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Monitoring the Evolution of Spatiotemporal Landscape Pattern in Megacity Beijing Using Long Time Series of Landsat Data

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Exploring the dynamics of an urban landscape pattern is significant for urban ecological environment evaluation. Previous studies on urban landscape monitoring are relatively few, making it difficult to comprehensively reflect the characteristics of urban landscape patterns. Here, we proposed a methodological framework to monitor the dynamics of the landscape pattern, vegetation coverage, and the habitat quality using the Landsat imagery obtained from 1999 to 2021 in Beijing, China. First, changes in the landscape characteristics associated with land use were explored by the transfer matrix and landscape metric analysis methods. Subsequently, the dimidiate pixel model was employed to analyze changes in regional vegetation coverage on a landscape perspective. Finally, the habitat quality was evaluated on the basis of remote sensing ecological index (RSEI) model, and the correlation between the habitat quality and the landscape index was retrieved using the gray correlation degree model. The results showed that the landscape pattern underwent fragmentation, and the edge effect was strong. A high vegetation coverage was dominant throughout the landscape, and a medium vegetation coverage was relatively scattered, especially in built-up areas. The landscape was highly fragmented in areas with a low vegetation coverage. There were significant regional differences in habitat quality, and the quality was higher in the northwest and western mountainous areas. Furthermore, there was a strong correlation between the habitat quality and the index-based landscape pattern, which demonstrated the distribution pattern of landscape types significantly impacts habits quality. Overall, these findings are significant for future urban planning and construction.

1. Introduction

Urbanization is accelerating at an unprecedented rate globally. China has experienced a rapid urbanization process over the past few decades,(1) and the proportion of population living in urban areas increased from 17.9 to 63.89% between 1978 and 2021.(2,3) Urbanization has transformed natural ecosystems into ones in which humans and natural systems are coupled, and

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material and energy flows have been changed; this has had profound effects on biodiversity, ecosystem functions, local and regional climates, and the quality of human existence.(1,2,4–6)

Analyzing the interactions between humans and the ecological environment from a landscape perspective can provide suggestions for protecting the regional ecological environment and effectively promoting regional sustainable development.(7) In areas that have been rapidly urbanized, the contradiction between human activities and the natural ecological environment is prominent. Clarifying the relationship between the landscape pattern, vegetation coverage, and the habitat quality can provide a theoretical basis for conducting in-depth research on how the spatiotemporal evolution of ecosystem services responds to the landscape pattern, thereby providing novel ideas for improving ecosystem services from the perspective of optimizing the landscape pattern.(8)

The rapid development of remote sensing technology has greatly promoted the analysis of urban landscape patterns in recent years. Remote sensing can be used to record a variety of spatial and temporal data related to covered land surfaces, and long-term series ranges have been shown to be effective in rapidly identifying spatiotemporal changes in regional ecological environments.(9–11) In this respect, Japelaghi *et al.* used Landsat satellite images from TM, ETM+, and OLI sensors to analyze the landscape patterns and change processes of the Central Zagros region, Iran in 1989, 2000, and 2013.(12) Using Landsat data, Zewdie *et al.* monitored the temporal dynamics of the urban landscape during the past three decades in Addis Ababa and analyzed the driving factors.(13) Landsat time series data provide rich information, and the temporal and spatial resolutions are suitable for use in comprehensively describing landscape changes and monitoring vegetation coverage.(14–16)

By exploring the fractional vegetation cover (FVC) and its dynamic changes, measuring the characteristics and causes of vegetation changes and the quality of the regional ecological environment is possible. The landscape pattern generally relates to the spatial pattern of a landscape, which comprises the spatial distribution of landscape spatial units (patches) with different sizes, shapes, and attributes, as well as their combinations. Changes in landscape pattern reflect the spatial distribution of the FVC and its dynamic characteristics under the comprehensive control of environmental heterogeneity and disturbance.(17) Analyzing changes in regional vegetation coverage from a landscape perspective is useful for determining the relationship between changes in landscape pattern through natural and ecological processes and those associated with human activities. It is also useful for determining the impact intensity, direction, and effectiveness of factors that have resulted in landscape pattern changes within a region, and for providing an important scientific basis for regional sustainable development decision-making.(18) Therefore, analyzing dynamic changes in partial vegetation cover and landscape pattern is of considerable significance.

Habitat quality refers to the ability of an ecosystem to provide individuals and populations with appropriate conditions for sustainable development, and it is the basis of ecosystem service functions and an important factor affecting biodiversity.(19–21) Previous studies have shown that changes in landscape pattern affect biodiversity and the distribution of ecosystem services.(22) Zhu *et al.* used the ordinary least squares (OLS) and geographically weighted regression (GWR) models to explore the impacts of urbanization and landscape pattern on habitat quality in

Hangzhou, China, and the results demonstrated that rapid urbanization has significantly and negatively affected the habitat quality in various areas, and the magnitude and direction of the impacts on habitat quality from changes in landscape pattern differ both temporally and spatially.(23) In the process of urbanization, the degree and mode of land development and utilization undergo profound changes that result in landscape pattern changes and the destruction of original habitat patterns. Therefore, it is necessary to determine the spatiotemporal evolution of landscape patterns and the quality of habitats, and to conduct a correlation analysis to determine the roles of certain factors.

In this study, we propose a methodological framework for monitoring the spatiotemporal evolution of the landscape pattern, vegetation cover, and habitat quality using long time series Landsat data in the mega city of Beijing. The main objectives were as follows: (a) to explore the spatiotemporal variations in landscape pattern during the process of urbanization from 1999 to 2021, (b) to investigate the dynamic changes in vegetation coverage from a landscape pattern perspective, and (c) to analyze and assess the spatiotemporal evolution of the landscape pattern and habitat quality and to conduct an associated correlation analysis.

2. Materials

2.1 Study area

Beijing, the capital of China, was selected as the study area (Fig. 1), which is located at the North of China (39°28′–41°05′N, 115°25′–117°30′ E). It is a metropolitan city and covers an area of 16,410 km^2. The terrain is low in the southeast and high in the northwest, with an average altitude of 43.5 m. Beijing has a warm temperate semi-humid and semi-arid monsoon climate, where summers are hot and rainy, and winters are cold and dry. The average rainfall over the past 30 years was 528 mm. Precipitation is unevenly distributed throughout the year and is mainly concentrated in the summer.

