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RESEARCH ARTICLE

A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data

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Abstract Landscape metrics or indices have been commonly used for quantifying landscape patterns. However, most of these indices are generally focused on simple analysis and description of the characterization of the geometric and spatial properties of categorical map patterns. These indices can hardly obtain the information about the spatio-temporal dynamic changes of landscape patterns, especially when multi-temporal remote sensing data are used. In this paper, a new landscape index, i.e., landscape expansion index (LEI), is proposed to solve such problems. In contrast with conventional landscape indices which are capable of reflecting the spatial characteristics for only one single time point, LEI and its variants can capture the information of the formation processes of a landscape pattern. This allows one to quantify the dynamic changes in two or more time points. These proposed indices have been applied to the measurement of the urban expansion of Dongguan in Guangdong province, China, for the period of 1988–2006. The analysis identifies three urban growth types, i.e., infilling, edge-expansion and outlying. A further analysis of different values of LEI in each period reveals a general temporal transition between phases of diffusion and coalescence in urban growth. This implies that the regularity in the spatiotemporal pattern of urban development in Dongguan, is consistent with the explanations according to urban development theories.

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Introduction

Landscape patterns are defined as the spatial arrangement of various landscape elements in different size and shape. The arrangement, which reflects the heterogeneity of landscape, is the result of various ecological processes at multiple scales (Bailey and Gatrell 1995; Csillag and Kabos 2002). Landscape patterns and their dynamic change processes have been the crucial components of landscape ecology (Forman and Godron 1986; Turner 1989; Wu and David 2002). Landscape pattern analysis is a primary research tool in landscape ecology that contributes to understanding spatial ecological dynamics. The analysis has received increasing attention in ecological research and the management community (Lehmkuhl and Ruggiero 1991; Cissel et al. 1999; Fu and Chen 2001).

Characterizing a landscape and quantifying its structural changes has become possible with the advances in remote sensing and geographic information system (GIS) techniques (Forman and Godron

1986). In recent decades, numerous landscape indices have been developed to quantify landscape structures and spatial heterogeneity based on landscape composition and configuration (O'Neill et al. 1988; Turner and Gardner 1990; Riitters et al. 1995; Matsushitaa et al. 2006). Theoretically, landscape indices refer to metrics developed for categorical map patterns. In other words, landscape indices are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics. These indices originate variously from statistical measures of dispersion (Pielou 1997), information theory (O'Neill et al. 1988), fractal geometry (Krummel et al. 1987; Plotnick et al. 1993) and percolation theory (Gardner et al. 1993; Li et al. 1996). Most of these indices can be calculated by using landscape analysis packages, such as FRAGSTATS (McCarigal and Marks 1995). Landscape indices have become increasingly popular for quantifying and characterizing various aspects of observed spatial patterns (Imbernon and Branthomme 2001; Zhang et al. 2006). However, there are some limitations with the generalization of relationships between landscape patterns and their change processes by using conventional landscape indices. Researchers use these indices to quantify the geometric and spatial properties of categorical map patterns, but seldom use them to obtain the information about the dynamic change processes of landscape patterns.

Quantifying landscape patterns and their changes is essential for the monitoring and assessment of ecological consequences of urbanization (Luck and Wu 2002). Urban dynamic processes, especially the tremendous worldwide expansion of urban population and urbanized area, have resulted in various impacts on the structures, functions, and dynamics of ecological systems at a wide range of scales (Luck and Wu 2002). Therefore, it is essential to characterize and understand the changing patterns of urban growth for alleviating these problems. The first step to understanding the ecology of cities is to adequately quantify urban patterns and project their spatiotemporal dynamics. Remote sensing and GIS techniques have been widely applied for describing the spatial structures of urban environments and characterizing patterns of urban structures (Li and Yeh 1998; Herold et al. 2003). Recently, the use of landscape indices has provided a new avenue for describing the spatial land use heterogeneity and urban morphological characteristics, and there has been an increasing interest in applying landscape indices in analyzing land use dynamics and urban growth processes (Alberti and Waddell 2000; Herold et al. 2002). However, there is a general lack of developing appropriate landscape indices for quantifying urban dynamics in two or more time points.

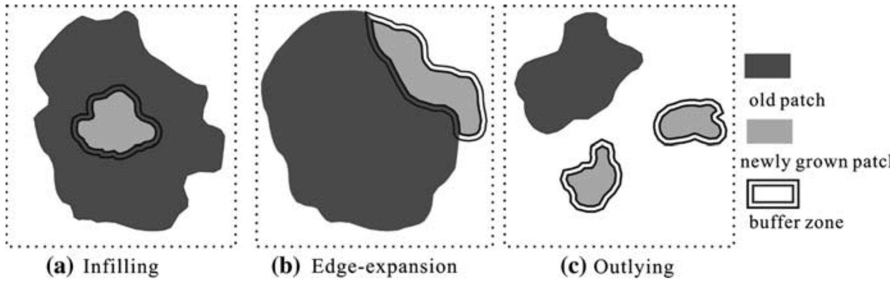
This paper develops a new index landscape expansion index (LEI), for better understanding of spatio-temporal land use dynamics in fast growing regions. Its variants, mean expansion index (MEI) and area-weighted mean expansion index (AWMEI), are also developed for improving the performance of urban expansion analysis. It is expected that LEI and its variants can be used to identify the expansion types of a certain landscape and its distribution patterns from multi-temporal remote sensing data. A fast growing region, Dongguan in south China, is selected for testing the proposed metrics.

