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Yetao Yang
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Using multitemporal Landsat imagery to monitor and model the influences of landscape pattern on urban expansion in a metropolitan region

Yetao Yang,^{a,b,*} Louis Ngai Yuen Wong,^b Chao Chen,^a and Tao Chen^a

^aChina University of Geosciences, Institute of Geophysics and Geomatics,
No. 388 Lumo Road, Wuhan, China

^bNanyang Technological University, School of Civil and Environmental Engineering, Singapore

Abstract. Studying the interaction between landscape patterns and temporal land-use changes in a metropolitan area can improve understanding of the urbanization process. Multitemporal remote sensing imagery is widely used to map the urbanization-caused temporal land-use dynamics, which mainly appear as built-up growth. Remote sensing integrated with landscape metrics is also used to quantitatively describe the landscape pattern of the urban area in recent literature. However, few studies have focused on the interaction between the pattern and the process of urbanization in a metropolitan area. We propose a grid-based framework to analyze the influence of the landscape pattern on the built-up growth by using the multitemporal Landsat imagery. Remote sensing classification method is used to obtain thematic land-use maps. Built-up growth is then extracted from the multitemporal classification results by a postclassification change detection. Landscape pattern, which is quantitatively described by landscape metrics, is derived from the thematic land-use maps. A grid-based method is used to analyze the spatial variation of landscape pattern and its related built-up growth. Finally, the spatial relationship between the landscape pattern and the built-up growth characters is assessed and modeled by using the mathematical regression method. The present study shows that an apparent correlation between landscape pattern and built-up growth exists. The correlation reflects the inherent influences of landscape pattern on urban expansion. The landscape pattern indicates the land development stage, while the urbanization stage determines the speed and style of the following built-up growth. Scales, including temporal scale and spatial scale, are important to modeling the landscape pattern effects on the built-up growth. The proposed analysis framework is efficient in detecting and modeling the landscape pattern effects on the built-up growth. © 2014 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JRS.8.083639](https://doi.org/10.1117/1.JRS.8.083639)]

Keywords: change detection; urban expansion; landscape metrics; interaction of pattern and process.

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1 Introduction

Urban expansion as a consequence of socioeconomic development under certain circumstances has increasingly become a major issue facing many metropolitan areas.¹ Remote sensing classification and change detection techniques using multitemporal images have advantages in characterizing the spatiotemporal trends of built-up growth, and providing a basis for projecting future urbanization processes.²⁻⁴ For nearly three decades, extensive research effort has been made on improving the performance of land-use dynamic mapping in urban areas by using remotely sensed images.^{5,6}

Landscape metrics (indices) are numeric measurements that quantify the spatial pattern of the land cover patches, land cover classes, or entire landscape mosaics within a geographic area.^{7,8} These metrics have long been used in landscape ecology to describe the ecologically important

*Address all correspondence to: Yetao Yang, E-mail: yetao.yang@gmail.com

relationships, such as connectivity and adjacency of habitat reservoirs.^{9–11} For research fields outside landscape ecology and across different kinds of environments, particularly urban areas, the landscape metrics are generally referred to as spatial metrics.^{12,13} Spatial or landscape metrics, in general, can be defined as quantitative indices to describe structures and patterns of a metropolitan area. Its use has become very popular in urbanization studies.^{13,14}

The tool of integrating remote sensing, spatial analysis, and spatial metrics has emerged to be very promising for understanding the spatiotemporal patterns of urbanization. Luck and Wu¹⁵ used a transect sample method to identify urbanization gradients. This method was shown to be able to reliably quantify the spatial pattern of urbanization and precisely determine the location of the urbanization center.^{16–18} Dietzel et al.¹⁹ proposed a hypothetical framework of landscape spatiotemporal changes in urban expansion process. The hypothesis was tested in many sites and has proven to be an efficient way to describe the spatiotemporal trend in urbanization.^{20–22} Continuously appearing spatial metrics also help to better assess the pattern of urbanization as reviewed by Bhatta et al.²³ Besides spending efforts on improving the landscape spatiotemporal pattern description, many researchers attempt to model the built-up growth induced landscape changes and discuss the ecological environment problems in the context of these changes.^{24,25}

The urbanization driving forces and built-up growth prediction models have been extensively studied for understanding the effects of existing conditions on subsequent urban sprawl, but these studies usually focus on the spatial proximity to certain favorable conditions.²⁶ The favorable conditions include transportation, topography, built-up rate, urban core, infrastructure, economy, policy, etc. These built-up growth driving factors are studied and integrated to predict future urban expansion. Plenty prediction models are available to simulate the urban expansion, such as multiple regression model, cellular automata model, gravity model, agent based model, and hybrid model such as the conversion of land use and its effects (CLUES) model.^{27–32} Besides the spatial proximity to the favorable conditions, the existing landscape pattern also affects the subsequent built-up growth location and speed. According to the concept of landscape ecology, the pattern and the process are interactional.³³ However, most of the current landscape studies of the urbanization focus on characterizing spatiotemporal patterns, and analyzing and modeling the built-up growth induced landscape changes.^{19,21,22,34} Little attention has been given to the effect of existing landscape patterns on the subsequent urban sprawl.

