

Article

Understanding Urban Land Growth through a Social-Spatial Perspective

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Abstract: To understand the urbanization process, it is essential to detect urban spatial growth and to study relations with social development. In this study, we take Wuhan as a case to examine urban land growth patterns and how social factors relate to the urban land evolution between 1990, 2000, and 2010. We first classify land cover using Landsat images and examine the urban growth patterns during various stages based on landscape metrics regarding the area, density, and shape. Afterwards, principal component analysis and census data are used to extract key social factors. Thirdly, we apply geographically weighted regression (GWR) to depict the link between urban land metrics and social factors. The results indicate that the urban land coalescence and diffusion simultaneously exist, for which redevelopment, infilling, and edge expansion dominate the city center, and diffusion dominates the peripheral areas. The social factors have global regression relationships with urban land areas while local spatial non-stationarity presents in the relationships with the urban land patch shape irregularities. Industrial upgrading, educational levelling up, and population aging show significant with local heterogeneities in the relationships. The simulation of the relationship provides a social-spatial perspective to understand urban land growth. The authors conclude that sustainable urban management should consider the coexistence of different urban spatial growth models and underline social transitions when examining the urban growth process. This works for cities in rapidly urbanizing countries or regions.

Keywords: urban land growth; urban expansion; fractal dimension; social transition; geographically weighted regression (GWR); Wuhan; China



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1. Introduction

The changes in growth patterns caused by China's rapid urbanization process are remarkable. Currently, widely accepted concepts of urban growth are related to population, economic, and spatial growth [1]. Spatial growth is concerned with the changes in the geographical space occupied by impervious surfaces, which connects to human intervention. It is also the focus of this research. Urban spatial growth is described as an alternating process of diffusion and coalescence in high-income countries [2,3]. The two are considered to occur at various stages, showing a spiral upward trend. The growth is presented through five common forms "infilling, extension, linear development, sprawl, and large-scale projects" [4].

The different growth patterns among cities distinguish the corresponding development stages and characteristics, and a simultaneous occurrence of these patterns is also common [5]. While population agglomeration and economic growth promote sustained urban growth, they have also accelerated the pace of suburbanization and the shrinking of urban centers [6,7]. Having first been carried out in high-income countries and regions, urban expansion and contraction have long been the focus of urban research. In

China's large cities, urban expansion has been the focal point of research in the past two decades [8–13], while research on urban shrinkage, redevelopment, or suburbanization has only appeared in recent years [14–16]. Case studies comparing cities in China to those in high-income countries/regions also exist [17]. However, research on urban management still has challenges to handle the different processes of growth and contraction [1].

Scholars study urban growth patterns from a macro-spatial scale and compare the patterns in different-income countries, to find common laws or differences for urban spatial growth in various stages. Findings on Beijing, Shanghai, Tianjin, and Guangzhou show that urban growth in these cities has almost been dominated by a coalescent period in the 1990s and 2000s with edge expansion [18]. Comparisons between 25 global cities in the 1990s, including Wuhan and Guangzhou, classified cities into four types as low-, high-, expansive-, and frantic-growth cities, suggesting that no low-density sprawl is shown in the Chinese case cities [19]. Both Wuhan and Guangzhou are categorized into high-growth cities with rapid, fragmented development. Though a few cities are involved in the macroscopic study, the studies are coarse. Thus, to explore the urban spatial growth pattern microscopically, a case study from its perspective is essential.

In recent years, most studies draw attention to single, developed cities in China. Li et al. (2017a) find that a variety of growth modes such as infilling, edge expansion, and leapfrog expansion concurrently took place in Beijing urban growth during 2000 and 2010 [20]. Gong et al. (2018) draw a similar conclusion for Guangzhou where the different modes developed alongside a reposition of “relative dominance” to reflect a dramatic process of change [21]. Lei (2019) finds that during 1988–1999 and 1999–2011, Shenzhen developed more expansively in 1988–1999 and 1999–2011, and “a higher percentage of infilling” in 2011–2015 [22]. Studies on other second-tier cities such as Tianjin and Nanjing draw similar findings. Chen et al. (2016) find that in 1980–2013, Nanjing grew from a combination to the separation “of residential and manufacturing land” [23]. The process promoted Nanjing to transform from a compact mononuclear city to a polycentric one, dominated on different stages by “infilling, extension, and enclave”. Liu et al. (2019) suggest that Tianjin's growth was dominated by edge expansion, strongly pushed by government planning a for project-driven development zone [5]. Literature has successfully explored urban land growth patterns within single cities, but more case studies on the second-tier cities in China are still essential to find a common law or differences for the growth process and to provide valuable information for city management.

Multi-mode-growth of urban space has led to significant spatial heterogeneity within city to a certain extent. To better serve the community residents, sustainable management needs to consider the complexity of the urban growth process. The spatial heterogeneity of urban growth is not only resulted in by physical conditions, but also by social structures and performances [24–27]. With the support of urban ecology theory and social ecology framework, researchers have developed strong academic interests in examining the relationships between social transformation and urban land growth [28–30]. It has become a consensus that the urban system is a human-dominated one. In an urban system, the social subsystem and the physical subsystem have the same weight, and the two interact with each other. With the socio-ecological approach, researchers understand the relationships between social and physical subsystems as a spirally upward drive-pattern-process-result (DPPR) flow or equally weighted bilateral interactions [29,31]. No matter from which point of view, the social-ecological approach regards the relationships between society and physical subsystems as an important field for studying the process of urban growth, providing valuable information for urban space management. From another point of view, due to the limitations of data, skills, methods, etc., how to examine the relationships still has a lot of room for improvement [32].

Empirically, urban spaces grow with the dominance of linear elements such as traffic lines and river/lake banks, constrained by the supply of land suitable for development, which is defined by natural elements such as hills/mountains, rivers/lakes as well as conservatory zones [24,33]. Besides physical factors, socio-economic development has been

recognized as triggers as well as consequences of urban spatial growth [26,27]. Academic attention toward socio-economic forces in literature is mainly focused on temporal relationships, for which population density and GDP are the most popular explanatory variables to interpret urban spatial growth. Even though both temporal and spatial features of urban growth are studied, focusing on the dual dimensions of time and space concurrently is not common when exploring how social factors are associated with urban growth. Further, the literature on the relationships based on cross-sectional data is scarce, mainly due to data unavailability [33], though few are published. For example, Han (2012) studies the dynamics of social influences on Beijing urban land growth for twenty years between 1980 and 2000 [12], suggesting that significant associations with spatial nonstationarity present at the relationships between social and physical subsystems. Despite the extensive research on the driving mechanisms of economic development on urban spatial growth, there is still a lack of analyses from the perspective of social dimensions such as age, employment, family size, mobility, and so on.

Global regression approaches such as Ordinary Least Square (OLS) regression, step-wise regression, and logit regression are popular methods used to model the relationships between demographic characteristics, economic development, and urban land patterns [27]. The global regression ignores the spatial heterogeneity of the relationship between urban spaces and social dimensions, which is far different from reality, whereas the local regression model can more closely reflect this element. To explore spatial non-stationarity, Geographically Weighted Regression (GWR), a local regression approach, is employed widely. GWR introduces geographic coordinates that define spatial locations as independent variables, and its results reflect the spatial non-stationarity of the regression relationship between explanatory variables and the dependent one [34]. Literature shows that GWR is used to detect how physical elements and economic development affect urban land growth [35,36], but it is necessary to pay more attention to social factors' links with the growth.

The main purpose of this research is to examine the growth pattern of a fast-growing second-tier megacity in China, using Wuhan as a case, and to analyze social dimensions' relationship with the spatial-temporal evolution. Research on Wuhan intends to understand the foundation for urban spatial changes, especially from a social perspective, which is important for framing eventual urban planning policy in second-tier cities of China and cities in rapidly urbanizing countries or regions. Specific questions are broken down to: (1) What are the spatial characteristics of urban land growth and the center–periphery relationships, measuring with landscape metrics? (2) How are urban spatial changes related to socio-demographic transformations? and (3) How do these relationships evolve longitudinally?

2. Materials and Methods

This study combines remote sensing and GIS technology with landscape metrics to map and quantify the spatiotemporal features of the Urban Development Zone (UDZ), the severest development area, in Wuhan from 1990 to 2010. We used impervious surfaces to measure the evolution of urban space and to analyze growth patterns. The research focuses on comparing the growth in neighborhood units and depicting the local differences in social relationships. It is outstanding by providing a distinct perspective for urban growth research. To achieve the objective, we carried out the extraction of urban land and computation of selected landscape metrics, the dimensionality reduction and extraction of social factors, and the regression modeling of the relationships.

2.1. The Study Area

Wuhan is the capital of the Hubei Province, being recognized as the base of the New Cultural Revolution and a major transportation hub in central China (Figure 1). Wuhan is divided by the Yangtze River and the Han River and has many other bodies of water. Over the past few decades, Wuhan's status has steadily been elevated from a regional center to a national center, with a continuous transformation of industrial and consistent economic

growth. Wuhan is a representative second-tier city in terms of population and investment agglomeration. Its growth is remarkable in the recent two decades, with corresponding notable social transformation as well as spatial expansion.

