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New indices to capture the evolution characteristics of urban expansion structure and form

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ABSTRACT

A quantitative description is the basis for correctly understanding the urban expansion process. Previous approaches were dedicated to identifying expansion types based on the boundary sharing rate, thereby depicting the evolution of urban expansion. These methods, however, focused on describing neighborhood relations and ignored urban global expansion structure and form information. In this study, we first propose a new index, the location centrality index (LCI), to capture the expansion structure characteristics by incorporating an "area-inverse distance" weighting algorithm and geometric features. Then, we propose another index, the location centrality aggregation index (LCAI), to depict the heterogeneous evolution of urban form by considering the attribute of the new patch. The location centrality and location aggregation types are identified to reflect the effect of new patches on the urban expansion structure and form based on LCI and LCAI, respectively. Two variants of LCI and LCAI are also proposed to reflect the global bottom-up characteristics of urban expansion. The LCI and LCAI were verified using four periods of Landsat images (1995, 2000, 2005, and 2010) of the Wuhan metropolitan area, China. The results show that the overall development trend of the expansion structure in the Wuhan metropolitan area was toward decentralization. The urban form had become generally separated, but tended toward aggregation from 2005 to 2010. Our findings also reveal that the LCI fills the gap in the dynamic assessment of urban expansion with previous indices by explicitly uncovering global structure characteristics. The LCAI achieves better performance than previous indices in identifying heterogeneous aggregation.

1. Introduction

Rapid global urbanization, especially in Asia, will last for a long time (United Nations, 2014). Urbanization is accompanied by the spatial expansion of urban land, with significant effects on resources, environment, and society (Carruthers and Ulfarsson, 2003; Grimm et al., 2008). The consensus is that the rational use of land resources requires a better understanding of the process of urban expansion (Echenique et al., 2012; Hansen et al., 2005; Herold et al., 2003). Therefore, the quantitative evaluation indices of urban expansion processes are being recognized as a powerful means of understanding urban expansion, which have been attracting increasing attention from the urban science community (Angel et al., 2010; Bhatta et al., 2010; Bramley et al., 2009; Tsai, 2005).

Landscape indices are widely used to describe the spatial pattern of urban expansion (Deng et al., 2009; Jenerette & Wu, 2001; Seto and Fragkias, 2005; Su et al., 2012; Zambon et al., 2018). Most landscape indices have been developed based on information theory, fractal geometry, and spatial statistics, and they are calculated using Fragstats software (Krummel et al., 1987; McGarigal and Marks, 1995; O'Neill et al., 1988; Plotnick et al., 1993). Nevertheless, landscape indices have an inherent defect: the indices can only describe the static pattern characteristics of a single time point; they cannot capture dynamic process information (Li and Wu, 2004). To compensate for this shortcoming, some dynamic indices have been proposed based on the spatial relationships between newly grown patches (new patches) and existing urban land (old patches). This is because the existing urban land is generally not "moved" or deurbanized, and the change in urban patterns is affected by the growth of new patches (Dietzel et al., 2005a, 2005b). For example, Xu et al. (2007) and Sun et al. (2012) used the ratio of the

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shared boundary length between new and old patches to the perimeter of the new patch to identify the expansion type. Liu et al. (2010) designed a landscape expansion index (LEI) by replacing the one-dimensional boundary sharing rate with the buffer sharing rate to depict the spatial relationship between new and old patches based on two-time-point data. Jiao et al. (2015), Jiao et al. (2018) proposed a multi-order landscape expansion index (MLEI) and a proximity expansion index (PEI) by using multi-temporal data and multi-buffers to reveal the timing transferability and spatial gradient of the expansion characteristics of new patches. The above mentioned methods share the commonality that they are all based on boundary sharing rate (BSR) or similar forms, and these BSRs often only reflect the spatial relationship between the new patch and its nearest old patch because of spatial constraints. These existing metrics measure the degree of sprawl of new patches based on neighborhood features, ignoring their spatial relationship with urban structure and form, which is reflected by urban lands as a whole.

However, since urban expansion is a multi-dimensional geographic process (Hamidi et al., 2015), it is inaccurate and biased in terms of only focusing on the description of the neighborhood dimension. For example, even if one new patch is closer to the old patches as a whole, the evaluation of the degree of sprawl may be the same as a new patch with an equal BSR (Fig. 1, new patches 1 and 3). Moreover, the sprawl evaluation may be very high because of a lower BSR, even if the new patch fills a gap in the urban core area (Fig. 1, new patch 2). The traditional demarcation of the location's "compactness" or "sprawl" based on this dimensional evaluation is thus partial and unclear. It is desirable to consider the global spatial relationship (i.e., the overall and dynamic structural characteristics) to enhance the reliability and robustness of urban expansion evaluation.

Existing studies on urban spatial structure focus on static characteristics, that is, the monocentric-polycentric development, the cluster, the network, and other levels (Angel et al., 2005; Fragkias and Seto, 2009; Rossi-hansberg and Wright, 2007; Tsai, 2005; Winsborough, 1962). The dynamic structural characteristics of the urban expansion process have been largely disregarded. In terms of structural meaning, that is, the manner of construction of something and the arrangement of its parts, the urban expansion structure can be defined as the composition and arrangement of new patches compared with entire old patches. Therefore, the location distribution of new patches in relation to the centers of old patches, that is, centrality, can be used to capture information about the urban expansion structure. According to the classic location theory and the central land theory (Thisse, 1987; Christaller, 1933), the distance from the urban land to the "center" affects the allocation of resources. Most existing methods regard centrality as the distance to one or several CBDs or city centers (Galster et al., 2001; Hamidi et al., 2015; Huang et al., 2007). Nevertheless, urban expansion is often accompanied by the growth of some special old patches, e.g., the growth "seed" (Dietzel et al., 2005a, 2005b) and the sub center. Such patches may be small and humble, but may possess huge potential for urban growth. Therefore, it is necessary to evaluate the location centrality with all the old patches comprehensively rather than with a single or several isolated and static urban centers to reflect the urban expansion structure.

In addition, existing dynamic metrics are inadequate to describe accurately the urban form evolution, that is, the urban shape change. These metrics disregard the attribute of the new patch itself (Jiao et al., 2018; Liu et al., 2010; Xu et al., 2007), which may affect urban form evolution significantly due to the aggregation of new and old patches. For example, even if the new patch has a weak neighborhood or structural relationship, it will have substantial aggregation effects because it fills a gap and promotes the integration of the urban form (Fig. 1, new patch 4). Moreover, the aggregation effect of the new patch is also based on its location distribution. Although the entire urban form evolves in a wave-like mode (Blumenfeld, 1954; Boyce, 1966; Dietzel et al., 2005a, 2005b; Duncan et al., 1962; Newling, 1969), not all new patches would be in the same stage of form evolution. The location aggregation of urban land is heterogeneous at the patch level, leading to considerable differences in the regional and global evolution of the urban form. Therefore, it is desirable to distinguish the difference in local form evolution caused by unbalanced expansion among regions directly.

In summary, most existing dynamic indices focus on local assessment of the degree of sprawl based on neighborhood relations at the patch level. There is a gap in evaluating the multi-dimensional characteristics

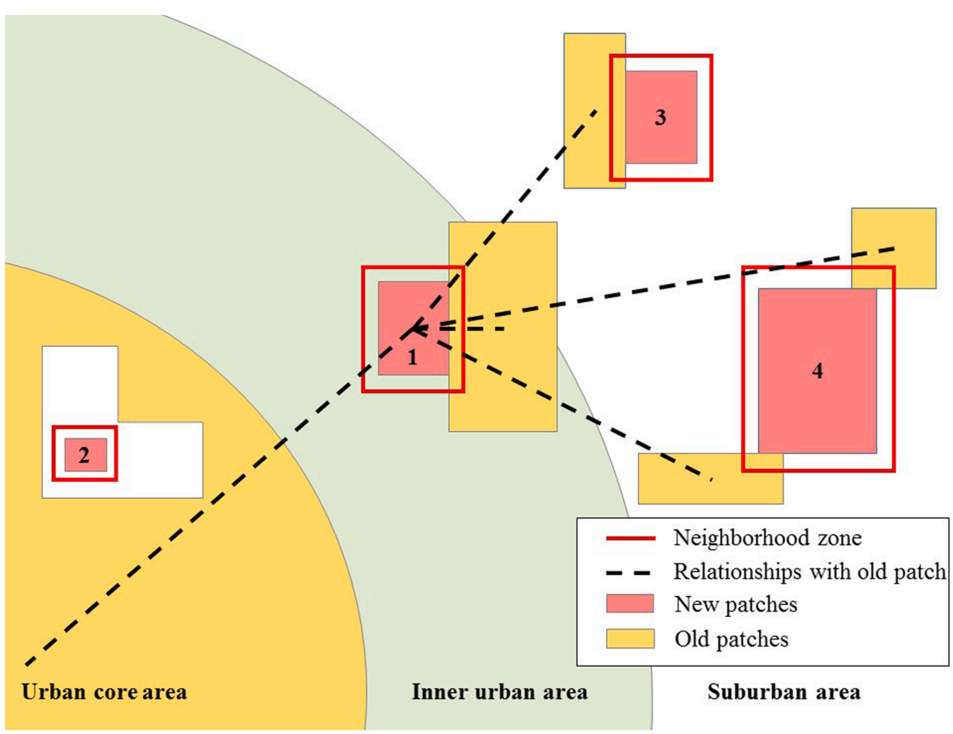

Fig. 1. Schematic of the urban expansion process illustrating the centrality and aggregation.

of expansion patches from a global perspective. Since urban expansion is a multi-dimensional process, the indistinct and simple division of urban expansion into compactness and sprawl based on one-dimensional neighborhood characteristics will lead to inaccuracy and hamper a better understanding of the spatial characteristics of the urban expansion process. The location centrality and aggregation of urban structure and form discussed in this study are significantly different from past characterization dimensions. Hence, it is necessary to propose new methods to measure these two-dimensional characteristics, avoiding the misinterpretation of the global urban expansion process based on indirect assessment.