The study performed by Dietzel et al.¹⁹ study shows that urbanization is an alternating process of diffusion and coalescence in spatiotemporal pattern. The phases of the diffusion-coalescence process indicate the spatial variation of the urbanization degree in a metropolitan area. The spatial variation of the urbanization degree leads to different development speed and style. Based on the collective observations and our understandings, we hypothesize that the development can be divided into several phases according to the landscape diffusion and coalescence characters. The landscape pattern, which is different in different phases, affects the speed and style of the built-up growth. In the early phase, the landscape is mainly occupied by homogeneous nonurban background. Built-up patches spot on this background and the speed of the built-up growth is low. In the midphase, due to the diffusion process, the landscape becomes highly fragmented with continuously appearing built-up patches. The built-up growth speeds up in this phase. In the final phase, due to the coalescence process, the built-up increase slows down. The new built-up mainly fills up the gaps between the early developed patches. A conceptual framework illustrating the hypothesis of landscape pattern effect on the built-up growth is shown in Fig. 1(a). The landscape pattern diffusion and coalescence processes can be represented by landscape metrics. The relationship between metrics value and built-up growth rate is shown in Fig. 1(b). The fragmentation index, such as patch density (PD) and contagion (CONTAG), shows a linear relationship with the built-up growth rate. The development degree metrics, such as largest patch index (LPI) and patch cohesion index (COHESION) of urban type, first show a positive relation and later a negative relation with the built-up growth rate. However, the two development degree indexes describe different aspects of the landscape pattern. The COHESION increases more sharply than the LPI during the urbanization process.

Urbanization process occurs over a wide range of geographic area, including fully developed urban core, highly disturbed suburban and lowly disturbed exurban. The development phase thus varies significantly within the metropolitan area. The urban core region is in the final phase of

Fig. 1 Theoretical signatures of landscape pattern effect on the built-up growth during the full cycle of the urbanization process. (a) landscape pattern effect on the built-up growth; (b) the relation between landscape metrics and built-up growth rate.

urbanization process with a coalescence pattern and a low built-up growth rate. The suburban region is in the midphase with a diffusion pattern and a high built-up growth rate. The exurban region possesses the original background pattern with a low built-up growth rate. Spatiotemporal analysis of landscape pattern will help discriminate the metropolitan area into subregions of different development phases.¹⁵ Based on the development phase and pattern variations of the subregions, the built-up growth speed and style can also be characterized according to the hypothesis. Understanding the relationship between the landscape pattern and the built-up growth will hence help predict the future urban expansion. The general pattern dynamics of urbanization (diffusion and coalescence) are evident in the spatial metrics. Studying the relationship between the landscape metrics and the built-up growth rate is a reasonable quantitative way to reveal the effect of spatial pattern on urban expansion.

Analyzing and modeling the effect of landscape pattern on built-up expansion in a metropolitan area can help develop a comprehensive understanding of the urbanization process. In this study, we choose the Beijing city as the experimental metropolitan area. The research objectives are: (1) setting up a grid-based framework to extract, analyze, and model the relationship of landscape metrics and built-up growth rate; (2) identifying the effect of landscape pattern on future built-up growth; and (3) assessing the temporal scale effect on modeling the relationship between landscape pattern and built-up growth. To address these objectives, multistage Landsat images and related landscape metrics are used for revealing the changes of land cover and performing the spatial pattern measurements.

2 Methodology

2.1 Study Area and Data

To reveal the influence of landscape pattern on urban expansion, we choose the Beijing city as the experimental area. Beijing, as the capital city of China, has been experiencing a rapid

development. The total population within its administrative boundary increased from 9.45 million in 1984 to 16.33 million in 2008. The built-up area expanded from 366 in 1984 to 1289 km² in 2008 (State Statistical Bureau of China, 1984, 2008),^{35,36} which indicates a double growth of the population and a three times growth of the built-up area in 25 years. For the past 30 years, the urban sprawl of the Beijing metropolitan area has mainly happened in three styles—around the urban center, along the transportation lines, and leapfrog development.³⁷ Land-use and landscape patterns have experienced dramatic changes due to the rapid development in this area.

Seven Landsat images were acquired for discerning the influence of landscape pattern on the built-up expansion in this study (Table 1), including four thematic mapper (TM) images acquired in 1988, 1991, 1994, and 1997 and three enhanced TM (ETM+) images acquired in 2000, 2003, and 2006. The acquired ETM+ products of years 2003 and 2006 were already gap-filled by combining multitemporal Landsat 7 ETM+ scan line corrector off (SLC-off) images. Therefore, the gap-filled process and its effects on accuracy were not considered in this study. A high temporal resolution of 3 years was selected for a temporal scaling-up effect test in the modeling process, as described in Sec. 2.4. The images were geo-referenced and resampled to 30 m × 30 m pixels. For all images, the root-mean-square error of the registration process was less than a third of a pixel. To facilitate the modeling, the relationship between landscape metrics and built-up growth is described in Sec. 2.4, a rectangular study area of size 84 km × 72 km was clipped from the original images for data processing as shown in Fig. 2.

