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URBAN DEVELOPMENT DYNAMICS BASED ON COPERNICUS DATA: CASE STUDY OF BRATISLAVA AND BUCHAREST

Monika KOPECKÁ, Daniel SZATMÁRI, Šimon OPRAVIL

Urban development dynamics based on Copernicus data: case study of Bratislava and Bucharest

Abstract: The expansion of metropolitan settlements has a direct impact on the quality of life of local people. Monitoring and forecasting its future development is a key prerequisite for taking fundamental measures to regulate land use, optimizing the functional use of urban space and building infrastructure, as well as proposing measures to eliminate negative side effects (e.g. urban heat islands). The aim of this paper is to document the visualization of built-up area dynamics on a regional level using selected Copernicus data, and also a sample of regression analysis focused on selected spatial determinants of development. These newly developed patches within the urban core were classified into three urban growth forms: edge expansion, infill, and outlying. To classify the urbanized area into these three forms, we computed the ratio of the common edge between a new patch and existing urban patches and the total perimeter of a patch. Deepening knowledge about the monitoring of land development using satellite data can help to provide accurate, up-to-date, and reliable data for the decision-making sphere.

Keywords: urbanization, regression analysis, Urban Atlas, Bratislava, Bucharest

Introduction

The expansion of urban areas to the surrounding land has an increasing impact on the environment, which has now been fully recognized as a significant global problem. A continuously increasing share of the population living in cities is considered to be one of the driving forces of global environmental change. As the spatial expansion of cities is becoming an increasingly rapid phenomenon, urban planners need to pay attention to the trends, patterns, and directions of urban growth for urban sustainable management (Millington et al., 2018). Understanding different driving factors of landscape changes at different hierarchical levels has important implications for future urban management and planning. The main priorities in the field of urban area monitoring are obtaining up-to-date information on the status and evolution of urban systems at different levels and developing innovative approaches to support efficient and sustainable urban development. For this purpose, data on the urban environment (e.g. air quality, emissions), population density, and quality of life need to be linked to data obtained by remote sensing and interpreted in a comprehensible way. Urban visualizations can create awareness of critical urban conditions and provide valuable insight into how cities perform and how people interact with the urban environment.

Urban and suburban environments are composed of a wide range of land cover classes. The expansion of urban areas requires new analytical approaches and new sources of data and information. Several recent developments in remote sensing have the potential to significantly improve the mapping of urban areas. They are related to the availability of data from new Very High Resolution (VHR) remote sensing systems and hyper-spectral sensors that can support detailed and accurate mapping of urban areas on different spatiotemporal scales (Herold et al., 2005).

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The Copernicus programme is one of the most important sources of data on the changing urban landscape. This programme offers information services that provide satellite Earth observation data and *in situ* (non-space) data. The information services provided are available free of charge to all users across the globe. The Copernicus Land Monitoring Service (CLMS) was jointly launched in 2012 by the European Environment Agency and the European Commission – DG Joint Research Centre. This service provides geospatial information on land cover and its changes, land use, ground motion, vegetation state, water cycle, and earth surface energy variables. The data can be used in various areas of the decision-making sphere such as spatial and urban planning, agriculture and food security, forestry, water management, nature conservation and restoration, rural development, ecosystem accounting, and climate change mitigation/adaptation. These big data provide new opportunities to uncover the hidden dimensions of urbanization and to better understand the processes taking place within the physical boundaries of cities. Land cover and land use mapping is one of the five main CLMS components and produces land cover classifications at different levels of detail in a pan-European and global context.

According to Feranec et al. (2016), urbanization is defined as a land cover flow representing the change of agricultural land, forest land, wetlands, and water bodies into urbanized and industrialized land. The construction of buildings designed for living, education, healthcare, recreation, and sport, as well as the construction of facilities for production, all forms of transport, and electric power generation, are grouped under the process of urbanization. Kopecká and Rosina (2014) focused on the preparation of an extended classification of urban land cover based on the CORINE Land Cover (CLC) nomenclature. The proposed classification consisted of 46 classes for artificial surfaces and was more suitable for precise observation of local peculiarities of urban land cover changes. However, more detailed data are needed for the local scale. Szatmári et al. (2018) presented an extended Urban Atlas (UA) nomenclature with 53 classes of predominantly urban landscape (according to the intensity of impermeable surfaces), farming landscape, semi-natural landscape, forest landscape, waterlogged areas, and waters. Recently, 3D models of urban areas have found use in cartography, urban planning visualization, and construction at the local level (Biljecki et al., 2017; Melown Technologies, 2019).

Urban data visualizations include maps of different time horizons based on remote sensing data representing maps of urban land cover changes. Xu et al. (2007) and Kuru and Yüzer (2023) classified the newly developed patches into three forms of urban growth: edge expansion, infill, and outlying based on their ratio. Kopecká and Rosina (2014) defined the processes of urban extension, urban infill, and other urban changes based on the conversion of CLC classes.

Various physical, socio-economic, proximity, neighborhood, and policy-related variables have been identified as the main drivers of urbanization. Several authors have pointed out that it is important to examine multiple factors and their interactions at different levels of urban land hierarchy (Li et al., 2013). Zhang et al. (2017) conducted a spatial analysis of land use data obtained from multi-temporal remote sensing images of Suzhou between 1986 and 2008. Three urban growth types were identified: infilling, edge expansion, and leapfrog. Furthermore, they used global and local logistic regressions to model the probability of urban land conversion based on a set of spatial variables. The global logistic regression model found the significance of proximity, neighborhood conditions, and socio-economic factors. Regression analysis is widely used for prediction and forecasting, where its use substantially overlaps with machine learning. In some situations, however, regression analysis can infer causal relationships between the independent and dependent variables. Importantly, regressions reveal relationships between a dependent variable and a set of independent variables in a fixed data set. To use regressions to predict urban growth or to infer causal relationships, it is necessary to justify why existing relationships have predictive power for a new context or why a relationship between two variables has a causal interpretation. Dahal and Lindquist (2018) applied a hierarchical approach to investigate the temporal and spatial dynamics of the determinants of urbanization, different urban growth forms, and land use in Treasure Valley, Idaho. They used local logistic regression models based on a set of 18 spatial variables. According to their results, it was confirmed that proximity to urban areas has the greatest impact on new development. The study also documented that growth factors and their impact vary across the study area and through the cycles of urbanization at different levels of the urban landscape. The authors also pointed out that forms and classes of urban growth are, in turn, associated with specific factors. For instance, proximity to the road networks and urban proximity are linked to infill, commercial, and multi-family residential development. Proximity to water bodies, elevation, and population density are correlated to edge expansion, residential, and single-family residential classes. Dinda et al. (2019) applied factor analysis with multiple regression analysis to determine urban growth factors. The major factors were detected by comparing the low land price, the distribution of reclaimed land, the benefit of open space in the urban fringe, and income opportunities. Different determinants are important in different scales. Their choice depends on the particular objectives of the research and can vary from global to local scale. Kuru and Yüzer (2023) developed a model predicting the possible expansion of urban areas according to the main criteria defined as proximity, natural environments, built-up environments, and planning decisions. The analytical hierarchical process determined the weights of each criterion and associated subcriteria.

