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## Original Research Article

### Understanding urban expansion and its landscape responses with long-term

### Landsat data in Guangzhou, China

**Abstract:** Quantifying spatio-temporal pattern of urban expansion is essential for understanding the ecological consequences of urbanization and supporting optimal urban management strategies. As one of most developed regions in China, Guangzhou has experienced rapid urban expansion over the past decades. However, little is known about the detailed process of urban expansion across long-term period. Combining remote sensing data with GIS techniques, we attempted to quantify the spatio-temporal pattern of urban expansion in Guangzhou. We mapped the urban landscape in Guangzhou using Landsat images between 1973 and 2017. The urban land developed and changed process was also examined, including urban expansion direction, urban expansion types, and landscape responses to urban expansion. The results showed that the building nearly increased by 90-fold from 1973 to 2017, and over half of newly developed the building mainly came from farmland. The edge expansion is the main type of urban growth. Urban trajectory presents that the expansion mainly occurred in southwest to northeast direction. Urban growth led to radical changes in urban landscape, which were witnessed by sharp decreases in soil and farmland. The results from this study provide the key information for future planning to make an eco-friendly megacity as well as sustainable development.

**Keywords:** Urban expansion; Landscape response; Guangzhou; Landsat

#### 1 Introduction

In recent decades, unprecedented urban expansion has led to the modification of the Earth's surface structure<sup>1,2</sup>. The urban land accounts for merely a small part of the Earth's land surface, but the acceleration of the urbanization process has had a significant impact on terrestrial ecosystems at different scales<sup>3-5</sup>, resulting in reduced biological diversity, impacted ecosystem services and function, changed biogeochemical cycles and climate<sup>6-10</sup>. With fast economic and population growth in China, rapid urban land expansion has tremendously changed the regional and continental environmental systems, leading to a lot of negative environmental impacts such as loss of arable land, fragmented habitats, elevated land surface temperature<sup>11</sup>. The rapid urban land expansion has threatened sustainable development<sup>12, 13</sup>. Therefore, given such political and sustainable development demands, accurate and updated urban expansion information and landscape change response information are crucially important to support sustainable development as well as the preservation of ecological and environmental conditions for researchers and governors<sup>12</sup>.

As the core of Pearl River Delta urban agglomeration and a pilot area of Guangdong-Hong Kong-Macao Greater Bay, Guangzhou is an excellent example for studying urban expansion related to its process, because it is one of the largest metropolitans and rapid developing areas in China or even the world. The socioeconomic factor was the primary driving force that directly and indirectly affected the composition of land cover in Guangzhou. Following urban sprawl, a large number of buildings have become one of the dominant urban landscapes in Guangzhou. Continuous urban expansion has led to many environmental issues in Guangzhou over the few decades, including large arable land loss, urban heat island and water pollution<sup>14-16</sup>. As the size and number of the building continues to grow, these impacts on the natural systems will become more apparent, the

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urban expansion brings huge pressure to the environmental quality and ecological systems. The rapid pace of the building growth is reshaping the morphology and function of urban. Guangzhou faces a huge challenge in maintaining trade-offs between regional development and ecological benefits, highlighting the need for a clear understanding on urban expansion process. Therefore, in-depth studies of urban expansion patterns are essential to promote sustainable urban development in Guangzhou.

Given the rapid urban development in Guangzhou, an accurate and long-term data on dynamic of urban expansion is highly vital to optimize land use patterns, to promote the effective development and to ensure urban sustainability. Moreover, comprehensive characterizing urban expansion process will provide basic and valuable information on monitoring of urban planning effects and modeling urban growth in Guangzhou. Out of these importance, a comprehensive study incorporating RS and GIS is conducted to analyze the spatio-temporal processes of urban expansion and landscape change within Guangzhou between the years 1973 and 2017. We first mapped the urban landscape with an integrated method, the changes on urban landscape is also evaluated. Then, we examined the spatio-temporal patterns of urban expansion, mainly including expansion types, expansion direction (or trajectory).

## **2 Materials and methods**

### **2.1 Study area and data source**

Guangzhou is located between 112°57'1.1"-114°3'19.57"E and 22°33'35.32"-23°56'1.99"N, and covers an area of about 7434.4 km<sup>2</sup> (Fig.1). Guangzhou, as the center of Pearl River Delta and the capital of Guangdong province, is the cultural, economic, and political center of south China. Guangzhou comprised of 12 districts, namely: Yuexiu, Tianhe, Haizhu, Liwan, Huangpu, Luogang, Panyu, Nansha, Baiyun, Huadu, Zengcheng and Conghua. Guangzhou has a typical sub-tropical maritime monsoon climate, in which persistent rain and clouds in spring and summer (two wet season) are a prominent climate feature<sup>17</sup>. The topography in Guangzhou has a low elevation in the south, but high in the northeast.

