Shape-weighted Landscape Evolution Index: An improved approach for simultaneously analyzing urban land expansion and redevelopment

Abstract: Urban redevelopment and the improvement of urban green coverages have become an important form of urban landscape evolution and have led to a decline in imperviousness. However, in the quantitative analyses of landscape patterns, such form has not been as widely considered as urban expansion dynamics represented by the growth of impervious surfaces. Furthermore, existing metrics ignore the different patch shapes in the identification of spatial evolution types, thereby significantly affecting the recognition of spatial relationships between new and existing patches. This study proposes a shape-weighted landscape evolution index (SWLEI) for simultaneously analyzing the landscape expansion and shrinkage types of patches in two or more periods. Compared with existing landscape expansion metrics, the SWLEI can depict the spatial relationships between new and old patches from a more detailed perspective and is thus more comprehensive and meaningful in terms of geospatial recognition. Empirical analysis in Hubei Province in central China indicated that dramatic urban expansion and small-scale urban built-up land use change occurred in 1990–2015. The changed urban patches can reflect the spatial patterns and distribution of urban redevelopment, and indicate the characteristics of the spatial optimization of urban land uses and urban greening. The characteristics of urban expansion and redevelopment patterns showed a distinctive disparity in different cities and periods. Urban growth became increasingly compact after 2005, and most cities experienced redevelopment at the early stage of urbanization and after 2005. Furthermore, the newly developed and changed urban patches were clustered in the central and eastern areas with advantageous physical and economic conditions.

Keywords: Patch shape; Landscape evolution patterns; Impervious surfaces; Urban expansion; Urban redevelopment

1 Introduction

Tremendous changes in urban landscapes have been observed around the world, especially in megacities, where urban growth and decay processes occur simultaneously (Bennett and Smith, 2017; Pan et al., 2019). On the one hand, rapid urban development has led to dramatic urban land sprawl over the past several decades (Herold et al., 2003; Li and Yeh, 2004; Xia et al., 2019a; Zeng et al., 2017), and this condition is accompanied by serious challenges in rural and urban environments (Deng et al., 2017; Fang et al., 2017; Fujii et al., 2017; Weng, 2007; Xu and Yang, 2019). On the other hand, accelerated urbanization has revealed an increasing demand for reusing urban lands once occupied by deteriorating villages, underused factories and low-density slums (He and Wu, 2009; Loures and Vaz, 2018; Pan et al., 2019; Shahtahmassebi et al., 2018; Wu, 2015). Considerable effort has been exerted to analyze urban evolution because of its substantial effects on human and nature systems (Dietzel et al., 2005b; Wang et al., 2018). Satellite remote sensing presents an effective way to investigate and reveal those alterations and characteristics of the Earth's surface (Fu et al., 2019; Qi et al., 2017; Sun et al., 2019; Zhang et al., 2014a). However, previous studies were largely centred on urban expansion represented by the growth of impervious surfaces, and conversion from impervious surfaces to other lands, such as green spaces, has been insufficiently studied. The characteristics of urban land use change could be explored using landscape metrics, which are useful tools for understanding urbanization (Aguilera et al., 2011; Jia et al., 2019; Lausch et al., 2015; Li and Wu, 2004). By contrast, quantitative analysis and metrics with regard to urban redevelopment remain lacking.

1.1 Remotely sensed data and urban redevelopment

Remotely sensed data have drawn considerable attention in the analysis and modelling of urban expansion. In this regard, the growth of impervious surfaces is a major indicator of the degree of urbanization (Ewing and Hamidi, 2015; Fan and Fan, 2014; Seto et al., 2012). Image pixels with more than half of built-up land represented by impervious surfaces are often defined as urban pixels. On the contrary, pixels dominated by vegetation (such as green parks) are not considered urban even though these areas may function as urban spaces in terms of land use (Schneider and Woodcock, 2008). Moreover, urban expansion is generally recognized as an irreversible geographical process, that is, there is no existing urban areas that deurbanize (Dietzel et al., 2005). However, the 'disappearance' of urban pixels can be observed during urbanization, which is mainly related to the phenomenon of urban redevelopment.

Urban redevelopment aims to improve land use efficiency of underused or inactive urban areas inside a city, such as brownfields (Rhodes and Russo, 2013; Thomas, 2002; Weber, 2010). Consequently, existing buildings are demolished and reconstructed into new structures that offer additional functions for cities (Chrysochoou et al., 2012; Rizzo et al., 2015). In China, urban redevelopment has led to the large-scale demolition of old, low-density urban areas and city villages in the past few decades (Dowall, 1994; Wu, 2015; Yu et al., 2019). In the United States and European countries, the redevelopment of brownfields has become an effective way to improve land use efficiency and alleviate the accelerated problem of land supply scarcity (Pan et al., 2019). Furthermore, the improvement of urban green coverages by building more green spaces has become a common phenomenon with the increasing demand of urban residents for sustainable and liveable urban environments (Sarkar et al., 2018; Sun and Shang, 2015). Urban redevelopment usually involves transformation from old buildings (i.e. urban built-up land) to demolished land (i.e. bare land), which can be regarded as an intermediate land use state. These changes can be identified as short- or long-term decreases of impervious surface coverages using remotely sensed data (Fu et al., 2019, Pan et al., 2019; Shahtahmassebi et al., 2018). From the perspective of time span, the transformation of urban built-up land with high impervious surface coverages into greens or urban vegetation can be noticed after a specific time point. Low-density urban land is sometimes rapidly reconstructed for increased density or renovation. Such development can be captured theoretically using short-interval images. However, the use of remote sensing technologies has not received sufficient attention in this field, and the quantitative analyses of the spatial evolution patterns of urban redevelopment remain limited.

1.2 Landscape metrics for analyzing urban evolution patterns

Landscape metrics are widely used as an effective analytical tool of urban evolution patterns with the help of geographic information system (GIS) and remote sensing technologies

(Forman and Godron, 1986; Lausch et al., 2015; Li et al., 2013; Turner, 1990; Wu et al., 2014). Many of these metrics can capture the spatial characteristics for single time points, but they cannot analyze dynamic spatiotemporal evolution processes (Liu et al., 2010; Ma et al., 2014; Xu et al., 2007). Thus, some spatial metrics have been developed to solve this problem. One such metric is the landscape expansion index (LEI), which has drawn considerable attention. The LEI was proposed by Liu et al. (2010) and is useful for quantifying the spatial patterns of landscape evolution and indicating its structural changes. It has also been commonly employed to measure urban expansion (Liu et al., 2014; Shi et al., 2012; Tian et al., 2014). Recently, scholars have achieved certain improvements to measure the multi-temporal information of urban dynamics and depict detailed spatial relationships between new and old urban patches (Jiao et al., 2015, 2018).

Despite the effort of these studies to analyze landscape evolution patterns, certain problems remain unsolved, particularly those related to the bidirectional changes in impervious surfaces and the identification of the evolution patterns of patches with special shapes. Firstly, most research in landscape evolution patterns has focused on urban impervious surfaces expansion (Li et al., 2013; Li and Yeh, 2004; Pan et al., 2019), but effective quantitative indices for recognizing the spatial patterns of impervious surface shrinkage in urban evolution are lacking. Urban landscapes are a complex combination of impervious surfaces, greens, soil and water (Lu et al., 2010; Li et al., 2016). Accelerated urbanization and industrial reconstruction have caused major adjustments and structural changes in urban areas (Shahtahmassebi et al., 2016). The improvement of urban green space systems and urban reconstruction in some megacities are an important approach to achieving urban sustainability (Huang et al., 2019; Newman, 1999). Therefore, urban impervious surfaces shrinkage has become an important landscape evolution pattern in urban development and can be identified to describe the spatial distribution of ecological restoration and land use optimization (Pan et al., 2019; Zhang et al., 2017).

Secondly, the buffer sharing rate is often used by existing landscape metrics to identify the growth modes of new urban patches (Liu et al., 2010). Nevertheless, all newly developed patches have the same buffer distance, which is generally small and fixed. In such cases, some patches with special shapes might be misidentified using these simple spatial metrics as they cannot consider the differences in sizes and outlines of new patches. For example, large, newly developed plots should be a good distance away from existing construction land in the process of urban development and construction, especially in densely developed urban areas, due to considerations of lighting, safety factors and landscape continuity. These plots will be identified as outlying growth using existing indices, given the many trees, green spaces and water bodies that often lie between them and existing urban areas. However, these patches should be adjacent or infilling growth in nature because they are often closely connected to existing urban areas instead of being potential growth points of urban development (Dietzel et al., 2005). Furthermore, the buffer distance often mismatches the spatial resolution of remote sensing images, thereby possibly causing the overvaluation of outlying–type patches (when the buffer distance is too small) or undervaluation of infilling–type patches (when the buffer distance is too large) (Jiao et al., 2015). Although some scholars have attempted to modify the buffer distance to make it equal to spatial resolution (Jiao et al., 2018), they cannot address this issue thoroughly for the mismatch between buffer zones and image pixels. The key to solving these problems is to propose an improved landscape index that considers patch shapes on the basis of raster data.

Therefore, the present study aims to propose a shape-weighted landscape evolution index (SWLEI), an improved approach for simultaneously analyzing urban land expansion and redevelopment patterns. Hubei Province, a fast-growing region in China, is regarded as a case study. We link urban evolution types with the theory of urban growth phases in Section 2. The SWLEI and its application methods, the study area and data process are described in Section 3. The results and discussions are presented in Sections 4 and 5, respectively, and the conclusions are summarized in Section 6.

2 Urban evolution types and the processes of diffusion and coalescence

The quantitative analysis of landscape dynamic characteristics with metrics provides useful descriptions for understanding landscape patterns in response to landscape change processes (Xiang and Clarke, 2003; Zhang et al., 2014b). Landscape processes and patterns tend to produce different landscape ecologies with added complexities caused by typically simultaneous expansion and shrinkage (Pan et al., 2019). Landscape expansion mainly involves three categories of spatial patterns, namely, outlying, edge–expansion and infilling and their combination or variants (Forman, 1995; Ewing, 1997; Schneider and Woodcock, 2008; Wilson et al., 2003). In this study, spatial patterns are extended to analyze landscape shrinkage, which is correspondingly defined as isolating, adjacent and enclosing types. A new patch that fills the gaps or holes between old patches or within an old patch can be regarded to be of infilling type. Similarly, an enclosing patch is an extinct patch that becomes a gap or a hole between or within existing patches. A new or extinct patch that is isolated from old patches can be defined to be of outlying or isolating type. An edge–expansion patch is a newly developed patch spreading around the periphery of initial patches. An extinct patch located in an edge is classified as an adjacent type.

Urban evolution, which involves urban expansion and redevelopment, has attracted considerable attention in the field of landscape ecological analysis. The spatial evolution of urban areas can be characterized as the oscillated processes of diffusion and coalescence of individual urban areas (Dietzel et al., 2005). At the early stages of cities, evolution starts with the growth of an urban seed or core area. As the seed spreads, it diffuses to new city development centers or cores, and this process is comparable to the pattern of outlying growth (Liu et al., 2010). Then, urban centers or cores spread unidirectionally from an edge, and this process is comparable to the edge–expansion pattern. As the diffusion process continues, organic growth leads to the infilling of gaps amongst existing urban areas, which is called the process of coalescence. Urban areas substantially change during these processes, where growth and redevelopment occur simultaneously (**Figure 1**). In the initial stage, reusing occupied urban land away from urban development centers or core areas refers to the isolating renewal type. Thereafter, urban growth tends to connect old urban areas around the periphery of urban cores.