2.2 Classification and Change Detection

In the urban expansion analysis, the most common method for generating a multitemporal series of landuse maps involves an independent classification of remote sensing images obtained on different dates. Although the strategy appears theoretically sound and simple, it faces challenges during map integration process, wherein classification errors from independently generated map products tend to compound themselves in the finished product.^{38–40} The errors associated with the multitemporal landuse maps can cause suspicious change detection errors that may seriously distort the representations of landuse and landscape pattern changes.⁴¹ The built-up growth and landscape pattern extraction accuracy are the foundation to model the pattern effects on urbanization process. A unified classification schema and a spatiotemporal integration classification method were used in this study to improve the coherence and accuracy of multitemporal remote sensing imagery process.

To ensure that the classification of multisource, multitemporal images can be compatible with each other, a unified land cover classification scheme was used (Table 2). The images were first classified into seven land cover types, namely water paddy, green paddy, postharvest paddy, impervious surface, city green, woodland, and water body. The initial classification results were then merged into four final classes, namely farmland, built-up area, woodland, and water body.

To reduce the classification and change detection errors in multitemporal series, a spatiotemporal integrated classification method proposed by Yang et al.⁴² was used to classify the images. The proposed method first extracts three types of imagery information including spectral, spatial,

Table 1 Data acquired and studied in this research.

Satellite	Sensor	Path/row	Resolution (m)	Acquisition date
Landsat 5	TM	123/32	30	September 28, 1988
Landsat 5	TM	123/32	30	May 6, 1991
Landsat 5	TM	123/32	30	August 28, 1994
Landsat 5	TM	123/32	30	September 21, 1997
Landsat 7	ETM	123/32	30	April 3, 2000
Landsat 7	ETM	123/32	30	July 28, 2003
Landsat 7	ETM	123/32	30	September 26, 2006

Fig. 2 Study area covering the Beijing metropolitan area.

and temporal contexts. These types of information are transformed to probabilities of each pixel belonging to different landuse types, respectively, in spectral, spatial, or spatial domains. Spectral, spatial, and temporal probabilities are then integrated using a probability model for a final classification. The spectral probability derived from a common maximum likelihood classifier, spatial probability derived from per-scene based object-oriented classifier, and temporal probability derived from a temporal trajectory calibration on the multitemporal spectral probability results based on landuse type transition possibility. The spatiotemporal information integrated method suppresses suspicious change caused by spectral confusion and enhances the consistency of landuse patch boundaries in time series.

2.3 Accuracy Assessment

Reference data are always a problem for classification accuracy assessment, especially for long time series. A multispectral 4-m resolution IKONOS image acquired in 1999 and land-use survey maps of scale 1:500 covering Beijing metropolitan area for years 1990 and 2004 were used

Table 2 Unified land cover classification scheme.

Level 1 classes	Level 2 classes	Description
Farmland	Water paddy	Paddies inundated by water
	Green paddy	Paddies with crops in green status
	Postharvest paddy	Paddies with crops clear-cut
Built-up area	Impervious surface	Construction areas
	City green	Parks, green belts, and lawns
Woodland	Woodland	Forest on west and north, shelter belts
Water body	Water body	Rivers, fish ponds, and reservoirs

to assist field investigations and accuracy assessment of the classification. We have chosen a stratified random sampling scheme for selecting sample points for classification accuracy assessment. On the 1997 image, 800 points were selected, which later projected on other scenes using their spatial coordinates. Five hundred sample points of 800 random points where we have confidence in visual interpretation to identify the land cover type were then input to geographic information system (GIS) and integrated with images as the reference data set.

2.4 Landscape Pattern Extraction

To discern the influences of different landscape patterns on the urban built-up growth, the pattern spatial variation should be quantitatively recorded. The multiple distance buffer¹⁶ and transect-based sample¹⁵ approaches are often used to analyze the trend of landscape pattern spatial change in the metropolitan area. Both methods, however, have shortcomings for modeling landscape pattern effects on the built-up growth. The multiple distance buffer method cannot capture the anisotropy of the urbanization process, while the transect-based sample method only focuses on several directions and cannot cover the entire metropolitan area. In order to facilitate the information extraction and GIS modeling process, the entire metropolitan area was split into subgrids. The grid-based method will be able to preserve the local landscape pattern characters and cover the whole metropolitan area.

An important step of the grid-based method is to select a proper grid size for GIS modeling. A proper size of the subgrids will represent the continuous spatial change characters of the landscape pattern from the urban core to the urban fringe, and to the rural area. The transect-based sample method can well describe the landscape pattern spatial change along the selected directions. It is also convenient for comparing the performance of different moving window sizes (grid sizes). The transect-based sample method is thus suitable for detecting the proper size of the grids. Yang et al.⁴³ used a transect across the entire Beijing metropolitan area from west to east to determine the proper grid size for landscape spatial variation characterization. Four different grid sizes of 3 km × 3 km, 6 km × 6 km, 9 km × 9 km, and 12 km × 12 km were tested. The size of 6 km × 6 km, which was found to be a more proper one, was adopted in this study. By splitting the study area into subgrids of size 6 km × 6 km each, with an overlap of 2 km between adjacent grids, 1360 subgrids (40 rows and 34 columns) were obtained in this study. The built-up growth rate and landscape pattern metrics were extracted at each grid for the subsequent analysis and modeling.

