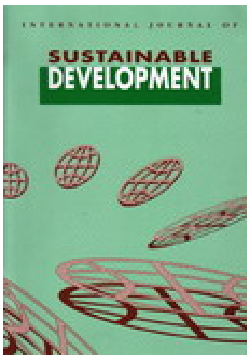

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Urban planning and land use using spatiotemporal evolution information graph model

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Abstract: The purpose of this study was to use a spatiotemporal evolution information graph model to simulate and predict urban land use (abbreviated as LU for convenience) patterns and propose reasonable urban development plans. The calculation of LU pattern based on a fractal model calculated the fractal dimension and patch density of LU, analysed urban spatial structure and divided urban planning (abbreviated as UP for convenience) land into residential land, industrial land, commercial land, public land and green space. The dimensions of these five modules were experimentally analysed. From 2002 to 2012, the dimension D in residential underground spaces was 1.4861–1.5847; that of the industrial underground was 1.4027–1.4457; that of the commercial underground was 1.1231–1.3365; that of the public underground was 1.3149–1.3456; that of the green underground was 0.9567–1.1627. From 2012 to 2022, the dimension D of residential land, industrial land, commercial land, public land and green underground increased to 1.6127, 1.4527, 1.3985, 1.3524 and 1.3357. From the perspective of patch density, the order of change amplitude was residential land > industrial land > public land > commercial land > green land.

Keywords: spatiotemporal evolution; urban planning; geographic information system; patch density; PD.

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1 Introduction

A city is a complex ecosystem, and its development and evolution process is not a simple linear superposition but presents a regular feature of 'structure energy process' at multiple levels such as macro, meso and micro. In the context of the continuous emergence of new substances such as material, energy and information, and the acceleration of the transformation from traditional material elements to modern information elements, urban spatial structure is also constantly changing.

Previous urban simulation methods only focused on planning constraints that hinder urban growth in specific regions. However, regional planning has produced planning policies that drive urban development, which were rarely considered in previous studies. Liang et al. (2018) designed two mechanisms in a future LU simulation model based on cellular automata. The first update mechanism considered the impact of transportation planning, and the second mechanism could simulate the guiding role of the planned development zone. The first mechanism was verified through simulation, and the results showed that the simulation accuracy was improved after considering transportation planning. In the simulation from 2013 to 2052, these two mechanisms resulted in a more realistic urban spatial pattern. The results could be used to determine potential urban expansion within the overall plan (Liang et al., 2018). The popularisation of navigation and information technology has increased the relevance of cognitive environment research for planning. Mondschein and Moga (2018) comprehensively planned the concepts and methods of the cognitive environment in other fields and proposed how planning and design practices align with the cognitive environment framework. The issues involved in cognitive environment research include the need for fair access, norms and rules for creating good urban forms, planning data and information systems, and participatory planning that integrates local knowledge and citizen participation. UP emerged to deal with the situation of market failure.

LU planning requires finding a balance between different conflicting social, economic and environmental factors, which is a complex task that can be found anywhere, including in Africa. Lubida et al. (2019) thought that Zanzibar City, Tanzania, was an example. This was because, on the one hand, this city had high tourism potential; on the other hand, the city structure and accessibility were also facing major challenges.

To prepare reasonable urban LU planning, considering and meeting various conflicting influencing factors was necessary. By taking Zanzibar as a case study, Lubida et al. (2019) proposed and demonstrated the use of geographic information systems (GIS) and multi-objective optimisation of LU planning to solve the problem. The development challenges were determined through research on relevant literature and interviews with experts. On this basis, Lubida et al. (2019) established two objective functions for LU planning. By optimising the objective function, the optimal LU plan for the base was formulated. The results showed that the proposed method and output could greatly promote the LU planning of Zanzibar Island. Adopting a similar approach for other developing African cities was strongly recommended (Bai et al., 2022). Helber et al. (2019) proposed a patch-based LU and land cover classification method based on Sentinel-2 satellite images. Helber et al. (2019) proposed a new dataset based on these images, which covered 13 spectral bands and consisted of 10 categories, with a total of 27,000 labelled and geo referenced images. The use of the most advanced depth convolutional neural network provided a benchmark for this novel dataset and its spectral bands. The overall classification accuracy reached 98.57%. The resulting classification system opened a door for many Earth observation applications. Helber et al. (2019) demonstrated how this classification system could be used to detect changes in LU and land cover and how it could help improve geographic maps (Lubida et al., 2019). The core area of UP is a spatial layout. Simple ones such as the width of roads and the height of buildings, while complex ones such as the complex transportation hubs in urban centres need to be positioned under the guidance of UP to complement each other.

The development of cities is a dynamic process, and their morphological characteristics are closely related to people, society, countries and the world. Therefore, the laws, trends and reasonable future directions of urban development are all disciplines that need to be studied. The article analyses and introduces the spatiotemporal evolution information graph model, UP and UP based on the spatiotemporal evolution information graph model, and it uses the spatiotemporal evolution information graph model to plan the city.