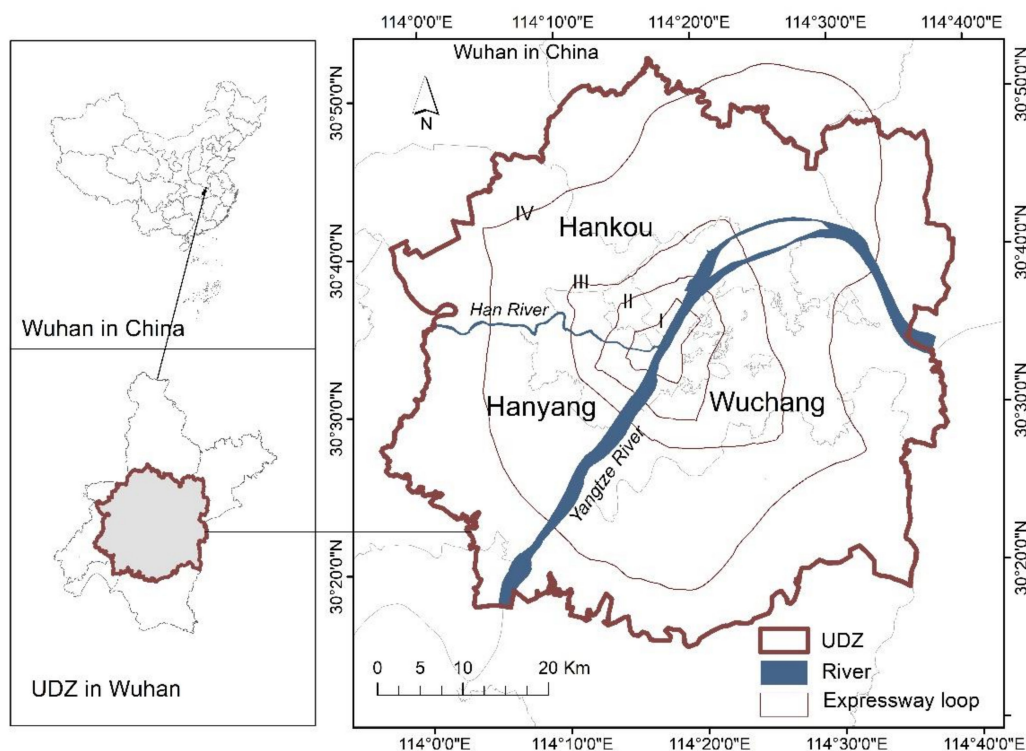


Figure 1. Map of the study area. Hankou, Hanyang, and Wuchang are three regions that are divided by the Yangtze River and the Han River. I, II, III, IV refer to the expressway loops from the center to the periphery.

In the research period, the population density is increasing in the city center, reflecting traditional secondary industry removal. Industrial upgrading has significantly reshaped the urban center. The employment of the tertiary industry increased significantly in the urban center in the 1990s, and in the periphery of the urban center in the 2000s. The employment of the secondary industry shows a continuous decline in the urban center and a significant increase in the periphery of the urban center in the 2000s (Appendix A, Figure A1).

2.2. Urban Land Extraction and Metrics Selection

We prepared temporal Landsat 5 Thematic Mapper (TM) images for the extraction of urban land. Rich-vegetation images in June and July were screened. However, because there are no suitable cloud-free images in 1990 and 2010, we considered a replacement by those in 1991 and 2011. Thus, the TM images employed are from 1991, 2000, and 2011, matching the social dimensions in 1990, 2000, and 2010, respectively. We then cut the images to the study area. The land cover extraction is based on the I–V–W (Impervious surface–vegetated area–water area) urban model. Band math is employed for the extraction (Appendix B). The water area was first masked using the modified normalized difference water index (MNDWI) [37]. The impervious surfaces were then extracted using a Modified Biophysical Composition Index (MBCI) we proposed, based on the Biophysical Composition Index (BCI) [38], for better distinguishing urban land and bare soil. The rest is vegetation area. An example of land cover extraction is presented in Figure 2.

$$\text{MBCI} = [(\text{BT} + \text{B} + \text{W})/3 - \text{G}]/[(\text{BT} + \text{B} + \text{W})/3 + \text{G}] \quad (1)$$

where top of atmosphere reflectance (TOA) and brightness temperature (BT) images are used for MBCI computation. BT is [0, 1] standardized bright temperature extracted from the thermal band (Formula (2)). B, W, and G stand for [0, 1] standardized brightness, wetness, and greenness are calculated using the Formula (3)–(5) based on the first, second, and third principal components of Tasseled Cap Transformation (TCT), respectively.

$$BT = (BT_0 - BT_{\min}) / (BT_{\max} - BT_{\min}) \quad (2)$$

where BT_0 , $BT_{\min}$, $BT_{\max}$ are the observed, minimum, and maximum values of the bright temperature, respectively, and

$$B = (TC1 - TC1_{\min}) / (TC1_{\max} - TC1_{\min}) \quad (3)$$

$$G = (TC2 - TC2_{\min}) / (TC2_{\max} - TC2_{\min}) \quad (4)$$

$$W = (TC3 - TC3_{\min}) / (TC3_{\max} - TC3_{\min}) \quad (5)$$

where TC1, TC2, TC3 are the first three TC components; $TCi_{\min}$ and $TCi_{\max}$ are the minimum and maximum values of the i th ($i = 1, 2, 3$) TC components, respectively. The brightness, greenness, and wetness surfaces are computed using the TCT coefficients of Landsat 5 TM data proposed by Crist et al. (1986) [39].

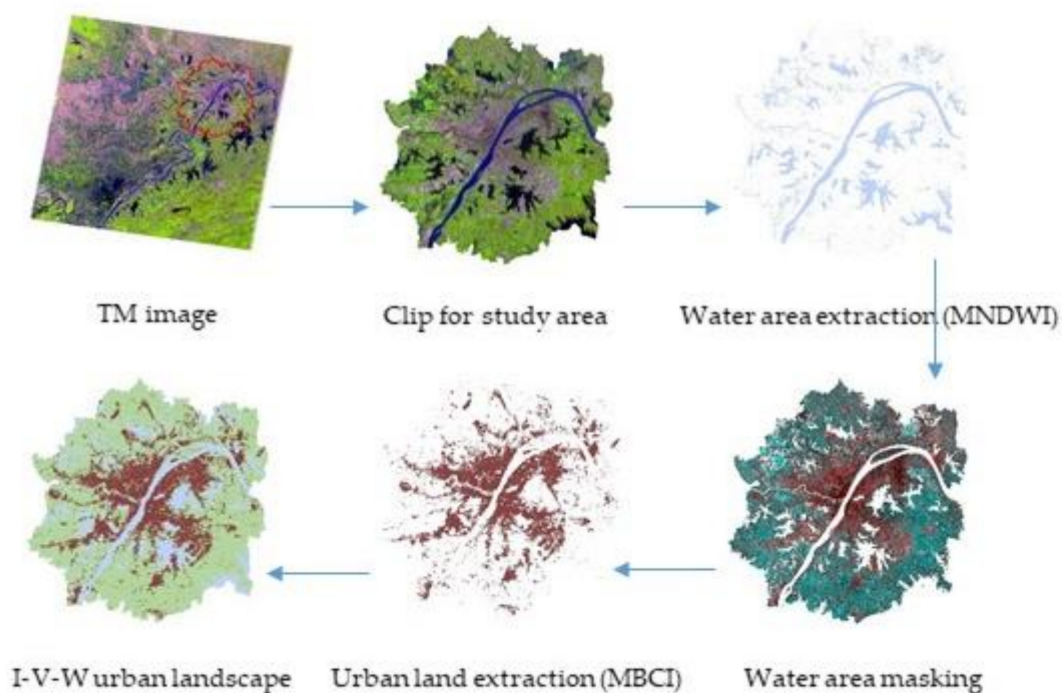


Figure 2. Example of the land cover extraction process (2011).

2.3. Selected Urban Land Metrics

Literature focuses on quantifying urban land growth patterns and further evaluates a variety of spatial, demographic, or social characteristics associated with those patterns [19,40]. Landscape metrics are widely introduced to describe the growth pattern [41,42]. Based on the connotation of the landscape indexes, the interrelationships in this case (Table A2) and in literature [1,40,43], we selected the total area (TA) of the impervious surface, the proportion of the landscape (PLAND), the patch density (PD), the largest patch index (LPI), and the area-weighted classification dimensions (FRAC_AM) to present the area, density, aggregation, and shape. PD measures the fragmentation as well as the scatter dispersion of urban land, while LPI gives a view on how the biggest

patches occupy the total landscape. They work together to express the composition and outstanding of the urban landscape. FRAC_AM measures the regularity or irregularity of the urban landscape patches. The indicators and their implications for urban land growth patterns are explained in Table 1 [1,40,43].

Table 1. Landscape metrics and urban land growth pattern.