Two landscape level metrics, namely PD and CONTAG, and two class level metrics for built-up, namely LPI and COHESION were extracted in this study (Table 3). These metrics were selected based on their ability of characterizing the overall pattern and the built-up type pattern of the urbanization. We used Fragstats 3.3 build 5 (Ref. 44) to calculate PD, CONTAG, LPI, and COHESION for each grid from 1988 to 2006. The computations were performed using the 8-cell (Queen's case) patch neighborhood rule, excluding the boundaries.

2.5 Modeling Landscape Pattern Effect on Urban Expansion

One thousand three hundred and sixty grids were involved in this study and each grid has its unique set of metrics' values and built-up growth rate. Normalization processing was used to

Table 3 Landscape metrics and their descriptions.

Landscape metrics	Abbreviation	Description
Patch density	PD	The number of patches per 100 hectares
Contagion	CONTAG	An information theory-based index that measures the extent to which patches are spatially aggregated in the landscape
Largest patch index	LPI	The ratio of the area of the largest built-up patch to the total area of the landscape
Patch cohesion index	COHESION	Physical connectedness of built-up type patches

improve the significance of the statistical relationship between the landscape pattern and the built-up growth rate. Landscape metrics were normalized to round values between 1 and 10. Since landscape metrics calculated by Fragstats have different value ranges, their normalization methods are different. The normalization methods for the four landscape metrics are shown in Table 4. Average built-up growth rate was then calculated according to the normalized landscape metrics' (NLM) values. The average built-up growth rate refers to the total built-up growth divided by the total area of grids with the same NLM value.

Selecting a proper temporal scale is a crucial preliminary task for modeling the relationship between the landscape pattern and the built-up growth. The newly built-up patches emerge with a certain under-control randomness that makes it difficult to characterize the relation on a very short temporal scale. On the contrary, if the temporal scale is too long, the landscape pattern constraint on the built-up growth will become meaningless because of over-development according to the present landscape pattern. Therefore, we tested a wide range of temporal scales in order to choose the proper scale. Since the experimental images have a temporal resolution of 3 years, temporal scales of 3, 6, 9, and 12 years were chosen as candidates. The relationship of landscape pattern and built-up growth rate was tested on these scales. The best one was chosen for the final modeling.

In order to explore the relationship between the built-up growth rate (dependent variable) and the landscape pattern metrics (independent variables), regression analyses were performed. Various regression analyses (linear, quadratic, exponential, and logarithmic) were carried out to ascertain the nature of significance of the causal factors (CONTAG, PD, LPI, and COHESION) on the built-up growth rate. Each landscape metric reveals a unique character of the landscape pattern associated with the built-up growth.

3 Results

3.1 Urban Expansion Measurement

3.1.1 Built-up growth

Table 5 shows the overall accuracy (OA), kappa coefficient (κ), user's accuracy and producer's accuracy of the four land cover classes. The OA ranges from 88.5% to 93.4% with the κ ranging from 0.835 to 0.895. Considering that once a place has been developed as a built-up area, it is unlikely to reverse back. Thus when such a change trajectory occurs, it is labeled as an error case

Table 4 Normalization method for PD, CONTAG, LPI, and COHESION metrics.

NLM value	Original value			
	PD	CONTAG	LPI	COHESION
1	0 to 4	0 to 46	0 to 10	0 to 82
2	4 to 8	46 to 52	10 to 20	82 to 84
3	8 to 12	52 to 58	20 to 30	84 to 86
4	12 to 16	58 to 64	30 to 40	86 to 88
5	16 to 20	64 to 70	40 to 50	88 to 90
6	20 to 24	70 to 76	50 to 60	90 to 92
7	24 to 28	76 to 82	60 to 70	92 to 94
8	28 to 32	82 to 88	70 to 80	94 to 96
9	32 to 36	88 to 94	80 to 90	96 to 98
10	>36	94 to 100	90 to 100	98 to 100

Table 5 The classification accuracy assessment of the Landsat images.

Year of image acquisition	OA (%)	κ	Built-up area		Farmland		Water body		Woodland	
			PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
1988	90.9	0.869	89.2	93.5	92.8	86.7	93.5	93.5	94.5	89.3
1991	93.4	0.895	88.9	92.1	93.9	89.7	93.5	100	93.9	88.5
1994	90.2	0.875	92.6	92.7	90.6	87.8	89.6	97.7	90.6	84.3
1997	89.5	0.843	89.6	92.8	89.6	90.8	91.3	93.3	92.6	90.7
2000	92.1	0.854	89.4	90.9	90.1	88.7	87.8	86.0	90.1	88.6
2003	93.1	0.870	90.0	91.4	88.5	86.4	88.2	96.8	88.5	89.3
2006	88.5	0.835	92.7	90.3	86.2	85.0	91.2	93.3	87.1	89.4

Note: OA, overall accuracy; PA, producer's accuracy; UA, user's accuracy; and κ , kappa coefficient.

for multitemporal imagery based change detection.⁴² In this study, the detected change trajectory error is 6.8%.

