Ecological Indicators 82 (2017) 50–60

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Urbanization impact on landscape patterns in Beijing City, China: A spatial heterogeneity perspective

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A R T I C L E I N F O

Keywords:
Landscape metrics;Urbanization mode
GWR
Compact green city Beijing City, China

A B S T R A C T

The temporal and spatial characteristics of landscape pattern change can reflect the spatial impact of urbanization on the ecological environment. Studying the relationship between urbanization and landscape patterns can provide supports for urban ecological management. Previous studies have examined the quantitative relationship between the social economy and landscape patterns of an entire region, but have not considered the spatial non-stability of this relationship. In this study, we characterized the landscape patterns in Beijing City, China during 2000 and 2010 using four landscape metrics, i.e. patch density (PD), edge density (ED), Shannon's diversity index (SHDI) and the aggregation index (AI). Geographically weighted regression (GWR) was employed to identify the spatial heterogeneity and evolution characteristics of the relationship between the urbanization of population density (POP), gross domestic production (GDP) and nighttime lighting (NTL), and landscape patterns. The evolution of urban landscape patterns indicated a decentralized, aggregated, and fragmented change from the downtown to the suburb and outer suburb. During the 10-year period, the average PD in the downtown increased by 100.6%, and the increase of AI in the suburb was the largest. The PD, ED and SHDI increased by different degrees in the outer suburb. The influences of different urbanization modes on landscape patterns were also different. Infilling mode made the landscape patterns more regular and integrated. The landscape was more broken and complicated under the edge-expanding mode, and the leapfrog mode made PD and SHDI increase slightly. In the relationship interpretation, GWR effectively identified the spatial heterogeneity, and improved the explanatory ability compared to ordinary least squares (OLS). The most intense response to urbanization was the forest landscape and the forest-cultivated land ecotone in the northwest of Beijing City, indicating that this region was ecologically fragile. The population density in the urbanization index had a direct effect on landscape patterns, while the PD affected by urbanization was greater than the shape, aggregation and diversity index. Affected by development policy, urban planning and other factors, the explanation degree of social economy to landscape patterns decreased in 2010. GWR is an effective method for quantifying the spatial differentiation characteristics of urbanization impacts on landscape patterns, which can provide more spatial information and decision criteria for the green development of a compact city.

1. Introduction

Issued by the Habitat III conference of cities on 20 October 2016, the New Urban Agenda pointed out by the middle of the century the world's urban population was expected to nearly double. This means that four of every five people will be living in towns or cities, making urbanization one of the most transformative trends in 21st century. Populations and socioeconomic activities are increasingly concentrated in cities, posing huge sustainability challenges in terms of housing, infrastructure, food security and natural resources management. Urbanization includes the changes of population, industrial structure and landscape types (Zhang and Su, 2016). The change of landscape types and proportions has been characterized by the conversion of ecological land such as forest land and grassland into agricultural land and construction land, and in some areas the agricultural land has been largely transformed into construction land (Weng, 2007; Liu et al., 2011). At the same time, the landscape patterns in rapidly urbanizing areas have presented a remarkable, highly fragmented feature. The single, continuous natural patches have become a complex, heterogeneous and discontinuous mosaics (Liu et al., 2014). The fragmented landscape hinders the spread of material and energy flow (Kreuter et al., 2001), and changes the regional energy, material and nutrient cycling process (McDonnell and Pickett, 1990). Thus, a fragmented landscape will affect the function and services of regional ecosystems

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http://dx.doi.org/10.1016/j.ecolind.2017.06.032
Received 23 December 2016; Received in revised form 8 May 2017; Accepted 16 June 2017

(Alberti, 2005; Estoque and Murayama, 2012; Peng et al., 2016b), resulting in a series of ecological and environmental problems (Li et al., 2010a; Jacobs, 2011), such as biodiversity loss, urban heat island effect, environmental pollution, soil erosion and so on (Wu, 2010; Schneiders et al., 2012; He et al., 2014; Zhou et al., 2014).

Understanding and solving the urbanization problems from the perspective of landscape pattern is one of the research hotpots in ecology and geography (Zhou et al., 2011; Shrestha et al., 2012; Estoque and Murayama, 2016). Landscape patterns can be quantified by landscape metrics, which are one of key tools to monitor, assess and manage the landscape (Li and Wu, 2004). The ecological consequences of urbanization can be understood by applying landscape metrics to describe and analyze the dynamic changes of regional landscape (Li et al., 2010b; Peng et al., 2016c; Schwoertzig et al., 2016). Landscape metrics have been extensively used for quantifying landscape patterns and their change. For example, Liu and Yang (2015) used landscape metrics to examine the size, pattern and nature of land use changes, demonstrating that landscape metrics could reveal the spatial characteristics and underlying processes of urban expansion. Kane et al. (2014) analyzed urban expansion based on landscape area, fragmentation, shape complexity and diversity. Su et al. (2014) analyzed the different responses of agricultural landscapes to urbanization by using urbanization indicators and landscape metrics. However, the changes of landscape patterns are spatially heterogeneous, and the evolution do not always move towards scattered and irregular forms. Different urban expansion modes and land use types will lead to different changes of landscape patterns.

Considerable studies have explored the relationship between landscape patterns and urbanization. The factors driving landscape change are mainly classified as biophysical and socioeconomic ones (Serra et al., 2008; Du et al., 2014; Maimaitijiang et al., 2015). Generally speaking, human activity can be reflected by socioeconomic factors, and nighttime light is the major factor in shaping the landscape. The soils, climate and other biophysical factors can also significantly affect the land use. However, because socioeconomic data are limited by statistical units, most of the studies have been conducted at city or county scale, and could not accurately reveal the spatial differentiation of the impact of socio-economic factors on landscape patterns (Ma et al., 2008). Many statistical models have been applied to describe the relationship between urbanization and landscape patterns, such as multiple regression and stepwise regression based on ordinary least squares (OLS) (Bagan and Yamagata, 2012). OLS model is a global parameter estimation technique (Zhang et al., 2009), based on two assumptions: (1) the model residuals do not exhibit spatial autocorrelation, and (2) the random disturbances have equal variance. When OLS model is applied to spatial data, these two laws are violated because of the non-stationary spatial distribution of natural data (land cover, and landscape metrics) and socioeconomic data (GDP and population density). Thus, OLS model only reflects global information and lacks the ability to explain the local relations. Relationships at different positions will be hidden. In addition, because of the similar geographical environment and the human disturbance, the landscape features of adjacent areas are more consistent than distant areas, and the landscape metrics will also exhibit spatial autocorrelation. Therefore, when exploring the relationship between landscape patterns and urbanization, the performance and interpretation power of OLS model is restricted. For the above reasons, OLS is no longer considered applicable to the study of relationships between landscape evolution and its driving forces.

Geographically weighted regression (GWR) reflects the spatial characteristics of relationships by constructing local regression equations at each grid in the study area, thereby avoiding the problems of spatial autocorrelation, heterogeneity, and non-stationarity (Brunsdon et al., 1996; Su et al., 2012; Hu et al., 2015; Tenerelli et al., 2016). The GWR model can compute the regression coefficients for each location to describe a spatial relationship precisely, and the distribution of residuals of GWR is more random in space than that of OLS (Foody, 2003). GWR has been widely used in spatial correlation studies (Su et al., 2016, 2017). For example, Tu and Xia (2008) used GWR to explore the spatial relationship between land use and water quality under the background of urbanization. Gao and Li (2011) applied GWR to explore the spatial non-stationary relationship between urban surface temperature and environmental variables, and demonstrated that GWR was an effective method for solving the geo-spatial non-stationarity problem. Pribadi and Pauleit (2016) studied the relationship between peri-urban agriculture and urban socioeconomic system at village and sub-district scales, and showed that GWR could identify the different impacts of economic activity, poverty and food security in various regions.