In this study, we will propose two novel indices, the location centrality index (LCI) and the location centrality aggregation index (LCAI), to characterize the features of urban expansion structure and form as well as explicitly quantify the centrality and aggregation heterogeneity of urban expansion. The two indices will be verified in Wuhan, a rapidly growing city in central China. The LCI and LCAI will also be compared with previous urban expansion indices to demonstrate their strengths explicitly.

2. Methods

2.1. Location centrality index

The location centrality of new patches is the degree of closeness to the center of the old patches. However, since old patches are more likely to be composed of many scattered patches, each old patch has its own center, which may be, or become, one of the centers of the whole city. For example, the center of local urban land may also function as the center to improve the allocation of surrounding resources. Therefore, the measurement of centrality should synthetically consider the location relationship with all the old patches rather than just one or several isolated urban centers.

The location centrality measurement thus reflects the spatial relationship characteristics of the entire urban expansion structure, unlike previous dynamic indices, which focus on the spatial relationship characteristics of the nearest neighborhood. As shown in Fig. 2a, when only the spatial relationship with the nearest old patch is considered, the distances from two new equal patches 2 and 3 to the center of old patch 1 is the same ($D_{21} = D_{31}$). Thus, it is easy to estimate location in the entire urban expansion structure inaccurately. As shown in Fig. 2b, when considering the spatial relationship of new patches with all old patches (patches 1 and 4), it is found that their locations are different, which is inconsistent with Fig. 2a. New patch 2 is closer to the center of old patch 4 ($D_{24} < D_{34}$), which indicates that the location centrality of new patch 2 should be higher, which also agrees with intuitive cognition. Therefore, it is necessary to establish a comprehensive measurement rule for location centrality. The rules are defined as follows: (1) the larger the old patch is, the more important it is and the greater its influence on location centrality measurement. This is because larger urban areas may provide more urban service functions. (2) The closer the old patch is to the new patch, the greater the impact on the measurement of location centrality of the new patch. (3) The location centrality of the new patch also depends on its spatial relationship with the center of the old patch.

Additionally, we used the centroid as the center of the old patch to create concentric circles of equal area. The positional relationship between the new patch and the concentric circle was used as the basis for location centrality. Based on the above rules, the location centrality index (LCI) has been designed as follows:

$$\mathrm{LCI}_i = \sum_{j=1}^{n} \frac{A_j d_{ij}^{-2}}{\sum_{j=1}^{n} A_j d_{ij}^{-2}} \cdot \sqrt{\frac{A_j}{\pi}} \cdot D_{ij}^{-1} \tag{1}$$

LCI_i is the location centrality of the i-th new patch; n is the total number of old patches, which differs in each study area and period; A_j is the area of the j-th old patch; d_{ij} refers to the nearest distance from the centroid of the i-th new patch to the boundary of the j-th old patch; and D_{ij} refers to the distance from the boundary of the i-th new patch to the centroid of the j-th old patch. $\sum\left(A_j d_{ij}^{-2} / \sum A_j d_{ij}^{-2}\right)$ can be regarded as the "area-inverse distance" weighting algorithm, which aims to establish a

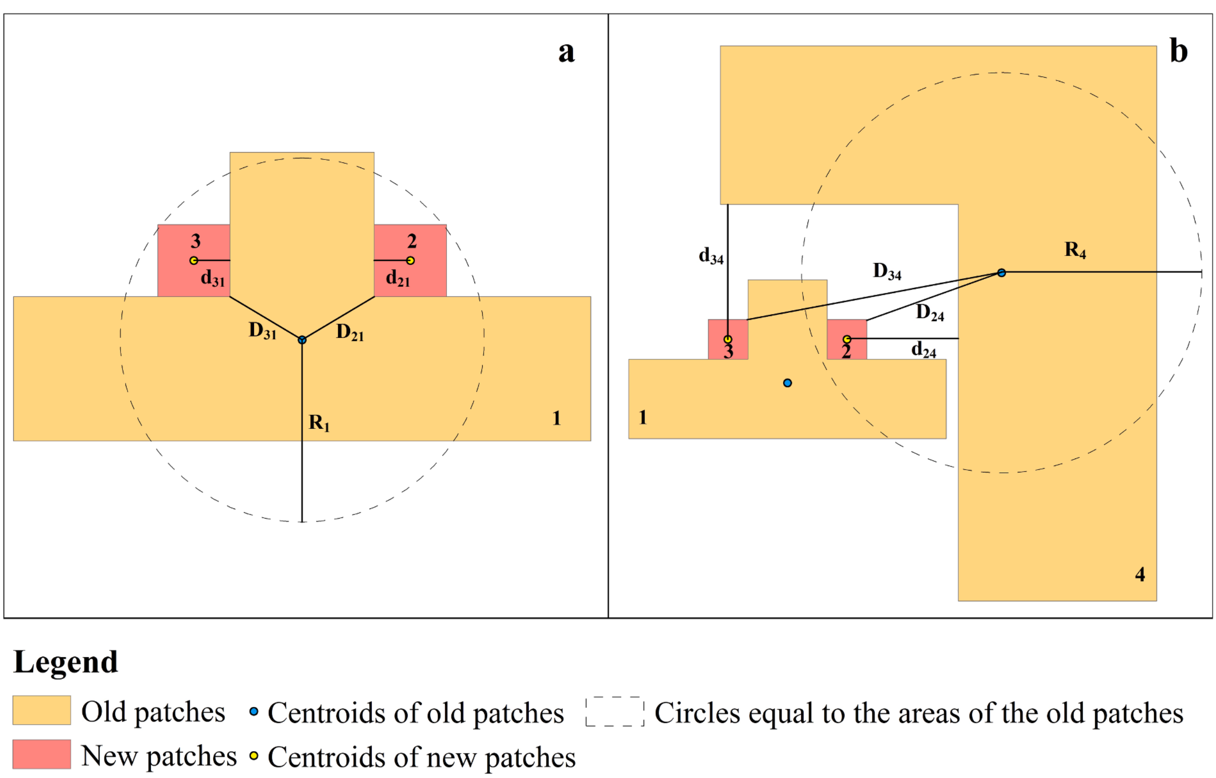

Fig. 2. The illustration of the design of the location centrality index based on overall structural characteristics.

quantifiable spatial connection between new patches and all old patches based on Rules 1 and 2. $\sqrt{A/\pi}D_{ij}^{-1}$ shows whether the new patch is close to the center of an old patch, representing the geographical significance of "centrality." The LCI is continuous in the range of (0, ∞), and a large value indicates high centrality. Furthermore, there is an example of the LCI calculation is presented in Appendix.

2.2. Location centrality aggregation index

Generally, a more concentrated distribution pattern of new patches will result in a more aggregated urban form. However, the attribute, that is, the area, of the new patch also determines the degree of aggregation. By comparing Fig. 3a and 3b, we see that the old patches (patches 2 and 3) and the centroid of the new patch (patch 1) are the same. Since d_{12}, d_{13}, D_{12}, and D_{13} have not changed, the location distribution pattern of new patch 1 has not changed. The change occurs in the area of the new patch, resulting in a stronger aggregation effect, which is reflected by the increase in r_1. This change makes the entire urban form more coherent and regular.

Therefore, to reveal the aggregation effect of urban expansion based on spatial configuration, it is necessary to not only reveal the locations of the new patches in relation to the old patches, but also characterize the attribute, that is, the area, of the new patch. To achieve this goal, we added the ratio of the radius of the equal area circle of the new patch to the distance from the old patch to the centroid of the new patch as a measurement to reveal the approximate attribute of the new patch. The radius of the equal area circle of the new patch could reflect the area attribute of the new patch. Moreover, the ratio could reflect the spatial locations of old patches in relation to the new patches, unlike the BSR indices, which mainly considered the spatial locations of new patches in relation to the old patches. This is because the aggregation is mutual, and the new and old patches collectively cause differences in the degree of aggregation. The location centrality aggregation index (LCAI) was designed as follows:

$$\mathrm{LCAI}_i = \sum_{j=1}^{n} \frac{A_j d_{ij}^{-2}}{\sum_{j=1}^{n} A_j d_{ij}^{-2}} \cdot \sqrt{\frac{A_j}{\pi}} \cdot D_{ij}^{-1} \cdot \sqrt{\frac{a_i}{\pi}} \cdot d_{ij}^{-1} = \sum_{j=1}^{n} \frac{A_j d_{ij}^{-2}}{\sum_{j=1}^{n} A_j d_{ij}^{-2} \pi} \cdot \frac{\sqrt{A_j}\sqrt{a_i}}{D_{ij} d_{ij}} \tag{2}$$

Here, a_i is the area of the i-th new patch. LCAI_i is continuous in the range of (0, ∞), and a large value indicates high aggregation. Furthermore, the LCAI is similar in form to the gravity formula ($F = GMm/r^2$). For example, $\sqrt{A}\sqrt{a}/D d$is similar to Mm/r^2, and $\sum\left(A_j d_{ij}^{-2} / \sum A_j d_{ij}^{-2}\right)$ can be considered a weighted term. This shows that the LCAI represents the approximate physical gravitation of the new and old patches, which expresses the spatial connection between them.

Indeed, LCAI is derived from LCI. It has an additional item, $\sqrt{a_i/\pi}/d_{ij}^{-1}$, but these two indices differ in the descriptive dimensions of urban expansion. For example, the new patch located in the center does not necessarily play a role in aggregation (e.g., new patch 2 in Fig. 1), while the new patch that plays a role in aggregation may not be close to the center from a global perspective (e.g., new patch 4 in Fig. 1).