Spatial modes of landscape expansion

Pattern-process analysis is one of the main threads in landscape ecological research, which aims at understanding the complex relationships between landscape patterns and landscape change processes (Schröder and Seppelt 2006). Resulting from interactions among different ecological processes and natural environments, landscape patterns can affect ecological processes in multiple ways, while ecological processes can facilitate the evolution of landscape patterns. One of such important ecological processes is landscape expansion (including urban growth, species spreading, desertification, soil erosion, etc.). It involves mainly three types of spatial pattern (Fig. 1), i.e., *infilling*, *edge-expansion*, and *outlying*, while other patterns can be regarded as variants or hybrids of these three basic forms (Forman 1995; Ellman 1997; Wilson et al. 2003).

An *infilling* type refers to the one that the gap (or hole) between old patches or within an old patch is filled up with the newly grown patch (Fig. 1a). Forman (1995) discusses *edge-expansion* type, defined as a newly grown patch spreading unidirectionally in more or less parallel strips from an edge (Fig. 1b). If the newly grown patch is found isolated from the old, then it would be defined as an *outlying* type (Fig. 1c).

Fig. 1 Three types of landscape expansion



Landscape expansion index

There are obvious limitations with conventional landscape indices for analyzing urban expansion in many fast growing regions. An essential one is that they can only quantitatively reflect the landscape patterns and their distribution for one single time point. Thus, the purpose of the proposed landscape expansion index (LEI) is to give a deeper insight of landscape patterns and temporal dynamics. In addition to identifying the types of landscape expansion, LEI can also be used to describe the process of landscape pattern changes within two or more time points.

LEI is defined by using the buffer analysis, which is one of the most important spatial analysis functions of GIS. The buffers are the zones with specified distances around a target geographical feature. The analysis can be used in queries to determine which entities occur either within or outside the defined buffer zone. Figure 1 illustrates the buffer zone of new patches with respect to three typical expansion forms mentioned above. A set of rules are heuristically proposed for identifying these growth patterns: (1) if a newly grown patch belongs to the infilling type growth, the buffer zone is mostly occupied by the old patch (Fig. 1a); (2) if the newly grown patch is the edge-expansion type, the area in buffer zone is mixed by vacant land (or other landscapes) and the old landscape (Fig. 1b); (3) if the newly grown patch belongs to the outlying type growth, its buffer zone is composed exclusively of vacant land (Fig. 1c).

In short, the LEI for a new patch can be defined and calculated through examining the characteristics of its buffer zone:

$$\mathrm{LEI} = 100 \times \frac{A_o}{A_o + A_v} \tag{1}$$

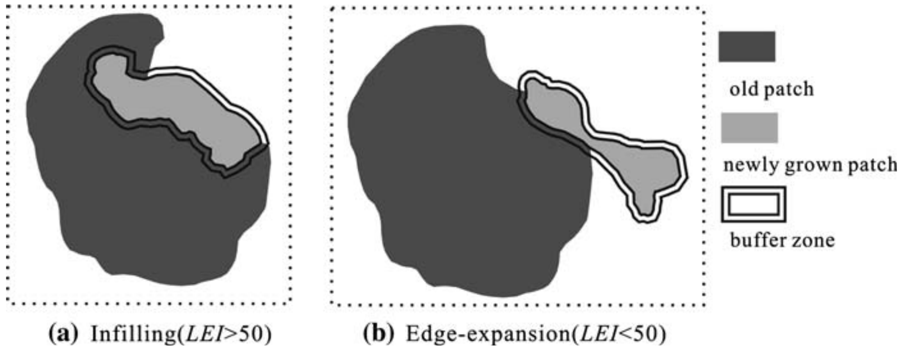
where LEI is the landscape expansion index for a newly grown patch, A_o is the intersection between the buffer zone and the occupied category, A_v is the intersection between the buffer zone and the vacant category.

According to this definition, the value of LEI varies in the range of $0 \leq \mathrm{LEI} \leq 100$. For example, suppose the occupied category in buffer zone shown in Fig. 1b has an area of 35, the vacant category in the buffer zone has an area of 45, then the LEI for the new patch in Fig. 1b is $100 \times \frac{35}{35+45} = 43.75$. Similarly, the LEI for the new patch in Fig. 1a results 100, and becomes 0 in Fig. 1c.