2 Basic knowledge of UP Based on spatiotemporal evolution information graph model

2.1 Spatiotemporal evolution information graph model

Spatiotemporal data is a hot topic in current data mining and has received considerable attention from many scholars. In addition, this topic can also be used in fields such as traffic management, crime analysis, disease monitoring, environmental monitoring, public health, and healthcare. Spatiotemporal data mining is a new research direction that has emerged in recent years. Its purpose is to analyse massive, high-dimensional spatiotemporal data and extract useful information from it.

Spatiotemporal data is a type of spatial data that is based on time and space, characterised by dynamic changes on a time scale. These spatial information all involve various types of information, including data, text, charts, and images related to the types, forms, textures, spatial location characteristics, internal connections, and laws of the Earth’s structural elements. It not only has significant temporal and spatial distribution characteristics but also has rich information, uncertainty and time-varying characteristics

(Helber et al., 2019). The traditional GIS only provides an explanation for a snapshot of data and cannot perform special processing on temporal information. Therefore, in reality, it is a static system that only represents the situation of events, cannot represent the development conditions of things and cannot predict future development (Hoque et al., 2022). However, the emergence of everything is inseparable from time, which is the generation of time data. Time data and information visualisation can be divided into static visualisation and dynamic visualisation.

The visualisation of static spatiotemporal data is usually achieved by overlaying elements that can reflect time changes on a two-dimensional map. Therefore, this method can better reflect the relationship between urban LU and LU. Different symbols, annotations, plotting symbols, charts and other elements can be used to represent spatio-temporal attribute data, and a thematic map of multiple periods can also be displayed and compared at the same time. Dynamic visualisation can present spatiotemporal data through various methods such as dynamic maps and three-dimensional GIS (Zhou et al., 2022). Displaying spatiotemporal data in the form of dynamic maps or three-dimensional scenes can more intuitively and vividly demonstrate the evolution process of various spatial information.

With the continuous development of three-dimensional GIS technology, spatiotemporal data has been able to be expressed three-dimensionally. By utilising spatiotemporal data of spatial targets, their movement process in three-dimensional space can be visualised and expressed, effectively solving the problem of representing the movement trajectories of targets with different heights on flat maps (Wu, 2022). A dynamic terrain map is an electronic terrain map that can intuitively and intuitively reflect the changes and processes of spatial information in time and space. Its research and development provide important theories and technologies for the visualisation of spatiotemporal data. With the continuous progress of data and information visualisation technology, people's ability to draw dynamic data is also improving. Visualisation technologies such as enterprise charts (ECharts) and data-driven documents (D3) are also widely used for the representation of spatiotemporal data.

2.2 Urban planning

In urban construction, transportation is a very important task. On the one hand, with the acceleration of urbanisation, the demand for urban transportation is increasing day by day, creating favourable conditions for its development; on the other hand, improving transportation accessibility and changing transportation modes have played a guiding and promoting role to a certain extent (Gaur et al., 2020). UP refers to the comprehensive deployment, specific arrangement and implementation management of the economic and social development, LU, spatial layout and various constructions of a city during a specific period. According to its operating procedures, it can be divided into two categories: plan formulation stage and plan execution stage.

Urban transportation planning refers to the launching of a series of actions to guide traffic in a planned way. Generally, it can be divided into broad and narrow sense. Broad sense transportation planning includes the following aspects: first, the planning of traffic infrastructure construction and development mainly refers to the planning of various traffic facilities construction and development in the construction of a comprehensive transportation system. The second is the planning of transportation organisation and management, mainly including planning for transportation organisation, business management, safety production management, etc. The narrow sense of transportation planning refers to the development planning of transportation infrastructure construction. On the basis of analysing and studying the interrelationships between historical and current transportation supply and demand conditions and regional population, economy and LU, it analyses and predicts transportation development needs, and then determines the scale, structure, layout and other plans for future transportation facility development and construction (Tariq and Mumtaz, 2023).

From a macro perspective, urban transportation and urban LU are interdependent. The continuous development of urban transportation system has led to corresponding changes in the nature of urban LU, which in turn affects urban spatial form, land structure and land intensity; accordingly, the change of urban LU characteristics also puts forward new requirements for the transportation system and promotes its continuous improvement, which leads to changes in the characteristics of transportation facilities, travel mode structure and traffic density (Schrotter and Hürzeler, 2020). Finally, a harmonious relationship between the transportation system and LU is formed. On this basis, the main factors affecting urban LU and transportation systems are analysed.

Therefore, the nature of urban LU is the root cause of urban transportation demand, which not only determines the source, volume and mode of transportation of the city but also restricts the structure and foundation of urban transportation from a macro perspective. To a certain extent, a series of travel behaviours of urban residents, such as going to work, work, shopping, and leisure, are all the transportation needs of the city.