The landuse and built-up growth of the Beijing city during the study period from year 1988 to year 2006 are shown in Fig. 3. The built-up growth concentrates around the urban core before year 1994. Leapfrog development appears after then and gradually becomes a major development style of the Beijing city. The amount of built-up growth of each observation interval from 1988 to 2006 is 23.67, 31.33, 70.00, 74.67, 121.67, and 200.33 km², respectively. Built-up growth rate calculated for each subgrid at 3-year interval is shown in Fig. 4, which can better demonstrate the built-up growth speed and the spatial distribution. The percentages of grids taking built-up growth rate below 1% for the six observation intervals are 91.90%, 85.96%,

Fig. 3 1988 to 2006 built-up growth of the study area.

Fig. 4 1988 to 2006 grid-based built-up growth rate.

57.17%, 52.98%, 33.07%, and 17.13%, respectively, which suggest that the urban expansion influences the whole metropolitan area gradually. The built-up growth speeds up and the leap-frog development mode is enhanced.

3.1.2 Spatiotemporal changes of landscape pattern

Landscape metrics extracted based on subgrids (Fig. 5) satisfactorily preserve the local landscape pattern characteristics and express the spatiotemporal change of the whole metropolitan area. Urban core, urban fringe, and rural area can be clearly distinguished from the landscape pattern spatial changes. In PD maps, the urban core and rural area subgrids are associated with low metric values, while urban fringe subgrids are associated with high metric values. The situation is reversed in CONTAG maps with low values in the urban fringe, while high values in the urban core and rural area. LPI maps give prominence to the urban core area and COHESION maps illustrate the extent of the urban expansion influence. Spatial changes of these landscape metrics express themselves as demarcated rings centered around the urban core in the metropolitan region. Temporal changes of the landscape metrics reflect the development of the urban core and urban fringe sprawl. The boundary of the urban core extends to occupy the early urban fringe area, while the urban fringe extends to occupy the early rural area. The urban fringe of the Beijing city has enlarged obviously in the course of time, which caused the mean value of subgrids' PD, LPI, and COHESION to increase, while that of CONTAG to decrease. The changes of landscape metrics reveal a fragmentation process of the Beijing city in the study period.

3.2 Temporal Scale Effects on Modeling

In order to discern the temporal scale effect on modeling the relationship of the landscape pattern and the built-up growth, temporal scales of 3, 6, 9, and 12 years with respect to different start points were tested in this study. Table 6 shows the part of the temporal scale test results. Temporal scales with respect to year 1988 cover low development rate during the study period, while scales with respect to year 2006 cover high development rate.

PD metric shows a linear relationship with the built-up growth rate. The coefficients of determination (R^2) for temporal scales of 3, 6, 9, and 12 years are 0.609, 0.801, 0.948, and 0.982 with respect to year 1988 and 0.670, 0.813, 0.886, and 0.897 with respect to year 2006. The coefficient of determination increases when the temporal scale is enlarged. CONTAG metric generally shows a linear relationship with the built-up growth. As the temporal scale enlarges from 3 to 12 years, the coefficients of determination are 0.867, 0.774, 0.887, and 0.788 with respect to

Fig. 5 Grid-based landscape metrics showing the spatiotemporal changes from 1988 to 2006. The pixel value is the normalized landscape metric value calculated by Fragstats.

year 1988 and 0.458, 0.500, 0.523, and 0.489 with respect to year 2006, indicating that the coefficients of determination are not particularly influenced by the temporal scale. The correlation between CONTAG and built-up growth is very sensitive to the development rate. High development rate will decrease the correlation between them. LPI shows a quadratic relationship with the built-up growth rate and the coefficient of determination steadily increases within the temporal scale of 9 years. COHESION is the only metric showing an exponential relationship with the built-up growth and the coefficient of determination also steadily increases within the temporal scale of 9 years. The coefficients of determinations with respect to year 1988 are higher than those with respect to year 2006, which reflects that the correlation between the COHESION and built-up growth is also sensitive to the development rate.

Temporal scale is crucial in modeling the relationship between the landscape pattern and the built-up growth. Built-up growth has a certain degree of randomness caused by many social and economic factors. Consequently, nonurban areas with a high development probability will not necessarily be the areas to be developed first. If the temporal scale is too small, subgrids with a high development probability according to their landscape pattern characteristics may not develop in such a short term. On the contrary, if the temporal scale is too large, built-up will overgrow and exceed the constraints of the present landscape pattern. A too short or too long temporal scale will affect the relation modeling of the landscape pattern and the built-up growth. The statistical relationship between pattern and process should, therefore,

Table 6 Landscape metrics and built-up grow rate modeling based on different temporal scales.

