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IDENTIFICATION AND LANDSCAPE PATTERN ANALYSIS OF PERI-URBAN AREAS: A CASE STUDY OF BUDAPEST, HUNGARY

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Abstract

The process of peri-urbanization in the context of globalization has become a global phenomenon. Taking Budapest as a case study, this study aims to develop a breakpoint clustering method that combines breakpoint method and spatial clustering to identify peri-urban areas (PUAs). Landscape metrics were used to analyze the structure and characteristics of various landscapes within PUAs. The results indicate that PUAs in Budapest occupy 39.63% of the area, predominantly consisting of artificial surfaces and agricultural land. In PUAs, artificial surfaces are the dominant landscape type, water bodies exhibit high aggregation and strong connectivity, while agricultural areas, forests and semi-natural areas show high fragmentation. The identification and landscape analysis of PUAs will provide significant insights for urban studies and governmental planning.

Keywords: peri-urbanization, breakpoint method, spatial clustering, landscape metrics

INTRODUCTION

Since the mid-20th century, numerous new regions characterized by an intermingling of urban and rural functions have emerged globally. This phenomenon has led to the progressive blurring of traditional urban-rural boundaries, now widely recognized as peri-urbanization. Currently, the development of Peri-urban areas (PUAs) has become a prevalent global trend. According to Eurostat (2022), approximately 35.9% of the European Union population resides in towns or suburbs, which overlap significantly with PUAs.

At present, there is no consensus on the definition of PUAs across different regions (Sylla et al., 2019). However, their transitional and hybrid characteristics are prominent in many regions (Gallent et al., 2006). First, PUAs are in a transitional phase regarding landscape and spatial functions, a phenomenon considered an intrinsic feature of urbanization (Johnson, 1974). Furthermore, urban and rural elements intermingle within PUAs, leading to a disorganized land use structure. Therefore, promoting the development of PUAs towards an orderly and efficient state can effectively prevent the waste of land resources, thereby facilitating the sustainable development of cities (Wandl & Magoni, 2017).

Accurate identification of PUAs' spatial boundaries is essential for their sound planning. The dynamism and ambiguity of the boundaries of PUAs have led to ongoing academic debates regarding their identification. Currently, there are no unified theories or methods for this purpose (Mortoja et al., 2020). Early studies often relied on empirical delineation of PUAs (Bryant et al., 1982), but this method faced significant regional constraints. Subsequently, With the introduction of multi-source data and digital technologies, quantitative research has increasingly supplanted qualitative methods. Scholars have begun to utilize technologies such as Geographic Information Systems (GIS) and Remote Sensing (RS) to identify PUAs (Zeng et al., 2022). Over the years, methods like breakpoint analysis and spatial clustering have emerged as popular methods, and their accuracy has been verified in multiple global contexts (Gonçalves et al., 2017; Zhu et al., 2022). In Europe, there are a few studies on identifying PUAs through spatial clustering. However, the application of the breakpoint method is not yet widespread.

In this context, this study aims to develop an innovative method that integrates the breakpoint method with spatial clustering to identify the spatial boundaries of PUAs. Landscape metrics were used to analyze the landscape structure and characteristics of PUAs. This study seeks to answer the following questions: Can the breakpoint clustering method identify the spatial boundaries of PUAs? What are the characteristics of land use and landscape patterns in PUAs? This research not only provides a foundation for in-depth studies of PUAs but also helps planners and managers in more effective planning and management of PUAs.

METHODS AND MATERIALS

Study area

Budapest is the capital and the largest city of Hungary. The Danube River bisects the city, with the western side predominantly mountainous and the eastern side mainly characterized by plains (Fig. 1). Budapest was formed in 1873 through the merger of Buda and Pest. The subsequent 30 years witnessed Budapest's most rapid phase of urban development and territorial expansion, a process that was interrupted by the onset of World War I (Beluszky, 1999). In 1950, "Greater Budapest" was established, incorporating independent settlements that were originally located in the suburbs. This process laid the foundation for the present structure of Budapest (Egedy et al., 2017). Budapest covers an area of 525.12 km^2 and had a permanent population of 1,750,216 in 2020 (Hungarian Central Statistical Office (KSH), 2023).