Metrics	Value	Meaning	Significance
TA	≥ 0	Total area of impervious surface, representing the size of urban space	Differences of size of urban land present overall view of urban growth
PLAND	≥ 0	Percentage of the area of urban land to the total area	Changes of urban land percentage reveal urban spatial growth pattern including improvement, infilling and expansion
PD	≥ 0	Patch density, number of patches per unit of total landscape. Here, urban patches are defined as homogenous regions of urban land.	A higher value of patch density indicates a more scattered and fragmented distribution of urban land patches. The value of PD is expected to increase until the later stages of individual urban patches gradually merge into continuous areas.
LPI	(0, 100]	Largest Patch Index, the percentage of urban land area comprised by the largest patch	LPI is a simple measure of the dominance of urban land patch
FRAC_AM	[1, 2]	Area-weighted mean patch (AM) fractal dimension equals 2 times the logarithm of patch perimeter divided by the logarithm of patch area, with the adjustment of patch area abundance (multiplied by the proportional of patch area to the sum of patch areas).	FRAC approaches 1 for shapes with simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

2.4. Social Factors Computation

Most literature takes population density and economic indexes as independent variables to interpret the urban landscape from only a temporal serial [44,45]. Few interpret urban landscape with integrated social factors, which cover more information about the social subsystem. Extraction of social factors is foundational for the quantitative measurement of relationships between social transitions and urban land growth. This study selected social variables based on census data in 1990, 2000, and 2010, to build a social factors system, which was further used to regress with urban landscape metrics for the interpretation of evolution. The variable selection was based on the rule that the correlation coefficient between variables in the same category is not equal or greater than 0.9. Fourteen variables (thirteen variables for 1990 due to the limitation of population mobility census) were selected; referring to people's age, migration, employment, education, and urbanization based on the census data. To reduce social dimensions, we used principal component analysis and eigenvalue greater than 1 criterion to extract the components. We further chose Varimax, an orthogonal rotation, to get clearer factor loadings and divisions. The social factors are named according to the loadings. The factor scores were computed with a regression approach, which was further employed to model the relationships with urban landscape metrics.

2.5. Regression Relation Modelling

A regression approach was employed to explore how to interpret urban land metrics from the social dimensions. This approach was chosen to examine if GWR, which is designed to identify whether relationships vary across space, better fits the relationships with the hypothesis that the regression relationships are spatially nonstationary in the study area, based on neighborhood unit. Traditional spatial data analysis widely uses global models, such as OLS regression. The basic assumption of global model variables is that

the relationship between predictors and outcome variables is spatially stationary. Global regression cannot detect spatial non-stationarity, which may exist. GWR is a statistical technique that allows measuring spatial changes in the relationship between explanatory variables and dependent variables within the framework of a local model [46]. The GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^k (\beta_j(u_i, v_i) \chi_{ij} + e_i) \quad (6)$$

where y_i is the value of the predicted variable at the coordinate location i , (u_i, v_i) represents the coordinates of i , $\beta_0(u_i, v_i)$ and $\beta_j(u_i, v_i)$ indicates the estimated intercept and coefficient for variable j at the coordinate location i .

Researchers typically utilize the Akaike Information Criterion (AICc) to compare the results from a “global” OLS regression with those from the “local” GWR [47,48]. Smaller AICc indicates that the introduction of spatial information can improve model fitting. Specifically, we first ran stepwise OLS regression to find the best models and obtained the significant social variables, which will be used to form the GWR model further. We tested the spatial autocorrelation of regression residuals using global Moran’s I . The null hypothesis is rejected while the p -value is significant (≤ 0.10), indicating the residuals clustered or scattered, rather than randomly distributed in space [49].

3. Results

3.1. Urban Landscape Evolution

Wuhan’s urban land has continued to grow rapidly since the 1990s. It has expanded from 16636 ha in 1991 to 73328 ha in 2010, an increase of up to 3.41 times (Figure 3, Table 2). The spatial growth accelerated in 2000 when China fully implemented a market-oriented reform of real estate and the financial system, higher education, etc. Further, the average annual increase of urban land was 1848 ha during 1991–2000, and 3467 ha during 2000–2011. During the 2000s, Wuhan’s urban space had an annual growth as rapid as 1.87 times that in the 1990s. The acceleration of the urban land growth since 2000 shows a temporal escalating of urban space. The value of PD and LPI, from the density and aggregation perspective, also continue to rise, with an acceleration during the 2000s. Compared to the density and aggregation metrics, the shape measurements do not present the same trends. From a global view, FRAC_AM had a slight decline during the 1990s and an increase between 2000 and 2011.

The overall metrics of TA and PLAND of urban land demonstrate a sufficient trend of urban land growth with edge or leapfrog expansion, while LPI expresses infilling or edge expansion in Wuhan during the 1990s and 2000s. The shape metrics of FRAC_AM disclose an infilling development in the earlier stage and an expansion in the latter, based on the regularity of the urban landscape patches.

Table 2. Urban land metrics in Wuhan Urban Development Zone (UDZ).

Urban Land	1991	2000	2011	1991–2000	2000–2011
TA (ha)	16,635.87	34,537.5	73,328.31	17,901.63	38,790.81
PLAND (%)	5.17	10.73	22.78	5.56	12.05
PD	1.16	1.31	2.28	0.15	0.97
LPI	1.62	2.93	7.71	1.31	4.78
FRAC_AM	1.245	1.239	1.270	−0.006	0.031

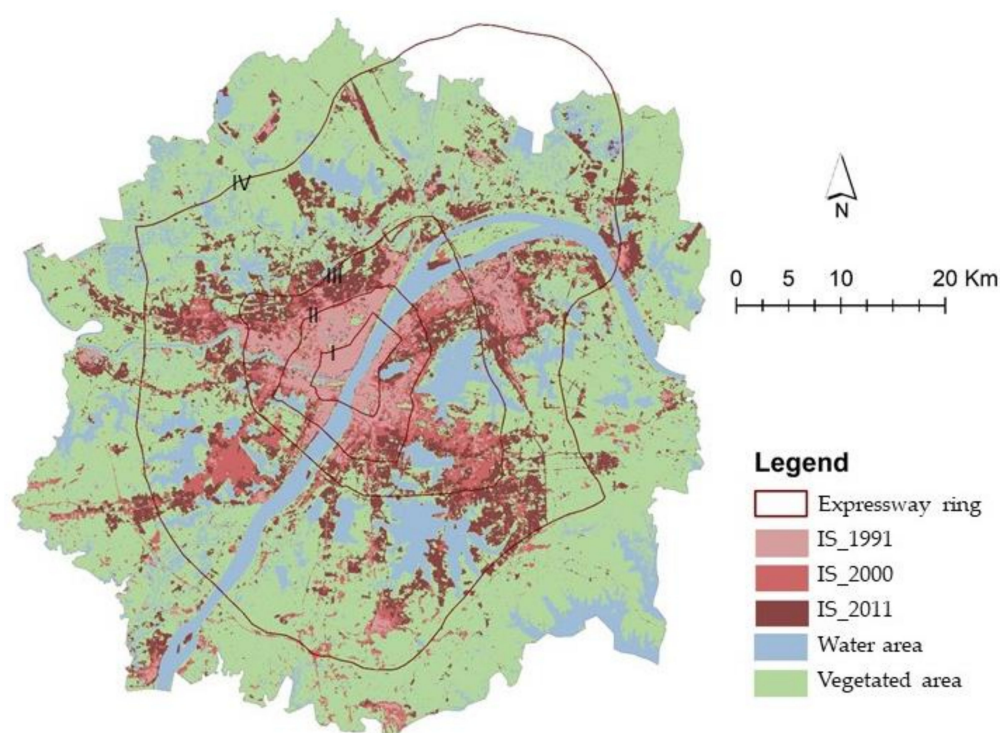


Figure 3. Urban land growth from 1990 to 2010. (IS: Impervious Surface).