From the perspective of overall layout, cities can be divided into three types: single-centre, multi-centre and strip.

The single-centre type is a developing 'one centre' urban development model. Specifically, due to the large number of retail, industrial and corporate areas in the central areas of such cities, a large population and job opportunities would be generated, which would lead to transportation demand in the central areas. Therefore, in urban transportation planning, it is necessary to increase the passenger capacity in the central city and make it a reasonable means of transportation, focusing on the development of urban public transportation. For example, ring roads are set up in the periphery of the central city to form a transmission and distribution ring-type transportation system (Gil, 2020).

Multi-centre cities are the main mode of urban development, which can be divided into various organisational forms such as centres, sub-centres, central clusters and towns. However, overall, the population distribution characteristics and job opportunity distribution characteristics of each city are basically the same. Generally, the distribution of population and job opportunities in these cities is relatively balanced, with a clear central location. In such UP, the transportation connection between the main and secondary centres must be made convenient and efficient, forming a 'point-to-point' rapid transportation network (Koryagin, 2018). Therefore, these types of cities are suitable for rapid development in urban areas and sub-centres. It includes transportation equipment such as high-capacity bus rapid transit (BRT) systems, subways, light rails, etc., while other areas form scattered and free 'network' urban transportation systems.

The belt type mainly refers to the layout of urban land that is constrained by natural conditions (such as rivers, mountains, canyons, etc.) and can only extend along the direction of river banks or valleys, forming a belt-type layout. This type of city has strong traffic directionality, and its transportation is mainly along the road system developed by the city, and the distance between them is also very large. Therefore, it is very suitable for the ‘axial’ urban transportation pattern with rail transit or large-scale public transportation as the main body (Bern, 2018).

In addition, the spatial pattern of the city’s proximity to mountains and the sea also has a significant impact on its external transportation entrances and exits. Generally speaking, cities are surrounded by the sea or mountains, and mountains and seas can affect the direction of entry and exit of the city. The urban transportation network structure is the backbone of a city and the direction of its development. The development of cities should make full use of the huge role of modern transportation systems in promoting the centrifugation of urban population and employment and promote the transfer of population and employed population in the urban centre (Mistree et al., 2022). Based on the topography and economic development characteristics of the city itself, scientific planning of transportation routes should be carried out. On this basis, the transformation from single-centre to multi-centre development has been achieved through the development of secondary and peripheral urban clusters.

At the same time, the urban transportation system provides a prerequisite for improving the quality of urban spatial structure and promoting the optimisation of urban land layout. In this way, the city can adjust the land through reasonable transportation planning layout to achieve the purpose of optimal land allocation. This leads to better utilisation of land, better utilisation of land and increased added value of land (Wang et al., 2023). On this basis, this aims to maximise the accessibility of the transportation line, thereby taking the corridor as the main line and developing new urban areas.

According to machine learning classification, the current algorithms used for urban problem research include clustering, classification, regression and association. The planning and planning model based on the clustering analysis algorithm in urban transportation is as follows:

$$P_i = \sum_k a_k N_{ki} = N_i \sum_k a_k \gamma_{ki} \tag{1}$$

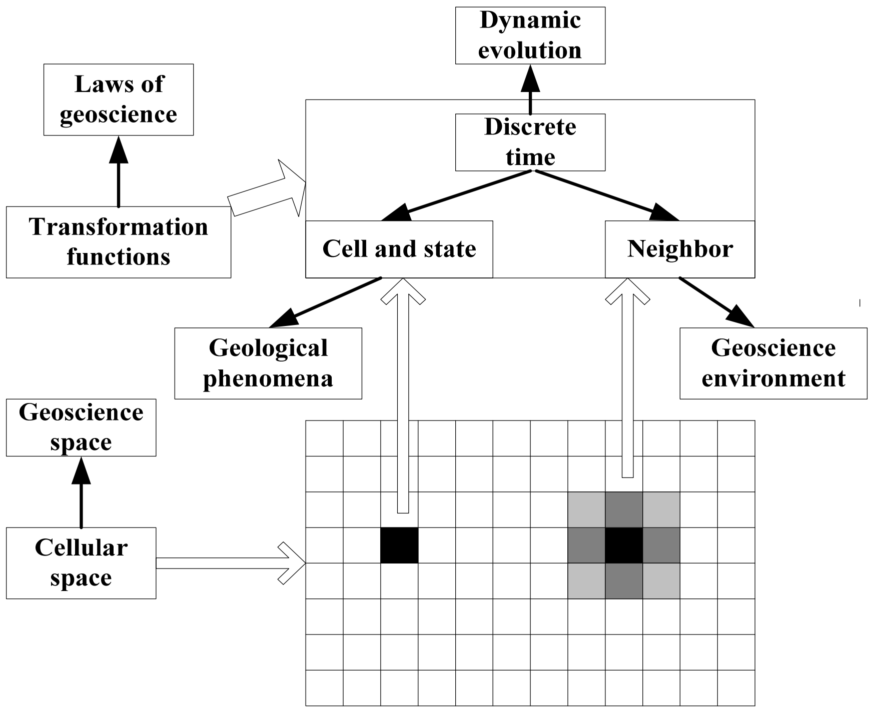
P_i is the planned unit travel volume of i; a_k is the travel rate of class k; N_{ki} is the number of i planned k^{th} households; N_i is the total planned quantity; however, the impact of transportation planning on the direction of urban development, the agglomeration of central areas, and the promotion of urban positioning must be included in each sub-item of the overall UP for comprehensive consideration, rather than being considered separately. In UP, transportation planning is an important part. It must be planned and constructed at the height of an overall UP. Transportation planning can not only facilitate people’s travel but also ignore the development of an urban economy (Gong et al., 2020).