The indicator of LEI can be used for interpretation of landscape expansion types. As described earlier that there are three major expansion types, it's straightforward to divide the whole range of LEI value into three discrete intervals to respectively represent these three types. Xu et al. (2007) used a threshold value of ratio between common edge (between existing and new urban patches) and patch perimeter to distinguish the urban expansion types. An expansion type is identified as infilling when the value of ratio is larger than 0.5. An edge-expansion growth is characterized by the value of ratio between common edge and patch perimeter being no more than 0.5. So, in this paper, an infill growth is defined by the area in buffer zone being occupied by old patch (A_o) at least 50% (Fig. 2a). An edge-expansion growth is characterized by the area in buffer zone being occupied by old patch (A_o) no more than 50% (Fig. 2b). Outlying growth is defined by a change from vacant land to newly grown patch occurring beyond existing old patch (Fig. 1c). So, if the LEI value of a new patch ranges (50, 100), then it will be assigned as the infilling type; if it ranges (0, 50), then the new patch will be defined as the edge-expansion type; and the new patch will be classified as the outlying type once its LEI value equals 0.

In many applications, the primary interest is in the pattern of the entire landscape mosaic. So, we proposed a variant of LEI at landscape level, called

Fig. 2 Infilling growth type and edge-expansion type



mean expansion index (MEI). MEI is integrated LEI of all patches over the full extent of the data by simple averaging. It is used to reflect the aggregate properties of the patch mosaic. MEI is defined by using the following equation:

$$\mathrm{MEI} = \sum_{i=1}^{N} \frac{\mathrm{LEI}_i}{N} \tag{2}$$

where LEI_i is the LEI for a new patch, and N is the total number of newly grown patches. A larger MEI value signals a more substantial compacting trend along with the landscape expansion.

An area-weighted mean expansion index (AWMEI) is further proposed by considering the weight of area for each patch. AWMEI is computed simply as area-weighted mean LEI. This weighted index equals to the sum, across all patches of LEI value multiplied by the proportional abundance of the patch. AWMEI can be defined as follows:

$$\mathrm{AWMEI} = \sum_{i=1}^{N} \mathrm{LEI}_i \times \left(\frac{a_i}{A}\right) \tag{3}$$

where LEI_i is the LEI for a newly gorwn patch, a_i is the area of this new patch, and A is the total area of all these newly grown patches. If the landscape expansion tends to be more compact, the area-weighted mean expansion index (AWMEI) will be larger. If the trend of landscape expansion is in a diffusion process, the vale of AWMEI will be smaller.

Study area and data processing

This paper aims to investigate the dynamics of landscape expansion using this innovative index LEI and its variants. By taking urban growth as an example of landscape expansion, these indices are used to identify the spatial modes of urban expansion. Three urban growth types will be identified: infilling, edge-expansion and outlying growth. These indices are applied to the pattern analysis of the urban landscape in Dongguan, a fast growing city in the east of Pearl River Delta, China (Fig. 3). The city is among the corridor between Guangzhou and Shenzhen, with a total area of 2,465 km^2. Its rapid urban expansion is closely associated with fast economic growth. A large amount of agricultural land has been lost in this region because of rapid urban development and poor land management (Yeh and Li 1997; Liu et al. 2008). In the period of 1988–2006, the urban area increased dramatically from 66.7 km^2 in 1988 to 853.2 km^2 in 2006.

TM satellite images in 1988, 1993, 1997, 2001 and 2006 were used to provide the inputs to the analysis. The study area consists of 2,693 $\times$ 1,864 pixels, with a ground resolution of 30 m. The geometric correction of TM images was carried out by using the PCI software. The correction was based on the ground control points (GCPs), which were evenly distributed over the study area. The correction accuracy was within 0.5 pixel according to the assessment. The object-based classification software, eCognition, was then used for supervised classification of these images. Accuracy assessment was conducted using the ground truth data. The classification accuracy was 92.0% for these images. Since the focus of this study was urban expansion, the land use types were further converted to only two classes: urban and non-urban.

Application and results

The classification results were further used to extract the urban areas of Dongguan for four periods, i.e.,

