

Article

Research on the Evolution Mode and Growth Characteristics of Urban Blue–Green Space Based on Landsat Data and National Policy Driven: A Case Study of the Shandong Peninsula Urban Agglomeration

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Highlights

What are the main findings?

- Total urban green space and blue space in the Shandong Peninsula urban agglomeration increased by 6.65% and 53.34%, respectively, from 2014 to 2023, accompanied by a significant improvement in vegetation greenness in most of the municipal district areas.
- The spatial structure of urban green spaces shifted from fragmented to more aggregated and contiguous patterns, with the landscape shape index decreasing by approximately 18.3%, indicating enhanced connectivity and structural integrity.

What are the implications of the main findings?

- The changes in UBGs are related to the implementation of national regional policies, and the effective implementation of policies may help alleviate urbanization pressure and promote the structural optimization of UBGs.
- The findings provide empirical evidence for cross-city collaborative blue–green space planning and integrated ecological governance at the urban agglomeration scale, offering a valuable reference for sustainable development in other rapidly urbanizing regions.

Abstract

Urban blue–green spaces (UBGSs) serve as irreplaceable ecological infrastructure that underpins ecosystem service provision and human well-being improvement in densely populated urban regions. Based on 10-year (2014–2023) Landsat 8 OLI remote sensing imagery, this paper systematically investigates the temporal–spatial evolutionary characteristics and potential socioeconomic and policy-related associations with UBGs changes in the Shandong Peninsula urban agglomeration (SPUA), a pivotal coastal urban agglomeration in eastern China. The results demonstrate that the total UBGs in the SPUA exhibited a pronounced increasing trend throughout the study period: the area of urban green spaces (UGs) expanded from 28,311.66 km² to 30,194.39 km², while urban blue spaces (UBSs) grew from 1108.02 km² to 1699.04 km². Concurrently, the ecological quality of UGs has markedly improved, with NDVI showing a significant upward trend in over one-third of the built-up areas, and vegetation greenness in cities such as Binzhou, Jinan, and Zibo



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increasing by more than 35%. Landscape pattern analysis reveals that the spatial structure of UGSs has transformed from a fragmented and scattered distribution to a centralized and contiguous layout. Specifically, the aggregation index (AI) and largest patch index (LPI) increased overall, while the landscape shape index (LSI) decreased by approximately 18.3%, indicating that the connectivity and structural integrity of urban green spaces have been substantially enhanced. National strategic policies, particularly the outline of ecological protection and high-quality development planning for the Yellow River basin, have effectively alleviated the encroachment pressure of population agglomeration and economic expansion on UBGs, and played a decisive regulatory role in promoting the structural optimization of blue–green spaces. These findings provide empirical evidence for cross-city collaborative planning and integrated ecological governance of blue–green spaces at the urban agglomeration level, and offer valuable reference for achieving sustainable urban development in other rapidly urbanizing areas.

Keywords: UGS; UBS; NDVI; fractional vegetation cover (FVC); Shandong peninsula urban agglomeration

1. Introduction

During the last forty years, China has witnessed an unprecedentedly fast and transformative urbanization, characterized by the continuous expansion of urban built-up areas [1]. As urbanization accelerates, the dramatic increase in impervious surfaces has caused profound alterations in land use patterns, triggering a series of ecological problems such as the urban heat island effect, ecosystem function degradation, and habitat fragmentation [2–4]. Against this backdrop, the significance of urban ecological infrastructure in mitigating urban environmental pressures and preserving ecosystem stability has become increasingly pronounced. Among these components, urban blue–green spaces (UBGSs), as a vital part of the urban ecosystem, are widely acknowledged as the key spatial vectors underpinning sustainable urban development [5]. UBGSs typically encompass natural, semi-natural, and artificial green spaces and water bodies that are either preserved or newly constructed during urban development, fulfilling multiple ecological and social functions within the urban ecosystem [6]. Previous research has demonstrated that UBGSs play an irreplaceable role in regulating urban climate [7,8], alleviating thermal environments [9], fostering carbon sink formation [10], conserving biodiversity [11], and mental health improvement [12]. As urbanization continues to progress and demographic patterns keep shifting, the strain on allocating urban land resources has grown significantly. As a result, rationally allocating and optimizing blue–green spaces in high-density built areas has become a key challenge for urban ecological governance and spatial planning. Therefore, systematically delineating the spatiotemporal evolution characteristics of UBGSs amidst rapid urbanization and identifying their driving mechanisms holds substantial practical importance for promoting urban ecological quality enhancement and achieving sustainable development goals.

With advancements in remote sensing technology and spatial analysis methods, satellite-derived remote sensing datasets have become an indispensable instrument for quantifying and evaluating the spatiotemporal dynamics of urban blue–green spaces [13]. Among the available satellite datasets, Landsat imagery offers several advantages for long-term UBGS monitoring. Its long and consistently calibrated data archive enables comparable observations across different years, while its free and open accessibility facilitates continuous monitoring over extensive areas [14]. Moreover, the 30 m spatial resolution and 16-day revisit cycle provide an appropriate balance between spatial detail, temporal

continuity, and regional coverage. The multispectral bands of Landsat also support the consistent calculation of vegetation and water indices, making the dataset particularly suitable for characterizing long-term changes in UGSs and UBSs at the urban agglomeration scale. Leveraging multi-temporal remote sensing imagery, researchers have conducted extensive studies on UBGs across various urban scales, focusing on aspects such as area change, spatial pattern, and ecological function. The study by Abdullah et al. [15] involved using Landsat data from various periods to examine the evolution of urban green and blue spaces in five prominent Bangladeshi cities. Their results demonstrated that the dominant driving forces leading to the shrinkage of urban blue-green spaces were accelerated population agglomeration and the massive expansion of impervious built-up areas caused by unregulated urban sprawl. Gong et al. [16] used a combination of multi-source remote sensing data and the InVEST model's urban cooling module to assess the spatial and temporal heterogeneity of cooling effects from blue-green spaces over the years from 1990 to 2020. The core findings of their study revealed a significant positive association between the magnitude of cooling effects and the level of urbanization, highlighting the critical role of UBGs in alleviating the urban heat island (UHI) effect and protecting public health. Yuan et al. [17] extracted UBGs information in the central urban area of Nanjing based on Landsat-8 OLI imagery, investigated the quantitative relationship between urban blue-green space patterns (UBGSPs) and carbon sequestration capacity, identified the key influencing factors shaping UBGSPs, and put forward targeted planning and design strategies for optimizing urban ecological spaces. Collectively, these prior studies have not only systematically clarified the long-term evolutionary trajectories of UBGs but also established a solid quantitative basis for assessing their multifaceted ecological impacts and guiding subsequent urban ecological governance practices. However, existing research exhibits certain limitations in terms of spatial scale and research perspective: on the one hand, most studies have focused on individual cities or local areas [18,19], neglecting the overall evolutionary characteristics and internal disparities of UBGs at the urban agglomeration scale; on the other hand, analyses of UBGs changes have predominantly concentrated on static patterns or single time periods, lacking a systematic depiction of long-term temporal evolution and phased characteristics [20]. Against the backdrop of China's urbanization transition from single-core city expansion to coordinated development of urban agglomerations, urban agglomerations have become the primary form for accommodating population aggregation, economic growth, and spatial expansion [21]. Significant differences exist among cities within urban agglomerations in terms of functional orientation, development stages, and ecological constraints, resulting in more complex spatiotemporal heterogeneity in the evolution of blue-green spaces [22]. Therefore, systematically identifying the long-term change characteristics of UBGs and analyzing their development patterns and response mechanisms from the perspective of urban agglomerations are of paramount importance for constructing a resilient urban ecological structure and enhancing the service capacity of regional ecosystems.

The Shandong Peninsula urban agglomeration (SPUA) stands as one of the pivotal urban clusters along China's eastern coastal regions and serves as a critical zone for ecological conservation and high-quality development in the downstream of the Yellow River basin [23]. Over the past few years, with the in-depth implementation of the Yellow River basin national strategy and the issuance of the development plan for Shandong Peninsula urban agglomeration (2021–2035) [24], the regional development objective has progressively transitioned from a single-minded pursuit of economic growth to an equal emphasis on ecological preservation and coordinated development. Against this policy backdrop, the preservation, restoration, and enhancement of blue-green spaces have been explicitly integrated into the overarching development framework of the urban agglomeration,

making the SPUA an ideal research area for exploring the evolutionary characteristics and response mechanisms of urban blue–green spaces under the influence of national strategic interventions.

Although prior research has examined the repercussions of urban development on ecological spaces, studies specifically concentrating on the SPUA region remain relatively scarce, particularly those offering a comprehensive analysis of the spatiotemporal dynamics, landscape structural changes, and socio-economic propel mechanisms of UBGs over an extended timeframe. To address these gaps, it is imperative to integrate remote sensing data, landscape pattern metrics, and socio-economic statistical information to elucidate the evolutionary patterns of blue–green spaces in the SPUA under the combined influences of rapid urbanization and policy interventions from a multidimensional perspective. Based on this background, this study sets the period from 2014 to 2023 as the research interval, systematically analyzing the spatiotemporal dynamic characteristics and driving factors of UBGs in the Shandong Peninsula urban agglomeration. This research pursues the following specific objectives: (1) Explore the spatiotemporal distribution characteristics of UBGs in the SPUA region, and clarify their evolution trends and development patterns throughout the study period; (2) delineate the variations in UGSs concerning scale, ecological quality, and landscape structure; and (3) evaluate the effects of population growth, economic development, and policy factors associated with national strategies on the evolution of UBGs. The findings of this study aim to furnish a quantitative basis for the optimal allocation of blue–green spaces and ecological governance at the urban agglomeration level, while it provides scientific references for the evaluation of the implementation effects of national strategies, high-quality regional development, and sustainable decision-making.

2. Materials and Methods

2.1. Study Area

The Shandong Peninsula urban agglomeration (SPUA) is situated in eastern China, at the lower reaches of the Yellow River. Spanning an approximate total area of 158,100 square kilometers, it encompasses all 16 prefecture-level cities within Shandong Province, namely Jinan (JN), Qingdao (QD), Zibo (ZB), Zaozhuang (ZZ), Dongying (DY), Yantai (YT), Weifang (WF), Jining (JN*), Tai'an (TA), Weihai (WH), Rizhao (RZ), Linyi (LY), Dezhou (DZ), Liaocheng (LC), Binzhou (BZ), and Heze (HZ) (Figure 1). Furthermore, as one of the most vibrant economic growth poles along China's eastern coast, the SPUA region had a permanent resident population exceeding 100 million by the end of 2024, with its gross domestic product (GDP) reaching 9.85 trillion RMB, accounting for 7.4% of the national total GDP. Since the proposal of the Yellow River basin ecological protection and high-quality development strategy in 2019, the strategic position of the SPUA in the Yellow River basin has been significantly elevated, and it is required to play a leading and exemplary role in regional coordinated development. In 2021, the Shandong provincial people's government promulgated the development plan for the Shandong Peninsula urban agglomeration (2021–2035), highlighting the significance of ecological preservation and coordinated advancement in the Yellow River basin [24]. This signifies that the SPUA has embarked on a path of synergistic development between ecological conservation and industrial upgrading, emphasizing the mitigation of environmental pressures during urbanization through scientifically planned blue–green spatial configurations.