2.3 UP based on spatiotemporal evolution information graph model

Compared with traditional GIS data models, the theory and practice of spatiotemporal data models are relatively lagging, but many new models have also been proposed. UP is a strategic, integrated, and comprehensive UP. At the same time, the characteristics of a city determine that the information it uses has spatial, temporal and multidimensional characteristics. With the development of network, computer and other technologies, the application of GIS in UP is also increasing. However, traditional GIS technology can only reflect the static form of towns (Asfaw et al., 2018). Urban spatial information can only reflect the current status of a city, and its historical status is completely different.

Therefore, the common factors of time and space must be introduced into UP management, so that the system can track the present and predict the future, as well as conduct retrospective analysis of past conditions. The GIS data model can be shown in Figure 1.

Figure 1 GIS data model



Based on the analysis of the distance and flow area of the flow, the velocity, intensity and other properties of the flow between geographical spatial units are established. At the same time, cell flow is selected by analysing the distance and properties of neighbouring cells. The local evolution rules of standard cellular automata can be expressed as follows:

$$f : S_1^{t+1} = f\left(S_1^t, S_N^t\right) \tag{2}$$

S_1^t is the important attribute set of the central cell, while S_N^t is the important attribute set of the neighbouring cell. Based on attributes, the local evolution rules of cellular states are as follows:

$$f_1 : S_1^{t+1} = f_1\left(A_1^t, S_1^t, S_N^t, A_N^t\right) \tag{3}$$

At present, cities have become the main gathering places for non-agricultural populations engaged in non-agricultural production. In its development process, with the gradual advancement of temporal and spatial dynamic factors, cities have increasingly become important carriers of geographical elements. Urban evolution is a process of multiple constituent elements merging and transforming with each other over time. The change of any element would have a significant impact on it, which is known as the 'butterfly effect'. This dynamic spatiotemporal change can generally be divided into two categories. One is the data objectively formed by their own elements in urban development, and the other is the time-varying data generated in UP and management. Time is similar to time and space. It is an axis with endpoints, measurable, reversible and extendable to the future (Brain, 2019). Therefore, along with space and attributes, it constitutes an important basis for urban elements. Space and time divide the city into paragraphs and can also showcase the current, past and future conditions of the city. The management of UP information has strong timeliness, such as planning land types (Silva and Marques, 2022). This characteristic is fully reflected in high-level and high-quality economic and technological development. Notably, if differences arise in the thematic plans, their emphasis on time elements is also different. For example, some situations change over time, while others change over time.

To meet the needs of these cities' urban spatiotemporal characteristics, urban planners must consider the following issues when constructing spatiotemporal data models. Firstly, in the process of urban development, the seed points that are most active and can match the scale should be the basis for fully recording events and states. Secondly, the time reference system specifically includes two parts: effective time and object time. Effective time refers to the time that exists in the database. The time of a thing refers to the time it exists in a database, which is usually earlier than the effective time. Both are expressions of the same object on different dimensions, with the difference being that the former is expressed at different time periods (time periods) while the latter is expressed at different time periods (Li et al., 2021). Third, the spatial element of a city usually spans time, while the temporal element spans space, just like the topological relationship between the current moat and the low water level in the past. Therefore, in urban spatial structure, various elements have different temporal characteristics in space, and there is a complex spatial structure between their spatial structures. A complex correlation is shared between their spatial structures. Fourthly, the organisational form of time, attributes and airspace data should also be considered, that is, the selection and application of spatiotemporal data patterns should be tailored to different urban characteristics.

