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Identifying determinants of urban growth from a multi-scale perspective: A case study of the urban agglomeration around Hangzhou Bay, China

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A B S T R A C T

Analyzing the spatial determinants of urban growth is helpful for urban planning and management. In a case study of urban agglomeration around Hangzhou Bay (China), four landscape metrics (total area, total edge, landscape shape index and aggregation index) were used to describe the landscape characteristics of the urban growth at two block scales (4 km and 7 km) during two temporal intervals (1994–2003 and 2003–2009). Spatial autocorrelation regression was employed to identify the geographic determinants of the urban landscape changes. The results indicated that the urban landscapes became more dominant, unstable, irregular and compact, especially in the centers of cities. These changes exhibited notable spatial variations and spatial autocorrelation at the two block scales. The distances to national and provincial roads influenced the urban pattern changes. The impacts of the urban centers on urban expansion gradually declined with the urbanization progress. The slope factor was the most influential determinant of urban growth. Our study emphasized the importance of considering the autocorrelation and scale effects when analyzing the determinants of urban growth. These findings may help land planners create policies and strategies for future urban development.

Introduction

Urbanization has become a global phenomenon. Over the past 30 years, the populations of urban districts have increased, and urban land has rapidly expanded. Urban land has replaced substantial amounts of undeveloped land, such as cropland and forest (Seto & Kaufmann, 2003; Tian et al., 2005). This rapid urbanization has promoted socioeconomic development and has improved the quality of life; however, it has also caused various ecological problems (Antrop, 2000; Botequilha Leitão & Ahern, 2002). Under such circumstances, investigating the urban growth process and its spatial determinants is fundamental for assessing and forecasting the ecological impacts of urbanization.

Many studies have explored the determinants of urban growth. These determinants include proximity variables (Li, Zhou, & Ouyang, 2013; Luo & Wei, 2009; Schnaiberg, Riera, Turner, & Voss, 2002; Yeh & Xia, 2001), topological variables (Dewan & Yamaguchi, 2009; Jenerette et al., 2007; Pijanowski, Tayyebi, Delavar, & Yazdanpanah, 2010; Tian, Qiao, & Zhang, 2012), neighborhood factors (Carrion-Flores & Irwin, 2004; Gustafson, Hammer, Radeloff, & Potts, 2005; Jiang, Deng, & Seto, 2013; Rui & Ban, 2011), socioeconomic factors (Dewan & Yamaguchi, 2009; Seto & Kaufmann, 2003; Sudhira, Ramachandra, & Jagadish, 2004) and policy guidance (Cheng & Masser, 2003; Liu, Zhan, & Deng, 2005; Tian et al., 2005; Xiao et al., 2006). Although these studies advanced our understanding of urban growth determinants, they had several limitations. First, previous cases only focused on the change in area of urban land (Fan, Wang, Qiu, & Wang, 2009; Liu et al., 2005). However, the determinants of landscape characteristics of urban growth, including shape, fragmentation and edge, were rarely analyzed. The analysis of spatial patterns of urbanization with ecological measures and landscape metrics provided an efficient approach for planners to describe urban processes and their consequences (DiBari, 2007; Herold, Couclelis, & Clarke, 2005). Second, spatial autocorrelation, where observations in close proximity exhibit similar attributes (Griffith, 1987), was seldom taken into account (Fielding & Bell, 1997). As mentioned previously, urban expansion is affected by various geographical

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factors. These factors always exhibit spatial autocorrelation and lead to the spatially autocorrelated patterns of urban growth (Gao & Li, 2011). Disregarding the existence of spatial autocorrelation leads to misinterpretation of the results (Overmars, De Koning, & Veldkamp, 2003; Verburg et al., 2002). Third, the temporal scale was ignored in most previous studies (DiBari, 2007; Luo & Wei, 2009; Xiao, Su, Wang, et al., 2013). Specifically, the comparison of the determinants at multiple spatiotemporal scales was not thoroughly investigated.

This study aims to apply geographic information systems (GIS), remote sensing (RS), spatial statistics and landscape metrics to investigate the landscape characteristics of urban growth and their geographic determinants at different spatiotemporal scales. Using the case of urban agglomeration around Hangzhou Bay (UAHB) in eastern coastal China, our objectives are to (1) analyze the landscape characteristics of urban growth patterns, (2) quantify the spatial autocorrelation of urban landscape pattern changes and (3) identify the geographic determinants of urban growth patterns at different spatiotemporal scales.

Study area

The urban agglomeration around Hangzhou Bay is located south of the Yangtze River Delta. This region includes five large megacities and twenty-five counties of the Zhejiang province. The UAHB covers 44,600 km^2 and has a population of approximately 24 million in 2009. It has a subtropical monsoon climate with a mean annual temperature of 17 °C and rainfall of 1450 mm. The northern region consists of plains, whereas the southwestern and southeastern regions are characterized by dense, steep forests (Fig. 1).

Following the market transition in 1994 and the local policy of “establishing urban agglomeration around Hangzhou Bay”, the UAHB has undergone rapid urbanization. The gross domestic product (GDP) in this region has experienced immense growth: it increased from 179 billion RMB in 1994 to 650 billion RMB in 2003 and to 1472 billion RMB in 2009. The population increased from 20.9 million in 1994 to 23.7 million in 2009. Furthermore, the urban population doubled, increasing from 4.5 million in 1994 to 9.1 million in 2009 (Zhejiang Statistical Bureau, 2010). This region also experienced a significant expansion of urban land and dramatic changes to the urban landscape configuration. The UAHB is a typical case to investigate the landscape characteristics of urban growth and their geographic determinants.