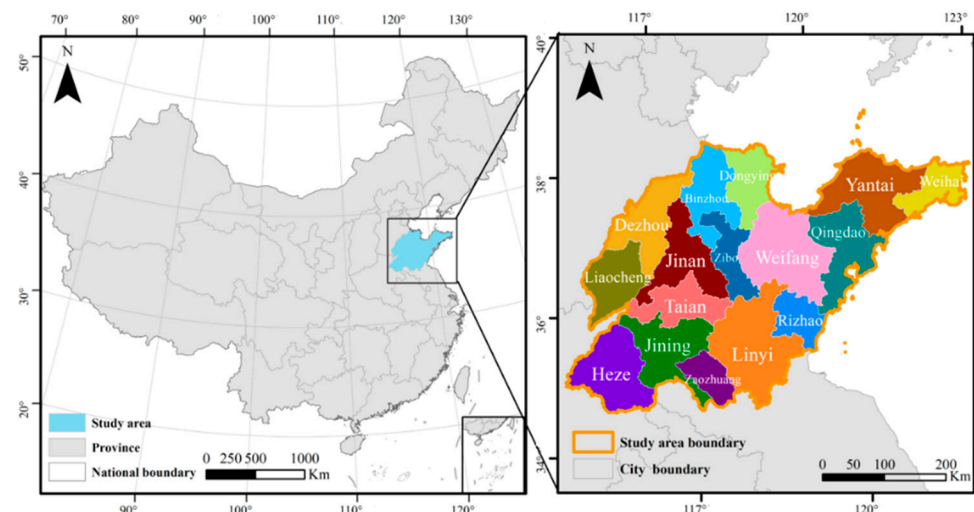


Figure 1. The geographic location pertaining to the urban agglomeration of the Shandong Peninsula. Including 16 prefecture-level cities: Binzhou (BZ), Dongying (DY), Dezhou (DZ), Heze (HZ), Jinan (JN), Jining (JN*), Liaocheng (LC), Linyi (LY), Qingdao (QD), Rizhao (RZ), Tai'an (TA), Weifang (WF), Weihai (WH), Yantai (YT), Zibo (ZB), and Zaozhuang (ZZ).

2.2. Data Operation

2.2.1. Remote Sensing Data

In this study, Landsat 8 OLI/TIRS satellite imagery serves as the primary data source for extracting UBGs. The data comes with a spatial resolution of 30 m and is updated on a 16-day cycle, making it highly suitable for land cover change detection and ecological environment monitoring at the regional scale due to its precise spatial resolution and comprehensive temporal frequency. Data acquisition and preprocessing are conducted on the Google Earth Engine (GEE) platform, which boasts extensive satellite image archives and robust parallel computing capabilities, significantly enhancing the processing efficiency of long-time-series remote sensing data. This study selected Landsat 8 OLI surface reflectance (Level-2) products spanning from 2014 to 2023. These products have undergone atmospheric correction using the LaSRC (land surface reflectance code) algorithm, which mitigates the influence of atmospheric aerosols and gases on surface reflectance, ensuring the consistency and reliability of data across different time phases. To accurately reflect vegetation growth and minimize interference from phenological variations, this study filtered image data from the annual plant growing season (typically from June to October). To enhance image quality and analysis reliability, images with cloud cover less than thirty percent are selected as the data source. For residual clouds, cloud shadows, and snow cover in the images, the quality assessment band (QA Band) and the CFMask algorithm were employed to mask and remove invalid pixels. This study takes the municipal district areas in the study area as the research object, focusing on the analysis of green space and water elements, and does not include the areas beyond the boundaries of the municipal district areas. The boundary data of the municipal district area is extracted from the county boundary data provided by the National Geomatics Center of China and was applied consistently throughout the 2014–2023 study period.

2.2.2. Socio-Economic Data

Urban expansion and shifts in environmental resource allocation are primarily driven by population growth and economic development. Expansion of urban construction land and increased resource demand are commonly driven by population agglomeration, while the degree of economic development has a direct impact on the investment in infrastructure and ecological conservation. To explore the consequences of national strategy on the

evolution of UBGs in the SPUA region from the socio-economic perspective, this research used population and economic data as the principal analytical measures. Population size is the basic variable to measure the intensity of urbanization and resource demand, and the economic development trend has dual attributes: on the one hand, it may aggravate the pressure of land development, but it also determines the financial investment ability of cities in environmental governance, green infrastructure construction, and ecological compensation. Especially after the coordinated development of the Yellow River basin and the enhancement of measures related to ecological protection were elevated to national major strategies, through examining the spatiotemporal relationship linking these two indicators to UBGs, the development mode of the SPUA can be effectively revealed, which provides scientific evidence for the future sustainable development evaluation and decision-making of the SPUA region. The population variable (POP) utilizes the statistical values of the annual permanent resident population in each city within the study area, and the economic indicators are the per capita gross domestic product (GDP) and environmental protection fiscal spending ratio (EPFSR) of each city in the same year. All relevant data are taken from the annual statistical yearbook published by each city and the statistical yearbook of Shandong Province.

2.3. Methodology

2.3.1. Extraction of Urban Blue–Green Space

In previous studies, the regions characterized by fractional vegetation cover (FVC) values greater than 0.6 within city administrative boundaries have typically been defined as urban green space (UGS). To verify and guarantee that this threshold is applicable, we made reference to the reviews by Cai et al. [25], and further corroborating evidence was also obtained from Gao et al. [26]. For example, Zhang et al. [27] adopted $FVC > 0.6$ as the criterion for urban green space in their analysis of urban green spaces in Beijing. Similarly, Yang et al. [28] considered $FVC > 0.6$ as effective urban greening coverage when examining changes in green spaces in Tianjin’s central urban zone. The applicability of the above thresholds to the SPUA is guaranteed by regional environmental consistency. The SPUA, Beijing, and Tianjin are all located in northern China and share broadly comparable warm-temperate monsoon conditions and seasonal vegetation characteristics, supporting the transferability of this threshold. These findings collectively indicate that the $FVC > 0.6$ threshold effectively distinguishes continuous and functional urban green vegetation from sparse surface vegetation and bare patches in the built environment, avoiding an overestimation of green space area caused by low coverage herbaceous patches. Therefore, using $FVC > 0.6$ as the threshold for extracting urban green spaces is reasonable and ensures the robustness of identifying green spaces within all municipal district spaces in the SPUA region. The FVC was calculated using Formulas (1) and (2), after which the maximum value composite of FVC was generated for each year.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

$$FVC = \frac{NDVI - NDVI_{Soil}}{NDVI_{Veg} - NDVI_{Soil}} \quad (2)$$

Note: $NDVI$ is defined as the normalized difference vegetation index, ρ_{NIR} denotes the near-infrared band, ρ_{RED} denotes the red band, FVC represents the fractional vegetation cover for each pixel, $NDVI_{Soil}$ corresponds to the $NDVI$ value of bare soil pixels, and $NDVI_{Veg}$ corresponds to the $NDVI$ value of fully vegetated pixels. Where $NDVI_{Soil}$ represents the 5th percentile $NDVI$ value of valid pixels in the annual municipal district area composite image, and $NDVI_{Veg}$ represents the 95th percentile $NDVI$ value. The

calculated FVC values were further constrained to the range of 0–1 to avoid abnormal values caused by residual noise.

UBSs typically refer to all surface water bodies found in urban settings, whether natural or human-modified, including but not limited to rivers, lakes (including artificial lakes), fountains, coastlines, wetlands, and ponds. For the extraction and monitoring of UBSs, existing studies often utilize the normalized difference water index (NDWI) for water extraction and discrimination, consistent with the approach advocated by Xu et al. [29] for advancing the monitoring and management of urban blue spaces. However, when extracting NDWI from remote sensing imagery, it is susceptible to interference from completely bare land and built-up areas. To mitigate these effects, existing research suggests that setting the NDWI threshold at 0.3 is most effective. For instance, Zhang, Zhao, He, Ren, Chang, Dou, Wang and Li [27] adopted an NDWI threshold of 0.3 when extracting urban blue spaces within the Beijing–Tianjin–Hebei urban agglomeration. Similarly, Zhu et al. [30] set the NDWI threshold to 0.3 for each image to distinguish between water and non-water areas in order to acquire perennial water data for the Caohai region of Guizhou during the period of 2019–2020. Roohi et al. [31] classified areas with $NDWI > 0.3$ as water bodies and considered this threshold reasonable for water extraction in most geographical environments. The above studies all indicate that when the $NDWI > 0.3$ threshold fully suppresses the spectral interference of bare land and impermeable building surfaces and accurately identifies stable water bodies throughout the year. Firstly, based on the preprocessed remote sensing images, the NDWI is calculated for each image using Formula (3), and then the final data is obtained through the maximum value synthesis method.

$$NDWI = \frac{\rho_{Green} - \rho_{NIR}}{\rho_{Green} + \rho_{NIR}} \quad (3)$$

Note: ρ_{Green} is the green band, and ρ_{NIR} is the near-infrared band.

Notably, since a uniform fixed threshold is applied to all time phases of remote sensing images, minor adjustments to the extraction threshold will only lead to a systematic offset of the absolute area values, without altering the overall temporal growth trend and spatial differentiation pattern of UBSs from 2014 to 2023. The core conclusions regarding the long-term evolution characteristics of UBSs are robust within a reasonable threshold range.

2.3.2. Sample-Based Validation of UBS Change Maps

To evaluate the reliability of the net UGS and UBS changes between the two endpoint years, 2014 and 2023, change maps were generated by overlaying the classification results from these two years. The UGS change map comprised four classes: stable non-UGSs, UGS gain, UGS loss, and stable UGSs. Similarly, the UBS change map comprised stable non-UBSs, UBS gain, UBS loss, and stable UBSs. A stratified random sampling strategy was applied across the built-up areas of the SPUA. For each change map, 500 validation points were randomly generated, with 125 points allocated to each of the four change classes. Thus, a total of 1000 validation points were used, including 500 points for UGS change validation and 500 points for UBS change validation. The reference change class of each point was manually determined by visually comparing the original Landsat 8 OLI imagery from 2014 and 2023 used in this study. Confusion matrices were subsequently constructed by comparing the classification results with the manually interpreted reference classes. Overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient were calculated to evaluate the accuracy of the change detection results.

