Global Sustainability

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Research Article

Cite this article: Cheng, C., Hu, Y., Li, F., Zhao, M., Wang, P. (2025). Impact of green and blue spaces on ecosystem services in Beijing: spatiotemporal dynamics and driving mechanisms. *Global Sustainability*, **8**, e27, 1–12. https://doi.org/10.1017/sus.2025.10009

Received: 14 June 2024
Revised: 10 March 2025
Accepted: 25 April 2025

Keywords:
Beijing; driving mechanism; ecosystem service; green and blue space; spatial planning strategies

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Impact of green and blue spaces on ecosystem services in Beijing: spatiotemporal dynamics and driving mechanisms

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Abstract

Non-Technical Summary. As cities like Beijing expand rapidly, green and blue spaces (GBS)—essential for ecosystem services (ESs) such as clean air, flood control, and recreation—are increasingly threatened. This 20-year study examines how urban expansion and policy interventions have shaped Beijing's GBS. While green initiatives have increased natural areas, unchecked urban sprawl has fragmented these spaces, reducing their environmental benefits. Satellite data and urban planning analyses underscore a key lesson: maintaining well-connected natural zones is critical for urban resilience. These findings are broadly applicable for rapidly growing cities globally, urging urban planners to integrate ecological conservation with development, and to safeguard healthy environments and vibrant communities.

Technical Summary. This study quantifies the spatiotemporal dynamics of urban GBS in Beijing, evaluating their essential role in delivering ESs and strengthening urban resilience. Although China has achieved substantial progress in urban greening, the ecological impacts of rapid urbanization on GBS configuration and connectivity have not been comprehensively quantified. Using an integrated analytical framework combining principal component analysis and multiple linear regression, we reveal how urban development strategies have shaped GBS dynamics over two decades. A spatially explicit analysis, utilizing geographically weighted regression, further elucidates the heterogeneous relationships among the normalized difference vegetation index, human footprint index, and ESs delivery capacity. Notably, socioeconomic incentives and green infrastructure governance—especially objective indicators such as forest, garden, and greenspace area—have effectively driven GBS expansion. However, urban expansion has led to pronounced fragmentation of peri-urban GBS, suggesting potential degradation of their ecosystem service support functions. These findings emphasize the need for adaptive GBS management strategies that balance ecological conservation with sustainable urban growth in rapidly developing cities.

Social Media Summary. Urban growth fragments green and blue spaces, reducing vital ecosystem services. Balancing conservation with development is essential for sustainable cities.

1. Introduction

Urbanization, defined by the transformation of rural landscapes into urban environments, significantly reshapes social, economic, demographic, and ecological systems (He et al., 2017; Wang et al., 2022). Central to this transformation are green and blue spaces (GBS), which encompass natural or seminatural ecosystems within urban boundaries, integrating vegetation, surface waters, and interconnected natural elements (Taylor & Hochuli, 2017). These spaces provide essential ecosystem services (ESs), including air purification, temperature regulation, mental health benefits, and recreational opportunities, all crucial for human well-being and urban sustainability (Liu et al., 2022; Meng et al., 2020; Wilson et al., 2024). Nevertheless, rapid urbanization has led to widespread degradation and fragmentation of GBS, limiting their ability to maintain ESs provision (Salvati et al., 2018; Yan et al., 2022).

From a landscape ecology perspective, the spatial configuration and connectivity of GBS – measured by metrics such as patch density, edge complexity, and network centrality – are critical determinants of ESs dynamics (Abdullah et al., 2022; Lamy et al., 2016). Research indicates that enhancing GBS patterns through green infrastructure and spatial connectivity strategies can improve ESs delivery (Feng et al., 2021; Li et al., 2005). However, integrating this knowledge into planning frameworks remains challenging (Seto et al., 2012; Wu, J. 2019).

Although nonspatial regression models (e.g., ordinary least squares [OLS], logistic regression) and spatial techniques such as geographically weighted regression (GWR) have been employed to analyze GBS-ES relationships (Brunsdon et al., 1996; Zhang et al., 2018), these methods often neglect temporal continuity and fail to capture the complex interactions among GBS structure, socioeconomic drivers, and policy interventions (Chen et al., 2022; Lourdes et al., 2022). Moreover, existing research rarely integrates interdisciplinary perspectives to address the ES supply–demand–flow triad, hindering the alignment of landscape governance with urban sustainability goals (Felipe-Lucia et al., 2022; Schröter et al., 2018).

China's urbanization trajectory, underpinned by ecological civilization and low-carbon development policies, offers a unique context for exploring these interactions. National strategies prioritize GBS conservation to address diverse demands from citizens and policymakers (Assis et al., 2023; Pinto et al., 2022), yet the effectiveness of policy implementation and the long-term impacts of urbanization on GBS remain not well understood (Sun & Zhao, 2018; Xu et al., 2019; Zhang et al., 2021). While studies have investigated the socioeconomic drivers of landscape change (Li et al., 2017; Wu, W. B., et al., 2021), few studies employ temporal frameworks to evaluate how urbanization phases interact with policy strategies to reshape GBS. Furthermore, the integration of smart city innovations and population-driven factors into GBS planning remains insufficiently developed, limiting the optimization of urban resilience strategies (Xia et al., 2023).

To address these gaps, this study explores the spatiotemporal evolution of GBS and ESs in Beijing over the past two decades, focusing on three key questions: (1) How have GBS patterns and related ESs shifted over time and space? (2) How have different stages of urbanization and development strategies influenced GBS configurations? and (3) Which spatial metrics are most important for connecting GBS dynamics with ESs provision?

2. Study area

Beijing, the capital of China, is located in the northwest corner of the North China Plain, bordered by Tianjin and Hebei province (N39°28′–N41°25′, E115°25′–E117°30′) (Figure 1). This expansive metropolis covers an area of 16,410 km^2, with mountains accounting for approximately 62% of the total land area, and spans 16 administrative districts. Beijing uniquely blends a rich historical legacy, dating back thousands of years, with its modern role as a global center for national politics, culture, international exchange, and scientific innovation. In 2020, Beijing was designated as an Alpha+ global city by the Globalization and World Cities Research Network (The World From GaWC, 2020), highlighting its significant global economic and political influence. That same year, the city's gross domestic product (GDP) reached 3.61 trillion RMB (about 515.714 billion U.S. dollars), with an urbanization rate of 87.5%. With a population of 21.9 million, the city allocated 243.9 billion RMB (about 3.48 billion U.S. dollars) to research and development initiatives. However, rapid economic growth and urbanization in Beijing have caused a significant reduction in GBS. In response, the Beijing government has introduced policies to improve the quality of these critical areas, enhancing the ecological network, and optimizing urban planning. These efforts underscore the government's commitment to sustainable urban development and its recognition of the essential role that GBS plays in strengthening the city's ecological resilience and livability.

3. Materials and methods

3.1. Data sources

For this comprehensive study, we used a diverse range of data sources, including land use, meteorological records, soil characteristics, the normalized difference vegetation index (NDVI), human footprint (HFP), road, and statistical data, as detailed in Table 1. Land-use data were obtained from the Resource and Environment Science and Data Center and classified into six categories: farmland, forest, grassland, open water, construction land, and barren land. Climatic variables – such as average annual precipitation, temperature, and potential evapotranspiration – were collected from 438 weather stations. Additionally, our dataset included soil properties such as soil depth, clay content, silt content, sand content, organic carbon content, and bulk density. All datasets were resampled to a consistent 100 × 100 m resolution to ensure precision and consistency across the analysis. Statistical data, crucial to our research, were drawn from 16 key factors, primarily sourced from authoritative publications such as the Beijing Statistical Yearbook, Beijing Economic Development Report, China City Statistical Yearbook, the State Information Center, and the National Bureau of Statistics.

