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Study on Landscape Pattern Index Analysis and Driving Mechanism of Park Green Space: A Case Study of the Central Urban Area of Shenyang

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Abstract

Existing research on the landscape patterns of urban parks and green spaces demonstrates a disproportionate focus across tiers within China's urban hierarchy. Numerous studies have concentrated on economically developed first-tier cities, such as Beijing, Shanghai, and Guangzhou. In contrast, medium-to-large non-first-tier cities, especially provincial capitals and emerging cities within the first- and second tiers, have been relatively understudied, although they have received increasing attention in recent years. This bias extends regionally, with studies predominantly examining cities in the more developed central and eastern regions, while less-developed areas and lower-tier cities receive significantly less attention. This study tracks changes in park quantity, spatial concentration, patch structure and driver associations at three planning-related time points. Shenyang provides a distinct cold-region and old industrial city case, shaped by long winters, industrial renewal and outward urban growth. Furthermore, to inform park and green-space planning in Northeast China's cold-climate cities, exemplified here by Shenyang, a major metropolis with a monsoon-influenced humid continental climate (Köppen Dwa), long cold winters, and relatively short warm summers, we document a shift in park distribution from the urban core to peripheral areas. Based on park vector layers reconstructed from planning documents, remote sensing interpretation and field verification, this study combined spatial analysis, landscape metric calculation and driver-association modeling. ArcGIS Pro was used to identify changes in distribution centers, directional extension and local clustering; FRAGSTATS 4.2 was used to calculate park landscape metrics; and SIMCA-P 14.1 was used to examine the statistical associations between selected landscape indicators and potential driving variables. The results show that the number and total area of parks in central Shenyang increased substantially from 2000 to 2024. Spatially, park distribution became less concentrated in the traditional inner city, while new clusters gradually appeared in peripheral districts and newly developed urban areas. The old urban core remained important, but its dominance weakened as park provision expanded outward. The landscape metric results further indicate that park expansion was accompanied by more irregular patch forms, stronger fragmentation and declining structural continuity. The driver association analysis suggests that climate conditions, population change, industrial restructuring, real estate investment, road construction and urban greening policies were related to different aspects of park landscape change. These associations should be interpreted as statistical relationships rather than direct causal effects. Overall, this study clarifies the spatial restructuring of park green spaces in a cold-region old industrial city and provides planning evidence for improving park connectivity, coordinating green space

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expansion with urban construction and supporting sustainable park system development in Northeast China.

Keywords: urban park; landscape pattern; driving forces; urban planning; sustainability

1. Introduction

Urban park systems are increasingly evaluated through quantity, spatial structure and ecological continuity. They enhance recreational opportunities, foster social interactions, and contribute to the health and well-being of residents. Additionally, they offer a variety of environmental benefits [1–6]. The social and ecological advantages derived from an urban park system are strongly dependent on both the quantity of parkland and its spatial distribution [7–12]. Furthermore, park performance is influenced not only by the total area of green space but also by its spatial configuration, which includes shape complexity, connectivity, and patch structure [13–18]. More specifically, landscape pattern metrics, such as connectivity, aggregation, patch size, and edge structure, theoretically underpin ecosystem service provision because they shape ecological flows, habitat continuity, microclimatic regulation, and the spatial stability of service delivery [19,20]. Therefore, assessing the sustainability of these ecosystem service benefits necessitates an examination of how parks and green spaces evolve over time and across different areas, as well as identifying the primary drivers of these changes, especially under conditions of rapid urban development [21–24].

Recent international studies have demonstrated that the discourse surrounding urban park development has evolved to focus not only on quantity but also on issues of accessibility, equity, planning quality, and the structural coherence of green systems. In Europe, recent research has shown that enhanced provision of parks and forests does not necessarily lead to improved accessibility throughout cities, and that planning for open and green spaces increasingly involves balancing efficiency with equity goals through local land-use regulations. These findings indicate that contemporary park research is shifting from a sole focus on the expansion of parks to include considerations of whether park systems are spatially accessible, socially equitable, and structurally well-organized [25–27]. Similar issues have been reported in major cities in Asia and other parts of the world. For instance, studies in large Chinese cities have identified persistent inequalities in park accessibility and significant discrepancies between park provision and residents' needs, while recent research has further shown that urban green-space inequality is often shaped by center–edge gradients, ecosystem-service disparities, and mismatches between supply and demand [28,29]. Collectively, these insights reveal a prevalent challenge in cities globally: park systems may continue to grow in size but still face issues related to fragmentation, accessibility inequalities, and the uneven distribution of ecological and social benefits [30,31].

Existing studies have examined urban green space change from the perspectives of spatial pattern, accessibility, ecological service provision and development drivers. These studies have shown that socioeconomic growth, land-use intensity and urban expansion are closely related to the quantity and structure of urban green space [32–35]. However, three aspects still require further attention. First, many studies continue to treat urban green space as a broad land-cover category, while urban parks themselves contain different functional types, including comprehensive parks, community parks, specialized parks and small recreational parks [36–39]. These park types may differ in scale, spatial location, service function and response to urban development, so their landscape trajectories should not be interpreted only at the aggregate green space level. Second, empirical evidence remains concentrated in megacities and economically advanced regions. Provincial capitals in Northeast China, especially cities with both cold-climate constraints and old industrial restructuring, have received less systematic attention. Third, although multivariate models are widely used to identify possible drivers of landscape change, their planning value depends on whether the results can be connected with concrete urban processes such as road network expansion, redevelopment of older built-up areas and the construction of new districts [40,41]. Shenyang provides a suitable case for addressing these issues. Its park system has developed under the combined influence of cold winters, seasonal vegetation constraints, industrial land renewal, population redistribution and outward urban growth. These conditions make the city different from many warm-region or coastal cities previously discussed in urban park studies. This study therefore focuses on three linked questions: how the number, area and spatial distribution of parks in central Shenyang changed from 2000 to 2024; how landscape metrics varied among different park types; and how selected natural, socioeconomic and urban construction variables were statistically associated with these changes. By focusing on a cold-region provincial capital undergoing old industrial transformation, this study aims to provide evidence for park system optimization, ecological connectivity improvement and coordinated green-space planning in rapidly restructuring urban areas. In this study, the boundary of the central urban area was adopted directly.

2. Materials and Methods

2.1. Overview of the Study Area

Shenyang, with an area of 12,860 km^2 and a population of approximately 9.2 million, was selected as the study city. According to the Shenyang City Territorial Spatial Master Plan (2021–2035), the spatial structure of the central city is described as comprising “one main city, three sub-districts, and two riverbanks.” The “one main city” refers to the urban core, which includes eight administrative districts: Huanggu, Tiexi, Yuhong, Heping, Shenhe, Dadong, Hunnan, and Sujiatun. This core area concentrates essential urban functions and serves as the primary focus for land-use-based development evaluation under the master plan. The quality of its development is considered indicative of the overall development level of the city. Consequently, this study concentrates on the central city to investigate the relationship between changes in urban park landscape patterns and their underlying driving forces. The central urban boundary used in this study follows a validated street-scale delineation of Shenyang. The previous delineation identified the urban core by integrating POI density, building density and road network density, and its threshold setting, indicator standardization and boundary validation were completed in that study. The present research used this boundary as a consistent spatial frame for analyzing park landscape change, and therefore did not repeat the urban core delineation procedure [42]. The delineated study area includes 78 streets, covers 236.07 km^2, and contains more than 50% of the city’s total population, as illustrated in Figure 1.