In this study, we designed the LCI to measure centrality to distinguish concentrated or decentralized urban expansion from a global perspective. As a characteristic measurement method of urban expansion structure, the LCI essentially measures the arrangement and combination of new patches. The LCAI, however, is designed to reflect the spatial connection between the new and old patches using its formula, whose form is similar to that of physical gravitation. The LCAI essentially describes the ability of new patches to fill gaps between old patches by measuring whether they are aggregated and separated. In fact, this aggregation effect is reflected in the urban form evolution, that is, the urban shape change.

2.3. Identification of urban expansion types

Traditionally, urban expansion types have been used to understand the changes in landscape patterns qualitatively based on quantitative results (Ellman, 1997; Forman, 1996; Liu et al., 2010; Wilson et al.,

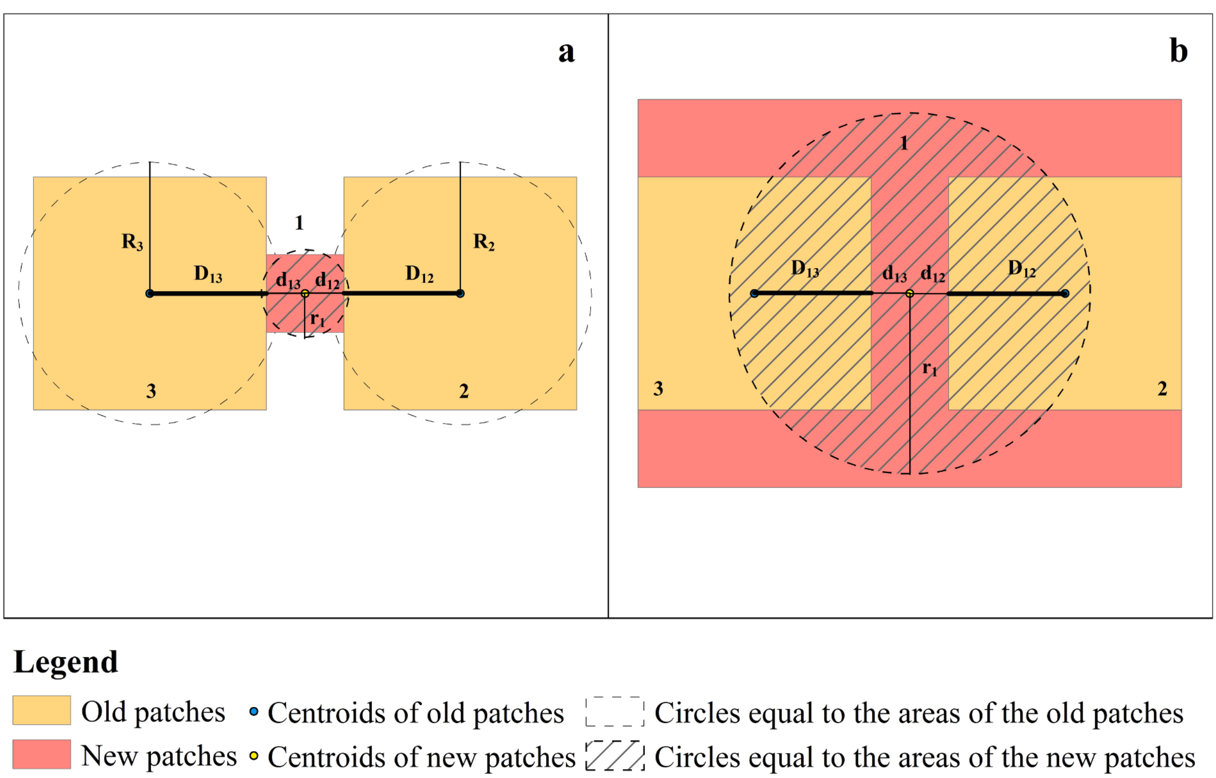

Fig. 3. The illustration of the design of the location centrality aggregation index based on the attribute of the new patch.

2003). Urban expansion can be classified into four types based on location centrality: core, center, adjacency, and margin types (Fig. 4). The LCI is essentially a weighted comprehensive reflection of the spatial location of new patches compared with each old patch. Therefore, the spatial location diagram for the location centrality types only depicts one old patch for a concise description. Because the circle is the most compact figure (Angel et al., 2010), the ratio of the radius of the equal area circle of the old patch to the distance from the new patch to the centroid of the old patch can be used to distinguish the location centrality type. The specific settings of the four types are as follows. The core type refers to the new patches that are extremely close to the centroid of the old patch, and the distance D from the centroid of the old patch is less than half of the equal area circle radius R of the old patch, that is, LCI > 2. The center type refers to the location of a new patch that is relatively close to the old patch, $R/2 \leq \mathrm{D} < R$, $1 < \mathrm{LCI} \leq 2$. The adjacency type refers to a new patch that is adjacent to the centroid of an old patch, $R \leq \mathrm{D} < 2R$, $0.5 < \mathrm{LCI} \leq 1$. Finally, the margin type refers to a new patch, which is isolated from the old patch, $2R \leq \mathrm{D}$, $0 < \mathrm{LCI} \leq 0.5$.

We also identified four types of location aggregation of new patches based on the types of location centrality to identify the evolution heterogeneity of urban form clearly in aggregation or separation. The location aggregation types based on the results of the LCAI are presented in Table 1.

The division LCAI value ranges of location aggregation types are the square of the division value ranges of the location centrality types based on the LCI. Based on the meaning of the LCAI, we further subdivided the aggregation types into three categories: high-aggregation, medium-aggregation, and slight-aggregation types. These three types in turn represent the degree of aggregation from high to low. The separation type represents new patches that do not aggregate with the original urban land.

2.4. *The characteristics of global urban expansion reflected by the LCI and LCAI*

Both the LCI and LCAI have been proposed to reflect the expansion characteristics of a single patch, but the process of urban expansion results from the combined effect of all new patches. Therefore, two variants of the LCI and the LCAI have been proposed to reflect the global

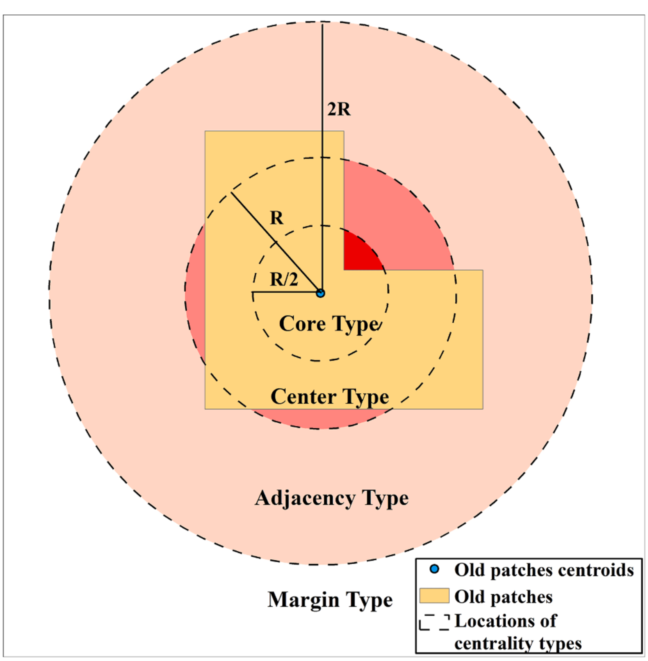

Fig. 4. The location centrality types classification.

Table 1
Attributes of location aggregation types.

	High-aggregation	Medium-aggregation	Slight-aggregation	Separation
LCAI	(4, ∞)	(1, 4]	(0.25, 1]	(0, 0.25]

characteristics of urban expansion from bottom-up. These two variants are the mean location centrality index (MLCI) and the mean location centrality aggregation index (MLCAI), both of which achieve the purpose of global reflection through a simple average. MLCI is defined by the following equation:

$$\mathrm{MLCI} = \sum_{i=1}^{m} \frac{\mathrm{LCI_i}}{m} \quad (3)$$

Here, m is the total number of the new patches, and $\mathrm{LCI_i}$ is the LCI value of the i-th patch. The higher the MLCI value, the more concentrated the overall expansion structure; the lower the MLCI, the more decentralized the overall expansion structure.

MLCAI can be defined as follows:

$$\mathrm{MLCAI} = \sum_{i=1}^{m} \frac{\mathrm{LCAI_i}}{m} \quad (4)$$

Here, $\mathrm{LCAI_i}$ is the LCAI of the i-th new patch. A larger MLCAI value indicates a more aggregated trend of urban form evolution. If the trend of urban form evolution is toward separation, the MLCAI value will be smaller.

3. Study area and data processing

We selected the metropolitan area of Wuhan, the largest city in central China and a region with rapid urban expansion, as the study area to verify the feasibility of the LCI and the LCAI for describing the evolution of urban patterns and forms. Four cloud-free satellite images were selected as basic data: (1) A Thematic Mapper (TM) image from December 5, 1995; (2) A Thematic Mapper (TM) image from November 7, 2000; (3) An Enhanced Thematic Mapper (ETM +) image from September 11, 2005; and (4) An ETM + image from September 17, 2010.

In the process of remote sensing image interpretation, we defined four image classification classes: urban land, vegetation, water, and others. The maximum likelihood method was selected to classify each image using ENVI 5.0, employing at least 50 samples for each class. We used online Google maps and Baidu maps as references to verify land use information. We further evaluated these training samples using ENVI 5.0, computing their separability using transformed divergence (TD) to check whether these samples clearly represent pre-defined classes. Then, the training samples were edited to ensure that the TD values were larger than 1.8. Additionally, we manually revised the misclassified pixels by comparing them with the original images and our reference data. Finally, we selected 150 samples to assess the accuracy of the classified images by employing a stratified random sampling strategy. The overall accuracies of the data from the four time points were evaluated as 86.2%, 88.4%, 85.3%, and 89.7%.