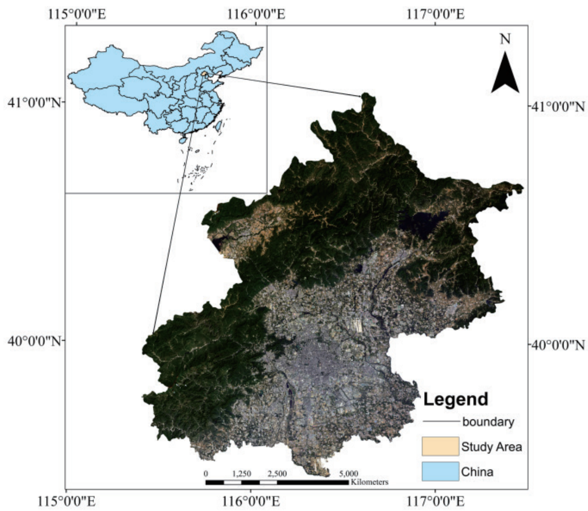

Fig. 1. (Color online) Geographical location of the study area, Beijing.

2.2 Data acquisition and preprocessing

Remote sensing images were provided by the Geospatial Data Cloud site, Chinese Academy of Sciences (http://www.gscloud.cn). Landsat 7 images taken between July and August in 1999, 2003, and 2009, and Landsat 8 images taken in July and August in 2014 and 2021 were obtained. Vegetation in the study area was flourishing during these periods, which was beneficial for studying the vegetation landscape. In addition, the low cloud content had only a minimal impact on image interpretation. The preprocessing of the multispectral Landsat imagery was performed using ENVI image analysis software (version 5.3) including radiation calibration, FLAASH-based atmospheric correction, and image mosaicking and clipping. A brief overview of the downloaded Landsat images is shown in Table 1.

3. Methods

The proposed approach for monitoring the dynamic changes in landscape pattern included a dynamic landscape analysis of the land use, vegetation coverage, and habitat quality of the study area, as illustrated in Fig. 2.

Table 1
Descriptions of the acquired Landsat images.

Data	Acquisition Date	Resolution (m)	Preprocessing
Landsat-7 ETM Images	1999-8-2 2003-7-28 2009-8-13	30	Radiation calibration, atmospheric correction, mosaicking, clipping
Landsat-8 OLI Images	2014-8-19 2021-8-6	30	

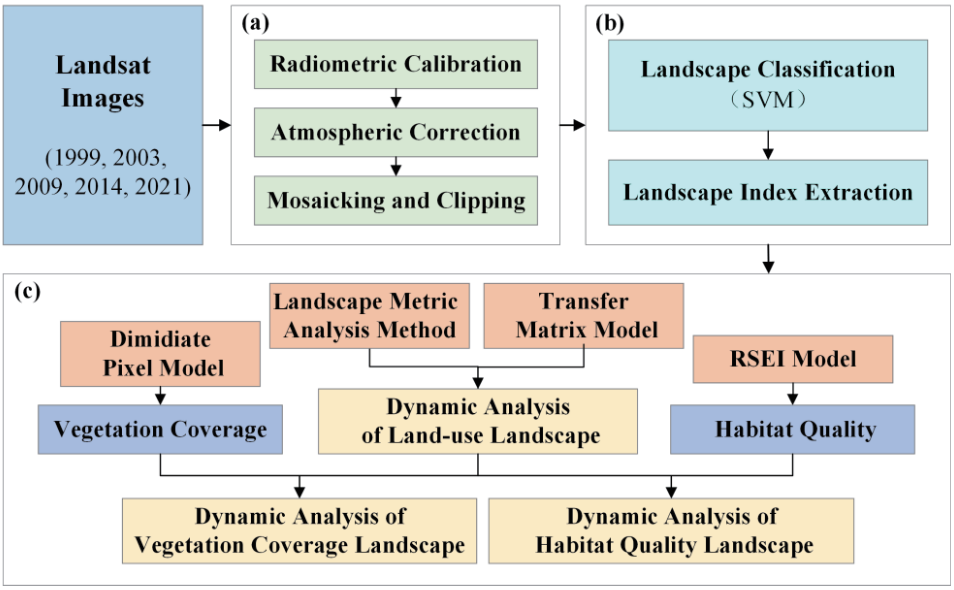

Fig. 2. (Color online) Workflow of study process: (a) data preprocessing, (b) landscape extraction, and (c) dynamic analysis of landscape.

The landscape distribution was obtained from the long time series images taken from 1999 to 2021 using the landscape transfer matrix and landscape pattern index methods, and the spatial structure and spatiotemporal evolution characteristics of Beijing were determined. The vegetation coverage information was retrieved using the dimidiate pixel model, and the changes in vegetation coverage from a landscape perspective were analyzed. The quality of the ecological environment was evaluated using the remote sensing ecological index (RSEI) mode, and the correlation between the ecological quality index and the landscape index of different landscape types was explored by gray correlation analysis.

3.1 Extraction of landscape index

Land use/land cover changes are important factors leading to changes in ecosystem type and landscape pattern. According to their actual distribution in the study site, the main landscape types were determined to be forest, grassland, farmland, construction land, bare land, water, and artificial vegetation. To obtain these landscape types, the support vector machine (SVM), which has shown an excellent performance in classification,[24] was used, and the reference data were manually outlined by visual interpretation. Subsequently, 75% of the reference data in each class that were evenly distributed in the study area were randomly and manually selected as the training data, and the remaining data were used for accuracy verification. The verification process showed that the overall accuracy was higher than 90% and that the Kappa coefficient was higher than 0.9, which met the experimental requirements. These landscape types are illustrated in Fig. 3.

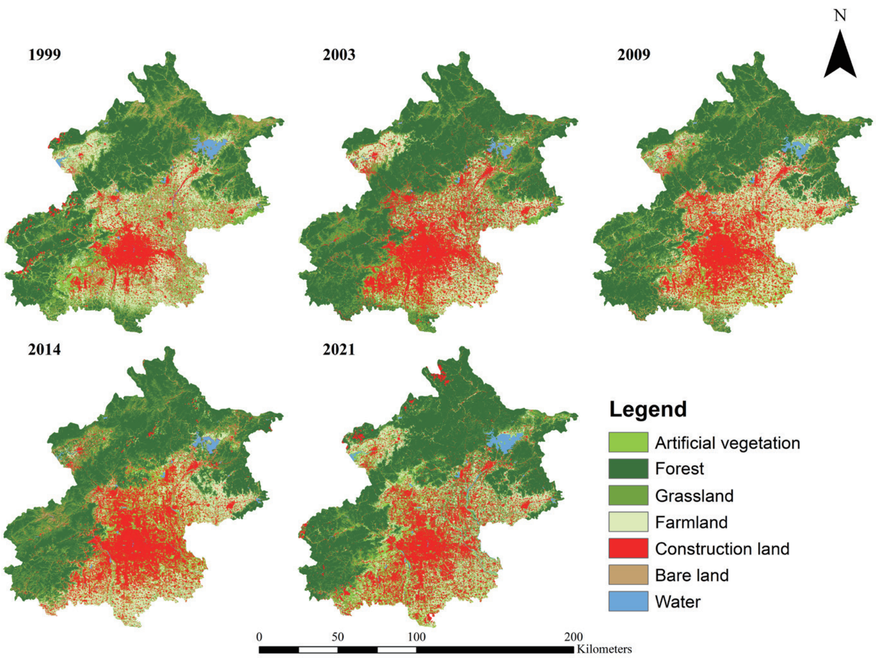

Fig. 3. (Color online) Classification of landscape types in different periods.