2.3.3. Urban Blue–Green Space Trends Analysis

To further elucidate the spatiotemporal evolution characteristics of the internal quality of UGSs within the SPUA region, this study introduces greenness trend analysis to compensate for the inherent limitation that UGS area statistics only reflect quantitative changes in green patches rather than vegetation ecological quality. Merely counting UGS area cannot capture hidden vegetation degradation or vitality improvement inside stable green patches, as well as the long-term effectiveness of urban ecological restoration projects. The incorporation of vegetation greenness trend analysis aims to reveal the spatiotemporal dynamics of the ecological functions of UGSs from a quality dimension. This approach is of significant importance for assessing the ecological resilience of the SPUA region in the context of rapid urbanization. The normalized difference vegetation index (NDVI), as one of the most effective indicators for characterizing vegetation growth vigor and nutritional status, enables detailed monitoring of the ecological functional fluctuations of green spaces [32,33]. In this study, the annual NDVI trend is selected as the core parameter. A method combining Theil–Sen median slope estimation and the Mann–Kendall (MK) non-parametric test is employed to detect the NDVI trend for each pixel within the study area on a per-pixel basis. A robust non-parametric statistical approach is offered by Theil–Sen slope estimation. Compared to the ordinary least squares method, it does not impose strict requirements on the normality of the data distribution and can effectively circumvent interference from outliers and noise in time-series data, making it suitable for long-term vegetation dynamics monitoring. In this study, the Theil–Sen median slope was calculated using all annual NDVI composite images from 2014 to 2023. For each valid pixel, a 10-year NDVI time series was first constructed based on the annual NDVI composite images. The slope was not derived only from the first and last years, nor was it calculated as a summation of multi-year images. Instead, the slope between every pair of years in the 2014–2023 NDVI time series was calculated. Since the study period contained 10 years, a total of 45 pairwise slopes were generated for each valid pixel. These slope values were then sorted in ascending order, and the median value was selected as the Theil–Sen slope. Therefore, the resulting slope represents the robust long-term vegetation greenness trend over the entire study period. The formula for calculating it is presented below:

$$\beta = \text{Median}\left(\frac{NDVI_j - NDVI_i}{j - i}\right) \quad (4)$$

Note: β represents the slope of the NDVI time series trend, where $NDVI_j$ and $NDVI_i$ denote the NDVI values in the j -th and i -th years, respectively. A β value greater than 0 indicates an increasing trend in vegetation greenness, while a β value less than 0 indicates a degrading trend.

The Mann–Kendall test is routinely employed for the purpose of assessing the statistical significance of observed trend changes. As a non-parametric test, the MK test does not require samples to conform to a specific distribution and is less susceptible to interference from a few outliers. Consequently, it is widely applied in detecting trends in vegetation, meteorological, and hydrological changes [34]. This study used the MK test for analyzing how NDVI evolved in both space and time inside the built-up sections of the SPUA between 2014 and 2023, seeking to discover if substantial changes have occurred in the urban green spaces of these built-up areas. When conducting the MK test, if the p -value is less than or equal to 0.05, the trend is considered to have undergone a significant change. Derived from the test results, this study classifies the NDVI trends into five distinct categories (Table 1).

Table 1. Analysis results of NDVI trend changes.

Judgment Condition	NDVI Trend Types
$ Z > 1.96$ and $\beta > 0.005$	Significant increase
$ Z \leq 1.96$ and $\beta > 0.005$	Insignificant increase
$ Z \leq 1.96$ & $-0.005 \leq \beta \leq 0.005$	No change
$ Z > 1.96$ & $-0.005 \leq \beta \leq 0.005$	
$ Z \leq 1.96$ and $\beta < -0.005$	Insignificant decrease
$ Z > 1.96$ and $\beta < -0.005$	significant decrease

Note: Z represents the test statistic within the MK framework. When $|Z| > 1.96$, the result is considered significant. β represents the Theil–Sen slope estimator.

For urban blue space, its evolutionary characteristics exhibit significant differences from those of vegetation. Unlike vegetation, which undergoes continuous physiological and ecological processes, urban water bodies are predominantly under the direct control of engineering measures such as artificial planning, river regulation, and hard embankment construction. Consequently, their spectral characteristics exhibit relatively minor interannual variability and lack analogous trends in growth vitality. Therefore, instead of conducting time-series pixel-wise trend analysis for UBSs, this study focuses on investigating their spatial agglomeration and differentiation patterns. To reveal the spatial structural characteristics of UBSs within the Shandong Peninsula urban agglomeration, this study employs Getis-Ord G_i^* hotspot analysis for local spatial autocorrelation analysis. This approach employs a comparison of feature attribute values within a local neighborhood to those of the global background, thereby distinguishing statistically significant high-value (hotspot) and low-value (cold spot) clusters. Compared to global autocorrelation metrics, the G_i^* statistic can precisely pinpoint local areas with extremely imbalanced water resource distribution. Notably, the attribute variable adopted for this spatial statistical model is the total area of UBS extracted by the NDWI threshold ($NDWI > 0.3$), rather than the raw continuous NDWI spectral index.

2.3.4. Analysis of Landscape Pattern of the SPUA

The evolution of the landscape pattern is the core spatial representation for measuring the coordinated development of regional ecology, society, and economy. Against the backdrop of rapid urbanization in the SPUA region, intertwined with the implementation of relevant national development strategies, quantitatively analyzing the morphological evolution of blue–green spaces is of significant importance for assessing the balance between urban expansion and ecological carrying capacity. By calculating ecologically meaningful landscape metrics, the complex spatial arrangement characteristics of patches can be transformed into comparable quantitative indicators, thereby enabling an in-depth revelation of the evolutionary patterns of blue–green spaces under the pressure of urban sprawl. This study utilizes Fragstats 4.2 software to assess three key indicators at the landscape level: The largest patch index (LPI) reflects the fractional coverage of the largest patch within the entirety of the study region, effectively identifying the dominance of core ecological source areas. Its numerical fluctuation reflects the stability of large-scale ecological matrices within a coordinated development framework [35]. The aggregation index (AI) reflects the spatial clustering characteristics of patches of the same landscape type. A higher AI value indicates a more concentrated spatial distribution of blue–green spaces, implying stronger connectivity within the regional ecological network [36]. The landscape shape index (LSI) measures the regularity and complexity of patch shapes; larger values suggest that the edges of blue–green spaces tend to be more fragmented [37], revealing a more

pronounced cutting effect of anthropogenic disturbance on natural landscape contours and indicating the intensity of spatial disturbance during the coordinated development process. The specific calculation method of landscape index is shown in Table 2. This study focuses on landscape analysis for the entire urban agglomeration and its urban green spaces, without conducting separate landscape metric calculations for UBS. The primary reason is that water bodies within cities are subject to strong, rigid constraints from topography and artificial planning, resulting in a relatively stable distribution with minimal change. Furthermore, their patch boundaries are typically in a long-term stable physical state, lacking the highly dynamic morphological evolution characteristics observed in green spaces, which limits the applicability of the aforementioned metrics.

Table 2. Landscape index formula and its ecological implications.

Landscape Indicators	Formula	Definition
AI	$AI = \frac{g}{g_{max}} \times 100$	Assessing the degree of spatial aggregation in land-use patches
LPI	$LPI = \frac{\max_{j=1}^m(a_{ij})}{A} \times 100$	The proportion of the largest landscape patches reflects the direction of human activity.
LSI	$LSI = \frac{0.25E}{\sqrt{A}} \times 100$	An index for measuring the complexity of patch shapes in landscapes

Note: g denotes the number of similar adjacent patches for the corresponding landscape type, while g_{max} represents the maximum possible number of such adjacencies. $\max_{j=1}^m(a_{ij})$ denotes the maximum patch area, A denotes the total landscape area, and E denotes the total length of landscape patch edges.

2.3.5. Analysis of the Relationship Between Urban Development Levels and the UBS Pattern

In quantitative studies investigating the impact of socio-economic factors on ecological spaces, traditional models have predominantly employed quadratic or cubic polynomial regression methods to analyze the effects of rapid urban development on the urban environment [38,39]. To mitigate the influences arising from policy interventions or economic structural transformations, this study adopts the Piecewise Linear Regression (PLR) model. This model can divide the entire study period into linear stages characterized by different evolution rates by identifying breakpoints where regression coefficients change significantly. This study conducted PLR analysis on regional data for the SPUA from 2014 to 2023 and used the midpoint of the research period in 2018 as the breakpoint. In this model, the dependent variable is defined as the UBS area within the study area. The independent variables primarily focus on reflecting the interaction between population dynamics and economic growth amidst urbanization evolution. Specifically, this study selects GDP as the core metric for characterizing economic growth, an indicator widely recognized in existing urban economic development research [40–42]. Concurrently, permanent population data is employed to assess trends in urban population density, and EPFSR is introduced to identify the moderating effect of policy interventions on the allocation of blue–green resources. The mathematical expression of the PLR model is presented in Equation (5).

$$Y = \begin{cases} \alpha_1 + \beta_{1i}X_i, & T \leq T_1 \\ \alpha_2 + \beta_{2i}X_i, & T_1 < T \leq T_2 \\ \vdots & \vdots \\ \alpha_n + \beta_{ni}X_i, & T_{n-1} < T \leq T_n \end{cases} \quad (5)$$

Note: α_n and β_{ni} correspond to the intercept and regression slope for each phase, respectively. X_i represents the selected socio-economic independent variables. T denotes the sample year, while T_n are the trend breakpoints.

3. Results

3.1. The Spatiotemporal Variation Pattern of UBGs Within the SPUA

3.1.1. Area Variations in UBSs and UGSs

The continuous advancement of urban construction and the driving force of sustained economic growth have caused substantial alterations in the UGSs within the built-up zones of the SPUA since 2014 (Figure 2). The results indicate an overall increasing trend in UGSs within the SPUA, with the total area expanding from 28,311.66 km² in 2014 to 30,194.39 km² in 2023. From a city-specific perspective, Bingzhou (BZ), Rizhao (RZ), and Jinan (JN) exhibited the highest growth rates in UGSs, reaching 24.5%, 21.3%, and 18.1%, respectively. Notwithstanding the overall increase in UGS area across all cities, their evolutionary processes generally presented a phased characteristic—initially rising, thereafter decreasing, and then a recovery. This pattern suggests that during the initial phase of rapid urban expansion, some green spaces were encroached upon by construction land. However, as ecological civilization construction continues to advance, urban renewal initiatives and green space planning policies, UGSs have undergone compensatory restoration and enhancement, thereby promoting the overall expansion of regional urban green spaces.