However, these old urban areas seem unsuitable for new urban development and would thus be redeveloped, thereby becoming an adjacent renewal type. After cities enter the middle and late stages, the existing urban areas become contiguous, and urban redevelopment is increasingly likely to occur within the existing urban patches; this characteristic describes the enclosing renewal type. In this study, we assume that these redeveloped urban patches can be observed as the ‘disappearance’ of urban pixels derived from remotely sensed data. The three renewal types are related to the three landscape shrinkage types.

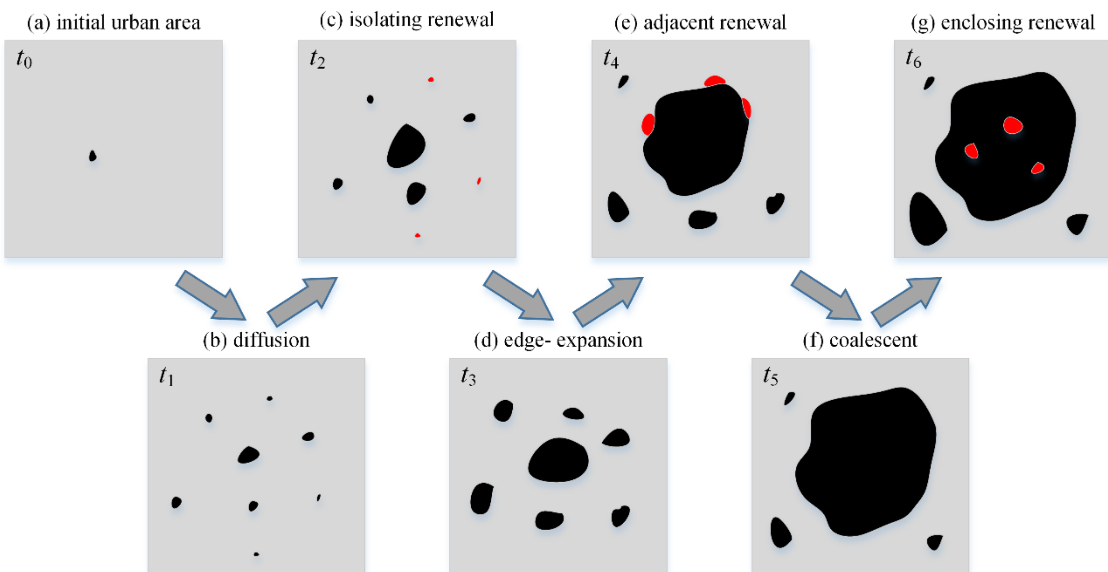

Figure 1. Urban evolution according to the theory of urban growth phases.

The diffusion and coalescence processes of urban development can be detected with landscape metrics (Liu et al., 2010). Landscape metrics are quantitative measurements that quantify the spatial patterns and morphology of a landscape using digital categorical maps with specific scales and resolutions. These measures are set to be definitive and patch-based to depict a landscape (Gustafson, 1998). Patches can be regarded as homogeneous regions classified as one category (i.e. urban, vegetation and water). This process involves the assumptions that the spatial transitions between different categories of patches are not gradual and that the edges between patches are distinct.

3 Methodology and data sources

3.1 SWLEI

In this study, buffer areas are defined on the basis of patch neighborhood, which refers to the set of all the neighborhoods of the pixels contained in a patch. In such cases, the landscape metrics can be calculated on the basis of raster data, which keep the features of landscape patches consistent with image pixels. As shown in **Figure 2**, mismatches between buffer zones and image pixels can be solved using patch neighborhoods. Existing dynamic metrics use one fixed buffer distance for all new patches, i.e. the geographical characteristics of new patches are not considered. As shown in **Figure 3**, when the distances between new patches (S_B, S_C, S_D) and the closest old patch (S_A) are slightly greater than the buffer distance (r = spatial resolution), the values calculated by existing metrics (i.e. LEI) are zero, and all the three new patches are identified as outlying ones. However, defining the new patches as outlying patches is not reasonable in terms of geographical cognition if the distance between new and old patches is negligible compared with the shape of the new patches (S_B, S_C). Moreover, the shape of new patches is not only about their size (i.e. area) but also about their outline (i.e. perimeter). For a new patch S_D, the distance between patches S_D and S_A cannot be ignored even though the area of patch S_D is equal to those of patches S_B and S_C. Furthermore, the relationship of patches S_A and S_C may have to be defined as outlying rather than adjacent in the geographic context if their intersection is negligible relative to the buffer area in the use of the neighbourhood distance (R) whilst considering shapes. In this study, an outlying grown patch can be defined using a pre-set threshold value to solve such issue.

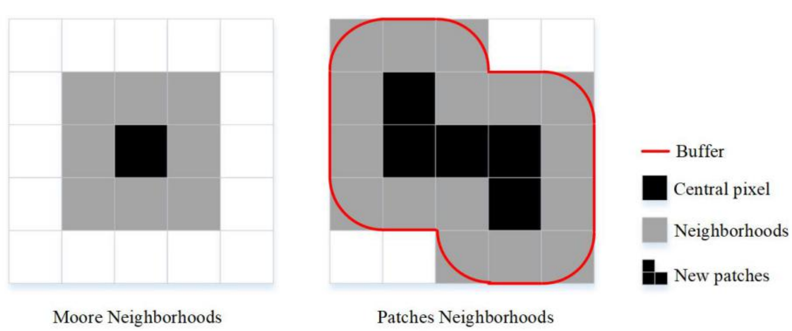

Figure 2. Buffer zones and neighborhoods of patches.

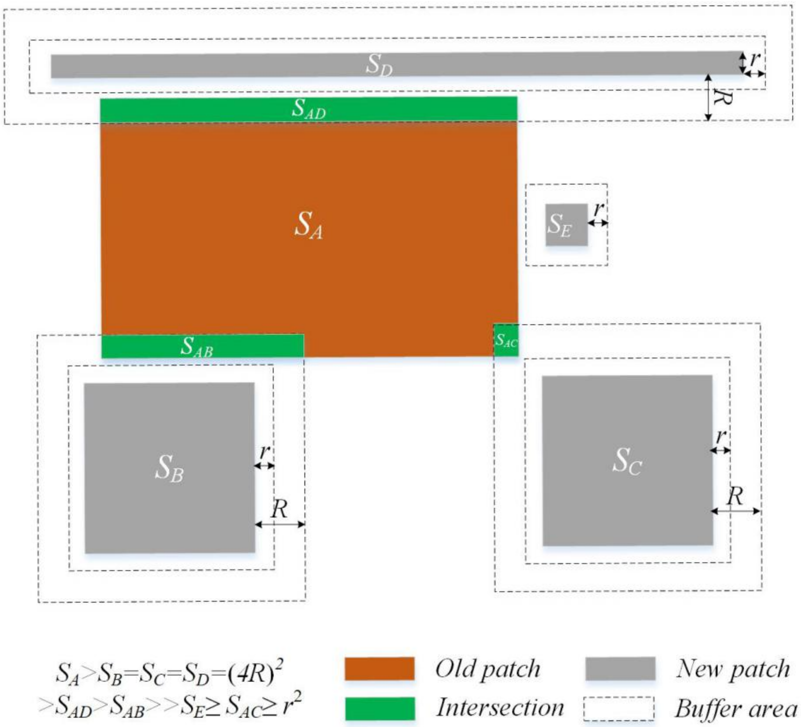

Figure 3. Relationships between new and old patches determined using different neighborhood distances.

Considering the above issues, we propose an improved landscape metric called the SWLEI to define the relationships between targeted and existing patches and depict the spatial patterns of landscape expansion and shrinkage. In particular, the SWLEI can simultaneously quantify the bidirectional changes in urban landscapes (e.g. urban impervious surfaces). Moreover, the neighborhood distance is calculated for each patch in accordance with its shape and the spatial resolution of images. The SWLEI can be defined by the following equations:

$$SWLEI_i = (-1)^{\lambda} \times \frac{N_i^*}{N_i} \times 100 \tag{1}$$

$$N_i = D_i \times P_i + 4 \times D_i! \tag{2}$$

$$D_i = \left\lceil \frac{S_i}{P_i} \right\rceil \tag{3}$$

where λ is a binary variable representing the status of the targeted patch (new or extinct patches) during the study period (t_0, t). If it is a newly developed patch at time t, then $\lambda = 0$; if the patch exists at time t_0 but disappears at time t, then it is defined as an extinct patch and $\lambda = 1$. N_i is the number of pixels in the neighborhood of the targeted patch at time t, and N_i^* is the number of pixels in the intersection area of the targeted patch's neighborhood with existing patches. D_i is the neighborhood radius, S_i is the number of pixels in the targeted patch, and P_i is the ratio of the targeted patch's perimeter to the spatial resolution. The LEI can be regarded as a special case of the SWLEI, with $\lambda = 0$ and $D_i = 1$. When $D_i > 1$, the patch neighborhood is extended to be a Moore neighborhood.

In this study, landscape evolution patterns are divided into two categories, namely, the growth modes of new patches and the shrinkage modes of extinct patches. The growth modes include infilling, edge–expansion and outlying, as shown in **Figures 4a–4c**. The shrinkage modes include enclosing, adjacent and isolating, as shown in **Figures 4d–4f**. Possible SWLEI values vary between –100 and 100. Large SWLEI values (absolute) indicate that the corresponding patches are closely connected to existing patches, and small SWLEI values (absolute) indicate that the corresponding patches are isolated. Specifically, a patch is defined as infill growth or enclosing shrinkage if at least 50% of the areas in its neighborhood are occupied by old patches. If the occupied areas are no more than 50% but larger than 1%, the patch is characterized as edge–expansion growth or adjacent shrinkage; otherwise, it can be identified as outlying growth or isolating shrinkage. Therefore, in this study, an SWLEI value within [50, 100] indicates an infilling new patch. If it is in the range [1, 50), then the new patch is defined as edge–expansion. If it is within (–1, 1), then the new patch is classified as outlying, and the extinct patch is defined as isolating. The extinct patch is defined as adjacent once its SWLEI value is within (–50, –1] or enclosing if the value is within [–100, –50].