3.2. Methods

Initially, we analyzed changes in both the types and areas of GBS components (Figure 2). Utilizing principal component analysis (PCA) and multiple linear regression (MLR), we identified the principal factors influencing GBS distribution. We then examined the spatiotemporal dynamics of four critical ESs: net primary productivity (NPP), carbon storage, soil conservation, and habitat quality. Concurrently, GWR was applied to assess the spatial impacts of these ESs. By employing PCA, MLR, and landscape pattern metrics over continuous time, this study seeks to advance the theoretical understanding of GBS-ES interactions and offer practical insights to help balance ecological protection with socioeconomic development in rapidly growing global cities.

3.2.1. Analyzing the composition of GBS

We examined changes in the types and areas of GBS in Beijing, focusing on farmland, forest, grassland, and open water across urban and suburban regions. Using the land use and land cover transfer matrix (see S.1), we mapped transformations in Beijing's GBS from 2000 to 2020, highlighting shifts in these key landscape components.

3.2.2. Influence of urban development on GBS area

(1) Index system of influencing factors

We identified 16 influencing factors based on previous research and by considering aspects of urban development, economic growth, and natural ecological conditions (Schirpke et al., 2023; Sorge et al., 2022). These factors are grouped into five domains: socioeconomic, technological innovation, nature, green infrastructure metrics, and environment.

(2) PCA and MLR analysis

We conducted PCA and MLR using SPSS 24.0 to assess the impact of urbanization on the GBS area. First, we used the GBS area as the dependent variable and 16 influencing factors as independent variables. To evaluate factor suitability for PCA, we employed

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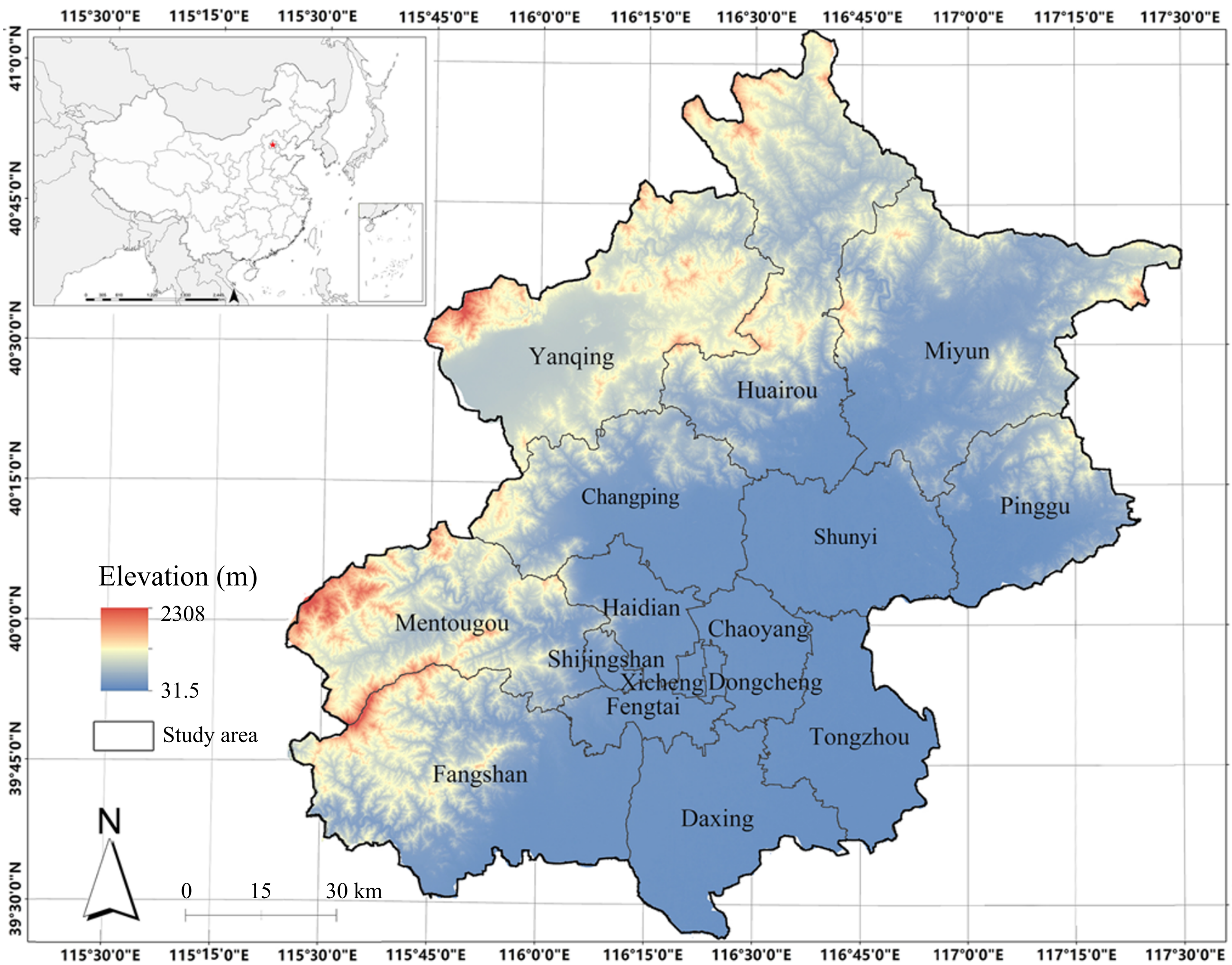

Figure 1. Topographical map of Beijing. Beijing includes 16 districts: the central city, which comprises Dongcheng, Xicheng, Fengtai, Chaoyang, Shijingshan, and Haidian districts; the outer suburbs (in the plain), including Tongzhou, Shunyi, and Daxing districts; the outer suburbs (in semi-mountainous areas), including Pinggu, Changping, and Fangshan districts; and the outer suburbs (in mountainous areas), including Huairou, Mentougou, Yanqing, and Miyun districts.

the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity to confirm whether the data were appropriate for PCA (Mathur, 2014). Bartlett's test yielded a significance of 0.00 and the KMO measure yielded a value of 0.783 (>0.7) for the 16 impact factors. Both results indicate suitability for PCA, confirming these principal components as acceptable substitutes for the 16 potential influencing factors (Table S2.1).

Next, we calculated the correlation matrix and identified eigenvalues, retaining components with eigenvalues greater than one that collectively accounted for over 75% of the variance. The PCA identified two principal components with eigenvalues of 11.13 and 1.99, explaining 82.21% of the sample variance (Figure S2.1). Based on the rotated component matrix and corresponding eigenvalues (Table S2.2), we characterized the first principal component F_1 as urban development, comprising 12 key factors: population density (X_1), GDP (X_3), primary industry (X_4), secondary industry (X_5), tertiary industry (X_6), consumer price index (CPI) (X_7), research and experimental development (R&D) (X_8), forested area (X_{12}), area of gardens and green spaces at year's end (X_{13}), green space area (X_{14}), average daily value of SO_2 (X_{15}), and average daily value of NO_2 (X_{16}). The second principal component F_2 represented the natural environment with two key factors: precipitation (X_9) and temperature (X_{10}).