Next, classified images were converted to vector maps, and urban patches were then extracted using ArcGIS 10.2. Simultaneously, we divided the patches based on the boundaries of the district administrative regions. In the absence of an existing urban zone that “moves” or deurbanizes (Dietzel et al., 2005a, 2005b), we used the urban land data of the later time point to erase that of the previous time point in order to acquire the new patches between these two time points. We used the ArcGIS 10.2 erase tool to achieve this. The number of new patches during 1995–2000, 2000–2005, and 2005–2010 was 8586, 7716, and 16862, respectively, while the number of old patches was 3749, 5321, and 6934 in 1995, 2000 and 2005 respectively. The distribution of urban land in 1995 and the new patches in the three study periods are shown in Fig. 5.

4. Results

4.1. Urban expansion structure: Concentrated or decentralized?

The Python programming environment embedded in ArcGIS 10.2 was used to write scripts and calculate the LCI values of the new patches from the three periods (1995–2000, 2000–2005, and 2005–2010) according to Eq. (1). The histogram of the LCI value distribution is shown in Fig. 6. The LCI distribution of the three periods appears to be concentrated in (2, ∞), which is the result of inputting values greater than 2 into a statistical value range. Between 1995 and 2000, the distribution of the number of new patches showed a decreasing trend, with an increase in LCI value, except for a decrease in (0, 0.1]. In the 2000–2005 period, a considerable number of new patches were distributed within (0.1, 0.2], with a decreasing trend at (0.2, 0.5] and an upward trend at (0.5, 0.7]. The number of patches then continued to decline with an increase in LCI value. The distribution trend of the 2005–2010 period's new patch LCI is similar to that of the second period, but the number of new patches increased during this period. These results show that the LCI value has a continuous distribution in the three periods, which proves that the LCI is a continuous index that can be used to reveal the gradual change in location and structure distribution of urban expansion.

To understand the evolution of the urban pattern of the Wuhan metropolitan area better, we performed statistics on the location centrality types of the three periods (Fig. 6d and Table S1 in the Appendix). From 1995 to 2000, Wuhan City was mainly dominated by the adjacency type of urban expansion, with a proportion of 36.14%. The proportions of the margin, center, and core types were 32.8%, 22.54%, and 8.52%, respectively. During the second period, the adjacency type of expansion decreased by 18.85%, while the margin type increased by 22.5%, becoming the main type of urban expansion. Since the proportions of the center and core types did not change significantly, the overall expansion structure of the city during the second period developed in a decentralized direction. During the third period, the proportion of the margin type increased by 8.44%, while the adjacency, center, and core types decreased by varying degrees. In particular, the core type reduced by 21.36%. In summary, the urban expansion of Wuhan continued to develop in the decentralized direction during these three periods. The new patches were more likely to be located in a marginal area. This urban expansion structure did not achieve intensive and economical utilization, which may have led to the waste of land resources.

The visualization results of the location centrality types of new patches from the three periods based on LCI values are shown in Fig. 7. It can be intuitively seen that the number of marginal new patches (LCI ∈ (0, 0.5)) increased significantly, which fragmented and scattered the entire urban pattern. On the other hand, the high centrality patches showed a trend of concentration and contiguity in the region. However, the new patches with high centrality were not necessarily located inside the city, although they may have appeared around the original urban land even in remote areas. This is because when the LCI measures centrality, it not only considers spatial relationship with the main urban area, but also spatial impact of the adjacent original urban land. The new patches with high centrality in the periphery were closely related to the center of the neighboring old patches, which facilitated intensive and

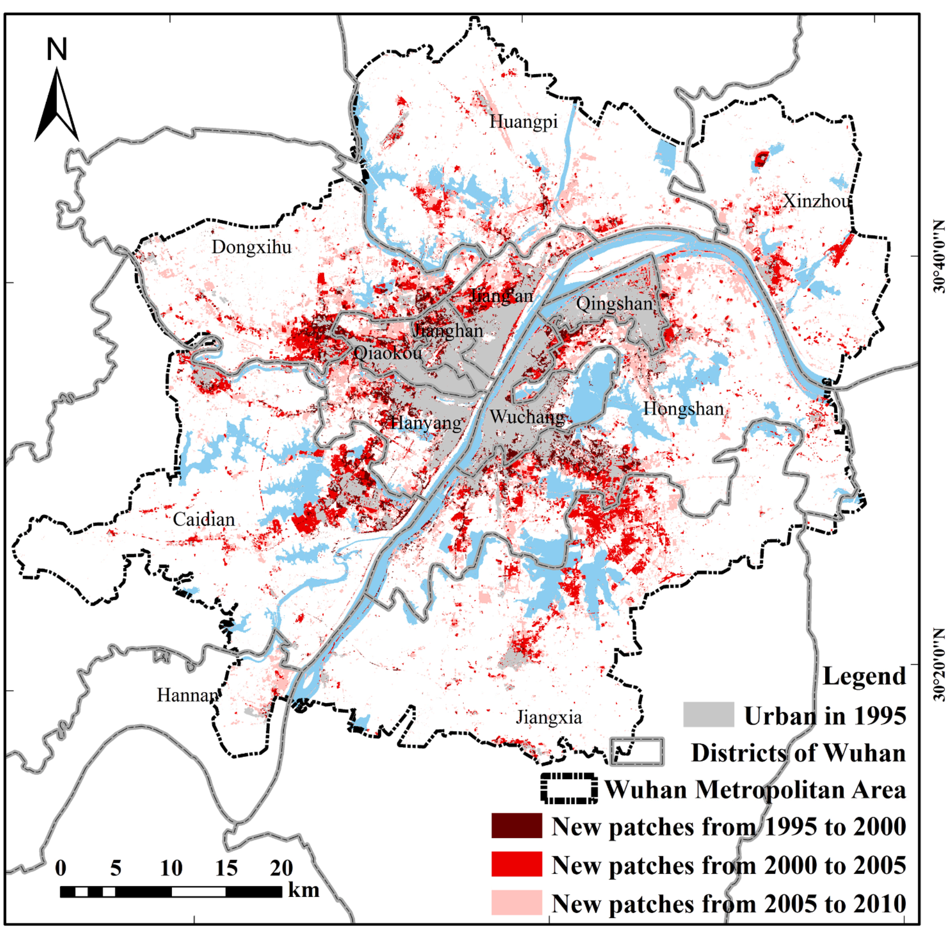

Fig. 5. Study areas.

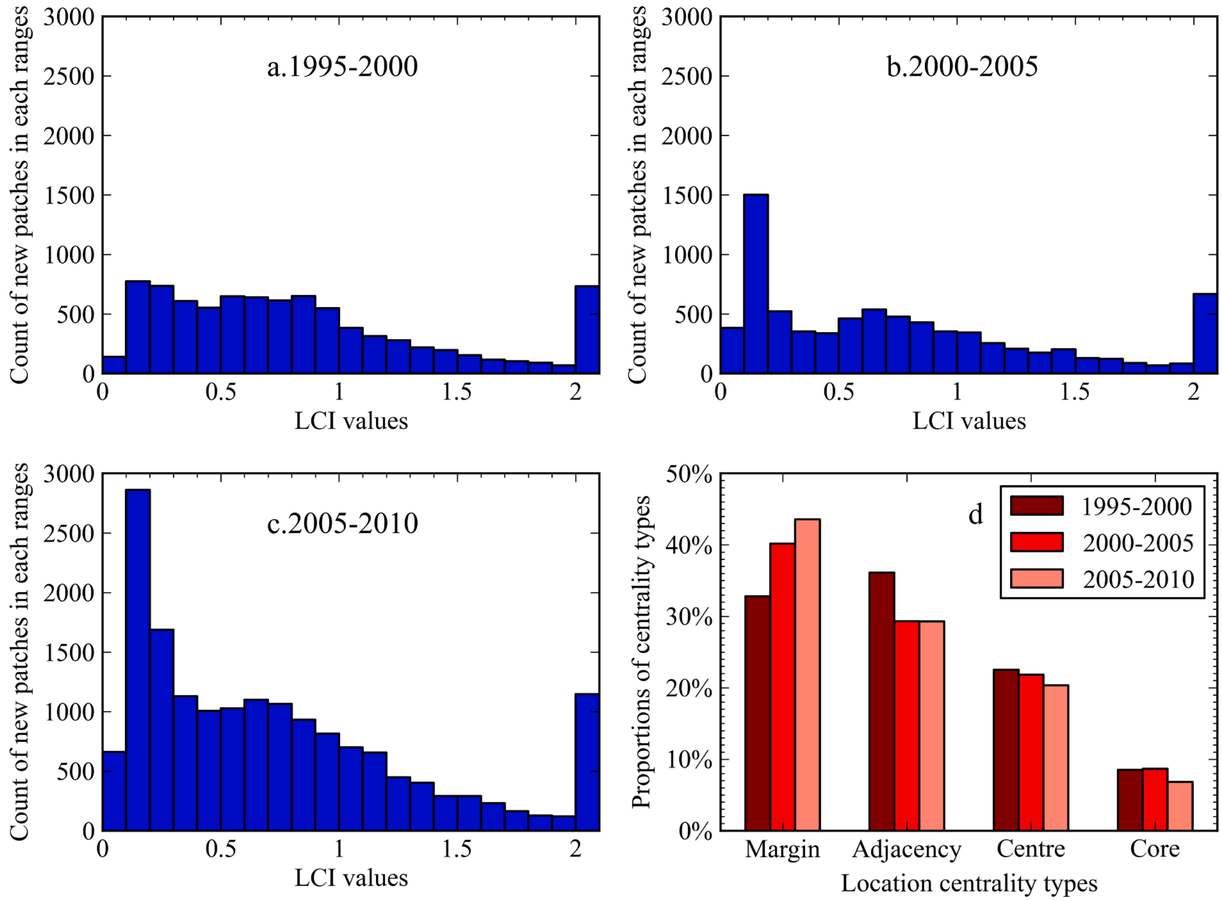

Fig. 6. Distributions of LCI values and centrality types in 1995–2000, 2000–2005, and 2005–2010.