The landscape pattern index can be used to quantitatively research and elucidate the structural composition and spatial configuration of a landscape as well as to describe landscape changes and establish the relationship between landscape patterns and processes. Both class-level and landscape-level metrics (Table 2) were measured in this study.

Table 2
Spatial metrics used in this study to measure landscape patterns.

Level	Dimensions	Metric	Range	Description
Landscape	Fragmentation/ aggregation	Patch Density (PD, n/km^2)	(0, +∞)	The total number of patches in the landscape, divided by the total landscape area
		Aggregation Index (AI, %)	[0, 100]	At the landscape level, it is computed as an area weighted mean class aggregation index, where each class is weighted by its proportional area
		Contagion (CONTAG, %)	[0, 100]	The overall probability that a cell of a patch type is adjacent to cells of the same type
	Shape and complexity	Edge Density (ED, m/ha)	[0, +∞)	The sum of the lengths of all edge segments in the landscape, divided by the total landscape area
		Area-Weighted Mean Fractal Dimension Index (FRAC_AM)	[1, 2]	Shape complexity weighted by the area of patches
	Diversity	Diversity Shannon's Diversity Index (SHDI)	[0, +∞)	The minus sum, across all patch types, of the proportional abundance of each patch type multiplied by the logarithm of that proportion
		Shannon's Evenness Index (SHEI)	[1, 1]	The observed Shannon's diversity index divided by the logarithm of the number of patch types
Class	Fragmentation	Number of Patches (NP)	[1, +∞)	The number of patches of the corresponding patch type
		Patch Density (PD, n/km^2)	(0, +∞)	The number of patches of the corresponding patch type divided by the total landscape area
	Dominance/ abundance	Largest Patch Index (LPI, %)	(0, 100]	The area of the largest patch of the corresponding patch type divided by the total landscape area
	Shape and complexity	Edge Density (ED, m/ha)	[0, +∞)	The sum of the lengths of all edge segments involving the corresponding patch type, divided by the total landscape area
		Landscape Shape Index (LSI)	[1, +∞)	A standardized measure of the total edge length or edge density of the landscape combined with the landscape area
	Aggregation	Aggregation Index (AI, %)	[0, 100]	The number of like adjacencies involving the corresponding class, divided by the maximum possible number of like adjacencies involving the corresponding class, which is achieved when the class is maximally clumped into a single compact patch
		Interspersion and Juxtaposition Index (IJI, %)	(0, 100]	The overall distribution and juxtaposition of each patch types. When its value is small, a certain type of plaque is considered only adjacent to a few other types.

The landscape-level indicators were selected from three dimensions of fragmentation and aggregation, shape and complexity, and diversity, which are aggregation index (AI), patch density (PD), contagion (CONTAG), edge density (ED), area-weighted mean fractal dimension index (FRAC_AM), Shannon's diversity index (SHDI), and Shannon's evenness index (SHEI), while the class-level indicators were selected from four dimensions of fragmentation, dominance and abundance, shape and complexity, and aggregation, which are number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), landscape shape index (LSI), aggregation index (AI), and interspersion and juxtaposition index (IJI). The combination of the above landscape indicators was used to describe the characteristics and changes of the comprehensive landscape structure.

3.2 Change detection for landscape of land use

The landscape index and landscape transition matrix based on the landscape and grade levels can intuitively and quantitatively reflect dynamic changes in landscape type and associated pattern. The landscape index selected at the landscape level was used to observe the pattern characteristics and changing trends of the overall landscape composed of all landscape type patches. The landscape index selected at the class level was used to observe the characteristics and changes of different landscape types. The transfer matrix was used to explore the change direction and area over time between different landscape types. The transfer matrix formula is

$$\boldsymbol{A_{mn}} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}, \tag{1}$$

where $\boldsymbol{A_{mn}}$ is the total study area (km^2) and a_{mn} shows the area transferred from landscape type m to n from time T_1 to T_2.

3.3 Landscape dynamics of vegetation coverage

Vegetation is the foundation and core of urban ecosystems, and vegetation coverage is an important parameter used to comprehensively quantify the urban vegetation status. Exploring the impact of vegetation coverage on the landscape pattern is highly significant for rationally planning urban green space systems and the layout of landscapes, in addition to improving urban ecological benefits and reducing the urban heat island effect. In this study, the FVC was calculated on the basis of the dimidiate pixel model, as shown in Eq. (2). The vegetation coverage distribution within the landscape was classified into different coverage levels, and the dynamic changes at different fractional vegetation levels were monitored. In addition, the correlation between the vegetation coverage of different land use types and the landscape index was explored using the Pearson correlation coefficient method.

$$F_c = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}, \tag{2}$$

where $NDVI$ is the actual NDVI value of the pixel, $NDVI_{veg}$ is the NDVI value of the pure vegetation pixel, and $NDVI_{soil}$ is the NDVI value of the bare soil pixel.

3.4 Dynamic monitoring of landscape changes to determine habitat quality

With the accelerating process of urbanization, land use patterns are constantly changing, and habitats that are suitable for biological survival tend to be fragmented, leading to the degradation or loss of habitat function. Assessing habitat quality and its changes, analyzing the spatial distribution characteristics and regional differences in different areas, and revealing the impact of landscape pattern characteristics on habitat quality are of great significance for maintaining the balance between natural ecosystems and regional sustainable development. The RSEI model was used to evaluate the ecological environment quality of the study area. The RSEI (range is [0,1]) was calculated by coupling the four indicators of greenness (NDVI), wetness (Wet), dryness (NDBSI), and heat (LST), as shown in Eq. (3), using principal component analysis, and the results were divided into five grades, from high to low. The area proportions of each ecological quality grade in each year were counted. To explore the relationship between the ecological quality and the landscape pattern, the gray relational analysis was conducted.

$$RSEI = 1 - PC1\left[f\left(NDVI, WET, NDBSI, LST \right) \right], \tag{3}$$

where $RSEI$ is the index of ecological quality, i.e., the larger the value, the better the ecological quality. $PC1$ represents the first principal component obtained by principal component analysis, which integrates the largest information of the input dataset. $NDVI$ is the normalized difference vegetation index; WET represents wetness; $NDBSI$ is the normalized difference build-up and soil index, and LST represents the land surface temperature.