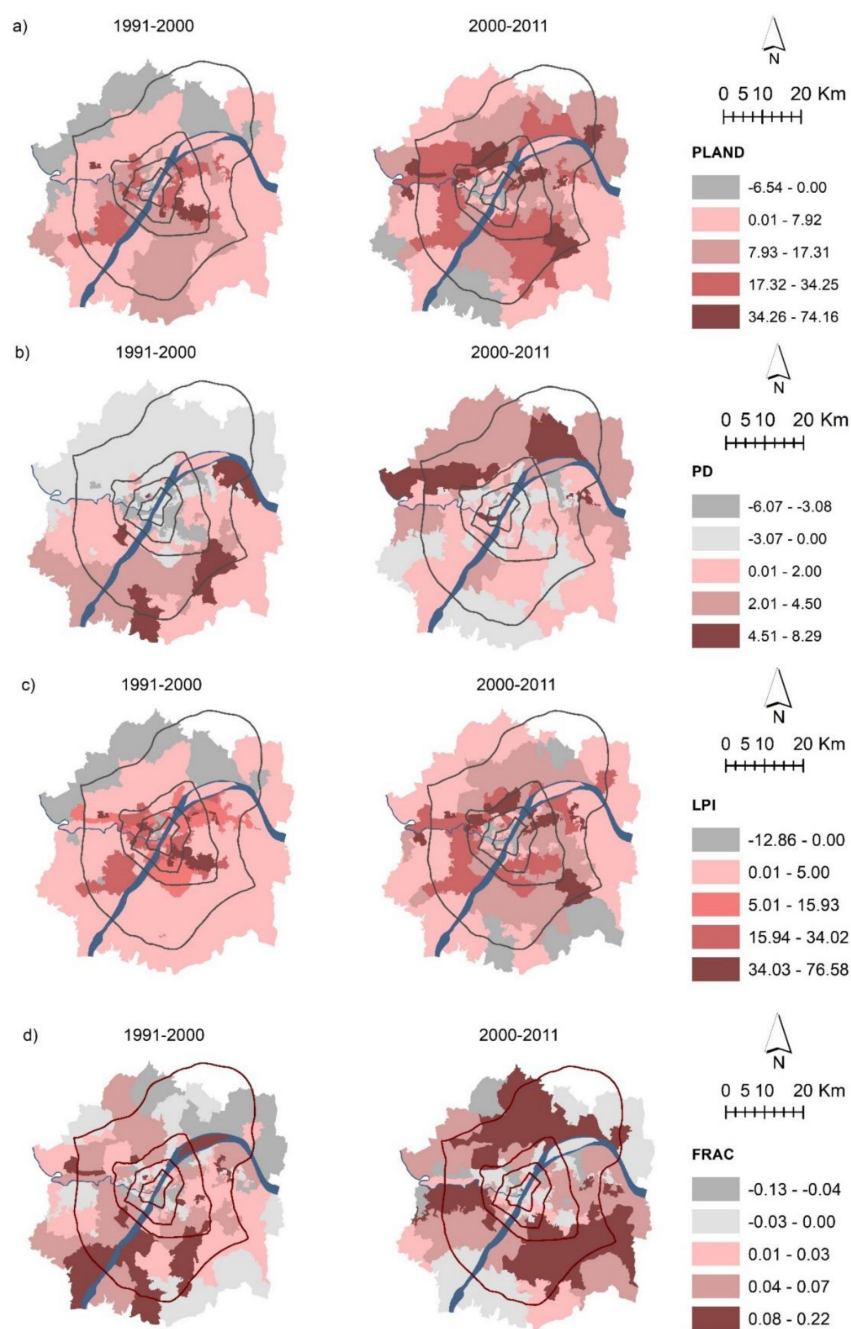
To detect the spatial differences of urban landscape within the study area, we further compute the metrics in each neighborhood to compare the evolution during the 1990s and 2000s. The comparison reveals how the urban land area, patch size or density, and patch regularity change and what spatial differences are presented. The spatial differences disclose urban land growth patterns during various stages. In the maps (Appendix A, Figure A2) with a static value of the metrics in different years, the city center with a stable urban landscape is featured with a higher PLAND, lower PD, higher LPI, and lower FRAC. It shows that the city center with the above features grew continuously while surrounding the center expanded with fragmented urban land.

Changes in the value of landscape metrics present urban spatial pattern evolution. Based on the literature [1,40,43], we describe urban land development using three main categories: regeneration/redevelopment, infilling, and expansion. Urban land expansion refers to edge expansion, urban fringe expansion, enclave expansion, and linear expansion [5,23,50,51]. Redevelopment may decrease the urban land patch fragmentation while increasing the regularities through human intervention, while it also could result in the fragmented and scattered urban land patch distribution. Infilling and edge expansion lead to the patch size increase and patch density decrease. Other types of expansion may result in an increase or decrease in patch fragmentation or dispersion. Thus, we listed the indication of value changes of urban land metrics (Table 3), which is the basis of further discussions regarding the evolution of urban land patterns.

Figure 4 presents the spatial features of urban landscape changes, including PLAND (a), PD (b), LPI (c), and FRAC (d). The shifts in PLAND and LPI show similar spatial characteristics, with a decrease in the city center and an increase in the neighborhood with significant urban land expansion. PLAND decreases throughout 1991 and 2011 in some neighborhoods in the city center, within the expressway Ring II. In the 1990s, urban land regeneration takes place mostly in the north of the Han River and west of Yangtze River, with the famous commercial street redevelopment. In the 2000s, the decrease of urban land in the city center is mainly a cause of the renewal of green and wetland along the Han River and Yangtze River. The changes of LPI show similar features of spatial distribution.

Table 3. Urban land development mode indicated by change of value of urban land metrics.

	Decrease	Increase
PLAND	Urban land regeneration, redevelopment, occur mostly in the city center	Urban land development (infill or expansion)
PD	(Re)development, infilling, or edge expansion, less fragmented or scattered, or less divided by other landscape	(Re)development, more fragmented or scattered, or more divided by other landscape
LPI	Urban land (re)development with land use change or decrease of the largest patch size with other landscape encroachment; Urban land expansion such as sprawl, enclave expansion, and so on	Urban land coalescence with infilling or edge expansion
FRAC_AM	Urban land (re)development, infilling development, or edge expansion	Urban land (re)development, diffusion with more fragmented or scattered distribution

**Figure 4.** Urban land metrics changes: (a) Changes of PLAND; (b) Changes of PD; (c) Changes of LPI; (d) Changes of FRAC_AM.

Shapes of patches represent urban land infilling or expansion, with a decrease or increase in the value of FRAC_AM. In the 1990s, FRAC_AM decreases in most neighborhoods of the city center (within expressway Ring II). Those with a significant increase of FRAC_AM in the 1990s are located out of Ring II, and especially in some satellite towns out of Ring III. At the same time, neighborhoods in the north and northeast of the Yangtze River have a decreasing FRAC_AM. In the 2000s, the neighborhoods with decreasing FRAC_AM expand from the city center to the east-west axis along the Han River and the main road between the East Lake and the South Lake. Those with an increasing FRAC_AM distribute in various directions, especially out of expressway Ring III. It indicates that in the city center, urban land grows with an infilling pattern while diffusion occurs mostly in the surrounding area. In the 1990s, the expansion in the outer area is outstanding in some neighborhoods in the south of the UDZ while it extends to different directions.

PD, the index for patch density, shows that the decrease is more outstanding in the 1990s than in the 2000s, with a concentration on the east-west axis (west along the Han River and east along the main road), as well as along the Yangtze River at the east bank. In the latter period, the decrease of PD in the city center continues with a slight degree. The PD decrease in the city center indicates that infilling development from the aggregated urban landscape with bigger-sized patches.

Combining the area, density, and shape indexes, we see that the city center is in a regeneration stage between 1991 and 2011, though the city center expands dynamically. The regeneration presents not only as infilling development of urban land but also as a replacement of urban land with developing more green or wet space. The redevelopment in the city center reshapes the urban land and permeable surface patches and provides an improved micro-environment for communities.

With a focus on the city center, the improvement of the urban landscape takes place in Hankou, the traditional commercial center during the earlier stage. In the latter stage, the improvement expands to Hanyang, and Wuchang, with more concentration along the Han River and the Yangtze River. During the 1990s, a slight increase of PLAND occurs within the expressway Ring I and partially in Ring II, which combined with the FRAC_AM decrease can be identified as infilling development. During the 2000s, a slight increase of PLAND takes place in Ring II with a decrease of the FRAC_AM, for which coalescence dominates the development. Outstanding expansion of urban land during the 1990s happen to the east (axis along the main road constrained by rivers), west (dispersed distributed expansion), and south (with the trigger of high increscent secondary industry zone) part, with a combination of the decreased LPI (which indicates the higher fragmentation of urban landscape patches) particularly in the east-west direction. Expansion in the 2000s mainly occurs out of Ring II, for which the FRAC_AM presents an outstanding increase (indicating the irregularity of urban landscape patches) in the surrounding neighborhoods, which are in line with the expressway network.

3.2. Interpretation of Urban Landscape by Social Factors

3.2.1. Extraction of Social Factors

The numbers of urban social dimensions extracted according to eigenvalue greater than 1 are 4, 4, and 5 in 1990, 2000, and 2010, respectively (Table 4). In 1990, the first dimension (Factor 1) is employment in nonagricultural industries, the second one (Factor 2) is the higher educated population, the third one (Factor 3) is the elderly population, followed by the local population and inflow population (Factor 4). Unlike the first and second dimensions, in 2000, the third and fourth dimensions change only slightly. In 2000, the first dimension is employment in the tertiary industry, among which the load of higher educated population reflects its close relationship with employment in the tertiary industry. The second dimension is employment in the secondary industry, which is closely related to the population with a high school education. Employment in the tertiary industry is still the first dimension in 2010, but education background closely relates to changes from higher level in 2000 to high school in 2010. At the same time,

higher education and the single population become the second dimension. The third dimension is still the aging population. However, at this stage, the contribution of aging population increased significantly compared with those in 1990 and 2000. Employment in the secondary industry constitutes the fourth dimension, which is negatively correlated with low-income occupations, reflecting the advantages of the optimization, and upgrading of the secondary industry accompanied by employment income. During this period, the floating population constituted the fifth dimension of urban society, reflecting its increased contribution to urban development. Changes in social dimensions and their connotations will be reflected in the physical landscape, with specific patterns.

Table 4. Social factors extracted, % of variance, and variable loadings.

