from Eurostat, the lowest value was 33.1% in 2017.

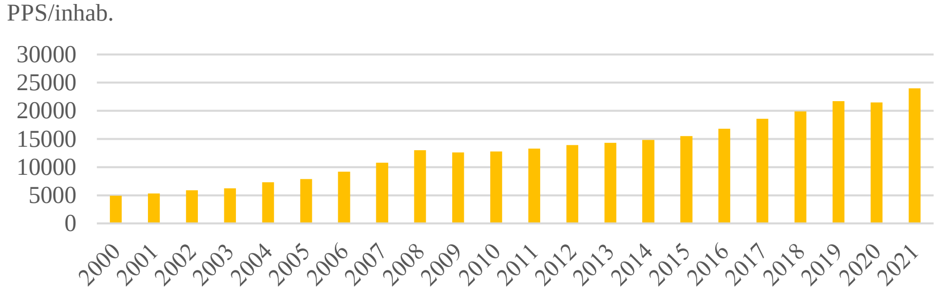
Figure 4. Gini coefficient of equivalised disposable income for 2010-2021 in Romania



Source: authors' representation based on Eurostat data (2022)

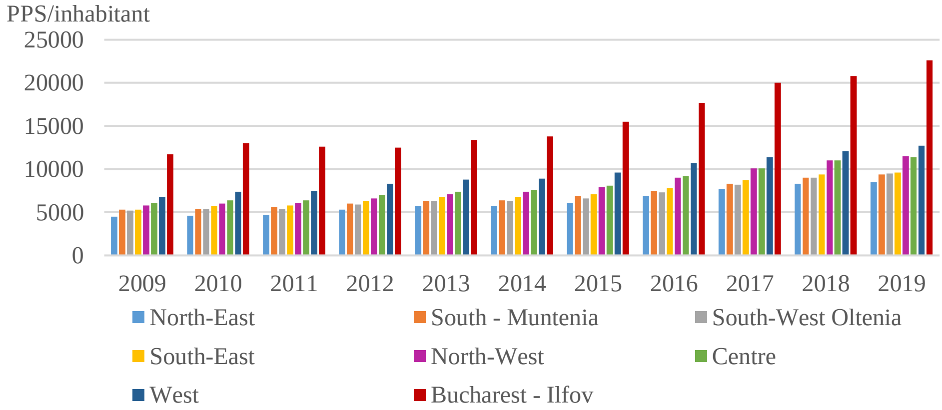
The GDP per capita at current market prices in Romania (Eurostat, 2023b) (Figure 5) shows two different stages for the period 2000-2021. First, the rise in values occurred until 2008 as a result of the funding provided by EU. The 2009 financial crisis caused the GDP to decline but after 2011, it began to rise once more until 2020, when a gradual decline was noted, primarily as a result of the pandemic. The greatest values were noted in 2021, and growth is most likely still possible in the near future.

Figure 5. Gross domestic product (GDP) at current market prices in Romania



Source: authors' representation based on Eurostat data (2023b)

Figure 6. Disposable income of private households by NUTS 2 regions for 2009-2019

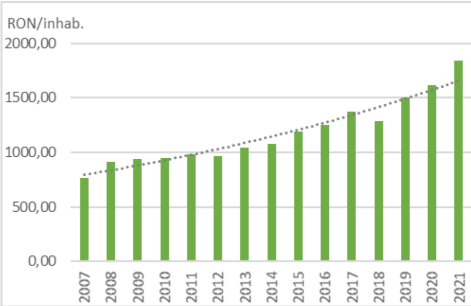


Source: authors' representation based on Eurostat data (2023c)

Eurostat also provides data about incomes at regional level. The disposable income of private households represents the balance of primary income and the redistribution of income in cash, expressed in purchasing power standard (PPS, EU27 from 2020), per inhabitant (Eurostat, 2023c). For Romania's regions (Figure 6), a large difference between the capital region and other regions could be remarked in each year. One encouraging finding is that all development regions' values exhibit a tendency towards growth. Bucharest-Ilfov region is the only one to surpass 15,000 PPS per inhabitant and has the highest values over the whole period of 2009-2019. West region, which has held its position over time, comes second. There is a competition for the Centre and North-East Regions: beginning in 2017, the values equalised over 10,000 PPS/inhabitant despite the fact that there were few differences observed throughout the entire period. Though their values continue to be below 10,000 PPS per inhabitant, South-East, South-Muntenia, and South-West cases also show the same evolution. Although the North-East region comes last, it generally follows the pattern of the previous regions.