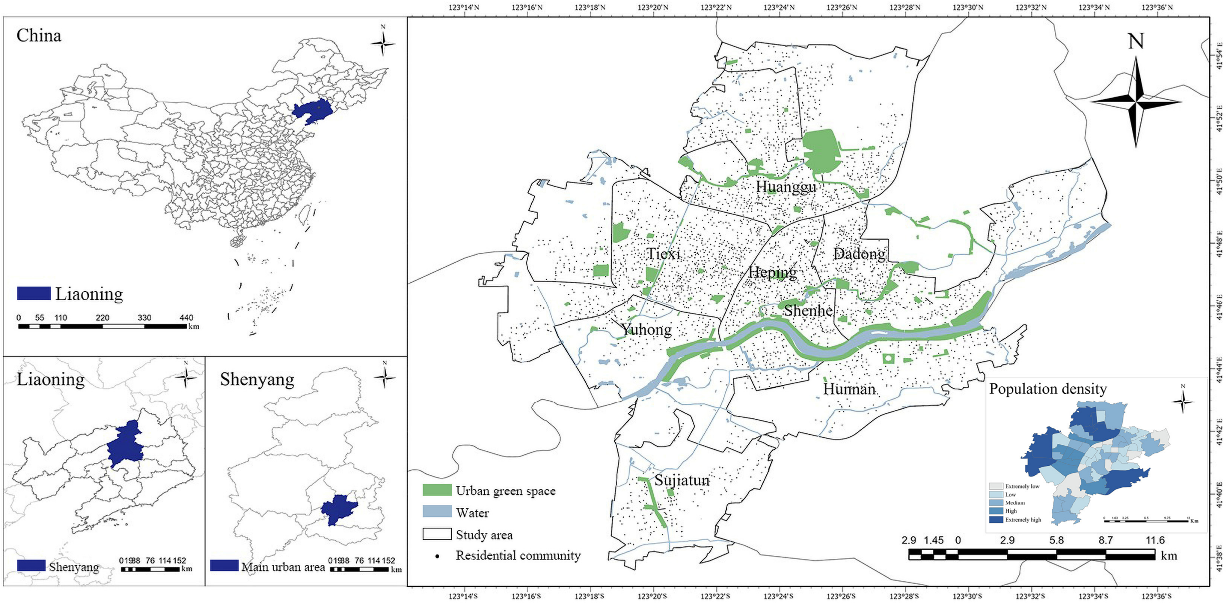

Figure 1. Study area and study object.

2.2. Data Sources and Preprocessing

2.2.1. Establishment of Park Database

The park database for 2000, 2010 and 2024 was reconstructed from multiple sources, including urban master plans, green space system plans, park-specific planning documents and field survey records obtained from relevant municipal planning and natural resources institutions in Shenyang. Field surveys were used to check park names, functional types, boundary consistency and current construction status. For the historical years, park polygons derived from planning documents and field verification were further compared with remote sensing interpretation results for 2000 and 2010. The consistency of reconstructed boundaries was evaluated using relative area difference and intersection-over-union (IoU), which helped to assess whether historical polygons matched the interpreted spatial extent. The comparison showed high overall consistency, with most parks presenting only minor area deviations and clear polygon overlap. After this verification, all park polygons were standardized and converted into a unified vector database. According to the Urban Green Space Classification Standard (CJJ/T85-2017) [43], the parks were classified into four types—comprehensive parks (P1), community parks (P2), specialized parks (P3) and pleasance parks (P4)—as shown in Table 1.

Table 1. Types of urban park landscapes and their characteristics.

	Category Name	Content	Main Functional Positioning
G11	Comprehensive Park	A comprehensive recreational space for the entire city or a larger area, emphasizing multiple activity types and relatively complete management/service facilities. In local practice, it is often further refined into composite zones such as “cultural science popularization, leisure and recreation, sports and health care, children’s play, and service management.”	Multi-functional composite recreation, certain ecological landscapes and public services
G12	Community Park	Emphasizing “proximity, daily use, and inclusiveness,” this category often focuses on the light exercise and rest needs of children, the elderly, and general residents. Local management standards often clearly define it as a neighborhood-type public space that “focuses on children’s play and the elderly’s rest and fitness.”	Nearby daily rest, friendly to children and the elderly, light exercise

Table 1. *Cont.*

	Category Name	Content	Main Functional Positioning
G13	Specialized Park	With "theme/resource/function specialization" as the core, it can undertake roles such as popular science education (botanical gardens, zoos), memorial and cultural exhibitions (historical gardens, sites/memorial types), and recreational and entertainment (amusement parks). Some cities have also included forest parks and the like in the management classification of "specialized parks."	Thematic specialization: popular science research, commemorative culture, recreational and entertainment, etc.
G14	Pleasance Park	The main focus is on micro recreational spaces that "fill in the gaps and blind spots," often corresponding to the current practice of "pocket parks/corner parks/small parks," etc. Some cities consider it a subordinate or supplementary type of community park in their park system.	Micro recreational spaces, filling blind spots; often connected to "pocket parks/street gardens."

Source: The author organized the classification criteria of urban park green spaces according to the Urban Green Space Classification Standard (CJJ/T85-2017) issued by the Ministry of Construction.

2.2.2. Analysis of the Relevant Data on the Landscape Layout of Urban Parks

The evolution of park landscape patterns in the central urban area has been influenced by multiple developmental factors. Over the period from 2000 to 2024, the park green space network in the central urban area of Shenyang underwent a gradual transformation from a relatively concentrated urban core pattern towards a more outwardly extended and structurally differentiated system. This transformation provides the temporal context for the present analysis. These factors were quantified and organized into three dimensions: the natural environment, socioeconomic conditions, and urban construction. Data on the average annual temperature were obtained from the National Meteorological Science Data Center (https://data.cma.cn/dataCollect/index.html (accessed on 1 October 2024)). Data on annual average precipitation were sourced from the Water Resources Department of Liaoning Province (https://slt.ln.gov.cn/ (accessed on 1 October 2024)). Information on elevation and slope was acquired from Earth Explorer-USGS (https://earthexplorer.usgs.gov/ (accessed on 1 October 2024)). Socioeconomic statistics were collected from the Shenyang Municipal Bureau of Statistics (accessed 1 October 2024), and urban construction variables were derived from high-resolution geospatial products provided by the Geospatial Data Cloud (both accessed on 1 October 2024).

2.3. Research Methods

The analysis proceeded through four steps: park database reconstruction, spatial distribution analysis, landscape metric calculation and driver association modeling, as shown in Figure 2. First, park data from different years were compiled into comparable vector layers. Second, standard deviational ellipse (SDE), area-weighted SDE and kernel density estimation were conducted in ArcGIS Pro. The SDE analysis was used to identify the movement of the distribution center and the main directional tendency of park distribution, while the area-weighted ellipse helped reflect the influence of large park patches on the overall spatial structure. Kernel density estimation was used to detect local concentrations and changes in clustering intensity over time. Third, FRAGSTATS 4.2 was used to calculate landscape metrics for 2000, 2010 and 2024, covering patch size, density, dominance, shape complexity, fragmentation, aggregation, diversity and connectivity. Finally, Pearson correlation analysis was used to reduce redundancy among candidate landscape metrics, and OPLS regression in SIMCA-P was used to examine statistical associations between selected landscape indicators and natural, socioeconomic and urban construction variables. Model reliability was checked through cross-validation and permutation testing, and the association structure was further interpreted with heat maps and network diagrams.

