

Article

Divergent Direct and Indirect Vegetation Responses Along Urbanization Trajectories in the Beijing–Tianjin–Hebei Region

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Abstract

Urban expansion exerts substantial pressure on regional ecosystems; however, how these effects propagate through direct and indirect pathways at the urban agglomeration scale remains insufficiently understood. Using nighttime light (NTL) and statistical yearbook data, we extracted the built-up areas across the Beijing–Tianjin–Hebei (BTH) region using a threshold-based approach to characterize expansion dynamics from 1992 to 2022. Furthermore, we applied the PKU GIMMS NDVI dataset within a conceptual framework to quantify the direct and indirect effects of built-up area expansion on vegetation. Expansion patterns varied markedly among cities: Beijing demonstrated concentric outward growth, Tianjin exhibited dual-core development, and cities in eastern and southern Hebei followed a leapfrog, dispersed pattern. Expansion rates and intensities also diverged considerably: Beijing and Tianjin sustained prolonged, high-intensity growth, whereas cities in northern and western Hebei expanded more gradually. The centroid of built-up areas remained relatively stable in Beijing and Tianjin but shifted in other cities, where expansion concentrated along one or two primary axes. Direct negative effects, driven by impervious surface expansion, intensified with increasing urbanization pressure, reaching approximately −54% in rapidly expanding urban agglomerations by 2007 and peaking at −67.43% at the city scale in Beijing by 2022. In contrast, indirect effects exhibited pronounced spatiotemporal heterogeneity: they fluctuated in rapidly expanding urban agglomerations but increased markedly in other areas after 2012. The strongest indirect positive effect peaked at the city level (64.85% in Handan in 2022), suggesting gradual vegetation recovery toward the end of the study period. These findings suggest that moderate-growth cities with remaining green space may exhibit relatively stronger ecological compensation potential, but this pattern requires further validation across broader urban agglomerations. This underscores the need for spatially differentiated planning to balance urban growth and ecological sustainability.



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1. Introduction

Urbanization is a defining feature of socioeconomic development and a primary driver of global land-use change. Since the Reform and Opening-up policy, China has undergone rapid urbanization: the urbanization rate rose from 17.92% in 1978 to 65.22% in 2022, while the national built-up area increased from 7438 km² in 1981 to 63,676 km² in 2022 [1]. Although rapid urbanization has driven economic growth and urban development [2,3], it has also caused severe ecological degradation and imposed substantial environmental pressure [4–6]. Consequently, understanding the spatiotemporal dynamics of urban expansion and its ecological consequences has become a research priority in sustainability science [7].

Urbanization is a persistent and pervasive process of land-use change that profoundly reshapes land surface properties, ecosystem functions, and ecological processes [8–10]. Urban expansion dynamics have been extensively examined at national and regional scales, particularly in rapidly urbanizing countries such as China, India, and Indonesia [11–13]. Prior to the adoption of the Reform and Opening-up policy, urbanization in the Beijing–Tianjin–Hebei (BTH) region was constrained by limited socioeconomic development. Since then, population influx and industrialization have driven sustained urban land expansion [14]. As one of China's most important urban agglomerations, the BTH region has faced mounting pressure on land resources and ecosystems from intensive urban development [15,16]. Built-up area expansion not only directly replaces vegetated land but also modifies landscape patterns and alters human activity intensity, thereby affecting regional ecological processes in the long term. Importantly, these ecological impacts cannot be explained solely by the extent of urban land. They are also governed by how urban areas expand, including the rate, spatial configuration, and directionality of expansion. As urbanization is expected to remain a dominant driver of future environmental change [17], systematically characterizing the spatiotemporal dynamics of built-up area expansion has become essential. Such analyses provide the foundation for understanding the mechanisms underlying ecological change and interpreting complex vegetation responses to urban expansion.

Early studies based on field experiments [18], process-based modeling [19], and remote sensing analyses [20] have consistently demonstrated that urban expansion can directly reduce vegetation cover and productivity. These negative effects are primarily associated with the replacement of vegetated surfaces by impervious surfaces [21]. More recent evidence suggests that the ecological consequences of urban expansion are more complex than previously thought. Urbanization-induced changes in microclimate and human management, including greening programs, irrigation, and fertilization, may enhance vegetation growth in some areas [22,23]. Consequently, the effects of urban expansion on vegetation should be viewed as the combined outcome of direct and indirect processes. Direct effects mainly represent vegetation loss caused by land conversion during urban expansion, whereas indirect effects result from changes in climate conditions, ecological processes, and management practices that accompany urbanization [21,24]. To distinguish these contrasting influences, Zhao et al. (2016) [25] proposed a dual-impact framework that has since been widely adopted to quantify direct and indirect vegetation responses across urban–rural gradients and regional scales.