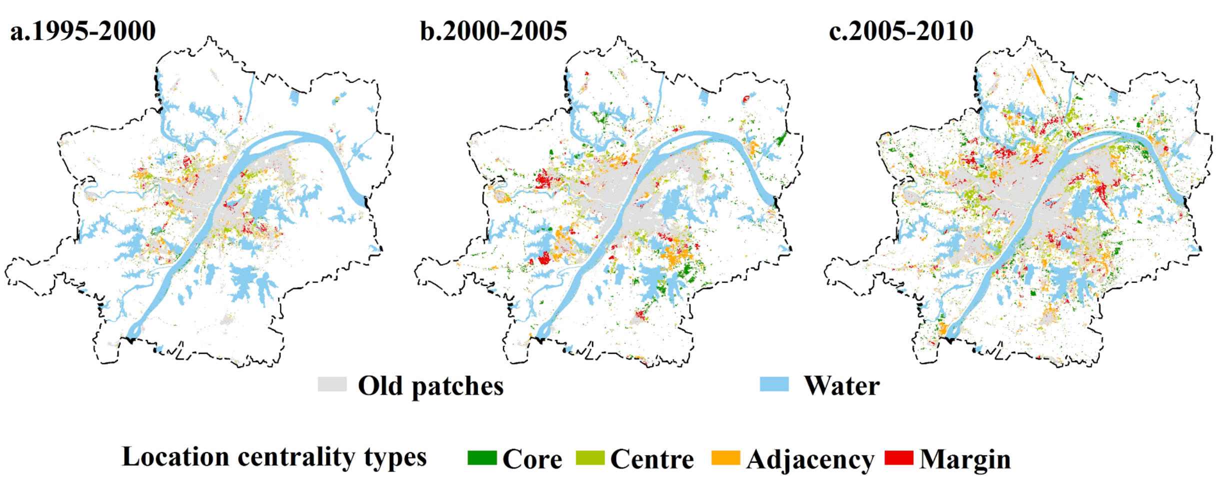

Fig. 7. The LCI spatial distribution of the three periods.

economical land usage in the peripheral areas.

4.2. Urban expansion form: Aggregated or separated?

We also revealed the urban form evolution using the urban expansion structure. The LCAI values of the new patches of the three periods (1995–2000, 2000–2005, and 2005–2010) were calculated according to Eq. (2), as shown in Fig. 8. The LCAI values of all three periods showed a bipolar distribution, mostly concentrated in (0, 0.2] and (4, ∞). The visualization results show that the LCAI can distinguish the process of aggregation and separation effectively, and that it provides a strong characterization of different degrees of aggregation. Since the (4, ∞) interval of the LCAI value range represents the high-aggregation type, we classify it as a bar on the graph to avoid a large difference in the data display. From 1995 to 2000, the LCAI distribution showed a decreasing trend initially in (0, 0.6]. It increased at (0.6, 1], but then decreased continuously. From 2000 to 2005, the LCAI distribution showed an increasing trend (0.2, 1], and then a decreasing trend. The LCAI distribution of the third stage is similar to that of the first period. Additionally, the LCAI values show a continuous distribution trend, proving that

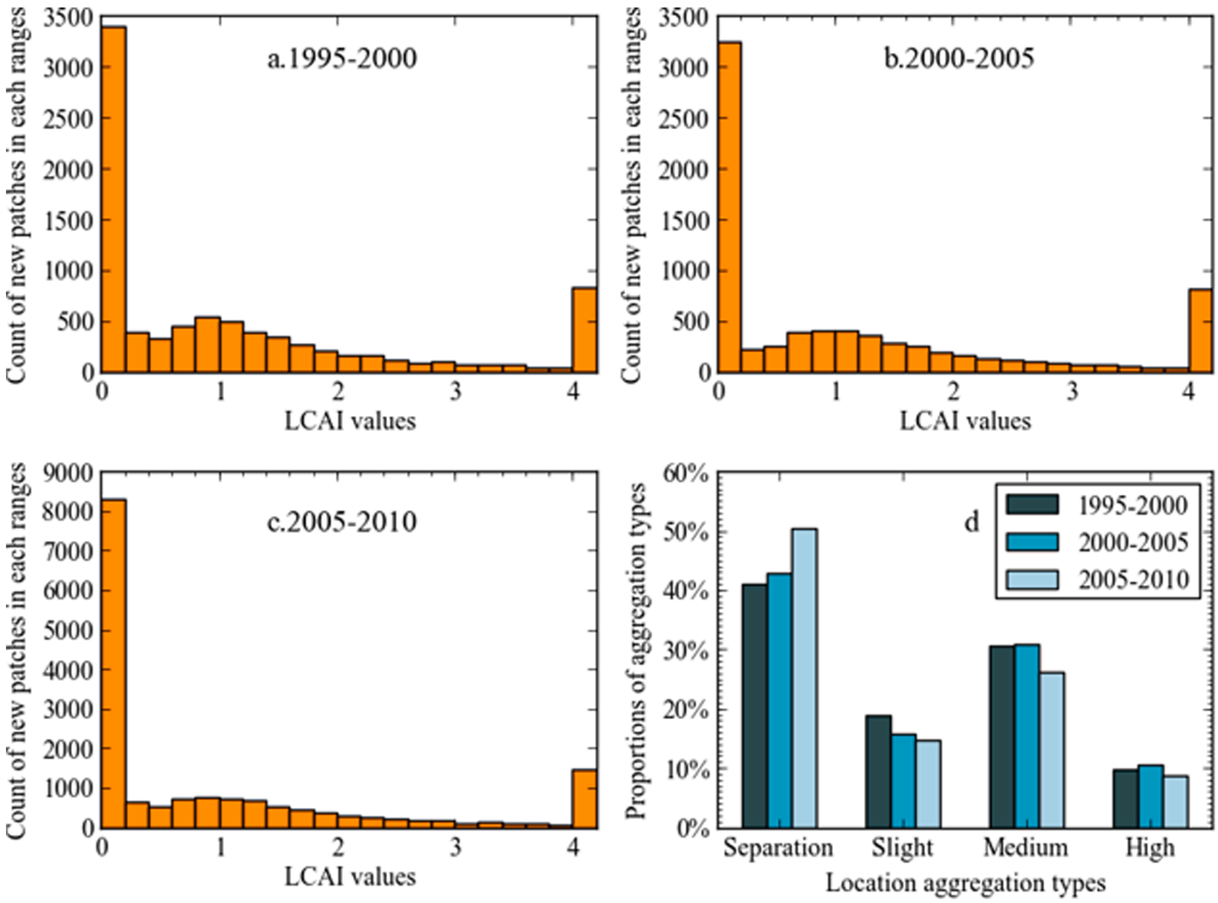

Fig. 8. Distributions of LCAI values and aggregation types in 1995–2000, 2000–2005, and 2005–2010.

the LCAI is also a continuous index.

The statistical results of the location aggregation types in the three periods are shown in Fig. 8d and Table S2 in the Appendix. From 1995 to 2000, the urban form evolution of the Wuhan metropolitan area was mostly of the aggregation types, which accounted for 59.1%. Among them, the medium-aggregation type accounted for the largest proportion (30.64%). This was followed by the slight-aggregation and the high-aggregation types (18.77% and 9.69, respectively). The separation type of evolution accounted for 40.9%. In the second period, the proportion of the medium-aggregation type decreased by 15.73%, while the high-aggregation and separation types increased by 8.47% and 4.94%, respectively. This shows that although the urban expansion pattern evolution was still dominated by the aggregation type during this period, and the aggregation effect of the new aggregation type patches was more obvious, the overall trend was in the direction of diffusion. In the third period, the proportion of separation type increased by 17.49%, while the high-, medium-, and slight-aggregation types decreased by 17.9%, 15.02%, and 6.38%, respectively. This shows that the urban expansion form had begun to shift to separation. The proportion of separation type continued to rise during the three periods, while slight-aggregation continued to decline. Although the medium- and high-aggregation types increased to an extent in the second period, their

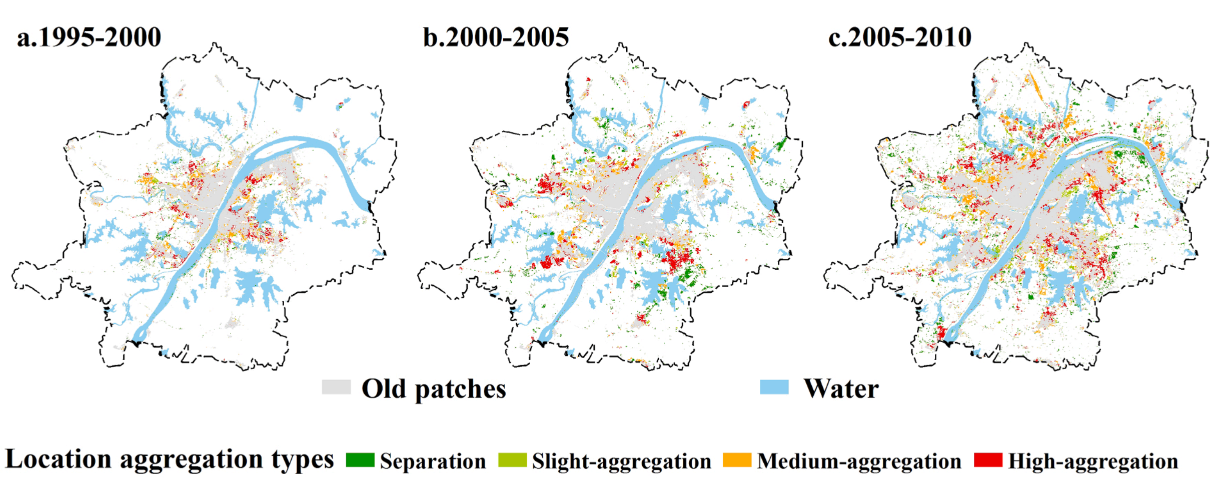

Fig. 9. The LCAI spatial distribution during the three periods.

overall changes reflected downward trends.