In the first decade of the 21st century, Beijing City experienced rapid urbanization (Peng et al., 2016a), and landscape patterns changed significantly. Land use in Beijing City is diverse, including highly urbanized areas, suburbs experiencing rapid urbanization, and well-preserved forest lands in the northwest of the city. The differences in urban development levels and terrain factors will inevitably cause spatial differences in the driving forces, so GWR is well-suited to examining the relationships between landscape changes and urbanization. The purpose of this paper is to explore the spatial heterogeneity of urbanization impact on landscape patterns in Beijing City using GWR. In particular, the main research objectives are as follows: (1) to use landscape metrics to identify the characteristics of landscape patterns in Beijing City during 2000 and 2010; (2) to explore the spatial non-stationarity of urbanization impact on landscape patterns; and (3) to compare the impacts of different urbanization factors on landscape patterns.

2. Methodology

2.1. Study area and data source

Beijing City is located in the north of the North China Plain at longitudes from 115°25′E to 117°30′E, and latitudes from 39°28′N to 41°05′N, with a total area of approximately 16,400 km^2. The elevation of terrain in Beijing City is high in the northwest and low in the southeast. Mountain area accounts for about 62% of the total area at elevations between 1000 m and 1500 m, and plain area is flat and open, accounting for about 38% of the total area at elevations between 20 m and 60 m. Beijing City is in a typical northern temperature zone, with sub-humid continental monsoon climate. The annual average temperature in Beijing City is 12.3 °C, and annual precipitation is 572 mm. Beijing City has 16 districts including Dongcheng, Xicheng, Haidian, Chaoyang, Fengtai, Shijingshan, Mentougou, Fangshan, Tongzhou, Shunyi, Changping, Daxing, Huairou, Pinggu, Yanqing and Miyun. According to urban and rural differences and topographical features, Beijing City can be divided into five urban development zones (Fig. 1): (1) Downtown, i.e. the inner city, including Dongcheng and Xicheng District; (2) Suburb, including Haidian, Chaoyang, Fengtai and Shijingshan District; (3) Outer suburb (in the plain), including Tongzhou, Shunyi and Daxing District; (4) Outer suburb (in semi-mountainous areas), including Pinggu, Changping and Fangshan District; and (5) Outer suburb (in mountainous areas), including Huairou, Mentougou, Yanqing and Miyun District.

Beijing city has a mosaic of complex landscape types. Under the comprehensive influence of the natural environment and social economy, urban construction land, suburban cultivated land and outer suburban ecological land in Beijing City exhibit a circular structure with the downtown as the core, and this structure is also consistent with the terrain of Beijing City. Construction land accounts for 20.92% of the total area in Beijing City. The suburb plain areas are dominated by cultivated land, and most of the mountainous areas in the northwest outer suburb are forest land, accounting for 13.93% and 46.18% of the total area of Beijing City, respectively in 2010.

Beijing City is the center of China's political activity, culture, science

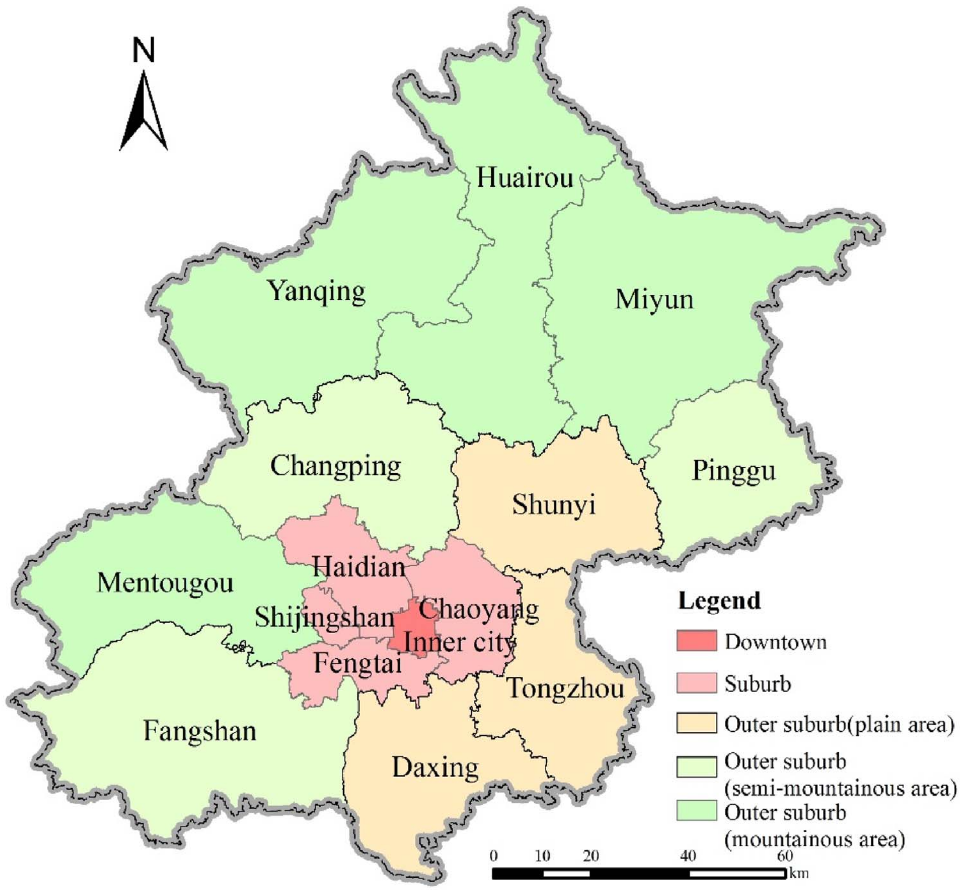

Fig. 1. Beijing City administrative divisions and five types of urban development zones.

and education. The first decade of the 21st century was an important period for Beijing City to implement modernization. In 2010, the resident population in Beijing City was 19.619 million, and the regional GDP reached 1377.79 billion yuan, an increase of 10.2% over 2009 according to the Beijing Statistical Yearbook. During 2000–2010, urban and rural construction land increased from 16.38% to 20.92% of the total area in Beijing City. Based on these significant changes, the period of our study was chosen in 2000–2010, which witnessed the typical stage of urbanization in Beijing City.

Land use and land cover (LULC) data for Beijing City in 2000 and 2010 were retrieved from the database of global surface coverage at a spatial resolution of 30 m (http://www.globeland30.org). Land use types are divided into eight categories: cultivated land, forest land, grassland, shrubland, wetland, water body, construction land, and bare land (Fig. 2).

The socio-economic data was obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn). The values of each raster are GDP and population per km^2, which are based on the county-wide GDP and demographic data, taking into account the geographical differentiation of the natural elements, and are generated at a point using spatial interpolation. The data set provides a finer resolution than administrative data sets for units-based geographical research. Human activity intensity was measured using the US government's Defense Meteorological Satellite Program Operational Linescan System Nighttime Lights remote sensing imagery (http://ngdc.noaa.gov/eog/dmsp.html). The data set had a 1 × 1 km spatial resolution and was corrected for inter-calibration and intra-annual composition according to the method of Liu et al. (2012).