Methods and materials

Mapping built-up areas

Built-up land was defined as the land used to build urban and rural houses, public facilities, factories, tourist attractions and military sites. The built-up land data, visually interpreted from Landsat TM/ETM+ images in 1994, 2003 and 2009, were obtained from Xiao, Su, Zhang, et al. (2013). Before interpretation, all images were standardized to the same reference spectral characteristics by atmospheric correction. Then, the images were geometrically rectified to the UTM coordinate system using the quadratic method. For each scene, at least 30 evenly distributed pixels served as ground control points (GCPs), and the root mean squared error (RMS error) of geometric rectification was less than .5 pixels. This precision requirement was met for all images. For details, see Xiao, Su, Zhang, et al. (2013).

Quantifying the urban expansion pattern

Many landscape metrics were developed in recent decades. Riitters et al. (1995) found high collinearity among landscape metrics and emphasized the importance of choosing metrics for monitoring landscape patterns. In this study, four selected metrics (i.e., total area (TA), total edge (TE), landscape shape index (LSI) and aggregation index (AI) (Table 1)) were good representatives in terms of land use patterns and structures. Based on the interpreted land use/land cover data, all landscape metrics in 1994, 2003 and 2009 were calculated by the FRAGSTATS software (McGarigal, Cushman, Neel, & Ene, 2002) at different landscape block scales. Metric analysis was preliminary tested at block sizes of 1–10 km (at 1 km intervals). The block sizes of 4 km and 7 km were selected as the units for the analysis because the values of the metrics exhibited larger variances, thus retaining adequate land use/cover (LULC) information while avoiding the noise (Xiao, Su, Wang, et al., 2013).

The changes in the urban landscape metrics were calculated as:

$$C_i = \frac{M_2 - M_1}{M_1} \times 100\% \tag{1}$$

where C_i is the change in the urban landscape metrics within temporal interval i, M_1 is the value of the metrics in the previous

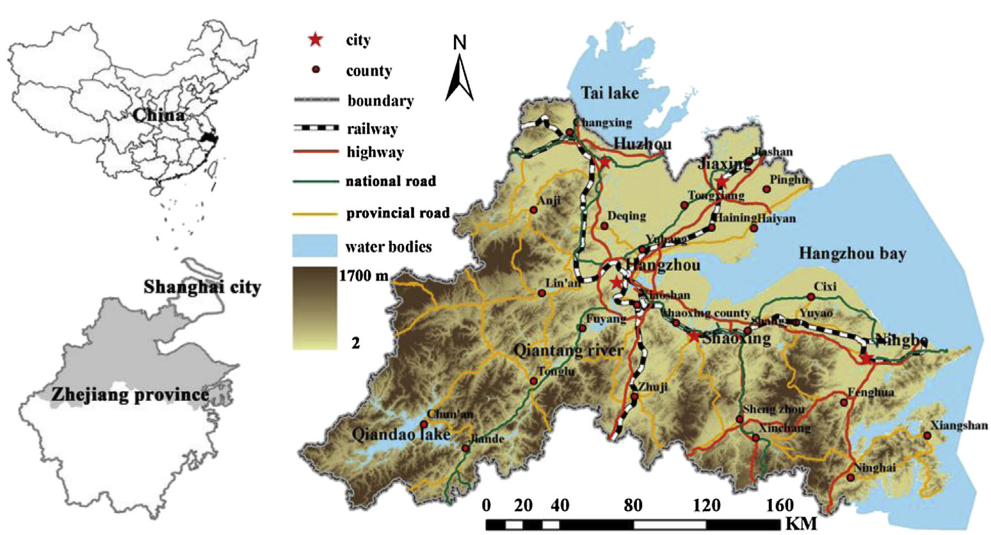

Fig. 1. The location of the urban agglomeration around Hangzhou Bay and the spatial patterns of the main roads, counties and cities.

Table 1
The landscape metrics selected for the study and their urbanization characteristics.

Metrics (abbreviation)	Formula	Description and relationship with urbanization level
Total area (TA)	$TA = \frac{\sum_{j=1}^{n} a_j}{10,000}$ (unit : ha) Where a_j equals to the area (m^2) of urban patch j.	Total area indicates the total area of one class-specially urban patch in our research. The value of TA will become greater with the urbanization.
Total edge (TE)	$TE = \sum_{j=1}^{n} c_j$ (unit : m) Where c_j refers to the edge length of urban patch j.	Total edge sums the length of edge of urban patches. It can be used to characterize the pattern of urban areas and level of planning. Higher urbanized areas have greater values in TE that indicate high fragmentation.
Landscape shape index (LSI)	$LSI = \frac{0.25 \times E}{\sqrt{A}}$ E is length of total urban landscape patches borderlines; A is the total area of urban patches.	Landscape shape index equal to the total length of patch edges within the urban landscape divided by the total area, adjusted by a constant for a square standard. It measures the shape complexity of urban landscape. The LSI will increase with increasing landscape shape irregularity or increasing amounts of edge within the urban landscape.
Aggregation index (AI)	$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right)\right] \times 100$ g_{ii} is the number of like adjacencies (joins) between pixels of urban patch based on the single count method. Max $\to g_{ii}$ is the maximum number of like adjacencies (joins) between pixels of urban patch based on single count method.	Aggregation index measures the degree of aggregation in urban class based on like cell adjacencies. It provides information about specific aspects of landscape composition and structure caused by urbanization and thus is helpful to explore process of urbanization toward stability. High values of AI indicate urban patches are highly clustered.

year, and M_2 is the value of the metrics in the following year. Each of the changes in the urban landscape metrics at each spatiotemporal scale was normalized and standardized. The normalization method was as follows:

$$d_i = \frac{D_i - D_{\min}}{D_{\max} - D_{\min}} \quad (2)$$

where D_i is the original value of the changes in the urban landscape metrics for block i, $D_{\max}$ and $D_{\min}$ are the maximum and minimum values of D_i among all blocks, respectively, and d_i is the normalized value of D_i.