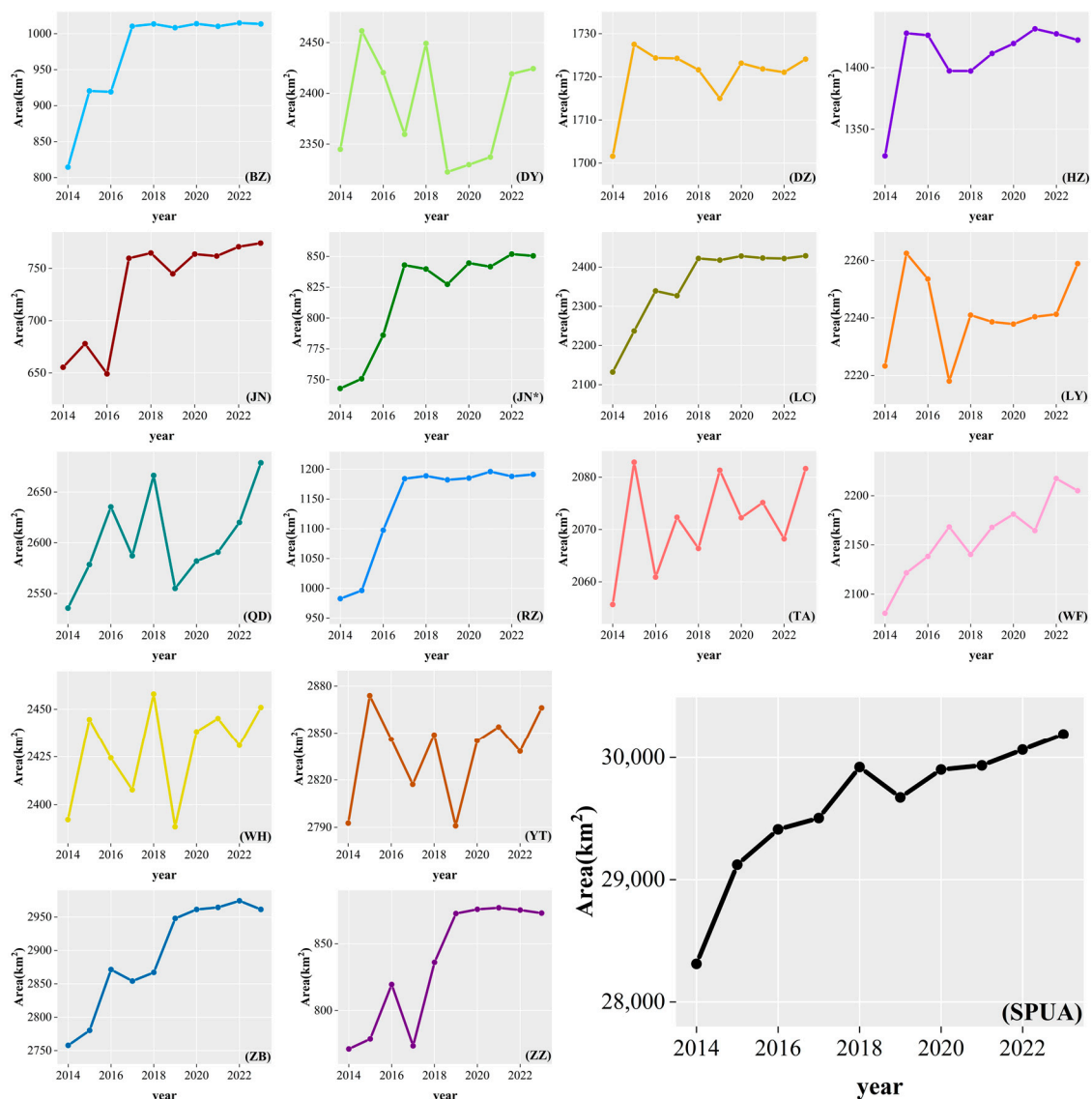


Figure 2. Annual changes in the area of UGSs in the municipal districts of the 16 cities in the SPUA region from 2014 to 2023.

Figure 3 illustrates the temporal change characteristics of UBSs within the urban areas of the SPUA. On the whole, the UBS area within the SPUA region showed a marked rising trend, growing from 1108.02 km² in 2014 to 1699.04 km² in 2023. Phase-specific analysis indicates a certain degree of decline in the UBS area during 2015–2017, a period when accelerated urban construction activities led to the encroachment or engineering modification of some water body spaces. However, since 2017, UBS has gradually recovered and shown a continuous growth trend. This shift is closely related to the strengthening of regional water ecological protection policies. The Shandong Province water resources protection regulations were officially promulgated in 2017 and implemented in 2018, institutionally reinforcing the protection and restoration of rivers, lakes, water sources, and aquatic ecological spaces, thereby providing crucial policy support for the recovery and expansion of urban blue spaces. Against this backdrop, ongoing water ecological restoration projects and comprehensive urban water environment management have driven the overall growth of UBSs in the SPUA region. From a city-specific perspective, the UBS area increased in most cities, with Jinan (JN), Heze (HZ), and Zaozhuang (ZZ) showing the most significant growth, with increases of 177.58%, 130.61%, and 101.98%.

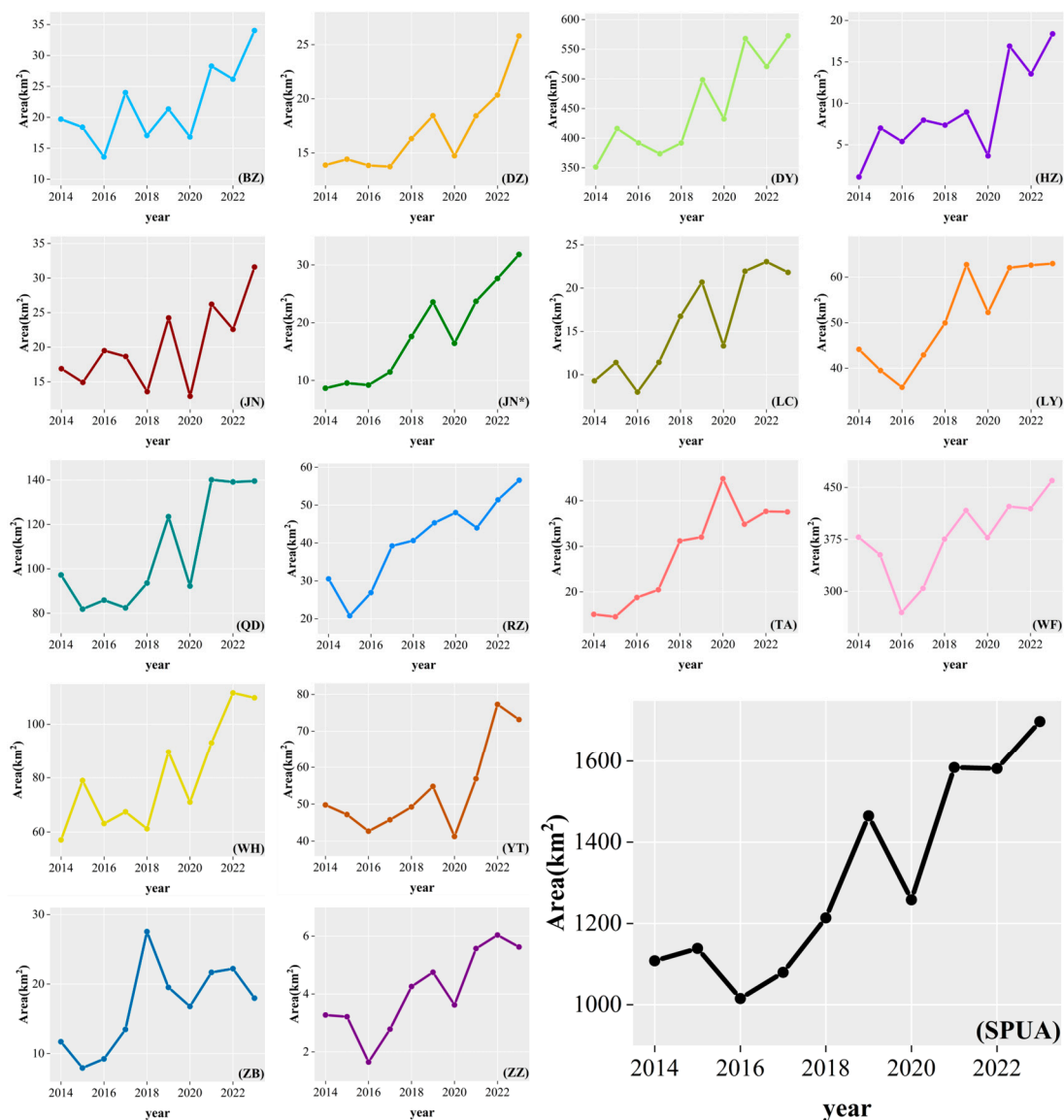


Figure 3. Annual changes in the area of UBSs in the municipal districts of the 16 cities in the SPUA region from 2014 to 2023.

3.1.2. Accuracy Assessment of UBSGS Change Detection

Figure 4 presents the confusion matrices for UBSGS change detection. The UGS change map achieved an overall accuracy of 86.20% and a Kappa coefficient of 0.816. The UBS change map achieved an overall accuracy of 83.60% and a Kappa coefficient of 0.781. These results indicate good agreement between the classification results and the reference data, supporting the reliability of the identified UGS and UBS changes across the built-up areas of the SPUA.

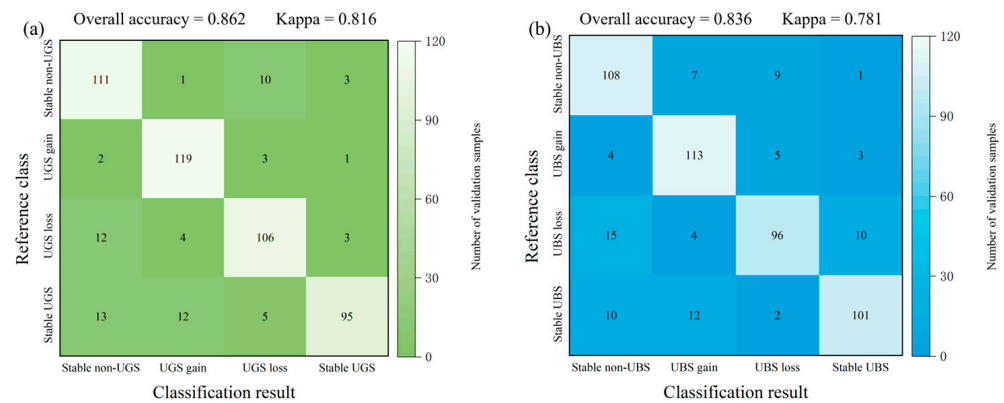


Figure 4. (a) Confusion matrix for UGS change detection. (b) Confusion matrix for UBS change detection.