2.2. Landscape metrics selection

Guided by previous study (Su et al., 2011), four landscape metrics with low correlation at landscape level were selected: patch density (PD), edge density (ED), Shannon's diversity index (SHDI), and aggregation index (AI). The ecological connotations of these landscape metrics are given by Peng et al. (2010) and Cushman et al. (2008). These metrics can reflect the composition, shape of the patches and aggregation of landscape in Beijing City. Among them, PD is the number of patches per spatial unit, reflecting the degree of landscape fragmentation. ED is calculated by dividing the total length of the patch boundaries by the total area, and increases when the patch shapes become irregular in the landscape. SHDI reflects the landscape heterogeneity, and is sensitive to the non-equilibrium distribution of patch types in the landscape. When there is only one patch type in the landscape, SHDI is equal to 0; and when the number of patch types increases or the area ratio of various patches is similar, SHDI increases accordingly. AI refers to the degree of non-randomness or aggregation of different patch types and the spatial configuration characteristics of landscape components.

In the analysis, the LULC maps were divided into 3 km × 3 km grids using the Create Fishnet tool in ArcGIS 10.2. The metrics in landscape level for each grid were calculated using the Fragstats 4.0 software (available from http://www.umass.edu/landeco/research/fragstats/fragstats.html).

2.3. Regression analysis

GWR model is an improvement on OLS model, allowing parameters to be locally estimated. GWR is able to generate local parameters to reflect spatial differentiation, including local R^2, local model residuals and local coefficients. Therefore, in the parameter estimation, complex

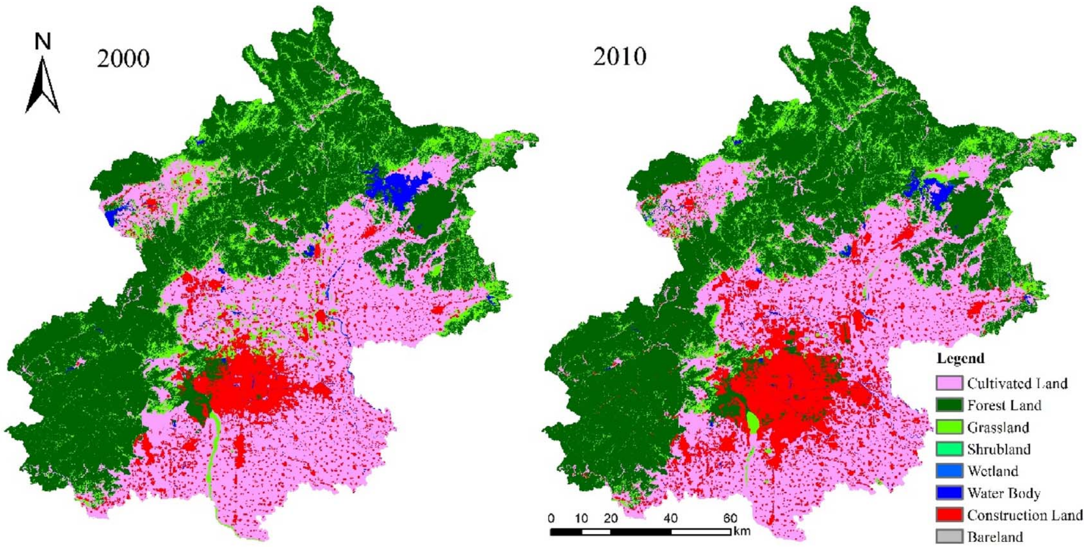

Fig. 2. Land use and land cover during 2000–2010 in Beijing City.

spatial differentiation can be identified, mapped and simulated. In contrast, OLS is a global regression model and parameter estimates are consistent across the entire study area.

OLS model can be expressed as follows (Dobson, 1990):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{1}$$

where x_i and y are the independent and dependent variables, respectively; β_0 and β_i represent the intercept and coefficient, respectively; k indicates the number of independent variables, and $\mathcal{E}$ is the error term.

GWR model is expressed as follows (Fotheringham et al., 2002):

$$y_j = \beta_0(u_j, v_j) + \sum_{i=1}^{k} \beta_i(u_j, v_j)x_{ij} + \varepsilon_j \tag{2}$$

where u_j and v_j are the spatial coordinates of the sample point j; $\beta_0(u_j, v_j)$ is the intercept at the location j; $\beta_i(u_j, v_j)$ is the local estimated coefficient of the independent variable x_{ij}; and ε_j is the error term.

GWR uses a distance-decay function to determine the scope of spatial dependence. The weights are spatially variable, and the nearer units produce stronger influence. Gaussian distance decay was used to express the weight function:

$$w_{ij} = \exp(-d_{ij}{}^2/b^2) \tag{3}$$

where w_{ij} is the weight of observation point j relative to its neighborhood point i; d_{ij} is the distance between observation points i and j; and b denotes the kernel function bandwidth. When the distance between the observation points is greater than the kernel bandwidth, the weight is close to 0; conversely, the weight value is 1 when the distance between the observation points is 0. In the GWR model, there are two types of kernel function: the fixed and the adaptive. Because this study used grid data, for which the density of sampling points in the space is uniform, the fixed-kernel bandwidth was chosen. Determination of the optimal bandwidth was based on minimizing the corrected Akaike Information Criterion (AIC).

Each of the four landscape metrics was used as the dependent variable, and POP, GDP and NTL were used as the explanatory variables. The OLS and GWR analyses were performed using the OLS and GWR tools in ArcGIS10.2. Before the regressions, the landscape metrics and socioeconomic data were normalized using the min-max standardized method.

The performance of the OLS and GWR models was compared using two statistics: adjusted R^2 and AIC (Yu, 2006; Clement et al., 2009). The higher the adjusted R^2 is, the stronger the ability of the independent variables interprets the dependent variables. Likewise, the lower the AIC value is, the better the model describes the observed data. Furthermore, to compare the ability of OLS and GWR to address the spatial autocorrelation of variables, the global Moran's I was calculated for the residuals of the two models. The global Moran's I reflects the spatial similarity of the spatial adjacency or neighboring units, and can detect the spatial autocorrelation of the model residuals. Moran's I values range from -1 to 1; values closer to -1 indicate the existence of negative spatial autocorrelation, values closer to 1 indicate the existence of positive spatial autocorrelation, and values closer to 0 indicate that there is little or no spatial autocorrelation. If the distribution of the residuals obtained from the regression model has obvious spatial autocorrelation, the assumption that residuals follow a random distribution is violated. The Moran's I of the two models' residuals was counted and compared using the spatial autocorrelation tool in ArcGIS 10.2.