Social Variables		1990				2000				2010				
		Social Factors Extracted, % of Variance, Loadings												
		Nonagricultural Industry Worker, High Income Population	Single and Higher Educated Population	Aging Population	Immigrants & Local Population	Tertiary industry Worker, High Income Population	Secondary Industry Worker	Aging Population	Immigrants & Local Population	Tertiary Industry Worker	Married Population with Minor Dependent	Local Population & Aging Population	Secondary Industry Worker	Immigrants
		F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4	F5
% of variance (%)		45.55	16.30	16.22	13.10	37.45	19.50	14.61	9.79	21.17	17.28	16.99	12.36	8.85
Urbanization	Nonagricultural population	0.956				0.786				0.835				
	Local population				0.886				0.748			0.854		
Migration	Intra-provincial immigrants				−0.909				−0.783					0.569
	Inter-provincial immigrants						−0.524							0.826
Age	Minor dependent	−0.913				−0.822					0.703			
	Elders			0.955				0.910				0.842		
Marital status	Married population		−0.853			−0.806					0.876			
	Divorced or widowed population			0.938				0.865				0.759		
Education background	High school educated population	0.964					0.647			0.802				
	Highly educated population		0.803			0.923					−0.803			
Employment	Secondary industry employment	0.860					0.864						0.743	
	Tertiary industry employment	0.776								0.887				
Occupation by income	High-income-occupation population	0.789				0.903				0.513				
	Low-income-occupation population	−0.984				−0.696							−0.794	

Note: Secondary/tertiary industry employment represents the population who work in the secondary/tertiary industry. Occupation by income refers to the population divided by different income-levels and occupation, which is concentrated to the population with occupations. It reveals the transformation of relationships between occupation and income.

3.2.2. Regression Results

We computed the urban landscape metrics regarding the area, density, shape regularity, and aggregation at neighborhood level to match the format of the explanatory variables and used them as dependent variables. The social factors represent the social subsystem with the transforming dimensions. Since PLAND is associated with LPI, and FRAC_AM is closely related to TA (Appendix C, Table A2), we used PLAND, PD, and FRAC_AM to conduct the regression simulation. The stepwise OLS regression determines the appropriate combination of significant explanatory variables, which provided a basis for constructing the GWR model. Based on the goodness-of-fit for regression model and standard residual spatial autocorrelation (Table 5), the GWR results for PLAND and FRAC_AM are more representative. In other words, the R^2 adjusted of GWR for PD is moderately low in 2000 and 2010, and the p-value of Moran's I is insignificant. The lower R^2 adjusted the lower the model fits. A significant p-value of Moran's I test is expected for the non-randomly spatial distribution of the standard residuals of regression models, vice versa.

Table 5. Parameters of geographically weighted regression (GWR) results.

	1990	2000	2010	1990	2000	2010	1990	2000	2010
Dependent variable	PLAND	PLAND	PLAND	PD	PD	PD	FRAC_AM	FRAC_AM	FRAC_AM
Explanatory social variables	Factor 1 *	Factor 1 *	Factor 1 *	Factor 1 *	Factor 1	Factor 1 *	Factor 1 *	Factor 1 *	Factor 1 *
	Factor 2	Factor 2 *	Factor 2	Factor 2 *	Factor 2 *	Factor 2	Factor 2	Factor 2 *	Factor 2 *
	Factor 3 *	Factor 3 *	Factor 3 *	Factor 3 *	Factor 3 *	Factor 3	Factor 3 *	Factor 3 *	Factor 3 *
	Factor 4 *	Factor 4 *	Factor 4	Factor 4	Factor 4	Factor 4 *	Factor 4	Factor 4	Factor 4 *
			Factor 5			Factor 5			Factor 5
GWR parameters									
Bandwidth	629,966	629,966	22,435	629,966	629,966	620,964	11,791	11,791	18,911
Residual squares	43936	53279	60448	723	411	505	0.1981	0.1645	0.2013
Effective number	4.01	5.01	9.56	4.01	3.01	3.01	22.86	28.31	17.38
Sigma	18.60	20.81	21.95	2.39	1.81	1.96	0.0428	0.0406	0.0414
AICc	1144.05	1147.96	1224.58	606.05	520.75	569.53	−437.64	−435.58	−463.98
R^2	0.6916	0.6081	0.5413	0.4024	0.0777	0.0956	0.4963	0.4693	0.4905
A^2 adjusted	0.6843	0.5953	0.5100	0.3882	0.0629	0.0818	0.3945	0.3239	0.4195
Global Moran's I of standard residuals of GWR									
Index	0.2120	0.1814	0.1112	0.0211	0.0234	−0.0180	−0.0065	0.0137	0.0558
ZScore	9.2705	8.6915	5.2575	1.2307	1.4402	−0.4698	0.0524	0.9911	2.8029
PValue	0.0000 **	0.0000 **	0.0000 **	0.2184	0.1498	0.6385	0.9582	0.3216	0.0051 **

Note: *, ** indicants significance level $p < 0.05$, and < 0.01 , respectively. Kenel type for GWR: Fixed; Bandwidth method: AICc. Binary strategies are for spatial weight metrics computation (i.e., a feature is either a neighbor (1) or not (0)).

The GWR models for the urban land area (PLAND) show that it is highly explained by the explanatory social variables, with R^2 adjusted of 0.6843 (1990), 0.5953 (2000), and 0.5100 (2010) (Table 5). From 1990 to 2010, the nonagricultural industrial employed population has presented significant associations with urban land growth (PLAND), with the transition from a mixture of tertiary and secondary industry in 1990 to a split of the nonagricultural industry as tertiary and secondary become defined as a different dimension in 2000 and 2010. In 2010, the link between the tertiary industry and urban space is significant, different from that of the secondary industry. The higher educated population has not significantly associations with the urban land area in 1990 but grew significantly since then. Secondary industrial employment associates with urban land areas significantly in 2000, but insignificantly in 2010. In 2010, only two social dimensions including tertiary industrial employment, local population and aging population significantly link with urban land areas.

The GWR models for FRAC_AM, to a great extent, indicate how close the urban land patch regularity associates to human interventions, with R^2 adjusted 0.3945 in 1990, 0.3239 in 2000, and 0.4195 in 2010. The models reveal the spatial differences of coefficients in each neighborhood, indicating that the sensitivity of urban land patch shape regularities

to social factors is different. The social factors significantly associated with FRAC_AM are the nonagricultural industrial employment (Factor 1) and higher-educated population (Factor 2) in 1990, which transited to the tertiary industrial workers (Factor 1), higher educated population (Factor 2), aging population (Factor 3), and secondary industrial population (Factor 4) in 2010. The significant factors in 2000 are similar to those in 1990, apart from the nonagricultural industries. The study demonstrated that urban land shape irregularity is significantly associated with the social landscape at neighborhood level. Regarding the standard residuals of the GWR models, Global Moran's I test shows that the p-values of 1990 and 2000 are insignificant, while in 2010 they are significant.

The GWR coefficient surface (Figure 5) reveals the spatial variations in the association of explanatory variables with urban land metrics and helps to better understand how humans intervene in the urban land patch shapes and growth spatial patterns. The transitions provide information for policies and local planning at various scales. In PLAND's GWR model, the coefficients of social variables differ little in space. Therefore, we focus on analyzing and interpreting the coefficient surface of the patch shape index FRAC_AM.

The coefficient surface for GWR in 1990 indicates that the associations of nonagricultural employment (Factor 1) and the elderly population (Factor 3) with the degree of regularity of urban land patch shapes present a pattern of concentric circles outward from the city center. The coefficients of factor 1 and factor 3 are opposite, and their associations (expressed as the absolute value of the coefficient) with the irregularity of urban patches show a downward trend from the city center to the outskirts. The coefficient of Factor 1 is positive, revealing that the nonagricultural industry development has an increased relationship with the shape index of urban land patches. The lower the value of the shape index, the simpler the shape. Further, the growth of the nonagricultural industry increases the irregularity of urban land patch shapes. The land patch shape index in the urban center is sensitive to the nonagricultural industry and the coefficients decrease with growing distance from the city center. Factor 3 is the elderly population, which is strongly associated with big-sized families (Pearson $R = 0.615$, $p < 0.01$). This factor, therefore, not only represents the elderly but also provides information on family size. Contrary to Factor 1, the regression coefficient of the elderly to the urban land patch shape regularity is negative. The absolute values of the coefficients also decrease from the city center to the periphery. In 1990, both the sensitivities of Factor 1 and Factor 3 (the absolute values of the coefficients) showed a decrease from the city center outwards. This was closely related to the concentration of urban social and economic development during this period and the aggregation of the city center.

In 2000, employment in the tertiary industry (Factor 1), employment in the secondary industry (Factor 2), and the elderly (big-size families) (Factor 3) had significant relationships with the regularity of urban land patch shapes. The regression coefficients of Factor 1 and Factor 2 are mostly positive, and those of Factor 3 are predominately negative. The coefficients of Factor 1 show a low-to-high trend from southwest to northeast, and those of Factor 2 show a low-to-high trend from southeast to northwest. Factor 3 has greater coefficients in the city center, along the Han River, and in the southeast. The spatial pattern of coefficient surfaces of nonagricultural industrial employments (factor 1 and factor 2) has transited from concentric circles in 1990 to sectoral differences separated by the main axis in 2000. The links of population aging (with decreased association with big-size families, Pearson $R = 0.473$, $p < 0.01$) are manifested as concentric circles extending westward and southeastward. The east-west axis is composed of the Han River and the eastward main road, reflecting the links of employment in the tertiary industry; while the north-south axis is formed by the Yangtze River, which reflects the association of employment in the secondary industry.