3.1.3. Spatiotemporal Trends of Vegetation Greenness and Hotspot Patterns of Urban Blue Space

The time-series variation in the mean NDVI in the municipal districts of cities within the SPUA from 2014 to 2023 is depicted in Figure 5. Overall, the average NDVI value in the municipal districts of the SPUA exhibited a steady upward trend, indicating a continuous improvement in urban greening levels for the duration of the study, with a more pronounced growth in the later phase as opposed to the earlier phase. Spatial differentiation characteristics reveal significant disparities in NDVI changes among different municipal districts (Figure 5b). Most cities demonstrated a substantial increase in greenness levels, with BZ and LC experiencing the most significant growth, both at 25%. This reflects the positive outcomes of urban greening construction and ecological restoration measures. This result suggests that urban green space in the SPUA region has not only expanded in scale but has also concurrently improved in ecological quality. However, the NDVI trend in a few individual cities was relatively flat; for instance, LC and LY showed a notable decrease in the proportion of significant greening trends, at 15% and 13%, respectively. This indicates that in localized areas, the intensity of urban expansion and construction may have exerted a certain inhibitory effect on vegetation growth. In general, the change characteristics of NDVI of urban built-up zones in the SPUA region reveal the pattern of overall improvement of the regional urban greening level, but the coexistence of differences between cities.

The results of the Getis-Ord G_i^* hotspot analysis (as shown in Figure 6) indicate that only Dongying exhibited statistically significant hotspot characteristics during the period from 2014 to 2023. For the remaining municipal districts, hotspots appeared either alternately or individually, and some counties or districts outside the results of the Getis-Ord G_i^* hotspot analysis (as shown in Figure 6) indicate that only Dongying exhibited statistically significant hotspot characteristics during the period from 2014 to 2023. For the remaining municipal districts, hotspots appeared either alternately or individually, and some counties or districts outside the built-up areas also displayed hotspot characteristics; however, these fall outside the scope of this study. Therefore, based on the hotspot analysis, urban blue space in most regions maintained relatively stable spatial changes. Furthermore,

given the relatively fixed geographical locations of water bodies within the SPUA region and their limited susceptibility to natural conditions, the areas where hotspots emerged were predominantly coastal. This suggests that the extent of water areas in the SPUA region tends to change stably rather than drastically. Areas also displayed hotspot characteristics; however, these fall outside the scope of this study. Therefore, based on the hotspot analysis, urban blue space in most regions maintained relatively stable spatial changes. Furthermore, given the relatively fixed geographical locations of water bodies within the SPUA region and their limited susceptibility to natural conditions, the areas where hotspots emerged were predominantly coastal. This suggests that the extent of water areas in the SPUA region tends to change stably rather than drastically.

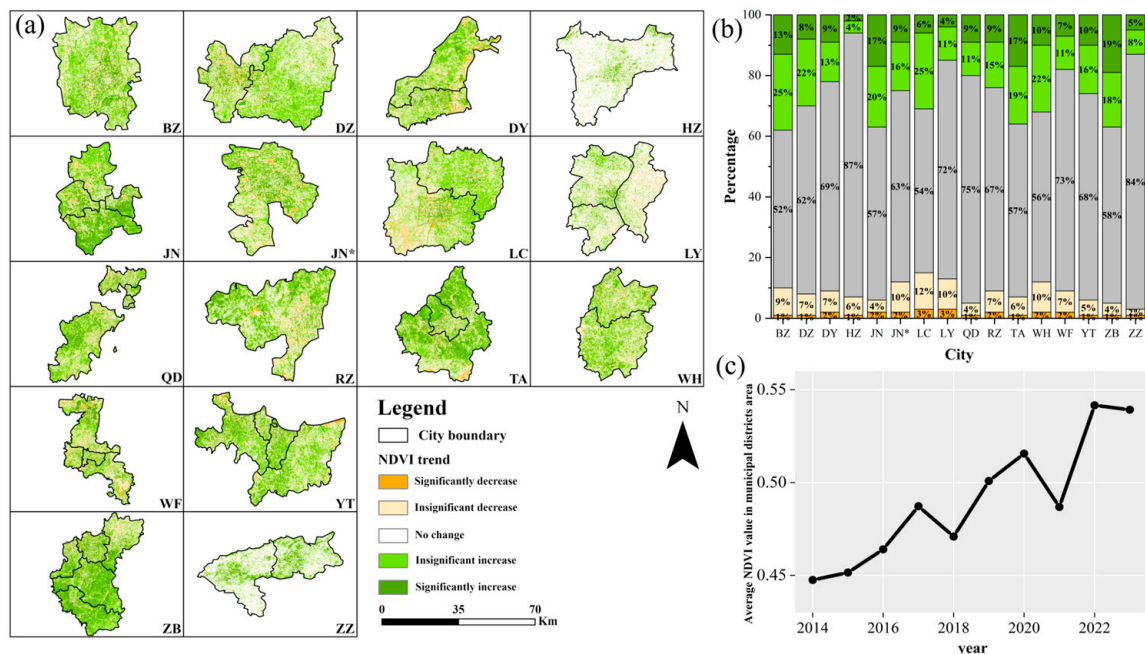


Figure 5. (a) NDVI variation trends observed in the SPUA region’s urban built-up zones from 2014 to 2023. (b) Percentage distribution of different NDVI trend classes in the SPUA urban built-up zones. (c) Average NDVI value of urban built-up zones within the SPUA region across 2014–2023.

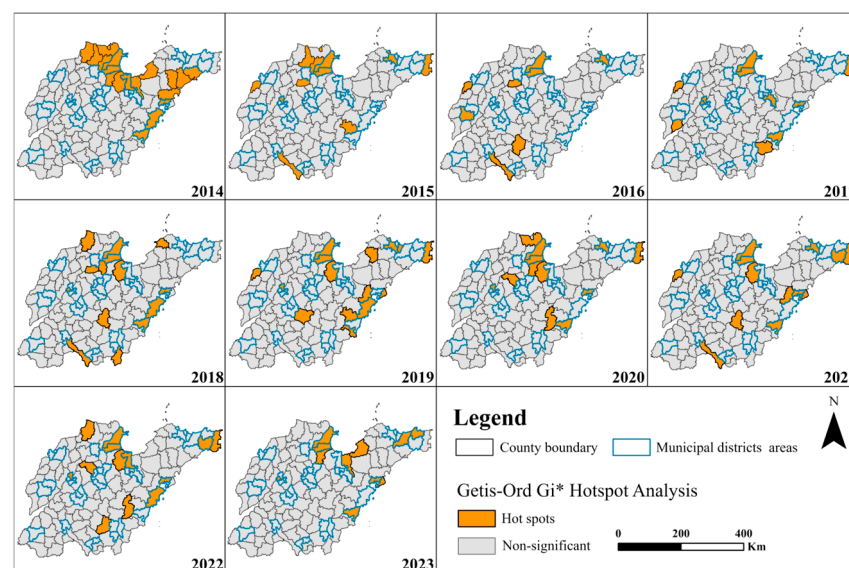


Figure 6. Getis-Ord Gi* hotspot analysis of the UBS area in the SPUA region from 2014 to 2023.

3.2. Spatiotemporal Dynamics in UGS Landscape Patterns

Figures 7 and 8 depict the evolutionary characteristics of the UGS landscape index for municipal district sections of the SPUA across the 2014–2023 timeframe. The overall landscape index of the SPUA region is calculated based on the average of each municipal district. On the whole, the UGS landscape pattern in the SPUA region showed obvious characteristics of phased evolution, and its aggregation index (AI) showed a change process of first fluctuating, then rising and tending to be stable. At the beginning of the study, AI declined in some years, indicating that the acceleration of urban expansion and the increase in construction activities led to the dispersion and fragmentation of green patches to a certain extent; however, with the continuous promotion of ecological constraint policy and urban green space planning, AI gradually rebounded, reflecting the transformation of UGS from a discrete distribution to a centralized and contiguous pattern. This process shows that the disturbance of early urban construction to the green space structure does not cause irreversible degradation, and the green space system is gradually restored and optimized under the intervention of later planning.

The changes in the largest patch index (LPI) further corroborate this trend. Overall, there was an upward trend in the LPI for UGSs in the SPUA region, with values rising from 93.4 to 97.5, indicating a continuous expansion in the scale of the dominant patches within urban green spaces. This result suggests that, during the development process, cities have progressively strengthened the protection of core green spaces and critical ecological areas. Through the development of park systems, the integration of green spaces, and the construction of ecological corridors, the formation and stabilization of larger-scale UGS patches have been promoted. As the pace of urban expansion has moderated, UGS protection has gradually shifted from incremental expansion to the optimization of existing stock. This is particularly evident after 2020, when the growth rate of LPI has leveled off, indicating that the UGS is progressively entering a relatively stable phase of development. At the city scale, variations in LPI changes among different cities reflect differences in regional development intensity and land development strategies. In some cities, the size of the largest UGS patch continued to increase, such as in WH and ZB, suggesting a better balance between land development and ecological protection during their urban expansion. In contrast, a few cities experienced periodic fluctuations in LPI, for example, DZ, HZ, and YT, revealing the ongoing dynamic trade-off between UGS protection and the demand for construction land under the pressure of economic growth.

The change in LSI reveals the optimization process of the UGS pattern from the morphological level. The LSI of UGS in the SPUA region demonstrated an overall decreasing trend during the study period, with a minimum value of 27.0 recorded in 2021, a decrease of about 18.3%, which showed that the shape of green patches gradually tended to be regular and the spatial structure was more compact. This result shows that with the promotion of regional collaborative development and refined urban management, scattered and irregular green spaces are gradually integrated into the green space network, with a clear structure, and the landscape pattern of UGS has changed from extensive expansion to high-quality and standardized configuration.