3. Results

3.1. Change of landscape patterns

The change ratios of landscape metrics during 2000 and 2010 were calculated, using the quantile grading method to map the changes. As shown in Fig. 3, landscape patterns in Beijing City changed greatly during the process of urbanization. Spatial differentiation features are obvious for all landscape metrics: (1) PD significantly decreased in the suburb and slightly decreased in the outer suburb (both semi-mountainous area and mountainous area). In the downtown and outer suburb (plain area), PD increased significantly. The significant increase of PD in the downtown area was due to the increase of the greening degree in this area. The new green space broke the original single construction land. As a result, the number of landscape patches increased. In Tongzhou and Daxing District, the increase of PD was mainly caused by the transformation from cultivated land to construction land, which made the whole landscape more fragmented. (2) Although ED change in the northern outer suburbs was not obvious with the change ratio between -0.05 and 0.05, the inner city and suburban areas experienced obvious ED changes. There was a concentric circular increase-decrease-increase pattern from the center of Beijing City to the outskirts. For example, ED in the downtown had a small increase, with significant decreasing in Fengtai, Haidian and Chaoyang District. In Daxing and Tongzhou District, ED showed a large-scale, high-intensity increase. (3) Although there was an increase in a small area of the downtown, SHDI significantly decreased in the surrounding areas. A marked increase also occurred in Daxing and Tongzhou District. The landscape types in

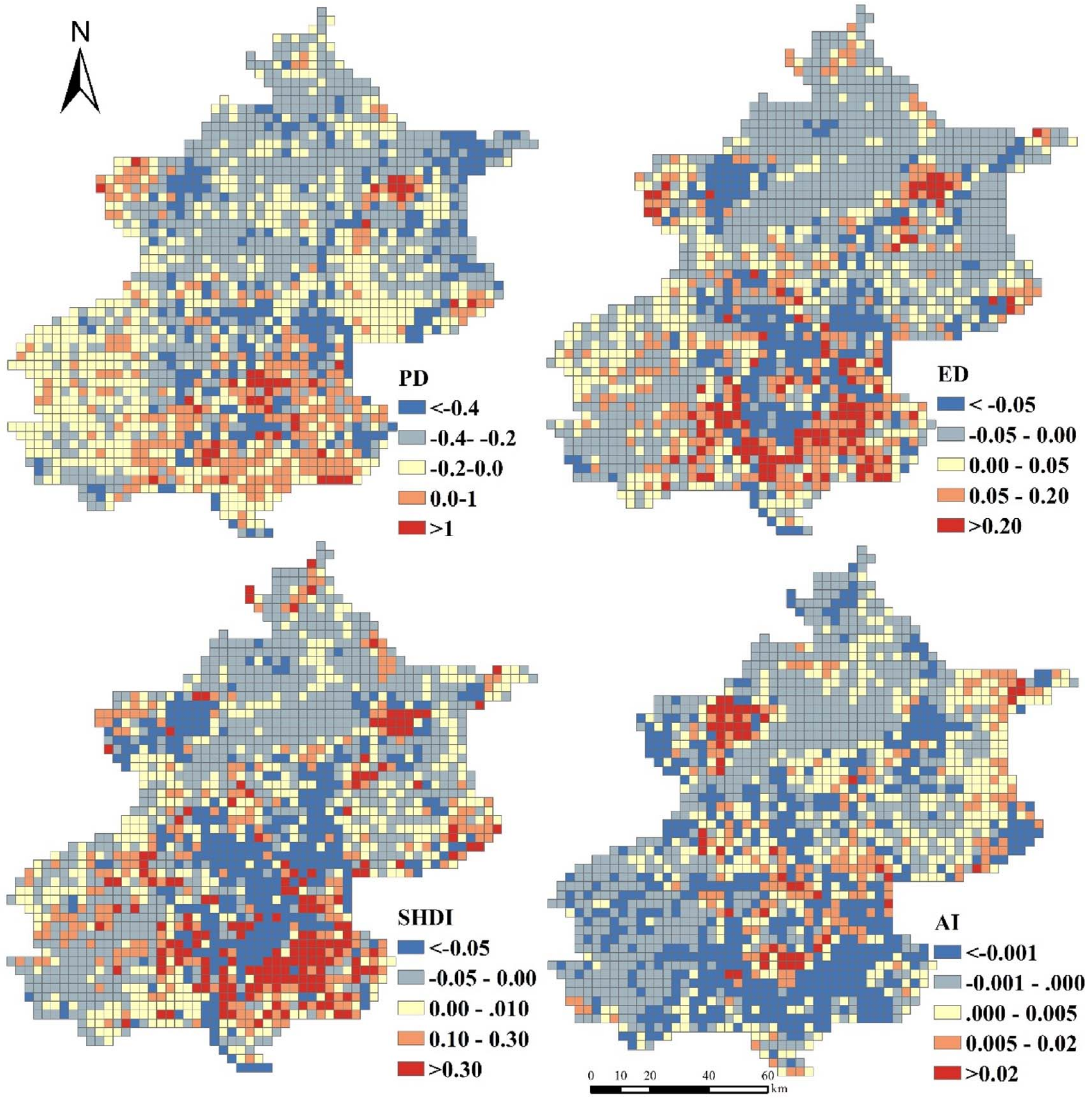

Fig. 3. Change ratio of four landscape metrics in Beijing City during 2000–2010.

Daxing and Tongzhou District remained single cultivated land and construction land, and the increasing SHDI indicated that the areas of two landscape types were evenly distributed in these regions. (4) AI increased significantly in the suburban areas and in the central area of Yanqing District. The further filling of construction land, and the continuous filling of cultivated land, replacing the original cultivated land and grassland, respectively, caused this change. The significant AI decrease occurred in the west of Tongzhou District and the north of Daxing District, while AI in remaining areas did not change observably.

As for the evolutional characteristics, the four landscape metrics corresponded to each other in space. The most obvious changes occurred in the southeast of Beijing City. At the same time, landscape change in the central urban and the suburban behaved in opposite directions. Among the four metrics, the change ratio of PD was the largest, ranging from −90% to 500%. The change ratio of AI was the smallest, ranging from −9% to 7%.

The direct cause of landscape patterns change in Beijing City is the urbanization of land use. We can compare the changes of landscape patterns from five urban development zones. As shown in Table 1, the downtown's urbanization level was already high in 2000. Along with the further development of urbanization during 2000–2010, urban green space such as parks was added and diluted the high coverage of artificial surface. As a result, PD increased by 100%, and ED increased by 1.6%, while SHDI and AI decreased slightly in the downtown. In 2000, landscape in the suburban was characterized by construction land and cultivated land. Driven by the urbanization, grassland and cultivated land in the suburbs were replaced by construction land, and the landscape agglomeration degree exhibited the largest increase. In the outer suburban plain areas, cultivated land accounted for the vast majority of the total area in 2000, almost reaching 82%. The urban expansion drove the conversion of cultivated land to construction land, which made the landscape more fragmented with irregular patch shape. As a result, PD, ED and SHDI increased by 2.6%, 5.1% and 18.2%, respectively. In the outer suburban semi-mountainous areas, the land use types were originally dominated by forest land and cultivated land. During 2000–2010, construction land expanded with the corresponding loss of cultivated land and grassland, which reduced the PD by 14.5% and made the whole landscape more agglomerated and regular. In the outer suburban mountainous area, the forest land was well preserved during the 10 years and there was no obvious change of landscape patterns. However, the amount of water body and wetland in Miyun District and Yanqing District were greatly reduced by the impact of urbanization (He et al., 2011). Along with the conversion of water body and wetland to grassland and cultivated land, one big patch was replaced by several small patches, leading to the increasing of PD.

As shown in Fig. 4, different urbanization modes also affected the

Table 1
Area proportion of main land use types in five urban development zones during 2000–2010.