Finally, we performed a stepwise MLR using the principal component scores (PCS) as independent variables and the GBS area as the dependent variable (Figure 4). We computed the PCS using the coefficient vector from PCA to normalize the original indicators. This analysis enabled us to determine the impact of the principal components on the GBS area from 2000 to 2020. Using the coefficient vector matrix from the PCA, we normalized the original indicators, which were then input into Z_{F1} and Z_{F2} to calculate the corresponding PCS. We expressed the two principal components as Equation (3). We introduced the normalized values of PCS and the GBS area ($R^2 = 0.952$) into the stepwise MLR model, as outlined in Equation (4).

(3) Obtaining key influencing factors

PCA is a dimensionality reduction technique that combines the original variables into new orthogonal variables while retaining as much information as possible. MLR of PCS assumes a

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Table 1. Description of main datasets used in the study

Layer	Description	Spatial scale	Temporal scale	Source
Land use	Six types	30m; raster, tif	Year, 2000, 2020	http://www.resdc.cn/
Meteorological data	Annual average precipitation, temperature, potential evapotranspiration	Shp,1:1,000	Year, 2000, 2020	Annual average precipitation and temperature were collected from http://cdc.cma.gov.cn. Potential evapotranspiration data was downloaded from the Global Aridity and PET Database from http://www.cgiar-csi.org/data/global-aridity-and-pet-database.
Soil properties	Soil depth, clay content, silt content, sand content, organic carbon content, and bulk density	Shp,1:1,000	Year, 2000, 2020	http://www.soilgrids.org
MODIS	Moderate-resolution imaging spectroradiometer dataset	250m; raster, tif	16 days, 2000, 2020	http://ladsweb.nascom.nasa.gov
Normalized Difference Vegetation Index (NDVI)	Annual maximum NDVI dataset	30m; raster, tif	Year, 2020	https://www.escience.org.cn/
Human Footprint (HFP)	The data serves as a quantitative metric, specifically devised to evaluate the extent of human influence on the Earth' terrestrial surface	1 km, raster, tif	Year, 2020	https://doi.org/10.6084/m9.figshare.16571064
Road data	Primary and secondary roads	/	Year, 2000, 2020	Openstreetmap
Statistics	16 factors	/	Four quarters per year, 2000–2020	Beijing Statistical Yearbook, Beijing Economic Development Report, China City Statistical Yearbook, State Information Center, and National Bureau of Statistics.

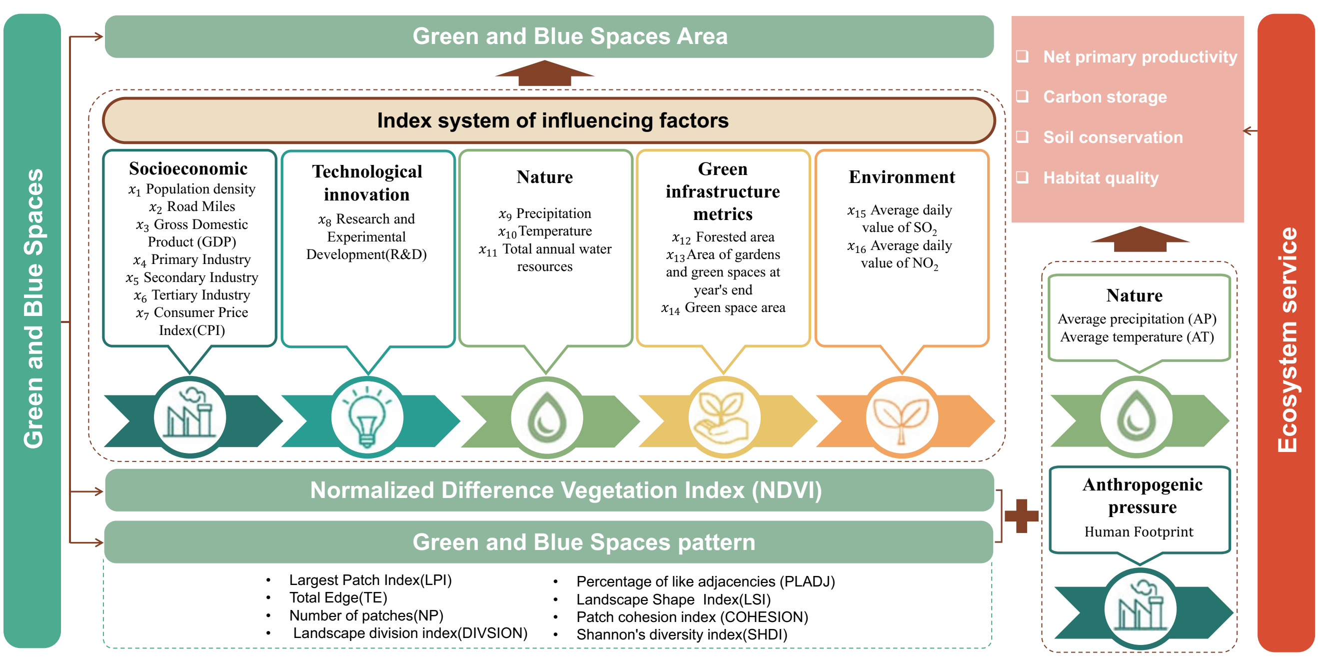

Figure 2. Schematic of the study framework.

linear relationship between the dependent variable and the principal components obtained from PCA (Guo et al., 2004; Tian et al., 2021). This allows for assessing the importance of each influencing factor. The formula for extracting the key influencing factors is presented in Equation (5).

3.2.3. Ecosystem services

Beijing's strategies proposed for GBS planning predominantly aim to enhance the GBS quality, which involves improving biodiversity and boosting ESs functionality. Moreover, there is a strong emphasis on green development, climate change mitigation, and the implementation of Nature-based solutions (NbS). In line with Beijing's commitment to sustainable development and ecological enhancement, our study focuses on key ESs, specifically NPP, carbon storage, soil conservation, and habitat quality. These ESs are critical for flood management, climate change mitigation, and biodiversity conservation. For detailed calculation methods, as referenced in Section S.3, we employed the Integrated Valuation of

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Ecosystem Services and Tradeoffs (InVEST) model to assess carbon storage, soil conservation, and habitat quality (Natural Capital Project, 2023). NPP was calculated using surface meteorological data, MODIS, and the Carnegie–Ames–Stanford Approach model (Field et al., 1998; Potter et al., 1993).

3.2.4. Calculating the GBS patterns

We characterized the GBS patterns using eight complementary landscape metrics, calculated in FRAGSTATS v4.2 (McGarigal et al., 2024) at both the landscape and class levels. These metrics, drawn from five functionally distinct categories (Table S4.1), offer a multidimensional view of landscape structure (Li et al., 2023; Šímová & Gdulová, 2012):

(1) Area dominance (largest patch index, LPI): Measures the proportion of the landscape occupied by the largest contiguous patch, highlighting dominant habitats and providing a baseline for ecological prioritization. (2) Edge dynamics (total edge, TE): Assesses the total length of all patch perimeters, capturing boundary-mediated processes such as species interactions and energy flow. (3) Fragment dispersion (number of patches, NP; landscape division index, DIVISION): NP counts discrete habitat fragments, while DIVISION quantifies degree of isolation. Both are inversely related to ecological resilience, as increased fragmentation limits species dispersal. (4) Spatial aggregation (percentage of like adjacencies, PLADJ; landscape shape index, LSI; patch cohesion index, COHESION): PLADJ measures clustering, LSI captures standardized shape complexity, and COHESION indicates overall functional connectivity. (5) Habitat heterogeneity (Shannon's diversity index, SHDI): Integrates patch richness and evenness, serving as an indicator of landscape-level biodiversity.