Identifying geographic determinants

The potential determinants based on literature

Various influential factors affecting urban growth have been considered by historical geographers (Antrop, 2000; Cheng & Masser, 2003; Gustafson et al., 2005). Several types of determinants have often been considered in previous studies (Table 2). When a region is opened by road networks, transportation accessibility becomes the most influential driving force of urban expansion (Antrop, 2000). The influential scope of urban centers is enlarged, even extending to remote rural areas. Close proximity to urban centers creates job opportunities, increases everyday convenience, and offers a higher level of education and medical treatments. Therefore, the effects of city proximity on urban sprawl have been widely analyzed (Gustafson et al., 2005; Sudhira et al., 2004). Lakes, reservoirs, streams and rivers are important for transportation and the diffusion of waste. A study in Michigan (Tombaugh, 1970) reported that the distribution of water bodies influences the choices of residential locations, particularly the locations of homes in rural areas (Schnaiberg et al., 2002). Topography can impact the density, size and spatial distribution of settlements (Tian et al., 2012). Slope and elevation are considered important geophysical factors affecting urban land expansion (Jenerette et al., 2007).

The variables selected in this study

Population and economic statistics, neighborhood variables and policy planning are widely assessed as driving factors of urban expansion patterns within large and rapidly urbanized regions (Sudhira et al., 2004; Tian et al. 2005). However, these indicators cannot be accurately converted into sequence grid data. All predictors referred to as "geographic determinants" in this paper are generally grouped into two categories: topology and proximity. Based on previous studies and data availability, topology was selected for site-specific characteristics. For the topology, the mean values and variances of the slope and elevation were calculated. The proximity variables included the distances to the railway, highways, national roads, provincial roads, the urban center and rivers.

The calculation of the selected variables

ASTER GDEM (version 2) was used as the elevation data source (Jing, Shortridge, Lin, & Wu, 2013; Tachikawa et al., 2011) because these data had a spatial resolution similar to that of the TM images.

Table 2
A summary of the determinants of urban expansion in the literature.

Type of determinants	Determinants
Proximity variables	Distance to road networks (Batisani & Yarnal, 2009; Cheng & Masser, 2003; Gustafson et al., 2005; Li et al., 2013; Luo & Wei, 2009; Rui & Ban, 2011; Yeh & Xia, 2001), Distance to urban centers (Cheng & Masser, 2003; Li et al., 2013; Luo & Wei, 2009; Sudhira et al., 2004) Distance to river and water (Batisani & Yarnal, 2009; Braimoh & Onishi, 2007; Luo & Wei, 2009; Schnaiberg et al., 2002)
Topological variables	Slope (Dewan & Yamaguchi, 2009; Gustafson et al., 2005; Jenerette et al., 2007; Li et al., 2013; Pijanowski et al., 2010) Elevation (Dewan & Yamaguchi, 2009; Jenerette et al., 2007; Li et al., 2013; Pijanowski et al., 2010; Tian et al., 2012)
Neighborhood factors	Soil quality (Aguiar, Câmara, & Escada, 2007; Batisani & Yarnal, 2009; Carrion-Flores & Irwin, 2004; Gustafson et al., 2005) LULC (Gustafson et al., 2005; Jiang et al., 2013; Rui & Ban, 2011)
Socioeconomic factors	Gross domestic product (GDP) (Dewan & Yamaguchi, 2009; Jiang et al., 2013; Liu et al., 2005; Seto & Kaufmann, 2003; Sudhira et al., 2004) Population (Braimoh & Onishi, 2007; Cheng & Masser, 2003; Dewan & Yamaguchi, 2009; Sudhira et al., 2004; Xiao et al., 2006)
Policy variables	Land use planning and guideline (Braimoh & Onishi, 2007; Cheng & Masser, 2003; Liu et al., 2005; Tian et al., 2005; Xiao et al., 2006)

The mean values and variances of the slope and elevation were calculated with the zonal statistical tool in ArcGIS 9.3 for each block. Based on the Zhejiang provincial DLG dataset (digital line graph at map scale 1:50,000), distances (Euclidean nearest neighbor distance) were calculated between grids and each geographic element (each category of roads, urban centers or rivers) using the ArcGIS 9.3 spatial analysis module. The geographic variables of the grids were averaged over each block. Last, the block values at each spatiotemporal scale were normalized and standardized. Equation (2) was used as the normalization method.

Spatial regression

Spatial data exhibit spatial autocorrelation and do not meet the assumption of conventional regression approaches, such as ordinary least squares (OLS) (Gao & Li, 2011). Global Moran's I is the most commonly used statistical test of the spatial autocorrelation in univariate map patterns (Tiefelsdorf, 2002). Its values range from -1 (a perfect negative correlation) to $+1$ (a perfect positive correlation). Negative values indicate negative spatial autocorrelation, whereas positive values indicate a positive relationship. A zero represents a random spatial pattern (Moran, 1950). Higher absolute values indicate that the changes have a stronger autocorrelation at the global level. Mixed regressive–spatial autoregressive models, which incorporate both regression and spatial autocorrelation, have been constructed for a better goodness-of-fit (Overmars et al., 2003). Spatial error and spatial lag models were applied to interpret the geographic determinants. In contrast to OLS, these two models consider the spatial dependency in the form of lag or error dependence (Anselin, Syabri, & Kho, 2005).