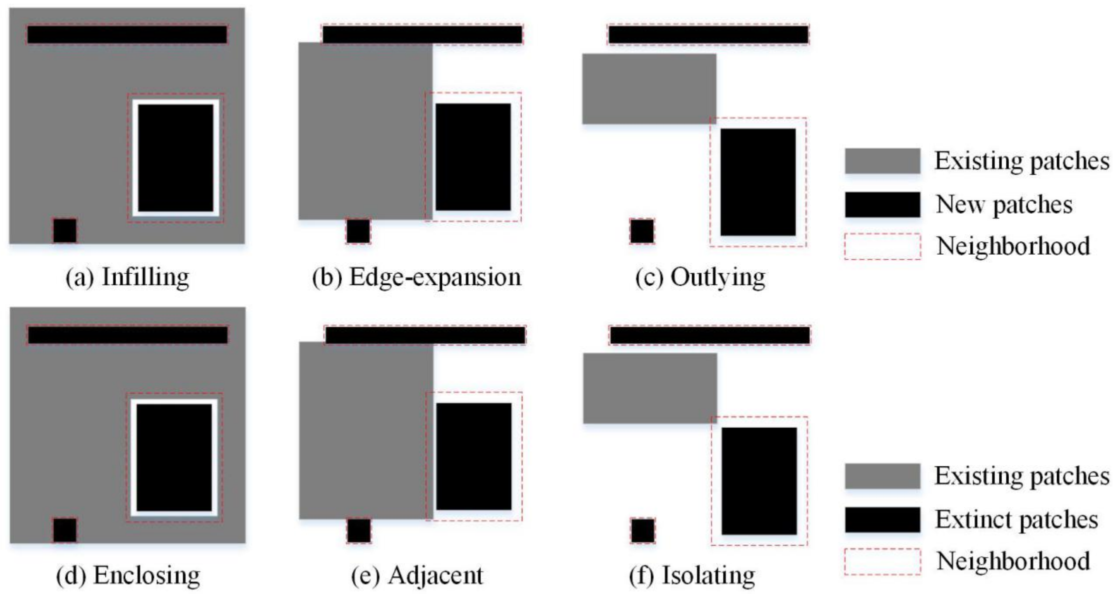

Figure 4. Landscape evolution patterns (a-c: patch expansion modes, d-f: patch shrinkage modes).

The SWLEI has the following characteristics. Firstly, it can identify the patterns of landscape shrinkage. Landscape evolution should include the generation and growth of landscape patches and the shrinkage and extinction of patches. Thus, studies on bidirectional landscape changes should attract added attention. Secondly, the SWLEI can recognize the spatial evolution patterns of patches with special shapes and describe their relationships with existing patches in terms of geographical meanings. Thirdly, this index is established on the basis of the neighborhood of image pixels, which is consistent with the spatial resolution of raster data. In this study, the LEI is selected for comparison. This index is a widely used and distinguished index of landscape expansion. It is also the foundation of the SWLEI, and other indexes designed for identifying landscape evolution types. In this study, the LEI is extended to measure the spatial patterns of extinct patches, as shown in Equations 1–3.

3.2 Study area and data processing

Hubei is a province in central China; it had a population of 59.02 million and a per-capita gross domestic product of more than US$ 9100 in 2017. Its economy ranks intermediately in the country, and its provincial capital, Wuhan, is a major transportation hub and an important political, cultural and economic center in China. Hubei Province consists of three urban agglomerations, namely, the Wuhan–centred, Xiang–Shi–Sui and Yi–Jing–Jing city groups. It is an important strategic core region for promoting the policies New Urbanization and Rise of Central China and ensuring national food and ecological security (Xia et al., 2019b).

The land use classification data of six periods (1990, 1995, 2000, 2005, 2010 and 2015), with a ground resolution of 30 m, were used to provide the inputs for analysis. These data were derived from the National Resources and Environment Database of the Chinese Academy of Sciences (National Land Use/Cover Database of China [NLUD-C]) (http://www.resdc.cn). The NLUD-C was built using Landsat TM and China–Brazil Earth Resources Satellite images, and its classification accuracies are more than 90% according to nationwide field verification. This database applies a classification system of six major land use types, namely, farmlands, forest, grasslands, water, built-up land and unused land (Lai et al., 2016). The built-up land is further classified as urban, rural settlement and industry–traffic land. This study focuses only on urban built-up land. Urban land is defined differently in previous research; impervious surfaces in terms of remotely sensed images have been widely used (Arnold and Gibbons, 1996). Therefore, ‘urban built-up land’ here is synonymous with ‘urban impervious surface’, which does not involve urban vegetation. Industry-traffic land is also excluded. For simplicity, the term ‘urban land’ is used to represent urban built-up land interpreted from satellite images. Therefore, in this study, urban built-up land use change should include the declines in urban impervious surfaces and transformation of urban built-up lands to industrial–traffic lands (**Figure 5**), which can be mainly attributed to urban redevelopment. Specifically, the declines in imperviousness of urban land use are related to the intermediate transformation of urban land to demolished land, as well as urban greening. Although most of urban greening may be due to the building of urban green spaces, some could be caused by the natural evolution of urban vegetations, for example, tree growth. Therefore, the identified urban redevelopment areas in this study may contain errors, which may lead to some overestimation.

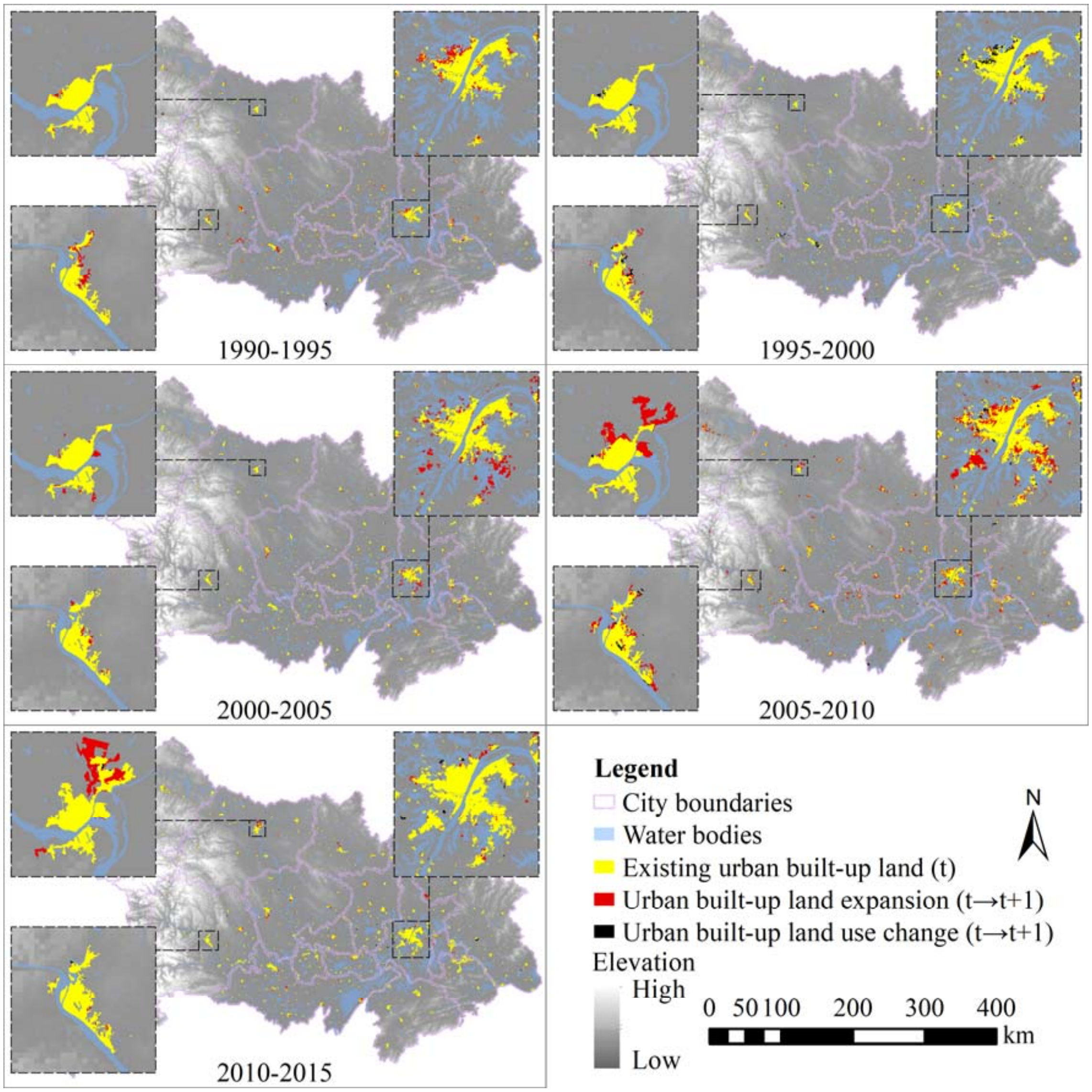

Figure 5. Urban land use evolution during different periods in Hubei Province.

4 Application and results

4.1 Characteristics of landscape evolution types based on SWLEI

We first identified the evolution types for each new and changed urban patch in each of the five periods (1990–1995, 1995–2000, 2000–2005, 2005–2010 and 2010–2015). **Figure 6** shows the spatial distributions of the different urban evolution types in all the cities. Three growth types and three renewal types of urban patches were identified by using the proposed SWLEI. The urban landscape of Hubei dramatically changed from 1990 to 2015. However, the urban landscape showed distinct growth and redevelopment patterns in different periods. In the first period (1990–1995), the patterns of urban growth were dominated by the edge–expansion and infilling types. The newly developed patches mainly appeared near the existing urban areas. Compared with urban growth patches, changed patches were hardly noticeable. During the period of 1995–2000, urban growth suddenly slowed down, and many enclosing renewal patches were found along the existing urban areas. During the period of 2000–2005, new patches under outlying growth were easily found, and edge–expansion type growth became predominant. Urban development occurred far from existing urban areas, exhibiting a scattered and disordered pattern. In 2005–2010, outlying growth was in a decreasing trend, and edge–expansion and infilling growths became dominant. Changed patches were evident, especially in large cities (e.g. Wuhan). In the last period (2010–2015), edge–expansion and infilling growths remained dominant in the study area. However, edge–expansion growth was decreasing, especially in large cities. Meanwhile, isolating and adjacent types were easily found. Consequently, the urban morphology became increasingly compact.