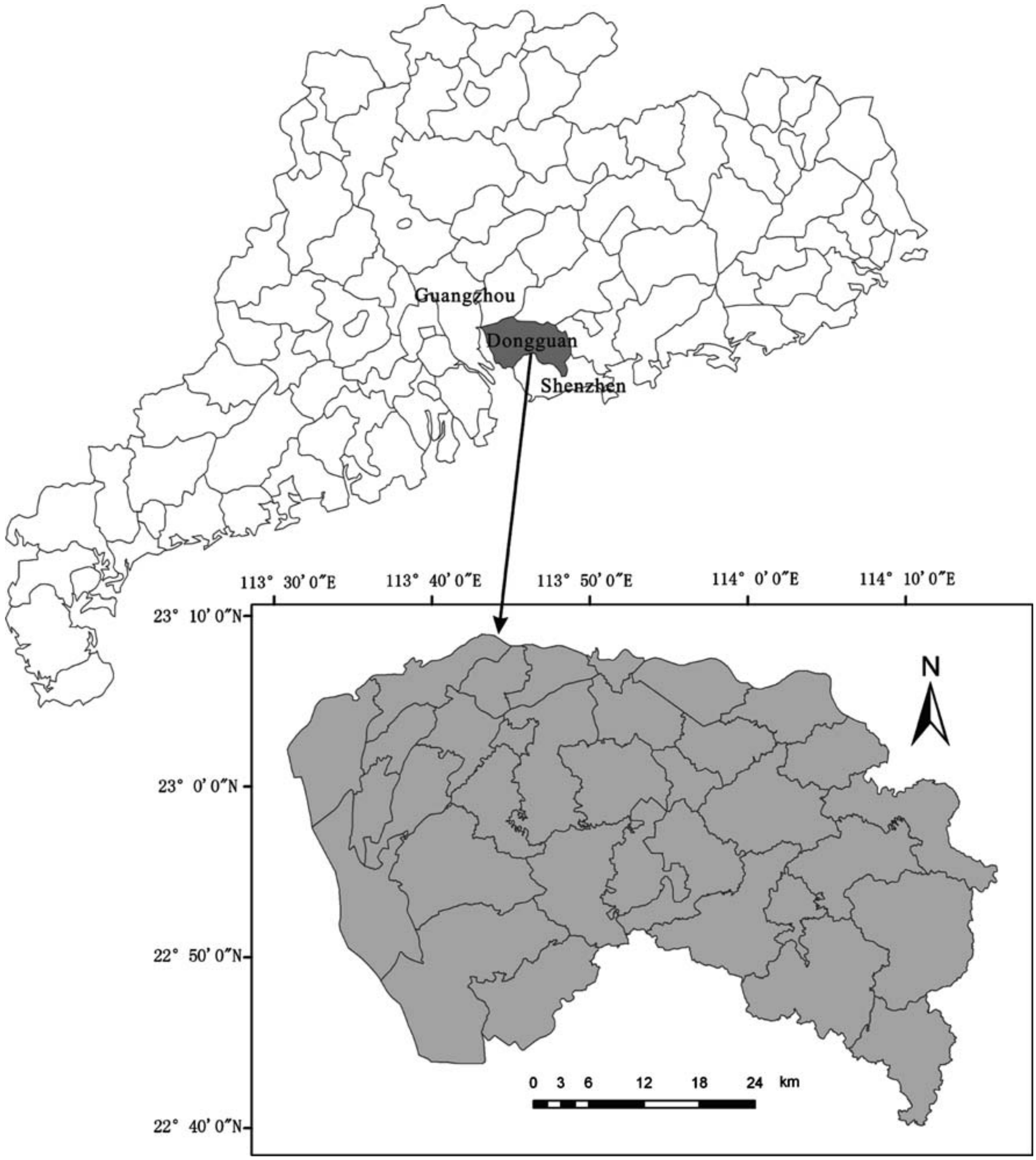


Fig. 3 Location of the study area (Dongguan)

1988–1993, 1993–1997, 1997–2001 and 2001–2006. The calculation of the LEI and its variants was implemented through the programming of Visual Basic 6.0. Firstly, land use data need to be converted into the vector format. Then, the buffer zones of all new patches are generated by executing the program. Buffers can be set at constant or variable distances based on feature attributes. In this paper, the buffers are created by using a constant distance of 1 m. Once the buffer zones of all growth patches have been obtained, they are overlaid with the old urban patches for calculating the area of the old urban patch within the buffer zones. Lastly, the LEI is calculated for each new urban patch according to equation (1). The buffer zones of the new urban patches were automatically generated by the program (Fig. 4); a, b and c refer respectively to the infilling type, the edge-expansion type and the outlying type.

The buffer distance may have an effect on the LEI value. Generally, the buffer distance should be set roughly equal to or smaller than the spatial resolution of remotely sensed data. It remains a question whether the value of LEI would be significantly changed if a different buffer distance (equal or smaller than 30 m) is used. In order to examine the effect of the buffer distance, we use ten different buffer distances to calculate LEI value. The buffer distance is varied between 1 and 30 m, i.e., 1, 2, 3, 4, 5, 10, 15, 20, 25 and 30 m. Then, the standard deviation (SD) of LEI value under different buffer distances for each newly grown patch is calculated. The standard deviation, which can provide a way to measure the robustness of LEI, is defined as follow:

$$\mathrm{SD}_i = \sqrt{(1/M)\sum_{j=1}^{M}\left(L_i^j - \hat{L}_i\right)^2} \tag{4}$$

where SD_i is the standard deviation of LEI for the ith newly grown patch with different buffer distances, M is the number of buffer distance, here $M = 10$, $\hat{L}_i$ is the mean LEI value of the ith newly grown patch under different buffer distance, and L_i^j represents the LEI value of the ith newly grown patch with the jth buffer distance.

Then, the mean SD value of all newly grown patches is calculated to measure the sensitivity of buffer distance:

$$\mathrm{MSD} = \sum_{i=1}^{N}\frac{\mathrm{SD}_i}{N} \tag{5}$$

where N is the total number of new patches.