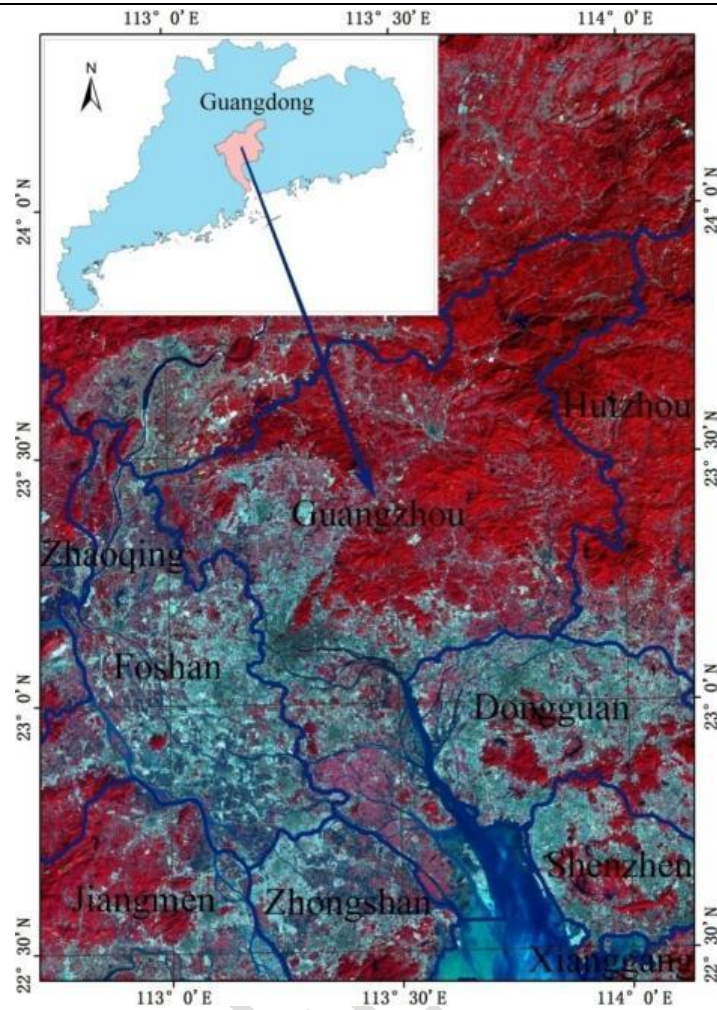


Fig.1 Location of study area (The false color image is the Landsat-5TM image collected on November 02, 2009).

Understanding the complex processes of urban expansion requires long-term records<sup>18</sup>. Eighteen Landsat images at nine periods from the U.S. Geological Survey (USGS) were used as imagery sources to monitor urban expansion over a 44 years period (Table 1). All of the used images were selected because they were cloud-free or cloud-few during October to December in each study period. Other ancillary data include the Guangzhou administrative map (2005) for delineation of the study boundary, the high-resolution image (2009) from Google Earth for selecting classification samples and assessing classification accuracy.

Table 1 List of Landsat images used in this study.

Years	Sensor	Acquired date (yyyy/mm/dd)	Number of GCP's for registration	Geometric for registration RMS error
1973	MSS	1973/10/25	16	±0.45
1979	MSS	1979/10/19	15	±0.49
1988	TM	1988/12/10	10	±0.33
1994	TM	1994/10/24	15	±0.35
2000	TM	2000/10/08	7	±0.17
2005	TM	2005/11/23	7	±0.005
2009	TM	2009/11/02	~	Master image
2013	OLI	2013/11/29	6	±0.002

## 2.2 Images pre-processing

The surface reflectance (SR) data of 2009 were obtained from the USGS EROS Science Products Architecture (ESPA, <https://espa.cr.usgs.gov/>), the rest were obtained from the USGS Earth Explorer (<https://earthexplorer.usgs.gov/>). Except for the 2009 SR data, the original digital numbers of these images were converted to the atmospheric radiance using the conversion formula from the USGS Landsat program<sup>19,20</sup>. Furthermore, two images (path 122 row 44, path 122 row 43) of each period were spliced together. To respond the resolution of the other Landsat instruments (TM, OLI), the MSS images were re-sampled to 30 m using the nearest neighbor resampling method<sup>21</sup>. The 2009 spliced SR image was used as a reference for registering the other eight spliced images, and the root mean square errors are limited within 0.5 pixels (Table 1).

Since the multi-temporal and multi-sensor images were used, it is necessary to normalize the variation in SR across all used images<sup>22-24</sup>. Comparing the pre-band spectral range, the Landsat time series images has similar or same spectrum range<sup>25</sup>, thus iteratively re-weighted multivariate alteration and detection (IR-MAD) transformation<sup>26</sup> was adopted to approximately adjust the differences of SR between used the images of Landsat. We used the 2009 mosaic SR image as reference for conducting the relative radiometric normalization procedure based on the IR-MAD transformation<sup>25,26</sup>, the atmospheric radiance of the other eight target images (include 1973MSS, 1979MSS, 1988TM, 1994TM, 2000TM, 2005TM, 2013OLI, 2017OLI) can be converted to the SR<sup>25-27</sup>. The SR (blue band, green band, red band, near infrared band, shortwave infrared 1 band, shortwave infrared 2 band) of 1988TM, 1994TM, 2000TM, 2005TM, 2013OLI and 2017OLI were corrected with respect to the year 2009 TM SR (blue band, green band, red band, near infrared band, shortwave infrared 1 band, shortwave infrared 2 band). For correcting the MSS imagery (three bands analogous to TM) with respect to the year 2009 SR image, the green, red and near infrared bands of the year 2009 SR image were used to match the SR of the MSS (1973, 1979). Finally, the SR of all used images was approximately adjusted to common radiometric scale based on the year 2009 SR image.