The aim of this paper is to present some examples of monitoring the dynamics of built-up areas at the regional level using the latest Copernicus data. An objective is a multi-temporal comparative analysis of the urban extension of built-up areas in two European capitals, Bratislava and Bucharest, with different population densities and economic conditions. The choice of the study areas was related to the solution of an inter-academic bilateral project aimed at urban dynamics research in Slovakia and Romania. We also present an example of a regression analysis to illustrate selected urban growth factors in two cities.

1. Methods and approaches

To identify urban land cover, UA data were used. UA provides pan-European reliable, intercomparable, high-resolution land cover and land use data for Functional Urban Areas (FUAs) with more than 50,000 inhabitants in EEA39 countries. FUA (initially referred to as LUZ – Large Urban Zone) coincides with the administrative boundary of NUTS 3, and the so-called Urban Core is defined by the administrative boundaries of the urban districts of Bratislava and Bucharest (LAU). Data are mainly based on a combination of (statistical) image classification and computer-assisted photo interpretation of VHR satellite images – in the case of Bratislava 2018 UA layer, Pleiades 1A, 1B, and PlanetScope with a spatial resolution of 2 m and 4 m, respectively; in the case of Bucharest 2018 UA layer, Pleiades 1A, 1B, and SPOT-6 with a spatial resolution of 2 m and 4 m, respectively. The nomenclature includes 17 urban classes with a minimum mapping unit (MMU) of 0.25 ha and ten rural classes with an MMU of 1 ha with an overall accuracy of 84% (Szatmári et al., 2019). Land cover change analysis was realized using layers for 2012 (t_1) and 2018 (t_2). The new urban fabric was identified in the second time horizon (2018).

As the focus was urban growth, all urban land cover classes were reclassified into two land classes: urban (developed) and non-urban (undeveloped). The urban land cover changes within FUAs were analyzed separately within the zone of the urban core defined by the administrative boundaries of the city, in the zone of adjacent outskirts 5 km from the city core border, in the suburban zone 10 km from the city core, and in the rural fringe zone (Šveda, 2011).

The newly developed patches within the zone of the urban core were classified into three urban growth forms: edge expansion, infill, and outlying. In order to classify the urbanized area into these three forms, we computed a ratio for each newly developed patch (Xu et al., 2007):

$$R_i = p_c/p_i, \tag{1}$$

where R_i is the ratio for a newly developed patch i, p_c is the common edge between patch i and existing urban patches, and p_i is the total perimeter of patch i. The value of R ranges between 0 and 1. Simple heuristic rules were applied to categorize the patches into the three urban growth forms. If $R_i > 0.45$, patch i is classified as infill; if $0 < R_i \leq 0.45$, patch i is classified as edge expansion; if $R_i = 0$, then patch i is classified as outlying.

Based on the literature review (Dahal and Lindquist, 2018) and the availability of the necessary data, we selected a set of independent variables (Tab. 1). The main data source of independent variables was Urban Atlas at t_1. The location of motorway links and railway platforms in 2012 was accessed from Overpass API, where historical Open Street Maps (OSM) data are stored. We also used the European Digital Elevation Model (EU-DEM) as a driving factor.

All independent variables were preprocessed using QGIS. All vector variables were rasterized to 30 meters in the first step to match the EU-DEM resolution. We calculated the proximity to highway links, railway platforms, vegetation areas, and water bodies. Roads and urban density were calculated using the Kernel Density Estimation tool. We also incorporated dummy variables of the presence of the zones of the urban core, zone of adjacent outskirts, suburban zone, and the rural fringe zone.

Tab. 1 Data sources for independent variables for the regression analysis

Independent variables	UA class code	Units	Data source
Environmental			
Elevation		meters (m)	EU-DEM
Slope		degrees	EU-DEM
Vegetation proximity	31000, 32000	meters (m)	UA
Water proximity	50000	meters (m)	UA
Transport networks			
Distance to motorway link		meters (m)	OSM
Distance to railway platform		meters (m)	OSM
Road density	12220	m/km^2	UA
Agglomeration			
Urban density	< 20000	m/km^2	UA
Zone of urban core		binary	UA
Zone of adjacent outskirts		binary	UA
Suburban zone		binary	UA
Rural fringe zone		binary	UA

To sample the dependent variable, we merged the areas of the new urban fabric, areas that were not changed between t_1 and t_2, and water bodies to exclude this class from sampling. We then randomly sampled 300 points for change and no-change areas, resulting in 600 samples of dependent variables. We ensured that samples were more than 100 meters apart to reduce autocorrelation and repeated this procedure for both cities.

Before conducting the regression analysis, all factors displaying substantial collinearity, defined as having a variance inflation factor exceeding 5 (Ott and Longnecker, 2010), were eliminated. Moreover, we assessed the mutual correlations among these factors (Fig. 1) and excluded those from any pair of highly correlated factors (with a Pearson correlation coefficient greater than 0.75) that demonstrated both greater collinearity and stronger correlation with other factors.

Given the binary nature of dependent variables (0 – no change, 1 – change), we used global logistic regression in this study. The binary response variable is connected through the logit function to the independent variables or determinants in logistic regression. This connection allowed us to transform the relationship into probabilities regarding the likelihood of an event, such as the development of new urban areas (Atkinson and Massari, 2011). We applied a logistic regression model using the Python statsmodels package. Before training, the set of samples for each city (Fig. 2) was split into train (70%) and test (30%) and the independent variables were standardized by transforming their values to achieve a mean of 0 and a standard deviation of 1, following the formula:

$$z = (x - \mu) / \sigma, \tag{2}$$

where z represents the standardized value, x denotes the original value of the independent variable, μ represents the mean of the independent variable, and σ represents the standard deviation of the independent variable.

The accuracy of the model was tested using the receiver operating characteristic (ROC) area under the curve (AUC) statistics comparing the false-positive error rate with the true-positive rate of estimated probabilities (Galletti et al., 2013). The AUC values typically fall within the range of 0.5 (random allocation) to 1 (perfect fit). Typically for land cover and land use change, for models to be considered successful, their AUC statistic should surpass a threshold of 0.75 (Prishchepov et al., 2013; Pazúr et al., 2014).

Based on the result of the regression model, we considered regression coefficients only if the Wald statistic test confirmed the resulting significance at a p-value lower than 0.05. Those factors that were non-significant were removed from subsequent analyses.