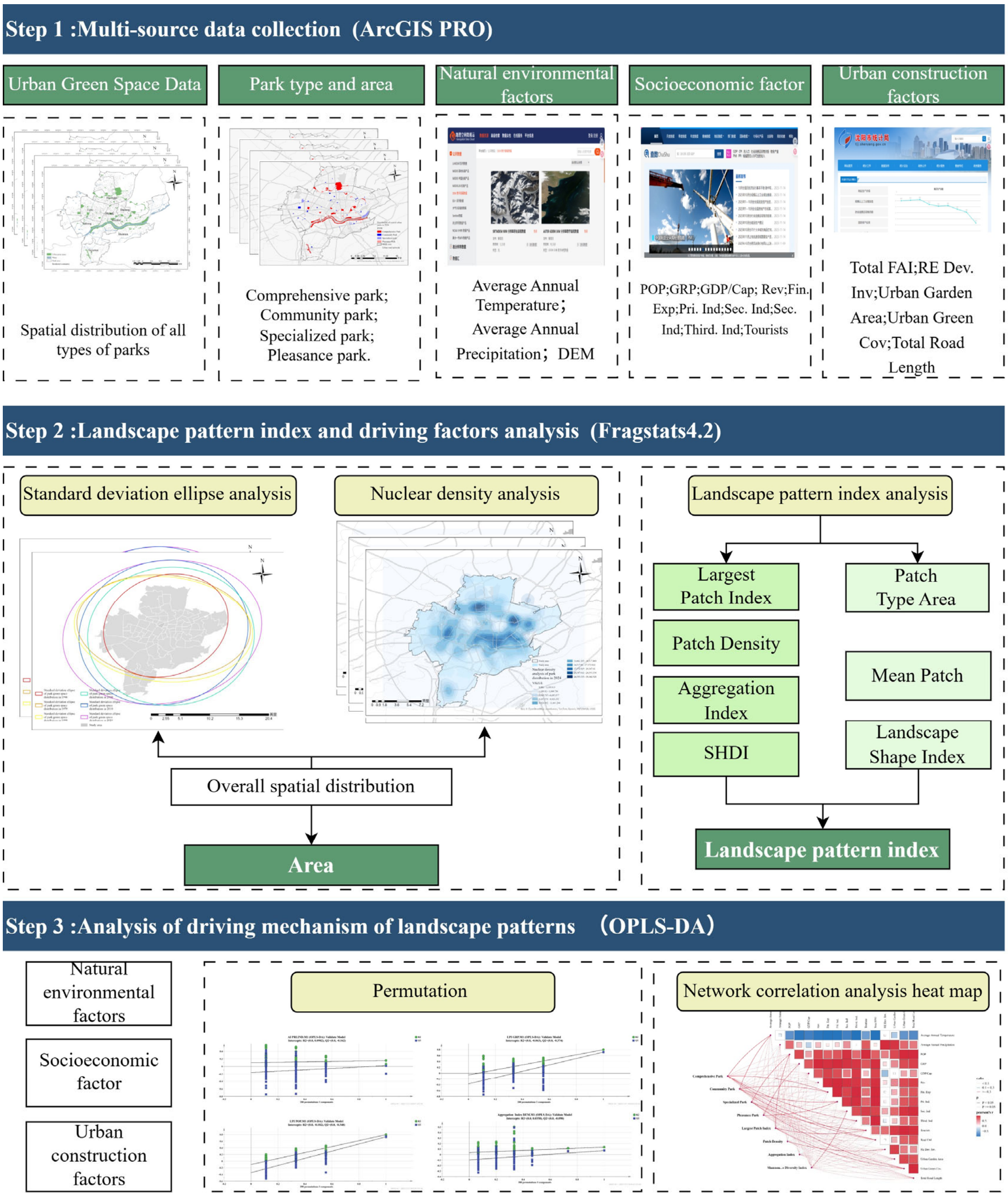

Figure 2. Workflow of data processing and statistical analysis.

2.3.1. Identification of Spatiotemporal Evolution of Park Green Spaces

Park distribution was compared across three planning nodes to identify changes in concentration, directional extension and peripheral clustering [44,45]. The study utilized remote sensing images from the years 2000, 2010, and 2024 to delineate the spatial distribution of park green spaces at three distinct time points. The years 2000, 2010 and 2024 were chosen as planning-related observation points, corresponding to different stages of Shenyang's central-city planning and territorial–spatial planning process. The year 2000 marks the late phase of the 1996–2010 central-city planning framework, 2010 signifies the transition to a new round of master plan revision and the 2006–2020 land-use planning cycle, and 2024 reflects the most recent stage, shaped by the 2016–2018 greening action plan and the ongoing territorial–spatial planning agenda towards 2021–2035. This method allowed for the collection of data concerning the spatial distribution and area of park green spaces, as illustrated in Figure 3. Initially, the mean latitude and longitude coordinates for each park green space were calculated to determine the geometric center of the standard deviation ellipse, which reflects the clustering tendency of all park locations. The formula used is as follows:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

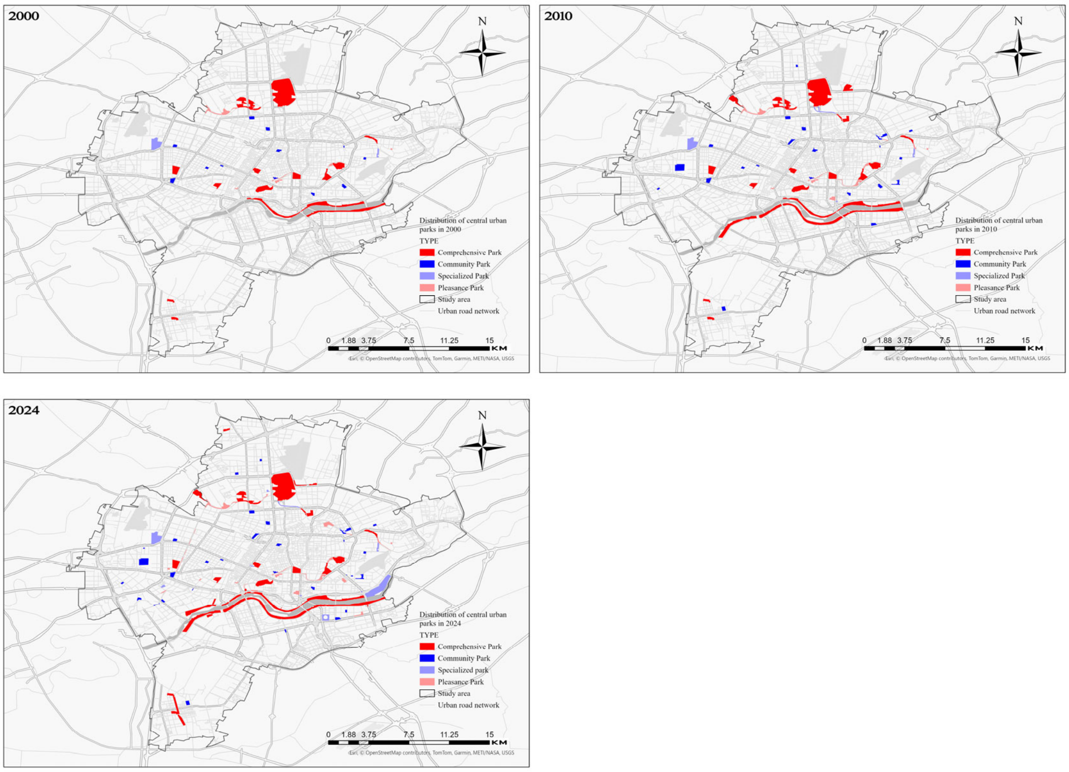

Figure 3. Spatial distribution of various types of park patches in the central urban area of Shenyang during the study period.

In this equation, n represents the number of parks, and x_i, y_i are the coordinates of the i-th park.

Subsequently, $\bar{x}$ and $\bar{y}$ were utilized to construct the covariance matrix, which indicates the correlation between the x and y coordinates of the park locations, reflecting the dispersion and orientation of the park distribution. The relevant formula is:

$$\sigma_{xy} = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \tag{2}$$

In this equation, σ_{xy} denotes the covariance between the x and y coordinates of the park locations.

The results were then processed in ArcGIS Pro to generate both the standard deviation ellipse and the area-weighted standard deviation ellipse of the park distribution.