From a landscape ecological perspective, urban expansion trajectories represent changes in landscape patterns, while direct and indirect vegetation responses reflect underlying ecological processes. Integrating the dual-impact framework with a pattern–process coupling perspective provides a theoretical basis for linking urban spatial dynamics with ecosystem responses. Nevertheless, most previous studies have focused on individual cities [23,26,27], whereas investigations at the urban agglomeration scale remain limited.

Crucially, existing regional assessments often treat urban growth as a uniform process, leaving the marginal influence of diverse spatio-temporal expansion trajectories on the balance between direct and indirect vegetation responses poorly understood. The key marginal contribution of this study lies in integrating multidimensional urban expansion trajectories with a dual-impact framework, thereby revealing how divergent urbanization pathways shape distinct vegetation response patterns and ecological compensation potential across an urban agglomeration.

To bridge this knowledge gap, we propose three testable hypotheses based on regional characteristics and landscape ecological theories: (1) direct negative effects will be strongest in rapidly expanding core cities due to the intensive physical displacement of natural cover; (2) indirect positive effects will progressively increase over time, driven by the lag and maturation of persistent urban greening and resource management; and (3) socioeconomic factors will dominate over natural constraints in driving built-up area expansion.

Therefore, this study focuses on the Beijing–Tianjin–Hebei (BTH) urban agglomeration from 1992 to 2022, a period characterized by rapid urbanization following China's economic reforms. Using nighttime light data (DMSP-OLS and NPP-VIIRS), NDVI products, and socioeconomic statistics, we examine the relationships between urban expansion dynamics and vegetation responses at both regional and city levels. Specifically, we pursued three objectives: (1) to extract built-up areas using a statistical thresholding method; (2) to characterize the spatiotemporal dynamics of built-up area expansion across four dimensions—expansion speed, intensity, compactness, and direction; and (3) to quantify the direct and indirect effects of urban expansion on vegetation growth at both the agglomeration and individual city levels. By integrating urban expansion dynamics with a dual-impact framework, this study offers insights into how different urbanization trajectories shape vegetation responses and advances understanding of ecological changes in rapidly urbanizing regions.

2. Materials and Methods

2.1. Study Area

The BTH region (113°04'–119°53' E, 36°01'–42°37' N) is located in the northern part of the North China Plain (Figure 1). It is bordered by the Bohai Sea to the east, Shanxi Province to the west, Henan and Shandong Provinces to the south, and Inner Mongolia and Liaoning Provinces to the north. With Beijing and Tianjin at its core, the region also includes 11 prefecture-level cities in Hebei Province. The region covers approximately 216,000 km², accounting for 2.3% of China's total land area, and represents one of the most important urban agglomerations in northern China. Land use in 2020 is dominated by cropland (43.73%), forest land (24.93%), and grassland (14.93%) [20]. Cropland predominates in the southeastern plains and around Zhangjiakou. Forests dominate the Taihang and Yanshan Mountains, while grasslands occur primarily in the western Taihang Mountains. Elevation decreases from northwest to southeast, yielding mountainous terrain in the northwest and extensive plains in the southeast. The region experiences a temperate continental monsoon climate, characterized by hot, humid summers and cold, dry winters.

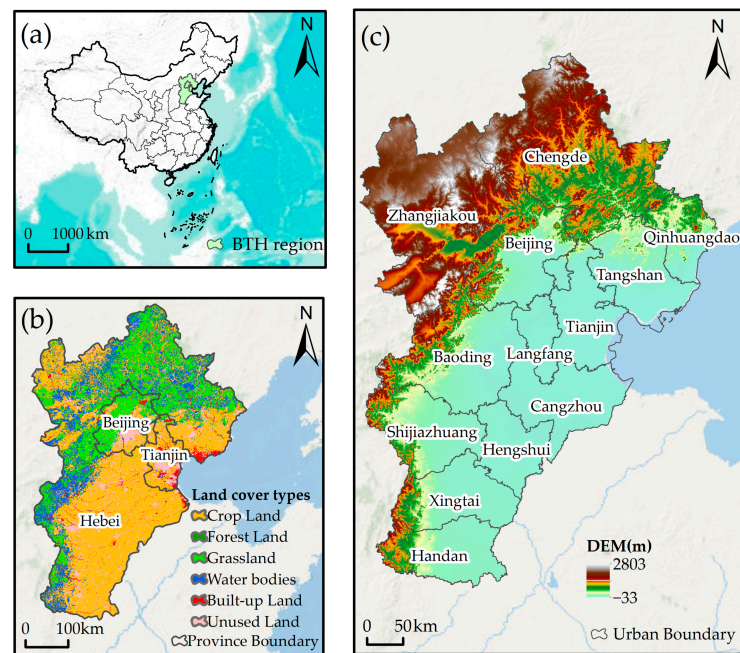


Figure 1. Overview of the BTH region: (a) geographical location of the study area; (b) land cover distribution in 2020 derived from the China Land Use/Cover Dataset (CNLUCC); and (c) elevation distribution derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM).