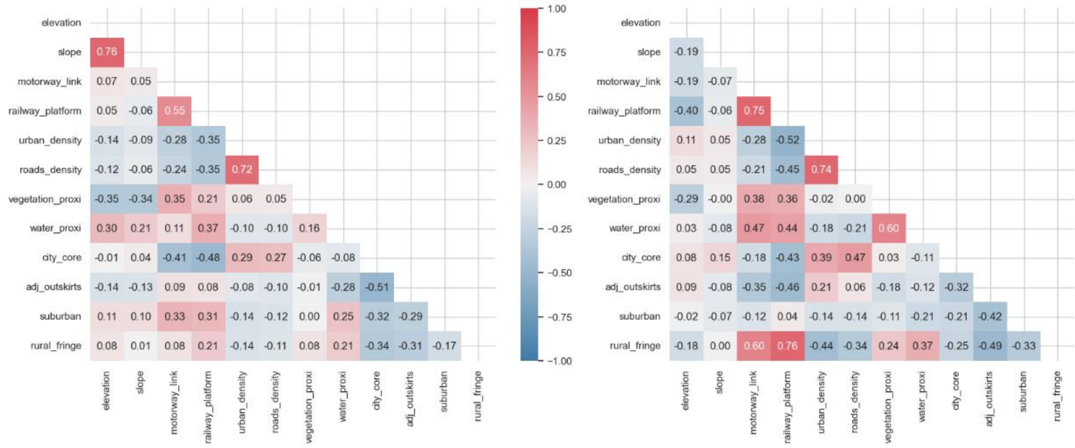

Fig. 1 Pearson's correlation coefficient between independent variables for Bratislava (left) and Bucharest (right)

2. Study areas

The city of Bratislava, the capital of Slovakia, and the city of Bucharest, the capital of Romania, were selected as the study areas for this analysis. Bratislava is situated in the Danubian Lowland, surrounded by the foothills of the Malé Karpaty mountains in the west. The city is situated in the south-western part of Slovakia, bordering Austria in the west and Hungary in the south. Bratislava is the country's largest city and political, cultural, and economic center. It lies on both banks of the Danube River, which crosses the city from the west to the south-east. The population of Bratislava by the end of 2022 was 476,922 inhabitants, with a population growth of more than 6.61% between 2000 and 2022. Due to its good-quality transport infrastructure, it is a territory with high potential for territorial development. However, the bordering mountains are a limiting factor for further expansion.

Bucharest is situated on the banks of the Dâmboviţa River, which flows into the Argeş River, a tributary of the Danube. Several lakes – the most important being Lake Floreasca, Lake Tei, and Lake Colentina – stretch across the city along the Colentina River, a tributary of the Dâmboviţa. The geography is exclusively plain and belongs to the Vlăsiei Plain (the entire Bucharest Plain). The city's elevation is 70–80 m above the level of the Black Sea. The geographical and administrative position assisted the development of major communication routes. Eight national roads and a highway depart from Bucharest, which also has four double railway routes that make it the central railway hub of the country. The business environment is attractive for Romanian and foreign investors because of the existing institutions, high-skilled labour force, and well-developed communication system. The population is roughly 1.9 million within the city limits and 2.15 million within the greater metropolitan area.

Although Bucharest is almost four times larger than Bratislava in terms of population, the area of FUA Bucharest, which is 107,809 ha, represents approximately half of the territory of FUA Bratislava (205,160 ha).

3. Results

The total area of newly developed patches between 2012 and 2018 was 2757 ha in Bratislava and 3094 ha in Bucharest. Spatial analysis of UA data within the FUA in both cities indicates that a significant majority of newly built areas are located in the suburban area within 10 km of the urban core. In Bucharest, up to 72% are in the zone of adjacent outskirts within 5 km of the urban core (Tab. 2). We used red shading in concentric zones to visualize the spatial distribution of changed developed areas, while urban development polygons were shown in contrasting yellow (Fig. 3 and 4). The chart in the right corner of the figure shows the ratio of changes within existing artificial surfaces and newly developed areas in the concentric zones.

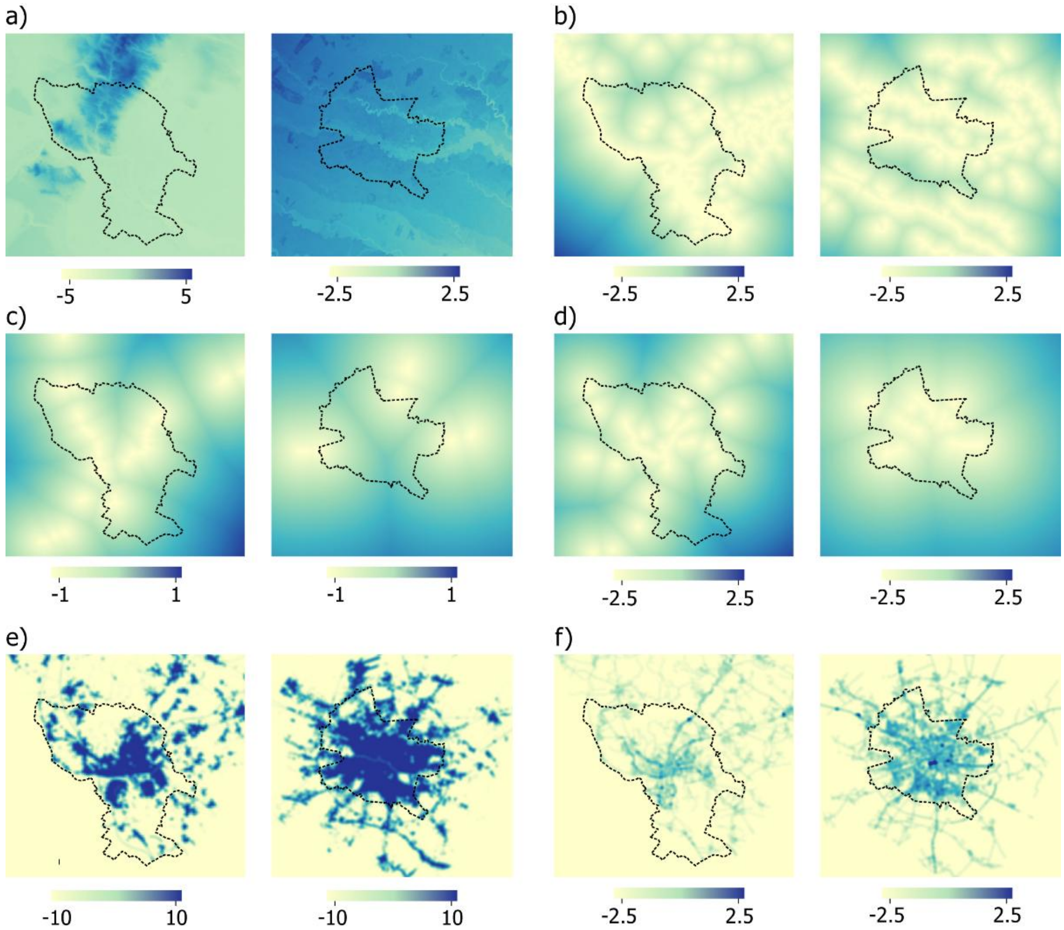

Fig. 2 Example of independent variables (standardized) used to model the occurrence of the new urban development in Bratislava (left) and Bucharest (right): a) elevation, b) water proximity, c) distance to motorway link, d) distance to railway platform, e) urban density, f) road density

Urban growth indicates a transformation of the vacant land or natural environment for the construction of urban fabrics, including residential, industrial, and infrastructure development. Within Bratislava, urbanization caused the most significant decrease in arable land (in total, 1098 ha), pastures (333 ha), permanent crops (155 ha), and forests (109 ha). The most significant increase was recorded in the class *Construction sites*, followed by *Urban fabric*, and *Industrial and commercial*

Tab. 2 Urban development in the years 2012–2018 in terms of share and area in concentric zones of the FUA of Bratislava and the FUA of Bucharest

