Analysis of the Spatial Morphology Characteristics of Urban Built-Up Areas in Shanghai

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Abstract. The morphological characteristics and spatial patterns of urban built-up areas reflect the characteristics of urban development. This paper takes Shanghai as the study area, uses the landscape pattern index to analyse the morphological characteristics and spatial patterns of urban built-up areas from different data sources. The results show that both the night-time light extraction data and the land use data show a high degree of aggregation and a low degree of fragmentation in Shanghai's land use. In addition, as night-time lighting is easily disturbed by landscape lighting, when extracting built-up areas in cities with rivers, attention should be paid to the fragmentation of built-up areas by water bodies to avoid affecting a calculation of the landscape pattern index.

Keywords: Night-time lighting · Landscape pattern index · Urban built-up area

1 Introduction

The morphological characteristics and spatial patterns of urban built-up areas reflect the characteristics of urban development [1]. Exploring the evolution pattern of land use and landscape pattern is conducive to revealing the human-land relationship at a deep level and has important guiding significance for coordinated regional development [2, 3]. Land use data can reflect social and regional changes and have a significant impact on the subsequent provision of goods and social services. At the same time, the night-light data can reflect the city lights, and is widely used in environmental impact analysis, light pollution assessment and other fields [4–15].

The paper uses the landscape pattern index to analyse the morphological characteristics and spatial patterns of urban built-up areas from different data sources: land use data and night-time lighting data.

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Table 1. Data sources

Data type	Land use data	Night-time lighting data
Data	Raster Data	NPP-VIIRS
Resolution	30 m × 30 m	≈500 m × 500 m
Year	2015	2016
Data Source	GIM Cloud	http://ngdc.noaa.gov/
Acquisition Year	2019	2019
Coordinate System	Albers_Conical_Equal_Area	GCS_WGS_1984
Datum	D_Krasovsky_1940	D_WGS_1984
Build-up-Area Extraction	Type = Urban Construction Land	DN > 24 (80%)

2 Data and Study Area

2.1 Data Source

The main data sources used in this paper are land use raster data and night-light remote sensing data. Data sources and parameters are shown in Table 1.

2.2 Study Area

Shanghai is the financial, economic, shipping and trade centre in China. 1978 to 2017, Shanghai's resident population grew from 11.04 million to 24.18 million, stabilizing after rapid growth from 1995 to 2010 (Fig. 1); GDP rose from RMB 27.281 billion to RMB 306.329 billion, ranking 1st in the country in terms of GDP. As of 2018, the value added of the tertiary sector in Shanghai increased by 8.7% over the previous year, accounting for 69.9% of the city's GDP (Fig. 2), and the level of urbanization has steadily increased.

3 Methodology

A landscape pattern analysis index is a simple quantitative index that can highly condense landscape pattern information and reflect certain aspects of landscape structural composition and spatial configuration. In this paper, a landscape index is calculated separately for the built-up areas extracted from the night-time lighting data and built-up areas focused on the original land use data, in order to obtain differences and similarities between the two in terms of landscape form and spatial pattern. The specific calculation technical indicators are listed in Table 2.

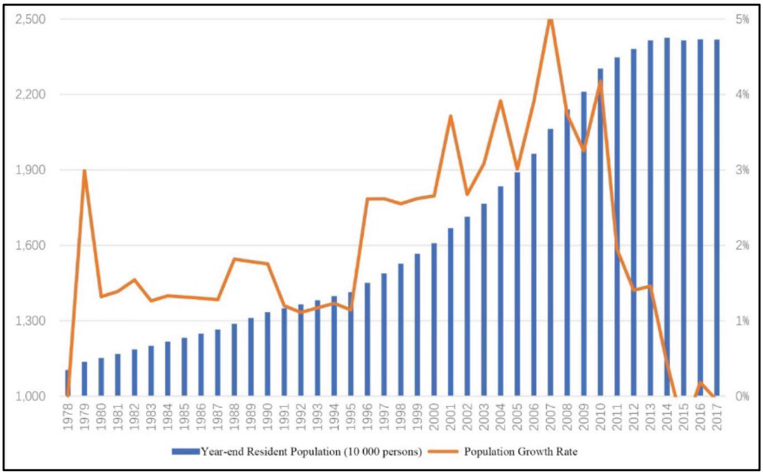

Fig. 1. Shanghai population

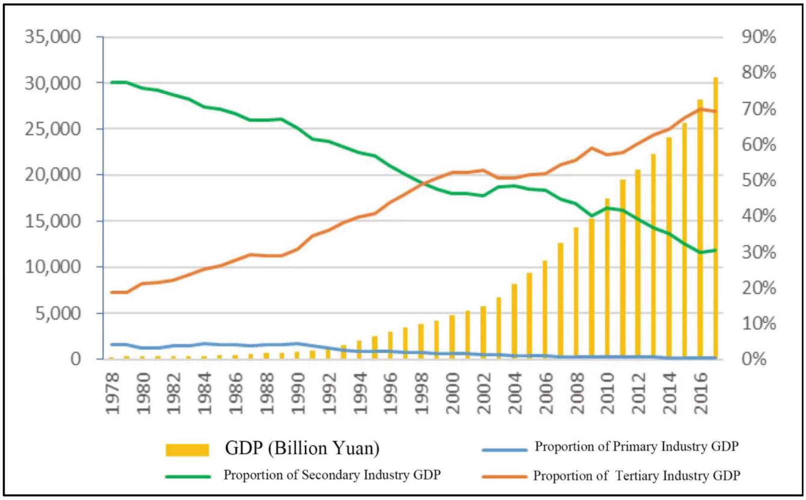

Fig. 2. Shanghai industry development

4 Results and Discussion

4.1 Results

Using the software Fragstats 4.2, the results of the landscape pattern index were calculated for the urban built-up area patches of Shanghai in 2015 and the built-up area patches of Shanghai in 2016 extracted from the night-time lighting data, respectively, and the results are shown in Table 3.