A smaller MSD value signals a more stable LEI value under the change of buffer distance. As shown in Table 1, the values of MSD for four periods with distances (1 m-5 m) are 0.078 (1988–1993), 0.074 (1993–1997), 0.076 (1997–2001) and 0.069 (2001–2006), respectively. The values of MSD for four periods are small, which indicates that the LEI value change slightly with different buffer distances (1–5 m). However, the MSD value with distances (10–30 m) is bigger than the MSD value with distances (1–5 m). The smaller is the buffer distance, the more stable of the value of LEI becomes. In this paper, the buffer distance is set equal to 1 m.

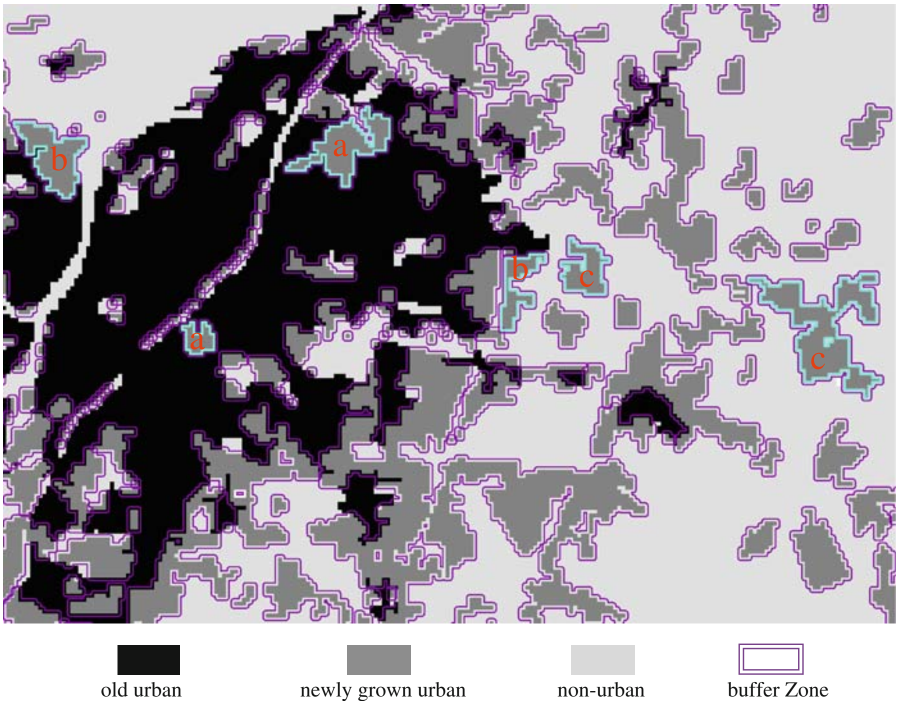


Fig. 4 Creation of buffer zones for capturing urban expansion types

Table 1 Sensitivity of LEI under different buffer distances based on MSD

Period	1988–1993	1993–1997	1997–2001	2001–2006
MSD (1–5 m)	0.078	0.074	0.076	0.069
MSD (10–30 m)	0.472	0.446	0.459	0.421

The histograms of LEI for four periods were produced to perform a quantitative analysis of the urban growth patterns (Fig. 5). Throughout all of the period (1988–2006), the value of LEI was in a decreasing trend. Additionally, Fig. 5 shows an interesting pattern of the histograms about the robustness of LEI. Despite the different development forms in the four periods, three LEI peaks, i.e., [0], [50–52], and [100], remained quite stable for all periods. Moreover, the three peaks can provide the evidence to set the thresholds of LEI values for determining the urban patch growth types. The patches within the three LEI peak zones had a dominant proportion among all the patches, i.e., 66% (1988–1993), 43% (1993–1997), 34% (1997–2001), and 37% (2001–2006) respectively for each period (Table 2). According to the analyses, several thresholds of LEI values were used to determine the urban patch growth types: (1) $50 < \mathrm{LEI} \leq 100$, the infilling type; (2) $0 < \mathrm{LEI} \leq 50$, the edge-expansion type; and (3) the outlying type if $\mathrm{LEI} = 0$.

Figure 6 shows the spatial distribution of different urban growth types in four periods. Three urban patch growth types were identified by using the proposed indices. Dramatic changes have occurred for the urban landscape of Dongguang from 1988 to 2006 because a great amount of agricultural land use has been transformed into urban land use. However, the urban landscape shows distinct growth patterns in different periods. In the first period (1988–1993), the patterns of urban growth were dominated by the outlying type (Fig. 6a). New development mainly took place along the major transportation networks, exhibiting a disordered and scattered pattern. Although the infilling-type growth was also identified in this period, it is much less dominated with some occasions in the city proper. Similarly, the edge-expansion-type growth was also less obvious because it was found mainly around town and district centers. During the period of 1993–1997, new patches labeled as outlying were less found while the edge-expansion-type growth took a predominant role (Fig. 6b). Meanwhile, the infilling-type growth was also intensified around town and district centers. During the period of 1997–2001, the outlying-type growth was still in a decreasing trend, and the edge-expansion-type and the infilling-type growth became dominated (Fig. 6c). In the last period (2001–2006), a spatial ring structure was formed in the whole city with a sequence of land use types. The edge-expansion-type and the infilling-type growth were still dominated in the study area. However, the edge-expansion-type was in a decreasing trend. As a result, the urban morphology became more compact (Fig. 6d).