	FUA Bratislava			FUA Bucharest		
Zones	patches	%	ha	patches	%	ha
Rural fringe	648	39.3	880.4	184	7.2	162.3
Suburban	207	12.6	310.2	512	20.0	552.3
Adjacent outskirts	406	24.7	695.4	1421	55.4	1734.8
Urban core	386	23.4	870.5	446	17.4	644.5

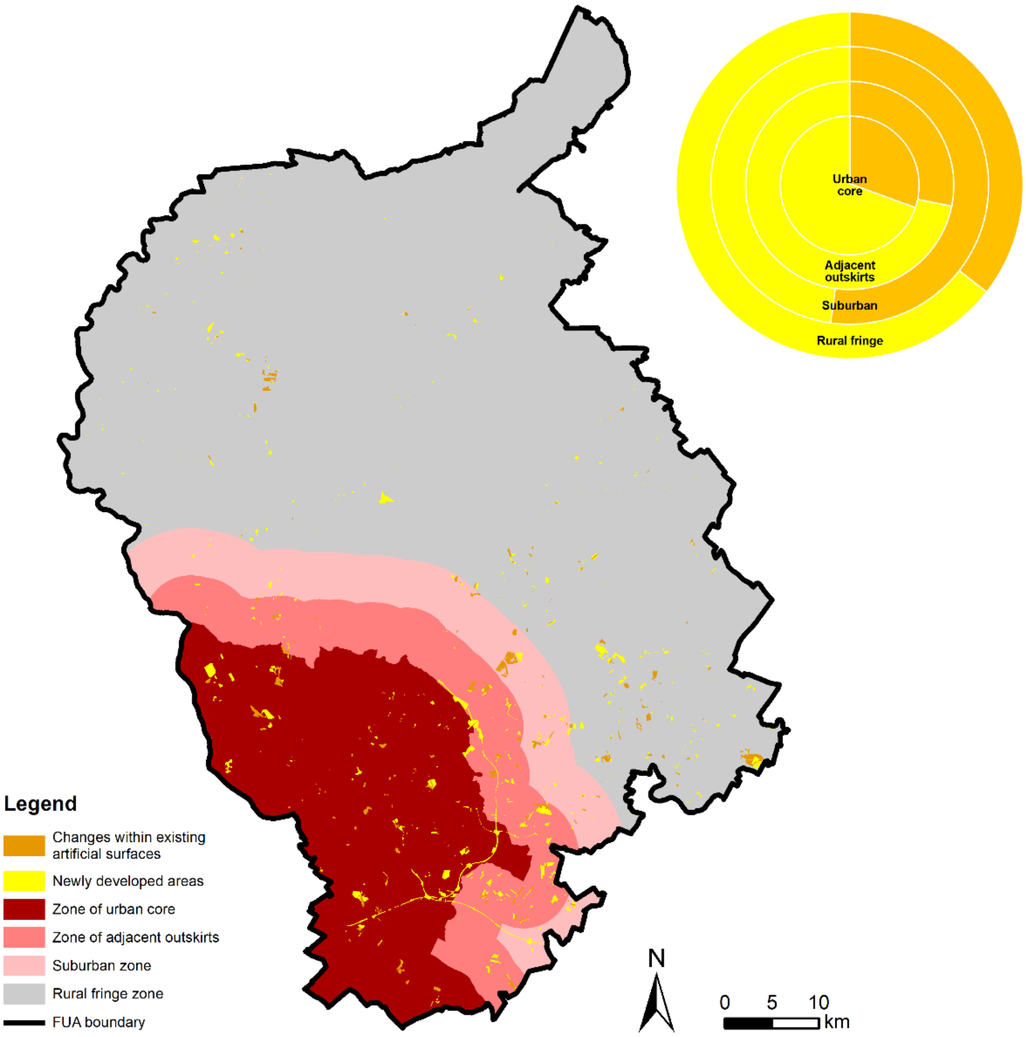

Fig. 3 Urban development between 2012 and 2018 in concentric zones of the FUA of Bratislava

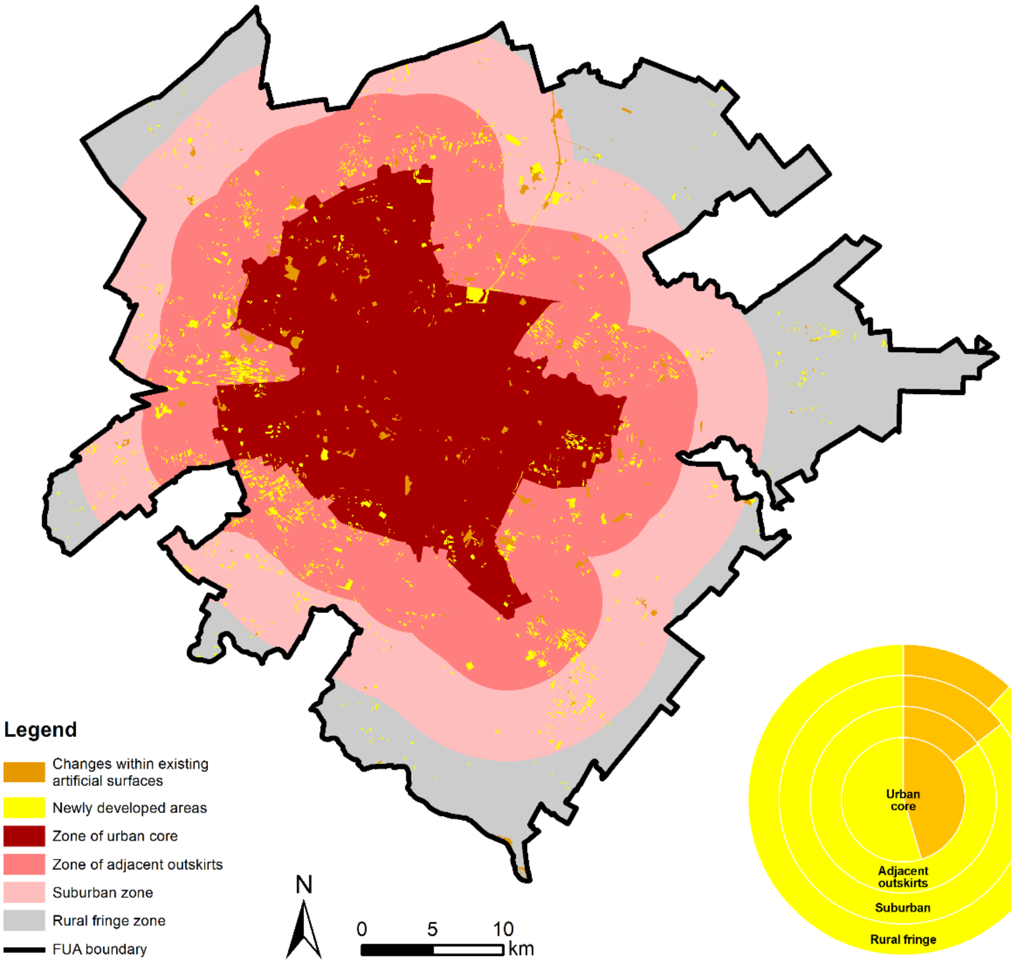

Fig. 4 Urban development between 2012 and 2018 in concentric zones of the FUA of Bucharest

areas. Graphical representation of land cover flows (Fig. 5) enables not only the assessment of the decrease and increase of individual land cover classes but also the comparison of trends in different study areas. This graph clearly documents changes within existing artificial surfaces and newly developed areas on the second hierarchical level of UA. Changes within existing artificial areas are represented by the conversion of 1X classes from 2012 to other 1X classes in 2018, including internal changes within one class at the third hierarchical level. Newly developed areas are represented by the conversion of 2X, 3X, and 4X classes to 1X classes in 2018. In terms of the number of polygons, the *Urban fabric areas* significantly predominated (Tab. 3 and 4). The most significant changes occurred in the area of the Danubian Lowland, north-east of the city center (Chorvátsky Grob, Slovenský Grob, Bernolákovo, Most pri Bratislava, Malinovo). Anthropogenic changes related to gravel mining on former arable land were also widespread.