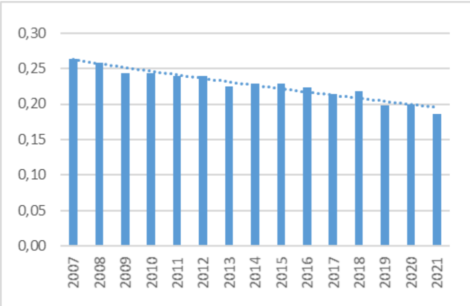
When the income per capita for the years 2007–2021 is calculated, a rising trend since EU membership can be observed (Figure 7). The economic crisis from 2009 affected the income values, which remained mostly the same until 2015, when they started to grow again until 2021. The average income per capita at the national level for the interval 2007-2021 is 1200 RON/inhabitant, which means that in 2021, the average was exceeded by over 600 RON. In addition, the Gini index was calculated based on the same data and it shows the decrease in inequalities (Figure 8). This fact results from the post-2008 global economic crises, which also had an impact on Romania, causing an economic recession (Török & Benedek, 2018). The explanation for the interdependence of the two diagrams is as follows: inequality declines with rising per capita income. Other authors (Eva et al., 2022; Rodríguez-Pose & Tselios, 2009; Rose & Viju, 2014) also acknowledged the negative relationship between income per capita and inequalities.

Figure 7. Evolution of the income per capita at the national level between 2007-2021



Source: authors' calculation based on data from the Ministry of Public Works, Development and Administration and National Institute of Statistics

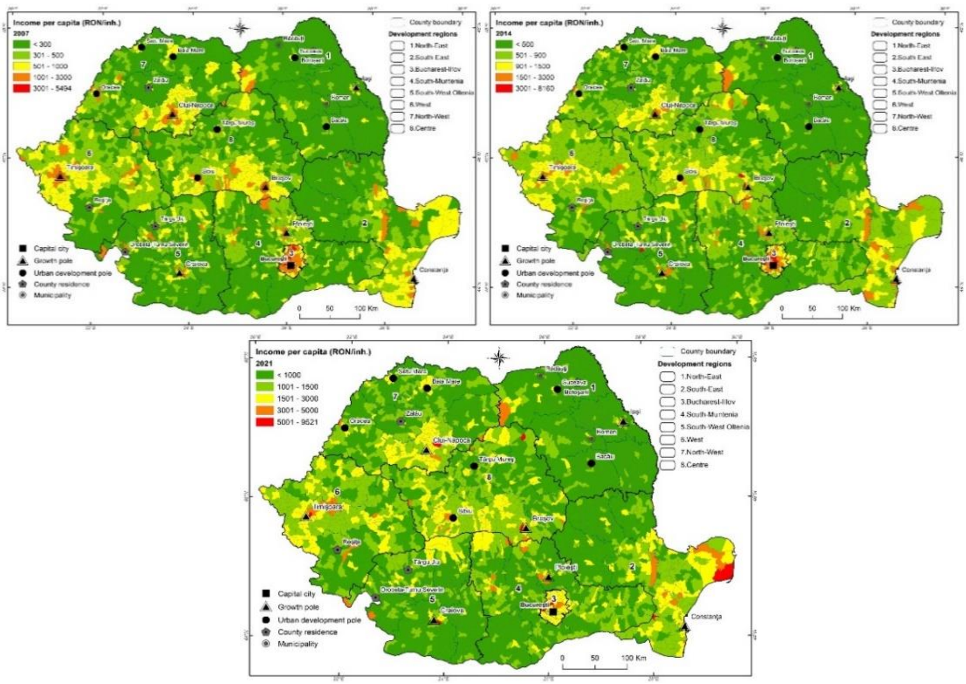
Figure 8. Gini Index for income per capita at county level between 2007-2021