Data

This research consistently employs data from the year 2020. Land use/ land cover data was modified based on the vector data from the Urban Atlas Land Cover/Land Use 2018 (European Environment Agency, 2020), in combination with the Sentinel-2 remote sensing imagery from 2020 and the land classification results by Gudmann and Mucsi (2022). The final data was converted to raster format with a 5m resolution. The nighttime light data was sourced from Chen et al. (2021), with a spatial resolution of 500 m. The population data was sourced from the WorldPop dataset (WorldPop 2020). The impervious surface data were derived from the global 30m impervious surface dataset developed by Zhang et al. (2022). All datasets were aligned to the WGS_1984_UTM_Zone_34N projected coordinate system in ArcGIS 10.8.

Given the precision of the collected data and the geographical extent of Budapest, the study unit was set to 500 m × 500 m. Therefore, 2,397 grids were delineated within Budapest's administrative boundaries. Subsequent spatial analyses of the indicator data were conducted based on these grids.

Framework of Breakpoint Clustering Method

This study is based on the hypothesis that within the spatial transect from urban centres to the peripheral rural areas, there are numerical abrupt breakpoints at the interfaces of PUAs with urban and rural areas. These breakpoints delineate the inner boundaries of PUAs at the urban interface and the outer boundaries at the rural interface (Liao et al., 2021). By collecting and classifying these points, PUAs can be effectively demarcated.

Evaluation indicators

Considering the hybrid characteristics of PUAs, this study selected four indicators from urban and rural dimensions: Proportion of impervious surface (PIS), Nighttime light intensity (NLI), Proportion of agricultural, forest and semi natural areas (PAF), Per capita land area (PCLA) (Table 1). The indicators of the urban dimension have higher values in urban areas and lower values in rural areas. Conversely, the indicators of the rural dimension display the opposite trend. The intermediate values of these indicators represent PUAs.

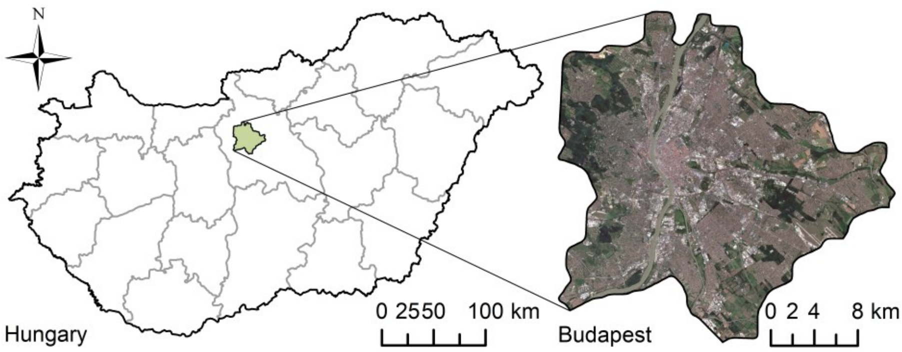

Fig.1 Location map and remote sensing image of Budapest

Table 1 Evaluation indicators of the PUAs

	Dimension	Indicator	Weight
Composite index	Urban	Proportion of impervious surface (PIS)	0.3397
		Nighttime light intensity (NLI)	0.4285
	Rural	Proportion of agricultural, forest and semi natural areas (PAF)	0.2298
		Per capita land area (PCLA)	0.0020

This study reversed the indicators of the rural dimension to facilitate analysis, and align their direction with the urban dimension indicators. Subsequently, the standardized data was processed using the entropy method (Zhu et al., 2020) to calculate the weights of these indicators (Table 1). Finally, these indicators were aggregated according to their weights to compute the grid values of the composite index (Freudenberg, 2003) (Fig. 2).

Breakpoint method

It is necessary to generate a sample point matrix radiating outward from a central point to study the spatial changes from urban to rural areas (Long et al., 2022). Specifically, the Hungarian Parliament Building was chosen as the central point. From this point, 360 radial lines at 1° intervals and 45 concentric circles with a 500 m spacing were drawn, covering the entire study area. The intersections of these radial lines and concentric circles created 9,362 sampling points (Fig. 3). These points were grouped according to the radial lines, resulting in 360 data series.

Subsequently, Matlab R2018a software was used to perform sliding t-tests on these data series. The principle of these tests is to examine whether the difference between the mean values of two sample groups is significant. As illustrated in Figure 4, data peaks exceeding the red line or falling below the yellow line in the test results were considered breakpoints. These breakpoints were collected and cross-validated with remote sensing imagery to eliminate anomalies.

Spatial clustering

The breakpoints were imported into QGIS 3.30.1 software for K-means clustering. K-means is an unsupervised clustering algorithm that automatically groups similar samples. The clustering divided the breakpoints into four types: Urban-Peri-urban points (UP), Peri-urban-Rural points (PR), Rural-Peri-urban points (RP), and Peri-urban-Urban points (PU). These types enable more accurate identification of the boundaries of PUAs. It is worth noting that urban-rural breakpoints may also occur within the study area, requiring further assessment in conjunction with the surrounding composite index values.