4. Results

4.1 Spatio temporal dynamics of land use within the landscape

Changes in urban land use are important factors affecting changes in landscape pattern. In this study, the spatiotemporal dynamic changes in land use were monitored using the Landsat images obtained from 1999 to 2021. To explore the effect, strength, and direction of factors leading to landscape pattern changes, land use changes from a landscape perspective and the relationship between changes in landscape pattern and changes in land use were analyzed.

4.1.1 Dynamic changes in urban land use

Figure 4 shows the proportional area of each landscape type in the overall landscape from 1999 to 2021. The landscape pattern was dominated by forest. Other main components were grassland, farmland, and construction land, and there were small areas of bare land and water. In addition, these landscape types have undergone significant dynamic changes over the past 22 years.

Seen from Fig. 4, the proportional area of forest increased by 5.85%, from 38.24% in 1999 to 44.09% in 2021. The areas covered by grassland showed a downward trend, with a proportional decrease in area of 5% from 16.27% in 1999 to 11.27% in 2021. The trend in farmland changes fluctuated, but the area decreased by 1.89% in the past. The proportional area of construction land increased significantly in 2003, with an increase of 7.32% compared with that in 1999; the highest level was reached in 2014, and this was followed by a slight decrease in 2021, reaching 17.42%. Areas of artificial vegetation accounted for a low proportion of the landscape area, but they still showed an increasing trend, and their value was the highest at 8.68% in 2014. The proportion of bare land decreased by 7.03% from 7.51% in 1999 to 0.48% in 2021. The area of water expanded, reaching a maximum of 2.27% in 2021.

To explore the transfer of area covered by one land use type to another type and the associated directional trends, a landscape transfer matrix (Table 3) from 1999 to 2021 was constructed. The increased area of forest was mainly related to conversion from grassland, with a net increase of 5.49%. The reduction in the area of grassland was thus mainly caused by the increase in forest area. The increased area of construction land was mainly derived from farmland and bare land, but changes in their use also increased the area of forest by 2.51 and 2.02%, respectively. Areas of bare land were mainly transformed into forest, grassland, farmland, and construction land.

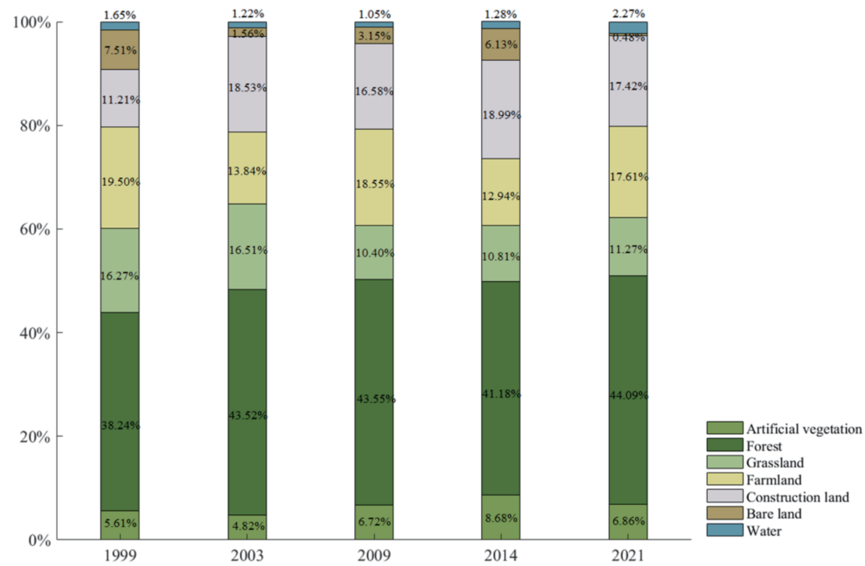

Fig. 4. (Color online) Area percentage of each landscape type from 1999 to 2021.

Table 3
Landscape change transfer matrix from 1999 to 2021.

		2021						
		Artificial vegetation	Forest	Grassland	Farmland	Construction land	Bare land	Water
1999	Artificial vegetation	185.44 1.13%	104.69 0.64%	153.52 0.94%	161.73 0.99%	285.92 1.74%	4.15 0.03%	24.70 0.15%
	Forest	205.56 1.25%	5231.68 31.91%	239.57 1.46%	400.20 2.44%	171.63 1.05%	1.51 0.01%	19.05 0.12%
	Grassland	175.05 1.07%	1138.67 6.95%	488.16 2.98%	592.05 3.61%	250.52 1.53%	9.93 0.06%	13.30 0.08%
	Farmland	324.23 1.98%	459.04 2.80%	529.96 3.23%	1307.73 7.98%	528.79 3.23%	20.66 0.13%	25.76 0.16%
	Construction land	123.40 0.75%	109.60 0.67%	165.55 1.01%	118.82 0.72%	1245.67 7.60%	24.53 0.15%	50.60 0.31%
	Bare land	99.52 0.61%	178.38 1.09%	262.97 1.60%	292.18 1.78%	356.46 2.17%	16.51 0.10%	24.79 0.15%
	Water	11.11 0.07%	6.04 0.04%	8.18 0.05%	14.01 0.09%	16.91 0.10%	0.77 0.00	213.88 1.30%

4.1.2 Dynamic changes in land use within the urban landscape pattern

As shown in Fig. 5, the fragmentation (measured according to NP and PD) of the landscape was mainly related to areas of grassland and artificial vegetation, followed by those of farmland, construction land, and forest; all showed decreasing to increasing changes in characteristics. According to LPI, the landscape of Beijing was dominated by forest and construction land, but the forest landscape had always occupied the largest area. In 2009 and 2014, the largest patch of forest accounted for a prominent and significant proportion of the landscape. The LPI values of forest and construction land showed an initial increasing trend and a subsequent decreasing trend with time. The ED value of the grassland landscape was consistently higher than those of the other vegetation landscape types, although the other vegetation landscape types also had high ED values; however, the changes in the ED values of grassland and farmland were unstable. The LSI values of grassland, artificial vegetation, farmland, and forest were greater than those of the other land use types, which indicated that the distribution of the vegetation landscape was relatively stable and the dynamic degree of vegetation landscape pattern was low. Each landscape type showed a high IJI index, while forest showed the lowest IJI index among the landscape types throughout the study period. The AI of all landscape types was also high, which showed that the landscape types had aggregate distribution characteristics.