Source: authors' calculation using Wessa (2016) software

Income per capita was represented for each of the 3181 localities (Figure 9) and the main purpose was to observe the overall evolution of this indicator at spatial level, without having any measure for clustering. At a first glance, the regions that have lower performances maintain their status for all the years: North-East, South-East, South-Muntenia and South-West Oltenia. There are also parts of regions that have lower values: the northern part of the North-West region, the south of the West region, and the east of the Centre region. In any case, it is simple to notice how the minimum wage has changed over time: from under 300 RON/inhabitant in 2007 to 500 RON/inhabitant in 2014 and 1000 RON/inhabitant in 2021. At the opposite side, the highest income is registered in the Bucharest-Ilfov region, but for the rest of the country, only the major cities have higher values. The suburban localities also exhibit higher values, as in the case of Cluj-Napoca, Timişoara, Braşov, Constanţa. Anomalies can also be observed; for example, the Danube Delta localities appear to have a higher income, but this is actually because the income is concentrated among a small number of residents.

Figure 9. Income per capita at the local level (2007, 2014 and 2021)



Source: authors' representation based on data from the Ministry of Public Works, Development and Administration and National Institute of Statistics

3.3. Clustering analysis

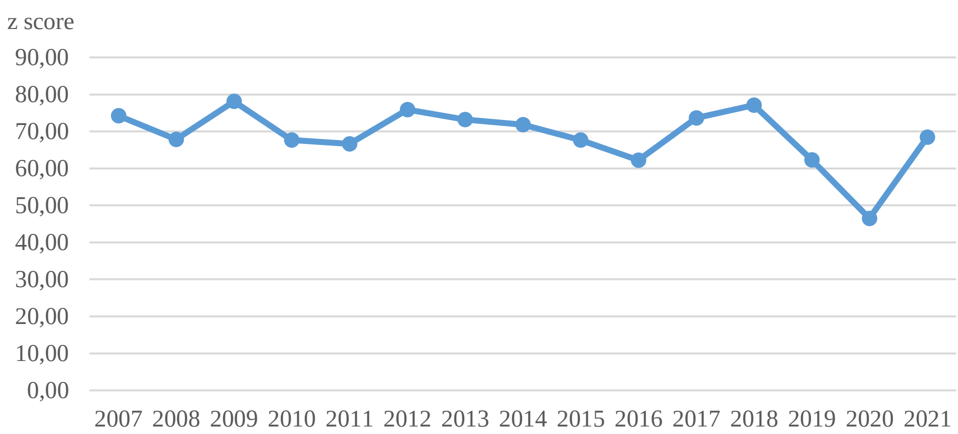
The income per capita values showed a tendency to cluster over the whole analysis interval, with a p-value of 0 and positive Index values ranging between 0.21 and 0.37 (Table 2). As for the z score, its values are also positive and over 50 except for 2020, when the values reached 46,5. If we compare the Index value and z score, a major drop can be observed for 2020, when the lowest values were recorded for both indicators (Figure 10). This demonstrates the clustering tendency's regression, which returned to normal in 2021.

Table 2. Evolution of Moran's Index for 2007-2021

Year	Moran's I	z-score
2007	0.35	74.26
2008	0.32	67.83
2009	0.37	78.11
2010	0.32	67.63
2011	0.32	66.67
2012	0.36	75.93
2013	0.35	73.21
2014	0.34	71.82
2015	0.32	67.71
2016	0.29	62.21
2017	0.35	73.61
2018	0.37	77.09
2019	0.30	62.34
2020	0.21	46.52
2021	0.33	68.41

Source: authors' representation

Figure 10. Evolution of z-score between 2007-2021



Source: authors' representation

Spatial heterogeneity is visible following the execution of Cluster and Outlier Analysis for the chosen years (Figures 11, 12, 13). For an easier interpretation, the results can be divided into two groups: on the one hand, clusters (High-High and Low-Low) which show the degree of similarity and, on the other hand, outliers (High-Low and Low-High) which indicate the dissimilarity in a certain area (Figure 14). At spatial level, Low-Low clusters are predominant in North-East, north of South-East region, South-Muntenia, South-West Oltenia and the northern part of the North-West region. Looking at the numbers for each region (Figure 15), North-East stands out with the highest number of Low-Low clusters (over 480) for each year. For the South-East and South-Muntenia regions, the number of Low-Low clusters tends to decrease from 2007 to 2021, whereas for South-West Oltenia, an increase from 170 clusters with low values in 2007 to 215 in 2021 can be observed. The North-West region started in 2007 with 125 clusters of low values, but the numbers decreased under 50 in 2021. All the other regions have insignificant numbers of Low-Low clusters.