Although metric intercorrelations are recognized (Cushman et al., 2008), our selection follows frameworks that emphasize nonredundant functional assessment (Peng et al., 2021; Wu, 2004). Area and edge metrics address habitat composition and boundary dynamics; fragmentation indices quantify impacts of habitat splitting; aggregation indices describe spatial arrangement; and diversity metrics capture ecological heterogeneity.

3.2.5. Spatial factors influencing ESs

We employed GWR to analyze the spatial factors influencing ESs. GWR is a localized modeling approach designed for spatial data with heterogeneity and autocorrelation (Georganos et al., 2017). It effectively addresses these spatial characteristics. Unlike ordinary least squares (OLS), which estimates global coefficients, GWR provides location-specific estimates, revealing spatial nonstationarity in relationships between variables. The GWR model can be expressed as follows:

$$y(m) = \beta_0(m) + \sum_{k=1}^{p} \beta_k(m) \cdot x_k(m) + \varepsilon(m) \quad (6)$$

where $y(m)$ is the response variable at location m; x_k is the value of the k_{th} independent variable; β_0 is the intercept; β_k is the local regression coefficient for x_k; and $\varepsilon(m)$ is the random error term at location m (Fotheringham & Oshan, 2016).

4. Results

4.1. Spatiotemporal dynamics and drivers of GBS

4.1.1. Characteristics of the change in types and area of GBS

Beijing experienced a substantial reduction in GBS coverage during rapid urban expansion from 2000 to 2020, with a net loss of approximately 1,200 km^2. This decline was driven mainly by the large-scale conversion of farmland into urban development zones. By 2020, forest accounted for the dominant land-use category (46%), followed by farmland (22.5%), construction land (20.8%), grassland (7.9%), open water (2.6%), and barren land (0.2%). Temporal analysis revealed contrasting trends: farmland and open water consistently decreased, while forests, barren land, and construction land expanded. Grasslands exhibited fluctuating patterns over time (Figure 3a). Quantitative assessments demonstrated a 7.8% decline in farmland (4,975.64–3,697.58 km^2), with 35% of this loss converted to construction land. Construction land increased by 7.2%, increasing from 2,232.49 to 3,412.32 km^2. Spatial analyses identified the peri-urban plains as major hotspots of land conversion (Figure 3b, 3c).

4.1.2 Key influencers of changes in GBS area

Based on the findings from PCA-MLR (Figure 4), we observed that urban development exerts a greater influence than natural environmental factors. The key influencers include the CPI (X_7), forested area(X_{12}), area of gardens and green spaces at the year's end(X_{13}), green space area (X_{14}), and average daily value of SO_2 (X_{16}). Thus, both socioeconomic indicators and green infrastructure variables emerged as critical determinants of GBS area changes. Moreover, the average daily value of SO_2 (X_{16}) —a major contributor to urban air pollution (Shams et al., 2021)—negatively affects both the urban ecosystem and GBS area.

4.1.3. Temporal variation in the impact on GBS area

Using PCA-MLR, we examined the temporal shifts in the influence of urbanization on the GBS area in Beijing from 2000 to 2020 (Figure 5). The year 2011 was identified as a pivotal inflection point in Beijing's urbanization process. From this point onward, the effect of urbanization shifted from restricting GBS expansion to actively promoting the enhancement and growth of these critical ecological resources, even though the overall GBS area continued to decline.

4.2. Spatial–temporal dynamics of ESs

4.2.1. Predominant increase in NPP in the northern mountains

NPP was significantly higher in the northwestern and northern mountainous regions, while the central urban plains showed substantially lower values (Figure 6a). From 2000 to 2020, NPP increased markedly in the outer suburban mountainous and semi-mountainous areas, particularly in Huairou, Miyun, and Pinggu districts, where values rose from 201.51 to 605.6 gC m^{-2}. In contrast, NPP in the central urban area declined, from −141.1 to 142.94 gC m^{-2}, representing a reduction of nearly 300 gC m^{-2}.

4.2.2. Elevated carbon storage in mountainous regions

The carbon storage pattern in the study area (Figure 6a) shows a distinct spatial gradient, decreasing from the peripheral mountains toward the urban core. Peripheral regions, particularly mountainous, semi-mountainous, and certain plains areas, exhibit significantly higher carbon storage (310.58–3543 gC m^{-2}), due to dense vegetation. In contrast, the urban center has considerably carbon storage (738–1540 gC m^{-2}), primarily as a result of dense infrastructure restricting carbon sequestration. The lowest carbon values (20.48–310.57 gC m^{-2}) are intermittently distributed across the area, highlighting potential sites for ecological restoration.

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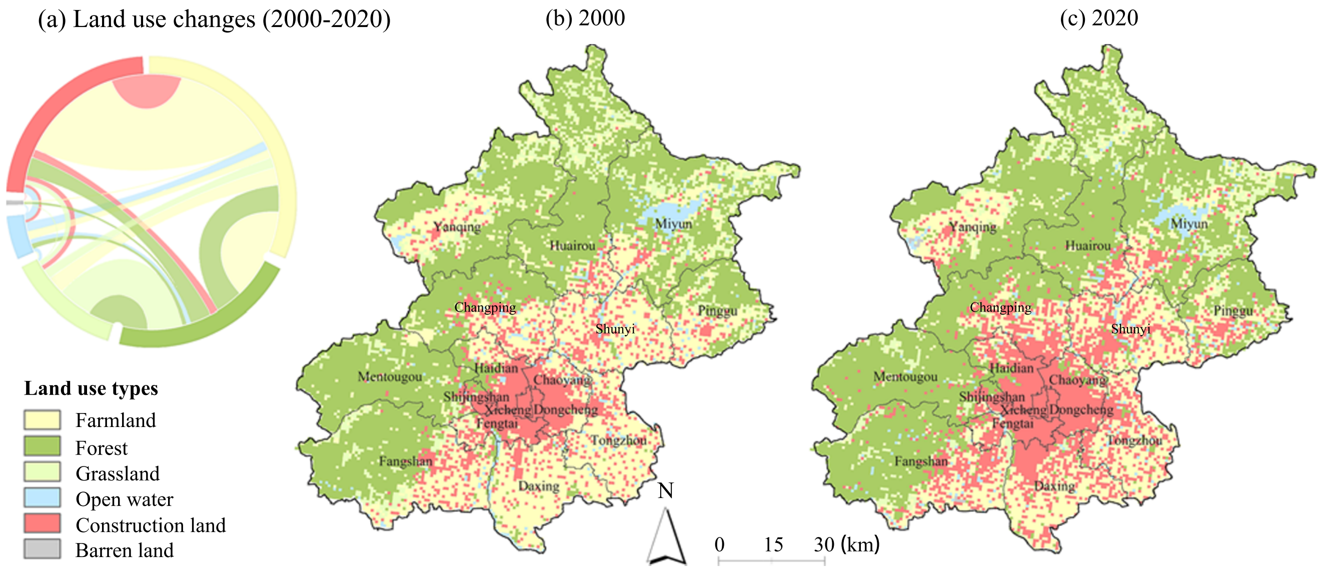

Figure 3. Changes in GBS types and areas in Beijing (2000–2020). (a) Chord diagrams depicting the shift in GBS types. (b) GBS types in 2000. (c) GBS types in 2020.