The dynamic change process of Beijing's landscape-level landscape index from 1999 to 2021 is illustrated in Fig. 6. As shown in the figure, the PD value of Beijing's landscape from 1999 to 2021 exhibited a sharply decreasing trend, followed by a stable trend and ultimately a gradually increasing trend. The largest PD value observed in 1999 (34.06 number/100 hm^2), indicating that landscape fragmentation in this year was higher than that in the other years. The ED showed an initial decreasing trend followed by an increasing trend, and it remained at a relatively high level

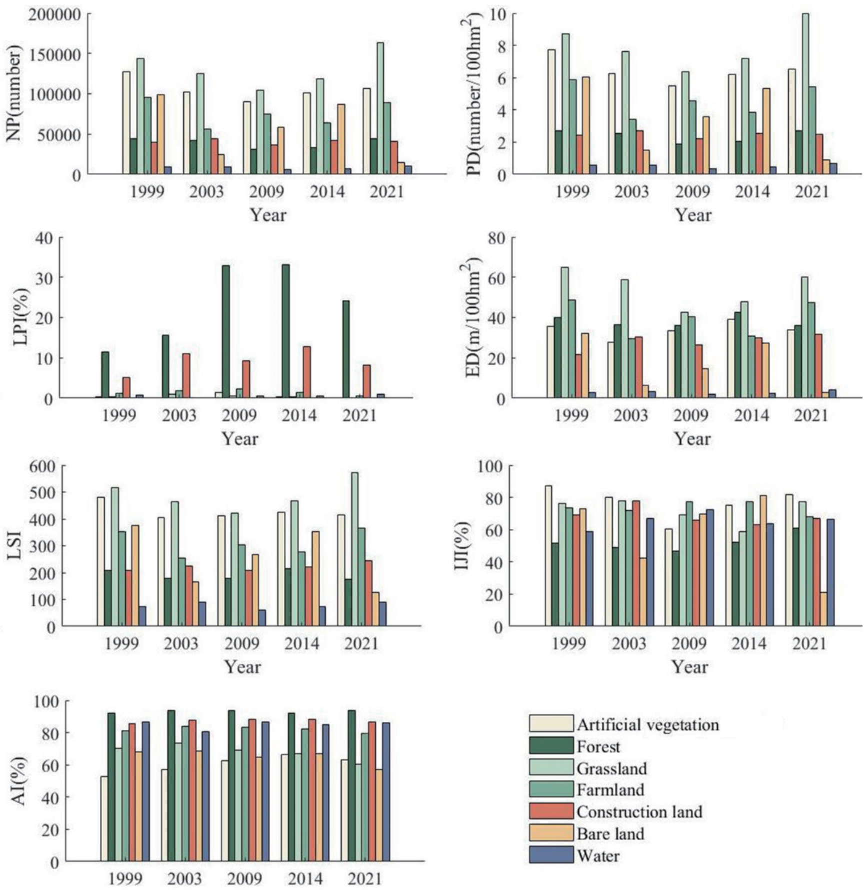

Fig. 5. (Color online) Dynamic changes in class-level index from 1999 to 2021.

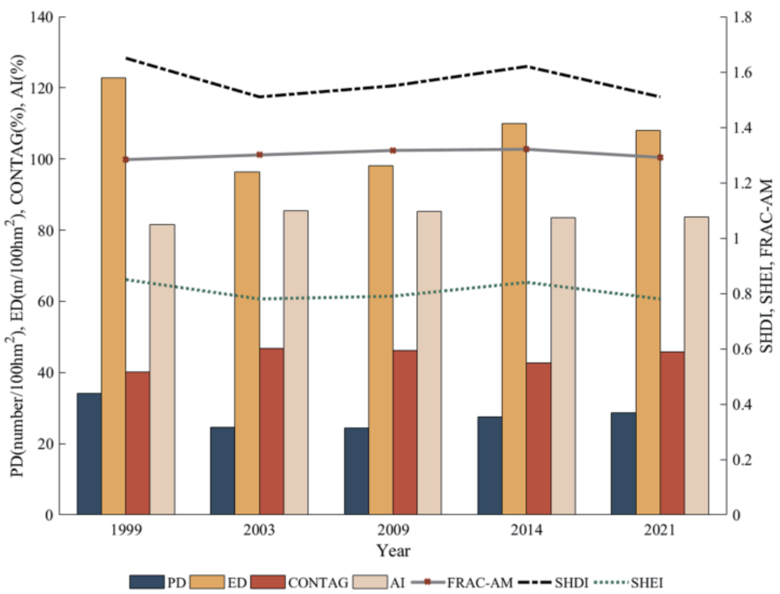

Fig. 6. (Color online) Dynamic changes in landscape-level index from 1999 to 2021.

throughout. The ED value reached a maximum of 122.82 m/hm^2 in 1999, indicating strong interference between landscape types. The FRAC_AM value was approximately 1.3, which indicated that the landscape remained in a complex state. The CONTAG value remained at a moderate level, indicating that the ductility and connectivity of the landscape were good. The SHDI remained between 1.5 and 1.65, reflecting the richness of landscape diversity in Beijing. The SHEI fluctuated around 0.8, which showed that the distribution uniformity among different landscape types had attained a relatively good balance. The AI remained above 80%, which indicated that the patches were closely clustered.

4.2 Spatiotemporal evolution of vegetation coverage within the landscape

To determine the relationship between landscape pattern changes, natural ecological processes, and human activities, spatiotemporal variations in urban FVC were monitored from 1999 to 2021 using dense and long time series Landsat data. The dynamic changes in regional vegetation coverage were subsequently analyzed from a landscape perspective.