The equation used in the spatial lag model is:

$$y_i = \lambda \sum w_{ij} y_i + x_i \gamma + \mu_i + \varepsilon_i \tag{3}$$

where i represents the spatial units at different spatial scales, y_i is the observation of the dependent variable (landscape metric changes) of i, λ is the spatial autoregressive parameter, w_{ij} is an element of a spatial weights matrix that describes the spatial relationships of all of the spatial units, x_i is the vector of observed parameters of spatial unit i, γ is a fixed matrix of explanatory variables, ε_i represents an independently and randomly distributed error term for observation i, and μ_i denotes a spatial specific effect.

The spatial error model assumes the dependent variable relies on a set of observed local indicators, but only the error terms are assumed to be spatially autocorrelated (Ye & Wu, 2011). Another condition is that unobserved factors also follow a spatial pattern. The equations are:

$$\sigma_i = \lambda \sum w_{ij} \sigma_i + \varepsilon_i \tag{4}$$

$$y_i = x_i \gamma + \mu_i + \sigma_i \tag{5}$$

where σ_i reflects the spatially autocorrelated error term and λ is the spatial autocorrelation coefficient (Elhorst, 2003).

Based on the Lagrange Multiplier diagnostics, the selection of an appropriate algorithm for the spatial regression was performed using GeoDa 0.9.5-i (Beta) software (Anselin et al., 2005). All regression models were run using one landscape metric change as the dependent variable and multiple geographic indicators as the independent variables. The independent variables for spatial regression were first chosen by the traditional variance-in-inflation method, considering the potential multicollinearity.

Results

Spatial patterns of urban landscape changes

The urban expansion patterns during two time intervals are illustrated in Figs. 2 and 3. The total area of built-up land increased by 111.1% in T1 (1994–2003). However, the increase in TA in T2 (2003–2009) was less than that in T1, with a net growth of 13.9%. The continuous increase in TE (70.8% in T1 and 7.6% in T2) resulted from the urban expansion, which generated more edges than natural land produces. Urban landscapes became more dominant and unstable with urbanization. Compared with the sharp increases in built-up areas and edges, LSI had slight growth during T1 and was stable during T2. These results indicate that the urban landscapes became more complex and irregular. The increases in AI during

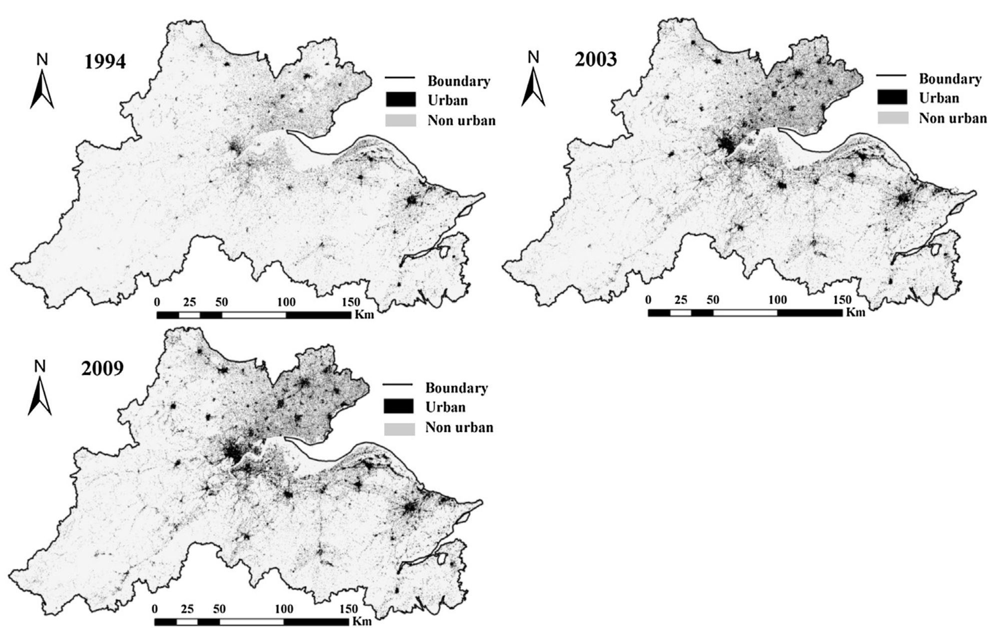

Fig. 2. Urban expansion from 1994 to 2009 based on the interpretation of the TM images.

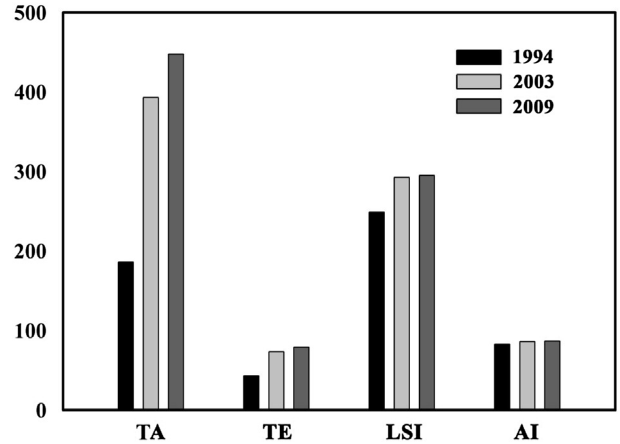

Fig. 3. Changes in metrics for urban landscapes at the entire region scale (total area (TA), total edge (TE), landscape shape index (LSI), aggregation index (AI); units for TA: 10^3 ha, TE: 10^6 m).

both T1 and T2 suggest that as a whole, the urban landscapes became more compact.