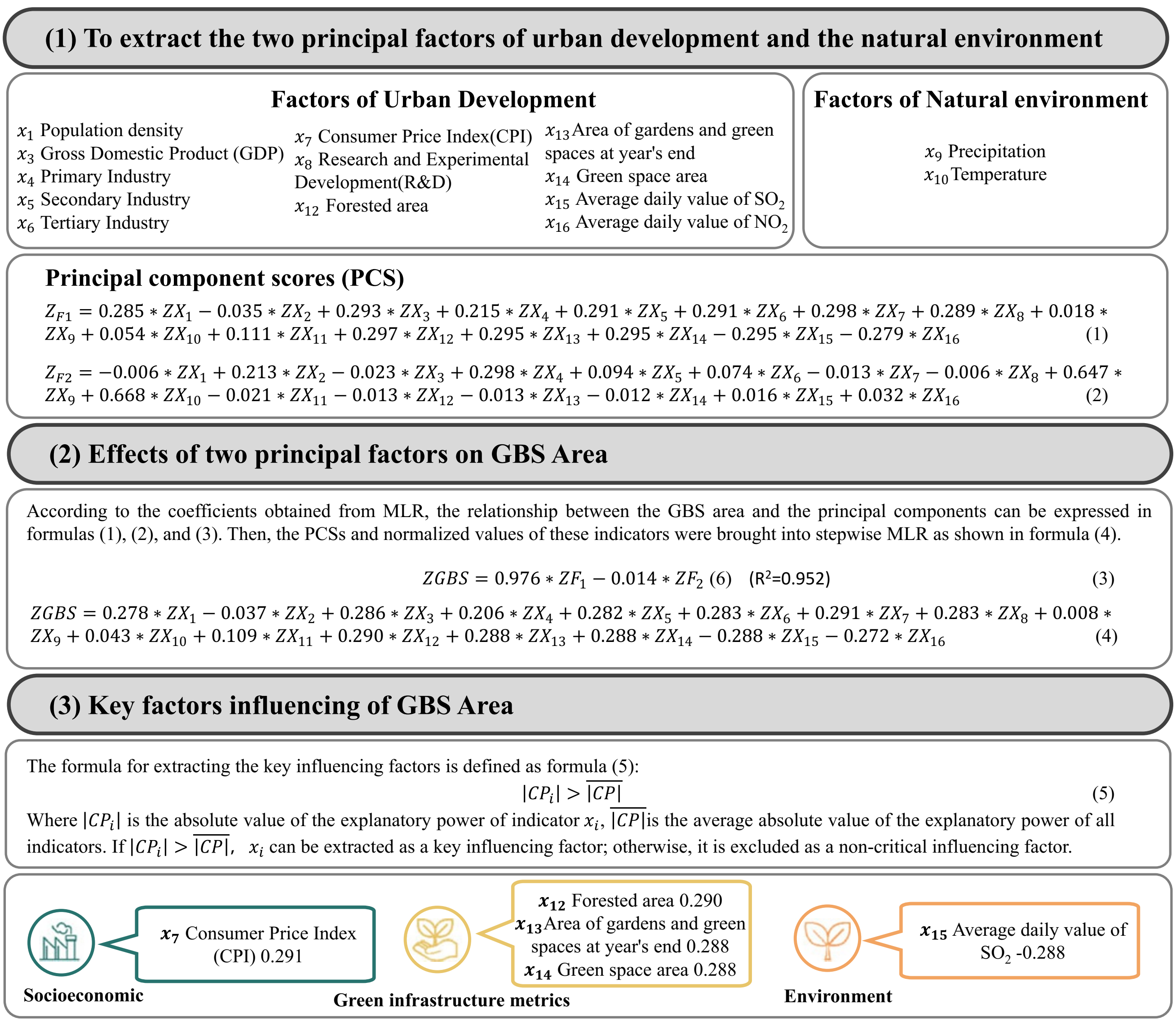

Figure 4. Application of PCA-MLR to identify the influential indicators and key factors driving changes in the GBS area.

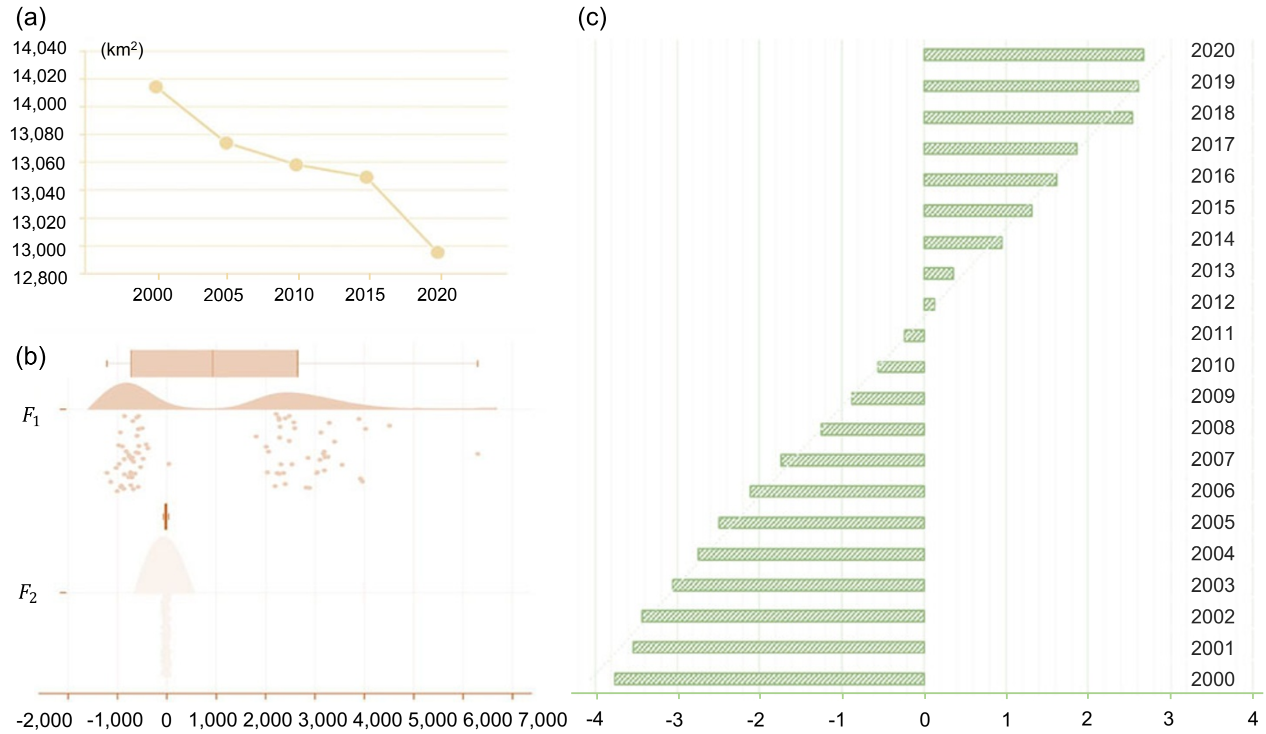

Figure 5. The impact of urbanization on the GBS area in Beijing (2000–2020). (a) The GBS area exhibits a declining trend. (b) The influence of principal components F_1 and F_2 is shown. (c) The influence of these principal components is illustrated, where negative values indicate adverse effects and positive values signify beneficial effects.