In the final step, park location data (x_i, y_i) were subjected to kernel density analysis in ArcGIS Pro to identify spatial concentrations of parks. The search radius was not fixed arbitrarily; instead, the default data-driven bandwidth provided by ArcGIS Pro was adopted, which is computed specifically for the input point pattern using a spatial variant of Silverman's rule-of-thumb. The formula is:

$$F(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \tag{3}$$

In this equation, $F(x)$ represents the estimated kernel density at point x, n indicates the number of park green spaces, k is the kernel function, h denotes the bandwidth, and $x - x_i$ represents the distance from the evaluation point to x_i. The function k is a radially symmetrical unimodal density function. The analysis results were then standardized and mapped onto a grid to produce the kernel density map of urban parks.

2.3.2. Screening of Park Green Space Landscape Pattern Index

Based on previous studies, the characteristics of the study area and the objectives of this research, an initial set of landscape metrics was compiled to describe the quantity and structural characteristics of park patches. The candidate metrics covered patch size, patch density, dominance, shape complexity, fragmentation, aggregation, diversity and connectivity. These metrics were calculated in FRAGSTATS 4.2 for the three selected years of 2000, 2010 and 2024.

Before the driver-association analysis, Pearson correlation analysis was used to identify metrics that contained overlapping information. When two or more indicators described similar structural characteristics, one representative metric was retained according to its ecological meaning, planning usefulness and ability to represent a separate aspect of park configuration. This screening process was intended to reduce redundancy among response variables and improve the interpretability of the subsequent model. It was not used to infer causal relationships.

Following this process, Division, Connect, Aggregation Index and Shannon's Diversity Index (SHDI) were selected as representative indicators for fragmentation, connectivity, aggregation and diversity. In addition, park area for each park type was retained as a basic supply indicator, because changes in park area remain essential for understanding the expansion and restructuring of the park system.

Average patch area (MPA): This index represents the average area of each patch and is used to reflect the average size of the patches. The formula is as follows:

$$MPA = \frac{\sum_{i=1}^{n} A_i}{n} \tag{4}$$

where A_i represents the area of the i-th park, and n is the total number of parks.

Patch density (PD): This index measures the number of patches per unit area, reflecting the distribution density of landscape patches. It is formulated as

$$PD = \frac{n}{A} \tag{5}$$

where n represents the number of patches of a certain type, and A is the total area of the study region.

Largest Patch Index (LPI): This index quantifies the percentage of the largest patch in the total landscape area, indicating the relative scale of the largest patches in the landscape. The formula is as follows:

$$LPI = \frac{A_{max}}{A_{\text{total}}} \times 100 \tag{6}$$

Here, A_{max} signifies the area of the largest park, and A_{total} is the total area of all parks.

Aggregation Index (AI): This index measures the degree of aggregation of landscape patches. A higher AI value indicates more clustered patches. The formula is as follows:

$$AI = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}{n^2} \tag{7}$$

where W_{ij} is the adjacency weight between parks i and j, and n denotes the total number of patches.

Shannon Diversity Index (SHDI): Measures the diversity of patch types in a landscape; higher values indicate greater diversity. The formula is as follows:

$$H' = -\sum_{i=1}^{n} p_i \ln(p_i) \tag{8}$$

In this formula, p_i is the proportion of patch type i, and n is the number of patch types.

Connectivity (C): This index describes the degree of connectivity between different patches, typically measured by the number of adjacent patches or a weighted connectivity measure. The formula is as follows:

$$C = \frac{\sum_{i=1}^{n} c_i}{n} \tag{9}$$

where c_i denotes the connectivity of patch i, calculated from its degree of adjacency to other patches, and n represents the total number of patches.

2.3.3. Driver Association Analysis of Park Landscape Change

For consistency, the landscape metrics used in the subsequent driver analysis were also calculated only for these three benchmark years rather than for annual intervals. Accordingly, the driver analysis in this study should be understood as a stage-based comparison across three representative time points spanning 2000–2024, rather than as a continuous annual time-series analysis. This study employed a multivariate linear regression model to systematically examine the relationships between landscape pattern indices and driving factors in park green spaces. Initially, we selected the most significant landscape pattern indices through Pearson correlation analysis. Subsequently, an orthogonal partial least squares (OPLS) regression model was employed to correlate the selected continuous landscape metrics with natural, socioeconomic, and urban construction factors. OPLS regression was adopted because the explanatory variables were interrelated and the study aimed to interpret associations rather than estimate direct causal effects. It was also preferred over standard PLS mainly because the separation of predictive and orthogonal variations facilitates model interpretation and the identification of drivers directly associated with the response variables. This approach aimed to identify both positive and negative statistical associations between the driving factors and the highly correlated landscape indices. Following this, we validated the accuracy and predictive ability of the regression model. After model validation, the association patterns were analyzed based on the results to elucidate the possible explanatory links of the observed changes. The fundamental formula for the OPLS regression is presented as follows:

$$Y = b_0 + \sum_{i=1}^{n} b_i X_i + \varepsilon \tag{10}$$

where Y represents the dependent variable (target variable); b_0 denotes the intercept term; X_i signifies the i-th independent variable; b_i is the corresponding regression coefficient; ε is the error term.

We assessed the model's plausibility by evaluating its predictive accuracy. In the model developed using SIMCA-P, the Q^2 value was obtained via cross-validation. A Q^2 value of 0.0975 or higher indicates that the model possesses sufficient robustness. The R^2Y value signifies the goodness of fit; a value exceeding 50% indicates that the model has high accuracy and predictive capability. The VIP (Variable Importance in the Projection) value indicates the significance of each independent variable in relation to the dependent variable within the model. A VIP value exceeding 1 denotes a strong correlation between the independent and dependent variables, with higher values indicating greater importance.

Overall, this analytical framework combines descriptive spatial analysis, landscape metric quantification, and multivariate driver interpretation. Standard deviational ellipse and kernel density estimation were used to identify the spatiotemporal evolution of park distribution. FRAGSTATS quantified changes in landscape structure, and OPLS regression interpreted the associations between selected landscape indices and multiple potentially collinear driving factors. This combination enables the study to progress from morphological description to structured explanation of changes in the park system. In addition to VIP values and regression coefficients, the OPLS models were evaluated using model fitting and predictive indicators provided by SIMCA-P, including R^2Y, Q^2, and permutation-based validation results, ensuring that the subsequent interpretation of driver–pattern relationships was supported by explicit model validation statistics.

3. Results

Using the ArcGIS PRO platform, a database of park type attributes was developed for the central city of Shenyang. This foundational data facilitated a statistical analysis of the number, area, and geographic distribution of urban parks from 2000 to 2024. The outcomes of this analysis are illustrated in Figure 3, which depicts the spatial distribution of various types of park patches in the central urban area of Shenyang during the study period.

3.1. Analysis of Overall Feature Evolution

A comparative analysis of the landscape composition of park green spaces in the primary urban area of Shenyang city for the years 2000, 2010, and 2024 is presented in Table 2. This table illustrates the evolution of both the number and the area of park green spaces. Over the period from 2000 to 2024, the number of park green spaces in the central urban area of Shenyang increased from 65 to 135, representing a 107.69% increase. Concurrently, the area of park green spaces expanded from 995.84 hectares to 2138.87 hectares, reflecting a growth of 114.83%.

Table 2. Number and area of park green space in the main urban area from 2000 to 2024.

Year	2000	2010	2024
Quantity	65	83	135
Area	995.84	1383.69	2138.87

The increase in park number and area reflects the combined influence of Shenyang's outward urban development, greening-oriented planning and public service provision in newly developed districts. As the built-up area expanded beyond the traditional inner city, peripheral districts provided more land opportunities for comprehensive parks, community parks and small recreational spaces. At the same time, renewal of older built-up areas and the construction of new residential and mixed-use districts created additional demand for nearby park services. Therefore, the observed growth in park area should be interpreted as a planning-related response to urban restructuring, land redevelopment and residents' increasing demand for everyday green space. The statistical relationships between this expansion and demographic, socioeconomic and urban construction variables are further examined in Section 3.3.