Temporal scale		Independent variable (x)	Regression equation	Coefficient of determination (R^2)
3 years	1988 to 1991	PD	$y = 0.244x + 0.022$	0.609
		CONTAG	$y = -0.267x + 2.716$	0.867
		LPI	$y = -0.158x^2 + 1.871x - 1.160$	0.602
		COHESION	$y = 0.307e^{0.916x}$	0.814
	2003 to 2006	PD	$y = 1.970x + 0.872$	0.670
		CONTAG	$y = -1.501x + 17.903$	0.458
		LPI	$y = -0.364x^2 + 2.017x + 13.308$	0.761
		COHESION	$y = 3.831e^{0.164x}$	0.504
6 years	1998 to 1994	PD	$y = 0.622x - 0.162$	0.801
		CONTAG	$y = -0.476x + 5.317$	0.774
		LPI	$y = -0.265x^2 + 3.026x - 0.606$	0.778
		COHESION	$y = 0.663e^{0.212x}$	0.826
	2000 to 2006	PD	$y = 3.943x - 0.643$	0.813
		CONTAG	$y = -2.131x + 26.118$	0.500
		LPI	$y = -0.475x^2 + 2.710x + 19.477$	0.858
		COHESION	$y = 6.950e^{0.140x}$	0.607
9 years	1988 to 1997	PD	$y = 1.477x - 0.579$	0.948
		CONTAG	$y = -1.186x + 12.837$	0.887
		LPI	$y = -0.454x^2 + 4.465x - 2.769$	0.909
		COHESION	$y = 1.481e^{0.221x}$	0.878
	1997 to 2006	PD	$y = 3.592x + 1.787$	0.886
		CONTAG	$y = -2.511x + 31.818$	0.523
		LPI	$y = -0.541x^2 + 3.165x + 22.871$	0.955
		COHESION	$y = 9.479e^{0.128x}$	0.697
12 years	1988 to 2000	PD	$y = 2.530x - 1.463$	0.982
		CONTAG	$y = -1.685x + 19.045$	0.788
		LPI	$y = -0.690x^2 + 6.697x + 4.766$	0.909
		COHESION	$y = 2.640e^{0.206x}$	0.874
	1994 to 2006	PD	$y = 4.4435x + 2.7016$	0.897
		CONTAG	$y = -2.7435x + 36.911$	0.489
		LPI	$y = -0.613x^2 + 3.192x + 28.436$	0.936
		COHESION	$y = 10.638e^{0.1326x}$	0.578

Note: x, normalized landscape metric (NLM) value, independent variable; y, built-up growth rate (%), dependent variable.

be detected on a proper temporal scale. According to the temporal scale test results as shown in Table 6, a temporal scale of 9-year appears to be proper for modeling the landscape pattern effects on the built-up growth. The coefficients of determination of regression analysis for most metrics at a 9-year scale are apparently higher than those at 3-year and 6-year scales on the whole. The differences of coefficients of determination at 9-year and 12-year scales are not significant, but the scale of 9-year is slightly better. It indicates that adopting a temporal scale larger than 9 years will not be able to obtain a more accurate model.

3.3 Modeling Results

3.3.1 PD and built-up growth

The PD metric shows a linear relationship with the built-up growth rate during the four periods spanning from 1988 to 2006 as shown in Fig. 6. The linear regression equation well fits the built-up growth rate at all periods for the NLM value up to 8, which corresponds to a PD value less than 32. Notice that when the NLM is greater than 8, the linear data points show a higher degree of deviation away from the regression equation. It is caused by very few subgrids with an NLM value greater than 8, which depress the statistical significance of the average built-up growth rate. To summarize, the PD generally increases with the built-up growth rate.

The slopes of the linear regression equations for the four periods 1988 to 1997, 1991 to 2000, 1994 to 2003, and 1997 to 2006 are 1.447, 2.252, 4.066, and 3.592, respectively. In other words, the slope increases up to year 2003 and then drops. The speed-up of urban expansion in the course of time, which is caused by a dramatic growth of the economy and population, steepens the linear equation slope before year 2003. Urban expansion of the Beijing city mainly concentrates around the urban core before the mid-1990s and the leapfrog development style gradually takes an important role since then. Built-up growth occurs at a reasonable distance from the urban core. The new development manner introduces mass built-up patches in the low PD area with NLM values of 4, 5, 6, and 7, which gentles the linear regression equation slope as shown in Fig. 6(d).

3.3.2 CONTAG and built-up growth

CONTAG metric also shows a general linear regression mode with the built-up growth rate, but the linear relationship is negative as shown in Fig. 7. The coefficients of determination of linear

Fig. 6 Patch density and built-up growth regression modeling of (a) 1988–1997; (b) 1991–2000; (c) 1994–2003; (d) 1997–2006.

Fig. 7 Contagion and built-up growth regression modeling of (a) 1988–1997; (b) 1991–2000; (c) 1994–2003; (d) 1997–2006.

regression equations are lower than those of PD metric, with values of 0.887, 0.854, 0.813, and 0.523, respectively, for the corresponding four periods. The linear relationship between the CONTAG metric and built-up growth rate drops significantly in the course of time, which becomes a nonlinear relationship in the periods of 1994 to 2003 and 1997 to 2006 as shown in Figs. 7(c) and 7(d), respectively. Fitting a quadratic regression equation for the period 1997 to 2006 returns a coefficient of determination of 0.926, which is higher than that of the linear regression relationship.