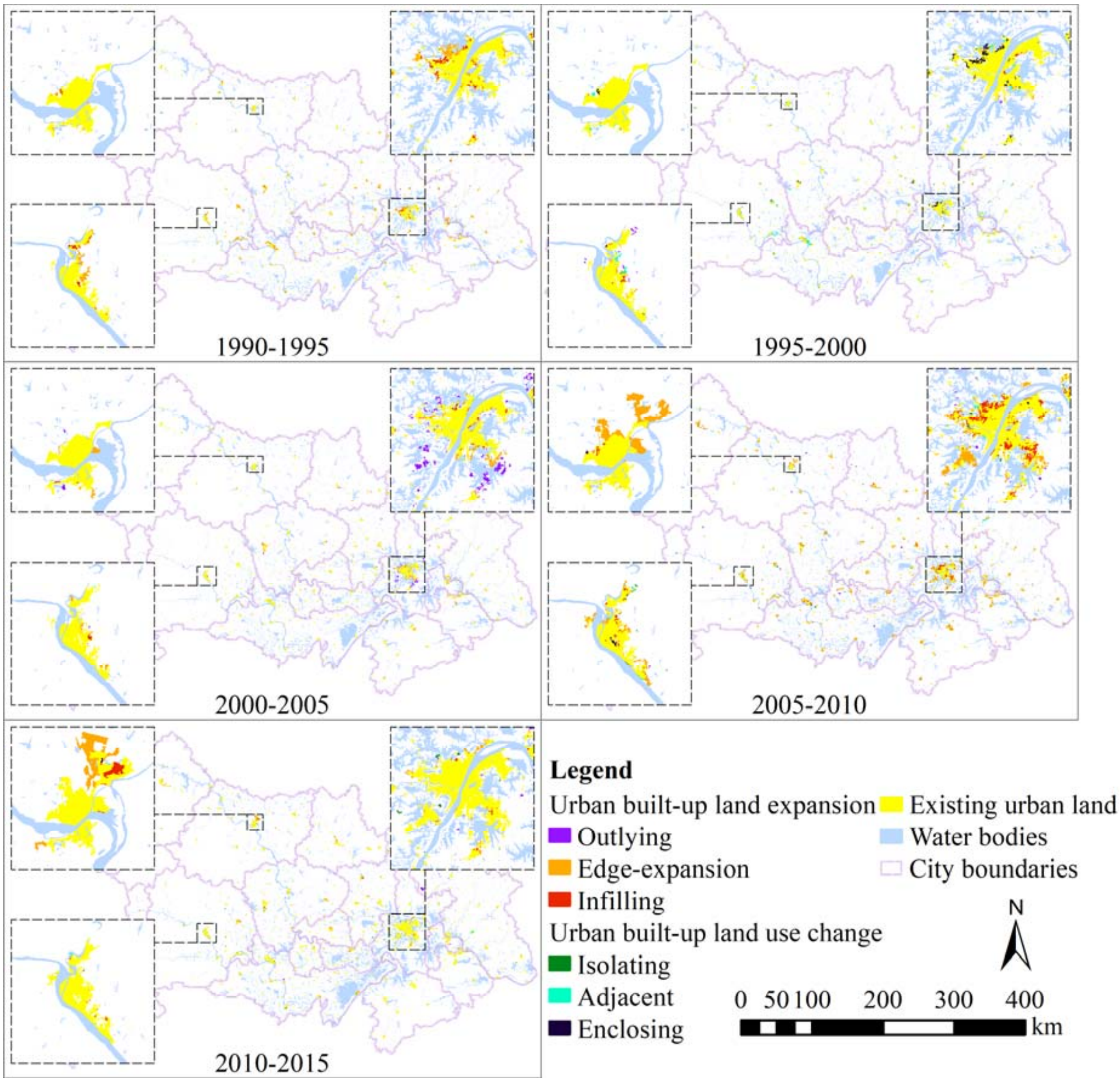

Figure 6. Spatial distribution of different urban evolution types in the five periods.

As shown in **Table 1**, the changes in the area and quantity proportions of the different evolution types for the five periods imply the transformation of spatial patterns. Overall, edge–expansion and adjacent renewal were the most prevalent types of urban evolution for the covered cities during the entire period. As for urban expansion, the area and quantity proportions of outlying growth experienced a significant increase in the first three periods (1990–1995, 1995–2000 and 2000–2005) and then decreased during the two succeeding periods (2005–2010 and 2010–2015). Opposite changes were identified in the infilling growth and edge–expansion. At the earliest stage (1990–1995), edge–expansion and infilling growth were the dominant forms of growth in terms of area and quantity, respectively. In this period, the urban form of cities was compact, and land use was intensive. During the second and third periods (1995–2000 and 2000–2005), the area proportion of infilling patches decreased to less than 10%, whereas the outlying patches increased to 42.63% and became the dominant type. In the meantime, edge–expansion growth experienced a significant decline in area and quantity, but it remained the main expansion type. Urban growth became increasingly scattered in these periods through edge expansion and outlying expansion represented as types of diffusion. In the period of 2005–2010, the proportion of infilling growth and edge–expansion increased dramatically, whereas the outlying type decreased by more than 30% in area and quantity. This finding indicated that urban diffusion was controlled effectively and that the cities grew in a compact manner. In the last period (2010–2015), the proportions of the expansion types remained unchanged, and the urban forms stabilised.

Table 1. Area and quantity proportions of different evolution types

Periods	Area proportion (%)						Quantity proportion (%)					
	Expansion types			Renewal types			Expansion types			Renewal types		
	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
1990–1995	7.11	70.31	22.58	35.17	62.01	2.82	4.72	56.25	39.03	13.49	47.62	38.89
1995–2000	23.34	64.87	11.79	12.14	58.80	29.06	18.98	44.88	36.14	5.71	48.57	45.71
2000–2005	42.63	48.19	9.19	2.64	90.52	6.84	39.13	44.87	16.00	3.13	59.38	37.50
2005–2010	10.22	68.23	21.56	34.04	52.77	13.19	8.29	51.62	40.09	10.43	45.13	44.44
2010–2015	18.49	64.95	16.56	34.60	52.79	12.62	8.92	44.13	46.95	4.30	44.09	51.61

Expansion: Type 1: outlying, Type 2: edge expansion, Type 3: infilling. Renewal: Type 1: isolating, Type 2: adjacent, Type 3: enclosing. The same definitions are used hereafter.

For urban redevelopment, adjacent and enclosing renewal were the dominant types in terms of quantity, whereas isolating renewal had small quantity proportions but relatively large area proportions. Isolating renewal decreased in area and quantity proportions during the first three periods (1995–2005) but increased to its original level in 2005–2010 and then remained over 34% in the area proportion. The area proportion of enclosing renewal was less than 3% in the first period (1990–1995), although it constituted 38.89% of the total amount of changed urban patches. Adjacent and isolating renewal were the main types of patch renewal in this period, accounting for 62.01% and 35.17%, respectively, of the area proportion. In this period, urban redevelopment occurred mainly in the urban periphery and was relatively far from the existing urban areas. The urban forms of cities were compact at this stage. During the following period (1995–2000), the area proportion of enclosing renewal increased to 29.06%, whereas the isolating type decreased by over 20%. Although adjacent renewal remained the dominant type, the landscape pattern became scattered. During the period of 2000–2005, enclosing and isolating types were replaced by adjacent type, which covered more than 90% of the total area. In the last two periods, enclosing and isolating types had significant increases, and the proportion structure was stable.

4.2 Comparison of SWLEI and LEI

Histograms were drawn for the SWLEI and LEI in different periods to perform a statistical analysis on the urban evolution patterns. The SWLEI and LEI values equal to zero indicated types of outlying and isolating. As shown in **Figure 7**, the histograms of the SWLEI and LEI showed similar robustness patterns. Despite the different development forms in the five periods, the following five peaks were found: [–100, –95], [–50, –45], [0, 5], [50,55] and [95,100]. These peaks can provide evidence for setting the thresholds of the SWLEI values in determining the evolution types of targeted patches. Major differences were found near the five peaks by comparing the frequency distributions of the SWLEI and LEI values in the different periods. On the basis of the different definitions of the SWLEI and LEI, we can infer that the SWLEI attempts to solve the misidentification of evolution types by the LEI. In other words, the SWLEI and LEI have similar abilities to identify the evolution types of new patches that are adjacent to old urban patches (the distance between them is less than the spatial resolution) or have small shapes (the area or length is not considerably larger than the spatial resolution). However, the SWLEI varies for large and non-adjacent patches, and reflects the spatial relationships between new and old patches in a comprehensive way.

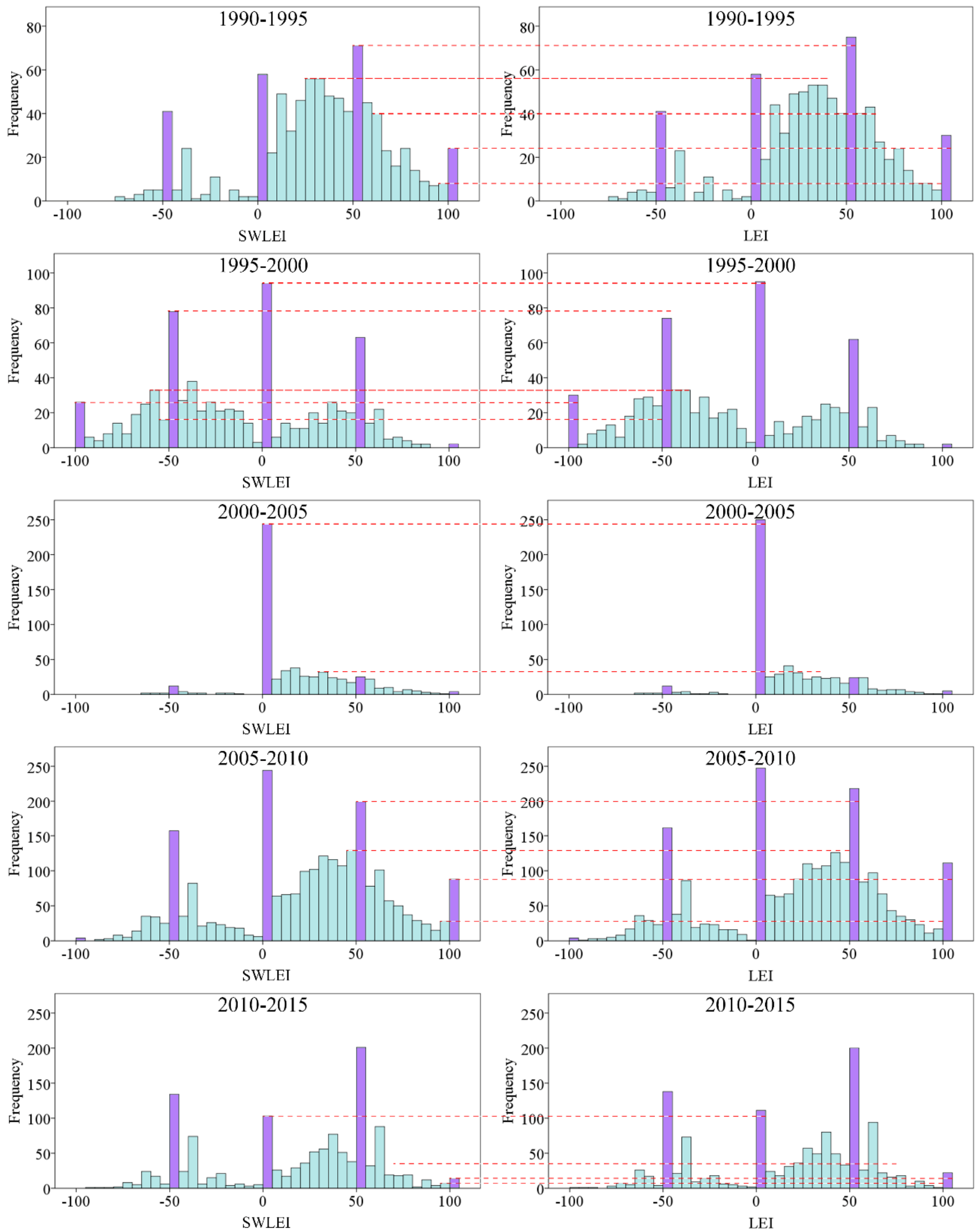

Figure 7. Robustness of SWLEI and LEI values based on histograms for different periods.

The different evolution modes identified by the SWLEI and LEI in the local areas were found and are shown in **Figure 8**. In Case 1, the distances between the new and existing urban patches were slightly larger than the spatial resolution (30 m) but substantially smaller than the sizes of the four new patches. These new patches were identified as outlying ones using the LEI. However, in terms of geographical spatial cognition, these patches were located near the old patches and usually geographically connected to existing urban areas through transportation networks (e.g. bridges and overpasses). In other words, these patches will not be new seeds or core areas for development. As shown in Cases 1.2 and 1.4, new urban patches may not occupy some important landscape spaces to keep the continuity of urban landscapes (e.g. river system and green belt) and protect urban ecosystems. Therefore, these patches were identified to be of the edge–expansion type by the SWLEI, and this assessment is reasonable. In Case 2, the four new patches were identified as edge–expansion by the LEI, although these patches were found to be of the infilling type from a broad view. If the neighborhood distance was small (i.e. 30 m), then the neighborhood of these new patches might not contain too much existing urban land. However, these newly developed patches were filling gaps between old patches or within old patches. Classifying these patches as infilling growth using the SWLEI would be accurate. In Case 3, half of the boundary for the four new patches is adjacent to the existing urban areas in one side. Therefore, these new patches were identified as infilling growth using the LEI. Nevertheless, such misidentifications were attributed to the irregular shapes of different patches. After the shapes of the new patches were considered, these newly developed patches were correctly classified as edge–expansion using the SWLEI. Overall, the spatial evolution patterns identified by the SWLEI were more realistic than those by the LEI from the perspectives of geographical meaning and cognition.