The visualization results of the location aggregation types of the new patches based on the LCAI classification of the three periods are shown in Fig. 9. It can be clearly seen that the new patches with a high degree of aggregation played an important role in aggregation, compensating for the gaps between the original urban lands and making the urban form more regular and compact. This proves that calculation results based on the LCAI can distinguish the heterogeneity of aggregation and separation types. In fact, urban expansion is a complicated geographical evolution process, and new patches in aggregation and separation processes do not exist alone; they coexist. For example, although the urban form of Wuhan City in the third period tended toward separation, a large number of new patches still played a critical role in aggregation. The LCAI-based identification of location aggregation types can distinguish the heterogeneity of urban form evolution and identify the local and overall aggregation characteristics of the expansion process comprehensively.

4.3. Evolution of structure and form of urban expansion

For a deeper understanding of the global evolution characteristics of urban expansion from 1995 to 2010, we calculated the mean location centrality index (MLCI) and the mean location aggregation centrality index (MLCAI) from a bottom-up view based on Eqs. (3) and (4) (Table 2).

The MLCI decreased continuously during the three periods. During the second period in particular, the MLCI decreased from 2.17 to 1.38, with a decline of 36.41%. These results indicate that the average centrality of the new patches decreased gradually, representing the development trend of the overall expansion structure, which tended toward decentralization. This shows that the location of new built-up land in Wuhan deviated from intensive and economical utilization from 1995 to 2010.

On the other hand, the MLCAI shows an initial sharply decreasing trend followed by a rising trend. In the first two periods, the MLCAI decreased from 110 to 10.14, with a decline of 90.78%, but the MLCAI increased by 59.47% in 2005–2010. This seems inconsistent with the results presented in Section 4.2, in which the aggregation types decreased while the separation type increased constantly in the 2005–2010 period. This is because the separation-type patches were often small and remote. Although they were greater in number, they could not cover the role of patches with a strong aggregation effect, especially in the third period. Therefore, the change trend of the MLCAI shows that although the urban form of Wuhan City became generally separated, it trended toward aggregation development between 2005 and 2010.

5. Discussions

5.1. Comparison of the LCI, LCAI, and other urban expansion metrics

Many studies focused on proposing methods for characterizing urban expansion to understand the dynamic process, such as S (Xu et al., 2007), LEI (Liu et al., 2010), MLEI, and PEI (Jiao et al., 2015, 2018). These indices generally use the BSR between the new and old patches. The LEI has been widely used in related research on urban expansion, and it can be considered representative of this type of index. This study compares the LCI, LCAI, and LEI to identify their differences. The LEI divides each new patch into three expansion types based on the degree of overlap between the buffer zone and the old patch: the infilling type, in which most of the new patch's buffer zone overlaps the old patch, $50 < \mathrm{LEI} \leq 100$; the edge-expansion type, in which the boundary sharing rate between the new and old patches is small, $0 < \mathrm{LEI} \leq 50$; and the outlying type, in which the new patch's buffer does not intersect with the old patch, $\mathrm{LEI} = 0$. This study chose 1 m as the buffer distance of the LEI, which is consistent with the original study (Liu et al., 2010). The calculated LEI results are shown in Table S3 in the Appendix.

Table 2
Calculation of the global expansion degree for Wuhan.

	1995–2000	2000–2005	2005–2010
MLCI	2.17	1.38	1.29
MLCAI	110.00	10.14	16.17

We used gradient analysis to reveal the differences between LCI, LCAI, and LEI because it is a very useful method to depict the heterogeneities of spatial distribution (Campo-Bescós et al., 2013; Jiao, 2015). Most existing methods regard centrality as the distance to one or several central business districts (CBDs) or city centers. In this study, the CBDs were identified from previous literature (Dong et al., 2019), which shows polycentric features from the traditional perspective of centrality. We then built a series of 1-km buffers from these CBDs (Fig. 10a). We used the 2005–2010 period to better show the differences between the three indices because the urban expansion intensity of this period was more intense. Based on these buffer sequences, we calculated the average LCI, LCAI, and LEI values of the new patches in each buffer. Further, we considered the value of the LCI-based core type as 2 and the value of the LCAI-based high-aggregation type as 4 to meet the requirement of turning the open range of the value range into a closed one. Finally, the statistical results of the normalized average within the buffer of the new patches are shown in Fig. 10b.

When compared with the LCI and LCAI, there is a significant difference in the average value distribution of the LEI along the distance gradient, although all three indices show a tortuous downward trend from the CBDs. The distribution of the LEI values shows an opposite trend when compared with the LCI and LCAI values; for example, in the 5-th buffer, the 12-th buffer, the 23-th buffer, etc. The LCI and LCAI differ as well. For example, the change trends in the range of the 5th to 26th buffers differ. However, it is worth noting that the distribution trends of the averages of these two indices in other ranges are similar. This shows that the location centrality and aggregation represented by the LCI and LCAI are similar within a certain range. This is because centrality and concentration are not complete opposites; there is a possibility of synergy. For example, aggregation may increase with proximity to the center, while separation may increase with distance from the center. However, regarding the difference in the distribution of averages between the LCI and LCAI, since the purpose of their measurement and the characteristics they measure are not consistent, they are more likely to be significantly different. This again confirms that the LCI and LCAI have their own advantages and they should be used to measure different expansion characteristics, namely, urban structure and urban form, respectively.

5.2. The urban expansion characteristics versus the location factors

Although LEI, LCI and LCAI are all designed to measure the characteristics of urban expansion, the urban characteristics they measure are different, which can also be seen from statistical results shown in Section 5.1. These differences may be determined by differentiated location factors that the indices focus on. The urban expansion processes of two regions from 2005 to 2010 were selected as examples to specifically compare the urban expansion characteristics versus the location factors determined by the LEI, LCI, and LCAI (Fig. 11). The first region is the Wuhan East Lake High-Tech Development zone, in which urban land grows rapidly. The second region is the urban area of Jiangxia District, which is relatively isolated from Wuhan City and can be regarded as its satellite city.

The calculated results of the LEI, LCI, and LCAI show obvious differences and similarities, reflecting different urban expansion characteristics (Fig. 11a–c). In the Wuhan East Lake High-Tech Development Zone, although some of the new patches in the northwest were closely related to old patches in the nearest neighborhood and were recognized

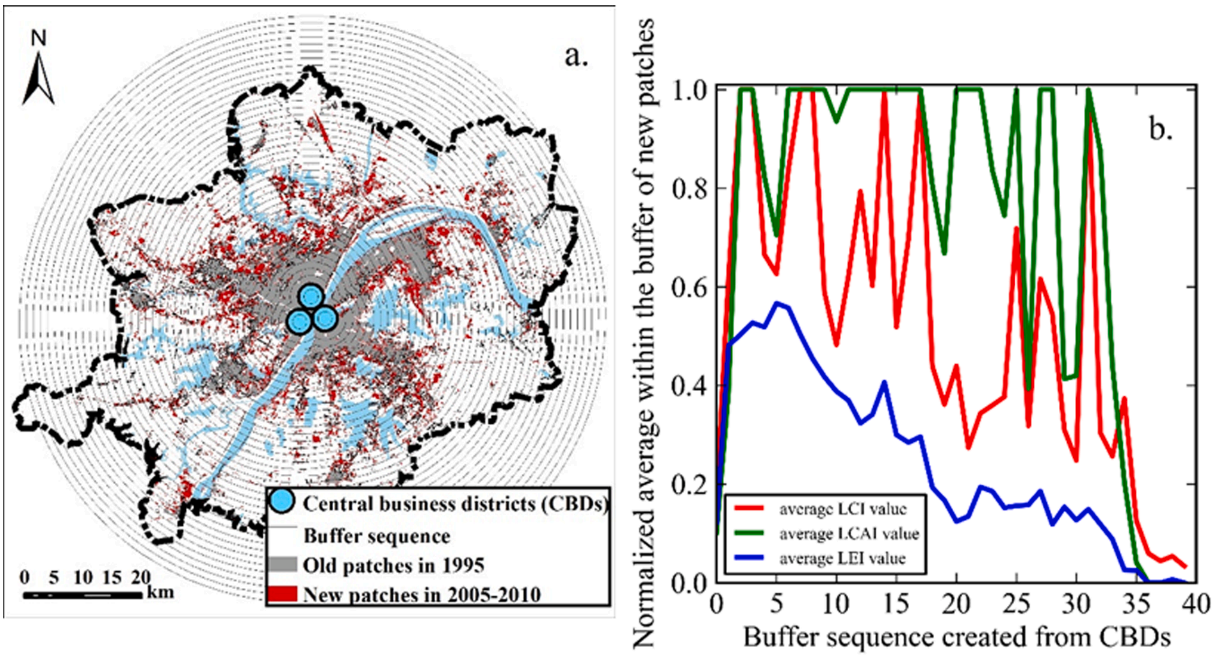

Fig. 10. The LCI, LCAI, and LEI gradient changes along the distance to the CBDs.

as infill by the LEI, they were classified by the LCI as adjacency type because they deviated from the center or sub center of the entire expansion structure (Fig. 11d and e). Moreover, although the expansion degree of new patches in the central part was larger, and they were recognized as edge-expanded by the LEI, they were recognized as the center type by the LCI after considering their spatial relationship with all the old patches, because their locations were close to the center of the surrounding urban land. In fact, these new patches were indeed located in the planned key development area of Wuhan City, which is similar to the sub center of urban growth. Some new patches in the northeast and southeast were classified as the edge-expansion type by the LEI, but were identified as the margin type by the LCI. This is because the old patches near these new patches were small and remote.