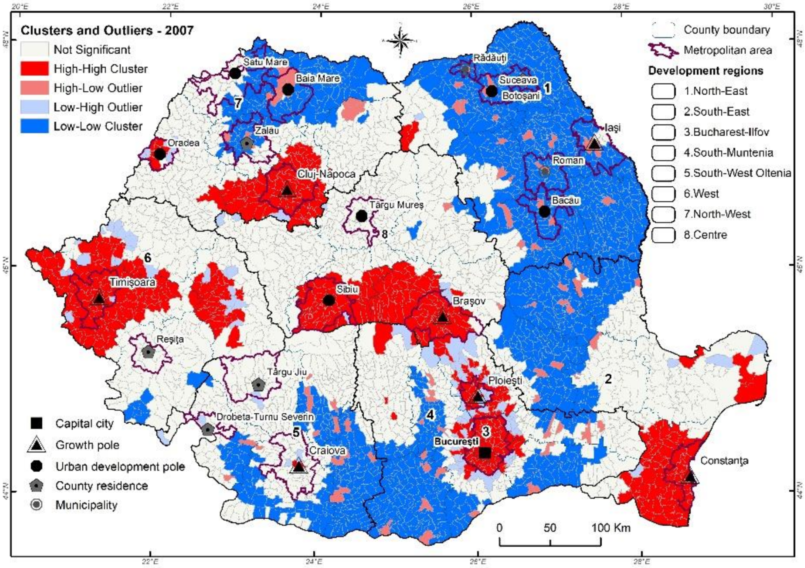
High-High clusters are noticed in the case of extended areas from Bucharest-Ilfov, West, Centre and South East regions for all years. In the case of North-West region, only the areas surrounding Cluj-Napoca are included in this class. It was possible to detect an expansion tendency for every High-High cluster. For South-East, North-West and Centre regions, there could be a positive evolution noted between 2007 and 2021, while South-Muntenia and West regions registered a decrease for that interval.

High-Low outliers include cities surrounded by TAUs with lower incomes from the regions where Low-Low clusters are localised. A significant increase could be observed in the case of North-East, South-West Oltenia, South-East and South Muntenia, which shows the development of some TAUs surrounded by low income ones. The North-West region registered a decrease until 2021, which means that the economic disparities tend to reduce. Centre and West are the regions with very few High-Low outliers.

At the opposite, Low-High outliers show TAUs with low value surrounded by a TAU with high value. This class is located at the periphery of High-High clusters and shows the urban-rural divide between high and lowincome TAU. The largest decrease was recorded in South-Muntenia, whereas increases were observed in North-West and Centre. Regions like North-East or South-West Oltenia have only a small number of Low-High Clusters, primarily due to the lack of high-income TAUs.

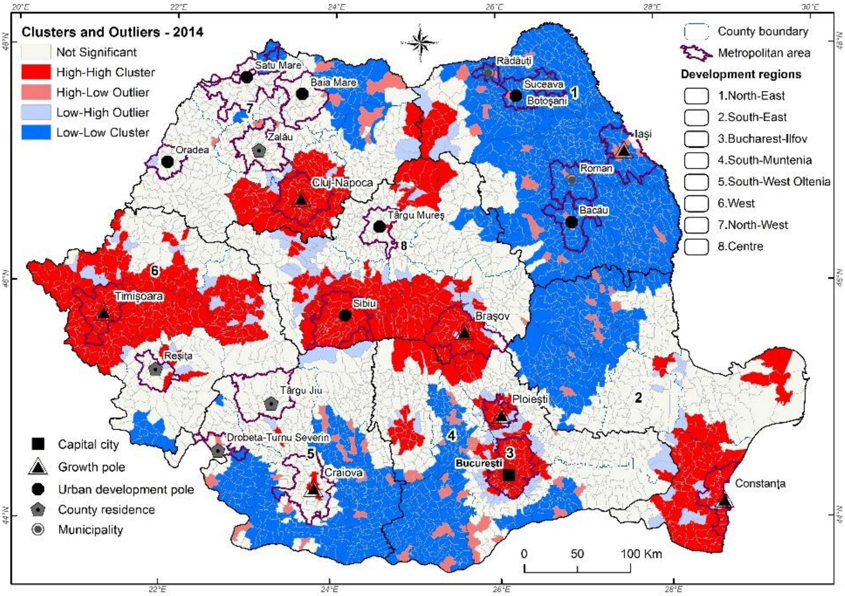
Bucharest-Ilfov has maintained through the years its High-High clusters, which shows the concentration of high incomes. Looking at the numbers ofnot categories, the South-Muntenia region is the only one that registered an increase, while the rest of the regions exhibit decreases over time. This demonstrates that the values are too diverse to be grouped together with clusters or outliers.