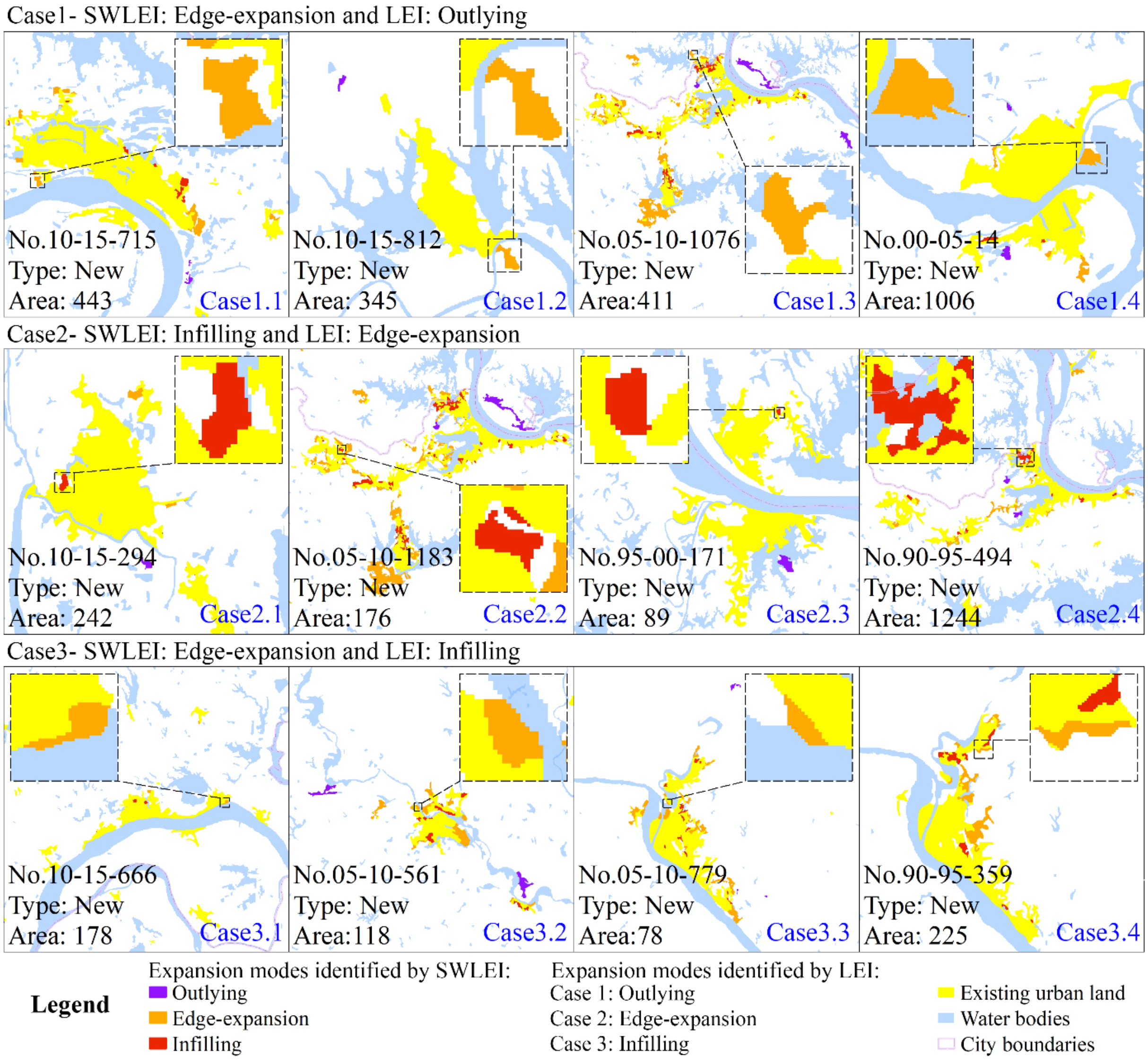

Figure 8. Evolution modes identified by the SWLEI and LEI in local areas (Area refers to the number of pixels).

In summary, compared with other landscape metrics (e.g. LEI), the proposed SWLEI can quantitatively identify the evolution types of all new patches in a more comprehensive and representative way; it transforms simple classification to detailed geographical spatial recognition. Therefore, the SWLEI is an improved dynamic metric with which urban evolution processes can be accurately and comprehensively understood.

4.3 Identification of redeveloped urban built-up land

With land use optimization and the construction of green spaces (e.g. parks), the enclosing and adjacent renewal of old patches inside urban areas are under the guidance of plans. These patches are mostly distributed along lakes or both sides of roads. To a certain extent, the recognition of these patches can provide references for constructing urban green infrastructure and renovating residential land. In the urban periphery, scattered isolating patches are transformed in response to regional development in a process that can be regarded as a kind of natural evolution. **Figure 9** shows two examples of urban patch redevelopment. The left case shows an isolating urban patch in the city of Wuhan, which was urban residential land in 2009 and rebuilt as industrial–traffic land in 2015. As Wuhan enters the era of high-speed railways, its local governments are actively updating the infrastructure around the city to meet the growing demand for travel. In this case, although the patch is still urban in terms of function, it is already defined as a changed urban patch because industry–traffic land is not included in the definition of urban land in this study. The right case shows another isolating urban patch in Yichang City, which was urban residential land with poor environments before 2010 and transformed to a villa district with a high greening rate in 2015. With the promotion of urban consumption abilities and upgrading concepts of residence, developers and governments are attempting to reactivate urban spaces through the construction of high-quality residential areas in old, low-density urban areas. In this case, the patch is identified as non-urban because vegetation dominates more than half of the pixels.

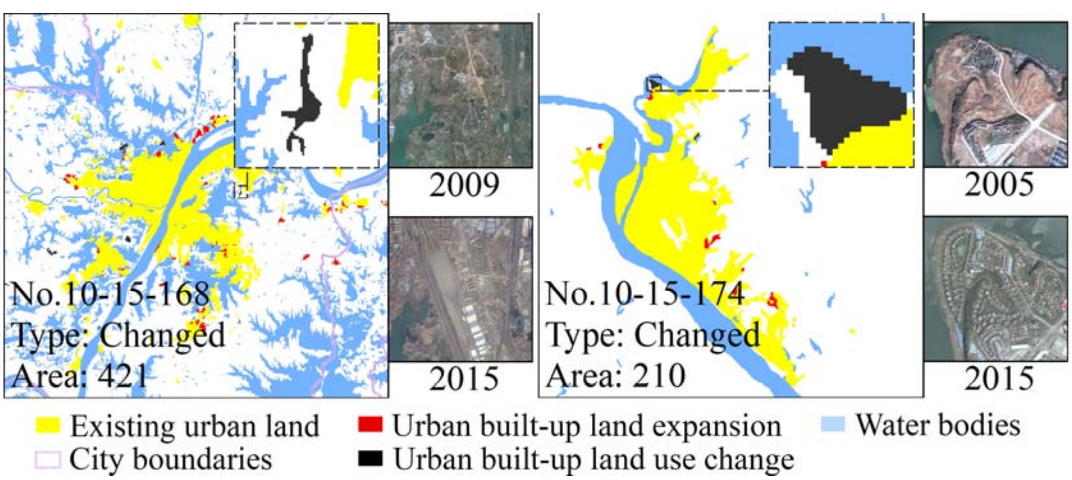

Figure 9. Examples of urban built-up land use change.

4.4 Evolution process and spatial disparity of urban expansion and redevelopment

As shown in **Figures 10–12**, the characteristics of urban expansion and redevelopment patterns showed a significant spatial disparity in different cities and periods. Urban expansion mainly occurred at the beginning of the 21st century. Wuhan, as the provincial capital, sprawled faster than did the other cities in terms of area and amount. After 2010, urban sprawl slowed down, especially for large cities (e.g. Wuhan). This phenomenon may be largely due to the fact that governments began promoting compact development after realizing the social and environmental problems caused by urban sprawl. In terms of spatial distribution, newly developed and changed urban patches were clustered in the central and eastern regions due to the restrictions of natural and economic conditions. The western cities in Hubei Province are not suitable for development because of their undulating terrain, high altitudes and harsh climate conditions. In addition, their lagged economies will hinder redevelopment.

The mean areas and area and quantity proportions of the urban expansion patterns varied in the different cities and periods from the perspective of urban growth. During the period of 1990–1995, all the cities were dominated by edge–expansion and infilling types, and a small number of outlying new patches were observed. However, the mean areas of these outlying new patches were relatively larger than those of the infilling patches and close to edge–expansion patches in most cities. In the following periods, the amounts and mean areas of newly developed urban patches significantly decreased during 1995–2000, dramatically increased after 2000 and slowed down after 2010. In 2000–2005, most cities primarily expanded through edge expansion, whereas cities such as Wuhan, Tianmen, Xiantao and Suizhou grew in an outlying spread, with over half of the total area of the new urban patches being outlying patches. This observation may be due to the physical conditions in these cities, which naturally block contiguous growth and generate many enclaves around original built-ups, thus forming a scattered urban structure. After 2005, most cities grew increasingly compact, with the area and quantity proportions of infilling growth considerably increasing.