Landscape metrics

After delineating the boundaries of PUAs, this study employed Fragstats software to quantitatively analyze the landscape patterns of the PUAs. We selected landscape metrics from the area, shape, subdivision, and aggregation dimensions at the class level to evaluate the

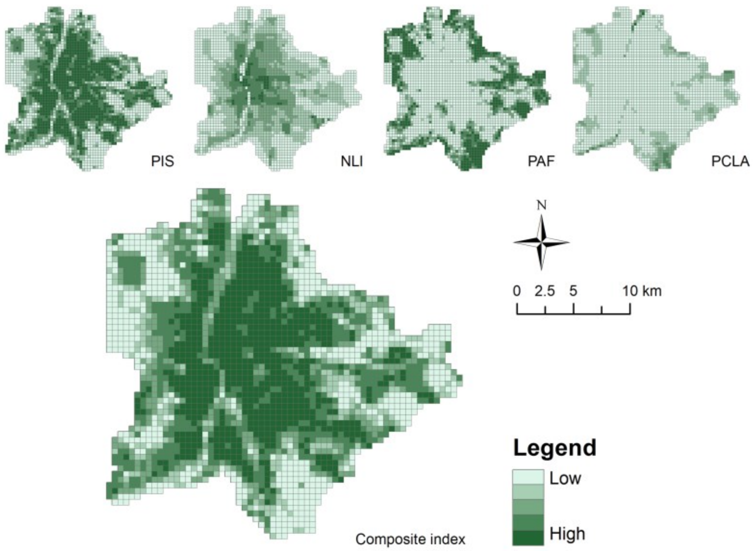

Fig.2 Grid values for indicators and composite index

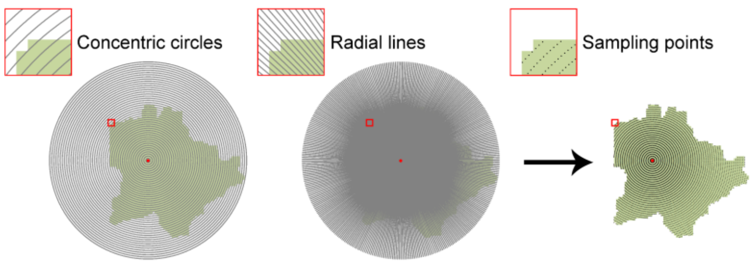

Fig.3 The process of establishing spatial sampling points

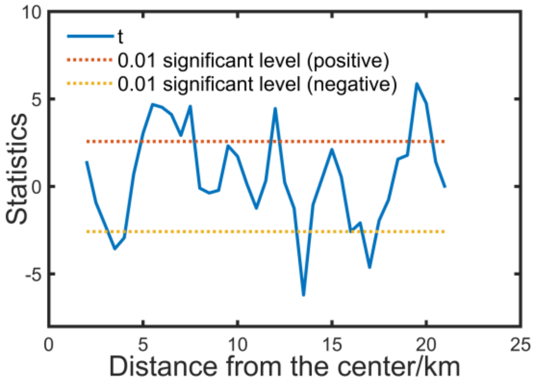

Fig.4 The sliding t-test result of the sample data series

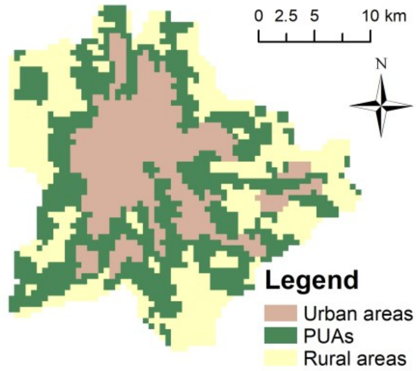

Fig.5 Spatial distribution of urban, peri-urban, and rural areas of Budapest

landscape within the PUAs. The chosen landscape metrics include Largest Patch Index (LPI), Mean Fractal Dimension Index (FRAC_MN), Number of Patches (NP), Effective Mesh Size (MESH), and Aggregation Index (AI) (Leitao & Ahern, 2002; McGarigal, 1995).

RESULTS

The identification results of PUAs

Utilizing the sliding t-test, we identified 1,163 breakpoints within the study area. Subsequent cluster analysis revealed 571 UP, 336 PR, 197 PU, and 59 RP. Based on these findings, we mapped the spatial boundaries of PUAs (Fig. 5).