The kernel density results reveal a gradual redistribution of park concentrations in central Shenyang, as shown in Figure 4. In 2000, the highest-density area was located in Shenhe District, with a peak value of 3753.85. Park distribution at this stage was still closely tied to the traditional urban core, and the main extension direction followed an east–west tendency. By 2010, park concentration had begun to extend beyond the original core. The strongest aggregation appeared near the Heping–Shenhe area, with a peak value of 9229.39, while additional concentrations emerged around Dadong, Tiexi and Huanggu districts, with peak values of 7554.13 and 5298.63. By 2024, park concentrations were no longer limited to the historical inner-city area. Several peripheral clusters became more visible, especially around newly developed urban districts, while the traditional core continued to function as an important concentration area. This pattern indicates that the spatial structure of Shenyang's park system became more dispersed and more closely connected with outward urban expansion.

Figure 4. Nuclear density analysis of parks in central urban area of Shenyang from 2000 to 2024.

3.2. Analysis of Landscape Pattern Index

The landscape pattern index was computed individually for four types of parks, as indicated in Table 3 and Figure 5. The analysis of the park green space landscape index over the last two decades demonstrates a consistent growth in both the number and the area of parks within the central city of Shenyang [22,36,37]. Notably, there has been a substantial expansion in the areas designated as comprehensive and community parks. The diminishing trend in the maximum patch index, from 0.87 to 0.6, signifies a declining predominance of comprehensive parks, highlighting the notable impact of human activities on these parks. Over the years, there has been a gradual reduction in the maximum patch index for each park type, amounting to a decrease of 16.1%, which suggests a relatively even distribution of various park types established by local authorities in Shenyang's central city. Throughout the research period, there was a general increase (by 52.5%) in the landscape shape index for all park types, indicating a growing complexity in park patch shapes and a gradual outward expansion in their spatial distribution.

Table 3. Statistical table of urban park landscape pattern indices for central Shenyang City during the study period.

Year	Type of Park	Patch Number	Patch Type Area (hm^2)	Mean Patch (hm^2)	Patch Density (%)	Largest Patch Index	Landscape Shape Index	Aggregation Index	Shannon's Diversity Index	Connect (500 m)
2000	P1	14	639.03	90.04	2.65	0.87	7.38	90.29	0.15	7.05
	P2	10	49.8	11.07	2.06	0.03	4.03	83.12		
	P3	4	95.54	60.66	1.76	0.16	1.84	95.13		
	P4	37	211.47	7.89	0.29	0.06	5.5	71.97		
2010	P1	19	887.35	95.55	2.66	0.68	9.1	89.36	0.17	3.23
	P2	15	94.33	13.54	2.66	0.08	5.76	83.18		
	P3	9	132.23	37.8	0.46	0.12	3.29	88.24		
	P4	40	269.78	10.57	1.96	0.07	7.07	71.35		
2024	P1	28	1474.8	85.37	2.71	0.60	10.25	90.29	0.18	2.16
	P2	42	182.66	10.67	3.31	0.08	6.13	83.12		
	P3	10	132.23	46.63	0.8	0.20	3.59	95.13		
	P4	50	349.18	7.45	4.71	0.06	8.63	71.97		

P1: Comprehensive park; P2: Community park; P3: Specialized park; P4: Pleasance park.

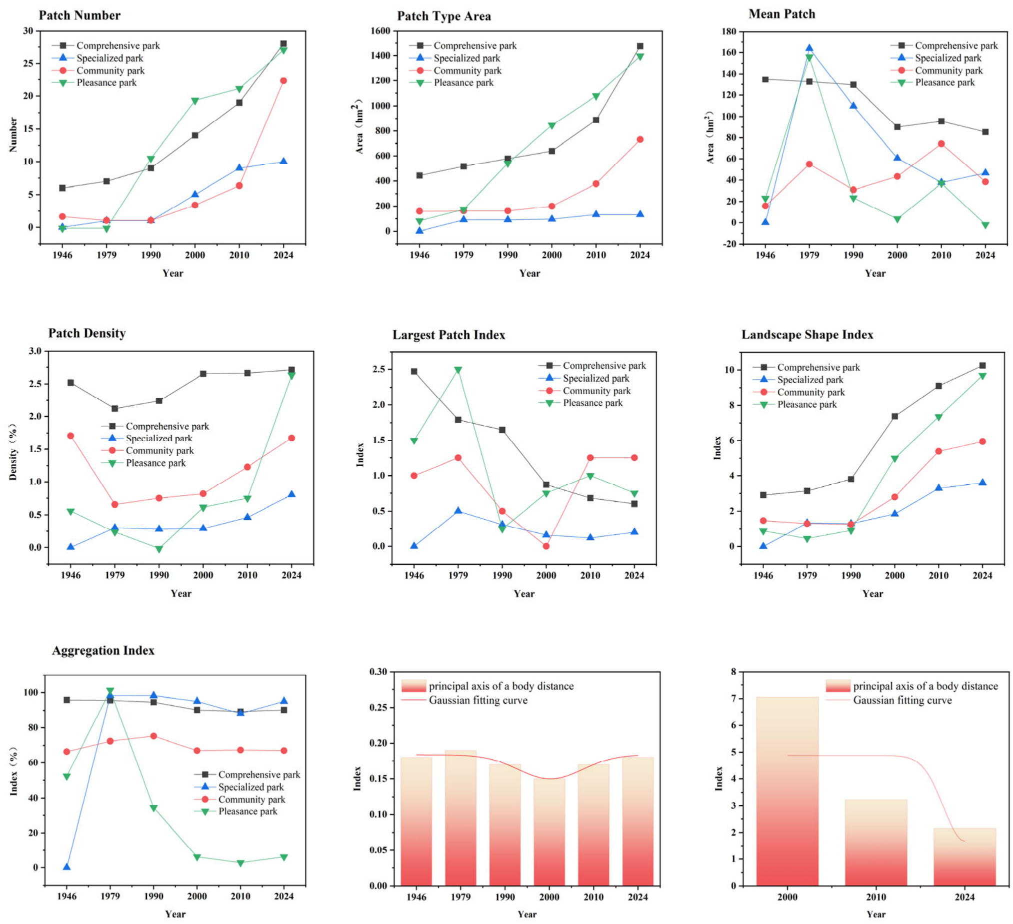

Figure 5. Comparative chart of changes in park landscape pattern indices in the central urban area of Shenyang city during the study period.

The analysis of the evolution of park green space fragmentation reveals that PD is an index of fragmentation levels across various types of parks [15–17], with the most pronounced changes observed in amusement parks. Between 2000 and 2010, amusement parks displayed a spatially cohesive distribution. However, following 2010, rapid urbanization led to a reconfiguration of amusement park layouts, resulting in increased fragmentation levels [46,47]. Notably, specialized parks experienced a reduction in PD during the research period, decreasing from 1.76 to 0.8, suggesting their prevalence in densely populated central urban areas characterized by consistent and evenly distributed patterns. The examination of the evolution of park green space connectivity indicates that the AI reflects the connectivity status of all park types. Initially, all park types experienced a decline followed by a return towards the baseline. Furthermore, the analysis of the evolution of park green space diversity shows that the SHDI not only reflects the diversity of landscape types but also the richness of the landscape structure and the balance of spatial layout. In the central urban area of Shenyang City, the SHDI for park green spaces increased linearly from 0.15 to 0.18 during the study period, indicating balanced development in green space construction and spatial equilibrium. Conversely, an examination of the evolution of park green space connectivity reveals a significant decline in the connectivity index, which decreased from 7.05 to 2.16. This decline indicates an increase in landscape fragmentation within park green spaces and highlights the growing complexity of connections between parks.