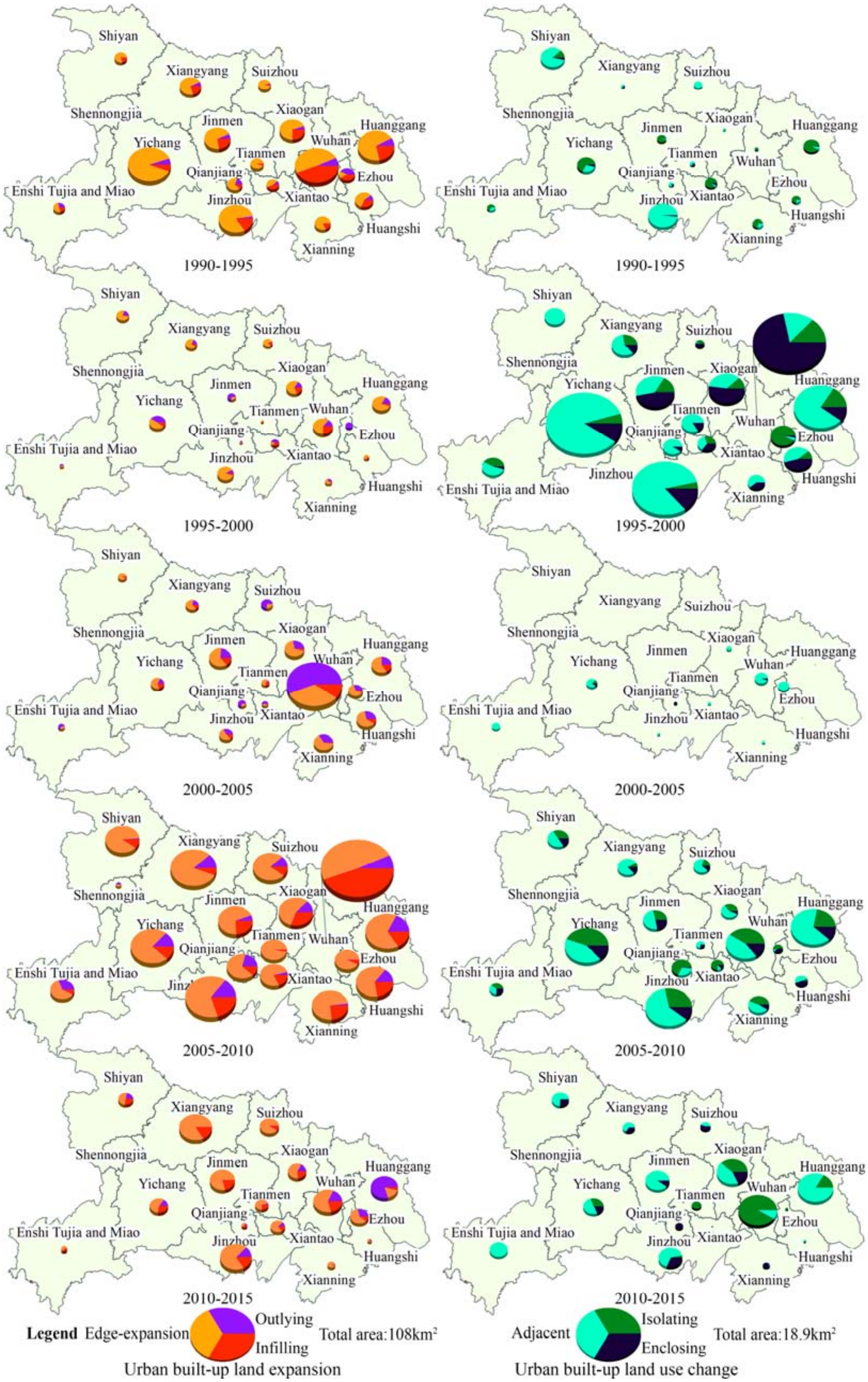

Figure 10. Area proportions of different evolution types for all cities in different periods.

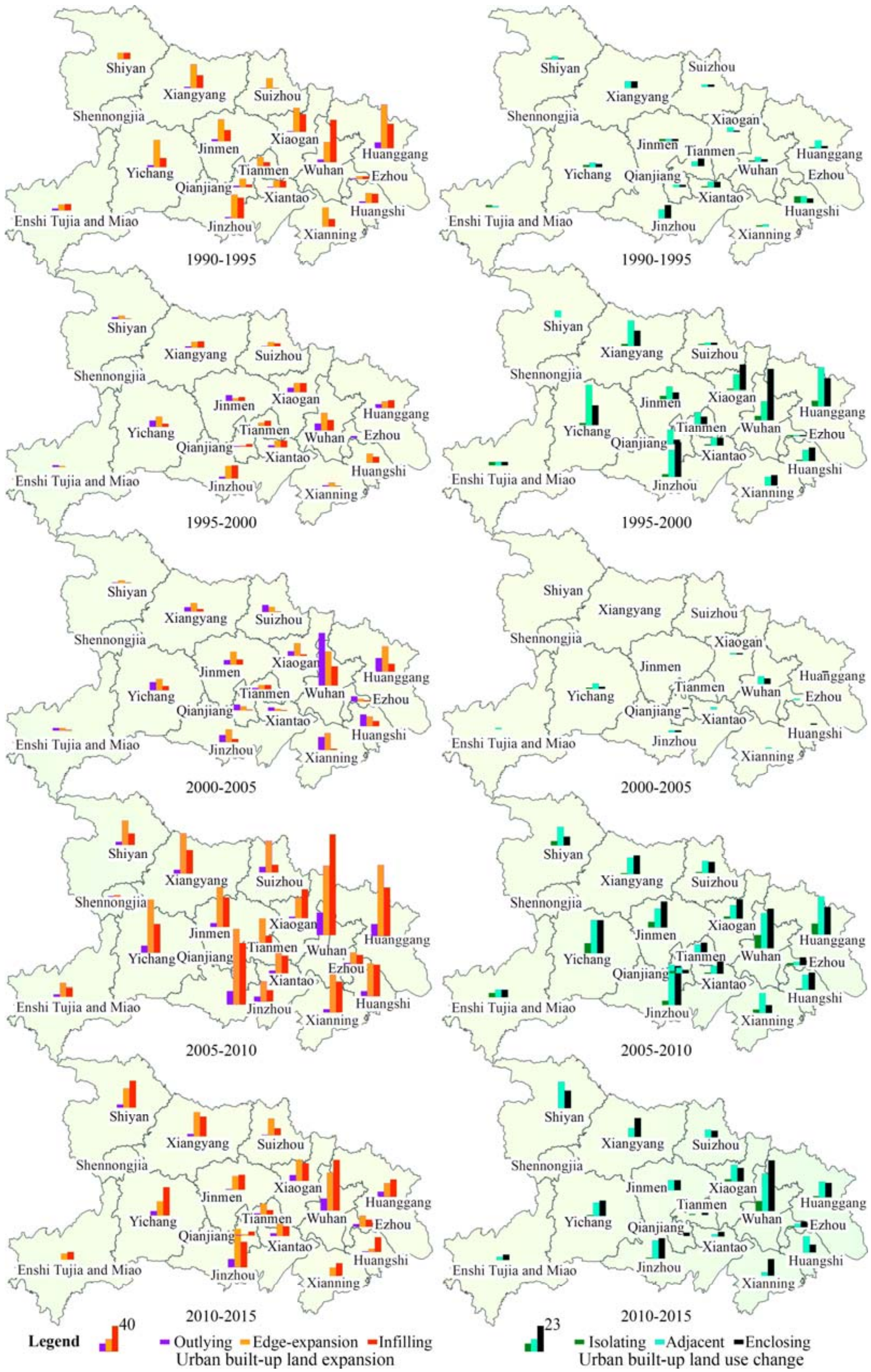

Figure 11. Quantity proportions of different evolution types for all cities in different periods.

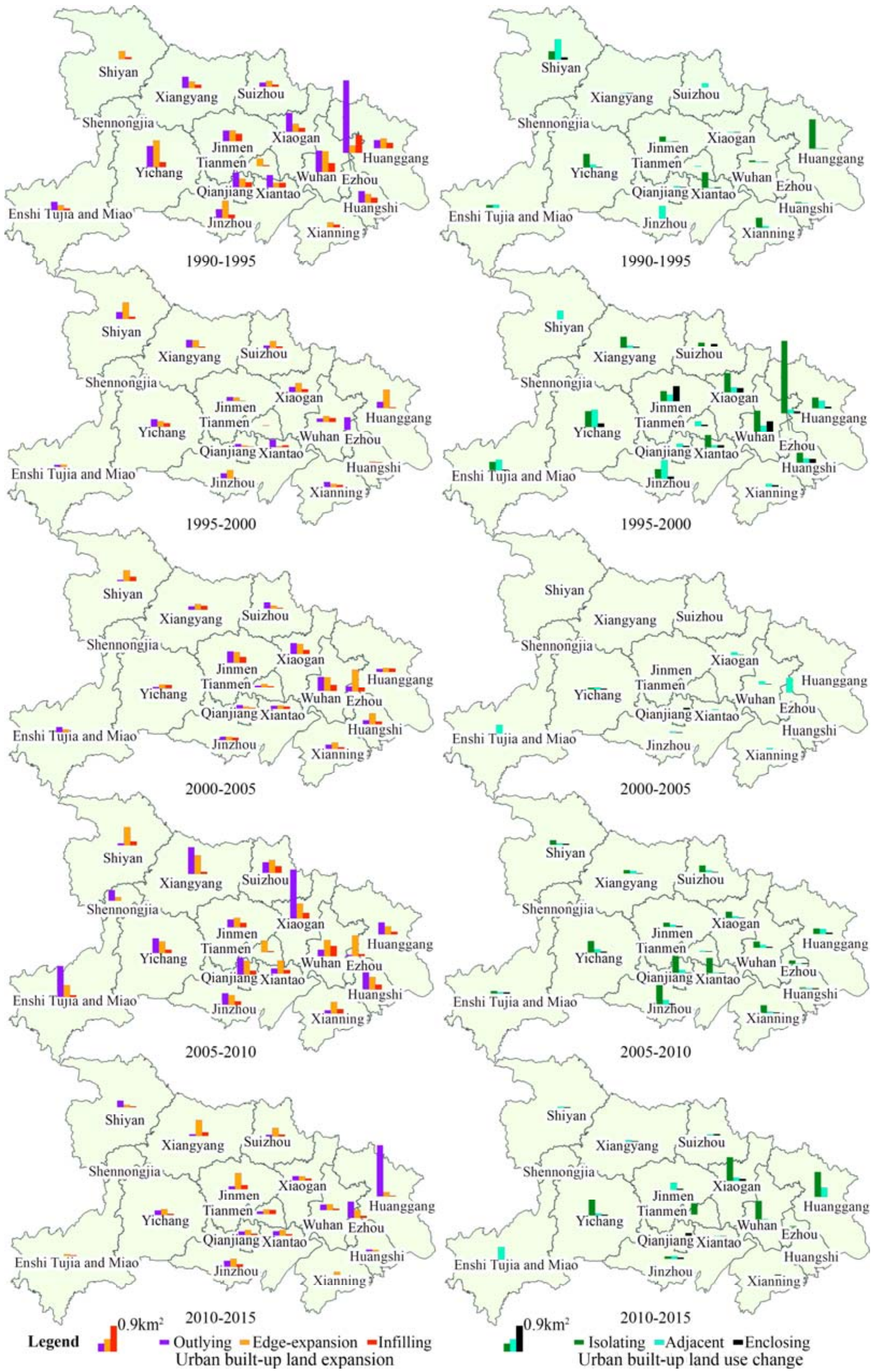

Figure 12. Mean areas of different evolution types for all cities in different periods.

As for urban redevelopment, most cities experienced two major periods, namely, 1995–2000 and after 2005. The first peak happened before the rapid and large-scale urban expansion that began in 2000. This finding may be attributed to the fact that the renewal and reconstruction of existing old urban areas and infrastructure were necessary and beneficial for new development at the early stage of urbanization. The fact that enclosing and adjacent renewal during this period accounted for most of the changed urban patches in area and quantity may provide evidence for this point. However, the mean areas of these two kinds of patches were always considerably smaller than those of isolating type. Thus, urban redevelopment that occurred within the existing urban areas was usually small in scale. After 2005, urban redevelopment became increasingly frequent, with isolating and adjacent renewal as the main types. During this period, these patches mainly appeared in urban fringes to optimize the unused or inactive urban patches. Enclosing renewal was also observed within the existing urban areas, and most of it was aimed at improving the liveability and sustainability of urban systems. With the accelerated urbanization process, the demand of urban residents for environment-friendly development was greatly increasing. Furthermore, the redevelopment patterns in Wuhan showed considerable differences from those in other cities, with isolating renewal constituting most changed urban patches in 2010–2015 mainly because of its scattered urban form.