Figure 11. Cluster and outlier analysis - 2007



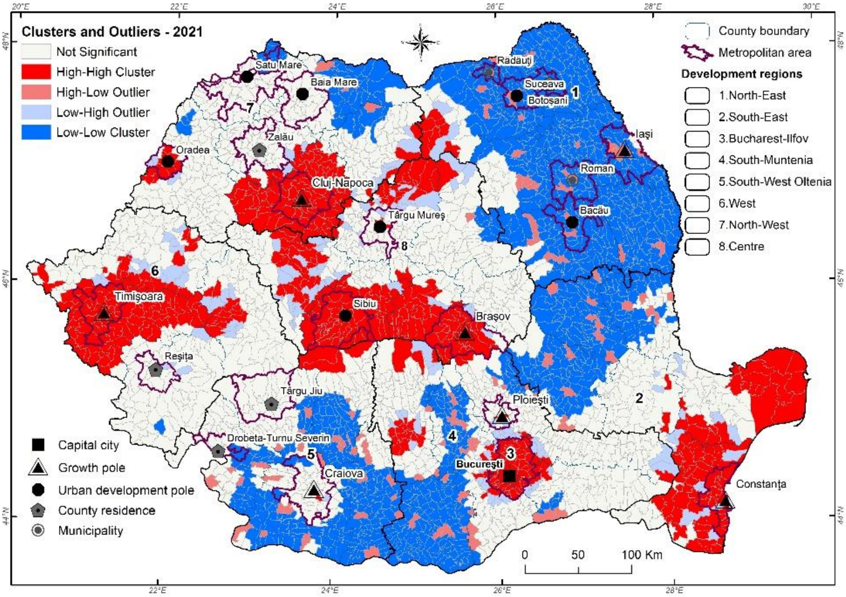
Source: authors' representation

Figure 12. Cluster and outlier analysis - 2014



Source: authors' representation

Figure 13. Cluster and outlier analysis - 2021



Source: authors' representation

Figure 14. Interpretation of cluster and outlier analysis

Similarity

High-High: cluster of high values

Low-Low: cluster of low values

Dissimilarity

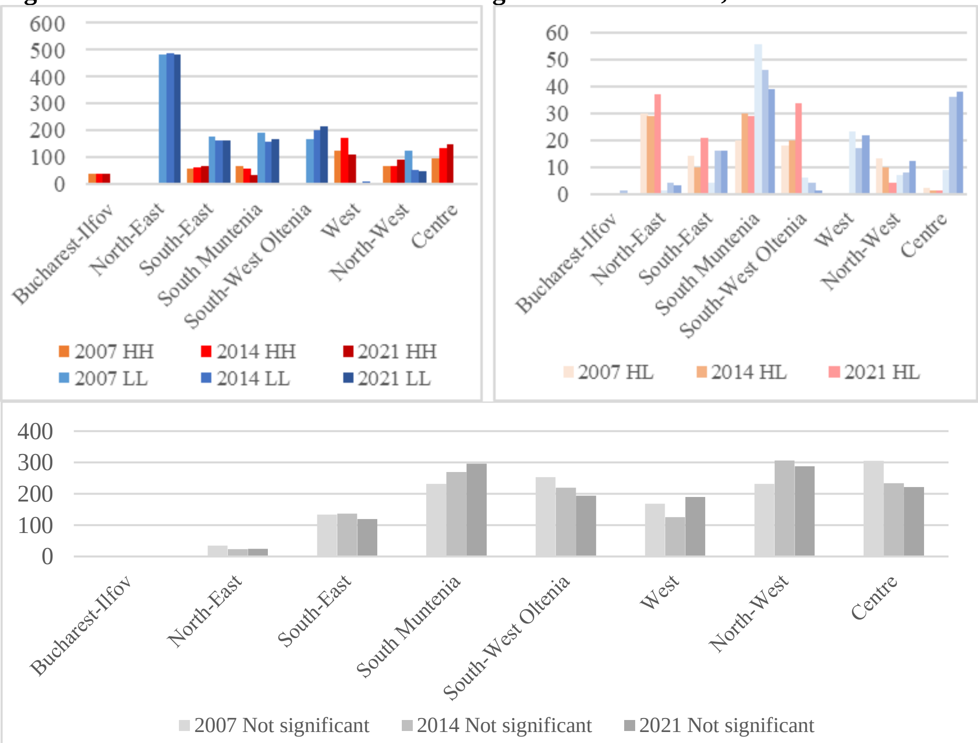
High-Low: spatial outlier (TAU with high value is surrounded by a TAU with low value)