2.2. Data Sources

Data sources are detailed in Table 1. To balance temporal resolution and long-term trend analysis, all datasets were harmonized at five-year intervals (1992, 1997, 2002, 2007, 2012, 2017, and 2022), thereby reducing short-term fluctuations and capturing the major stages of urban expansion. Nighttime light (NTL) data for built-up area extraction were sourced from the SVNL dataset [28], which provides annual global NTL observations. The dataset was generated by correcting interannual inconsistencies in DMSP-OLS data and reconstructing VIIRS-like NTL data using a U-Net deep learning super-resolution model with Landsat NDVI as auxiliary information. The reconstructed NTL data were then integrated with observed NPP-VIIRS data to produce spatially continuous and temporally consistent long-term records. Although SVNL substantially improves the consistency of long-term NTL observations, uncertainties may still remain in areas with complex lighting conditions, particularly in dense urban cores and urban fringe areas [28].

Vegetation data were derived from the PKU GIMMS NDVI dataset [29], which provides NDVI observations at a 15-day temporal resolution. The dataset was generated by reconstructing the GIMMS NDVI3g product using biome-specific back-propagation neural network (BPNN) models trained with extensive Landsat NDVI samples for 1982–2015, and was subsequently extended to 2022 through pixel-wise random forest consolidation with MODIS NDVI. The dataset was validated using extensive Landsat NDVI samples and achieved a higher accuracy ($R^2 = 0.97$) than the original GIMMS NDVI3g dataset ($R^2 = 0.94$). Compared with many existing long-term NDVI products, it efficiently removes uncertainties associated with NOAA orbital drift and AVHRR sensor degradation. Owing to its high reliability and long-term spatiotemporal consistency, this dataset is well suited for vegetation change analysis [30,31]. Annual NDVI was obtained by averaging all 15-day observations within each year.

Table 1. Summary of datasets used in this study.

Dataset Name	Variables	Spatial Resolution	Time Period	Source
SVNL	Nighttime light	15 arc-seconds	1992–2022 (5-yr intervals)	https://doi.org/10.6084/m9.figshare.22262545.v8 (accessed on 10 September 2025)
PKU GIMMS NDVI	NDVI	1/12°	1992–2022 (5-yr intervals)	https://zenodo.org/records/8253971 (accessed on 10 September 2025)
SRTM DEM	Elevation (X7)	30 m	2000	https://earthexplorer.usgs.gov (accessed on 10 September 2025)
Global Surface Water	Water bodies	30 m	1992–2022 (5-yr intervals)	https://jeodpp.jrc.ec.europa.eu/ (accessed on 10 September 2025)
China Statistical Yearbook	Built-up area, GDP per capita (X1), Population density (X2), and Local general public budget expenditure (X3)	Administrative unit	1992–2022 (5-yr intervals)	https://www.stats.gov.cn (accessed on 10 September 2025)
TerraClimate	Precipitation (X4), Temperature (X5), Solar radiation (X6)	1/24°	1992–2022 (5-yr intervals)	https://www.climatologylab.org/terraclimate.html (accessed on 10 September 2025)
Administrative boundaries	Administrative divisions	Province/City	2021	https://www.gscloud.cn (accessed on 10 September 2025)

Drivers of built-up area expansion comprise natural environmental and socioeconomic factors. Natural environmental factors represent topographic and climatic conditions, whereas socioeconomic factors reflect economic development, population pressure, and government investment. Elevation data were obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model, which was treated as a static topographic factor throughout the study period because elevation is relatively stable over time. Temperature, precipitation, and solar radiation data were derived from the TerraClimate dataset. Socioeconomic factors include GDP per capita, population density, and local fiscal expenditure, sourced from relevant statistical yearbooks. In addition, auxiliary datasets—including administrative boundaries, statistical records of built-up areas, and surface water distribution data—were used to support spatial analysis and to mask out non-built-up land during processing.

2.3. Methods

2.3.1. Built-Up Area Extraction

Built-up areas were extracted from NTL data using a statistical thresholding method calibrated against official yearbook records. In NTL imagery, urbanized areas are typically characterized by continuous high-brightness pixels, whereas rural areas generally exhibit low or near-zero values. The extraction procedure consisted of three steps. First, all NTL pixels were ranked in descending order of brightness. Second, each NTL brightness value was successively evaluated as a threshold, and the cumulative area of pixels with brightness values equal to or greater than the threshold was calculated and compared with the corresponding officially reported built-up area. Finally, the threshold that minimized the area difference was selected as the optimal threshold, and the corresponding pixels were classified as built-up areas. This method offers an efficient, objective way to determine annual extraction thresholds [32]. This procedure was applied to extract built-up areas in the BTH region for 1992, 1997, 2002, 2007, 2012, 2017, and 2022. Year-specific thresholds were determined independently using the corresponding annual statistical records,

while the same statistical thresholding procedure was consistently applied throughout the study period. Combined with the temporally consistent SVNLC dataset, this ensured the comparability of built-up area extraction across different years.