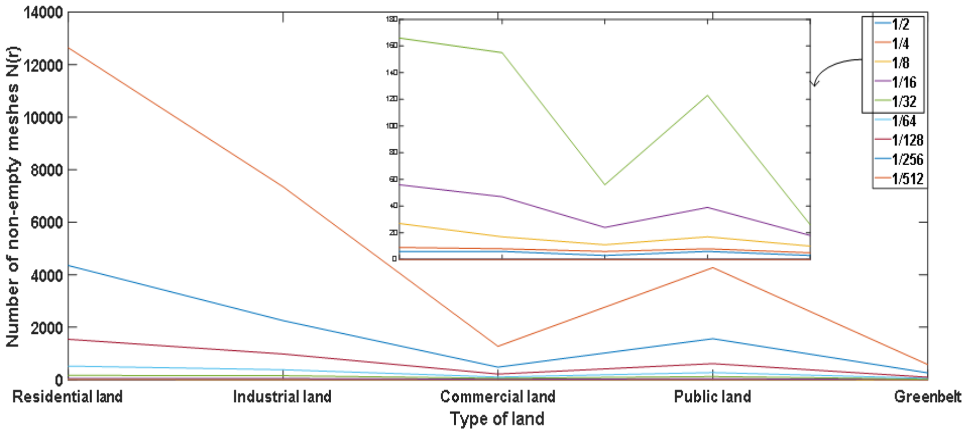
3 Calculation of LU pattern based on fractal model

3.1 LU evaluation under different land types

To analyse the value of LU, land is divided into residential, industrial, commercial, public and green land. The data on these lands were analysed. City S was selected based on UP data from 2002 to 2022. Starting from 2002, calculations were conducted every 10 years, totalling three times. The non-empty grid number N (r) under r was also obtained for various types of land using GIS algorithms. The results for 2002 are shown in Figure 2.

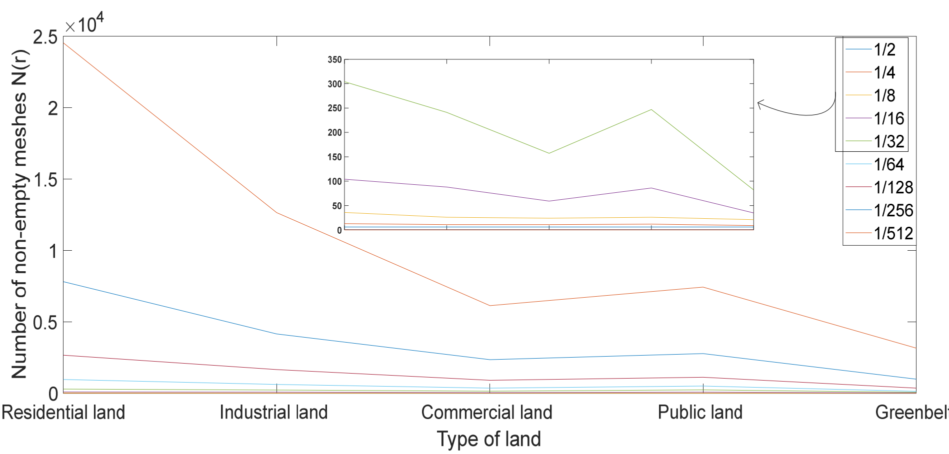
To obtain linear regression, for a fixed number of samples, the predictive ability of the model decreased with the increase of dimension D (dimension D was the spatial dimension, and D = 2); as the dimensionality increases, if the model needed to perform well, the required number of data samples would also increase (Olcese, 2021). To obtain the dimensionality D and correlation coefficients of different types of land in different non-empty grid numbers under different r, this would be calculated. The results of dimensionality D calculation for different land in different years are shown in Figure 5.

Figure 2 Number of non-empty grids for different lands under different r conditions in 2002 (see online version for colours)



The results for 2012 are shown in Figure 3.

Figure 3 Number of non-empty grids for different lands under different r conditions in 2012 (see online version for colours)



The results for 2022 are shown in Figure 4.

Analysis of these indicated that from 2002 to 2012, the dimension D increased from 1.4861, 1.4027, 1.1231, 1.3149 and 0.9567 in residential, industrial, commercial, public and green underground land, respectively, to 1.5847, 1.4457, 1.3365, 1.3456 and 1.1627. From 2012 to 2022, the dimension D increased to 1.6127, 1.4527, 1.3985, 1.3524 and 1.3357. From 2002 to 2012 and then to 2022, dimension D was increasing in residential, industrial, commercial, public and green land.

The calculation results of correlation coefficients for different lands in different years are shown in Figure 6.

Figure 4 Number of non-empty grids for different lands under different r conditions in 2022 (see online version for colours)