## 2.3 Urban landscape classification

We adopted the feature composite classification scheme to extract the urban landscape. Firstly, the normalization different water index (NDWI) and normalization different vegetation index (NDVI) (Equation (1) and Equation (2)) were calculated for the all SR images. Then, NDWI and NDVI images were stacked into the SR image of each study period. Two five-layers images (MSS) and seven eight-layers images (TM, OLI) were obtained to apply classification.

$$NDWI = \frac{B_g - B_n}{B_g + B_n} \quad (1)$$

$$NDVI = \frac{B_n - B_r}{B_n + B_r} \quad (2)$$

where  $B_g$ ,  $B_n$ ,  $B_r$  represent green, near infrared, and red bands of Landsat imagery.

The urban landscape was broken down into six categories: building, forest, soil, farmland, shrub-grass, and water. All urban landscape classifications were identified using a support vector machines (SVM) technique. Firstly, larger than 1500 points were randomly generated within the overlapped area between the year 2009 TM SR image and the quasisynchronous high-resolution

image from Google Earth. Then, these points were visually divided as building, forest, soil, farmland, shrub-grass, and water; of more than 200 random sample points for each classification, half of them were employed for validation and the other half were employed for training. The training sample points were employed to train the SVM classifier based on an eight-layers imagery from the year 2009 layer-stacked image <sup>21</sup>. Based on the validation samples, an error matrix was used for evaluating accuracy <sup>28</sup>. The results of accuracy assessment are found in Table 2.

In order to verify whether the five-layers image (green, red, near infrared bands, and NDVI, NDWI images) meet urban landscape classification, a new classifier for the SVM was developed using the same training samples as the eight-layers imagery, whereas only five-layers (green, red, near infrared bands, and NDVI, NDWI images) from the year 2009 layer-stacked image were used. The accuracy was also assessed with the same validation samples, as tabulated in Table 2. Although only five-layers were used, the classified result was similar to the eight-layers SVM approach (Table 2).

Table 2 The accuracy assessment results of the different classification methods (unit: %).

		Water	Building	Soil	Forest	Farmland	Shrub-grass
Eight-layers	Producer's accuracy	96.08	92.00	86.05	90.38	81.13	78.43
	User's accuracy	98.00	92.00	74.00	94.00	86.00	80.00
Five-layers	Producer's accuracy	95.92	90.00	84.78	87.04	80.00	82.35
	User's accuracy	94.00	90.00	78.00	94.00	80.00	84.00

In this study, an elaborated atmospheric correction was employed to minimize the differences between used images (see section 2.2), and to get relatively consistent SR in various Landsat images <sup>23, 26</sup>. Moreover, SVM classifiers (five-layers and eight-layers) generated from the 2009 layer-stacked image is a practical bridge between used images. Therefore, consistent and valid results of classification could be expected using the five-layers SVM classifier for MSS images and the eight-layers SVM classifier for TM and OLI images <sup>21</sup>.

#### 2.4 Quantification of landscape responses with urban expansion

A matrix system was generated through a GIS application using classification maps of the region for the years 1973, 1979, 1988, 1994, 2000, 2005, 2009, 2013, and 2017, to quantify how much water, soil, forest, shrub-grass, and farmland were converted directly and indirectly to building. These nine time points enabled the definition of nine conversion episodes, 1973–1979, 1979–1988, 1988–1994, 1994–2000, 2000–2005, 2005–2009, 2009–2013, 2013–2017, and 1973–2017, which could be used to track the process of landscape change due to urban expansion.

#### 2.5 Quantifying the spatio-temporal patterns of urban expansion

The spatial-temporal process of urban expansion was measured from different dimension. We used GIS technique to estimating the types and direction of urban expansion in Guangzhou. Three types of urban expansion were identified using Equation (3) <sup>29, 30</sup>. Urban expansion types are defined as outlying if  $S = 0$ , edge if  $0 < S < 0.5$ , and infilling if  $S \geq 0.5$ . The three expansion types are illustrated in Fig.2.

$$S = \frac{L_c}{p} \quad (3)$$

where  $L_c$  is the length of the common edge between a new and existing building patch, and  $p$  is the perimeter of the new building patch (Fig.2).

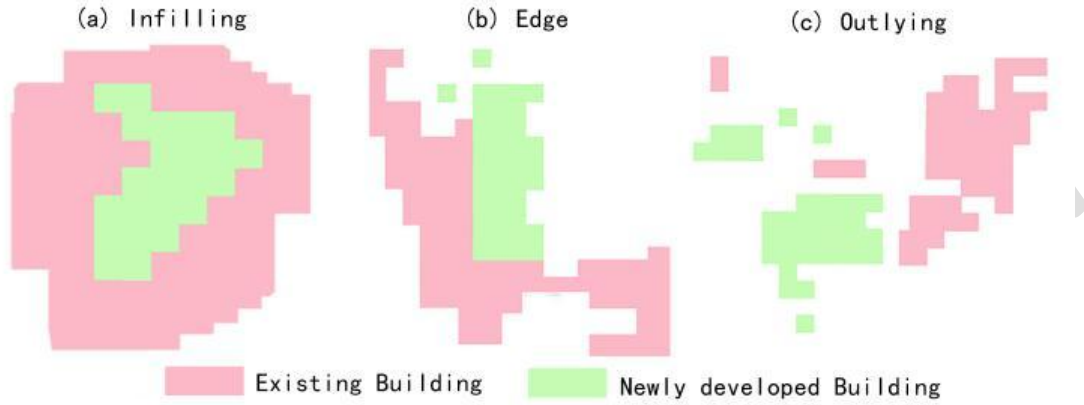


Fig.2 The three types of urban expansion: (a) Infilling, (b) Edge, (c) Outlying.