Land use types	Year	Downtown	Suburb	Outer suburb(plain area)	Outer suburb(semi-mountainous area)	Outer suburb(mountainous area)
Construction land	2000	92.78%	44.51%	14.29%	8.17%	2.04%
	2010	93.90%	57.36%	23.98%	11.43%	2.84%
Cultivated land	2000	1.92%	35.29%	81.91%	35.27%	16.37%
	2010	0.01%	21.30%	73.58%	34.77%	17.99%
Forest land	2000	2.23%	13.00%	0.46%	46.46%	64.96%
	2010	3.31%	16.21%	0.79%	46.62%	65.53%
Water body	2000	3.06%	0.90%	0.78%	0.51%	2.56%
	2010	2.78%	0.86%	0.66%	0.45%	1.27%

evolution of landscape patterns in Beijing City. Three urbanization modes have been widely discussed in previous literature: infilling, edge-expansion and leapfrog development (Liu et al., 2010; Li et al., 2013a,b). All three urbanization modes are apparent in Beijing City. The infilling mode accounted for 8.32% of the new construction land, while the edge-expansion mode accounted for 78.99%, with the leapfrog mode for the other 12.69%. Thus, the edge-expansion mode was dominant in Beijing City. The infilling mode was mainly concentrated in the inner city, and moved to four districts in the suburbs along with urban expansion. The urbanization process was characterized by further connection of construction land, which made the PD and SHDI decrease and the landscape patches become more regular and aggregated. Edge-expansion mainly occurred in the outer suburbs such as Daxing, Tongzhou, Shunyi and Changping District (Peng et al., 2016d). The cultivated land was transformed into construction land, and urbanization led to the increase of landscape diversity, fragmentation and shape complexity. The leapfrog mode was prevalent far away from the downtown area and located in the semi-mountainous and mountainous areas. Spatial distributions of these sites were relatively scattered. In Fangshan and Yanqing District, a small part of this region was detected to experience the leapfrog mode. New construction land was found in the original forest land and grassland, leading to a slight increase of PD and SHDI.

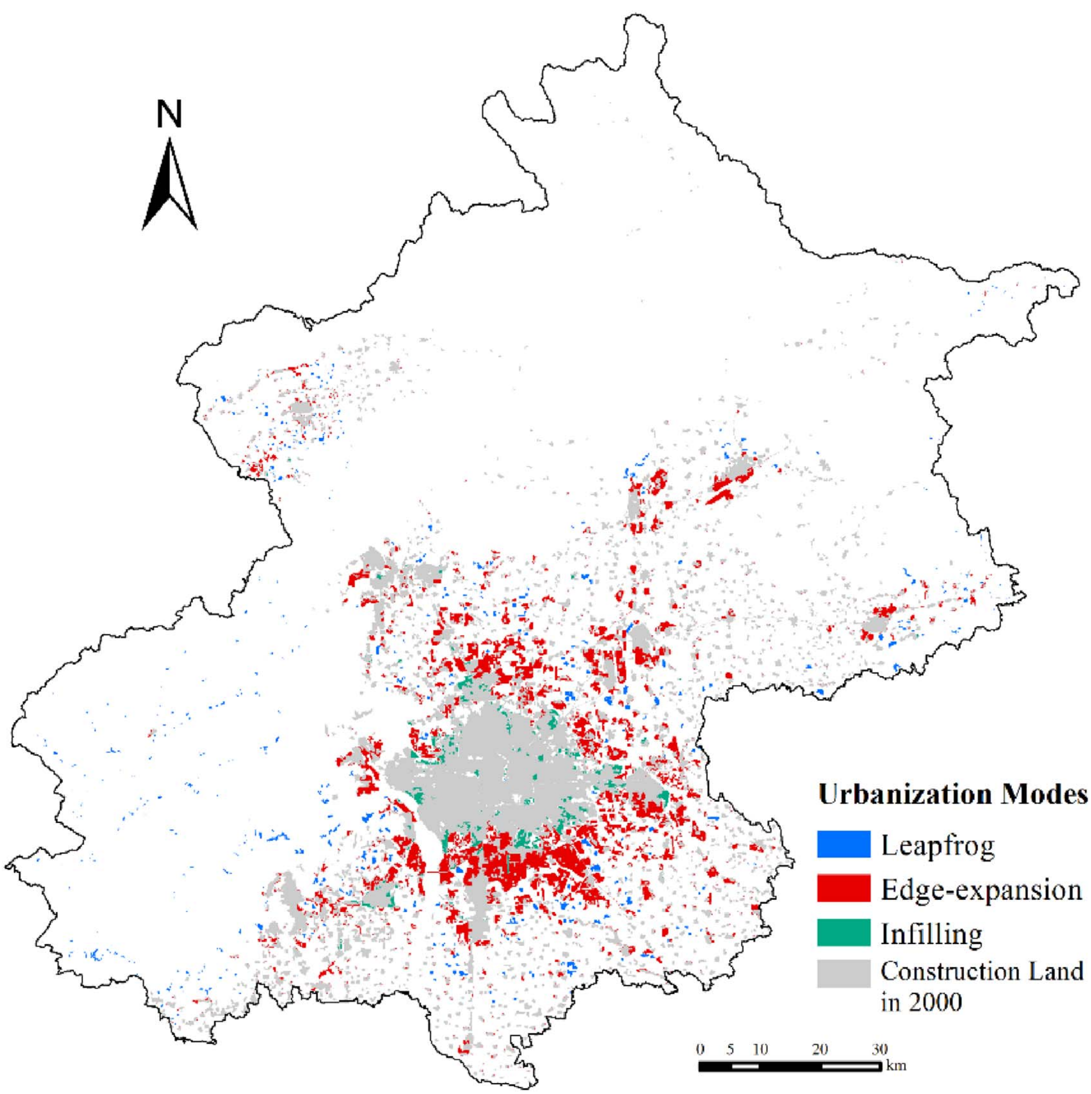

Fig. 4. Spatial distribution of urbanization modes in Beijing City during 2000–2010.

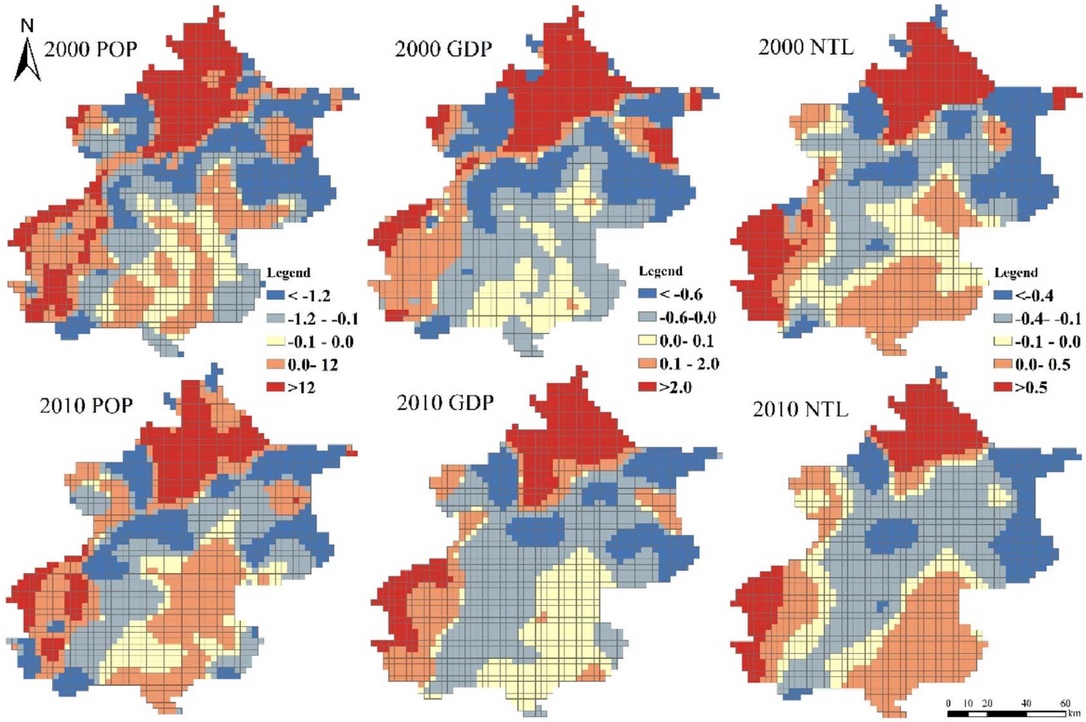

Fig. 5. Spatial patterns of correlation coefficients between patch density (PD) and socioeconomic driving forces: POP (population density), GDP (gross domestic production) and NTL (nighttime lighting).