Figs. 4 and 5 indicate that the changes in all selected metrics in T1 were generally higher than those in T2. The rates of change of TA and AI in urban centers were higher than those in rural areas (located in the northwestern and southwestern areas of the UAHB). The opposite patterns were found in TE and LSI. All of these results indicated that urban landscapes became more dominant, compact and dense in urban central areas. The western mountainous regions and remote villages established more irregular and scattered urban landscapes.

Spatial autocorrelations of urban landscape pattern changes

The urban landscape metric changes across the study area, in terms of global Moran's *I*, are displayed in Figs. 4 and 5. The aggregation index had low values of Moran's *I* at all spatiotemporal scales. At both spatial scales, global Moran's *I* for TE was greater than .7 in T1 and decreased to ∼.35 in T2; TA experienced similar trends. The results indicate that the areas and edges of patches had explosive and centralized growth in T1, but the growth had slow and localized changes in T2. LSI had a global Moran's *I* value close to .7 in T1, which was much higher than that in T2. Generally, our results showed that spatial autocorrelation widely existed in the urban landscape changes. Each global Moran's *I* of urban metric changes in T1 was higher than that in T2; however, the indicators at 4 km and 7 km scales were nearly the same. High values of global Moran's *I* in T1 suggested that the urban expansion followed a regionalized pattern across the rapid urbanization stage, whereas in T2 it became a more localized phenomena.

Spatial determinants of urban growth

The determinants of the urban landscape patterns obtained from spatial regression are shown in Tables 3 and 4. During T1, the changes in the landscape metrics at the two spatial scales, including area (TA), edge (TE) and shape (LSI), can be explained by the two models because almost all of the R^2 values were greater than .6 (up to .8 in some cases). In contrast, the changes in AI were poorly explained by the geographic variables. In a general comparison of the two time intervals, all values of R^2 in T2 were lower than those in T1. Compared to T1, which showed nearly the same values of R^2 at both spatial scales, the changes in the urban landscape pattern during T2 were better predicted at the 7 km scale.

For the indicators of the spatial model, the distance to the rivers was not a primary factor of the urban landscape pattern changes. The elevation did not affect the expansion of urban patches. However, the slope influenced the distribution of urbanization (i.e., the two variables (Slp_m and Slp_v) were correlated to the changes of all landscape metrics). The negative relationships between distance to urbanization and landscape metric changes (TA and TE) observed during T1 were not observed during T2; thus, the influence of urban centers declined. The national and provincial roads affected almost every metric change at all scales. Highway had a negative impact on urban expansion, whereas railways were not correlated with the changes in the urban landscape metrics.

Discussion and conclusions

Spatial determinants of urban growth

The building density was found to be negatively correlated with the distance to the shorelines of lakes, streams and rivers (Schnaiberg et al., 2002). Houses and factories were generally constructed close to rivers, which provided favorable environmental conditions and convenient transportation. In our study area, the districts near Hangzhou Bay and along the Qiantang River were always the most prosperous, but the growth rates were not very high considering the large base numbers. Meanwhile, the existence of lakes, ponds and rivers resulted in traffic in the economically lagging southwestern and northern areas near Qiandao Lake and Tai Lake. Consequently, urban growth was not correlated with the distance to rivers. The prosperity of private economies in the small towns of Zhejiang province and the incredibly high land prices in urban districts weakened the influence of urban centers on urban growth. People tend to live and build factories in small towns because of the lower land prices and the more comfortable life. Liu et al. (2005) examined the topographical factors of urban growth and observed that the lower gradient plains were always more favorable for urban land expansion. Similarly, our results revealed that the slope exerted more influence on the urban landscape pattern changes than the elevation did. Herzog et al. (2001) compared the urban landscape change features of four different industrialized periods from 1914 to 1989 in Saxony, Germany. Urban expansion initially occurred in the low-lying areas that were close to water resources and in areas with convenient transportation. Once all of the low-lying positions were occupied, the urban sprawl occurred in flat areas. The slope factor was the determinant of urban growth in our study. In a case study of Guangzhou, Fan et al. (2009) also found that the traffic network had a large influence on urban expansion, and different types of roads had different impacts. The national roads had the strongest influence on urban expansion, followed by the provincial roads. In our study, railways and highways had no influence, while national and provincial roads substantially affected the urban landscape changes. Although railways and highways played important roles in the countrywide transportation in China, they exhibited weaker driving effects on the urban expansion in adjacent areas. Railways and highways do not feature exits between stations or ports; therefore, they seclude adjacent land along both sides. Moreover, they cause tremendous noise. Because of their greater connectedness, national and provincial roads, which are convenient transportation routes, are likely to be the elements around which people build new structures.