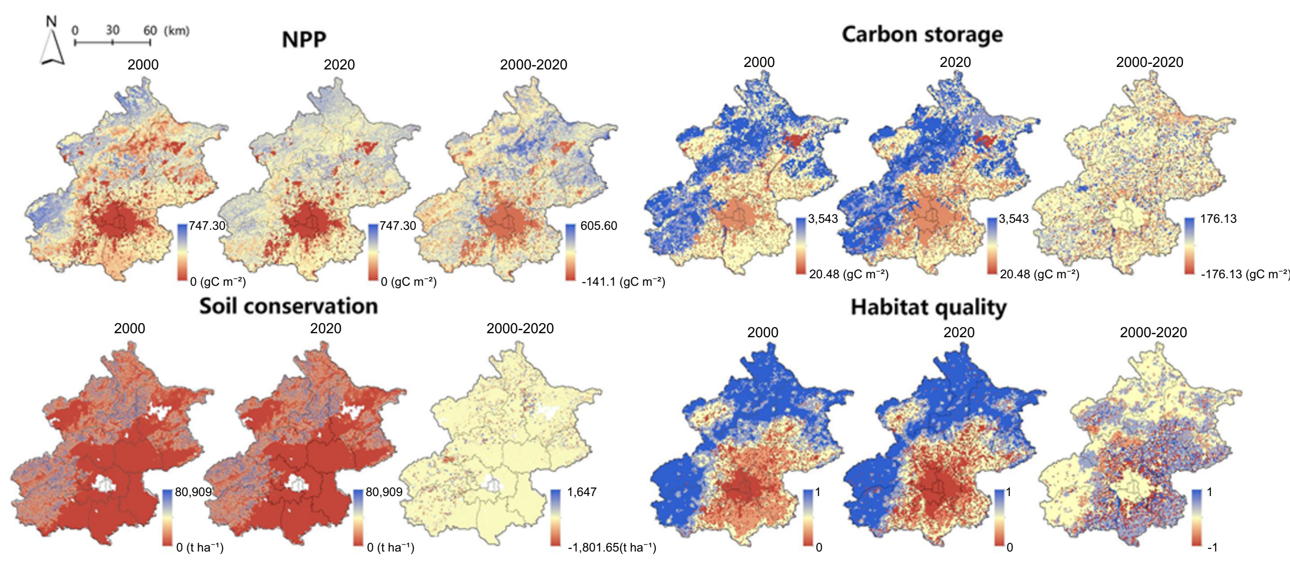

Figure 6. Spatial–temporal dynamics of ecosystem services in Beijing (2000–2020).

From 2000 to 2020, carbon storage increased notably in regions such as west Fangshan, the Mentougou–Changping junction, Miyun, and along the Yongding River in Daxing (21.41–176.12 gC m^{-2}), attributed to reforestation and green development initiatives. Conversely, carbon storage decreased in the central city and adjacent regions—including northern Miyun, western Tongzhou, and northern Daxing—with reductions ranging from −176.12 to −25.56 gC m^{-2}.

4.2.3. Subtle shifts in soil conservation

Soil conservation capacity in the study area has shown only minor changes, primarily in the mountainous regions (Figure 6c). Changes were sporadic and largely confined to the outer mountainous and semi-mountainous suburbs. Soil conservation values ranged from 53.95 to 809.09 t ha^{-1}, reflecting strong conservation practices and effective land management. However, the mountainous regions remain vulnerable to localized landslides, presenting

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ongoing challenges for soil conservation. In contrast, lower values ($0–15.86 \text{ t ha}^{-1}$) were mainly observed in the plains.

4.2.4. Habitat quality improved in plains and semi-mountainous regions

The study area has generally experienced an overall improvement in habitat quality, although localized areas of degradation persist (Figure 6d). Significant gains in habitat quality have been detected in the adjacent plains and semi-mountainous regions, encompassing Changping, Shunyi, Tongzhou, Daxing, and Pinggu. These improvements are likely linked to the integration of ecological considerations in urban planning. Additionally, traditionally recognized natural habitat strongholds, particularly in the mountainous districts, have shown similar positive trends. Notably, enhanced habitat quality in specific areas within Mentougou and Yanqing districts aligns with the objectives of the Beijing Call for Biodiversity Conservation and Climate Change. Conversely, some transition zones between urban centers and suburban regions continue to experience habitat degradation, underscoring the importance of targeted restoration strategies to achieve comprehensive habitat conservation across the region.

4.3 The influence of GBS on ESs

4.3.1. Impact factors of ESs

Our analysis indicates that NDVI and HFP exert a more significant influence on ESs than GBS patterns or natural variables, such as average precipitation (AP) and average temperature (AT) (Figure 7). Higher NDVI values are positively correlated with enhanced ESs ($r > 0$, $p < 0.05$), reflecting healthier, more productive vegetation. In contrast, increasing HFP, which indicates human impact and is often associated with habitat loss and degradation, shows a negative correlation with ESs ($r < 0$, $p < 0.05$).

4.3.2. The impact of NDVI and HFP on ES

Our results underscore the importance of a dual strategy for ecosystem management: promoting vegetation quality and reducing anthropogenic pressures through sustainable practices. The GWR model, which generates adjusted R^2 values, coefficients, and residuals for each grid (Tables S5.1 and S5.2), provides a clear representation of spatial heterogeneity in model performance. The spatial patterns of NDVI and HFP impacts on ESs (Figure 8) demonstrate substantial spatial variability. Specifically, NDVI has the strongest influence on NPP, carbon storage, soil conservation, and habitat quality in mountainous areas, while HFP exerts broad impacts, particularly across urban and plain regions.

4.3.3. Impact of GBS patterns on ESs

Indices such as LPI, PLADJ, and COHESION generally show decreasing trends, while TE, DIVISION, LSI, and SHDI tend to increase. The NP shows a decrease followed by an increase across the study area from 2000 to 2020 (Figure S4.1a). This pattern suggests reduced patch dominance, aggregation, and connectivity, alongside gradual increases in patch number, density, total edge length, edge density, fragmentation, shape complexity, and landscape diversity. These changes indicate a trend toward greater fragmentation of GBS patterns, which may impact ecosystem resilience.

The fragmentation of GBS patterns appears to be increasing, with greater landscape heterogeneity observed in areas converted to constructed land (Figure 3). The most notable changes were observed in NP (Figure S4.1b). Alterations in LPI, TE, LSI, DIVISION, PLADJ, COHESION, and SHDI show consistent trends across regions, with both increases and decreases apparent. The evolving GBS pattern, particularly in areas experiencing extensive construction, suggests a potential link between urban expansion and the fragmentation and heterogeneity of natural landscapes.

These patterns suggest that the GBS fragmentation may influence the structural integrity and functional capacity of ESs (Figure 7). Our findings indicate that increased fragmentation of GBS patterns could have a negative effect on ESs, with TE, NP, DIVISION, and SHDI showing negative correlations with carbon storage and soil conservation. In contrast, COHESION appears to be positively correlated with all four ESs. The fragmentation of contiguous habitats into isolated patches may hinder ecological functions such as soil conservation and carbon sequestration, potentially leading to a heterogeneous spatial distribution of ESs, with some regions showing enhanced or significantly diminished NPP and habitat quality.