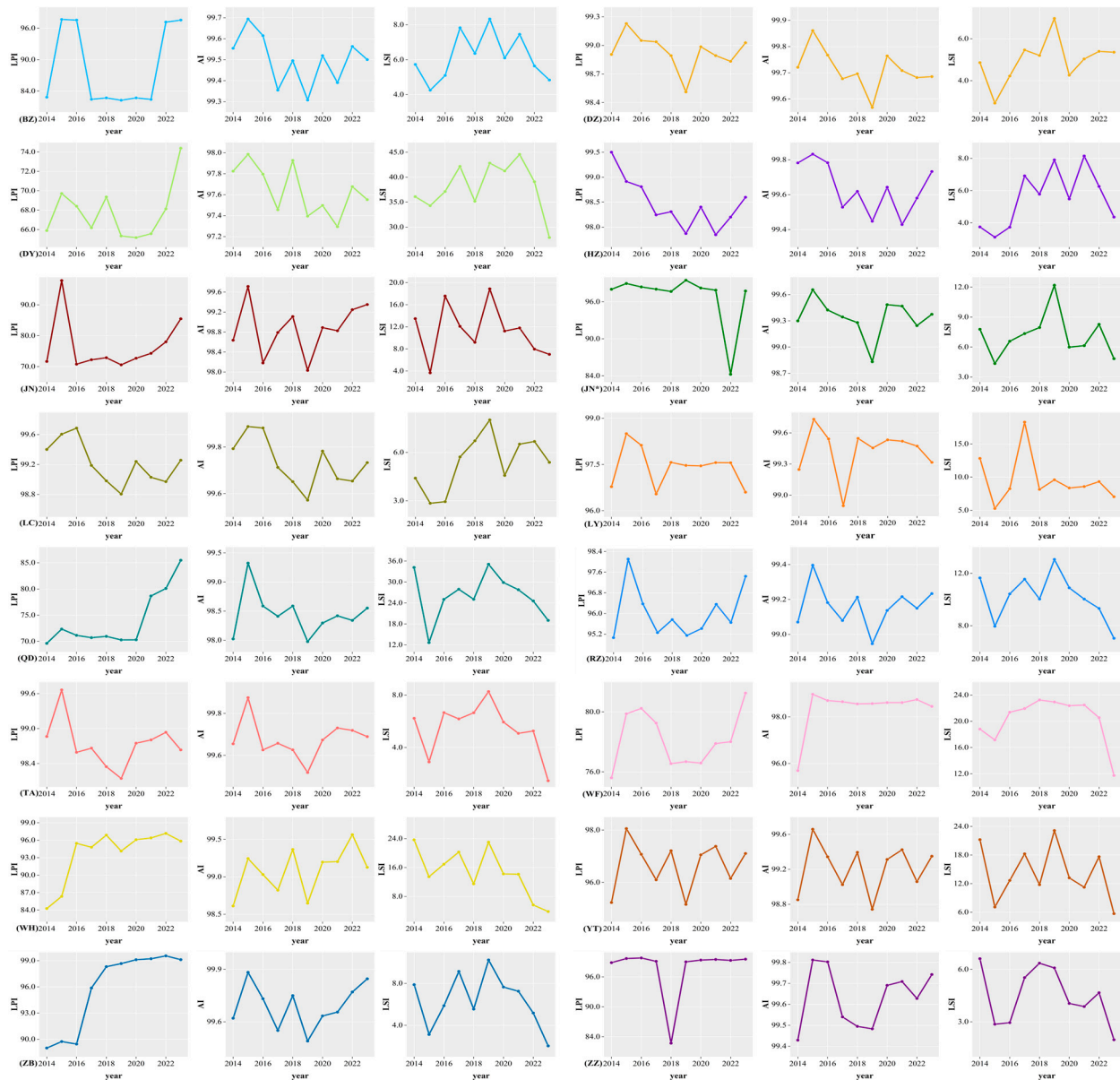


Figure 7. Variations in the landscape index for municipal district regions across different cities between 2014 and 2023.

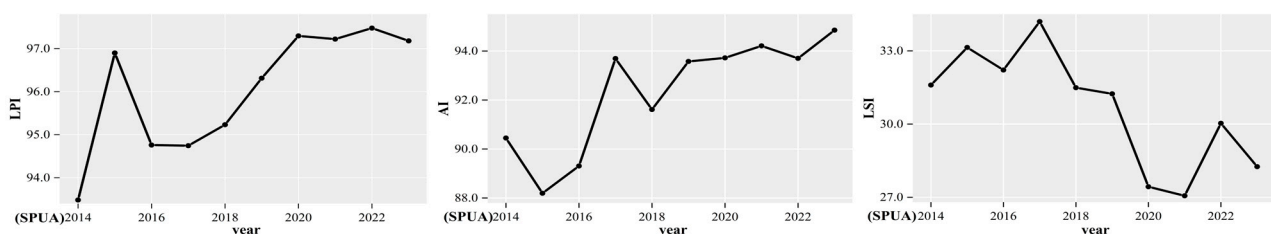


Figure 8. Variations in the landscape index for municipal district regions in the SPUA region between 2014 and 2023.

3.3. Analysis of the Relationship Between UBGs and Socioeconomic Indicators

The influence of GDP, population, and EPFSR upon UBGs in the SPUA is shown in Tables 3 and 4. In these tables, k1 represents the regression slope for the early urban expansion phase (2014–2018), and k2 represents the slope for the later phase (2018–2023), designed to capture the phased differences in the influence of socio-economic factors on

UGSs and UBSs. The results indicate that there are significant differences in the degree and direction of impact of various socioeconomic factors on UBSs across cities in the SPUA region, exhibiting distinct temporal phase-change characteristics. Regarding demographic factors, their influence on UGSs demonstrated strong explanatory power in most cities, although the direction of this influence varied. In cities such as BZ, DZ, and RZ, the goodness of fit between the population and UGS was high ($R^2 > 0.85$), indicating that demographic change was a crucial driver of UGS evolution in these areas. In some cities, population growth exhibited an inhibitory effect on the UGS during the early phase (k1), whereas this negative influence diminished or even turned positive in the later phase (k2). This suggests that pressures on urban green space from population growth were alleviated to some extent, owing to the strengthening of urban management and green space planning policies. However, in cities like LY, QD, and YT, the correlation between the population and UGS was relatively weak, indicating that the selected socio-economic variables themselves cannot fully explain the changes in the UGS, which may be influenced by other factors such as changes in land use structure or policy factors. The impact of GDP on UGS exhibited significant spatial heterogeneity overall. In cities such as JN, JN*, RZ, and ZB, the goodness of fit between GDP and UGS was high (R^2 mostly above 0.8), and the later-phase slope (k2) was generally steeper than the early-phase slope (k1). This indicates that these cities progressively strengthened an ecology-prioritized development pathway amidst economic growth, advancing green space construction in tandem with economic development. In contrast, the relationship between GDP and UGSs in some cities showed fluctuations or even negative trends, such as LY and LC, reflecting that during periods of intense economic expansion pressure, the expansion of construction land may have encroached upon UGSs. The relationship between GDP and UBS also exhibited substantial inter-city heterogeneity. Relatively high goodness of fit was observed in BZ, DZ, HZ, LC, QD, TA, and YT ($R^2 = 0.79\text{--}0.89$). Among these cities, BZ, HZ, LC, QD, TA, and YT shifted from negative or near-zero k1 values to positive k2 values, indicating that GDP growth and UBS expansion tended to move in the same direction during the later phase. In contrast, LY and RZ retained negative later-phase slopes, and WH shifted from a positive k1 to a negative k2, indicating that GDP growth was not consistently accompanied by UBS expansion in these cities. The influence of EPFSR on UGS was generally significant across SPUA cities, with R^2 values ranging between 0.6 and 0.8. This indicates that the environmental protection fiscal expenditure ratio has a strong explanatory power for UGS evolution. For instance, JN* with an R^2 of 0.82, YT with an R^2 of 0.95, and RZ with an R^2 of 0.88 exhibited high goodness of fit, indicating that increased investment in environmental protection contributes to the expansion and quality improvement of UGSs. In comparison, the impact of EPFSR on UBSs showed even more pronounced inter-city variability (Table 4). In cities such as LC ($R^2 = 0.95$) and TA ($R^2 = 0.89$), EPFSR demonstrated strong explanatory power for UBS, suggesting that changes in water space were largely driven by policy investments and environmental remediation projects. Conversely, in cities like ZB, WH, and HZ, the relatively lower R^2 values indicate that the evolution of urban blue space might be more constrained by natural conditions or historical water system patterns. Notably, in some cities, the influence of EPFSR on UGS was stronger than on UBS, implying a potential investment prioritization towards green spaces over blue spaces during urban development under conditions of limited fiscal resource allocation.

Table 3. Analysis results of the relationship between socio-economic indicators and UGSs.

City	Population			GDP			EPFSR		
	R ²	k1	k2	R ²	k1	k2	R ²	k1	k2
BZ	0.93	23.45	−2.64	0.85	3.15	0.02	0.22	−2.14	0.80
DY	0.33	14.98	−0.68	0.76	1.15	0.50	0.70	−2.73	0.70
DZ	0.91	151.05	−0.68	0.81	70.78	−9.07	0.71	0.41	0.88
HZ	0.85	10.42	−0.37	0.85	3.16	0.01	0.65	−7.47	9.27
JN	0.86	3.94	0.37	0.88	10.06	20.10	0.69	4.55	14.10
JN*	0.95	4.33	−0.13	0.94	4.15	14.22	0.82	−8.98	5.44
LC	0.96	8.67	1.03	0.42	−0.74	0.30	0.71	−9.79	17.56
LY	0.28	41.91	−0.15	0.31	0.11	−10.13	0.66	2.68	−0.60
QD	0.37	0.17	74.31	0.81	−120.01	110.07	0.58	4.52	−1.35
RZ	0.99	21.72	0.72	0.99	0.62	10.12	0.88	−3.74	−11.96
TA	0.63	17.01	−0.62	0.34	−0.09	0.90	0.70	−1.32	3.43
WF	0.83	0.08	0.02	0.83	−5.86	39.82	0.75	7.59	2.36
WH	0.67	6.21	−2.70	0.66	34.17	60.02	0.91	−3.04	1.48
YT	0.52	−2.98	21.53	0.82	101.25	234.66	0.95	1.26	−4.83
ZB	0.61	63.25	3.99	0.91	−40.27	0.06	0.38	−5.35	−8.55
ZZ	0.85	1.66	10.26	0.85	−0.12	13.77	0.76	−2.92	1.52

Table 4. Analysis results of the relationship between socio-economic indicators and UBS.

City	Population			GDP			EPFSR		
	R ²	k1	k2	R ²	k1	k ²	R ²	k1	k2
BZ	0.79	11.24	−1.23	0.89	−0.55	1.02	0.68	−4.11	0.16
DZ	0.31	1.23	−0.83	0.88	0.27	2.36	0.80	−0.26	0.21
DY	0.77	1.27	87.18	0.27	0.14	−5.51	0.71	5.73	−0.35
HZ	0.81	0.30	−52.43	0.80	−224.23	330.01	0.34	−24.23	8.51
JN	0.90	−14.01	20.62	0.64	−285.80	111.09	0.87	−0.80	2.94
JN*	0.87	0.12	0.73	0.78	0.11	0.02	0.89	−46.72	108.70
LC	0.57	0.70	0.66	0.82	−138.88	0.32	0.95	−491.49	−12.27
LY	0.89	−0.29	0.48	0.74	−0.80	−134.82	0.82	0.82	−3.29
QD	0.81	−0.39	1.25	0.79	−329.81	123.03	0.78	−9.81	3.03
RZ	0.88	−4.80	2.19	0.79	−744.04	−136.41	0.66	−7.13	13.41
TA	0.80	227.04	0.08	0.88	−0.34	0.45	0.89	0.02	−5.78
WH	0.35	−112.84	7.52	0.73	0.16	−0.19	0.43	−21.82	27.55
WF	0.74	−8.50	8.03	0.57	−1.07	0.06	0.83	−121.94	26.46
YT	0.80	2.23	−3.37	0.85	−0.01	0.11	0.70	3.49	5.49
ZB	0.68	2.00	−5.68	0.37	10.04	0.53	0.27	−73.19	−144.89
ZZ	0.61	−0.11	0.25	0.16	−249.65	110.01	0.63	9.65	7.97

The comprehensive analysis indicates that the response of UBGs to socio-economic factors within the SPUA exhibits significant city-specific variations and distinct phase characteristics. The influence of population and GDP is, to a certain extent, constrained by the stage of urban development. In contrast, EPFSR, as a policy-regulatory variable, has played a crucial role in the optimization of both UGSs and UBSs. Future urban planning should place greater emphasis on the synergistic allocation of green and blue spaces. By optimizing the UBGs pattern through a rational fiscal expenditure structure alongside promoting economic development, ecological sustainability can be achieved at the regional scale.