3.3. Correlation Analysis Between Landscape Index and Driving Factors

The study utilized correlation analysis and OPLS regression to investigate the relationships between park landscape indices and potential driving factors during the benchmark years of 2000, 2010, and 2024. The aim was to identify the key variables most significantly associated with differences in park area and landscape structure across these representative stages of development. The primary driving forces included natural elements, socioeconomic aspects, and urban development factors [24,35]. Orthogonal partial least squares regression analysis (OPLS regression) was applied to park area and landscape pattern indices using these three categories of data.

As Table 4 illustrates, among the natural environmental factors, mean annual temperature and mean annual precipitation displayed relatively clear association patterns with changes in park green space fragmentation and aggregation. Mean annual air temperature (VIP = 1.01, RC = 2.36) was positively associated with the Division index, whereas mean annual precipitation (VIP = 1.35, RC = −2.09) was negatively associated with the Division index. In terms of aggregation, both mean annual temperature (VIP = 1.23, RC = 1.81) and mean annual precipitation (VIP = 1.14, RC = 1.75) showed positive associations with the Aggregation Index.

Table 4. Analysis of park landscape pattern evolution and natural factors driving.

Natural Factors	Area								Landscape Pattern Index							
	Comprehensive Park		Community Park		Specialized Park		Pleasance Park		Division		Connect		Aggregation Index		Shannon's Diversity Index	
	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC
Average Annual Temperature	0.56	0.39	0.79	−1.6	0.91	−3.42	0.28	−2.5	1.01	2.36	0.45	0.55	1.23	1.81	0.91	0.79
Average Annual Precipitation	0.93	−0.01	0.22	−0.13	0.79	−0.12	0.85	−0.04	1.35	−2.09	0.73	−0.90	1.14	1.75	0.46	0.06

VIP: Variable Projection Importance; RC: Regression Coefficient. If the VIP value is greater than 1, it indicates that it is an important influencing factor, with larger values having a more significant impact; a positive RC indicates a positive correlation between the driving force and the park landscape pattern, whereas a negative RC indicates a negative correlation, the same below.

As demonstrated in Table 5, several socioeconomic factors, including the growth of the resident population, the output value shares of primary and secondary industries, and the number of tourists, were associated with changes in park green space area. The increase in the resident population was positively associated with the expansion of comprehensive park areas (VIP = 1.09, RC = 0.19) and amusement park areas (VIP = 1.07, RC = 1.68). However, it showed a negative coefficient for the development of community park areas (VIP = 1.26, RC = −1.37). The rise in primary industry output value was negatively correlated with the expansion of comprehensive parks (VIP = 1.05, RC = −1.06) and community parks (VIP = 1.14, RC = −1.05). This trend was particularly noticeable when the primary industry focused on agriculture and forestry, which led to a strain on land resources in densely populated urban centers, thereby hindering the expansion of parks and green spaces. In contrast, the increased share of secondary industry output was positively associated with the expansion of comprehensive park areas (VIP = 1.06, RC = 1.20) and community park areas (VIP = 1.15, RC = 1.15), which may reflect the relationship between industrial development, urban land restructuring and increased demand for public green space provision.

Table 5. Analysis of park landscape pattern evolution and socioeconomic factors.

Socioeconomic Factors	**Area**								**Landscape Pattern Index**							
	Comprehensive Park		**Community Park**		**Specialized Park**		**Pleasance Park**		**Division**		**Connect**		**Aggregation Index**		**Shannon's Diversity Index**	
	VIP	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**
POP	1.09	0.19	1.26	−1.37	0.99	−1.72	1.07	1.68	1.20	−2.49	0.69	−0.80	0.19	0.45	0.8	−1.6
GRP	0.87	−0.79	0.98	−0.8	0.63	−0.71	0.73	−0.74	1.34	−1.54	1.03	−0.92	0.03	0.04	0.49	−0.56
GDP/Cap	0.75	−0.32	0.86	−0.44	0.75	−0.32	0.56	−0.22	1.39	−0.44	1.15	−0.64	1.3	0.27	0.19	−0.08
Rev	0.79	−0.68	0.91	−0.73	0.57	−0.57	0.65	−0.61	1.36	−1.40	0.90	0.74	0.04	0.04	0.43	−0.44
Fin. Exp	0.87	−0.73	0.98	−0.78	0.6	−0.63	0.73	−0.68	1.34	−1.41	1.04	−0.88	0.02	0.01	0.48	−0.5
Pri. Ind. %	1.05	−1.06	1.14	−1.05	0.81	−1.15	0.91	−1.08	1.28	−1.84	0.85	−0.86	0.52	−0.01	0.64	−0.91
Sec. Ind. %	1.06	1.2	1.15	1.15	0.84	−1.24	0.92	−1.22	1.28	−2.07	0.84	−0.90	0.09	0.16	0.66	−1.04
Third. Ind. %	0.91	−0.76	0.98	−0.81	0.61	−0.66	0.77	−0.71	1.34	−1.39	1.00	−0.86	0.04	−0.04	0.5	−0.52
Tourists	0.91	1.01	1.04	1.03	0.71	0.88	0.75	0.92	1.34	−1.81	0.98	−0.98	0.12	0.18	0.51	−0.69

POP: Resident Population; GRP: Gross Regional Product; GDP/Cap: GDP per Capita; Rev.: Revenue; Fin. Exp.: Financial Expenditure; Pri. Ind. %: Proportion of Primary Industry Output Value; Sec. Ind. %: Proportion of Output Value of the Secondary Industry Output Value; Sec. Ind. %: Proportion of Output Value of the Secondary Industry; Third. Ind. %: Proportion of Output Value of the Tertiary Industry; Tourists: Number of Tourists.

Regarding the landscape pattern index, all socioeconomic factors were negatively correlated with the Division index. Notably, the gross regional product (VIP = 1.03, RC = −0.92), per capita gross product (VIP = 1.15, RC = −0.64), regional financial expenditure (VIP = 1.04, RC = −0.88), and the proportion of tertiary industry output (VIP = 1, RC = −0.86) exhibited inverse associations with landscape connectivity, indicating a strong link between these factors and the declining trend in connectivity. Furthermore, an increase in GDP per capita was positively correlated with the Aggregation Index (VIP = 1.3, RC = 0.27), highlighting the close relationship between socioeconomic factors and changes in connectivity and aggregation.

Urban construction variables, such as real estate development investment, urban garden green space area, and urban green coverage, were found to significantly correlate with changes in park green space area, as shown in Table 6. Notably, real estate development investment positively correlated with the expansion of both community park area (VIP = 1.01, RC = 1.18) and specialized park area (VIP = 1.29, RC = 1.31). In contrast, urban garden green space area and urban green coverage often displayed negative coefficients across various types of parks. For the landscape indices analyzed, several factors related to urban construction emerged as particularly important for the Division and Connectivity metrics, indicating that infrastructure expansion significantly influences changes in fragmentation and connectivity of parks during these development stages. By contrast, urban garden green-space area was negatively correlated with the development of all park types, serving as a critical factor affecting park area change. Urban green coverage was also negatively correlated with the development of all park types, with particularly strong effects on comprehensive park areas (VIP = 1.07, RC = −1.29) and community park areas (VIP = 1.17, RC = −1.22). Concerning the landscape pattern index, all urban construction factors were negatively correlated with the Division index. However, investments in fixed assets across society (VIP = 1.10, RC = −0.87), real estate development (VIP = 1.03, RC = −1.13), and the total length of urban roads (VIP = 1.16, RC = −0.93) negatively correlated with landscape connectivity.

Table 6. Analysis of park landscape pattern evolution and urban construction factors.