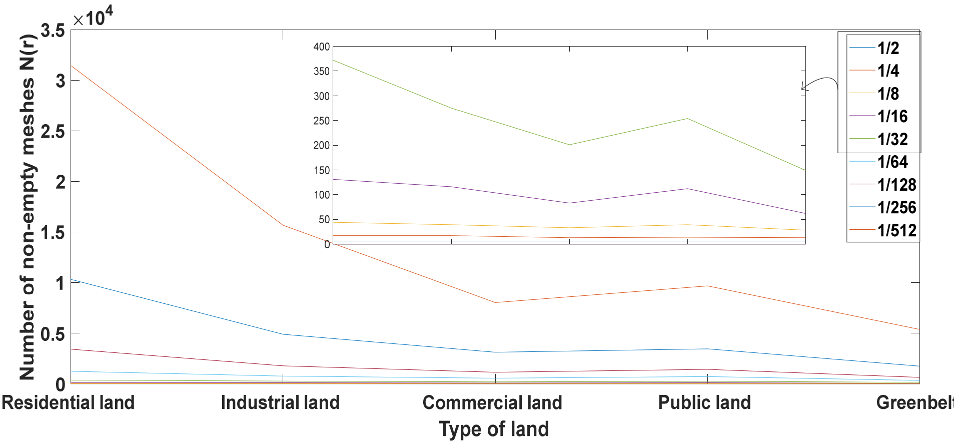


Figure 5 Dimension d results of different lands in different years (see online version for colours)

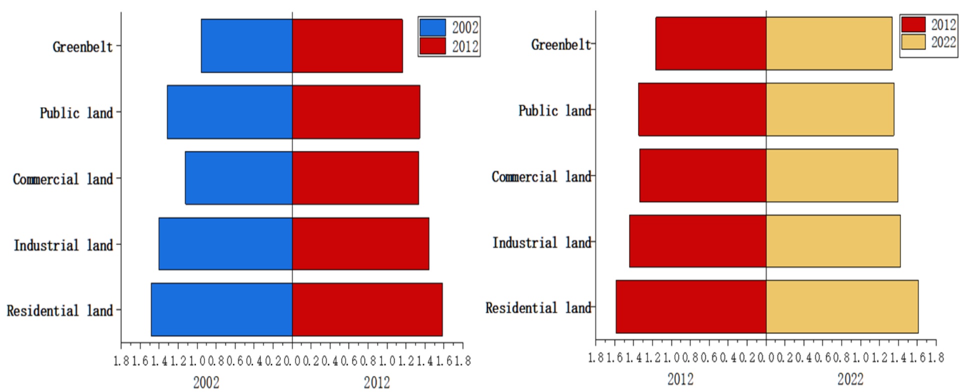
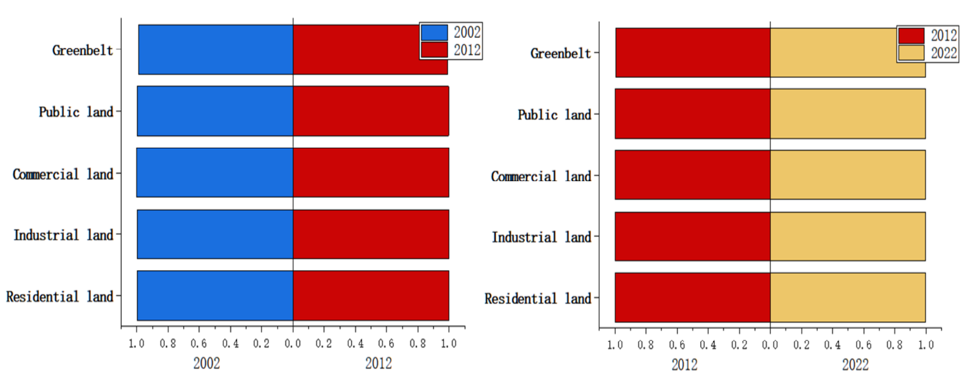


Figure 6 Calculation results of correlation coefficients for different lands in different years (see online version for colours)

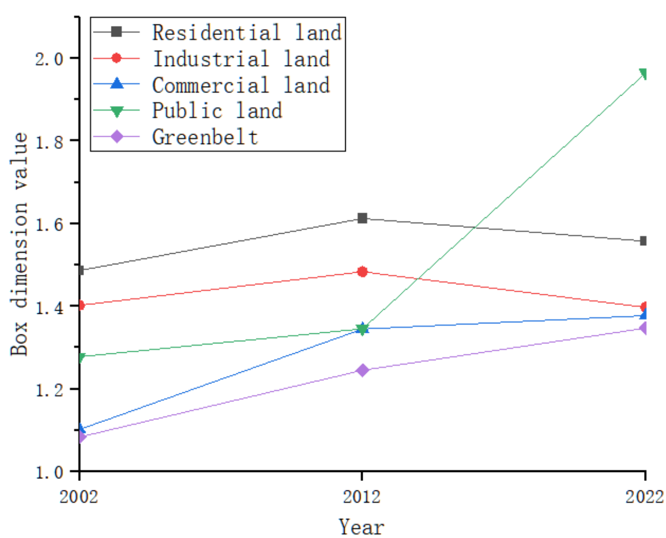


3.2 Evaluation of the characteristics of urban LU

The fractal dimension can quantitatively characterise the spatial complexity of the image surface and its texture characteristics. When using different dimensions for texture feature description, the accuracy varies (Lv et al., 2021a). The non-empty grid number N (r) under r was obtained using the aforementioned GIS algorithm, and box dimension analysis was subsequently performed. The analysis results for each land are shown in Figure 7.