CONTAG metric measures the degree of aggregation of multitype land patches. A high value is associated with a landscape containing a few large and clustered patches such as urban core and rural area, whereas a low value is associated with a landscape containing many small and dispersive patches such as the urban fringe area. Since the urban fringe is the most active belt of the built-up growth, the high built-up growth rate occurs at subgrids of a low CONTAG value. This is why CONTAG and built-up growth show a negative relationship. Due to the speed-up of the built-up growth and leapfrog development since the mid-1990s, the subgrids of median CONTAG values also experience a high rate of development for they have more room to accommodate the new built-up. It accounts for the departure of the built-up growth rate from the linear regression line at median metric values, especially in the period of 1997 to 2006.

3.3.3 LPI and built-up growth

LPI metric shows a quadratic regression mode with the built-up growth rate. The coefficients of determination for the four periods are 0.909, 0.915, 0.917, and 0.955, respectively, as shown in Fig. 8. LPI is a metric to represent the development degree. It will reach a high value when a subgrid is highly developed and the built-up patches coalesce to form a large built-up patch, while a low LPI value represents a grid having no or only spotted small built-up patches. Mass built-up growth will not happen in the already developed or almost undeveloped areas. So the high growth rate occurs on subgrids with median LPI values. The NLM values corresponding to the turning points of the quadratic equation for the four periods are 5, 5, 4, and 3, and the corresponding LPI values are 50, 50, 40, and 30, respectively. The decreasing trend of the NLM values reflects that the less developed subgrids have experienced a high rate of built-up growth, which is caused by the leapfrog development mode.

Fig. 8 Large patch index of built-up type and built-up growth regression modeling of (a) 1988–1997; (b) 1991–2000; (c) 1994–2003; (d) 1997–2006.

3.3.4 COHESION and built-up growth

COHESION is the only metric showing an exponential regression mode with the built-up growth rate. The coefficients of determination for the four periods are 0.878, 0.837, 0.847, and 0.504, respectively, as shown in Fig. 9. The COHESION metric measures the physical connectedness of the built-up type patches, which reflects the degree of development and the remaining room for accommodating new built-up. When COHESION value increases, the built-up growth rate will therefore also increase.

The most obvious change of the exponential regression equation with time is the increase of the coefficient and the drop of the exponent. The coefficients for the four periods are 1.481,

Fig. 9 Built-up patches cohesion and built-up growth regression modeling of (a) 1988–1997; (b) 1991–2000; (c) 1994–2003; (d) 1997–2006.

2.257, 2.497, and 9.479, and the exponents are 0.221, 0.206, 0.239, and 0.128, respectively. Especially in the period 1997 to 2006, the leapfrog development mode leads to a median built-up growth at low COHESION, such as at NLM values of 2, 3, and 4. This leads to a gradual change of the relationship between COHESION and the built-up growth rate to a linear regression. There is an obvious drop of the built-up growth rate at the NLM value of 10, which affects the fitting of the exponential regression equation. Subgrids of an NLM value equal to 10 are almost fully developed regions with little developable room, so the built-up growth rate for these grids decreases.

4 Discussion

In this study, the influence of landscape pattern on the built-up growth of the Beijing metropolitan region is studied. Beijing has been suffering from a rapid urban growth over the past several decades. A comprehensive study of the expansion speed and pattern of Beijing can serve as a practical reference for other similar large cities in developing countries. The urban expansion of the Beijing city can be divided into two stages during the study period.^{37,45} At the first stage, before the middle of 1990s, urban expansion was concentrated around the urban core and the expansion was slow. At the second stage, since the middle of 1990s, the leapfrog development style appeared and the speed of built-up growth has increased several times. Four landscape metrics were chosen and their relations with the built-up growth were tested to reveal the influence of landscape spatial pattern on the urban sprawl. Each selected metric shows a good regression relationship with the built-up growth rate. The results verify the hypothesized relationship between the landscape metrics and built-up growth rate. The fragmentation metrics (PD and CONTAG) show a linear relationship with the built-up growth rate. The development degree metrics (LPI and COHESION of urban type) first show a positive relation and later a negative relation with the built-up growth rate. It proves that the existing landscape pattern will undoubtedly dominate the subsequent built-up growth location, style, and speed to some degrees. The present study of the four periods spanning over 18 years shows that the interaction between landscape pattern and built-up growth is inherent, no matter what kinds of urban development style, speed, and starting point are involved. The findings of this study will thus provide an important clue for research on the mechanism of built-up growth in urbanization processes.

Scale is an important issue for spatiotemporal related modeling. An improper scale will introduce errors to the results, even leading to wrong conclusions.⁴⁶ In order to choose a proper temporal scale to model the relationship between the landscape pattern and the built-up growth, a wide range of temporal scale ranging from 3 to 12 years is tested in this study. The results prove that the temporal scale is crucial to describe the relationship between the landscape pattern and the urbanization process correctly. Built-up growth in the urbanization process will certainly respond to landscape pattern. The exact locations of built-up growth, however, are associated with some degrees of randomness in a short time, although it is dictated by the landscape pattern characteristics on the whole. Locations of high probabilities to develop are not necessarily the areas to be developed first. The response of the built-up growth to the landscape pattern therefore can only be realistically detected on a proper time span. The hysteretic nature of the response makes the choice of a proper temporal scale a critical issue before modeling the interaction between the landscape pattern and built-up growth.