3.2. Relationship change between landscape metrics and socioeconomic driving forces

GWR model produces adjusted R^2, coefficient and residual of each grid, which can clearly express the fitting effect in different locations, and thus identify spatial heterogeneity. Figs. 5–8 showed spatial distribution of coefficients between socio-economic factors and landscape metrics. It could be seen the driving forces of urbanization on landscape patterns changed with the variation of spatial position.

For PD, socioeconomic factors had significant positive driving effects on the forest landscape in the northern mountainous areas, and had somewhat positive driving effects on cultivated land in areas such as Daxing, Tongzhou and Shunyi District. However, urbanization had negative impacts on cultivated land in Changping, Miyun, Pinggu and

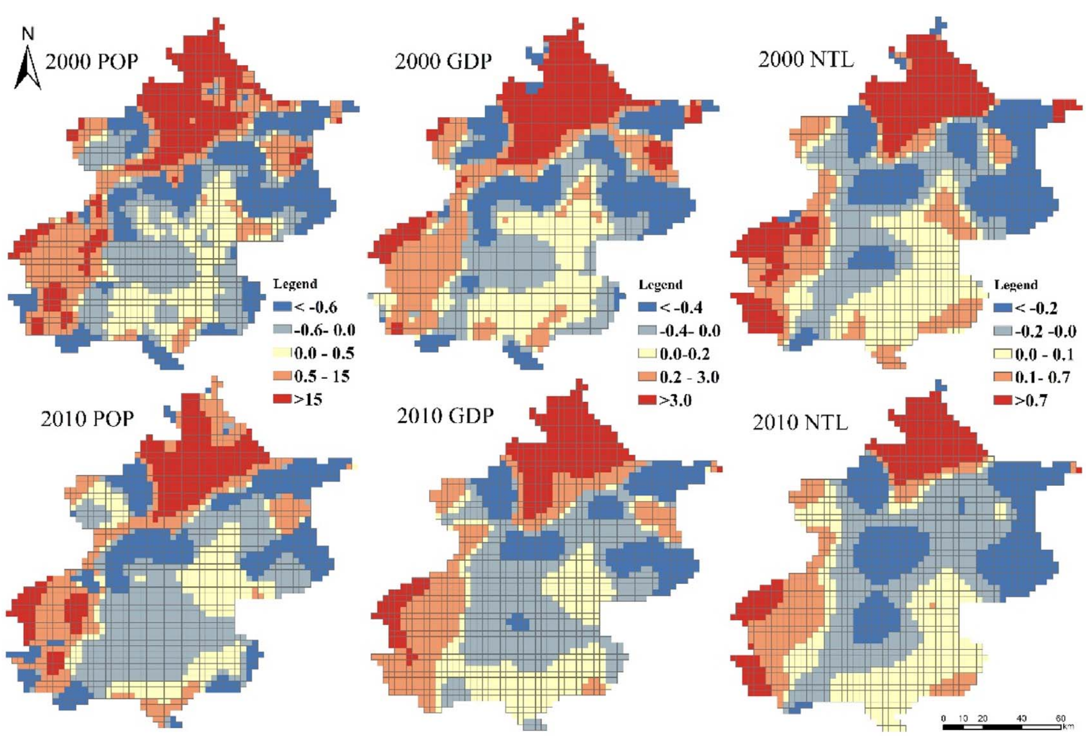

Fig. 6. Spatial patterns of correlation coefficients between edged density (ED) and socioeconomic driving forces: POP (population density), GDP (gross domestic production) and NTL (nighttime lighting).

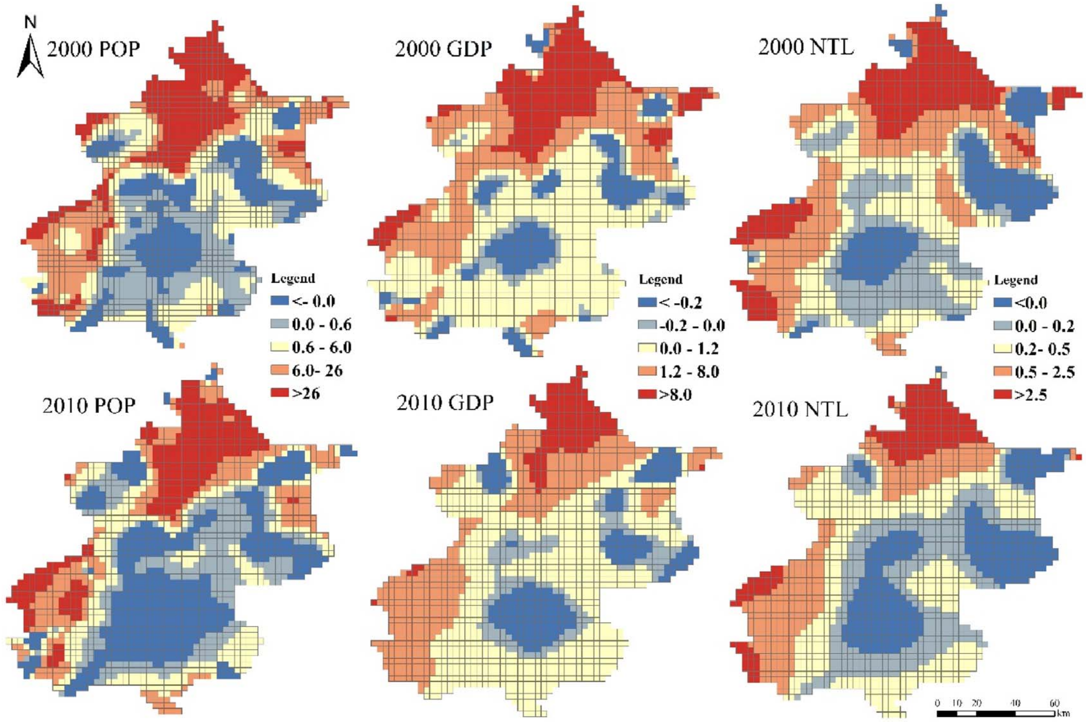

Fig. 7. Spatial patterns of correlation coefficients between Shannon Diversity Index (SHDI) and socioeconomic driving forces: POP (population density), GDP (gross domestic production) and NTL (nighttime lighting).

Yanqing District. The positive driving effect on PD in forest land was mainly caused by urbanization, which transformed some forest land into grassland and cultivated land, and thus made the forest landscape more fragmented. The overall pattern of the relationships between social economy and PD in 2010 was consistent with that in 2000, and the circular structure was more obvious in 2010. In the study period, spatial range of the positive influence significantly expanded in Daxing, Tongzhou and Shunyi District.