Urban expansion trajectory was characterized by the changes of Gravity Center (GC). The concept of Gravity Center is used to identify the weighted center of the building, mapping the GC change of the building estimated the spatial direction of urban development<sup>31</sup>. The GC migration was described based on the alteration of the gravity center coordinate (GCC)<sup>31</sup>. The GCC is measured by Equation (4) and Equation (5).

$$X = \frac{\sum_{i=1}^n P_i X_i}{\sum_{i=1}^n P_i} \quad (4)$$

$$Y = \frac{\sum_{i=1}^n P_i Y_i}{\sum_{i=1}^n P_i} \quad (5)$$

where  $X$  and  $Y$  are the GCC for the building,  $X_i$  and  $Y_i$  are GCC of the  $i$ th patch,  $P_i$  is area of the  $i$ th patch,  $n$  is number of patches in the building.

To examine the spatial pattern of expansion and its change over time, four class-level spatial metrics were selected to capture the pattern of three urban expansion types from different dimensions, i.e. the patch density (PD) equals the number of patches of the corresponding patch type divided by total landscape area, the mean patch area (MPA) measure the average area of all patches in the landscape, the landscape shape index (LST) quantify the irregularity of the landscape, and the clumpiness index (CLUMPY) describes the proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution. Four indices describe four key aspects feature of the landscape: density, size, edge, and aggregation respectively. The comments and calculation method of four spatial metrics can be found in the help document of FRAGSTATS software version 4.2.

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### 3 Results

#### 3.1 Landscape responses of urban expansion

The resulting landscape maps generated for the studied area are shown in Fig.3, respectively. During the period 1973–2017, the building areas grew from 0.26% to 23.04% of the study area, the building nearly increased by 90-fold, the change in the area of building indicated that Guangzhou experienced rapid urban expansion over the 44 years period. The building kept on expanding from 1973, the mean annual growth rates of the building also increased greatly, which were 3.83, 5.40, 22.25, 23.34, 47.24, 66.33, 110.60 km<sup>2</sup>/year for the seven periods of 1973–1979, 1979–1988, 1988–1994, 1994–2000, 2000–2005, 2005–2009 and 2009–2013, respectively, indicating that the urbanization process of Guangzhou has been accelerated from 1973 to 2013. But the mean annual growth rates of the building decreased during 2013–2017 (101.19 km<sup>2</sup>/year), indicating that the speed of urban expansion in Guangzhou tends to slow down.