Fig. 5 Robustness of LEI based on the histograms for four periods

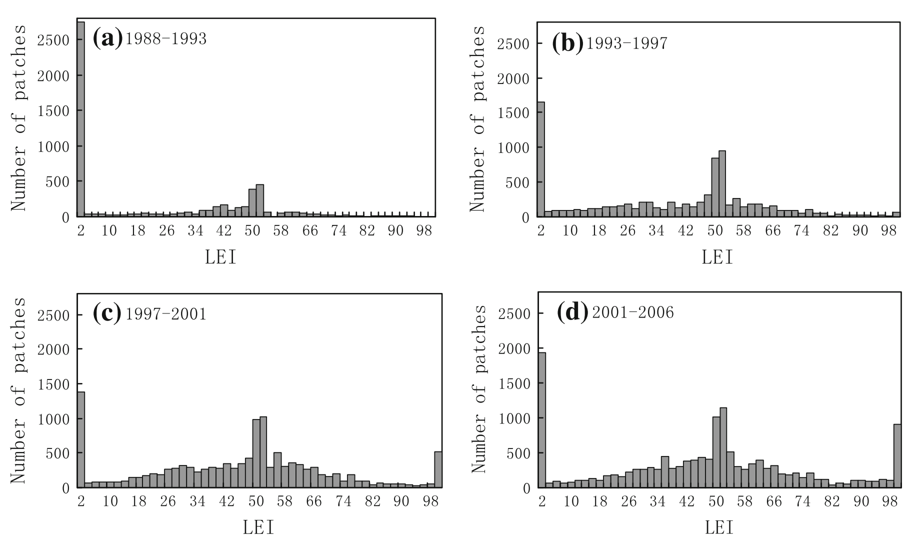


Table 2 Stable distribution of three peaks in terms of the number of patches and the patch proportion for four periods

Period	1988–1993		1993–1997		1997–2001		2001–2006	
LEI interval	Number of patches	Patch proportion	Number of patches	Patch proportion	Number of patches	Patch proportion	Number of patches	Patch proportion
0	2,744	49	1,646	18	1,384	11	1,935	13
50–52	983	17	2,104	24	2,434	19	2,562	18
100	4	0	70	1	511	4	913	6
Total	3,316	66	3,820	43	4,329	34	5,410	37