Urban Construction Factors	Area								Landscape Pattern Index							
	Comprehensive Park		Community Park		Specialized Park		Pleasance Park		Division		Connect		Aggregation Index		Shannon's Diversity Index	
	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC	VIP	RC
Total FAI *	0.79	−0.23	0.91	−0.68	0.54	−0.51	0.65	−0.57	1.36	−1.29	1.10	−0.87	0.3	0.82	0.42	−0.4
RE Dev. Inv. *	0.5	−0.58	1.01	1.18	1.29	1.31	0.37	−0.41	1.39	−1.42	1.03	−1.13	0.2	0.2	0.29	−0.31
Urban Garden Area *	1.34	−1.86	1.34	−1.58	1.1	−2.1	1.22	−2.27	1.16	−2.90	0.49	−0.63	0.38	0.98	0.89	−2.13
Urban Green Cov. *	1.07	−1.29	1.17	−1.22	0.85	−1.27	0.92	−1.3	1.28	−2.16	0.83	−0.91	0.15	0.27	0.65	−1.07
Total Road Length *	0.68	−0.58	0.82	−0.65	0.52	−0.48	0.55	−0.51	1.37	−1.31	1.16	−0.93	0.25	0.4	0.37	−0.36

* Total FAI.: Fixed Asset Investment in the Whole Society; RE Dev. Inv.: Real Estate Development Investment; Urban Garden Area: Urban Garden Green Space Area; Urban Green Cov.: Urban Green Coverage; Total Road Length: Total Length of Roads.

4. Discussion

4.1. Correlation Between Driving Factors and the Evolution of Landscape Pattern Index

Figures 6 and 7 facilitate an investigation into the correlation between spatial structural changes in park green space layouts in 2000, 2010, and 2024, and the corresponding changes in influencing factors. The findings indicate a positive correlation between socioeconomic and urban development factors and the transformation of the extent of park green spaces. Moreover, all determinants exhibit a robust correlation with changes in landscape metrics. The specifics are detailed below.

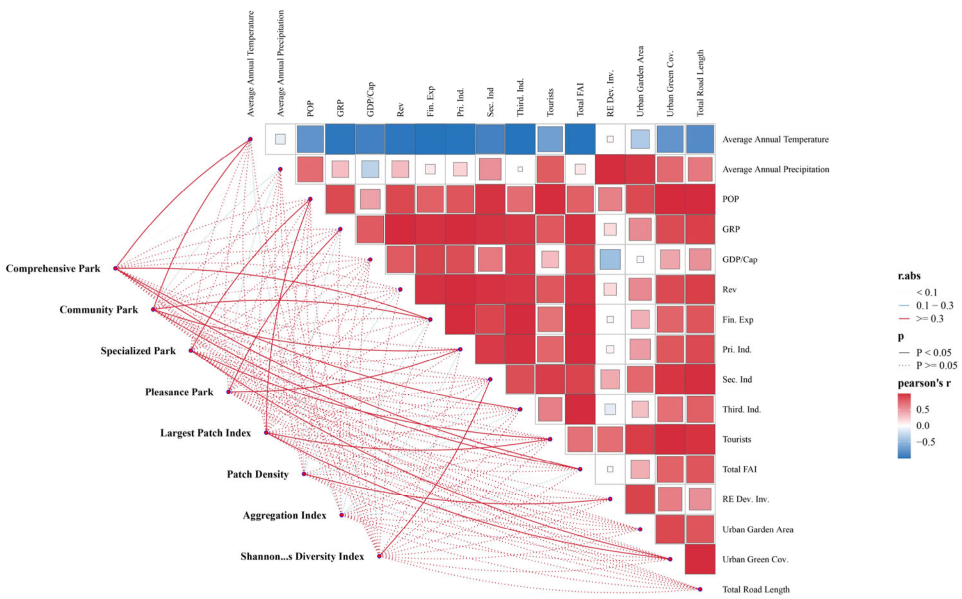

Figure 6. Network analysis heat map of the influence of natural factors, socioeconomic factors and urban structure factors on park area and landscape pattern index.

The OPLS regression analysis reveals that variations in air temperature and precipitation were significantly associated with changes in the Division index and the Aggregation Index of park green spaces. Mean annual temperature was positively correlated with the Division index (RC = 2.36), whereas mean annual precipitation was negatively correlated with the Division index (RC = −2.09). In addition, both average annual temperature

(RC = 1.81) and average annual precipitation (RC = 1.75) were positively correlated with the Aggregation Index, indicating that climatic variation was closely associated with changes in park landscape structure. The combined impact of these factors could lead to decreased fragmentation of green spaces and increased landscape aggregation under favorable climatic conditions.

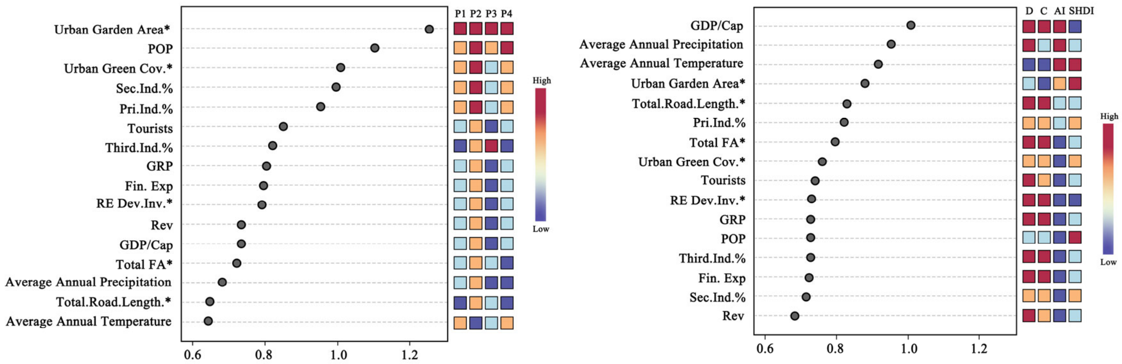

Figure 7. Variable Importance in Projection. * Total FAI.: Fixed Asset Investment in the Whole Society; RE Dev. Inv.: Real Estate Development Investment; Urban Garden Area: Urban Garden Green Space Area; Urban Green Cov.: Urban Green Coverage; Total Road Length: Total Length of Roads.

The influence of social and economic factors on the growth of various types of park areas exhibits marked heterogeneity. These factors include the number of permanent residents, the proportion of output value from primary industries, and the proportion of output value from secondary industries. The number of permanent residents significantly and positively affects the overall growth of park areas (RC = 1.68), yet it adversely impacts the growth of community park areas (RC = −1.37). This indicates that while population growth increases the demand for leisure and recreational spaces, the development of community parks has not kept pace with this demographic increase. In contrast, the proportion of the primary industry significantly and negatively affects the growth of both comprehensive and community parks (RC = −1.06 and −1.05, respectively). This negative impact may be attributed to the primary industry's extensive reliance on land resources, which limits the expansion of urban parks. Conversely, an increase in the proportion of the secondary industry positively correlates with the growth of park areas (RC = 1.2 and 1.15, respectively), suggesting that industrial advancement during urbanization facilitates park development.

The landscape pattern index demonstrates that various socioeconomic factors, including resident population, regional GDP, per capita GDP, and industrial structure, were significantly associated with changes in the Division index and connectivity of park green spaces. In particular, several socioeconomic variables showed negative associations with the Division index, while GDP, per capita GDP, and the tertiary industry proportion were also negatively correlated with landscape connectivity. These findings suggest that socioeconomic development was closely associated with structural changes in park green spaces during urbanization.

Among the factors influencing urban construction, investment in real estate development is positively correlated with the expansion of park areas. This correlation is particularly pronounced in the promotion of community parks and specialized parks, exhibiting RC of 1.18 and 1.31, respectively. These findings suggest that real estate investments have propelled the enhancement of urban park green spaces, especially within residential and commercial areas, where enhanced park facilities contribute added value. Conversely, an increase in the area dedicated to urban garden green spaces has negatively impacted the growth of comprehensive parks, community parks, specialized parks, and recreational parks, with RCs of −1.86, −1.58, −2.10, and −2.27, respectively. This trend indicates that the expansion of garden green spaces might consume a significant portion of urban land, and the prioritization of green space construction has imposed constraints on the development of other park types. In summary, investment in real estate development and the expansion of urban garden green spaces play distinct roles in the development of park green spaces. While the former supports the growth of park areas, the latter may hinder the development of specific types of parks due to spatial constraints.