5. Discussion

5.1. Socioeconomic and green infrastructure metrics as key influencers

This study emphasizes the pivotal role of socioeconomic and green infrastructure metrics in shaping GBS development in urban areas, with particular focus on the CPI as a key indicator. As China's economic growth progresses, urban residents increasingly prioritize the quality of their living environments, thereby driving the demand for improved GBS in cities such as Beijing. This shift is reflected in changing consumption patterns that place greater emphasis on environmental concerns. Research suggests that residents are willing to financially support green space preservation (Lo & Jim, 2010), although some argue that the government should spearhead these efforts (Xu et al., 2020). Green infrastructure metrics, as objective indicators of the built environment, can indirectly reflect the effectiveness of policy implementation. Therefore, we posit that urban ecology policies and development strategies play a critical role in advancing GBS, as evidenced by the impact of factors such as forest area and garden space on urban planning. These findings underscore the interconnectedness of economic prosperity, public policy, and environmental priorities in shaping urban landscapes.

5.2. Spatiotemporal variability in the impact of urban development strategies on GBS

Between 2000 and 2020, Beijing's urban development strategies underwent notable transformations, mirroring broader shifts in China's urbanization and landscape management paradigms (Wang, 2018). This section analyses how the impacts of these strategies varied across space and time, with particular emphasis on the shift from rapid urban expansion to more ecologically oriented planning.

From 2000 to 2010, Beijing experienced intensive urban growth, which was largely detrimental to its GBS. Key urbanization drivers—including land use transformation and deindustrialization—facilitated the conversion of farmland to urban, promoting exurban sprawl, axial expansion, and suburbanization. For instance, the deindustrialization of the late 1990s spurred the development of residential and commercial zones along the urban fringe. This phase of uncoordinated urban growth

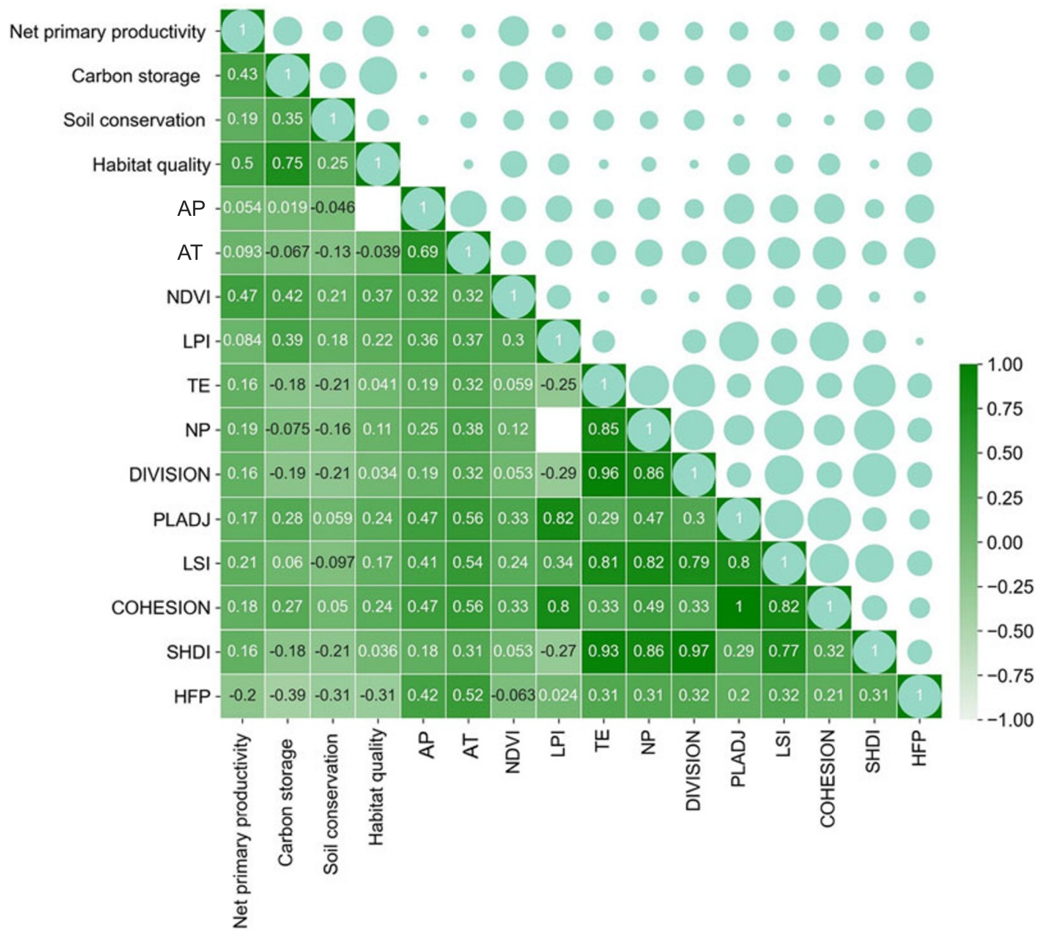

Figure 7. Factors influencing ecosystem services in Beijing (2000–2020) ($p < 0.05$).

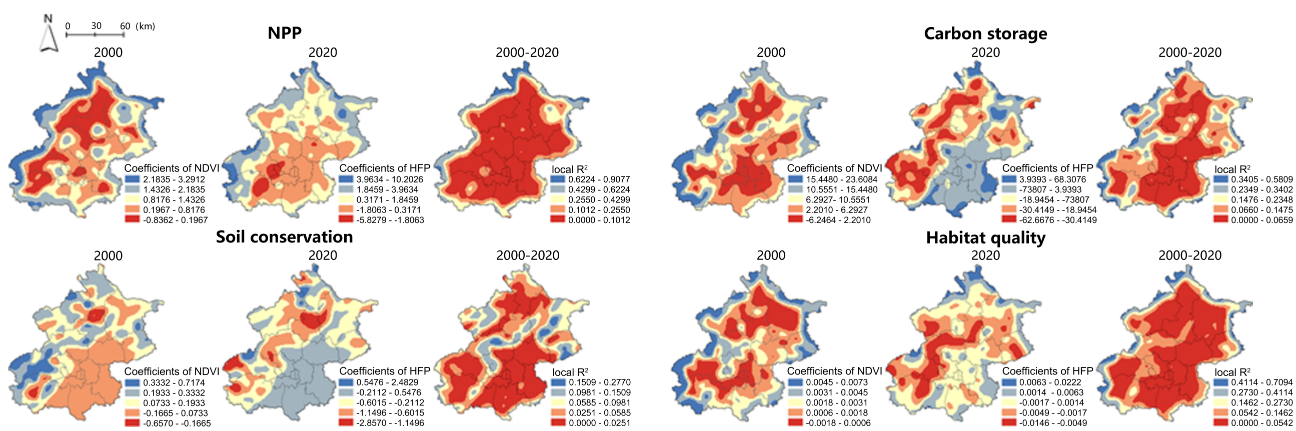

Figure 8. Spatial distribution of coefficients and local R^2 values for the relationships between NDVI, HFP, and ecosystem services in Beijing (2000–2020).

frequently compromised GBS, degrading ecological integrity. Subsequent rapid urbanization, particularly following the 2008 Olympics, intensified these effects, with substantial expansion of technology parks and real estate ventures in suburban districts. As a result, GBS suffered marked reductions, underscoring the negative correlation between urbanization and ecological space during this period.