Low-High: spatial outlier (TAU with low value is surrounded by a TAU with high value)

Not significant: neither clusters nor outliers, each TAU has different values from the values of its neighbours

Source: authors' representation

Figure 15. Number of clusters/outliers at regional level for 2007, 2014 and 2021



Source: authors' representation

Overall, looking at the numbers for the three years, at the national level (table 3), it can be noticed that the percentage of TAUs included either in clusters, or in outliers is higher (58%) than the ones from the Not significant class (42%), but the values differ across time. From the total number of clusters and outliers, Low-Low values are predominant (over 57%). Even if the percentage decreased from 64% in 2007 to 58% in 2014, in 2021, a minor increase can be noticed. In this case, a prediction in the future cannot be made. For High-High clusters, the highest percent was registered in 2014 (almost 30%). However, there is a tendency of reducing the number of TAUs until 2021. When it comes to High-Low and Low-High outliers, an increase could be noticed over the years.

Although spatial clusters can be examined at the regional level, the secondary purpose of the study was to test whether metropolitan areas could form clusters or outliers based on income per capita and how patterns evolved over time. At a first glance (Figure 16), the High-High clusters include Bucureşti, Cluj, Timişoara, Braşov, Sibiu and Constanţa MAs, which shows that the metropolitan areas maintained high-income values for the entire interval. A different situation can be noticed in the case of Ploieşti MA: although in 2007 and 2014, it had several TAUs with High-High clusters, in 2021, their number drastically decreased. Oradea MA is in a different situation; it had five High-High clusters when it first started in 2007, lost them all in 2014, and then added them back in 2021. An interesting situation can be observed in the case of Low-Low clusters. The regions with lower incomes provide the same economic context for metropolitan areas: Iaşi, Botoşani, Suceava, Rădăuţi, Roman and Bacău. Their situation does not seem to improve over the years, but only remain stationary. Of course, there are also metropolitan areas that managed to change their status; Zalău and Baia Mare had most of their TAUs included in Low-Low clusters in 2007, but in the next years, they became not significant, which means that income values are so diverse that they cannot be included in any category. This could also be an issue because it may hide the true development state of the area.

Table 3. The number of clusters/outliers for 2007, 2014, 2021

Year	HH	% from total clusters	LL	% from total clusters	HL	% from total clusters	LH	% from total clusters
2007	459	25.19	1160	63.67	97	5.32	106	5.82
2014	554	29.71	1079	57.86	100	5.36	132	7.08
2021	508	27.49	1083	58.6	126	6.82	131	7.09

Year	Total clusters/outliers (HH+LL+HL+LH)	% from total TAUs	Not significant	% from total TAUs
2007	1822	57.28	1359	42.72
2014	1865	58.63	1316	41.37
2021	1848	58.09	1333	41.91