However, in the urban area of Jiangxia District, the LEI and LCI values of the new patches showed a decreasing trend from the local center to the outside, which indicates that the expansion degree and centrality of these patches showed a similar development trend (Fig. 11g and h). Nevertheless, it can be clearly seen that the centralities of the northern patches were higher than the southern patches, which were all recognized as edge-expansion types by the LEI. This is because the northern patches were closer to the center of the entire city.

The LCAI results are quite different from those of the LEI and LCI (Fig. 11c, f, and i). This is because the aggregation measured by LCAI not only considers overall structural properties, but also innovatively adds the measurement of the attribute of the new patch. In the urban area of Jiangxia District, the new patches in the north were more aggregated compared with the south (Fig. 11i). This indicates that the degree of aggregation identified by the LCAI is centripetal, and that it focuses more on integration effect in terms of the overall urban form. However, in the central part of the Wuhan East Lake High-Tech Development Zone, although the spatial relationship of the new patches with the nearest or all old patches was not the closest, the degree of aggregation was recognized by the LCAI to be at the highest level. This is because these new patches connect many old patches, compensate for the gaps between the old patches, and exert a strong aggregation effect (Fig. 11f). This strong aggregation effect is not only determined by their locations, but also by their large area.

In summary, different urban expansion characteristics, i.e., urban expansion degree, centrality and aggregation, are measured by designing indices. The various aspects of urban dynamic evolution are then depicted by considering different location factors. The LEI focuses more on reflecting the jump or expansion degree of the new patches compared with the locations of the nearest old patches, and lacks information of the overall urban land. Other existing dynamic indices of urban expansion have similar shortcomings. The LCI compensates for this shortcoming, as it can comprehensively identify the centrality of the new patches compared with the locations of main center, the sub center, or the potential center. Thus, LCI can show the structural properties of urban expansion better. The LCAI specifically considers the role played by the new patch's spatial characteristics, that is, its area, which is disregarded in other dynamic indices of urban expansion. Based on this, the LCAI could reflect the spatial locations of old patches in relation to the new patches, unlike the BSR indices, which mainly considered the spatial locations of new patches in relation to the old patches (Section 2.3). Therefore, the aggregation could be described better, because the new and old patches collectively cause differences in the degree of aggregation. The LCAI can comprehensively identify the spatial heterogeneity of the aggregation or separation process, providing a new perspective for understanding changes in urban form.

6. Conclusions

Although dynamic indices that describe the urban expansion process already exist, they only focus on one-dimensional characteristics, resulting in an inadequate understanding of the urban expansion process. Clear and meaningful dimensional characteristics like location centrality and aggregation, for example, should be quantitatively described in relation to the ambiguous measurement of "compactness" or "sprawl." The LCI and LCAI have been proposed to depict the dynamic evolution of the urban expansion structure and form by measuring centrality and aggregation at the patch level.

The LCI and LCAI have the following advantages: (1) since the LCI and LCAI ranges are continuous, the gradients of location centrality and aggregation can be comprehensively reflected; (2) the LCI reflects the geographical significance of "centrality" and the LCAI represents the physical gravitation between new and old patches to a certain degree; (3) the location centrality and location aggregation types can be identified in the urban expansion structure and form based on the LCI and

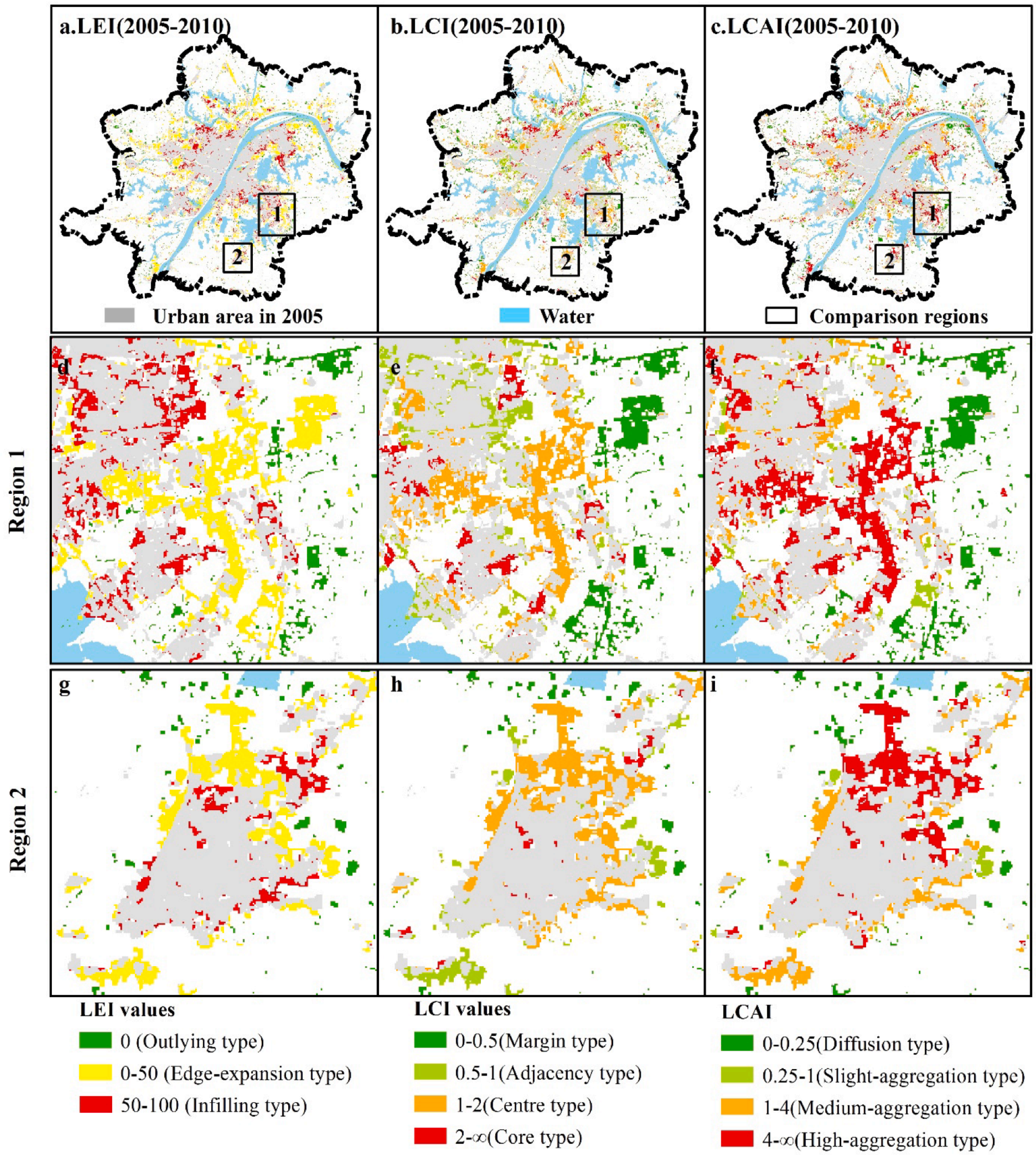

Fig. 11. LEI, LCI, and LCAI comparison.

LCAI to reflect the effect of a new patch; and (4) two variants of the LCI and LCAI, the MLCI and MLCAI, have been proposed to represent the different global dynamic features of urban expansion from a bottom-up perspective.

The Wuhan metropolitan area, a rapid growth region in central China, was selected as the study area to verify the LCI and LCAI during three periods (1995–2000, 2000–2005, and 2005–2010). The following results were obtained: (1) the proportion of margin type expansion had continued to increase, while the adjacency, center, and core types had gradually declined to varying degrees; (2) the proportion of separation type had continued to rise; however, the medium-aggregation type had continued to decline while the slight- and high-aggregation types had first risen and then declined in the third period; (3) the MLCI result indicates that the development trend of the overall expansion structure tended toward decentralization; and (4) the change trend of the MLCAI shows that although the urban form of Wuhan City became generally separated, it tended toward aggregation development between 2005 and 2010.

By comparing the LCI, LCAI, and other existing dynamic metrics, we found that they depict various aspects of the urban expansion process. The existing dynamic metrics focus more on reflecting the jump or expansion degree of the new patches compared with the nearest old patches, and lack information on the expansion structure of the new patches in relation to the overall land. The LCI compensates for this shortcoming. The LCI can comprehensively identify the centrality of the new patches compared with the main center, the sub center, or the potential center, and it can be used to determine whether the spatial growth of the city is intensive and economical. Meanwhile, the LCAI can identify aggregation heterogeneity, providing a new perspective for understanding urban form evolution.

Future research will include analysis of large-scale urban expansion or comparison between cities based on the LCI and LCAI. Moreover, additional dimensional applications based on these two indices should be discussed. The LCI and LCAI are also expected to reveal the spatial characteristics of urban expansion comprehensively and from multiple angles with other metrics covering various aspects for a deeper understanding of the mechanism of the expansion process.