The coefficients of the 2010 GWR model show that employment in the tertiary industry (Factor 1), higher educated population (Factor 2), and the aging population (associated with small-size family) (Factor 3) have a negative association with the degree of urban land patch shape regularity. The links with secondary industry employment (Factor 4) are

positive. That is to say, the more developed the secondary industry, the higher the shape index value, and the more irregular the land patch shape. Those neighborhoods are in the developing stage. Conversely, the more developed the tertiary industry, the simpler the shape of the urban land patch, the denser the highly educated and the elderly, the simpler the shape of the urban land patch. Such neighborhoods are relatively mature and have the most human intervention in the urban landscape. In terms of spatial characteristics, the coefficients of the employment in the secondary industry, higher educated population, and the elderly with urban land patch shape regularity are in a sectoral form, while the links of the employment-population in the tertiary industry and patch shape regularity are in the form of concentric circles. The neighborhoods with high coefficients of the secondary industrial employment are mainly located in Hankou, north of the Han River and west of the Yangtze River. Those with high coefficients of the tertiary industrial employment are mainly located in the city center. The neighborhoods most linked with the higher educated population are mainly located in the southeast region. The higher educated population in this area is dense, due to the aggregated distribution of research institutes and universities. Those with high coefficient of the elderly (small-scale households) are distributed in the northeastern region. This area is led by the port industry and the chemical industry.

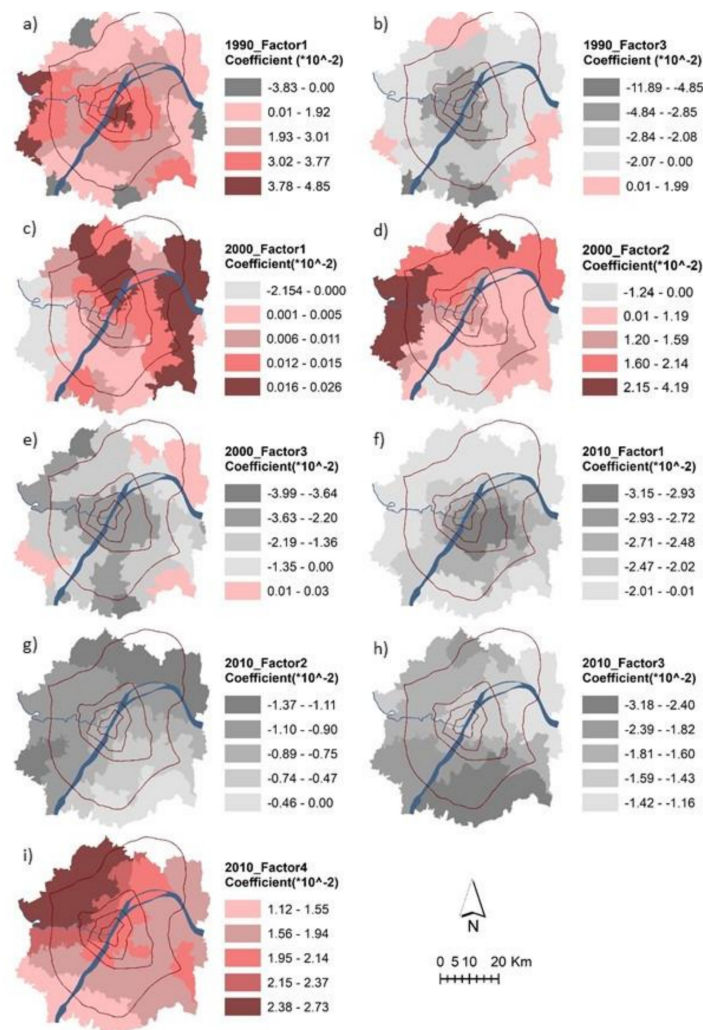


Figure 5. Coefficient of GWR interpreting FRAC_AM in 1990, 2000, and 2010. (a) Coefficient of Factor 1 in 1990; (b) Coefficient of Factor 3 in 1990; (c) Coefficient of Factor 1 in 2000; (d) Coefficient of Factor 2 in 2000; (e) Coefficient of Factor 3 in 2000; (f) Coefficient of Factor 1 in 2010; (g) Coefficient of Factor 2 in 2010; (h) Coefficient of Factor 3 in 2010; (i) Coefficient of Factor 4 in 2010.

4. Discussion

4.1. Urban Land Growth Pattern

Rapid urbanization reshapes the social and physical landscape within urban areas. With the aggregation of tertiary industry and the improvement of the environment, the city center evolves with the increase or decrease of impervious surface and the more regular patch shapes. Infilling and edge expansion result in more regularity of shape as well as larger size urban land patches. Meanwhile, the city outskirts brought by expansion imply a higher fragmentation and dispersion. The urban land growth generates a compact and aggregated center and a more fragmented outskirt. The fragmentation of urban land does not present an outstanding degradation with the distance to the city center, due to biased development along the road and river axis as well as different socio-economic clusters. However, focusing on the development axis, the degradation of urban land aggregation and increased fragmentation followed by the distance is still the common phenomena with those in other cities [17,19].

Urban spatial growth patterns vary depending on the socio-economic stage. Since the 1990s, the second-tier city has been in a transition stage, which is defined by rapid population agglomeration and economic growth, resulting in the continued growth of urban land, with small areas of infilling or redevelopment in the city center. During the latter decade, the scope of infilling in urban centers has expanded, and the fringe areas demonstrate multidirectional expansion. This is different from the development in the earlier decade when the urban growth relied on existing built-up areas and along the river and transportation axis. Overall, the urban center has been expanding, which is dominated by redevelopment, infilling development, or patch-edge expansion, while the outer areas are dominated by varieties of expansion, such as fringe expansion, enclave expansion, and industrial park clustered expansion. Industrial upgrading and removal guided by technological progress put forward requirements for optimal land use within corresponding construction space provision. Therefore, the accompanying development of urban expansion and infill is the main theme of China's urban growth in a certain period in the future.

Redevelopment in the city center has taken place during the two decades, which is outstanding in the latter decade. It has been promoted through the reconstruction of the old city center and the relocation of polluting industries. The redevelopment gave more focus to improving vegetation areas or renewal of wetland, which presents by a decrease of impervious surface area. The shrinkage of urban land in some neighborhoods of the city center reflects urban environmental upgrading. The redevelopment is based on traditional secondary industrial removal. Thus, it marks not only environmental improvement but also economic upgrading.

4.2. Heterogeneity of Interpretation from Social Perspective

Cities are important carriers of social-economic development. The urban spatial form is significantly associated with socio-economic growth. The formation of China's second-tier cities is still in its coalescence stage, coinciding with population and economic agglomeration, which presents as infilling and expansion of urban land. The evolution of the urban social landscape has a significant association with land growth. Different social clusters and their intervention in urban growth form spatial differences in urban landscapes. The links of social evolution with the urban landscape were in the form of concentric circles in 1990, changed to a sectoral form with an outstanding axis in 2000, and further developed into a combination of concentric circles and sectoral form in 2010. This also reflects the social-spatial features formed under the mechanism of policy.

From 1990 to 2010, the spatial differentiation of nonagricultural industries closely linked with the urban spatial landscape. In 1990, the first social dimension nonagricultural employment was mostly in the central area of the city. In 2000, nonagricultural employment was divided into employment in the tertiary industry and employment in the secondary industry, and the sectoral form was characterized by axial separation along the river and

the main road. In 2010, employment in the tertiary industry was concentrated in urban centers, while the secondary industry showed sectoral spatial characteristics. In the 1990s, the transformation of traditional industries was in its infancy, and its association with urban landscape spatial heterogeneity was relatively low. In the 2000s, the effect of industrial restructuring was remarkable. At this stage, the socialist market economy was promoted in an all-around way, and the dual-track development of planned industrial restructuring and market-oriented industrial clusters promoted the rapid construction of industrial parks. The industrial park attracts capital and employment concentration, which further promotes the development of urban space. While transforming traditional secondary industries into high-tech and high-value-added ones, they have also shifted from being dispersed in the center of the city to being concentrated in the periphery of the city. This has an impact on the formation of a sectoral pattern of urban land. The transformation and spatial transfer of the secondary industry are accompanied by the expansion of the tertiary industry in the urban center.

The elderly population is also a significant factor related to the growth of urban space. This factor reflects the family size closely related to it. The weight of big-size households was higher in the 1990s, while that of small households increased significantly in the 2000s.

In contrast to 1990, the population with a higher-income occupation became a significant factor associating with urban land growth in the 2000s. In 1990, the nonagricultural industry workers had a high school education background, and the contribution of the population with a higher education background was relatively low. In 2000, the population with higher education backgrounds was linked to tertiary industry employment. With the expansion of higher education in the 2000s, the contribution of this population to the urban growth pattern was outstanding.