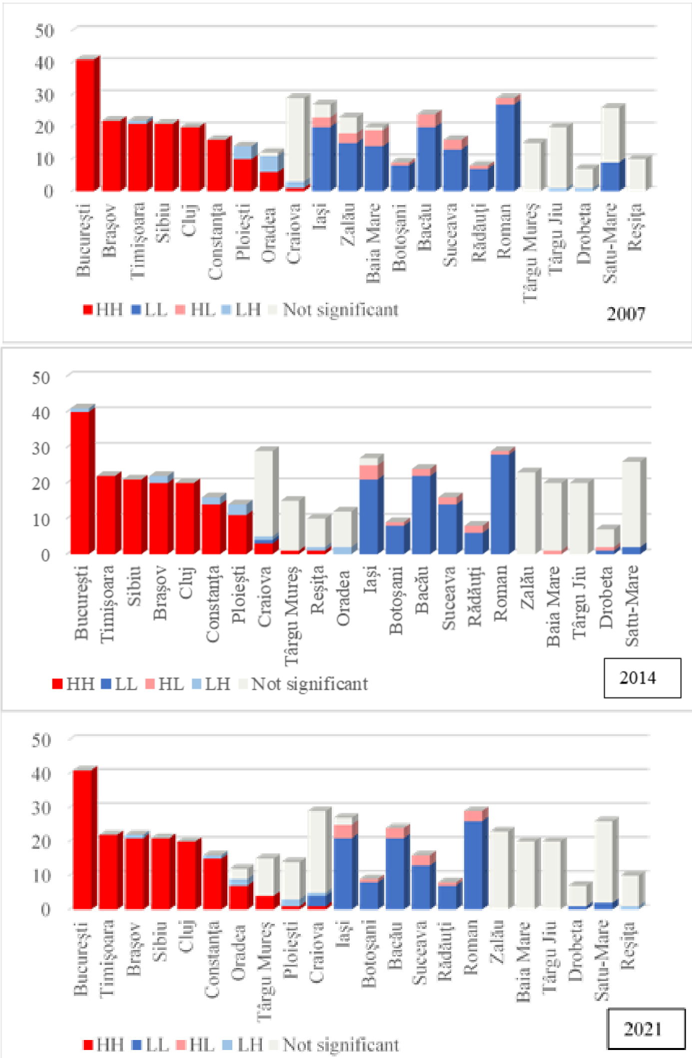
Source: authors' representation

As in the case of regional level, the outliers are determined by the localisation of the clusters. Low-High outliers are part of metropolitan areas with High-High clusters and they indicate the strong divide between wealthy TAUs and lagging-behind ones. Conversely, High-Low outliers are typically found in urban areas where Low-Low clusters are more prevalent. Their image is that of urban centres encircled by lower-income localities. In the case of Iaşi MA, not only is the city is in this category, but also some neighbouring communes, which shows that the urban centre may have positive influences on other communes.

The last group of TAUs are the one included in the Not significant category. They do not have a pattern to follow in association, thus they can belong to any metropolitan area. For all three years, Craiova MA had the largest number of not significant TAUs, mixed with various proportions of other clusters or outliers. Apart from Zalău and Baia Mare MAs, which were included in this category after 2007, other metropolitan areas can be noticed: Târgu-Jiu, Satu-Mare, Reşiţa and Drobeta.

This indicates that there are no clusters or outliers among the income per capita values because they are so dispersed.

Figure 16. Spatial clustering at metropolitan level for 2007, 2014 and 2021



Source: authors' representation

4. Discussions

After representing the cluster and outliers based on income per capita, several asymmetries can be outlined. At the regional level, the clusters of Low-Low values are associated with a high percentage of rural population: North-East, South-Muntenia and South-West Oltenia (Török & Benedek, 2018). The regions where the urban population prevails, like West and North-West are at the opposite. Looking at the spatial structure typology, High-High clusters correspond to core regions and Low-Low ones to periphery regions (Benedek, 2015; Török & Benedek, 2018). The only rural localities that seem to benefit from the advantage of proximity are the suburban ones, which have access to better job opportunities and higher quality of life (Török & Benedek, 2018). In Iaşi's case, the emphasis is on the "privileged" rural areas that are close to the urban centre. Nevertheless, one cause of regional disparities is the urban-rural divide, which needs to draw the policy makers' attention.

Particular attention needs to be paid to the outliers; High-Low outliers – TAUs with high income surrounded by others with low income and Low-High outliers – low-income TAU surrounded by high income. Török and Benedek (2018) also associated their position nearby Low-Low clusters and respectively High-High clusters. Usually, High-Low outliers are small and medium size cities surrounded by lower income levels and Low-High outliers are rural TAUs at the periphery of extended High-High clusters.

As Rodríguez-Pose & Tselios (2009) stated, the richer regions with lower inequalities may create advantages for neighbouring regions via the trickling down effect. The problem is that, in the absence of external influences, the poor regions surrounded by others with the same level of economic development will probably remain in the same state.