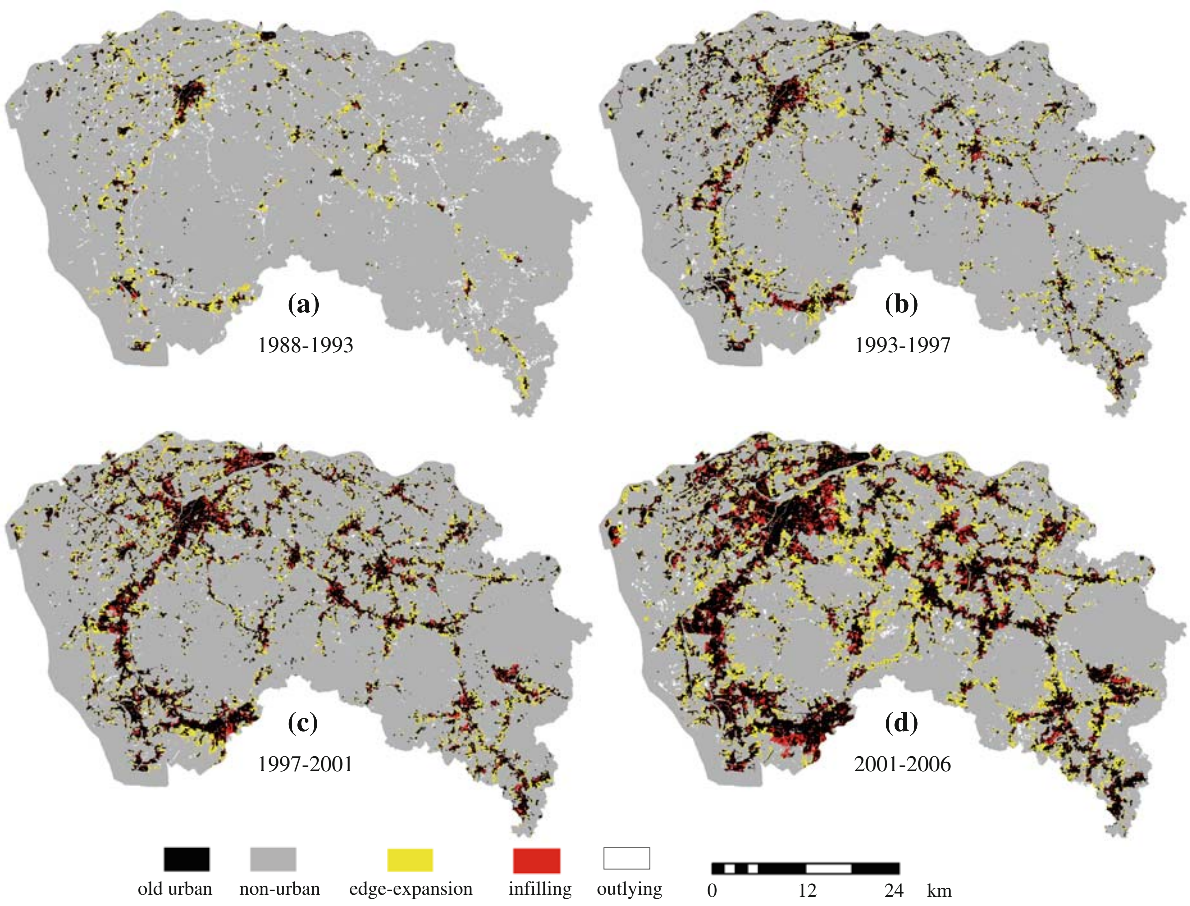


Fig. 6 Spatial distribution of three urban growth types in the four periods

The detailed information about the three growth types was obtained by calculating their total area for the four periods (Fig. 7). Throughout all of the 18-year period, the edge-expansion was the primary growth type except in the period of 1988–1993. In this period, the outlying type occupied 47% of the total newly developed urban land, while the infilling type growth only occupied 9%. The edge-expansion type accounted for a considerable proportion of 45%. In the period of 1993–1997, the proportion of the outlying type dramatically reduced to 14%. In contrast, there was a tremendous increase of the proportion of the infilling type (16%) and especially the edge-expansion type (70%). Between 1997 and 2001, the proportion of the outlying type continuously declined and became least dominated (8%).

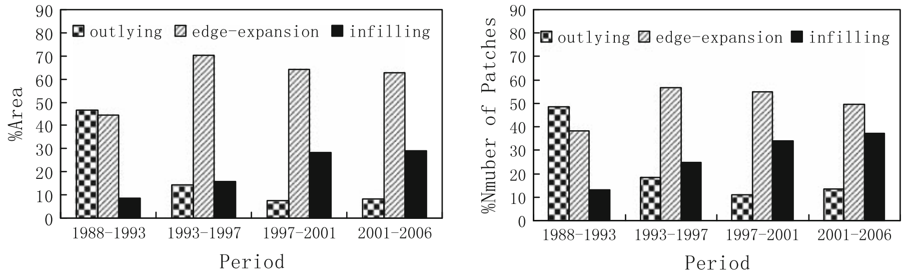


Fig. 7 Percentages of growth area and number of patches for the three urban growth types in the four periods

The percentage of the edge-expansion type and the infilling type increased persistently up to 64 and 28% respectively. In the period of 2001–2006, the situation had only a trivial change with the result of 8, 63 and 29% for the outlying type, the edge-expansion type and the infilling type, respectively.

Meanwhile, the number of patches (NP) for the three urban growth types exhibited some regularity in the temporal patterns (Fig. 7). The outlying type had a proportion of 49, 18, 11 and 13% in the four periods respectively, showing a remarkably decreasing trend. NP proportion of the edge-expansion type was 38% in the period 1988–1993. It increased to 57% in the period 1993–1997 and later decreased gradually to 50% in the period 1993–2006. Joining the edge-expansion type with an evidently rising trend, the infilling type had a proportion of 13, 25, 34, and 37% during the four periods respectively.

To better understand of the morphology and its development trends of the study area, the mean expansion index (MEI) and area-weighted mean expansion index (AWMEI) were calculated for the growth patterns from 1988 to 2006 based on equation (3) and (4). As shown in Table 3, the mean expansion index (MEI) increased from 20.63 in 1988–1993 to 43.83 in 2001–2006. However, it was obviously that the largest increase was observed during 1988–1997. This indicates that the urban growth type had transferred from the outlying to the edge-expansion in this period. In the period of 1997–2006, MEI increased slightly (from 41.74 to 43.83), and the urban growth pattern was quite stable. The area-weighted mean expansion index (AWMEI) was 13.58, 29.48, 39.30 and 39.53 in the four periods respectively. The changes of AWMEI values showed an interesting trend. AWMEI increased dramatically during the period of 1988–2001, while increased slightly in 2001–2006. As a whole, the results of MEI and AWMEI show a clear ascending trend. This implies that the city tended to be more compact.