As depicted in Table 2, the area of PUAs in Budapest is 237.50 km², accounting for 39.63% of the total area, which is higher than that of rural and urban areas. This proportion is close to 34.2% for towns and suburbs in Hungary, as reported by Eurostat (2018). Furthermore, through an overlay analysis of Fig.5 and the urban structural map of Budapest (Finta, 2013), we discovered that the PUAs show significant overlaps with the suburban zone and the transitional zone in the urban structure map. There are also partial overlaps with the hilly zone and the Danube zone.

It can be observed that Budapest exhibits a predominantly monocentric spatial structure. Urban areas are predominantly concentrated in the central region, with several isolated large patches located in the eastern and southern parts. PUAs are primarily distributed around urban areas, often exhibiting a wedge-shaped spatial structure that extends from the periphery into the inner parts of the city. These areas connect independent urban patches with the central urban area. Additionally, there are some scattered small patches of PUAs located near the boundaries of Budapest. Rural areas are located in the peripheral spaces of Budapest, separated from the urban areas by the PUAs.

Land use in urban, peri-urban and rural areas

Merging the identification results and the land use/ land cover data, we analyzed land use in urban, peri-urban and rural areas (Fig. 6). In urban areas, the proportion of artificial surfaces is the highest. Water bodies primarily consist of a segment of the Danube River that flows through the urban area. Forests and semi-natural areas are distributed as small patches. Agricultural areas constitute the smallest proportion and are located primarily at the peripheries of the urban areas.

In PUAs, artificial surfaces remain predominant, although their proportion is slightly lower compared to urban areas. Besides artificial surfaces, agricultural land has the largest area, primarily located in the boundary zones adjacent to the rural areas of the PUAs. Forests and semi-natural lands continue to be distributed in small patches. Water bodies are mainly found in the northern and southern sections of the Danube River in Budapest, as well as in its tributaries and several small lakes. Wetlands are only sparsely distributed in the southern tributaries of the Danube River.

In rural areas, agricultural areas have the largest area, followed by forests and semi-natural lands, and artificial surfaces. Water bodies are distributed in the northernmost and southernmost sections of the Danube River within the study area, as well as in its tributaries and a number of small lakes. The least proportion of wetlands is found in the southern and eastern parts of Budapest.

Table 2 Area of different land types in urban, peri-urban, and rural areas of Budapest

Land types	Urban areas (km^2)	PUAs (km^2)	Rural areas (km^2)
Artificial surfaces	151.31	201.10	47.46
Agricultural areas	0.45	20.73	93.50
Forest and semi natural areas	0.81	9.21	55.86
Wetlands	0.00	0.06	0.36
Water bodies	5.18	6.40	6.82
Sum	157.75	237.50	204.00