4. Discussion

4.1. The Impact of Urban Development on UBGs

Urban development and natural ecosystems share a highly complicated relationship. Consequently, how urban growth alters the structure and function of ecological spaces has become a topic of increasing attention. Urban expansion is largely driven by economic growth and population agglomeration. The effects of these two factors on UBGs differ notably depending on the stage of development. Existing research has demonstrated that economic growth exerts a significant influence on urban ecological spaces, although the direction and intensity of this influence are not constant [43–45]. On one hand, economic development may exert pressure on the ecological environment through land development and resource consumption. From another perspective, economic growth also provides the necessary financial support and technical conditions for ecological restoration and environmental governance. Some studies have pointed out that economic growth may exert a beneficial influence on the ecological environment during specific stages [46,47]. It should be noted that economic development is not equivalent to ecological improvement. The alleviation of urban ecological pressures cannot be achieved by economic growth on its own. According to the outcomes of the PLR model, this study indicates that the relationship between GDP and UBGs in the SPUA region exhibits pronounced phased changes across different developmental stages (Tables 3 and 4). In some cities, GDP and UBGs showed a significant positive correlation in the early phase, implying that economic growth laid a sufficient financial foundation for the creation of blue–green spaces. During the early stages of urban development, industrialization and urbanization processes drove the rapid expansion of infrastructure and public services. City governments typically concurrently promote the construction of green spaces and waters to enhance the ecological service functionality and improve the city’s image, thereby enabling GDP growth and UBG expansion to evolve in a synergistic manner. This is also reflected in the results showing changes in the area of UBGs (Figures 2 and 3). During the rapid urbanization phase prior to 2018, both UGs and UBSs showed an upward trend in most cities. During the later phases of urban growth, the slope from regressing GDP against UBGs declines, potentially turning negative, indicating that the crowding-out effect of economic expansion on UBGs is beginning to emerge. Nevertheless, some cities, by adjusting their development strategies, gradually incorporated ecological protection into their urban development goal systems, mitigating the adverse influence of economic growth on UBGs to some extent. This trend matches the earlier findings that came from analyzing the UBG area and landscape patterns, suggesting that in the later stages of development, cities tend to focus more on enhancing the quality and structural stability of UBGs, rather than solely pursuing areal expansion.

The impact of population growth on UBGs also exhibits pronounced phased characteristics and city-specific variations. The results of this study indicate that, in several cities, population growth had a positive effect on UBGs in the early phase, which may be closely related to supportive greening and ecological construction policies implemented during the initial stage of rapid development (Table 3). During this phase, the urban population had not yet reached its carrying capacity ceiling, land resources were relatively abundant, and population growth was often accompanied by the simultaneous expansion of public green spaces and water bodies [48,49]. However, as populations continued to concentrate and urban density increased, the demand for residential, commercial, and industrial land rose significantly. Limited land resources were gradually prioritized to meet the demands of urban functional expansion, thereby inhibiting further growth of UBGs and leading to a shift in the linkage between population and UBGs, turning from positive to negative. A shift from negative to positive characterized the evolutionary trajectory of

the population–UBGS relationship in some cities, in contrast. This suggests that during the initial urban development phases, the focus on housing and infrastructure might have taken precedence over blue–green spaces, leading to their slower development. When urban development became increasingly mature, local governments changed their priorities. Rather than focusing solely on expanding urban scale, they began to concentrate on raising the quality of life for residents and protecting the ecological environment, promoting the restoration and expansion of UBGSs through policy guidance and financial investment. Overall, the response of UBGSs to economic growth and demographic changes in the Shandong Peninsula urban agglomeration exhibits significant phase characteristics and spatial heterogeneity. Economic and population growth often provided impetus for UBGS expansion in the early stages of urban development but may have constrained it in later stages. Only through rational planning guidance and policy intervention can urban growth achieve coordinated development with the protection and optimization of UBGSs.

4.2. Constructive Effect and Challenges of National Strategic Policies

Following the initial proposal of the sustainable development idea, integrated development has gradually turned into a key concern in the regional governance and ecological protection of urban agglomerations [50]. Against the backdrop of rapid urbanization in China, national development strategies have continuously reinforced the fundamental role of ecological space in urban development, profoundly influencing the evolution of urban blue–green spaces. As an important economic agglomeration area in coastal areas, the change in UBGSs in the SPUA region has typical policy-driven characteristics in the process of undertaking national strategies and regional policies. The proposal of ecological protection and a high-quality development strategy of the Yellow River basin in 2019 has defined the leading position of the SPUA in the basin. Subsequently, the release of the Shandong Peninsula Urban Agglomeration Development Plan (2021–2035) in 2021 [24] further integrated ecological protection and coordinated development into the core framework of urban development. This has made the quality and structural optimization of UBGSs a key consideration in urban planning, profoundly reshaping the evolutionary trajectory of regional ecological space. Cities such as JN, QD, and BZ play core roles in the implementation of these policies, and their UBGS changes vividly demonstrate a high priority placed on ecological construction (Figure 5b). The NDVI increases in BZ and JN rank among the highest in the region, reaching 38% and 37%, respectively, significantly outpacing other cities and establishing them as benchmarks for the improvement of greening levels within the SPUA. Qingdao also achieved several consecutive years of positive growth in the UGS area (Figure 2). As the provincial capital, Jinan’s planning focuses on the systematic governance of “mountains, rivers, forests, farmlands, lakes, and grasslands,” promoting the construction of parks, wetlands, and ecological corridors within and around the central urban area to form an interconnected green network (Figure 9). Through continuous development from 2014 to 2023, Jinan not only achieved an 18.1% increase in UGS area but also facilitated the transition of green spaces from fragmented distribution to a concentrated and contiguous pattern by integrating fragmented green patches and constructing large-scale ecological patches. This process is also reflected in the changes in landscape metrics: with the deepening of regional ecological policies, the AI for UGSs in the entire SPUA initially fluctuated, then increased and stabilized. The LPI rose from 93.4 to 97.5, while the LSI decreased by approximately 18.3%. These findings indicate that policy-guided green space integration has effectively enhanced spatial connectivity, reduced fragmentation, and led to a more optimized green space structure.

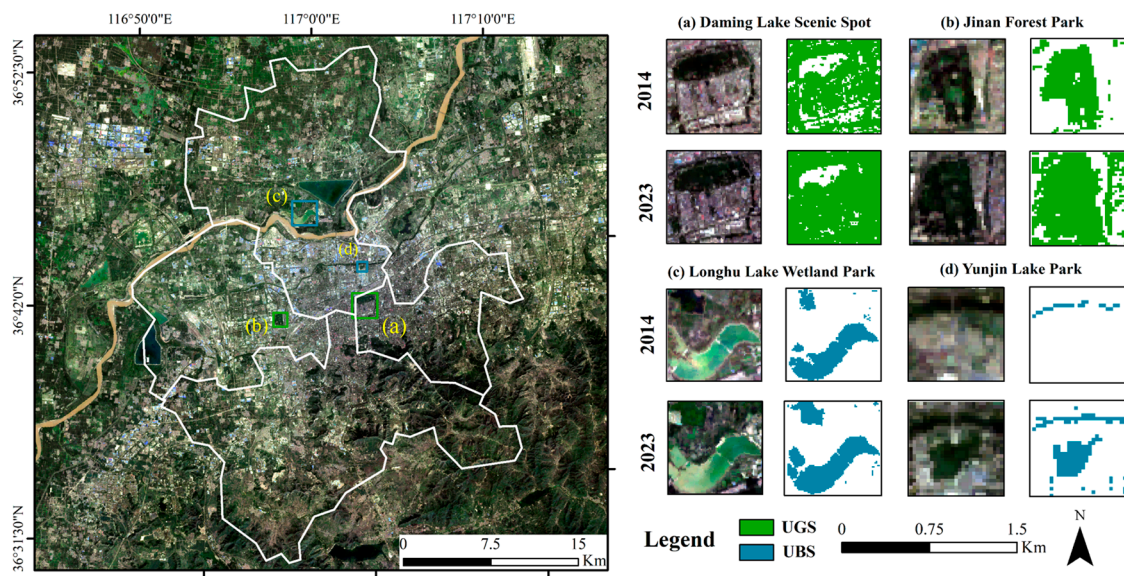


Figure 9. Comparison of UBGs in Jinan urban built-up zones from 2014 to 2023.

In terms of the protection of UBS, the publication of the Shandong Province water resources protection regulations in 2017 and their implementation in 2018 [51] provided important institutional guarantees for the protection of water bodies, directly promoting the restoration and expansion of UBSs in the SPUA region. After 2017, the UBS area in the SPUA region transitioned from a periodic decline to continuous growth, increasing overall from 1108.02 km² in 2014 to 1699.04 km² in 2023, with particularly notable increases in JN, HZ, and ZZ. Getis-Ord Gi* hotspot analysis revealed that DY consistently exhibited significant UBS hotspot characteristics throughout the study period. Meanwhile, Jinan, through water body restoration projects such as Longhu Wetland and Daming Lake (Figure 9), achieved synergistic optimization of artificial water bodies and natural water systems, serving as a typical case of policy-driven aquatic ecological protection. These results collectively confirm the core role of policy-oriented investment in the restoration of water body spaces.

Furthermore, according to the Shandong Peninsula Urban Agglomeration Development Plan (2021–2035), the Shandong Peninsula urban agglomeration coordinates regional development with the Provincial capital economic circle (PEC), Jiaodong economic circle (JEC), and Lunan economic circle (LEC) as its core frameworks. The functional orientations of these three economic circles differ significantly, and these differing orientations have resulted in distinct spatial characteristics in the evolution of UBGs. Specifically, the PEC, with JN at its core, encompasses ZB, TA, LC, DZ, BZ, and DY, focusing on ecological protection in the Yellow River basin and the radiating driving force of the provincial capital. The JEC, centered on QD, includes YT, WH, WF, and RZ, emphasizing coastal ecological synergy and blue economy development. The LEC comprises LY, ZZ, JN, and HZ, oriented towards ecological barrier construction and distinctive development in southern Shandong. The functional division of labor among the three economic circles has profoundly shaped the spatial pattern and evolutionary state of UBGs in the SPUA region.