Urban spatial patterns reflect social and economic policies on the physical landscape. For example, the industrial upgrading policy explains the relocation of traditional industries as well as the cluster of industrial parks. The higher educated population is, on the one hand, the product of China's higher education reform, while it is also the result of Wuhan's local higher educated talent attraction as a city where high-tech industries and universities are gathered. Further, the elderly population and reduced family size are a manifestation of the long-term implementation of China's population policy.

Compared with 1990 and 2000, the floating population, a key part of urban society, became a social dimension with a higher contribution in 2010. However, its intervention in urban land use is not significant. From a comparative perspective, the links between influx population and urban patch irregularity are much weaker in the second-tier city than in the first-tier ones. From 1990 to 2000, the influence of social factors in China's second-tier cities on the shape of urban land use does not reflect the spatial heterogeneity at the neighborhood level. The spatial nonstationary in second-tier cities only manifested in 2010.

4.3. Illustration on Urban Growth Simulation and Management

By portraying how the physical landscape relates to social factors through spatial and longitudinal perspectives, the urban reshaping process is disclosed.

The population in the urban area has been agglomerating during the two decades, though the city center became less dense due to the diversification of the social and economic division and the market-oriented development, as well as the specialization of urban spatial functional zoning. As policies unlock to attract people in big cities, like the loosening of household registration and the attraction of a higher-educated population, the urban growth is expected to present a continuous agglomeration. On the other hand, although the population density in the central areas of the second-tier city is declining, land infill development continues, which is linked with the agglomeration of the tertiary industry. The population density is in the growing stage among the peripheral areas of the city center. This social and economic agglomeration explains the differences between

spatial growth patterns. Multi-mode development needs to be considered concurrently to respond to socio-economic development to better serve people.

Social factors' interpretations toward urban landscape metrics offer a potentially powerful approach to forecast urban spatial patterns. Thus, a following up with social landscape transformations is essential for introducing the social dimensions as important predictors to simulate urban space. The study also provides a reference for urban managers considering different socio-economic policies' scenarios when configuring urban landscape. For example, policies related to the household registration system, real estate market, and large projects that orient industrial clustering should be considered.

Different scenario-based social dimensions and social landscapes are expected to result in different urban land growth patterns. In most urban areas, impervious surface expansion dominates the spatial growth, though based on ecological-friendly people-centered development mode, redevelopment and improvement have been outstanding in the city center. The expansion of the urban center accelerated in the second-tier city during the 2000s but compared with first-tier cities, it lags in stages [12]. Given the prohibitive cost of the reversion from impervious surfaces to permeable ones, governmental dominance is very essential during the process rather than the market hand. The improvement is accompanying traditional industry removal or community upgrading, which further benefit residents with a better environment.

5. Conclusions

The study takes a major step in identifying urban land growth patterns and the relationships with social factors, from spatial and longitudinal perspectives. We conclude that urban land growth is the physical manifestation of a set of interrelated socioeconomic factors. It provides a social perspective for urban land growth, through the social dimensions' interpretation of physical landscape distribution and evolution. The examination of this relationship provides a social perspective for understanding the process of urban growth. At the same time, the social attributes of the physical landscape are expressed through visualization of the relationships.

In this case, urban land patterns are significantly associated with the nonagricultural industry, the highly educated, and the aging population. Industrial removal and upgrading present a crucial association with urban land growth patterns, with which education background levelling up is accompanied. The aging is reflected in the urban land growth with the implication of big-size families during the former decade and small-size families in the latter. From a spatial pattern perspective, the social links with the urban land growth are conceptualized as a concentric form in 1990, a sectoral form along the river and road axis in 2000 and a mixed pattern with concentric and sectoral in 2010.

The relationships portray that China's second-tier city's improvement of the urban landscape is with industry upgrading and ecological environment bettering. While the government's strategies do signal ecologically friendly redevelopments, cities are still being challenged with the negative ecological impacts brought by the cost of vegetation area and wetland. The social-physical links implicate that social dynamics should be emphasized in the configuration of urban land as well as the permeable surface.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The remote sensing images are from open source on the U.S. Geological Survey (USGS) website. But the census data are not publicly available due to the restriction of confidentiality agreement.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

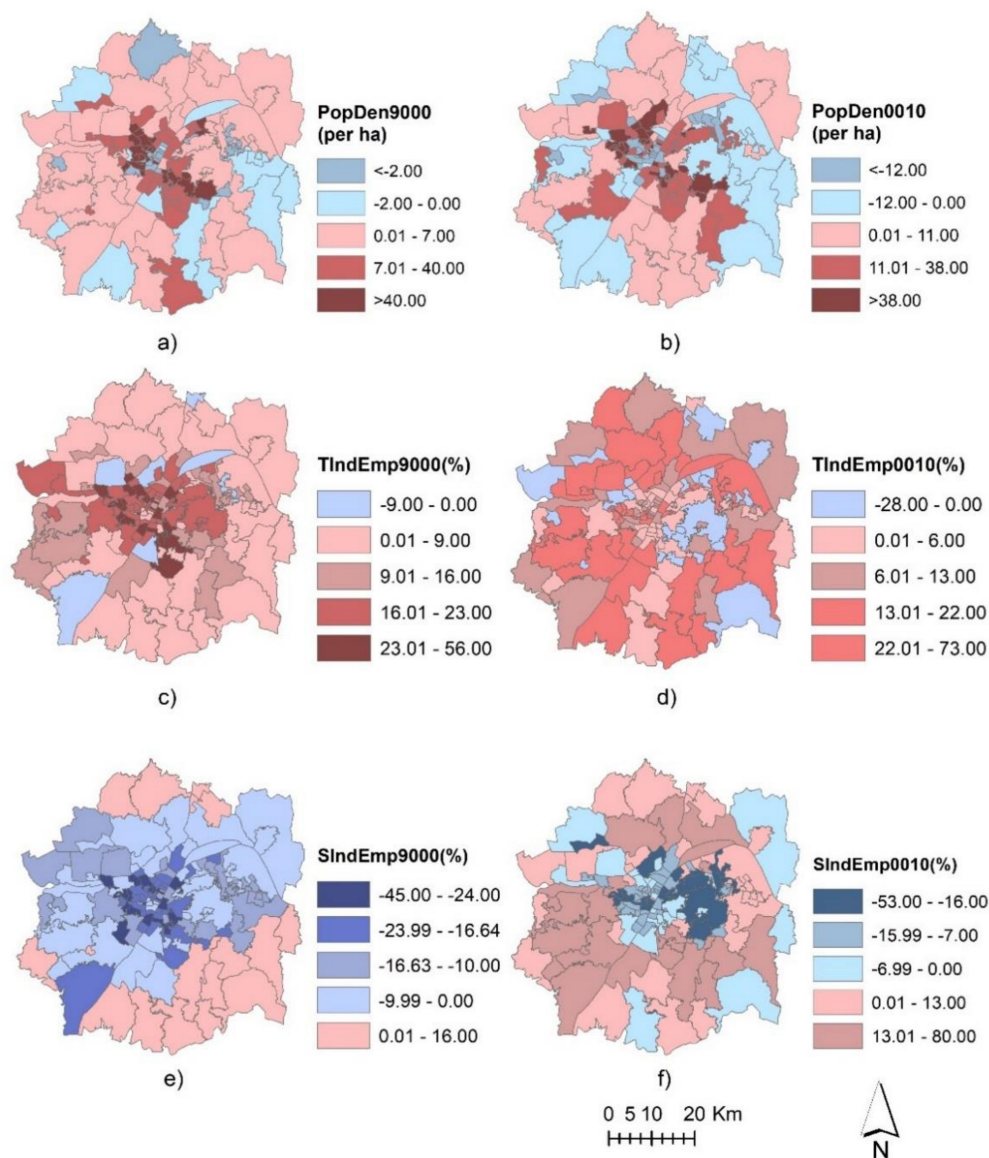


Figure A1. Population density changes. (a) Change of population density between 1990 and 2000; (b) Change of population density between 2000 and 2010; (c) Change of tertiary industry employment between 1990 and 2000; (d) Change of tertiary industry employment between 2000 and 2010; (e) Change of secondary industry employment between 1990 and 2000; (f) Change of secondary industry employment between 2000 and 2010. The population density is decreasing in the city center (a,b). The industrial upgrading has significantly reshaped the urban center. The employment of the tertiary industry increased significantly in the urban center in the 1990s (c), and in the periphery of the urban center in the 2000s (d). The employment of the secondary industry shows a continuous decline in the urban center (e) and a significant increase in the periphery of the urban center in the 2000s (f).