Table 2. Landscape pattern indices

Landscape pattern index	Description	Connotation
CA/TA	Sum of area of all patches	Land area
NP	Total number of patches	Reflects the spatial pattern of the landscape and is used to indicate patchy heterogeneity, usually positively correlated with landscape fragmentation
MPS	Ratio of patch area to number of patches	Average site size, the smaller the value, the greater the fragmentation and is key to expressing landscape heterogeneity
LSI	Indicators of the shape of the patchy landscape	Complexity of site shape
LPI	Proportion of the largest patches in a given patch type to the overall landscape area	Identify the dominant patch types in the landscape, indirectly reflecting the direction and magnitude of anthropogenic disturbance
COHESION	Degree of physical connectivity between patches	Reflects the state of aggregation and dispersion of patches in the landscape

Table 3. Landscape pattern index results

Year	Type	CA/TA	NP	MPS	LPI	LSI	COHESION	AI
2015	Land use data	1051.72	66.00	15.94	44.87	15.54	99.87	98.65
2016	NPP-VIIRS	1923.89	128.00	15.03	73.18	14.55	99.92	99.07

4.2 Discussion

The built-up area extracted from the night-time lighting (2016) was compared to the government-published statistics on the built-up area of the city. The data was compared with the built-up area in the site data used in this paper. The results are shown in Table 4.

(1) Exploring the reasons for the similarity of the results

It can be seen that the spatial aggregation pattern of the construction sites and the complexity of the site shape show that the results of the identification are similar to the actual results, and the difference between the MPS values is not significant, which proves that the spatial fragmentation of the two is consistent and the spatial differentiation is also similar. However, the difference between the two indicators of total area and number

Table 4. Comparison of landscape pattern index results for deleted river channels

Year	Type	CA/TA	NP	MPS	LPI	LSI	COHESION	AI
2015	Land use data	1051.72	66.00	15.94	44.87	15.54	99.87	98.65
2016	Night-light extraction without river	1902.25	144.00	13.21	47.74	15.32	99.87	99.01
2016	Night-light extraction with river	1923.89	128.00	15.03	73.18	14.55	99.92	99.07

of patches is large, which may be related to the inclusion of other built-up land, such as: rural settlements and other built-up land, as mentioned in the previous section. It can be speculated that although there is a large difference in the area of built-up areas between 2015 and 2016, there may be a similar spatial pattern in terms of site refinement, and the built-up areas of the city may have fractal characteristics.

(2) Exploring the reasons for the variability of results

In recent years the development of municipal landscape construction and factory and mine traffic and other site construction in Shanghai, landscape lighting and factory and mine lighting for night-time lighting data extraction of the built-up area caused by the interference gradually increased. Because night-time lighting data is not sensitive to interference from landscape lighting and industrial lighting, it is difficult to distinguish the two from the normal urban built-up areas by night-time lighting data. Therefore, the removal of landscape and industrial lights may help to improve the accuracy of urban built-up area extraction. Commonly used methods for landscape and mine identification are mostly based on the hybrid identification of multi-spectral satellite remote sensing images, but the accuracy of the identification of urban built-up areas and mines is lower than that of urban built-up areas and landscapes (e.g. green areas and water bodies). The landscape lighting adjacent to water bodies may cause an enhancement of the lighting index at night in the area due to the reflection of the water bodies.

The reason for the large difference between the extracted data and the LPI of the actual site data may also be related to the water bodies. Looking at the built-up area and land use raster data for the night-time light extraction, it can be seen that although the proportion of misidentified water bodies in terms of area is small overall, the ability to identify this natural geographical division will have a greater impact on its landscape pattern index as the Huangpu River passes through the study area.

The results show a greater improvement in the similarity of the LPI values, thus demonstrating that the main source of error in the LPI values is the river and canal landscape lighting that cannot be excluded from the night-time lighting data.

5 Conclusions

Night-time lighting is highly disturbed by landscape lighting around water bodies, and most cities will have landscape lighting decorating major river channels. Therefore, when extracting built-up areas for cities with river canals crossing them, the river canal areas should be manually removed to ensure the accuracy of the characteristics of site patch pattern.

Although there is a large difference between the site area and the amount of patch data, the identification results are more similar to the actual results in terms of the spatial aggregation pattern of the built-up areas and the complexity of the site shape. Therefore, there may be fractal features in the spatial shape of the built-up area of Shanghai.

Therefore, improvements can be made and further research can be carried out in the following aspects.

(1) To check and correct the land use data through remote sensing images, field research and statistical data checking, in order to improve the accuracy of the land use data.
(2) To refine the scale of the study and to investigate and verify the existence of fractal characteristics of construction land patches.

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