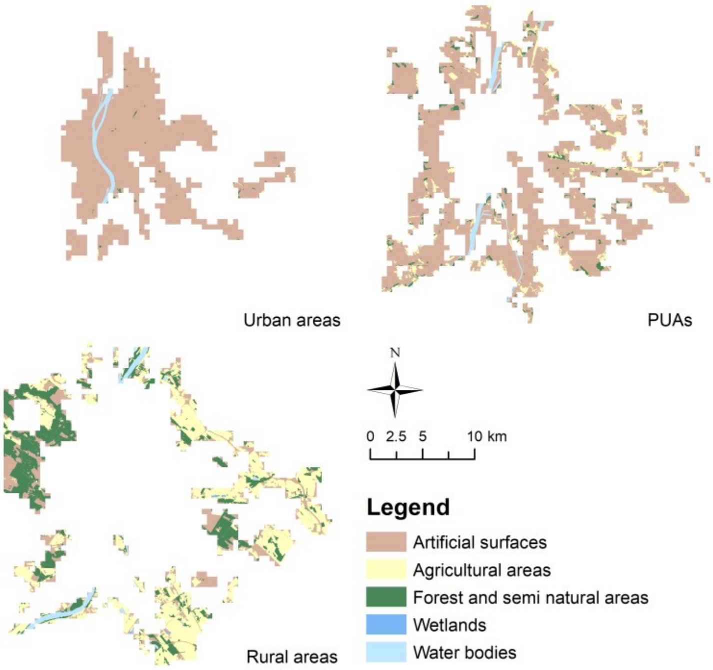

Fig.6 Land use types in urban, peri-urban and rural areas

Landscape Patterns in PUAs

The results of the landscape metrics further illustrate the spatial characteristics of various land types within the PUAs (Table 3). There are 95 patches of artificial surfaces within the PUAs. Its LPI and MESH values significantly exceed those of other land types, indicating the presence of one or more large patches of artificial surfaces with high connectivity between patches. This suggests that artificial surfaces are the dominant landscape type within the PUAs. The FRAC_MN value of the artificial surfaces indicates that they have the highest boundary complexity, undoubtedly influenced by human activities. The high AI value of artificial surfaces further reflects the high degree of aggregation among its patches. The number of water body patches is relatively low, while the other metrics are second only to those of artificial surfaces. Water bodies are predominantly distributed in linear shapes, with a small portion distributed in block-like forms. They exhibit relatively high connectivity and aggregation, and their shapes are relatively complex. Wetlands, with both the smallest area and the fewest number of patches, exhibit the lowest values across most metrics, resulting in a relatively low presence within the PUAs. In contrast, agricultural areas, as well as forest and semi-natural areas, have the highest number of patches. They lack large patches and generally exhibit simpler patch shapes. These characteristics reflect a higher degree of fragmentation for these two landscape types, with connectivity and aggregation levels being relatively low within the PUAs.

DISCUSSION

The Budapest 2030 Long-Term Urban Development Concept (Budapest 2030) categorizes Budapest into five distinct zones based on their characteristics and functions (Finta, 2013). The inner zone, located in the city centre, is completely encompassed by the urban areas identified in this study. The transitional zone, dominated by economic functions and characterized by its diversity, has a significant proportion of unused land. Both urban areas and PUAs cover this zone. The suburban zone typically comprises detached houses and isolated large housing estates with low population density. In this zone, certain areas have been identified as urban areas, while PUAs and rural areas cover the rest. The hilly zone, rich in forest resources and preferred by the affluent class for residence, is predominantly enveloped by PUAs and rural areas. The Danube zone, weaving through urban, peri-urban, and rural areas, exhibits varying landscapes along the river. The overlap of PUAs with these zones reflects the

Table 3 Landscape metrics in PUAs

Land types	LPI	FRAC_MN	NP	MESH	AI
Agricultural areas	0.2111	1.1078	443	1.3454	96.3032
Artificial surfaces	29.3688	1.1430	95	3144.9001	99.3109
Forest and semi natural areas	0.1503	1.1000	318	0.3568	95.7000
Wetlands	0.0117	1.0877	4	0.0005	95.7359
Water bodies	1.0088	1.1215	28	4.9487	98.3760

diversity and complexity of PUAs in the context of urban planning.

Given these characteristics, the developmental trajectory of PUAs significantly influences the formation of a compact settlement structure. The concept of a compact settlement structure was mentioned in the Budapest 2030 and the National Spatial Plan (2018). It implies high-density development, mixed land use, and limitations on urban expansion. Rational land planning, well-developed infrastructure and ecological networks within PUAs can facilitate the formation of compact settlement structures, thereby advancing sustainable urban development.

The methods adopted in this study integrate multi-source remote sensing data with statistical approaches, offering an innovative method for identifying PUAs. The breakpoint method effectively reduces the subjective biases that may be introduced when applied across different areas. Clustering of breakpoints reduces the complexity of boundary identification. Therefore, the combination of these two methods can adapt to diverse and complex study areas.

Nevertheless, we have identified several limitations of this method. Firstly, the computational steps involved are relatively complex. Subsequent research should further investigate how to improve this method's operationality and data processing capabilities. Secondly, when applied across different study scales, attention must be paid to the transformation of grid units. It is necessary to avoid noisy or coarse data due to inappropriate grid sizes. To address these issues, we suggest employing variance analysis and scale sensitivity analysis in subsequent research to determine the optimal size of the research unit.

CONCLUSION

This study identified PUAs in Budapest using the breakpoint clustering method. These areas are wedge-shaped and distributed around the periphery of the urban region, serving as transitional zones between urban and rural areas. In PUAs, the primary land types are artificial surfaces and agricultural areas. The calculation results of landscape metrics indicate that artificial surfaces are the dominant landscape type in PUAs, with water bodies exhibiting high aggregation and strong connectivity. In contrast, agricultural areas, forests and semi-natural areas show high levels of fragmentation. Precise boundaries not only provide a fundamental basis for in-depth research on PUAs but also enhance the attention of governments and planners, promoting better planning and regulation of these areas. Given the dynamic nature of PUAs, future research could employ longitudinal data for the dynamic monitoring of PUAs to grasp their spatial changes more comprehensively.

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