4.2.1 Dynamic FVC changes

Figure 7 shows the spatial distribution of the FVC within Beijing's landscape. A high FVC was mainly concentrated in the west and north of the study site. These areas include the Yanshan and Xishan mountains, respectively, where vegetation resources are very rich, and the areas cover approximately 10400 km^2, accounting for 62% of the total land area of Beijing.[25] The

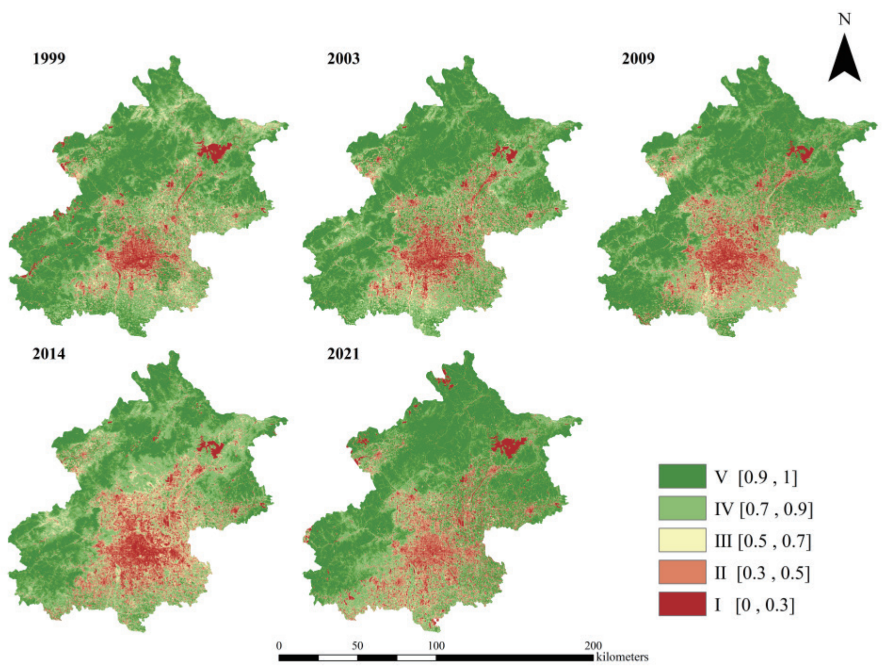

Fig. 7. (Color online) Distribution of FVC within the landscape.

vegetation cover diminished with proximity to the city center. Low-vegetation-coverage areas were mainly concentrated in areas of urban construction.

Figure 8 shows the dynamic changes in proportional FVC area at different levels. The vegetation landscape in Beijing was dominated by a high FVC (level V). In 2014, the high FVC decreased significantly within the landscape, whereas all the other landscape types increased. Landscapes with FVC at levels I and II were concentrated on impervious surfaces in urban areas, which increased in area from 1999 to 2014. It indicated an increase in the human modification of natural surfaces, but a decrease in this phenomenon was found in 2021 to a certain extent.

4.2.2 Correlation analysis between FVC and landscape pattern

Table 4 shows the correlation obtained using the Pearson correlation coefficient between the FVC of each landscape type and the class-level landscape index of this landscape type. Table 4 shows that the correlation between FVC and ED was the highest at 0.7776, which implied that with an increase in vegetation coverage, the ED of the landscape also showed an increasing trend. There was a positive correlation between FVC and NP and PD with a correlation of 0.5456, which was representative of fragmentation and indicated that with an increase in

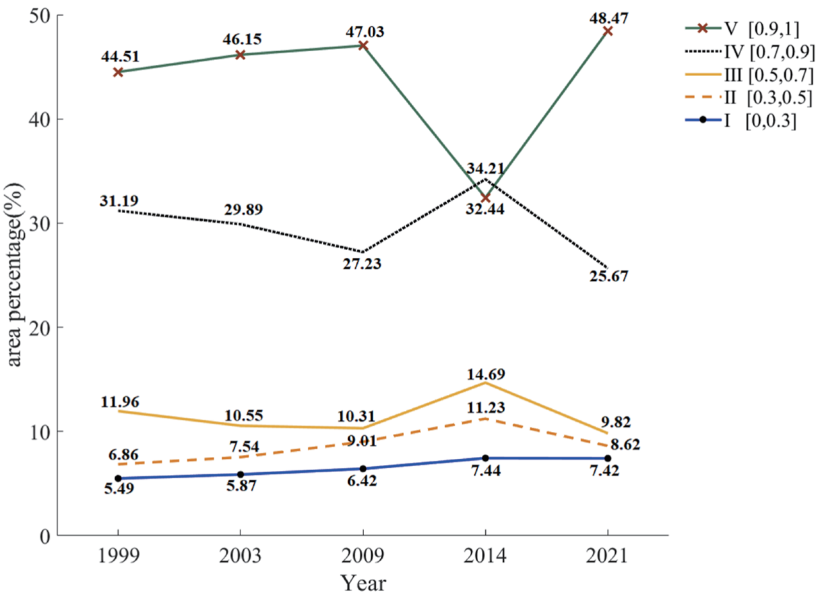

Fig. 8. (Color online) Dynamic changes in the proportional area of different grades for FVC degrees.

Table 4
Correlation between FVC degree and class-level landscape index.

	NP (number)	PD (number/km^2)	LPI (%)	ED (m/hm^2)	LSI	IJI (%)	AI (%)
Correlation coefficient	0.5456	0.5456	0.3349	0.7776	0.5379	0.1270	−0.0057

vegetation coverage, landscape fragmentation increased to a certain extent. The correlation between FVC and LSI was 0.5379, which showed that with an increase in vegetation coverage, the landscape patch shapes tended to become more complex. The correlation between FVC and LPI was 0.3349, which showed that with an increase in vegetation coverage, there was an increase in patch area of the largest landscape type. In summary, increasing the vegetation coverage in Beijing increased the landscape fragmentation, enabled the development of landscape patch shapes that were increasingly complex, increased the area of the largest patch type, and increased the ED.

4.3 Dynamics of spatiotemporal changes in the habitat quality of the landscape

To discuss the distribution of habitats and associated changes under different landscape patterns, the degree of habitat quality and the change in habitat quality in 1999, 2003, 2009, 2014, and 2021 were assessed using the RSEI model in this study. The spatial distribution characteristics and regional differences of various regions in the study site were analyzed, and sensitive areas that require habitat protection focus were identified. In addition, the correlation between the habitat quality and the landscape pattern index were explored to reveal the impact on habitat quality from dynamic land use changes and their spatial pattern characteristics.