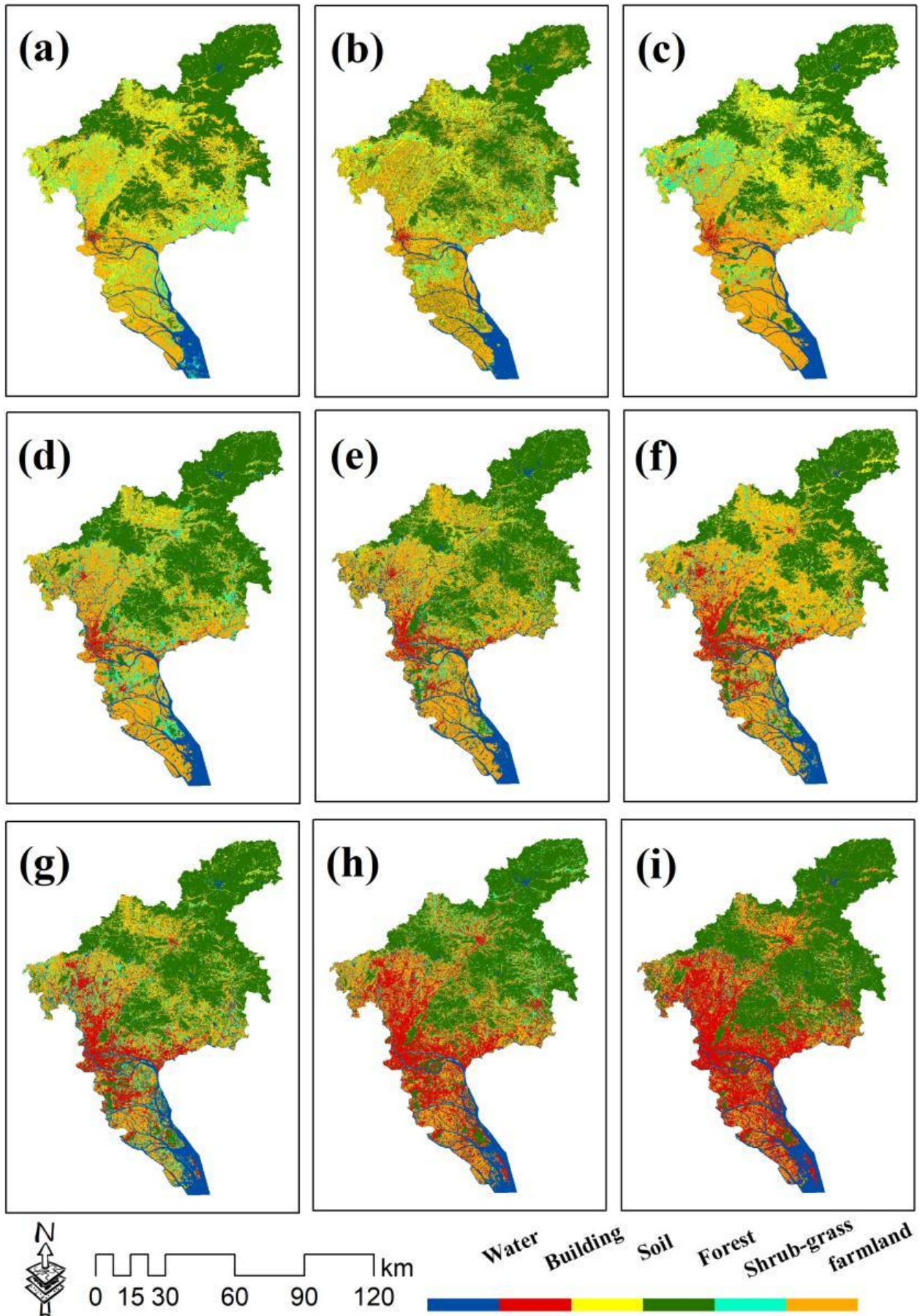


Fig.3 Landscape maps of the studied area for the years: (a) 1973, (b) 1979, (c) 1988, (d) 1994, (e) 2000, (f) 2005, (g) 2009, (h) 2013 and (i) 2017.

The analysis of landscape change revealed a 93.03% decrease in soil, a 66.39% decrease in shrub-grass, a 49.66% increase in water, a 19.76% increase in forest, with a 40.35% decrease in farmland between 1973 and 2017, and urban landscapes has been dramatically changed (Fig.4). The first majority landscape of the study area was forest, the total area of forest fluctuates during these years, but the overall trend is increasing, the forest area in this region in 2017 was 3432.13 km<sup>2</sup>, accounting for 46.17% of the total area. The largest area change was found in soil, the soil area drastically reduced during 1973-2017. And the area of soil was falling since 1988. The area of farmland fluctuates during 1973-2005, the area of farmland was falling since 2005, with a high rate of decline over the period of 2005 to 2017. The total area of water fluctuates during whole period, which was found obviously lower in 2000. The total area of shrub-grass fluctuates during these years, but the overall trend is downward.

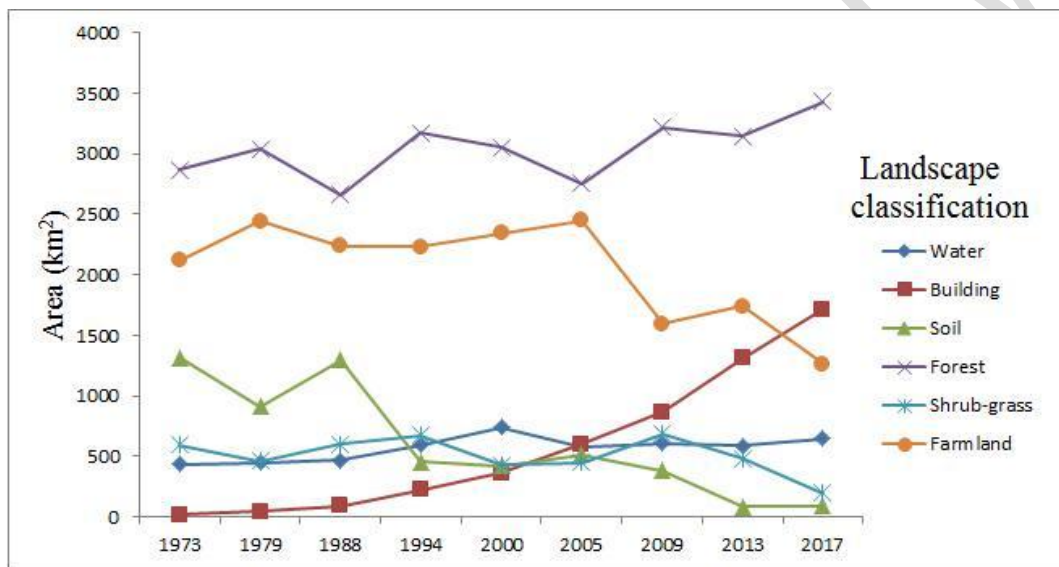


Fig.4 Area change of different landscape in Guangzhou during 1973-2017.

The expansion of building (+1693.5 km<sup>2</sup>) was the leading urban landscape change from 1973 to 2017, in a fast speed. How the other landscapes converted to the building was captured from 1973 to 2017, and the landscape responses processes caused by urban expansion are listed in Table 3. Over the period of 1973–2017, massive new building was developed on land that was previously soil or farmland, with most converted from farmland (807.84 km<sup>2</sup>, both directly and indirectly), followed by soil (481.99 km<sup>2</sup>, both directly and indirectly). For all study periods, a same conversion phenomenon was observed, which lots of other landscapes were continuously converted to the building.