The landscape pattern index indicates that various socioeconomic and urban development factors significantly affect the fragmentation and connectivity of park green spaces. Increases in total fixed asset investment, real estate development investment, and total length of roads typically align with the expansion of urban infrastructure. This expansion frequently leads to the division of green spaces into smaller sections, thus exacerbating the fragmentation of park green spaces, as evidenced by negative RCs. Simultaneously, these factors are negatively correlated with landscape connectivity, suggesting that the expansion of infrastructure, particularly roads and real estate development, may compromise the connectivity of green spaces. Moreover, while the increase in urban garden green spaces might enhance urban greening, the lack of effective connectivity planning could inadvertently result in reduced landscape connectivity.

4.2. The Significance of This Study for Urban Park Green Spaces

This study demonstrates that the increase in the number and area of parks in Shenyang did not necessarily lead to an ecologically improved park system. Although urban parks experienced significant expansion from 2000 to 2024, this expansion coincided with increased fragmentation and decreased connectivity, indicating that quantitative growth might be accompanied by structural degradation. From the perspective of landscape ecology, such a pattern suggests increased patch isolation, weakened ecological flows, and a diminished capacity of the park system to support habitat continuity and stable ecosystem service provision. The correlations with natural environmental factors imply that climate conditions are not merely background variables but significant ecological constraints that shape the park landscape structure. Prominent relationships between temperature, precipitation, and either fragmentation or aggregation suggest that climatic variations may influence vegetation growth conditions and patch suitability, thereby impacting the spatial continuity of urban green spaces. For cold-region cities like Shenyang, this is particularly critical as seasonal stress may exacerbate the ecological vulnerability of fragmented park systems. In such settings, the ecological consequences of fragmentation can vary significantly with the season, given that shortened growing periods, winter low-temperature stress, delayed spring recovery, and phenological shifts may influence cooling, habitat support, and other ecological services even in the context of an increasing total park area [40,41,48].

The associations with socioeconomic factors reveal that urbanization reshapes not only the quantity of park green space but also its spatial organization. Population growth, economic expansion, and industrial restructuring were closely linked to fragmentation and declining connectivity, indicating that rapid urban development tends to segment green space into smaller, more isolated patches. Ecologically, this suggests that economic growth may increase the demand for green space while simultaneously compromising the integrity of the urban green network through land-use conversion and functional restructuring. Urban construction factors provide clear evidence of direct structural disturbance. Road expansion, real estate development, and other construction-related investments were strongly correlated with increased fragmentation and reduced connectivity, demonstrating that infrastructure growth increasingly disrupts spatial linkages among park patches. Consequently, future park planning should expand beyond area-oriented greening and focus more on structural optimization by protecting core patches, strengthening corridor and stepping stone connections, and coordinating park layout with road networks and urban expansion. In this way, urban parks can serve not only as recreational spaces but also as ecologically connected green infrastructure systems [49].

From a planning perspective, the Shenyang case shows that park area growth needs to be assessed together with patch continuity, service distribution and ecological linkage [50]. This is because fragmentation and declining connectivity can offset the ecological and public service benefits of quantitative growth. These findings have direct implications for park planning and urban governance in rapidly urbanizing, cold-climate cities, where coordinating park expansion, spatial structure, and ecological connectivity is essential to improve environmental quality and residents' well-being. From a scientific perspective, this study contributes to the literature in three significant ways: it provides long-term evidence from an emerging first-tier city beyond the better-studied megacities [51], it specifically focuses on urban parks rather than broad green space categories, and it integrates spatiotemporal pattern analysis with multivariate driver analysis within a unified framework [52].

The Shenyang case echoes international evidence on the trade-off between green space expansion and structural connectivity, while also adding evidence from a cold-region old industrial city undergoing spatial restructuring. This is because accessibility, structural coherence, and ecological functioning may evolve unevenly across different urban areas [53]. In this context, the case of Shenyang reflects a broader challenge observed in both European and Asian urban settings: park systems may continue to expand in area while still experiencing fragmentation, accessibility inequality, and trade-offs between expansion and ecological performance [54]. Compared with findings from larger metropolitan areas, the evolution of Shenyang's park system exhibits both common and distinctive features. Similarly to many rapidly urbanizing large cities, Shenyang has undergone an outward expansion of park provision and a transition from a concentrated central pattern to a more multicentric structure. However, the Shenyang case should not be interpreted as merely replicating megacity trajectories. First, as a cold-climate city, the ecological consequences of fragmentation are likely to be exacerbated by seasonal stresses, freeze–thaw processes, and shorter growing periods [55]. Thus, a more dispersed cluster pattern does not automatically mean stronger ecological functioning, as quantitative expansion may still coincide with weakened connectivity and greater structural vulnerability. Second, as a historically industrial city undergoing restructuring, park growth in Shenyang appears to have been influenced by the combined effects of inner-city functional adjustment, redevelopment of older built-up areas, and new development in peripheral districts. This helps explain why the park system exhibits simultaneous area expansion, persistent core dominance, emerging secondary cores, and declining connectivity. Hence, the contribution of the Shenyang case lies not only in broadening the scope of evidence beyond megacities but also in demonstrating that in cold-climate, old industrial cities, park system evolution may follow a redevelopment-linked and structurally uneven multicore trajectory.

4.3. Limitations and Future Research Directions

In the examination of drivers of urban landscape patterns, although the roles of natural environmental, socioeconomic, and urban construction factors in shaping landscape evolution have been elucidated, enhancing model accuracy and explanatory capability requires future experimental verification of causal relationships. Given the field's characteristics and data constraints, policy adjustments and urban planning changes may have intricate effects on driving mechanisms, with some factors proving challenging to capture and quantify. The driving forces and their interrelationships remain subject to the simultaneous influence of multiple factors. Future research could employ more advanced three-dimensional and multidimensional modeling techniques, such as system dynamics models and geographically weighted regression models, to more effectively grasp the intricate interplay among diverse factors. Due to research duration limitations, studies covering extensive timeframes or diverse domains may inadequately consider local variations and specific occurrences, potentially overlooking crucial dynamic factor shifts.

5. Conclusions

This study examined changes in the urban park system of central Shenyang from 2000 to 2024. The results show that both the number and total area of parks increased markedly during the study period, reflecting the influence of urban expansion, greening-oriented planning and public service provision in newly developed districts. However, the growth of park area was accompanied by increased fragmentation, more complex patch forms and declining connectivity. Spatially, park distribution became less dependent on the historical inner-city concentration, while new park clusters gradually emerged in peripheral development areas. This indicates that the park system became more spatially dispersed, but outward expansion did not automatically improve ecological continuity.

The landscape metric and driver association results further show that changes in park structure were related to natural environmental conditions, socioeconomic development and urban construction variables. Average annual temperature and precipitation were mainly associated with fragmentation and aggregation, while population change, industrial structure and real estate development investment were linked to park area expansion and changes in connectivity. Differences among driver groups suggest that park landscape change in Shenyang was shaped by the combined influence of cold-climate conditions, old industrial restructuring, land redevelopment and infrastructure construction.

The findings provide practical evidence for park system optimization in cold-region cities. For Shenyang, future planning should strengthen the connections among comprehensive parks, community parks, specialized parks and small recreational spaces, especially in peripheral districts and areas transformed from older industrial land. Greater attention should be given to ecological corridors, road network coordination and the continuity of green infrastructure during urban expansion. Scientifically, this study adds case-based evidence from a Northeast Chinese provincial capital undergoing cold-climate constraints and old industrial transformation. It shows that spatial decentralization of parks may occur together with weaker structural continuity, and that park expansion needs to be coordinated with ecological linkage planning to support more sustainable urban green space development.

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