CRediT authorship contribution statement

Jiafeng Liu: Conceptualization, Methodology, Software, Validation, Writing - original draft. **Limin Jiao:** Conceptualization, Resources, Project administration, Funding acquisition. **Boen Zhang:** Formal analysis, Writing - original draft. **Gang Xu:** Writing - original draft, Project administration. **Ludi Yang:** Writing - original draft. **Ting Dong:** Project administration. **Zhibang Xu:** Resources. **Jing Zhong:** Writing - review & editing. **Zhengzi Zhou:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Angel, S., Parent, J., Civco, D.L., 2010. Ten compactness properties of circles: Measuring shape in geography. Can. Geogr. 54 (4), 441–461. https://doi.org/10.1111/j.1541-0064.2009.00304.x.

Angel, S., Sheppard, S., Civco, D. L., Buckley, R., Chabaeva, A., Gitlin, L., ... & Perlin, M. (2005). The dynamics of global urban expansion (p. 205). Washingtonˆ ed. c dc: World Bank, Transport and Urban Development Department.

Bhatta, B., Saraswati, S., Bandyopadhyay, D., 2010. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. Appl. Geogr. 30 (1), 96–111. https://doi.org/10.1016/j.apgeog.2009.08.001.

Blumenfeld, H., 1954. The tidal wave of metropolitan expansion. J. Am. Plann. Assoc. 20 (1), 3–14.

Boyce, R.R., 1966. The edge of the metropolis: The wave theory analog approach,. British Columbia Geographical Series 7, 31–40.

Bramley, G., Dempsey, N., Power, S., Brown, C., Watkins, D., 2009. Social sustainability and urban form: evidence from five british cities. Environ. Plan. A 41 (9), 2125–2142. https://doi.org/10.1068/a4184.

Campo-Bescós, M. A., Muñoz-Carpena, R., Kaplan, D. A., Southworth, J., Zhu, L., & Waylen, P. R. (2013). Beyond Precipitation: Physiographic Gradients Dictate the Relative Importance of Environmental Drivers on Savanna Vegetation. PLoS ONE, 8 (8), 15–17. https://doi.org/10.1371/journal.pone.0072348.

Carruthers, J.I., Ulfarsson, G.F., 2003. Urban sprawl and the cost of public services. Environ. Plann. B Plann. Des. 30 (4), 503–522. https://doi.org/10.1068/b12847.

Christaller, W. (1933). Die Zentraler Orte in Sudteutschland. Jena.

Deng, J.S., Wang, K.e., Hong, Y., Qi, J.G., 2009. Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization. Landscape Urban. Plann. 92 (3-4), 187–198. https://doi.org/10.1016/j.landurbplan.2009.05.001.

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. Geograph. Inform. Sci. 19 (2), 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. Plann. B Plann. Des. 32 (2), 231–246. https://doi.org/10.1068/b31148.

Dong, T., Jiao, L., Xu, G., Yang, L., Liu, J., 2019. Towards sustainability? Analyzing changing urban form patterns in the United States, Europe, and China. Sci. Total Environ. 671 (April), 632–643. https://doi.org/10.1016/j.scitotenv.2019.03.269.

Duncan, B., Sabagh, G., Van Arsdol, Jr., M.D., 1962. Patterns of City Growth. Am. J. Sociol. 67 (4), 418–429. https://doi.org/10.1086/223165.

Echenique, M.H., Hargreaves, A.J., Mitchell, G., Namdeo, A., 2012. Growing Cities Sustainably: Does Urban Form Really Matter? J. Am. Plan. Assoc. 78 (2), 121–137. https://doi.org/10.1080/01944363.2012.666731.

Ellman, T. (1997). Infill: The Cure for Sprawl? Arizona Issue Analysis 146.

Forman, R.T.T., 1996. Land Mosaics: The ecology of landscapes and regions. Trends Ecol. Evol. 11 (12), 521. https://doi.org/10.1016/0169-5347(96)88908-7.

Fragkias, M., Seto, K.C., 2009. Evolving rank-size distributions of intra-metropolitan urban clusters in South China. Comput. Environ. Urban Syst. 33 (3), 189–199. https://doi.org/10.1016/j.compenvurbsys.2008.08.005.

Galster, G., Hanson, R., Ratcliffe, M.R., Wolman, H., Coleman, S., Freihage, J., 2001. Wrestling Sprawl to the Ground: Defining and measuring an elusive concept. Housing Policy Debate 12 (4), 681–717. https://doi.org/10.1080/10511482.2001.9521426.

Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008. Global Change and the Ecology of Cities. Science 319 (5864), 756–760. https://doi.org/10.1126/science:1150195.

Hamidi, S., Ewing, R., Preuss, I., Dodds, A., 2015. Measuring Sprawl and Its Impacts: An update. J. Plann. Educ. Res. 35 (1), 35–50. https://doi.org/10.1177/0739456X14565247.

Hansen, A.J., Knight, R.L., Marzluff, J.M., Powell, S., Brown, K., Gude, P.H., Jones, K., 2005. Effects of exurban development on biodiversity: Patterns, mechanisms, and research needs. Ecol. Appl. 15 (6), 1893–1905. https://doi.org/10.1890/05-5221.

Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: Measurement, analysis and modeling. Remote Sens. Environ. 86 (3), 286–302. https://doi.org/10.1016/S0034-4257(03)00075-0.

Huang, J., Lu, X.X., Sellers, J.M., 2007. A global comparative analysis of urban form: Applying spatial metrics and remote sensing. Landscape Urban Plann. 82 (4), 184–197. https://doi.org/10.1016/j.landurbplan.2007.02.010.

Jenerette, G.D., Wu, J., 2001. Analysis and simulation of land-use change in the central Arizona - Phoenix region, USA. Landscape Ecol. 16 (7), 611–626. https://doi.org/10.1023/A:1013170528551.

Jiao, L., 2015. Urban land density function: A new method to characterize urban expansion. Landscape Urban Plann. 139, 26–39. https://doi.org/10.1016/j.landurbplan.2015.02.017.

Jiao, L., Liu, J., Xu, G., Dong, T., Gu, Y., Zhang, B., Liu, Y., Liu, X., 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. Landscape Urban Plann. 137, 30–39. https://doi.org/10.1016/j.landurbplan.2014.10.023.

Krummel, J.R., Gardner, R.H., Sugihara, G., O'Neill, R.V., Coleman, P.R., 1987. Landscape Patterns in a Disturbed Environment. Oikos 48 (3), 321. https://doi.org/10.2307/3565520.

Li, H., Wu, J., 2004. Use and misuse of landscape Índices. Landscape Ecol. 19 (4), 389–399. https://doi.org/10.1023/B:LAND.0000030441.15628.d6.

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. Landscape Ecol. 25 (5), 671–682. https://doi.org/10.1007/s10980-010-9454-5.

McGarigal, K., & Marks, B. J. (1995). FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. doi:10.2737/pnw-gtr-351.

Newling, B.E., 1969. The spatial variation of urban population densities. Geogr. Rev. 59 (2), 242. https://doi.org/10.2307/213456.

O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H., Graham, R.L., 1988. Indices of landscape pattern. Landscape Ecol. 1 (3), 153–162. https://doi.org/10.1007/BF00162741.

Plotnick, R.E., Gardner, R.H., O'Neill, R.V., 1993. Lacunarity indices as measures of landscape texture. Landscape Ecol. 8 (3), 201–211. https://doi.org/10.1007/BF00125351.

Rossi-Hansberg, E., Wright, M.L.J., 2007. Urban structure and growth. Rev. Econ. Stud. 74 (2), 597–624. https://doi.org/10.1111/j.1467-937X.2007.00432.x.

Seto, K.C., Fragkias, M., 2005. Quantifying spatiotemporal patterns of urban land-use change in four cities of china with time series landscape metrics. Landscape Ecol. 20 (7), 871–888. https://doi.org/10.1007/s10980-005-5238-8.

Su, S., Xiao, R., Jiang, Z., Zhang, Y., 2012. Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale. Appl. Geogr. 34, 295–305. https://doi.org/10.1016/j.apgeog.2011.12.001.

Sun, C., Wu, Z.F., Lv, Z.Q., Yao, N., Wei, J.B., 2012. Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. Int. J. Appl. Earth Obs. Geoinf. 21 (1), 409–417. https://doi.org/10.1016/j.jag.2011.12.012.

Thisse, J.F., 1987. Location theory, regional scence, economics. J. Regional Sci. 27 (4).

Tsai, Y.-H., 2005. Quantifying urban form: Compactness versus 'Sprawl'. Urban Stud. 42 (1), 141–161. https://doi.org/10.1080/0042098042000309748.

United Nations. (2014). World Urbanization Prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352). In New York, United. https://doi.org/10.4054/DemRes.2005.12.9.

Hoffhine Wilson, E., Hurd, J.D., Civco, D.L., Prisloe, M.P., Arnold, C., 2003. Development of a geospatial model to quantify, describe and map urban growth. Remote Sens. Environ. 86 (3), 275–285. https://doi.org/10.1016/S0034-4257(03)00074-9.

Winsborough, H.H., 1962. City growth and city structure†. J. Regional Sci. 4 (2), 35–49. https://doi.org/10.1111/j.1467-9787.1962.tb00903.x.

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. Landscape Ecol. 22 (6), 925–937. https://doi.org/10.1007/s10980-007-9079-5.

Zambon, I., Benedetti, A., Ferrara, C., Salvati, L., 2018. Soil Matters? A multivariate analysis of socioeconomic constraints to urban expansion in mediterranean Europe. Ecol. Econ. 146, 173–183. https://doi.org/10.1016/j.ecolecon.2017.10.015.