Table 3 Quantifying landscape responses with urban expansion, based on the other landscapes transferred to building from 1973 to 2017 in Guangzhou (unit: km<sup>2</sup>).

	Water	Soil	Forest	Shrub-grass	Farmland
1973–1979	0.92	4.40	2.57	1.46	13.60
1979–1988	1.30	11.47	4.80	6.47	24.58
1988–1994	1.59	5.60	10.47	20.21	98.66

1994–2000	4.17	2.68	13.93	52.89	66.38
2000–2005	19.94	7.55	34.53	55.64	118.53
2005–2009	20.43	5.91	36.48	63.75	138.75
2009–2013	22.79	18.70	67.52	161.82	171.56
2013–2017	72.07	2.86	98.76	15.83	215.22
1973–2017	45.32	481.99	134.64	223.67	807.84

### 3.2 The patterns of urban expansion

Three urban expansion types were identified and the contribution of each in the eight periods was illustrated in Fig.5. Throughout all of the 44-year, the edge was the primary expansion type (over 55% in any one period), the landscape surrounding the building area was gradually eroded because of the edge expansion. In the first period (1973–1979), the infilling type occupied only 3.88% of the total newly developed building, while the outlying type occupied 37.11%. In contrast, the percentage of the infilling type increased to almost 31.91% between 2013 and 2017, while the outlying type occupied 10.10%. The areas of infilling expansion were less than the areas of outlying expansion in 1973–1979, 1979–1988, 1988–1994, and 1994–2000, but the areas of outlying expansion were less than the areas of infilling expansion in 2000–2005, 2005–2009, 2009–2013 and 2013–2017. In the period of 2013–2017, the rate of edge and outlying expansion was lower than that in the period of 2009–2013, but the rate of infilling expansion was faster than that in the period of 2009–2013.

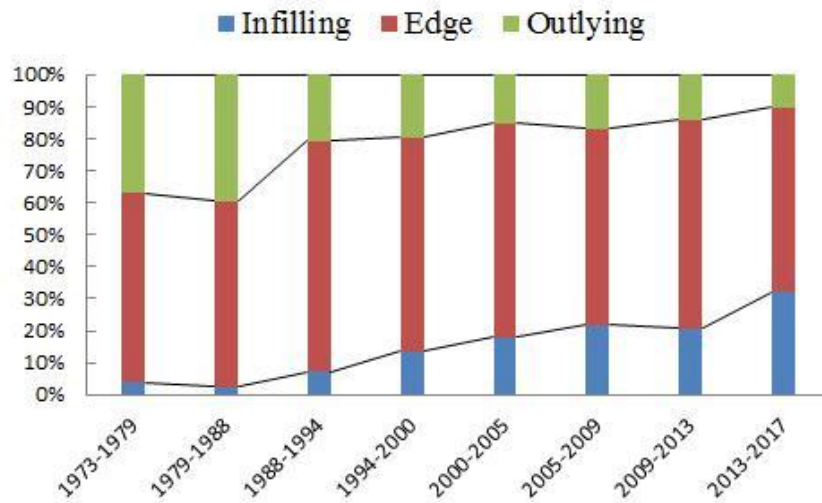


Fig.5 Area percentage of urban expansion type for Guangzhou within study period.

The GC migration of the building reflected the direction of urban expansion. It can be seen from Fig.6 that the direction of expansion trended toward the northeast in Guangzhou. Due to the northeast of Guangzhou contains large tracts of soil and farmland and forest, along expanding in this direction a large amount of soil and farmland and forest had been replaced by the building.