The box dimension values from 2002 to 2012 to 2022 in Figure 7 indicate that the box dimension values for residential land ranged from 1.4867 to 1.6127 to 1.5579. The figure shows that residential land had a higher box dimension compared to other land. The box dimension values of residential land indicate that from 2002 to 2012, City S showed a growth trend in residential land, resulting in City S showing a compact spatial layout. From 2012 to 2022, residential land showed a contraction trend; the box dimension values of industrial land ranged from 1.4024 to 1.4837 to 1.3975. This value allows the inference that before 2012, industry in cities significantly developed, leading to an increase in industrial LU. However, since 2012, industrial parks were planned and relocated from the city. The box dimension values showed a decreasing trend since 2012; in the box dimension of commercial land, the values ranged from 1.1024 to 1.3452 to 1.3779, indicating an upward trend in commercial LU. Therefore, focusing on the development of commercial centres in UP for the city was possible; on public land, the values ranged from 1.2784 to 1.3457 to 1.9642. From 2012 to 2022 marked a vigorous development of public resources. Thus, after 2012, the city focused on the development of the tourism industry, leading to a linear upward trend in box dimension values (Lv et al., 2021b).

Figure 7 Box dimension analysis of each land (see online version for colours)



4 LU pattern calculation based on landscape index

4.1 Landscape index

Landscape pattern analysis refers to the transformation of real landscape systems into digital landscapes, selecting appropriate landscape pattern indices to analyse and explain them to reflect the spatial characteristics of landscape structure. Analysis is usually conducted from three levels. The first is based on the characteristics of individual patches. The second method is to analyse patch types composed of several individual patches, and the third method is to analyse landscape mosaics composed of several patch types (Hong et al., 2021). The article analyses patch types composed of several individual patches and landscape mosaics composed of several patch types. The analysis results would be drawn based on patch density (PD), largest patch index (LPI), landscape shape index (LSI) and aggregation index (AI).

4.2 Evaluation of LU patch level

The results of PD analysis for each period are shown in Figure 8.

Figure 8 PD index by period (see online version for colours)

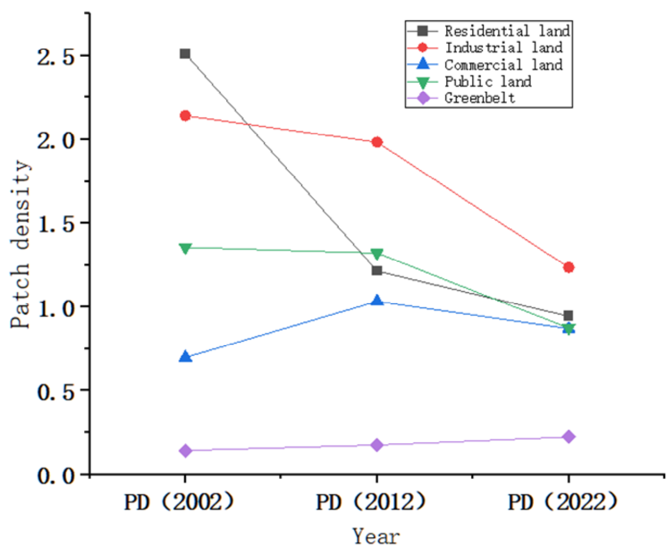
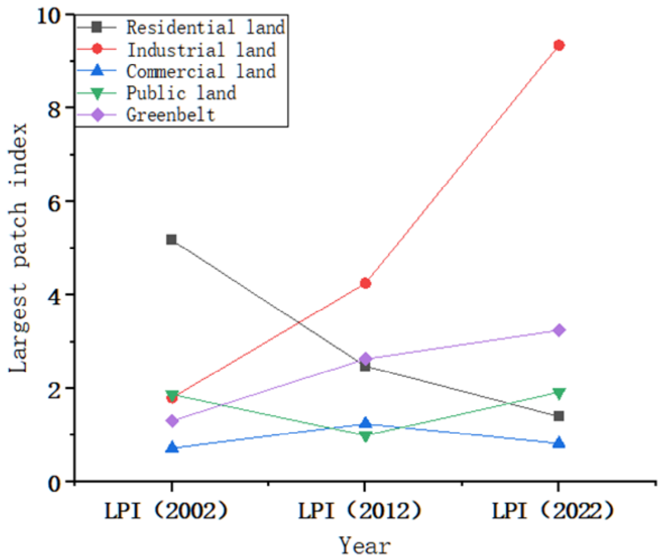


Figure 8 shows that from 2002 to 2012, the PD showed a decreasing trend in residential land, a decreasing trend in industrial land, an increasing trend in commercial land, a decreasing trend in public land and an increasing trend in green space. From 2012 to 2022, residential land showed a decreasing trend; industrial land showed a decreasing trend; commercial land showed a decreasing trend; public land showed a decreasing trend; green space showed an increasing trend.