4.3.1 Spatiotemporal variations in RSEI

Figure 9 shows the distribution of RSEI quality within the landscape, and Fig. 10 shows the proportional areas of different RSEI quality levels within the landscape. As evident from the figures, the ecological quality of most areas in Beijing was excellent from 1999 to 2021 (most

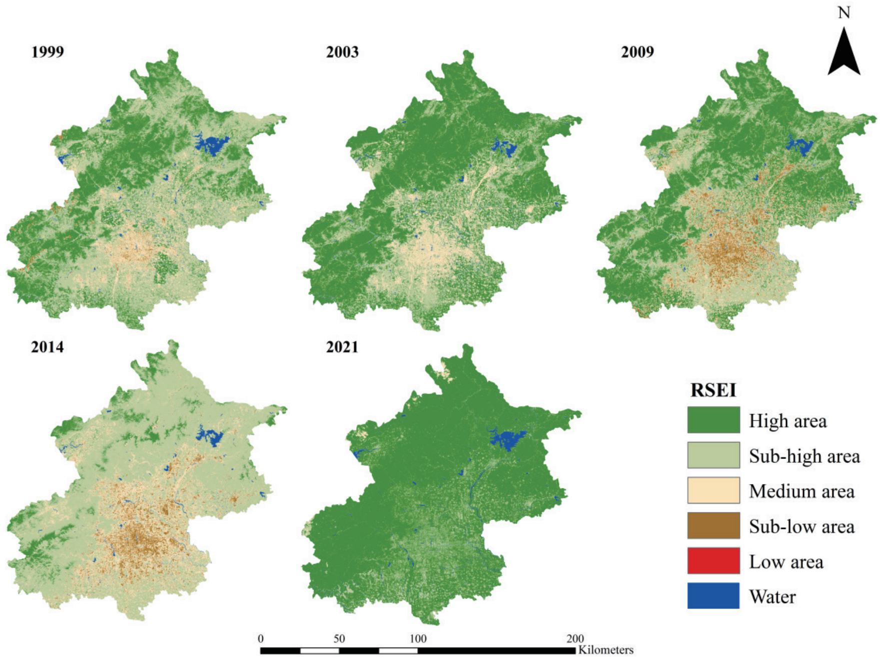

Fig. 9. (Color online) Distribution of RSEI quality in the landscape.

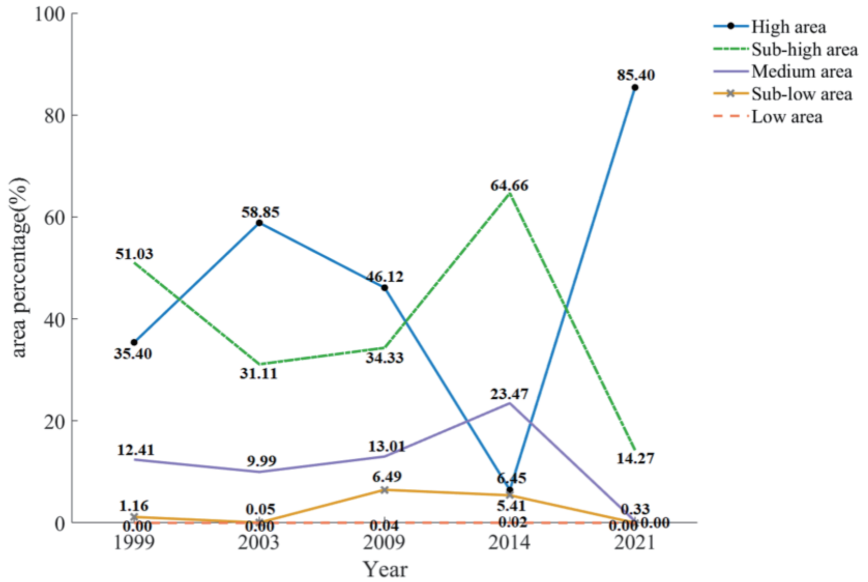

Fig. 10. (Color online) Dynamic changes in proportional areas of different RSEI grades.

areas were high/sub-high). However, in 2014, the proportional area considered to have a high ecological quality dropped sharply, and that of a sub-high/medium ecological quality significantly increased. Combining these results with the vegetation coverage analysis in the previous section, this phenomenon most likely occurred because of the impact on the ecological quality from the abnormally large reduction in high-density vegetation coverage landscape in 2014. This result further proves that the vegetation landscape is important for maintaining ecological quality.

4.3.2 Relationship between RSEI and landscape pattern

To explore the impact of landscape pattern evolution on ecological quality, a correlation analysis was carried out on the landscape index and its RSEI value of each land type. As shown in Fig. 11, the relationships between the RSEI, class-level landscape index, and landscape areas were measured, which quantitatively revealed the effect of landscape pattern changes on the ecological quality. The RSEI showed a strong correlation with all landscape indices and landscape areas, with correlation values exceed 0.60. The correlation between AI and RSEI was highest at 0.9355, indicating that landscape aggregation had a great impact on ecological quality. The correlation between IJI and RSEI was the second highest at 0.9144, indicating that the distribution among landscape patches was constrained by ecosystem conditions. Moreover, landscape patches of the same type are distributed adjacent to each other, and the connectivity (continuity) between landscapes is strong. The correlation between ED and RSEI was 0.9084, and that between LSI and RSEI was 0.8784, which showed that the complexity of landscape shapes and the edge effects produced by the complex shapes were closely related to changes in ecological quality. Combined NP and PD represented landscape fragmentation, and their

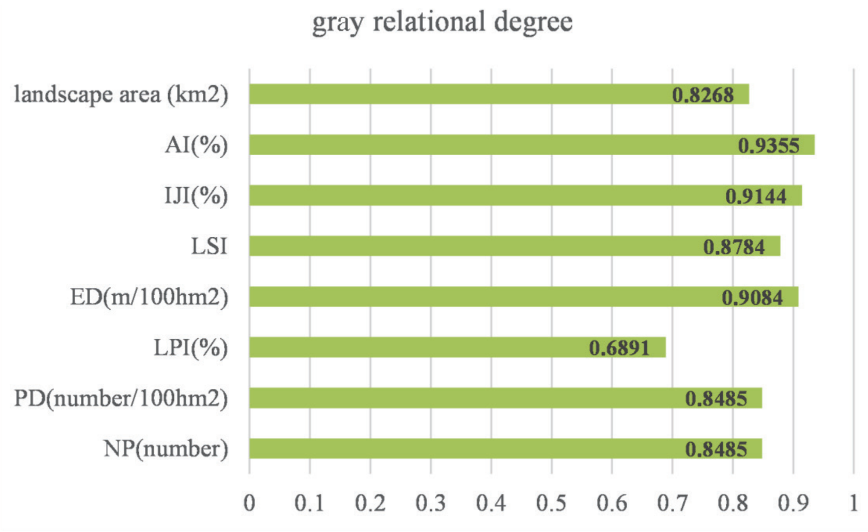

Fig. 11. (Color online) Degree of gray relationship between RSEI quality and landscape index.

correlation with RSEI was 0.8485, which indicated that landscape fragmentation had a considerable effect on ecological quality. The correlation between the landscape area and the RSEI was 0.8268, showing that a change in landscape type area greatly affected the ecological quality. The impact of changes in landscape area on the ecological quality reflected the disturbance to ecology caused by a transforming and unstable landscape structure. The correlation between LPI and RSEI was the lowest, but also reached 0.6891, which showed that the size of the landscape patch also had a certain impact on the ecological quality, whereas the change in landscape patch size also affected the change in landscape fragmentation; therefore, the relationship between LPI and RSEI also reflected the impact of landscape fragmentation on the the ecological quality. The above analysis results showed that there was a strong correlation between the landscape index and the ecological quality.