5 Discussion and limitations

The identification of spatial relationships between targeted patches (new or changed) and old patches is useful for the analysis of urban landscape evolution. The proposed SWLEI in this study solves the following problems. Firstly, the existing literature is centred on the spatial patterns of urban sprawl represented by the growth of impervious surfaces, but spatial pattern of urban redevelopment has not been widely explored. This study develops an improved metric to describe the emerging features of urban redevelopment. Secondly, existing metrics are sensitive to the spatial resolution of maps due to mismatches between buffers and image pixels (Jiao et al., 2015, 2018). Determining a reasonable buffer radius with a clear geographical meaning is difficult. Patch neighborhood is adopted in the SWLEI to solve this issue. The rapidly urbanized Hubei Province in central China was selected as a case study to empirically analyze the characteristics of urban spatial evolution. Hubei has been facing an urgent need for re-planning and managing the obsolete factories and underutilized buildings in urban areas because of the increasing population growth and the continuous loss of arable land resources. Moreover, brownfields, urban villages and decayed downtowns cannot meet the demand of rapid development of cities. Therefore, governors are determined to implement urban renewal policies. For example, Wuhan City issued a policy of city village reconstruction in 2004 and attempted to comprehensively redevelop its underused and low-density urban areas.

Our results could be utilized as reference and inform the planning practices of urban growth and redevelopment in other cities. Different urban growth patterns create various impacts on future urban forms, thereby influencing natural and built environments, transportation infrastructure and vitality of cities (He et al., 2018). For example, edge–expansion and outlying expansion, represented as types of diffusion, generate a dispersed urban form and spatial structure, as well as a series of social and environmental problems, such as ecological deterioration, land resource wastage and agricultural land reduction. The change of urban built-up land is essentially a process of redevelopment and optimization of urban land uses. This redevelopment is mostly represented by the 'disappearance' of scattered construction land in suburbs or the improvement of urban greenery and urban upgrading in urban areas. Urban redevelopment is partly due to the increasing demand of urban residents for ecosystem services during the urbanization process. Urban greens play an important role in the environmental sustainability of urban systems. Therefore, the identification of changed urban patches can be conducive to a comprehensive understanding of evolution patterns and reveal the spatial characteristics of urban ecological restoration. The unused or inactive areas inside cities should be redeveloped into new and functional spaces. Thus, the change of urban patches is also related to urban land use optimization, and analyzing these patches can provide effective support for urban planning.

However, this study also has certain limitations, which need further research. Firstly, there is no field verification for the identification of urban redevelopment in this study. Therefore, it is still unknown whether urban built-up land use changes are real urban redevelopment or not. Urban built-up land use changes identified in the present study can only reflect land use cover changes, which may be attributed to the natural evolution of urban vegetations, such as tree growth. Secondly, urban redevelopment not only decreases impervious surface coverages but also increases imperviousness. However, thematic map techniques classify each pixel in an image as a single definite type. Therefore, this study can detect inter-class conversion (i.e. new or changed urban patches) but not intra-class changes (land use function change or urban intensification). The drawbacks of land use classification data contribute to an underestimation of urban redeveloped areas as urban redevelopment may not necessarily lead to changes in land use type. Thirdly, given the data limitation, 30 m ground resolution images with an interval of 5 years were used in this study to reveal and measure the spatial characteristics of urban redevelopment. However, many urban redevelopments can be finished in five years and cannot be detected using remotely sensed images, especially in rapidly urbanizing regions in China. Therefore, results obtained based on a five-year time interval may be biased and fail to represent the actual spatial and temporal patterns of urban redevelopment. Overall, knowledge gaps remain in monitoring urban redevelopment and greening using GIS and remote sensing technologies. Finally, the assessment regarding the comparison between the SWLEI and LEI could be intuitive and subjective. No quantitative measurement based on real data supports the superiority of the SWLEI. Besides, the significance of SWLEI regarding urban redevelopment might be vague, since there are still limited studies on different redevelopment patterns.

This study focuses on urban redevelopment from the perspective of urban land use change. Redeveloped areas with unchanged land use categories (e.g. urban built-up land) are excluded, and the identified results may also have errors. Additionally, given that most open-access satellite data are median or low-resolution data, high-quality remotely sensed data can be scarce and valuable. Han et al. (2019) identified and evaluated functional and morphological urban redevelopment at the block level using open-source point-of-interest data and street networks. For future studies, multi-temporal high-resolution satellite images and geospatial open-source data can be combined to advance the quantitative analysis of urban redevelopment. Furthermore, urban redevelopment can reflect the change and transformation of urban functions in urban built-up areas (Zhou et al., 2016), and its spatial patterns will provide valuable contributions to the analysis of urban functional agglomeration and diffusion.

6 Conclusion

Similar to urban expansion, urban redevelopment has become an important landscape evolution pattern in urban development, especially in rapidly urbanized areas. However, effective approaches that detect and quantitatively analyze such phenomenon using remote sensing and GIS are lacking. In this study, the potentials of median resolution land use classification data in the analysis of urban expansion and redevelopment were explored. An improved and effective metric named the SWLEI was proposed to analyze the detailed dynamic processes in the urban landscape of Hubei Province. Five periods were selected: 1990–1995, 1995–2000, 2000–2005, 2005–2010 and 2010–2015. The results showed that the SWLEI can depict the spatial relationships between new and old patches via geospatial recognition in a more comprehensive and meaningful way compared with existing landscape expansion metrics. Furthermore, the SWLEI can discover the characteristics of urban land use optimization and urban greening by capturing the spatial patterns and distribution of urban redevelopment. The empirical analysis showed dramatic changes in the urban landscape in Hubei from 1990 to 2015, with distinctive characteristics of urban expansion and redevelopment patterns in different cities and periods. The proposed method may lead to a new understanding of urban land use change and landscape patterns with regard to urban expansion and redevelopment processes. Finally, the results in this work can contribute to the spatial planning of urban renewal and urban greening and to the awareness of urban renewal issues in GIS and urban landscape studies.

Acknowledgements

We would like to thank the financial support from Chan To-Haan Endowed Professorship Fund of the University of Hong Kong and Collaborative Research Fund (CRF C7028-16G) of the Hong Kong Research Grant Council. We also thank anonymous reviewers and the editor for their constructive comments. Furthermore, we are very grateful to Miss Li Yishiqin for providing us insightful suggestions.

References

Aguilera, F., Valenzuela, L.M., Botequilha-Leitão, A., 2011. Landscape metrics in the analysis of urban land use patterns: A case study in a Spanish metropolitan area. Landsc. Urban Plan. 99, 226–238. https://doi.org/10.1016/j.landurbplan.2010.10.004

Arnold, C.L., Gibbons, C.J., 1996. Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. J. Am. Plan. Assoc. 62, 243–258. https://doi.org/10.1080/01944369608975688

Bennett, M.M., Smith, L.C., 2017. Advances in using multitemporal night-time lights satellite imagery to detect, estimate, and monitor socioeconomic dynamics. Remote Sens. Environ. 192, 176–197. https://doi.org/10.1016/j.rse.2017.01.005

Chrysochoou, M., Brown, K., Dahal, G., Granda-Carvajal, C., Segerson, K., Garrick, N., Bagtzoglou, A., 2012. A GIS and indexing scheme to screen brownfields for area-wide redevelopment planning. Landsc. Urban Plan. 105, 187–198. https://doi.org/10.1016/j.landurbplan.2011.12.010

Chuanglin, F., Chenghu, Z., Chaolin, G., Liding, C., Shuangcheng, L., 2017. A proposal for the theoretical analysis of the interactive coupled effects between urbanization and the eco-environment in mega-urban agglomerations. J. Geogr. Sci. 27, 1431–1449. https://doi.org/10.1007/s11442-017-1445-x

Deng, X., Gibson, J., Wang, P., 2017. Management of trade-offs between cultivated land conversions and land productivity in Shandong Province. J. Clean. Prod. 142, 767–774. https://doi.org/10.1016/j.jclepro.2016.04.050

Dietzel, C., Herold, M., Hemphill, J.J., Clarke, K.C., 2005a. Spatio-temporal dynamics in California's Central Valley: Empirical links to urban theory. Int. J. Geogr. Inf. Sci. 19, 175–195. https://doi.org/10.1080/13658810410001713407

Dietzel, C., Oguz, H., Hemphill, J.J., Clarke, K.C., Gazulis, N., 2005b. Diffusion and Coalescence of the Houston Metropolitan Area: Evidence Supporting a New Urban Theory. Environ. Plan. B Plan. Des. 32, 231–246. https://doi.org/10.1068/b31148

Dowall, D.E., 1994. Urban Residential Redevelopment in the People's Republic of China. Urban Stud. 31, 1497–1516. https://doi.org/10.1080/00420989420081391

Ewing, R., 1997. Is Los Angeles-Style Sprawl Desirable? J. Am. Plan. Assoc. 63, 107–126. https://doi.org/10.1080/01944369708975728

Ewing, R., Hamidi, S., 2015. Compactness versus Sprawl. J. Plan. Lit. 30, 413–432. https://doi.org/10.1177/0885412215595439

Fan, F., Fan, W., 2014. Understanding spatial-temporal urban expansion pattern (1990–2009) using impervious surface data and landscape indexes: a case study in Guangzhou (China). J. Appl. Remote Sens. 8, 083609. https://doi.org/10.1117/1.jrs.8.083609

Forman, R.T.T., 1986. Landscape ecology. Wiley, New York.

Forman, R.T.T., 1995. Land mosaics: The ecology of landscapes and regions. Cambridge University Press, Cambridge.

Fu, Y., Li, J., Weng, Q., Zheng, Q., Li, L., Dai, S., Guo, B., 2019. Characterizing the spatial pattern of annual urban growth by using time series Landsat imagery. Sci. Total Environ. 666, 274–284. https://doi.org/10.1016/j.scitotenv.2019.02.178

Fujii, H., Iwata, K., Managi, S., 2017. How do urban characteristics affect climate change mitigation policies? J. Clean. Prod. 168, 271–278. https://doi.org/10.1016/j.jclepro.2017.08.221

Gustafson, E. J., 1998. Minireview: Quantifying Landscape Spatial Pattern: What Is the State of the Art? Ecosystems 1, 143–156. https://doi.org/10.1007/s100219900011

Han, Z., Long, Y., Wang, X., Hou, J., 2019. Urban redevelopment at the block level: Methodology and its application to all Chinese cities. Environ. Plan. B Urban Anal. City Sci. https://doi.org/10.1177/2399808319843928

He, S., Wu, F., 2009. China's Emerging Neoliberal Urbanism: Perspectives from Urban Redevelopment. Antipode 41, 282–304. https://doi.org/10.1111/j.1467-8330.2009.00673.x

Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens. Environ. 86, 286–302. https://doi.org/10.1016/S0034-4257(03)00075-0

Huang, B., Zhou, Y., Li, Z., Song, Y., Cai, J., Tu, W., 2019. Evaluating and characterizing urban vibrancy using spatial big data: Shanghai as a case study. Environ. Plan. B Urban Anal. City Sci. 2399808319828730. https://doi.org/10.1177/2399808319828730

Jia, Y., Tang, L., Xu, M., Yang, X., 2019. Landscape pattern indices for evaluating urban spatial morphology – A case study of Chinese cities. Ecol. Indic. 99, 27–37. https://doi.org/10.1016/j.ecolind.2018.12.007

Jiao, L., Liu, J., Xu, G., Dong, T., Gu, Y., Zhang, B., Liu, Y., 2018. Proximity Expansion Index: An improved approach to characterize evolution process of urban expansion. Comput. Environ. Urban Syst. 70, 102–112. https://doi.org/10.1016/j.compenvurbsys.2018.02.005

Jiao, L., Mao, L., Liu, Y., 2015. Multi-order Landscape Expansion Index: Characterizing urban expansion dynamics. Landsc. Urban Plan. 137, 30–39. https://doi.org/10.1016/j.landurbplan.2014.10.023

Lai, L., Huang, X., Yang, H., Chuai, X., Zhang, M., Zhong, T., Chen, Z., Chen, Y., Wang, X., Thompson, J.R., 2016. Carbon emissions from land-use change and management in China between 1990 and 2010. Sci. Adv. 2, e1601063. https://doi.org/10.1126/sciadv.1601063

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R.-U., Tischendorf, L., Walz, U., 2015. Understanding and quantifying landscape structure – A review on relevant process characteristics, data models and landscape metrics.