The results of the LPI analysis for each period are shown in Figure 9.

Figure 9 shows that the LPI showed a decreasing trend in residential land, an increasing trend in industrial land, an increasing trend in commercial land, a decreasing trend in public land and an increasing trend in green space from 2002 to 2012. From 2012 to 2022, residential land showed a decreasing trend; industrial land showed an increasing trend; commercial land showed a decreasing trend; public land showed an increasing trend; green space showed an increasing trend.

Figure 9 LPI by period (see online version for colours)



4.3 Evaluation of LU patch types and levels

The results of LSI analysis for each period are shown in Figure 10.

Figure 10 shows that the LSI showed a decreasing trend in residential land, an increasing trend in industrial land, an increasing trend in commercial land, an increasing trend in public land and an increasing trend in green space from 2002 to 2012. From 2012 to 2022, residential land showed an increasing trend; industrial land showed a decreasing trend; commercial land showed an increasing trend; public land showed a decreasing trend; green space showed an increasing trend.

The results of AI analysis for each period are shown in Figure 11.

Figure 11 shows that the AI showed a decreasing trend in residential land, an increasing trend in industrial land, a decreasing trend in commercial land, a decreasing trend in public land and a decreasing trend in green space from 2002 to 2012. From 2012 to 2022, residential land showed a decreasing trend; industrial land showed an increasing trend; commercial land showed a decreasing trend; public land showed an increasing trend; green space showed a decreasing trend.

Figure 10 LSI by period (see online version for colours)

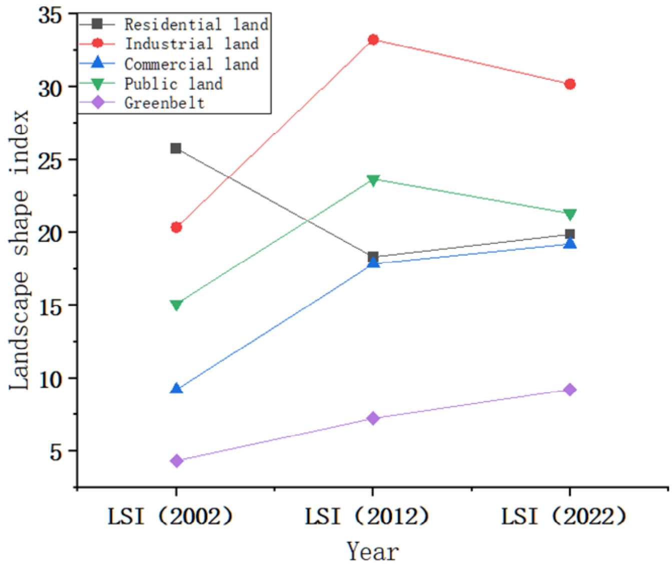
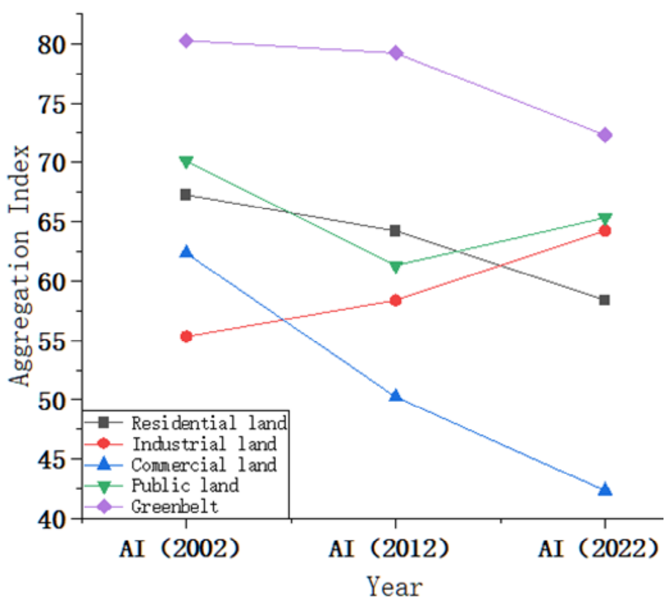


Figure 11 AI by period (see online version for colours)



5 Conclusions

The article mainly analysed the basic knowledge of UP based on the spatiotemporal evolution information graph model and further understood the UP of the spatiotemporal evolution information graph model, UP and spatiotemporal evolution information graph model. The calculation of LU pattern based on the fractal model and landscape index indicated that from the perspective of PD, the order of change amplitude was residential land > industrial land > public land > commercial land > green land. From 2009 to 2017, no significant fluctuation was observed in the shape index of the five types of functional land. The order of aggregation in 2002 was green space > public land > residential land > commercial land>industrial land. The analysis process of the article still has shortcomings. The evolution of urban morphology and LU structure was a complex process. Due to the limited time for data collection and investigation, this article only selected five types of urban functional land for analysis, potentially resulting in incomplete types of results.

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