In order to evaluate the different responses of UBGs to the planning guidance of three economic circles, the slope changes in UGSs and UBSs for each economic circle from 2014 to 2023 were analyzed (Figure 10). The findings indicate that the PEC showed the steepest urban green space growth slope at 85.20, then the JEC (slope = 48.24) and the LEC (slope = 30.76). The high UGS growth rate in the PEC is directly linked to the implementation of the strategy for coordinated development of environmental protection and high quality in the lower Yellow River. Jinan, as the core city, promoted both the quantity and

quality of UGSs through the construction of urban parks, integration of fragmented green spaces, and development of the Yellow River ecological corridor. This is evidenced by the continuous increase in AI and LPI, alongside a decrease in LSI, confirming the policy-driven optimization of green space connectivity and scale. DY and BZ, as estuary cities of the Yellow River, leveraged wetland protection and ecological restoration policies to become significant contributors to UGS growth within the PEC. The synergistic development of coastal wetlands and urban green spaces, in particular, strengthened the regional ecological barrier function. The JEC ranked second in UGS growth slope, with coastal cities such as QD and YT achieving linked development of coastal green spaces and urban parks under policy impetus. UGS growth in the Lunan economic circle was relatively modest, primarily constrained by the level of economic development and the relatively limited environmental protection fiscal expenditure ratio. In cities like LY and HZ, some natural spaces were encroached upon during urban expansion, resulting in an overall growth rate lagging behind the other two economic circles. In terms of UBS, the PEC had the greatest change slope of 33.48, with the JEC at 32.00 and the LEC at 7.53. The growth amplitude of the PEC was slightly higher than that in the JEC, closely related to the advancement of water ecological governance and constructed wetland restoration projects in the Yellow River basin. In contrast, the UBS growth in the LEC was markedly slower, presumably due to its relatively steady water resources environment and insufficient allocation of ecological protection fiscal investment towards blue spaces. These findings indicate that UBGs within different economic circles have followed differentiated optimization pathways. The formulation of future policies should be in line with the functional orientation of each economic circle and strengthen the overall coordination of the blue–green space layout to enhance the service efficacy of the regional ecosystem.

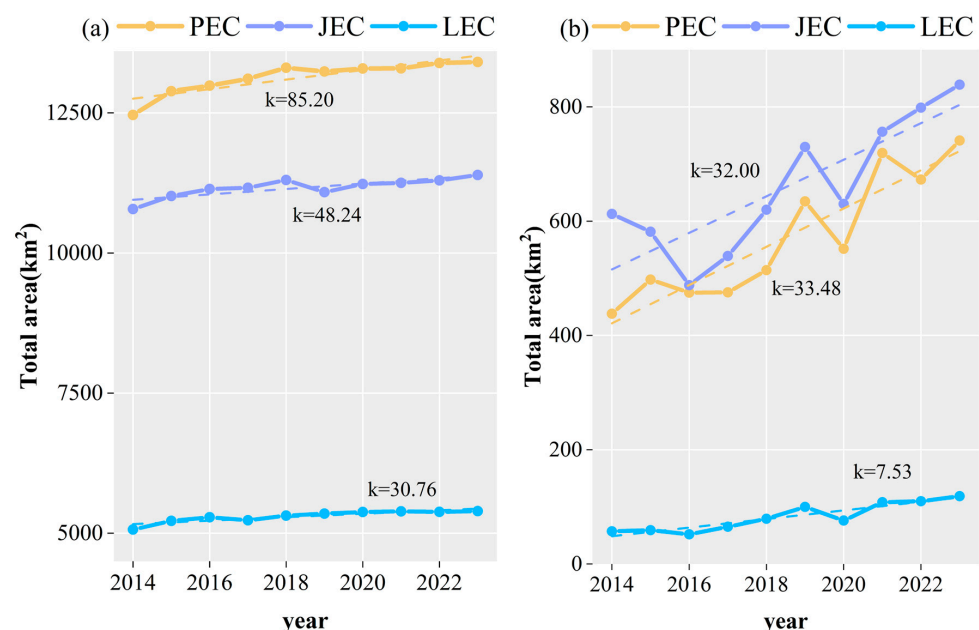


Figure 10. Trends of UBGs change in the three major economic circles of the SPUA region (Provincial capital economic circle, PEC; Jiaodong economic circle, JEC; Lunan economic circle, LEC) from 2014 to 2023. (a) UGS change trend. (b) UBS change trend.

4.3. Research Limitations and Prospects

This research examined the spatiotemporal development patterns of UBGs in the SPUA area using long-time-series satellite images and utilized a PLR model to assess and evaluate the instructive impacts of social indicators and environmental protection investments on UBGs. Nevertheless, certain shortcomings of this study should be recognized,

and future research could be developed further in these respects. To begin with, due to the high difficulty of data acquisition and the shortage of computing resources, this study utilized free land satellite data for UBSG extraction and monitoring. Although the temporal resolution and coverage of this data source meet the research objectives at the regional scale, its 30 m spatial resolution may result in the omission of smaller green patches (such as street greening) and subtle water bodies in the city center, consequently having some impact on both the correctness and the overall scope of spatial pattern analysis. In addition, although the sample-based validation confirmed the overall reliability of the net UGS and UBS change maps between 2014 and 2023, some class-specific uncertainties remained. The relatively lower producer's accuracies for stable UGS (76.0%) and UBS loss (76.8%) indicate that these two change classes were more susceptible to misclassification. This uncertainty may be associated with mixed pixels resulting from the 30 m spatial resolution of Landsat imagery, the sensitivity of the FVC and NDWI thresholds, fragmented green patches, narrow water bodies, shoreline pixels, and seasonal water-level variations. Because the reference change classes were determined through visual interpretation of the original Landsat imagery, the reported accuracy represents validation at the Landsat spatial scale. Future inquiries are suggested to utilize remote sensing data of a higher resolution, including Gaofen-2 or PlanetScope commercial high-resolution imagery, with expanded multi-source datasets such as drone imagery data and field investigation data, to increase extraction accuracy and more detailed disclosure of spatial pattern characteristics at the micro level and dynamic variations in UBSGs in the SPUA. In addition to spatial-resolution limitations, the threshold-based extraction method introduces uncertainty into the estimated UGS and UBS areas. Although $FVC > 0.6$ and $NDWI > 0.3$ were selected based on previous studies conducted in comparable urban environments, pixels close to these thresholds may be classified differently because of mixed-pixel effects, seasonal vegetation conditions, water turbidity, building shadows, and variations in surface reflectance. Applying the same thresholds and preprocessing procedures throughout 2014–2023 improves the consistency and comparability of the interannual results but does not completely eliminate uncertainty in the absolute area estimates and percentage changes. The sample-based assessment supports the overall reliability of the detected UGS and UBS changes between 2014 and 2023; however, it does not constitute an independent validation of every annual area estimate. Future research should therefore conduct multi-threshold sensitivity analyses and incorporate higher-resolution imagery, unmanned aerial vehicle observations, and field surveys to further quantify extraction uncertainty and validate annual UBSG dynamics. Furthermore, while the present study quantitatively analyzed the influence of socio-economic factors such as population (permanent population), GDP, and EPFSR on UBSGs, further exploration of other potential driving forces remains necessary. The evolution of UBSGs is a complex socio-ecological coupling process. Beyond the aforementioned socio-economic indicators, the specific implementation intensity of land use policies and the spatial patterns of urban expansion may significantly affect the stock and quality of UBSGs. Future research could integrate multi-source data, including land use data, territorial spatial monitoring data, and planning policy documents, to construct a more comprehensive indicator system and analytical framework, thereby enabling an in-depth exploration of the underlying driving mechanisms of UBSG evolution in the SPUA region. Finally, the advancement of UBSGs is driven by the dynamic relationship between natural environmental conditions and human activities, which presents analytical challenges when using single linear regression methods. Although Piecewise Linear Regression effectively revealed turning point characteristics along the temporal dimension, it struggles to fully capture the spatial non-stationarity and non-linear interactions among driving factors. For a more accurate understanding of how UBSG development patterns unfold, future research

should turn to advanced analytical tools: techniques in machine learning, geodetectors, and simulations across various scenarios. By using these methods, one can quantify and identify the main dominant factors and the coupling effect and also simulate how ecological space evolves under different policy scenarios, establishing a robust scientific basis for enhancing the design of the SPUA blue–green areas and advancing sustainable development in the region.

5. Conclusions

Using Landsat 8 OLI remote sensing data acquired between 2014 and 2023, this study carried out the extraction of UBGs for the SPUA region. The research first statistically analyzed the UBGs area within the SPUA region, then investigated the evolutionary patterns of its landscape configuration. Subsequently, a sample validation was conducted to assess the accuracy of blue–green space extraction in the municipal district areas of cities in the SPUA region from 2014 to 2023. The results showed that the overall accuracy rates for the UGS and UBS change maps were 86.20% and 83.60%, respectively, with Kappa coefficients of 0.816 and 0.781, respectively, confirming the overall reliability of the change detection results. Furthermore, it assessed the greening development trends in the built-up areas of each city within the SPUA by combining Sen's Slope estimation with the Mann–Kendall test. Finally, the study analyzed the associations between UBGs and factors including urban development, national strategies, population, GDP, and the proportion of environmental protection fiscal expenditure. The principal conclusions are as follows: (i) Within the scope of the research, the SPUA region's UBGs improved in both area and quality. Urban green space increased overall by 6.65%, with BZ, RZ, and JN exhibiting the most significant growth rates; urban blue space area expanded by 53.34%, with JN, HZ, and ZZ recording the highest increases. NDVI trend analysis indicates that vegetation greenness improved significantly in most municipal district areas, particularly in cities such as BZ, JN, and ZB. (ii) The UGS landscape pattern within the SPUA region showed a tendency toward clustering and ordering. There was an overall rise in both the AI and the LPI, but the LSI dropped by approximately 18.3%. This indicates a shift in green spaces from a dispersed and fragmented state towards a concentrated, contiguous, and structurally stable configuration, with significantly enhanced ecological connectivity and integrity. (iii) The evolution of UBGs was temporally associated with the implementation of national and regional ecological strategies. Following the implementation of the Yellow River basin ecological protection and high-quality development strategy and related plans, the growth trends of both UGSs and UBSs strengthened in several cities. Piecewise regression results demonstrate that environmental protection fiscal expenditure has positive explanatory power for the expansion of blue–green spaces, particularly prominent in cities like JN and YT. This finding suggests that policy guidance and financial investment may have contributed to reducing urban expansion pressure and supporting UBGs optimization. Overall, this study reveals the optimization path and response mechanisms of UBGs in the SPUA region under the guidance of national regional strategies, providing empirical evidence and a decision-making reference for coordinating urbanization with ecological protection and optimizing territorial spatial patterns.

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