Similarly, in Bucharest, arable land and pastures were the most important areas for the origin of new urbanized polygons. In contrast to Bratislava, the dominant changes were *Urban fabric* and *Industrial and commercial areas* in favor of arable land and pastures, either in terms of area or the number of polygons. *Construction sites* were less represented than in Bratislava (Tab. 5 and 6). The changes significantly dominated the zone of adjacent outskirts 5 km from the city. In contrast to Bratislava, where the city's growth is limited by the state border with Hungary and Austria and partially by the Little Carpathian mountains, Bucharest, located on the plain, is growing evenly in all directions.

From the point of view of forms of urban growth in the city core, similar trends were recorded in Bratislava (Fig. 6) and Bucharest (Fig. 7).

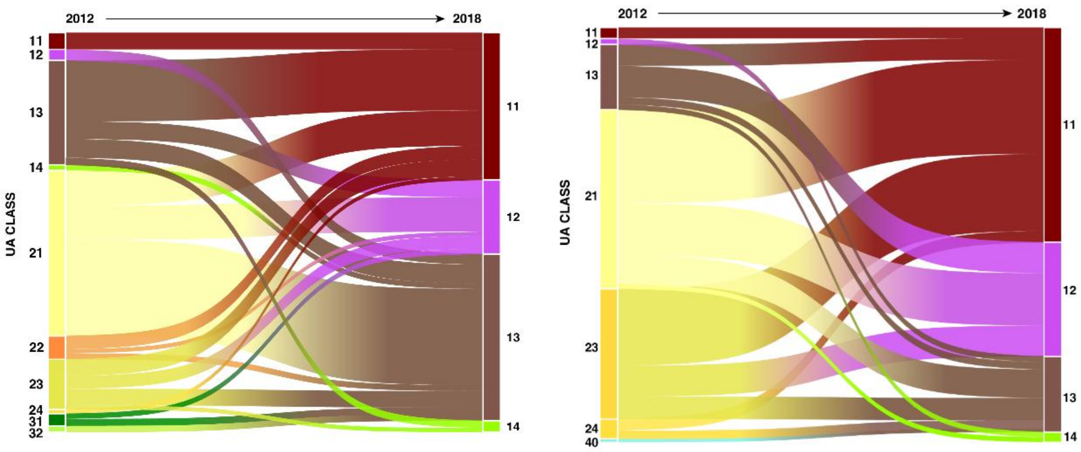

Fig. 5 Graphic representation of land cover flows in the years 2012–2018 in the FUA of Bratislava (left) and the FUA of Bucharest (right)

Tab. 3 Urbanization between 2012 and 2018 within the FUA of Bratislava in hectares

	UA class code	Arable land (annual crops)	Permanent crops	Pastures	Complex and mixed cultivation	Forests	Herbaceous vegetation associations
UA class code		21	22	23	24	31	32
Urban fabric	110	232.6	88.5	110.9	27.2	10.0	19.2
Industrial and commercial units	121	195.5	24.7	72.6	2.6	34.8	15.1
Road and rail network and associated land	122	31.2	2.7	12.9	0.3	0.3	1.9
Mineral extraction and dump sites	131	84.1	0.0	4.8	0.0	22.7	5.5
Construction sites	133	503.6	31.7	78.7	1.6	23.1	28.7
Land without current use	134	48.7	7.1	25.8	5.4	0.0	7.4

The edge expansion accounted for 25% in Bratislava and 15% in Bucharest (Tab. 7). In Bratislava, the expanding urbanization took more than 286 ha of vacant land during the relevant six years. The most extensive type of change (more than 179 ha) was that of arable land to construction sites, followed by pastures (26 ha), and permanent crops (9 ha). The distinct reduction of arable land is also attributable to the construction of a highway bypass of the city and several big shopping malls and residential zones (Bory, Slnečnice, Podunajská brána, etc.).

Tab. 4 Urbanization between 2012 and 2018 within the FUA of Bratislava by number of polygons

	UA class code	Arable land (annual crops)	Permanent crops	Pastures	Complex and mixed cultivation	Forests	Herbaceous vegetation associations
UA class code		21	22	23	24	31	32
Urban fabric	110	230	82	122	50	20	21
Industrial and commercial units	121	65	13	33	2	7	6
Road and rail network and associated land	122	50	13	24	2	2	3
Mineral extraction and dump sites	131	22	0	4	0	4	3
Construction sites	133	88	14	37	3	19	15
Land without current use	134	51	13	30	10	0	10

Tab. 5 Urbanization between 2012 and 2018 within the FUA of Bucharest in hectares

	UA class code	Arable land (annual crops)	Pastures	Complex and mixed cultivation	Forests	Herbaceous vegetation associations
UA class code		21	23	24	31	32
Urban fabric	110	667.1	545.9	82.5	2.7	4.5
Industrial and commercial units	121	320.5	181.8	17.1	15.9	0.0
Road and rail network and associated land	122	50.5	37.1	1.1	0.0	0.0
Mineral extraction and dump sites	131	35.4	35.9	0.0	10.4	0.0
Construction sites	133	138.5	106.8	55.6	2.7	5.9
Land without current use	134	27.3	16.7	4.0	0.0	0.0

The total area of urban extension for the urban core in Bucharest was almost 127 ha during the investigated period. It was primarily connected with the transformation of agricultural land into construction sites and residential areas.

The structure of the settlement landscape does not change only beyond the boundaries of the compact urban fabric. Apart from open spaces filled in by new construction, large areas of land without current use are transformable into trade-administrative centers or new residential quarters. In both cities, urban infill played a much more significant role in urbanization than edge expansion. This form of urban growth in Bratislava was twice as large (545 ha); in the case of Bucharest, it was four times larger (503 ha).

In Bratislava, the biggest reduction of the class *Construction sites* within urban infill was in favor of residential areas (82 ha). Distinct urban infilling is also evident due to the construction of new residential areas via the conversion of all agricultural classes: arable land (12 ha), permanent crops, especially vineyards (11 ha), and pastures (10 ha).