Ecol. Modell. 295, 31–41. https://doi.org/10.1016/j.ecolmodel.2014.08.018

Li, C., Li, J., Wu, J., 2013. Quantifying the speed, growth modes, and landscape pattern changes of urbanization: A hierarchical patch dynamics approach. Landsc. Ecol. 28, 1875–1888. https://doi.org/10.1007/s10980-013-9933-6

Li, H., Wu, J., 2004. Use and misuse of landscape indices. Landsc. Ecol. 19, 389–399. https://doi.org/10.1023/B:LAND.0000030441.15628.d6

Li, L., Lu, D., Kuang, W., 2016. Examining urban impervious surface distribution and its dynamic change in Hangzhou metropolis. Remote Sens. 8, 265. https://doi.org/10.3390/rs8030265

Li, X., Yeh, A.G.O., 2004. Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. Landsc. Urban Plan. 69, 335–354. https://doi.org/10.1016/j.landurbplan.2003.10.033

Liu, X., Li, X., Chen, Y., Tan, Z., Li, S., Ai, B., 2010. A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. Landsc. Ecol. 25, 671–682. https://doi.org/10.1007/s10980-010-9454-5

Liu, X., Ma, L., Li, X., Ai, B., Li, S., He, Z., 2014. Simulating urban growth by integrating landscape expansion index (LEI) and cellular automata. Int. J. Geogr. Inf. Sci. 28, 148–163. https://doi.org/10.1080/13658816.2013.831097

Loures, L., Vaz, E., 2018. Exploring expert perception towards brownfield redevelopment benefits according to their typology. Habitat Int. 72, 66–76. https://doi.org/10.1016/j.habitatint.2016.11.003

Lu, D., 2010. Detection of urban expansion in an urban-rural landscape with multitemporal QuickBird images. J. Appl. Remote Sens. 4, 041880. https://doi.org/10.1117/1.3501124

Ma, Q., He, C., Wu, J., Liu, Z., Zhang, Q., Sun, Z., 2014. Quantifying spatiotemporal patterns of urban impervious surfaces in China: An improved assessment using nighttime light data. Landsc. Urban Plan. 130, 36–49. https://doi.org/10.1016/j.landurbplan.2014.06.009

Newman, P.W.., 1999. Sustainability and cities: Extending the metabolism model. Landsc. Urban Plan. 44, 219–226. https://doi.org/10.1016/S0169-2046(99)00009-2

Pan, Z., Wang, G., Hu, Y., Cao, B., 2019. Characterizing urban redevelopment process by quantifying thermal dynamic and landscape analysis. Habitat Int. 86, 61–70. https://doi.org/10.1016/j.habitatint.2019.03.004

Qi, Z., Yeh, A.G.O., Li, X., 2017. A crop phenology knowledge-based approach for monthly monitoring of construction land expansion using polarimetric synthetic aperture radar imagery. ISPRS J. Photogramm. Remote Sens. 133, 1–17. https://doi.org/10.1016/j.isprsjprs.2017.09.009

Rhodes, J., Russo, J., 2013. Shrinking smart?: Urban redevelopment and shrinkage in Youngstown, Ohio. Urban Geogr. 34, 305–326. https://doi.org/10.1080/02723638.2013.778672

Rizzo, E., Pesce, M., Pizzol, L., Alexandrescu., F.M., Giubilato, E., Critto, A., Marcomini, A., Bartke, S., 2015. Brownfield regeneration in Europe: Identifying stakeholder perceptions, concerns, attitudes and information needs. Land Use Policy 48, 437–453. https://doi.org/10.1016/j.landusepol.2015.06.012

Sarkar, C., Webster, C., Gallacher, J., 2018. Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. Lancet Planet. Heal. 2, e162–e173. https://doi.org/10.1016/S2542-5196(18)30051-2

Schneider, A., Woodcock, C.E., 2008. Compact, Dispersed, Fragmented, Extensive? A Comparison of Urban Growth in Twenty-five Global Cities. Urban Stud. 45, 659–692. https://doi.org/10.1177/0042098007087340

Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. U. S. A. 109, 16083–8. https://doi.org/10.1073/pnas.1211658109

Shahtahmassebi, A.R., Song, J., Zheng, Q., Blackburn, G.A., Wang, K., Huang, L.Y., Pan, Y., Moore, N., Shahtahmassebi, G., Sadrabadi Haghighi, R., Deng, J.S., 2016. Remote sensing of impervious surface growth: A framework for quantifying urban expansion and re-densification mechanisms. Int. J. Appl. Earth Obs. Geoinf. 46, 94–112. https://doi.org/10.1016/j.jag.2015.11.007

Shi, Y., Sun, X., Zhu, X., Li, Y., Mei, L., 2012. Characterizing growth types and analyzing growth density distribution in response to urban growth patterns in peri-urban areas of Lianyungang City. Landsc. Urban Plan. 105, 425–433. https://doi.org/10.1016/j.landurbplan.2012.01.017

Sun, Y., Shang, J., 2015. Factors affecting the health of residents in China: A perspective based on the living environment. Ecol. Indic. 51, 228–236. https://doi.org/10.1016/j.ecolind.2014.04.036

Sun, Z., Xu, R., Du, W., Wang, L., Lu, D., 2019. High-Resolution Urban Land Mapping in China from Sentinel 1A/2 Imagery Based on Google Earth Engine. Remote Sens. 11, 752. https://doi.org/10.3390/rs11070752

Thomas, M.R., 2002. A GIS-based decision support system for brownfield redevelopment. Landsc. Urban Plan. 58, 7–23. https://doi.org/10.1016/S0169-2046(01)00229-8

Tian, L., Chen, J., Yu, S.X., 2014. Coupled dynamics of urban landscape pattern and socioeconomic drivers in Shenzhen, China. Landsc. Ecol. 29, 715–727. https://doi.org/10.1007/s10980-014-9995-0

Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns. Landsc. Ecol. 4, 21–30. https://doi.org/10.1007/BF02573948

Wang, C., Wang, Y., Wang, R., Zheng, P., 2018. Modeling and evaluating land-use/land-cover change for urban planning and sustainability: A case study of Dongying city, China. J. Clean. Prod. 172, 1529–1534. https://doi.org/10.1016/j.jclepro.2017.10.294

Weber, R., 2010. Selling City Futures: The Financialization of Urban Redevelopment Policy. Econ. Geogr. 86, 251–274. https://doi.org/10.1111/j.1944-8287.2010.01077.x

Weng, Y.C., 2007. Spatiotemporal changes of landscape pattern in response to urbanization. Landsc. Urban Plan. 81, 341–353. https://doi.org/10.1016/j.landurbplan.2007.01.009

Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, S., & Arnold, C., Wilson, E.H., Hurd, J.D., Civco, D.L., Prisloe, M.P., Arnold, C., Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, S., & Arnold, C., 2003. Development of a geospatial model to quantify, describe and map urban growth. Remote Sens. Environ. 86, 275–285. https://doi.org/10.1016/S0034-4257(03)00074-9

Wu, J., Wei-Ning Xiang, Zhao, J., 2014. Urban ecology in China: Historical developments and future directions. Landsc. Urban Plan. 125, 222–233. https://doi.org/10.1016/j.landurbplan.2014.02.010

Xia, C., Zhang, A., Wang, H., Zhang, B., 2019. Modeling urban growth in a metropolitan area based on bidirectional flows, an improved gravitational field model, and partitioned cellular automata. Int. J. Geogr. Inf. Sci. 33, 877–899. https://doi.org/10.1080/13658816.2018.1562067

Xia, C., Zhang, A., Wang, H., Zhang, B., Zhang, Y., 2019. Bidirectional urban flows in rapidly urbanizing metropolitan areas and their macro and micro impacts on urban growth: A case study of the Yangtze River middle reaches megalopolis, China. Land Use Policy 82, 158–168. https://doi.org/10.1016/j.landusepol.2018.12.007

Xiang, W. N., Clarke, K.C., 2003. The Use of Scenarios in Land-Use Planning. Environ. Plan. B Plan. Des. 30, 885–909. https://doi.org/10.1068/b2945

Xu, C., Liu, M., Zhang, C., An, S., Yu, W., Chen, J.M., 2007. The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. Landsc. Ecol. 22, 925–937. https://doi.org/10.1007/s10980-007-9079-5

Xu, W., Yang, L., 2019. Evaluating the urban land use plan with transit accessibility. Sustainable Cities and Society 45, 474–485. https://doi.org/10.1016/j.scs.2018.11.042

Yu, T., Liang, X., Shen, G.Q., Shi, Q., Wang, G., 2019. An optimization model for managing stakeholder conflicts in urban redevelopment projects in China. J. Clean. Prod. 212, 537–547. https://doi.org/10.1016/j.jclepro.2018.12.071

Zeng, C., Yang, L., Dong, J., 2017. Management of urban land expansion in China through intensity assessment: A big data perspective. J. Clean. Prod. 153, 637–647. https://doi.org/10.1016/j.jclepro.2016.11.090

Zhang, L., Weng, Q., Shao, Z., 2017. An evaluation of monthly impervious surface dynamics by fusing Landsat and MODIS time series in the Pearl River Delta, China, from 2000 to 2015. Remote Sens. Environ. 201, 99–114. https://doi.org/10.1016/j.rse.2017.08.036

Zhang, Y., Linlin, X., Weining, X., 2014. Analyzing spatial patterns of urban carbon metabolism: A case study in Beijing, China. Landsc. Urban Plan. 130, 184–200. https://doi.org/10.1016/j.landurbplan.2014.05.006

Zhang, Z., Wang, X., Zhao, X., Liu, B., Yi, L., Zuo, L., Wen, Q., Liu, F., Xu, J., Hu, S., 2014. A 2010 update of National Land Use/Cover Database of China at 1:100000 scale using medium spatial resolution satellite images. Remote Sens. Environ. 149, 142–154. https://doi.org/10.1016/j.rse.2014.04.004

Zhou, G., Li, C., Li, M., Zhang, J., Liu, Y., 2016. Agglomeration and diffusion of urban functions: An approach based on urban land use conversion. Habitat Int. 56, 20–30. https://doi.org/10.1016/j.habitatint.2016.04.002