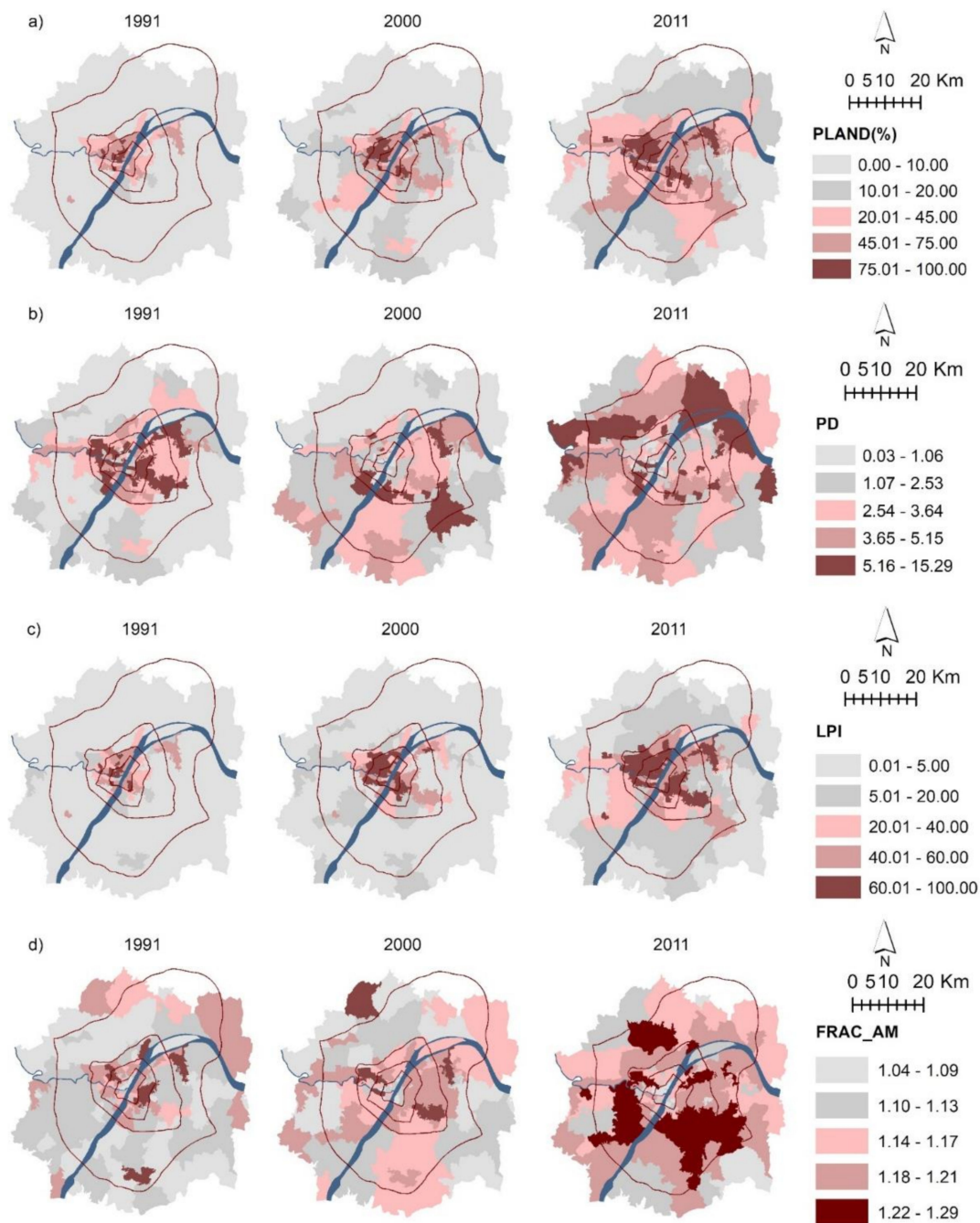


Figure A2. Urban land metrics maps. (a) Maps of PLAND; (b) Maps of PD; (c) Maps of LPI; (d) Maps of FRAC_AM. The dynamics of the urban land distribution present that the urban land first expands along rivers and the main road axis, then toward others. The expansion is mostly defined by outward and multidirectional characteristics. In the 1990s, the urban space expansion concentrated in the southwest and the east. During the 2000s, however, impervious surfaces expanded to the west and the northeast to the Yangtze River. In 2011, urban land presents distributions in various directions.

Appendix B. Process of Urban Land Extraction

In this study, land cover is extracted based on the I–V–W (Impervious surface–vegetated area–water area) urban model. Surface reflectance images, top-of-atmosphere reflectance (TOA) images, and bright temperature (BT) images converted from the thermal band are collected, to better fit the requirement of band math further used for the band math is employed for the extraction. The water area was first masked using the modified normalized difference water index (MNDWI) [37].

To extract impervious surfaces, we proposed a Modified Biophysical Composition Index (MBCI), based on the Biophysical Composition Index (BCI) [38]. The BCI is for better distinguishing urban land and bare soil. It is computed based on Tasseled Cap Transformation (TCT), particularly relying on the first three components, which represent brightness, greenness, and wetness. MBCI introduces bright temperatures (converted from the thermal band) into the BCI equation. To ensure that MBCI is more accurate in identifying impervious surfaces, we compared the separability of MBCI and BCI based on training samples, for which we selected 207 pixels for urban lands (impervious surface) and 611 for the permeable surface in 2011, 207 and 661 in 2000, and 207 and 661 in 1991. The comparison shows that MBCI has more significant separability than BCI. Based on the training samples, the threshold value for impervious is determined as -0.05 , -0.25 , and -0.25 for 1991, 2000, and 2011, respectively. The impervious surfaces are then drawn according to the MBCI threshold.

In detail, the formulas for MNDWI and MBCI are as follows.

$$\text{MNDWI} = (\text{Green} - \text{MIR}) / (\text{Green} + \text{MIR}) \quad (\text{A1})$$

Surface reflectance data is used for MNDWI computation, where Green and MIR represent the green band (Band 2) and the middle infrared band (Band 5), respectively.

$$\text{BCI} = [(B + W)/2 - G] / [(B + W)/2 + G] \quad (\text{A2})$$

for which TOA images are used for the computation and where B, W, and G stand for [0, 1] standardized brightness, wetness, and greenness are calculated using the equations based on the first, second, and third principal components of Tasseled Cap Transformation (TCT), respectively.

$$B = (\text{TC1} - \text{TC}_{\min}) / (\text{TC1}_{\max} - \text{TC1}_{\min}) \quad (\text{A3})$$

$$G = (\text{TC2} - \text{TC2}_{\min}) / (\text{TC2}_{\max} - \text{TC2}_{\min}) \quad (\text{A4})$$

$$W = (\text{TC3} - \text{TC3}_{\min}) / (\text{TC3}_{\max} - \text{TC3}_{\min}) \quad (\text{A5})$$

where TC1, TC2, TC3 are the first three TC components; $\text{TC}_{i_{\min}}$ and $\text{TC}_{i_{\max}}$ are the minimum and maximum values of the i th ($i = 1, 2, 3$) TC components, respectively. The brightness, greenness, and wetness surfaces area computation using the TCT coefficients of Landsat 5 TM data are proposed by Crist et al. (1986) [39] (Table A1).

Table A1. Landsat-5 TM Tasseled Cap Coefficients [39].

Band Feature	TM1	TM2	TM3	TM4	TM5	TM7
Brightness	0.2909	0.2493	0.4806	0.5568	0.4438	0.1706
Greenness	−0.2728	−0.2174	−0.5508	0.7221	0.0733	−0.1648
Wetness	0.1446	0.1761	0.3322	0.3396	−0.6210	−0.4186

$$\text{MBCI} = [(BT + B + W)/3 - G] / [(BT + B + W)/3 + G] \quad (\text{A6})$$

TOA and BT images are used for MBCI computation, where BT is [0, 1] standardized bright temperature extracted from the thermal band, which is computed as:

$$BT = (BT_0 - BT_{\min}) / (BT_{\max} - BT_{\min}) \quad (7)$$

where BT_0 , $BT_{\min}$, $BT_{\max}$ are the observed, minimum, and maximum values of the bright temperature, respectively.

Appendix C

Table A2. Coefficient of Pearson correlation between different metrics (example in 2010).

	TA	PLAND	PD	LPI	TE	ED
TA	1	−0.258 **	0.087	−0.317 **	0.854 **	0.205 *
PLAND	−0.258 **	1	−0.405 **	0.987 **	−0.563 **	0.024
PD	0.087	−0.405 **	1	−0.475 **	0.288 **	0.601 **
LPI	−0.317 **	0.987 **	−0.475 **	1	−0.610 **	−0.064
FRAC_AM	0.653 **	−0.252 **	0.326 **	−0.317 **	0.533 **	0.660 **
	LSI	FRAC_AM	PARA_AM	CONTIG_AM	COHESION	AI
CA	0.647 **	0.653 **	−0.042	0.042	−0.168	−0.059
PLAND	−0.757 **	−0.252 **	−0.739 **	0.744 **	0.423 **	0.791 **
PD	0.416 **	0.326 **	0.433 **	−0.436 **	−0.232 **	−0.435 **
LPI	−0.797 **	−0.317 **	−0.714 **	0.719 **	0.425 **	0.775 **
FRAC_AM	0.521 **	1	−0.013	0.011	−0.309 **	−0.107

Note: *, ** indicates $p < 0.10$, < 0.05 , < 0.01 , respectively. TA: Total (Class) Area, PLAND: Percentage of Landscape, PD: Patch Density, LPI: Largest Patch Index, TE: Total Edge, ED: Edge Density, LSI: Landscape Shape Index, FRAC: Fractal Dimension Index, PARA: Perimeter-Area Ratio Distribution, CONTIG: Contiguity Index Distribution, COHESION: Patch Cohesion Index, AI: Aggregation Index. _AM: Area weighted mean.

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