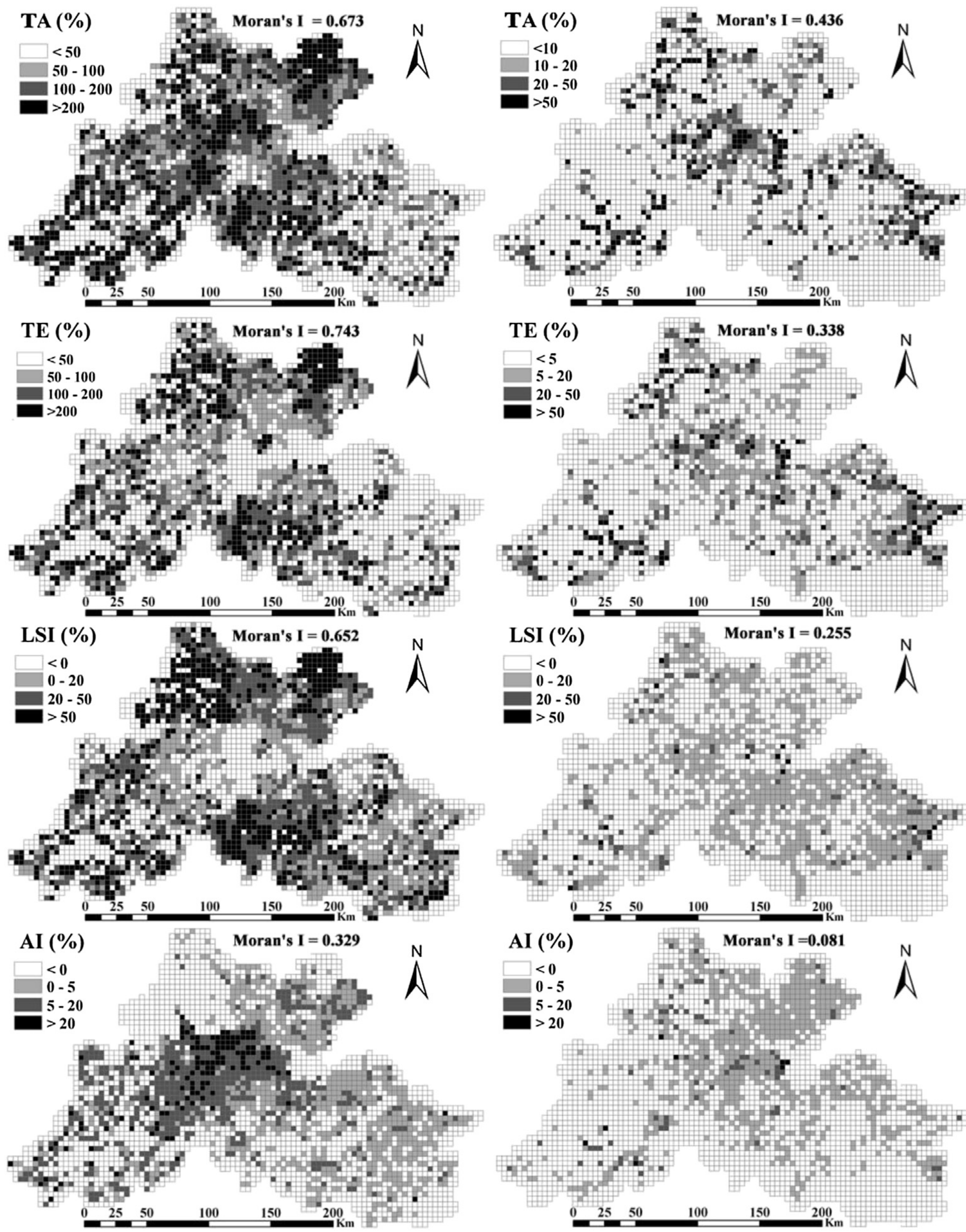

Fig. 4. Thematic maps showing the urban landscape changes of the urban agglomeration around Hangzhou Bay at the 4 km scale: T1 (1994–2003) in the left column and T2 (2003–2009) in the right column (total area (TA), total edge (TE), landscape shape index (LSI), aggregation index (AI)).

The slope variables were the main factors that impacted TA, suggesting that the flat area were more likely to experience urban development than the surrounding areas. The distances to national and provincial roads were correlated with LSI and TE. Similar to the results of Reed, Johnson-Barnard, and Baker (1996), national and provincial roads have been cited as significant contributors to the fragmentation and complexity of the urban landscape. Analyzing the determinants of the landscape pattern changes at multiple scales revealed that the mean value of elevation influenced the changes in LSI at the 7 km scale. This indicated that 7 km was the best scale to investigate the relationships between the urban landscape pattern changes and elevation. The distance to urban centers affected TE in T1; however, this relationship did not exist in T2. The reason could be that during the initial stage, irregular units near the urban centers tended to transform into urban areas, while in the latter stage, urbanization occurred in areas both near to and far from the urban centers.

Scale effects

Scale must be taken into consideration because most landscape indices are sensitive to grain and extent (Turner, O'Neill, Gardner, & Milne, 1989; Wu, 2004). In our study, a variety of spatiotemporal scales were used for analyzing the urban growth. Moran's I and R^2 values were higher at 4 km than at 7 km, and the spatial lag model interpreted better than the spatial error model, especially at the 4 km scale. Messner and Anselin (2004) used spatial regression models to demonstrate spatial patterns of homicide in a case study of U.S. counties. A spatial lag model indicated that the geographic clustering of homicide was consistent with a diffusion process. Moreover, in our