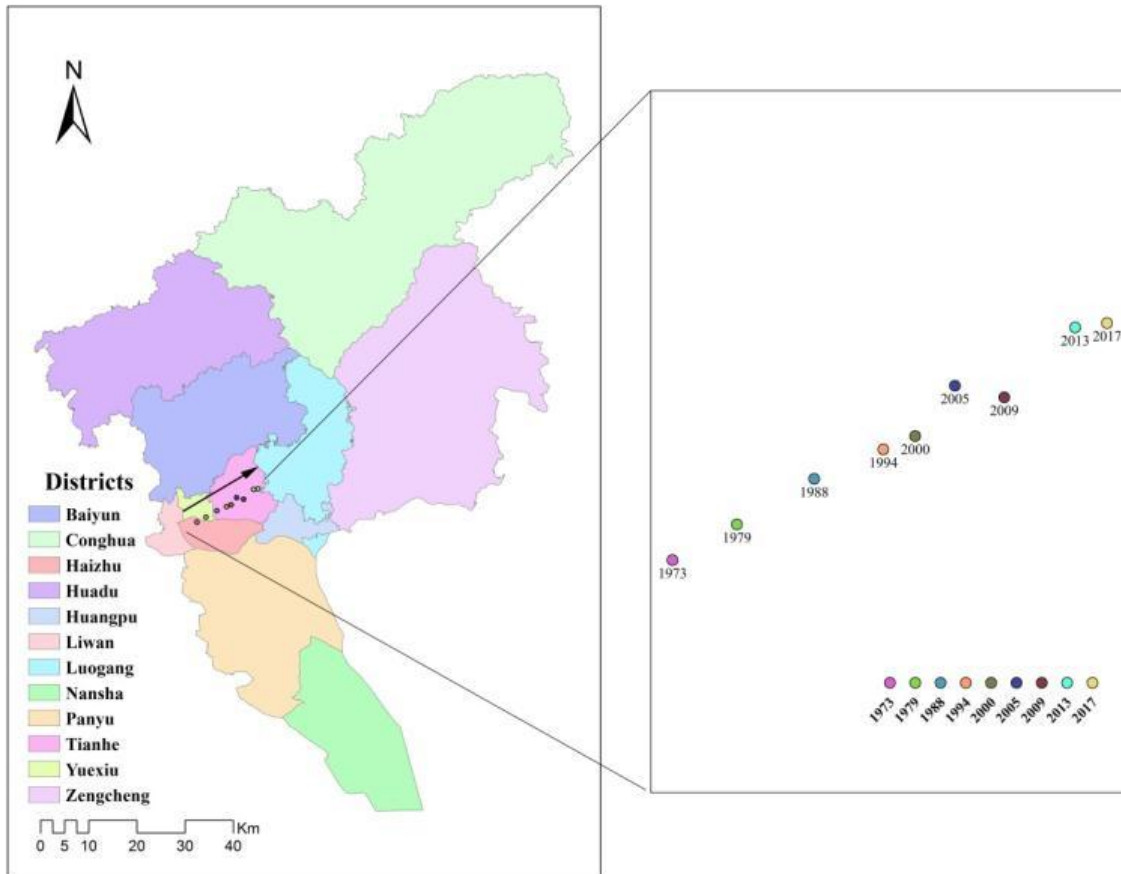


Fig.6 Direction of urban expansion was observed between 1973 and 2017 in Guangzhou.

The metric characteristics shown in Fig. 7 reflect the dynamic patterns of the urban expansion. The MPA of the edge type is higher than the other two types, but the MPA of three expansion types has a slight decrease trend. The MPA of the infill type decreased from 0.42 ha to 0.32 ha, the edge type declined from 1.14 ha to 0.73 ha, and the outlying type reduced from 0.26 ha to 0.18 ha. The PD of the infill and edge types grew continuously with accelerating urbanization in Guangzhou, the infill type has a higher growth rate than the edge type. The PD of the outlying type reached its peak in 2009-2013 (112.78). The LST of all types increased fleetly, outlying reached its peak in 2009-2013. The CLUMPY of all types declined, the infill and outlying types decreased sharply.

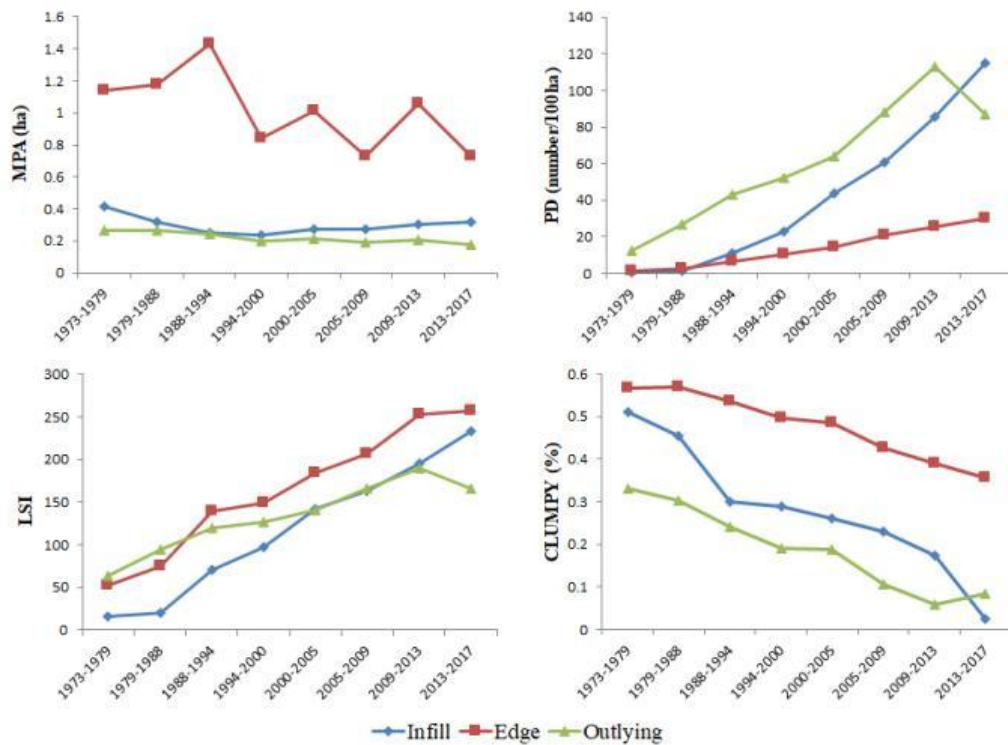


Fig.7 Patterns of three urban expansion types was characterized from 1973 to 2017 in Guangzhou.