5. Discussion

In this study, a methodological framework was developed and evaluated for its use in monitoring and analyzing fine dynamic changes in the urban landscape pattern of Beijing based on the use of long time series of Landsat data. The results showed the applicability of using the model to monitor such changes and those related to vegetation landscape patterns, and the changing factors could be comprehensively analyzed from multiple dimensions. This method provides an unprecedented and significant operational advance in enabling the simultaneous analysis of factors driving urban vegetation landscape changes from a habitat quality vegetation coverage perspective.

The extraction of refine landscape type is useful for researching the roles of small-scale landscape elements and ecological ecotones within the landscape structure. In this study, seven refined landscape types (forest, farmland, construction land, grassland, artificial vegetation, water, and bare land) were derived from remote sensing data. Guo *et al.* extracted four typical landscape type categories and quantified their impacts on land surface temperature.(26) In addition, Yang *et al.* analyzed spatial and temporal pattern changes of the landscape based on four derived landscape types.(27) With the enhanced ability to obtain geospatial data (high resolution, multitemporal, and multidimensional) and the continuous improvements in computing performance, it is possible to analyze refined landscape patterns.

With respect to spatiotemporal variations in class-level landscape index, the fragmentation of the vegetation landscape showed an initially decreasing trend followed by an increasing trend from 1999 to 2021. These results are consistent with the conclusions of Qiu *et al.*(28) who summarized that the degree of landscape fragmentation is closely related to the level of urbanization, and it undergoes different dynamic changes during different urbanization stages. With the rapid advancement of urbanization, anthropogenic activities have markedly changed the surface morphology and landscape pattern of cities, which makes the urban landscape appear highly fragmented.(29,30) The increased fragmentation of the urban landscape has caused a considerable disassociation of natural habitats, simplified the species composition, changed urban ecological cycle processes, affected ecosystem services, and endangered the sustainable development of cities.(31–33) Therefore, the dynamic monitoring of vegetation landscape fragmentation using a long time series provides useful results that can be used in the rational planning of the urban landscape.

Exploring the dynamic changes in vegetation coverage and landscape pattern shows the process by which urbanization interferes with various vegetation landscape types and the impact that it has on ecological quality, and it also enables the associated law of evolution to be analyzed.(34) Our results showed that high vegetation coverage is mainly distributed in the north and west of the study site, and this is in good agreement with findings of previous studies.(25,35) It is evident from the correlation between the vegetation coverage and the landscape pattern index that medium- and high-vegetation-coverage areas have become more fragmented. A previous study demonstrated that vegetation patches have become increasingly fragmented as a result of the spread of human settlements, impervious surfaces, and transportation networks.(36) The landscape ED is also higher under medium and high vegetation coverages, and the existing study showed that dynamic agriculturally driven economic activities in municipalities with an extensive developed road network have resulted in a landscape that has become more regularly shaped and heavily fragmented with a higher ED.(37)

Analyzing the quality of the regional habitat from a landscape perspective is useful for quantitatively revealing the role that landscape pattern changes have on habitat quality. In this study, the gray correlation analysis showed a strong correlation between the habitat quality and the landscape pattern index. Areas with a low habitat quality were found to be mainly concentrated in the urban center and its peripheral areas where anthropogenic activities are intense. These areas are mainly dedicated to urban construction and development, and the degree of landscape fragmentation is high. Areas with a high habitat quality were seen to be concentrated in the north and west of the study site where there is high forest vegetation coverage and rich biodiversity. In general, the habitat quality in Beijing followed the progression of urbanization from 1999 to 2014. However, by 2014, urbanization had reached a certain level and people were considerably aware of the need to protect the environment; thus, the habitat quality subsequently improved thereafter. The results of this study show that to avoid landscape fragmentation and improve resilience to ecological disturbance, it is necessary to strengthen the protection and construction of the integrity, connectivity, and systemicity of landscape types that have high ecological suitability.

6. Conclusions

Changes in landscape pattern are often the result of the interaction between humans and nature, and they have a profound effect on regional ecosystem services and sustainable development.(8) Previous studies have mainly focused on how variations in land cover, vegetation cover, and habitat quality affect the landscape pattern, but few have simultaneously and quantitatively analyzed the land cover, vegetation cover, and habitat quality. In this study, we explored the spatiotemporal dynamic changes in landscape pattern during urbanization over the past two decades in Beijing and investigated the spatiotemporal evolution of vegetation coverage and habitat quality from a landscape pattern perspective. From 1999 to 2021, the landscape pattern in Beijing underwent considerable changes: areas of forest land and construction land increased and areas of grassland, farmland, and bare land decreased. The landscape pattern showed a fragmented trend, the degree of mutual separation in the landscape was large, and the edge effect was strong. The overall landscape concentration was high and landscape patches were densely distributed. The vegetation landscape in Beijing was dominated by a high vegetation coverage from 1999 to 2021, and changes in vegetation coverage at different levels were mainly related to a transformation from high to medium vegetation coverages from 2009 to 2021. From the perspective of spatial pattern changes within the landscape, medium-vegetation-coverage areas became highly fragmented, especially in urban areas where there was a low vegetation coverage. Landscape fragmentation under a low vegetation coverage intensified, and the spatial structure of the landscape became increasingly complex. The habitat quality in the study area showed obvious regional differences, and it was superior in the northwestern and western mountainous areas. The results of the gray relational analysis showed a strong correlation between the habitat quality and the landscape pattern index, which demonstrated that the distribution pattern of the landscape types determined spatial differences in habitat quality to a certain extent and that changes in landscape pattern had a large effect on changes in habitat quality.

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