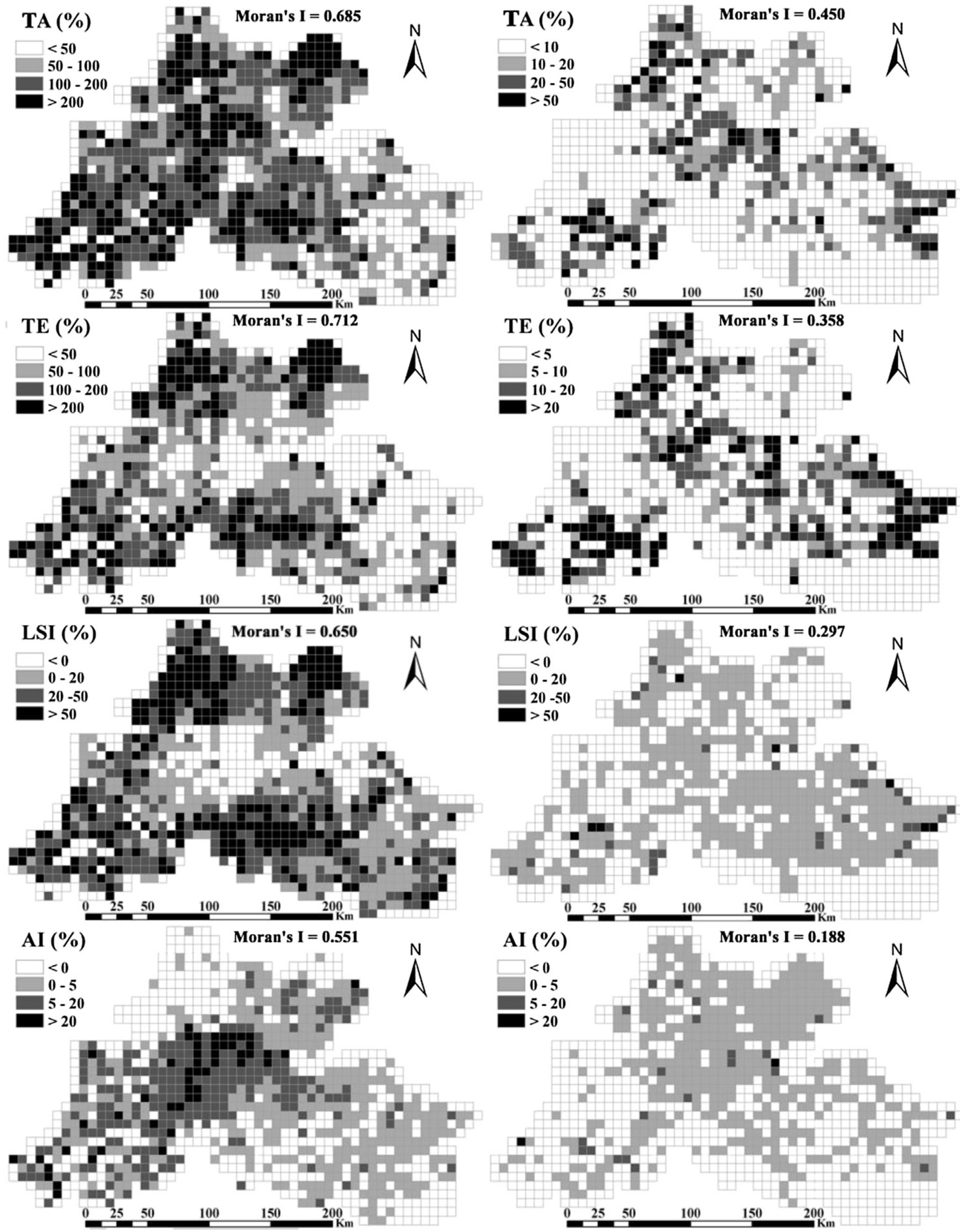

Fig. 5. Thematic maps showing the urban landscape changes of the urban agglomeration around Hangzhou Bay at the 7 km scale: T1 (1994–2003) in the left column and T2 (2003–2009) in the right column (total area (TA), total edge (TE), landscape shape index (LSI), aggregation index (AI)).

study, the spatial error model was likely more effective than the spatial lag model at a larger grid scale (7 km). This might be attributed to the trend for the differences overcoming the similarities among the blocks with the increased distances.

The regression diagnostics also showed that the spatial lag model was valid for analyzing the urban expansion of the UAHB in T1. Our analysis during T1 seemed to reveal diffusion processes, and the residual spatial autocorrelation during T2 could be adequately attributed to unmeasured predictor variables. Dietzel, Herold, Hemphill, and Clarke (2005) reported that urban land areas increased monotonically, while the edge density and complexity of the urban landscape increased initially, peaked at various times and then decreased, exhibiting a unimodal shape. The results of the urban growth analysis were affected by the measurement interval. Thus, temporal scale should also be considered an important influential factor. Our results exhibited clear spatiotemporal differences, emphasizing the importance of changing the grid sizes and time intervals when characterizing the changes of urban landscape patterns.

Landscape metrics and spatial regression

Landscape metrics are useful in recognizing dynamics or patterns of land use/land cover changes (Aguilera, Valenzuela, & Botequilha-Leitão, 2011; Botequilha Leitão & Ahern, 2002; Tischendorf, 2001). Urban landscape changes can uncover the different spatiotemporal characteristics of urban sprawl (Frohn & Hao, 2006; Yang et al., 2012). Because different metrics vary in descriptive power and sensitivity, the selection of appropriate metrics is the key to success in modeling landscape progress.

Table 3
The coefficients of the spatial regression between urban landscape changes and geographic determinants at the 4 km scale ($n = 3040$).