Tab. 6 Urbanization between 2012 and 2018 within the FUA of Bucharest by number of polygons

	UA class code	Arable land (annual crops)	Pastures	Complex and mixed cultivation	Forests	Herbaceous vegetation associations
UA class code		21	23	24	31	32
Urban fabric	110	712	484	109	5	7
Industrial and commercial units	121	244	111	25	3	0
Road and rail network and associated land	122	65	26	2	0	0
Mineral extraction and dump sites	131	10	11	0	4	0
Construction sites	133	80	56	3	1	2
Land without current use	134	40	23	6	0	0

The urban infill registers the highest rates of urban development in Bucharest. The increase in residential areas within the urban core is mainly associated with the conversion of arable land (54 ha), pastures (45 ha), construction sites (30 ha), land without current use (25 ha), and green urban areas (over 10 ha). The industrial and commercial units were primarily enlarged by transforming existing artificial areas, namely construction sites (54 ha) and land without current use (49 ha).

The urban growth form classified as outlying has in both study areas only a marginal proportion (6.5% in Bratislava and 3.8% in Bucharest).

Our results of logistic regression documented that environmental factors (specifically proximity to water bodies and elevation) remained the major driving factors of new development in both study areas (Tab. 8 and 9). Elevation remains a significant driver for Bratislava (Tab. 8), whereas in Bucharest, proximity to water bodies (Tab. 9) was the only significant driver. Both of these variables were negatively correlated with urbanization, which is in line with the findings of Liao and Wei (2014) and Dahal and Lindquist (2018). The Malé Karpaty mountains in Bratislava and the nearby water bodies in Bucharest constrain urban growth patterns, impacting infrastructure development and accessibility. In contrast, transportation networks did not emerge as significant factors for new urban area development, which differs from the results of Müller et al. (2010) and Alqurashi et al. (2016). Urban agglomeration factors were also not significant in either city.

We therefore ran a second logistic regression model where we set the Urban core zone variable as the reference variable (Intercept) and let the model estimate the effects of the other zone variables relative to this reference zone (Tab. 10). In this case, adjacent outskirts and rural fringe zones remain significant factors of the new urban area development for Bucharest; the zone of adjacent outskirts shows a positive correlation with new urban development, in contrast to the rural fringe zone. A comparison of the AUC statistics indicates a noticeably higher accuracy for the Bucharest model than for Bratislava (Fig. 8).

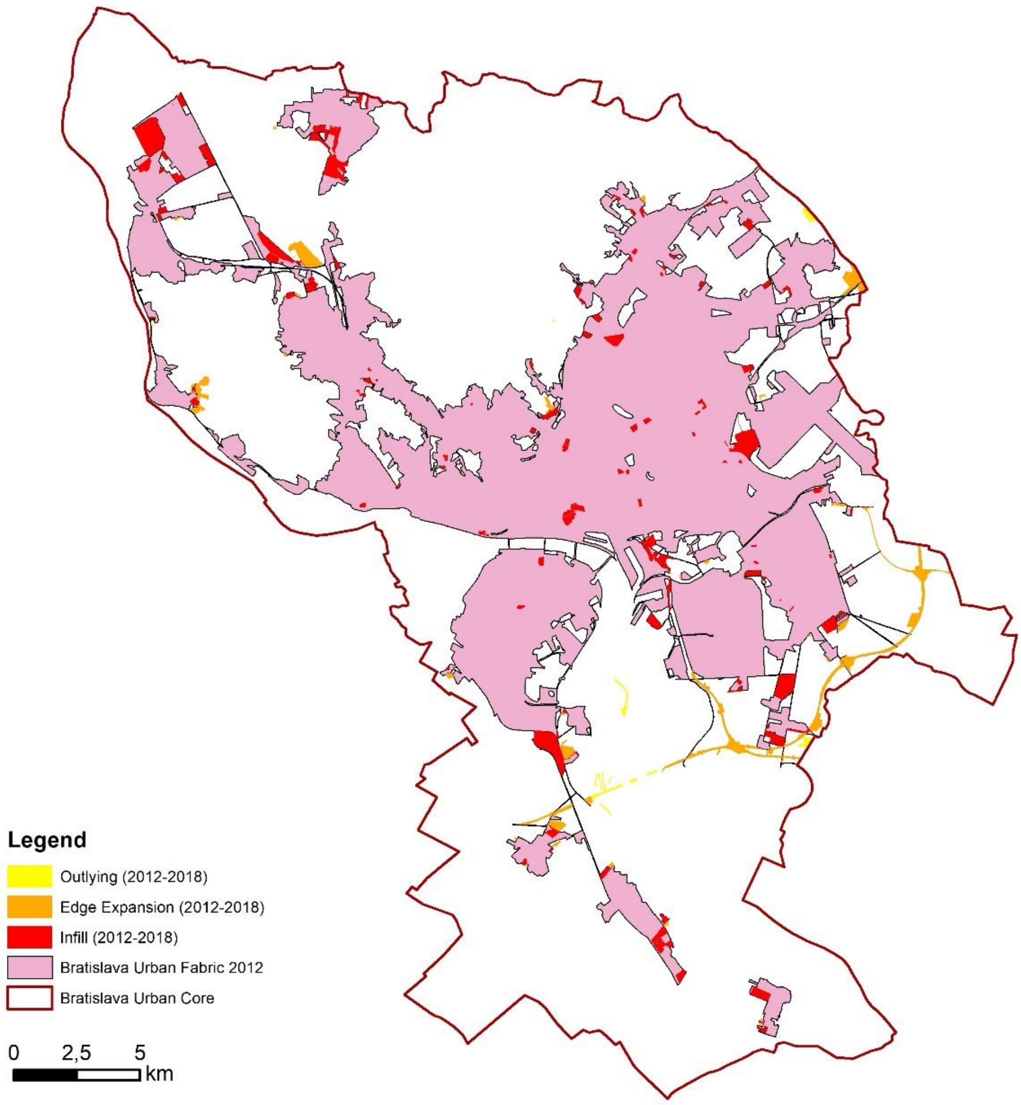

Fig. 6 Urban development between 2012 and 2018 in concentric zones of the FUA of Bucharest

While the logistic regression analysis presented valuable insights into the driving factors of new urban development in Bratislava and Bucharest, the exclusion of certain socio-economic and population variables may limit the comprehensiveness of the analysis. Exploring additional factors in these domains could enhance the understanding of urbanization dynamics.