Table 3 MEI and AWMEI of newly grown urban patches in the four periods in Dongguan

Period	1988–1993	1993–1997	1997–2001	2001–2006
MEI	20.63	34.77	41.74	43.83
AWMEI	13.58	29.48	39.30	39.53

Studies have indicated that urban growth manifests wave-like properties (Blumenfeld 1954; Boyce 1966; Newling 1969). Dietzel et al. (2005) proposed that the urban growth process could be described as a general temporal oscillation between the phases of diffusion and coalescence based on the theory of urban growth phases (Cressy 1939; Duncan et al. 1962; Winsborough 1962). Urban growth can be characterized as having two distinct processes, diffusion and coalescence, with each process following a harmonic pattern. As shown in Fig. 8, the spatial evolution of urban areas oscillates between the diffusion and coalescence of individual urban areas. In the initial stage, the process starts with the expansion of an urban seed or core area (Fig. 8a). As the seed grows, it disperses growth to new development centers or cores (Fig. 8b), and this diffusive process is comparable to the outlying type growth (Dietzel et al. 2005). Thereafter, the urban growth is around the periphery of the initial urban land (Fig. 8c), which is comparable to the edge-expansion type. As the process continues, urban development would more likely to take a way of gradually infilling up the gaps among the existing urban patches, hence the process is termed coalescence (Fig. 8d).

As shown in Figs. 5, 6 and 7 and Tables 2 and 3, there are two distinct phases for the rapid urbanization process in Dongguan from 1988 to 2006, This is

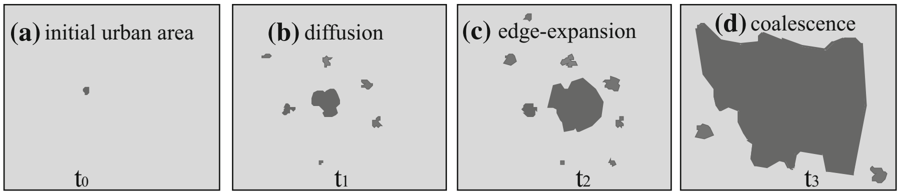


Fig. 8 Urban evolution according to the theory of urban growth phases

consistent with the theory of urban growth phases and the "diffusion-coalescence" model. In 1988, urban patches were mainly distributed in the city center. Along with the development of urbanization, more individual urban development patches are formed, causing a peak in the number of the outlying type growth patches. As the values of both MEI and AWMEI were quite small at the initial period (1988–1993), the urban development was more regarded as diffusion, and most of the newly grown patches are classified as the outlying type. As a result, multiple new growth centers emerged from these newly growth patches. As the growth continued, neighborhood patches became increasingly connected because of the growth mechanism. In the period of 1993–2006, the edge-expansion type and the infilling type started to take a more important position in the light of their enlarging proportions (Fig. 7), and the higher values of both MEI and AWMEI implied that the urban development in this period tended to be "coalesced". These evidences prove that the LEI and their variants proposed in this paper can effectively provide a quantitative analysis of urban development mechanisms, and thus examine the theories of urban growth phases.

Conclusions

Although numerous landscape indices have been proposed on the description or analysis of landscape patterns for a specific time point, they can hardly reflect the basic mechanisms governing the process of landscape changes. Being the supplement to the conventional landscape indices, the LEI and its variants proposed in this study are more capable of quantifying the spatial patterns of landscape expansion within two or more time points. These proposed indices can examine the way in which a landscape evolves, and reveal the relationships between the spatial distribution of a landscape as well as its evolution process. The implementation of this model is rather convenient since the buffer zones of patches can be automatically delineated by the proposed program.

Urban growth is a sort of critical process from an ecological point of view. By using the proposed LEI and its variants, this paper investigates the urban growth processes in Dongguan for four periods, i.e., 1988–1993, 1993–1997, 1997–2001 and 2001–2006. The analyses has demonstrated that the proposed landscape expansion index (LEI) can be used to identify various growth types, i.e., infilling, edge-expansion, and outlying. LEI provides a systematic, simple, and replicable method that can be use to describe the urbanization processes in a way that considers both the amount of changes and the spatial patterns. The urban development trajectory of Dongguan shows different spatial expansion modes during the whole period. In the initial period of 1988–1993, the outlying expansion was the dominant growth type. NP proportion of the outlying type growth occupied 49% of the total newly developed urban land, while the infilling type growth only occupied 9%. The edge-expansion type accounted for a considerable proportion of 38%. According to the theory of urban growth phases, the city in this period is experiencing the "diffusion" phase. From 1993 to 2006, NP proportion of the outlying type growth decreased gradually, i.e., 19% (1993–1997), 11% (1997–2001), 13% (2001–2006), while the edge-expansion type and the infilling type growth started to take a more important position in the light of their enlarging proportions, which implied that the urban development in this period tends to be the "coalescence" phase.

The variants of LEI can provide additional information about urban expansion. In the whole period, the increasingly values of MEI (from 20.63 to 43.83) and AWMEI (from 13.58 to 39.53) also indicate that the old scattered and disordered "diffusion" phase was transformed into a more compact “coalescence” phase based on the development mechanisms.

This study has demonstrated that the processes of diffusion and coalescence can be clearly identified in the spatio-temporal development of Dongguan. The regularity of urban development processes detected by these indices is consistent with the theories of urban growth phases. This indicates that LEI and its variants can become an important tool for capturing the complex dynamics of urban growth by using multi-temporal remote sensing data. These indices can thus provide useful information about the patterns and change processes of the urban landscapes.

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