For ED, socioeconomic development had a certain degree of negative impact in the downtown and four suburb districts, and had a strong negative impact on the forest and cultivated land ecotone. The positive driving effect on the forest landscape in the north was stronger than cultivated landscape in the southeast. In 2010, the range of the negative effects of urbanization on ED further expanded. The socioeconomic

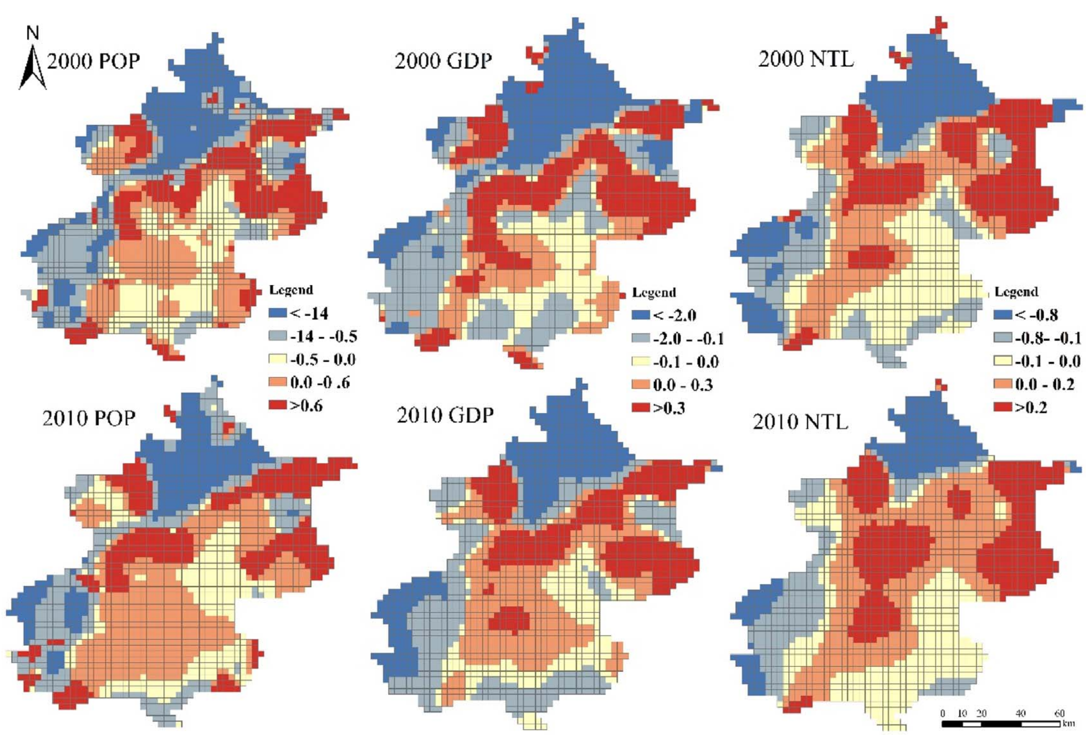

Fig. 8. Spatial patterns of correlation coefficients between aggregation index (AI) and socioeconomic driving forces: POP (population density), GDP (gross domestic production) and NTL (nighttime lighting).

factors drove the construction land to be further connected in the downtown and suburbs, making patch shapes more regular.

For SHDI, in the downtown and suburban, the number of landscape types decreased when the social economy was developed. The population density had the greatest range of negative impact on SHDI, and the degree and range of the impact were further enhanced in 2010. Although the negative impact of GDP on SHDI was within a small range, the intensity was the largest, indicating that human activities (POP and NTL) had a large range of negative impact on SHDI, and economic activities had a deeper impact. For the forest landscape in the northwest, urbanization made more landscape types. Mainly due to the socioeconomic impact, a single forest landscape was broken into more complex landscapes consisting of forest land, grassland and cultivated land.

For AI, urbanization had a positive impact in the downtown and suburbans, and the positive influence on the mosaic landscape of cultivated land and forest land in the outer suburb was great. From 2000–2010, the positive influence of social economy on AI expanded from the suburb to Tongzhou and Daxing District. With the increased urbanization in Tongzhou and Daxing District, the socioeconomic impact on AI changed from a negative driving force to a positive one. In the early stage, the expansion of construction land reduced AI, but in the later period, individual patches of construction land gradually became connected with the increasing AI.

4. Discussion

4.1. Comparison of OLS and GWR models

The adjusted R^2 and AIC comparisons between OLS and GWR models were shown in Tables 2 and 3. For the adjusted R^2, OLS model was poorly fitted because of the spatial heterogeneity of the driving mechanism. The adjusted R^2 of GWR model ranged from 0.357 to 0.748, all higher than that in corresponding OLS model, indicating that GWR model could explain the socioeconomic impact on landscape patterns greatly. The AIC of GWR model was lower than that of OLS model, indicating that GWR model performed better than OLS model in quantifying urbanization impact on landscape patterns.

Moran's I indexes for OLS and GWR model residuals were shown in Table 4. Moran's I index of OLS model varied in the range of 0.577–0.724, showing a certain spatially positive correlation. In contrast, Moran's I index of GWR model was smaller than that of the corresponding OLS model, showing that GWR model had taking spatial autocorrelation of variables into consideration.

4.2. Comparison of urbanization impact on landscape metrics

In sum, landscape patterns of the forest land, and forest and cultivated land ecotone in the north and northwest of Beijing City was strongly influenced by socioeconomic factors, but the cultivated landscape in southeastern plain was not significantly affected by urbanization. In the mountainous areas, the scope of human activities was small, and the degree of urban development was weak. As a result, the forest landscape was preserved more completely than elsewhere. Once this area was developed at a large scale, the effect of urbanization on the forest landscape would be very strong. On the contrary, by 2000 the southeastern plain area had already been affected by human activities. Urbanization would result in the expansion of construction land, making the landscape more fragmented and irregular. In the forest and cultivated land ecotone, land use types were rich, and the intensity of human activities was between the former two areas. The development of social economy promoted the expansion of cultivated land into forest land and grassland, and the expansion of construction land into forest land and cultivated land, both resulting in a more agglomerated landscape pattern with more regular shape and less diversity.

In this study, POP, GDP and NTL were used to represent urbanization, and their explanatory ability and degree of influence were different. In terms of adjusted R^2 (Table 2), the ability to explain the evolution of landscape patterns decreased from POP to GDP, and to NTL in turn, and it was the same in terms of the influence degree as shown in Figs. 5–8. As a result, the impact of population density on landscape patterns was more direct than that of GDP and NTL. As we know, urban development in China is driven by population growth. The size of the population reflects the intensity of human activities and interference directly. Highly correlated with population density, GDP and NTL can indirectly affect landscape patterns.

Four metrics of PD, ED, SHDI and AI were used to quantify landscape patterns in Beijing City, and the degrees they were affected by urbanization differed. The influence of socioeconomic factors on the four landscape metrics varied from strong to weak in the order of PD, AI, ED and SHDI. During the rapid urbanization process, land use change directly led to the appearance of more patches of construction land, which affected patch density of the whole landscape. The impact degree of socioeconomic factors on aggregation and shape complexity of the landscape was the next strongest, with landscape diversity for the weakest. All the findings indicated that urbanization had more influence on the number of patches than on patch shape and spatial

Table 2
Comparison of adjusted R^2 from GWR (Adjusted R^2_G) and OLS (Adjusted R^2_O) models.