	TA		TE		LSI		AI	
	T1[a]	T2[b]	T1[a]	T2[b]	T1[a]	T2[a]	T1[a]	T2[a]
Ele_m								
Ele_v								
Slp_m	−.052	−.112	−.031	−.053		−.036	−.031	−.026
Slp_v	−.027				−.006	.045		
Dis_u	−.033							
Dis_r								
Dis_ra								
Dis_hi							.039	.013
Dis_n		−.094		−.051	.004	−.013	−.022	
Dis_p					.010	.023	−.027	−.016
Cons	.060	.107	.089	.515	.088	.323	.199	.191
Wy/lam	.737	.649	.842	.556	.838	.488	.653	.377
R^2	.671**	.413**	.750**	.293**	.647**	.190**	.364**	.115**

T1 means the changes of metrics from 1994 to 2003 and T2 is that from 2003 to 2009.
**Significant at the 99% confidence level.
Abbreviation: total area (TA), total edge (TE), landscape shape index (LSI), aggregation index (AI), mean value of elevation (Ele_m), variance of elevation (Ele_v), mean value of slope (Slp_m), variance of slope (Slp_v), distance to urban centers (Dis_u), distance to rivers (Dis_r), distance to railways (Dis_ra), distance to highways (Dis_hi), distance to national roads (Dis_n), distance to provincial roads (Dis_p), constant of models (Cons), Wy of spatial lag model (Wy), lambda of spatial error model (lam).
[a] Spatial lag models.
[b] Spatial error models.

Table 4
The coefficients of the spatial regression between urban landscape changes and geographic determinants at the 7 km scale ($n = 1042$).

	TA		TE		LSI		AI	
	T1[b]	T2[b]	T1[b]	T2[b]	T1[a]	T2[a]	T1[b]	T2[b]
Ele_m		.098				−.071		
Ele_v								
Slp_m	−.147	−.202		−.074			−.073	−.039
Slp_v	−.048		−.046		$-4.65^{*}e^{-3}$	.041		
Dis_u	−.419		−.095			.083		
Dis_r								
Dis_ra								
Dis_hi							.197	.036
Dis_n		−.141		−.071		−.047	−.105	−.024
Dis_p			−.071		$3.58^{*}e^{-3}$		−.047	
Cons	.269	.157	.579	.471	.083	.294	.345	.202
Wy/lam	.816	.616	.844	.534	.844	.499	.743	.439
R^2	.727**	.434**	.707**	.322**	.645**	.235**	.515**	.137**

T1 means the changes of metrics from 1994 to 2003 and T2 is that from 2003 to 2009.
**Significant at the 99% confidence level.
Abbreviation: total area (TA), total edge (TE), landscape shape index (LSI), aggregation index (AI), mean value of elevation (Ele_m), variance of elevation (Ele_v), mean value of slope (Slp_m), variance of slope (Slp_v), distance to urban centers (Dis_u), distance to rivers (Dis_r), distance to railways (Dis_ra), distance to highways (Dis_hi), distance to national roads (Dis_n), distance to provincial roads (Dis_p), constant of models (Cons), Wy of spatial lag model (Wy), lambda of spatial error model (lam).
[a] Spatial lag models.
[b] Spatial error models.

Along with urban sprawl issues, spatial models of the regional development process provide new avenues for investigating the complexities of urbanization (Henry, Schmitt, & Piguet, 2001). Many studies (Luo & Wei, 2009; Seto & Kaufmann, 2003) have emphasized the spatial autocorrelation in analyzing urban sprawl. The high Moran's *I* values of the urban metric changes in this study also confirmed the existence of autocorrelation. Spatial methods were better suited to exploring the relationships between urban growth and geographic variables. We quantitatively analyzed the scale-specific relationships between the urban growth and geographic indicators using spatial lag/error regression. The high Moran's *I* and R^2 values of the spatial regression model indicated that it is an efficient tool for modeling urban landscape changes.

Management implications

The high quality agricultural land, accounting for a large portion of flat areas, was very vulnerable to urbanization. For local governments, selling land to developers can generate more revenue than using the land for agriculture. The loss of flat areas for agriculture due to the rapid urban growth should be a concern for the central government. The continuous construction of various types of roads influenced lifestyles and accelerated urban expansion. Currently in China, people prefer to build their houses along these extended open roads (the national and provincial roads) instead of living in central urban areas. Considering the effects of transportation on urban expansion, reasonable road network planning is urgently needed to solve the unbalanced development in the UAHB.

According to the hypothesis of temporal patterns by Dietzel et al. (2005), the UAHB has already experienced its diffusion stage. In recent decades, many large cities in China have become more scattered as they expand. Rapid urbanization caused complex and fragmented landscapes, which led to the inefficient use of land resources. Additionally, striking a balance between housing and jobs and implementing an efficient public transportation system relies on further research and vigorous land use planning.

Limitations

Despite the insights into urban growth patterns from this study, there are still methodological limitations. First, due to the availability of TM data, we chose only three representative time series of images to obtain the urban growth information. Longer historical datasets will be applied in further research. Second, we considered only topography and proximity for the geographic determinant analysis. Urban planning and other indicators may account for the unexplained effects of the spatial regression. (3) Only two block scales were analyzed, whereas further research on scale effects could utilize additional grid sizes. Furthermore, the visual interpretation of the remotely sensed imagery had shortcomings compared with advanced computer-assisted techniques. Computer-based spatial metrics and spatial statistics are calculated at the pixel level and are nearly impossible to calculate using visual interpretation.

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