The inherent relationship between the landscape pattern and the built-up growth provides a way to predict the built-up growth location and the amount in the dynamic process of urbanization. However, the relationship between them will not remain unchanged in the course of time. Comparing the regression equations of landscape metrics and built-up growth rate from different time spans, regression coefficients are found to experience obvious changes. The regression mode even changes from linear to quadratic for CONTAG metric, which is due to the changes of urban expansion style and speed in the course of time. Urban expansion style and speed in turn are controlled by external factors, such as economy, population, policy, etc. The speed-up urban expansion and the leapfrog development manner in the Beijing metropolitan region induce regression relation changes during the study period. Since year 1997, urban expansion has

greatly accelerated and many satellite towns have gradually developed. These urban expansion style changes reform the regression equations. So attention should be paid to the built-up growth speed and the style changes of different urbanization phases. The coefficients of regression equations should be modified according to different urbanization style in order to more realistically model the built-up growth. In the urban expansion prediction models based on the raster or vector spatial factor maps, such as cellular automaton and multiple regression, if the urban expansion style changes are considered by modifying the parameters of the models, the prediction accuracy will improve remarkably.⁴⁷

In this study, the grid-based method excels in extracting the landscape pattern and built-up growth rate, and modeling the relationship between them. It satisfactorily captures the local landscape pattern characteristics and spatial changes of the entire metropolitan area. The regular grids also facilitate the data manipulation and modeling in the large area. It should be cautious that the size of subgrid, which defines the spatial scale of the modeling process, is also an important issue. The proper grid size should be small enough to represent the spatial variation of landscape pattern for different degrees of development, whereas large enough to suppress the discontinuities and jumps associated with landscape pattern spatial change. The grid-based method has been extensively used to study spatiotemporal changes of landscape pattern,^{15,48} which is related to choosing a proper grid size to split the entire study area into subgrids.

5 Conclusions

Landscape metrics, including PD and CONTAG at the landscape level and LPI and COHESION at the class type level, show certain relations with the built-up growth. The relationship between landscape pattern and built-up growth is inherent, no matter what kinds of expansion style, speed, and starting point the metropolis is taking. Scale is crucial in modeling the relationship between landscape and built-up growth. Spatial scale will affect the landscape pattern extraction, while temporal scale will affect the built-up growth rate extraction. A spatial scale of 6 km with a 2 km overlap between adjacent grains can satisfactorily capture the local landscape pattern characters and reveal its spatial changes. A temporal scale of 9 years can satisfactorily suppress the built-up growth randomness and minimize the effect of over-development on the relation modeling.

The relationships between the landscape metrics and built-up growth are based on the urbanization characters. The development phase of the land can be concluded from the landscape pattern diffusion-coalescence process. In different phases, the speed and style of the built-up growth are different. In the early phase, built-up patches spot on homogeneous nonurban background and the speed of the built-up growth is low. In the midphase, the built-up growth speeds up and the landscape gets fragmental. In the final phase, the built-up increase slows down and the new built-up mainly fills up the gaps between the early developed patches. So the landscape pattern can be used to deduce the speed and style of the new built-up growth. The regression equation can well match the relationship between the built-up growth and the landscape metrics.

Urban expansion is a dynamic process. Its speed and style will not remain unchanged in the course of time. Under the influence of external economical, social and political factors, the urban expansion will exhibit different speeds and styles in different periods. This leads to the dynamic relationship between the landscape pattern and the built-up. Studying the dynamic traits of the relation will help better understand different urban expansion phases. Different urban expansion phases, distinguished by built-up growth style and speed, can be revealed from the regression equations of different periods.

Future work will focus on how to use the inherent relationship between the landscape pattern and the built-up growth for the urban expansion prediction modeling. Existing landscape pattern, unlike policy and economy factors which control the urban expansion style and speed, will constrain new built-up locations and amounts. At a given built-up growth speed and style, integrating the landscape pattern in prediction modeling will help determine the probability of urbanizing the nonurban landuse patches. To achieve this goal, two issues need further intensive study. The first one is the method for quantifying the changes of urban expansion style and speed effect on modeling the relationship between the landscape pattern and the built-up growth rate.

The second one is the method for integrating the landscape metrics and favorable condition proximity, in order to assess the development probabilities of the nonurban patches.

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Yetao Yang is currently an associate professor at the Institute of Geophysics and Geomatics, China University of Geosciences. His main research interests include RS/GIS-based spatial analysis and modeling for urban land use and landscape dynamics and environmental applications.

Louis Ngai Yuen Wong is currently an assistant professor in the School of Civil and Environmental Engineering at Nanyang Technological University, Singapore. His academic pursuits are fundamental and applied research of engineering geology and geotechnical engineering.

Chao Chen is currently a professor at the Institute of Geophysics and Geomatics, China University of Geosciences. His research focuses on GIS of resource and environment applications.

Tao Chen is currently an associate professor at the Institute of Geophysics and Geomatics, China University of Geosciences. His research focuses on remote sensing of global change and Earth observations and environmental applications.