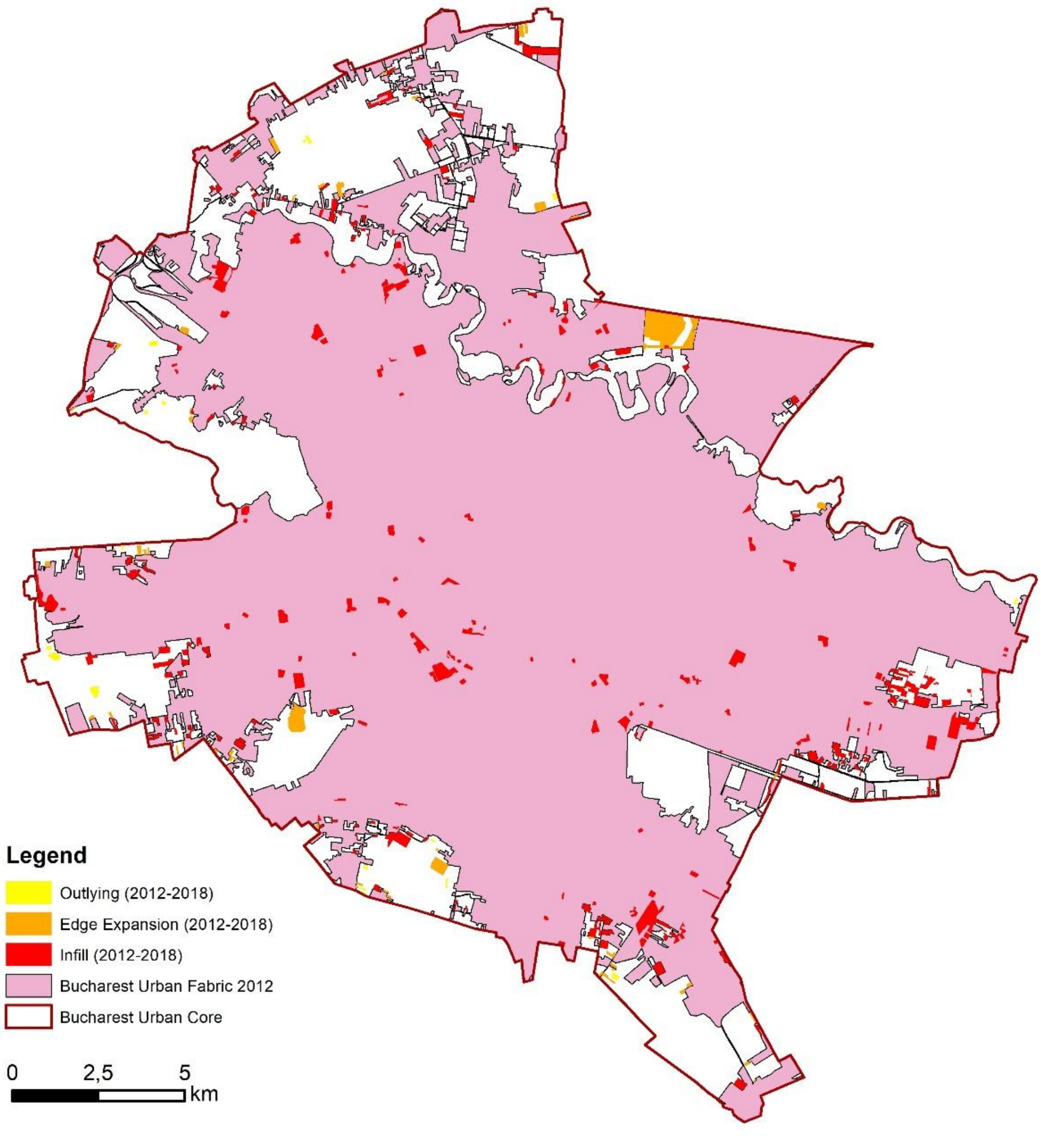

Fig. 7 Urban development between 2012 and 2018 in concentric zones of the FUA of Bucharest

Tab. 7 Representation of urban growth forms within the urban core of Bratislava and Bucharest

	Bratislava urban core			Bucharest urban core		
Zones	**patches**	**%**	**ha**	**patches**	**%**	**ha**
Outlying	25	6.5	34.8	17	3.8	14.6
Edge expansion	96	25.0	286.2	67	15.0	126.8
Infill	263	68.5	545.0	362	81.2	503.1

Tab. 8 Regression model summary for the Bratislava model

Variables	Coefficient	Standard error	z	Wald p-test > |z|
Intercept	0.71	1.38	0.52	0.61
Elevation	-1.46	0.31	-4.74	0.00
Distance to motorway link	0.09	0.16	0.58	0.56
Distance to railway platform	-0.60	0.17	-3.58	0.00
Urban density	-0.29	0.16	-1.88	0.06
Road density	0.09	0.15	0.61	0.54
Vegetation proximity	-0.18	0.14	-1.35	0.18
Water proximity	0.28	0.15	1.95	0.05
City core	-0.89	1.39	-0.64	0.52
Adjacent outskirts	-0.22	1.38	-0.16	0.87
Suburban	-1.46	1.39	-1.05	0.29
Rural fringe	-0.96	1.39	-0.69	0.49

Tab. 9 Regression model summary for the Bucharest model

Variables	Coefficient	Standard error	*z*	Wald p-test > |*z*|
Intercept	-0.03	1.26e+07	0.00	1.00
Elevation	0.03	0.15	0.19	0.85
Slope	-0.13	0.14	-0.88	0.38
Distance to motorway link	-0.03	0.18	-0.16	0.87
Urban density	0.38	0.21	1.82	0.07
Road density	-0.22	0.19	-1.15	0.25
Vegetation proximity	-0.24	0.21	-1.16	0.25
Water proximity	-0.46	0.20	-2.26	0.02
City core	0.26	1.26e+07	0.00	1.00
Adjacent outskirts	1.62	1.26e+07	0.00	1.00
Suburban	-0.23	1.26e+07	0.00	1.00
Rural fringe	-1.68	1.26e+07	0.00	1.00

Tab. 10 Second regression model summary for agglomeration variables

	variables	coefficient	standard error	z	Wald p-test > |z|
Bratislava	Intercept	17.41	7254.41	0.00	1.00
	Adjacent outskirts	-16.92	7254.41	0.00	1.00
	Suburban	-18.13	7254.41	0.00	1.00
	Rural fringe	-17.68	7254.41	0.00	1.00
Bucharest	Intercept	0.22	0.35	0.63	0.53
	Adjacent outskirts	1.37	0.41	3.31	0.00
	Suburban	-0.48	0.44	-1.11	0.27
	Rural fringe	-1.93	0.54	-3.57	0.00

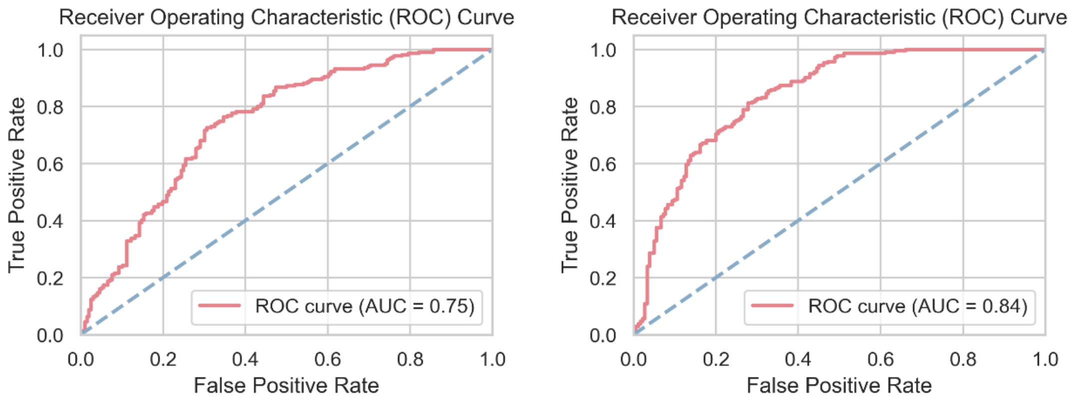

Fig. 8 Comparison of AUC statistics of the Bratislava (left) and Bucharest model (right)

Discussion

Functional regional taxonomy based on functional city regions has been addressed in several studies (e.g. Bezák, 2000; Bezák, 2014; Halás and Klapka, 2020; Šveda, 2011). Although the authors' approaches differ methodologically, it is clear that the crucial role in defining functional regions is primarily played by the availability of data on the population, its activities, and spatial ties. The primary indicators of functional links creating a functional region are attendance at work (school) and the allocation of jobs. In all functional urban regions, there is a distinction between a core consisting of one or several cities and a periphery connected to the core by a network of connections of various kinds, the intensity of which decreases with increasing distance from the core. In contrast to these approaches within the UA project, the FUA coincides with the administrative boundary of NUTS 3. Similarly, the Urban Core area is defined exclusively based on the administrative boundaries of the urban districts of Bratislava and Bucharest (LAU); no functional links were analyzed for its definition. When interpreting the results, it is therefore necessary to consider that the input data come from a pan-European database, which does not take into account the regionally used classification of functional urban regions.