The identification of spatial clusters or outliers can help decision makers to distribute the policies according to the region's needs. The principle is that the measures that suit a region might not be proper for another one, so differentiations should be made between development policies (Andrews et al., 2020; Goschin, 2014). As Gavriluţă et al. (2020) remarked, overall, the fiscal policy in Romania has a minor impact on reducing inequality and poverty and this could be a sign that specific intervention for each region should be implemented.

Nistor (2012) considers that, in the case of Romania, Foreign Direct Investments (FDI) should be distributed not only in the capital region, but also in the rest of the country. Nevertheless, the strengths of the region (labour costs, human capital, education and skills, infrastructure) are the ones which encourage a foreign company to choose a certain region (Nistor, 2012). Pascariu & Ţigănaşu (2017) remarked that even if CEE countries attracted Foreign Direct Investments (FDI) for large urban centres, growth poles and capital, the regional disparities increased. This might also be the case of Romania, which specifically invested financial resources through the Regional Operational Plan 2007-2013 in the growth poles, expecting the spillover effects for the localities surrounding the urban centres. On the contrary, the prioritization of urban growth poles increased regional disparities (Benedek et al., 2019).

Smętkowski (2013; 2017) links the regional imbalances with the process of metropolitanisation, in the sense that the dynamic urban centres benefit from European funds more than other areas and this could increase inequalities, which is also true in the case of Romania's metropolitan areas.

Conclusions

This paper aimed to analyse income inequalities at the spatial level by using Spatial Statistic Tools for the period 2007-2021. First, the tendency towards clustering was observed through the application of Moran's Index. Second, Cluster and Outlier Analysis was used to identify clusters of high/low-income values and outliers (high income TAUs surrounded by low income and vice versa). The results show the strong divide between rural and urban localities, mostly between the eastern and the western side of the country. The Associations of TAUs with higher incomes (High-High clusters) are present in the West, Centre and North-West regions, whereas North-East, South-Muntenia and South-West Oltenia have the largest number of TAUs associated with low-income levels (Low-Low clusters). This finding is in line with previous research (Benedek, 2015; Török & Benedek, 2018), which concluded that geographic location and proximity matters as causal factors of income distribution. The additional value of the present study is the fact that the analysis is performed for three years, and consequently, various tendencies can be noticed. For instance, the number of Low-Low clusters tends to rise in South-West Oltenia region, while remaining mostly unchanged in the North-East. In the North-West region, their number recorded a major decrease from 2007 to 2021, which means that the region is making real progress in achieving regional balance.

Another purpose of the study was to identify the clusters and outliers within existing metropolitan areas. The results show that, throughout the whole 2007-2021 period, the Bucharest, Cluj, Timişoara, Constanţa, Sibiu and Braşov metropolitan areas maintained a significant number of High-High clusters, all of them located in the higher-income regions.On the other hand, Iaşi, Bacău, Roman, Suceava and Botoşani displayed a large number of Low-Low clusters, with only the urban centres included in the High-Low outliers. There is another category of metropolitan areas, i.e., Târgu Jiu, Drobeta, Zalău, Satu-Mare and Baia Mare, in which not significant values were recorded. This indicates that there is too much variation in the income values to include them in either clusters or outliers.

The spatial dimension of regional disparities, which can aid decision makers in developing and implementing focused strategies (Andrews et al., 2020; Goschin, 2014; Török & Benedek, 2018), embodies the study's practical significance.

The study's limitations stem from the fact that cluster and outlier analyses only identify spatial clusters based on a single indicator - in this case, the incomes per inhabitant - leaving out other potential causes of inequality. Furthermore, the distance affects the size of each cluster and outlier group; the greater the distance, the greater the number of clusters and outliers. The study examined the spatial relationships between each member's revenue per person and concentrated on the distance specified by law for the expansion of metropolitan areas. The presence of clusters in each metropolitan area shows the correlation with the region's welfare (with Low-Low clusters in North-East and South-West regions and High-High clusters in West, Centre, South-East, and North-West regions). In conclusion, the distance should be selected based on the particulars of the research and its purpose.

Subsequent avenues for investigation could concentrate on the socio-demographic, travel habits, foreign investments, and other variables that may account for the income clustering. The correlation between local income and other indicators could be examined through statistical techniques incorporated into multidimensional approaches to determine which factors are most crucial for regional development.

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