		2000			2010		
		POP	GDP	NTL	POP	GDP	NTL
PD	Adjusted R^2_O	0.056	0.107	0.14	0.066	0.189	0.219
	Adjusted R^2_G	0.748	0.725	0.628	0.683	0.663	0.564
ED	Adjusted R^2_O	0.03	0.067	0.061	0.046	0.093	0.097
	Adjusted R^2_G	0.681	0.649	0.546	0.611	0.586	0.471
SHDI	Adjusted R^2_O	0.001	0.005	0.035	0.002	0.010	0.025
	Adjusted R^2_G	0.595	0.567	0.449	0.533	0.506	0.357
AI	Adjusted R^2_O	0.030	0.071	0.067	0.046	0.098	0.105
	Adjusted R^2_G	0.685	0.655	0.555	0.617	0.592	0.480

Table 3
Comparison of AIC from GWR (AIC_G) and OLS (AIC_O) models.

		2000			2010		
		POP	GDP	NTL	POP	GDP	NTL
PD	AIC_O	−829.0	−929.7	−998.8	−1059.4	−1318.1	−1386.1
	AIC_G	−2993.6	−2930.7	−2470.1	−2903.5	−2840.0	−2422.4
ED	AIC_O	−1067.1	−1139.5	−1126.8	−999.8	−1091.3	−1100.7
	AIC_G	−2852.1	−2771.8	−2396.8	−2512.5	−2444.6	−2047.3
SHDI	AIC_O	−254.4	−264.8	−320.3	−440.0	−454.6	−483.0
	AIC_G	−1661.9	−1627.9	−1283.9	−1701.0	−1643.6	−1213.9
AI	AIC_O	−966.4	−1044.6	−1036.7	−895.7	−997.1	−1011.9
	AIC_G	−2777.5	−2697.2	−2328.5	−2433.9	−2367.2	−1974.9

Table 4
Comparison of Residual Moran's I index for GWR (I_G) and OLS (I_O) models.

		2000			2010		
		POP	GDP	NTL	POP	GDP	NTL
PD	I_O	0.724	0.698	0.697	0.715	0.663	0.661
	I_G	0.113	0.178	0.328	0.223	0.286	0.411
ED	I_O	0.665	0.648	0.652	0.654	0.628	0.631
	I_G	0.086	0.152	0.286	0.182	0.252	0.369
SHDI	I_O	0.584	0.585	0.577	0.586	0.585	0.580
	I_G	0.066	0.133	0.263	0.168	0.241	0.362
AI	I_O	0.670	0.652	0.655	0.659	0.631	0.633
	I_G	0.083	0.150	0.285	0.180	0.249	0.368

aggregation, with landscape diversity for the least influence.

From 2000to 2010, the driving effect of social economy on landscape patterns changed dramatically. Overall, the influence of socioeconomic factors in 2010 was less than that in 2000, indicating that landscape patterns in 2010 was also affected by other factors such as land use policy, urban planning and industrial structure adjustment. During 2000–2010, the population density increase only led to a significant increase of POP influence on landscape patterns in the downtown and suburbs. In the same period, the positive impact of GDP and NTL expanded in the downtown and suburbs, and the negative impact significantly decreased in the northern mountainous areas. The contrast indicated that the impact of POP on landscape patterns was mainly concentrated in the downtown and suburbs, while for GDP and NTL the influencing area could be extended to the outer suburban mountainous areas.

4.3. Implications for compact green city development

During the process of global urbanization, the United States of America has experienced a serious suburbanization, and the expansion of cities has resulted in enormous pressures on the transportation, energy and natural ecosystems. Unlike urban sprawl in the USA, European cities have shown a compact development trend. Compact development is a kind of city development model based on intensified development within the region (Breheny, 1997). The basic principle of compact development is to reduce the need for transportation and energy, and to reduce environmental pollution by increasing the density of development in a relatively compact area, so as to form a better ecological environment for human living (Jim, 2013).

The concept of compact city has key implications for avoiding unorderly urban sprawl in China (Chen et al., 2008). However, unlike the USA and most European countries, China has both continuous prosperity in urban centers and continual expansion of urban construction land in the suburbs and outer suburbs; thus, the compact city model must be adapted to local conditions in China. This study showed that there was spatial heterogeneity in the impact of urbanization on landscape patterns in Beijing City. Using GWR to measure correlation coefficients between socioeconomic factors and landscape patterns, important decision-making information could be provided for planning regional compact green city.

Three recommendations could be drawn for planning regional compact green city in Beijing City. Firstly, the protection of green space should be strengthened in the downtown and suburbs to restore landscape diversity. In 2000, main land use type in this region was the construction land; furthermore, the natural or semi-natural green space gradually disappeared during the subsequent ten years. Although parks and other urban green space were constructed, the negative impact of urbanization on SHDI during the decade deepened. Thus, decision-makers should focus on protecting natural or semi-natural green space and constructing additional green landscapes to increase the diversity of urban landscape.

Secondly, the expansion of construction land should be planned rationally in the outer suburb plain area of Beijing City. In the process of outward urban expansion from 2000 to 2010, a large number of construction land patches occupied the coverage of cultivated land, resulting in a more fragmented landscape. Therefore, it is necessary to implement the compact city concept during the process of new urban districts development. The growth of construction land in some areas should be limited, and infilling and recycling development should be encouraged to inhibit landscape fragmentation.

Thirdly, decision-makers should focus on protecting the forest landscape in the outer suburb mountainous area, and the forest, grass and cultivated landscape in the outer suburb semi-mountainous area. Although landscape patterns in these two regions did not change dramatically during the study period, and the socioeconomic development was slow, there was the strongest response to urbanization. Only a little human disturbance can lead to obvious change of these landscapes. A zone in which development is prohibited should be set up in mountainous and semi-mountainous areas to avoid unorderly urban expansion. In the mountainous areas, the integrity of the forest landscape should be focused. In the semi-mountainous area, the diversity of land use types should be maintained, improving ecological resilence of the mixed landscape.

5. Conclusions

Due to rapid urbanization, human activities have drastically changed landscape patterns in Beijing City. On the basis of quantifying the evolution of landscape patterns, GWR model was used to identify the spatial non-stationary relationship between urbanization and landscape patterns. Landscape patterns were characterized by such four landscape metrics as PD, ED, SHDI and AI, with urbanization characterized by population density, GDP and nighttime lighting.

The results showed that landscape patterns in Beijing City were greatly changed along with the process of urbanization during 2000–2010 and showed obvious spatial differentiation. Different urbanization modes and development zones influenced the evolution of landscape patterns variously. GWR was proved to be effectively identify the spatial non-stationarity of urbanization impact on landscape patterns. In Beijing City, the response of western and northern forest landscape and the forest and cultivated ecotone to urbanization was the strongest. Among driving factors, population density directly affected landscape patterns, while the impacts of GDP and NTL were indirect. In 2010, the factors affecting landscape patterns were more complicated and the explanatory power was lower than that in 2000. The reason for the difference may be due to the adjustment of development policy, the industrial structure and the overall plan in Beijing City. In summary, there was significant spatial heterogeneity in the relationship between socioeconomic driving factors and landscape patterns, and the concept of compact development should be adapted to local conditions in Beijing City.

Spatial scale is one of the key issues in ecology and geography. Because landscape patterns are scale-dependent, landscape patterns change and associated driving forces are also sensitive to observation grain or extent. The grid size was chosen as 3 km × 3 km in this study, considering the spatial resolution of available land cover data (30 m) and socioeconomic data (1 km). In the future, the scale effect of urbanization impact on landscape patterns should be fully explored through transforming grid size in the spatial dimension. As to the temporal scale, urbanization impact on landscape patterns can be measured more finely by extending the time series to 30 years or more, and by reducing the time interval to 5 years, the period of socioeconomic development plan in China.

Acknowledgment

This research was financially supported by the National Natural Science Foundation of China (No. 41322004).

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