#### 4 Discussions

This study integrated remote sensing and GIS to analyze the spatio-temporal processes of urban expansion. The IR-MAD transformation was employed to deal with the SR differences between Landsat images, and using the SVM to effectively identify the urban landscape over long-term period. The IR-MAD transformation can reduce the bias caused by different environmental conditions and instruments in the multi-temporal Landsat images<sup>25-27</sup>. Meanwhile, SVM classifiers (five-layers and eight-layers) generated from the same data (2009 layer-stacked image) is a practical bridge between used classification images, the use of consistent training samples will greatly improve the efficiency of mapping urban landscape. The used methodological framework in this study provides an effectively approach to rapidly extract urban landscape using multi-temporal, multi-sensor Landsat series imagery.

Take Guangzhou as the research region, this study evaluated the dynamics of urban expansion and evolution of landscape change and patterns of different expansion types. Since the reform and opening up in 1978, accompanied by the rapid development of social economy and the massive increase in population, high-density apartment buildings and industrial park and urban infrastructure contributed to rapid urban expansion. The urbanization process, with no sign of slowing down, is the most visible and powerful force that has brought about fundamental transitions in land use and landscape pattern in Guangzhou. As a consequence, the dramatic urban expansion has induced rapid landscape changes. In Guangzhou, most of the area surrounding urban is used for agriculture. Much of the expansion occurred on the urban fringe along the southwest to northeast direction. Urban expansion through edge erosion therefore occurs mostly at the expense of farmland and the surrounding soil. Spanning the 44 years, the urban landscape pattern underwent rapid changes from being dominated by natural and semi-natural landscape to gradually dominated by artificial building landscape, resulted in the loss of soil, forest and farmland and a homogenization of landscape types<sup>6, 32</sup>, contributes a significant threat to the services and function of ecosystem in Guangzhou<sup>17, 33</sup>.

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Durative urban expansion is projected to impact on landscape pattern in the future <sup>34</sup>, there are would grievously threat to the regional ecological security and food support. Therefore, a key question facing governors now is how to manage urban expansion and its direct and indirect ecological consequences, a sustainable development strategy guiding future directions and optimal patterns of urban land growth needs to be developed to minimize the impacts on natural and semi-natural landscape caused by urban expansion in Guangzhou.

The edge expansion was the primary urban expansion type throughout the 44-year period. With the development of time, the proportion of infill type gradually increased, while that of outlying type decreased. This implied that when the growth space has been compressed and the urban form becomes more compact, the main type of urban expansion may gradually turn to infill growth. Comparing the urban expansion patterns of Beijing, Nanjing and Tianjin, we found that the dominating expansion type is significantly different in various urban, such as Nanjing with infilling expansion <sup>12</sup>, Beijing with both edge expansion and infilling expansion <sup>34</sup>, Tianjin with outlying growth <sup>34</sup>. The regional development conditions and development strategies may contribute to the main causes of these differences. Our results are also significantly different from the result of Sun et al. (2013)<sup>35</sup> in Guangzhou, mainly because Sun et al. (2013)<sup>35</sup> study just focused on the core area of Guangzhou.

Urban expansion pattern is a dynamic process in space and time. Four indices were employed to measure the spatial patterns of three types of expansion at different times. Because the edge expansion is dominant, the MPA of the edge expansion is higher than that of the other two types. A decrease in the MPA is an indication that large-scale contiguous building clusters are gradually decreasing, which is also reflected in the decrease of the CLUMP index. The LST of the three expansion types gradually increased, and the majority of patches became more complex and irregular in shape. The combination of increasing patch density and decreasing mean patch area is an indication that the landscape of all expansion types is occurring more fragmented and dispersed. With rapid urban development, the landscape of three expansion types changed dramatically in size and structure, becoming more scattered and more complex configurationally and geometrically.

## 5. Conclusions

The present study focuses on an analysis of the urban expansion pattern and landscape responses of one of China's largest city, which is rapidly developing. The data produced in this study implied Guangzhou is a highly dynamic region where the landscape has changed dramatically. A large portion of the natural and semi-natural landscape has been converted to the building since 1970s, urbanization has been a major driver of landscape conversion in Guangzhou. Our study provides a more in-depth understanding of variations in urban expansion patterns in Guangzhou and can be used to optimize the irrational landscape pattern of urban expansion and related issues. It is not only of important theoretical and practical significance to provide necessarily geographic information for planning and policy making, but also for metropolitan area with rapidly growing economies and populations to realize the sustainable use of urban land resources.

Our results point out the emergence of an expansion process where edge growth sites impact on specific land uses or land covers (soil, farmland, forest, etc.). However, Guangzhou's urbanization process shows no signs of slowing down in the short term. In this state, the edge expansion and outlying expansion should be strictly restricted, and the infilling development should be used as the preferred mode for urban development. Mainly because the infilling expansion model is usually related with a compact urban spatial pattern and edge expansion or outlying expansion model with a scattered one, and the compact urban spatial pattern has more advantages than the scattered one <sup>34</sup>.

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Urban landscape change is one of the greatest human impacts on the terrestrial environment. The form of urban development today will control and influence resource use, environmental condition and ecological security in time yet to come. If the urbanized extent is not effectively controlled by land use policy, the constant increase in building may be seriously threat to the surrounding natural landscape, and in the near future the urban environment of Guangzhou might reach an irredeemable condition. For future development, it is essential that a sustainable land use strategy is produced that will minimize the amount of natural and semi-natural landscapes that will disappear due to urban expansion. Urban authorities should use appropriate land use policies and urban planning to manage the urban land for future sustainable development in Guangzhou.

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