From 2011 to 2020, Beijing shifted its urban development strategies to prioritize ecological sustainability, resulting in positive impacts on GBS. This period marked a recalibration of urbanization efforts, aligned with China's broader goal of fostering an ecological civilization (NDRC, 2014; Zhu et al., 2020). Policies were implemented to renovate parks, restore waterways, and significantly expand urban tree cover. The Green Beijing Action Plan

(2010–2012) epitomized this shift, promoting "*Humanistic Beijing, Science and Technology Beijing, and Green Beijing*" as core development philosophies. Key initiatives included the Plain Forestation Project launched in 2012, which aimed to plant approximately 1 million mu (around 666.7 km^2) of trees over 5 years. This project resulted in green space coverage rising to 62%, forest cover reaching 44%, and forest stock volume expanding to 25.2 million m^3. By 2021, Beijing's overall greenery coverage reached 48.5%, and per capita public green space reached 16.6 m^2, meeting United Nations standards. These efforts underscore the city's commitment to integrating and enhancing GBS within the context of ongoing urbanization.

Despite these gains, Beijing still encounters obstacles in safeguarding and expanding its GBS. Issues such as the continued loss of farmland, reduced landscape connectivity, and increasing spatial heterogeneity underscore ongoing urban pressures. Addressing these challenges will require long-term, adaptive strategies, including comprehensive urban ecological restoration and policies that reconcile urban growth with ecological integrity.

5.3. Developing rational GBS planning to safeguard the balance between the supply and demand of ESs

The intricate network of landscape processes – spanning planning, construction, and land use – significantly shapes the availability, demand, and effectiveness of GBS in delivering essential ESs (Li & Fan, 2022; Wang et al., 2021). Achieving balance between the supply and demand for ESs requires a targeted optimization of GBS composition and structure (Chen et al., 2023). Beijing has implemented large-scale greening projects that have notably improved ecological health, environmental quality, and overall livability. However, rapid population growth—from 9.043 million in 2000 to 21.893 million in 2020, as reported in the Beijing Statistical Yearbook 2000-2021 (2022)—has increased pressure on GBS and the ESs they support. To ensure a sustainable balance between ESs supply and demand, we propose the following recommendations:

5.3.1. Strategic integration with urban development priorities

Our analysis reveals that socioeconomic dynamics and green infrastructure metrics profoundly shape GBS. We advocate integrating sustainable spatial planning with adaptive urban growth to synchronize ecological goals with urbanization patterns. Effective ecological conservation and restoration depend on comprehensive socioeconomic incentives and enabling policy frameworks (Howell, 2022). This approach ensures that economic development supports—rather than undermines—urban livability and ecosystem integrity. Importantly, mainstreaming nature-positive development strategies—including low-impact infrastructure and biodiversity-informed land use—will reduce anthropogenic pressures and foster mutually beneficial human–nature relationships.

5.3.2. Vegetation quality as a critical driver of ES

High-quality vegetation is indispensable for sustaining and enhancing ESs (Qiu et al., 2023). Our analysis revealed that NDVI exhibited significant correlations with key ecosystem functions: including NPP ($r = 0.47, p < 0.05$), carbon sequestration ($r = 0.42, p < 0.05$), soil conservation ($r = 0.21, p < 0.05$), and habitat quality ($r = 0.37, p < 0.05$). These results underscore NDVI's effectiveness in indicating ecosystem vitality, resilience to degradation, and biodiversity maintenance, all of which are fundamental to ecosystem service provision. Given the complexity of ecological dynamics, enhancing vegetation quality across Beijing's GBS will require an integrated approach that combines ecological restoration with adaptive management, moving beyond traditional biomass-focused methods. Potential strategies include adopting sustainable agroecological practices, reintroducing native species, and utilizing precision resource management approaches such as data-driven irrigation and nutrient optimization. Furthermore, deploying real-time, multiscale monitoring systems will enable early detection of emerging stressors, such as invasive species or pathogens, thereby supporting timely interventions to mitigate cascading ecological impacts.

5.3.3. Spatial optimization of GBS

Statistically significant correlations ($p < 0.05$) between landscape metrics and ESs identify strategic opportunities for targeted interventions to address ecological trade-offs in urban planning. First, prioritizing large, structurally connected habitat cores (high LPI and COHESION) enhances carbon sequestration (LPI: $r = 0.39$; COHESION: $r = 0.27$) and habitat integrity (PLADJ: $r = 0.24$), while mitigating soil degradation caused by fragmentation (DIVISION: $r = -0.19$). Second, managing edges by implementing vegetated transition buffers at ecotones reduces soil erosion vulnerability (TE: $r = -0.21$) without compromising land use efficiency. Third, aggregating functionally complementary patches (e.g., wetlands with riparian corridors) strengthens cross-service synergies, as evidenced by habitat quality's positive correlation with PLADJ ($r = 0.24$). Landscape complexity requires context-specific calibration: simplified configurations (low LSI) stabilize erosion-prone areas, whereas moderate edge heterogeneity (LSI: $r = 0.17$ for habitat quality) enhances biodiversity. Adaptive zoning policies guided by metric thresholds (e.g., critical NP and DIVISION values) enable dynamic optimization of GBS configurations under urban expansion. This spatially informed framework moves from rigid area-based targets toward functional landscape design, advancing carbon neutrality, biodiversity conservation, and soil resilience in an integrated manner.

5.4. Limitations

This study has three methodological limitations that warrant cautious interpretation: (1) Policy implementation is assessed using built-environment indictors, rather than through a comprehensive analysis of policy texts. While this approach captures spatial implementation patterns, it may overlook the semantic nuances of policy discourse. Future research could integrate natural language processing-based policy mining with geospatial metrics to distinguish rhetorical intent from actual outcomes. (2) The ESs scope excludes urban agriculture and cultural services, both important for human well-being. Future studies should consider tiered ESs assessment frameworks and participatory cultural mapping to expand ESs coverage while maintaining methodological rigor. (3) Potential redundancy exists among the eight selected landscape metrics, which may reduce analytical precision. Future work should refine metric selection to enhance the specificity and accuracy of the analysis.

6. Conclusions

In the context of rapid urbanization, the influence of GBS on ESs in China merits careful consideration from both landscape management and scientific perspectives, with potential implications at national and global scales. As the nation's capital, Beijing offers a valuable case study for exploring these dynamics. The

https://doi.org/10.1017/sus.2025.10009

results suggest that socioeconomic variables and green infrastructure indicators are key factors influencing the spatial and temporal variability of GBS. Using a multimethod approach, this study provides quantitative evidence that changes in GBS patterns can affect ESs, particularly highlighting possible differences in the spatial roles of NDVI and HFP. Additionally, the research indicates potential risks related to GBS fragmentation that could impact the provision of ESs, highlighting the value of integrated spatial planning of GBS. While the focus is on Beijing, the methodologies and findings may offer useful references for other rapidly urbanizing regions, and contribute to the ongoing discourse on sustainable GBS development.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/sus.2025.10009.

Acknowledgements. None.

Author contributions. C.C. conceived the study, analyzed the data, and drafted the manuscript. Y. H. collected and analyzed the data. L. F., M. Z., and P. W. provided critical revisions and feedback.

Funding statement. This study was supported by the National Natural Science Foundation of China (Grant No. 71734006).

Competing interests. The authors declare no competing interests.

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