Due to the interpretation of the results, the method of their visualization is essential so that the presented data can be understood as best as possible. Additional graphs showing the ratio of changed and new anthropogenic areas within individual concentric zones were part of the innovative cartographic processing of UA data. The improved way of visualizing UA data is the main contribution of this study.

Conclusion

Urban areas are highly dynamic and the landscape is changing rapidly. Remote sensing data and the Copernicus database provide low-cost and up-to-date spatial data that can be used to provide useful information for city managers and planners. The presented examples document mapping of urban dynamics based on land cover change analysis from which secondary socio-economic information and other invisible elements of urban infrastructure can be derived.

The assessed changes showed that the process of urbanization played a significant role in both cities during the monitored period. A comparison of urban development in Bratislava and Bucharest points to a similar share of urban growth forms. We found that environmental factors were most significant for both cities, especially elevation for Bratislava and distance to water bodies for Bucharest. However, only a few factors were significant for both cities. For a better comparison of driving factors for new urban development in Bratislava and Bucharest, we need to identify new driving factors, primarily in socio-economic and population domains. Moreover, we need to look at the significance of driving factors through the prism of model accuracy. Both models show reasonable accuracy with AOC statistics; however, finding new driving factors could also improve the model accuracy, and thus the significance of existing factors could increase.

The growth of new urbanized areas has taken place mainly at the expense of arable land. The significant proportion of areas under construction indicates that the urbanization process will continue in the coming years, and the landscape will continue to change dynamically. A multi-temporal spatial analysis can help to identify the size, direction, and rate of urban construction or destruction of natural resources. Green urban infrastructure is essential for the biodiversity of urban ecosystems and for people. With an increasing population, the urban infill in Bucharest documents the significance of monitoring internal land uses, especially urban greenery within the town, to avoid the negative effects of the high soil sealing. Optimal visualization of these processes leads to a better understanding and representation of urban dynamics and helps in developing alternative concepts of spatial structure and changes in cities.

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R e s u m é

Dynamika urbánneho rozvoja na základe údajov programu Copernicus: prípadová štúdia Bratislava a Bukurešť

Rast metropolitných sídiel má priamy vplyv na kvalitu života miestnych obyvateľov. Sledovanie a prognózovanie ich budúceho vývoja je kľúčovým predpokladom pre prijatie zásadných opatrení na reguláciu využívania územia, optimalizáciu funkčného využitia mestského priestoru, budovanie infraštruktúry, ako aj navrhovanie opatrení na elimináciu negatívnych javov (napr. mestské ostrovy tepla). Cieľom tohto príspevku je prezentovať vizualizáciu dynamiky urbanizácie na regionálnej úrovni na príklade Bratislavy a Bukurešti v rokoch 2012 – 2018, a tiež príklad regresnej analýzy zameranej na vybrané priestorové determinanty rozvoja. Monitorovanie urbanizácie si vyžaduje nové analytické prístupy a nové zdroje údajov a informácií. Program Copernicus je jedným z najdôležitejších zdrojov údajov o meniacej sa urbanizovanej krajiny. Tento program ponúka bezplatné údaje zo satelitného pozorovania Zeme, ako aj z nich odvodené databázy (napr. CORINE Land Cover, Urban Atlas). Služba Copernicus Land Monitoring Service (CLMS) bola v roku 2012 implementovaná Európskou agentúrou pre životné prostredie a Spoločným výskumným centrom Európskej komisie. Táto služba poskytuje geopriestorové informácie o krajinnej pokrývke a jej zmenách, využívaní krajiny, pohybe zemského povrchu, stave vegetácie, vodnom cykle a premenných povrchovej energie Zeme. Dáta môžu byť použité v rôznych oblastiach rozhodovacej sféry, ako je územné a mestské plánovanie, poľnohospodárstvo a potravinová bezpečnosť, lesné hospodárstvo, vodné hospodárstvo, ochrana a obnova prírody, rozvoj vidieka, ekosystémové účtovníctvo. Na základe údajov Urban Atlas z rokov 2012 a 2018 boli triedy krajinnej pokrývky na záujmovom území preklasifikované do dvoch tried: urbanizované a ostatné. Zmeny krajinnej pokrývky v rámci funkčných mestských oblastí (FUA) boli analyzované samostatne v rámci koncentrických zón: zóny mestského jadra, v priľahlej zóne 5 km od hranice jadra mesta, v suburbánnej zóne 10 km od jadra mesta a vo vidieckej okrajovej zóne (Šveda, 2011). Priestorová analýza na báze údajov Urban Atlas v oboch mestách dokumentuje, že významná väčšina areálov novej zástavby sa nachádza v zázemí do 10 km od jadra mesta, pričom v Bukurešti je až 72 % novovzniknutých zastavaných areálov v zázemí do 5 km od mestského jadra. Novovzniknuté areály zástavby v mestskom jadre boli rozdelené do troch foriem rastu: rozširovanie okrajov, zahusťovanie a odľahlá výstavba. Kritériom pre zaradenie do jednotlivých foriem rastu je pomer celkového obvodu novovzniknutého zastavaného areálu a spoločnej hranice s existujúcim zastavaným územím. Nakoniec sme použili binárnu logistickú regresiu na analýzu vplyvu vybraných premenných na klasifikáciu pravdepodobnosti lokalizácie budúcej zástavby. Boli analyzované tieto priestorové determinanty urbanizácie: nadmorská výška, sklon, vzdialenosť od lesov, vzdialenosť od vodných plôch, vzdialenosť od diaľnice, vzdialenosť od železničného nástupišťa, hustota cestnej siete. Výsledky regresnej analýzy dokumentujú, že pre obe mestá boli najvýznamnejšie environmentálne faktory, a to nadmorská výška v prípade Bratislavy a vzdialenosť od vodných plôch v prípade Bukurešti. Pre lepšie pochopenie hybných síl urbanizácie v uvedených metropolách bude potrebné identifikovať ďalšie, najmä socioekonomické faktory. Prezentované mapové výstupy vhodným spôsobom vizualizujú vybrané informácie zo satelitných údajov a programu Copernicus a poskytujú presné, aktuálne a spoľahlivé údaje pre samosprávu a územné plánovanie.

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