To evaluate the reliability of the extracted built-up areas, a two-step accuracy assessment was performed (Table 2). First, comparison with official statistical records showed that relative errors between the extracted built-up areas and yearbook data were consistently below 5%. Although the absolute error was 166.82 km² in 2022, this remained within an acceptable range for regional-scale urban expansion studies. Second, spatial accuracy was assessed using 1000 stratified random sample points against the China Land Cover Dataset (CLCD). The sample points were stratified into two classes (built-up and non-built-up), with 500 randomly selected points allocated to each class to avoid class imbalance in the accuracy assessment. The CLCD provides annual land-cover maps at 30 m spatial resolution over a continuous 30-year period. Relative to other widely used land-cover products—including GLC_FCS30, Global30, and FROM-GLC10—CLCD offers superior temporal continuity and has been extensively applied in Chinese land-cover studies [33]. The overall accuracy (OA) ranged from 75.10% to 81.99%, while the Kappa coefficient ranged from 0.51 to 0.66. Potential uncertainties may arise from the blooming effect of NTL data, mixed pixels along urban boundaries, and discrepancies between remotely sensed built-up areas and official statistical records. These results indicate that the extracted built-up areas demonstrate acceptable spatial consistency at the regional scale and are suitable for subsequent spatiotemporal analyses.

Table 2. Validation of extracted results in the BTH region from 1992 to 2022.

Year	1992	1997	2002	2007	2012	2017	2022
Statistical data (km ²)	1343.50	1521.30	2241.87	2919.45	3374.08	4086.18	4461.19
SVNL data (km ²)	1299.89	1486.95	2160.97	2851.83	3252.48	3974.36	4294.37
Error value (km ²)	43.61	34.35	80.90	67.62	121.60	111.82	166.82
Relative error	3.25%	2.26%	3.61%	2.32%	3.60%	2.74%	3.74%
OA	75.80%	76.60%	81.99%	80.07%	78.37%	77.30%	75.10%
Kappa	0.53	0.57	0.66	0.64	0.60	0.58	0.51

2.3.2. Urban Expansion Dynamics

The spatiotemporal dynamics of built-up area expansion in the BTH region were characterized using a set of complementary indicators, including expansion speed, expansion intensity, compactness, centroid shift, and expansion orientation. Expansion speed describes the average annual rate of built-up area growth during a given period [34], whereas expansion intensity measures the extent of land-use change per unit time [35]. The corresponding equations are as follows:

$$V = (U_{n+i} - U_i) / n \quad (1)$$

$$E_q = \frac{U_{n+i} - U_i}{UA \times n} \times 100\% \quad (2)$$

In Equations (1) and (2), V and E_q denote expansion speed and expansion intensity, respectively; U_i and U_{n+i} represent the built-up areas in year i and year $n + i$, UA is the total land area of the urban agglomeration (administrative area), and n is the time span.

Compactness was used to characterize the spatial configuration of built-up areas and to evaluate the degree of concentration during urban expansion [36]. Higher compactness

values indicate a more regular shape and a more concentrated spatial distribution of built-up land. The compactness index was calculated as follows:

$$BCI = 2\sqrt{\pi U_i} / P_i \quad (3)$$

In Equation (3), BCI is the compactness index, ranging from 0 to 1. Higher values indicate a more concentrated spatial distribution. U_i is the built-up area in the i -th year, and P_i is the perimeter of the built-up area in the i -th year.

Centroid shift reflects the spatiotemporal dynamics of regional development [34]. The coordinates of the built-up area's center of gravity (x, y) are calculated as:

$$\begin{cases} x = \frac{\sum_i w_i \times x_i}{\sum_i w_i} \\ y = \frac{\sum_i w_i \times y_i}{\sum_i w_i} \end{cases} \quad (4)$$

In Equation (4), w_i is the weight of the i -th discrete object, defined as the ratio of its area to the total built-up area, and (x_i, y_i) are its coordinates.

The distance of the center of gravity shift is calculated as:

$$D_{n+1} = \sqrt{(y_{n+1} - y_n)^2 + (x_{n+1} - x_n)^2} \quad (5)$$

In Equation (5), D_{n+1} is the shift distance, (x_n, y_n) and (x_{n+1}, y_{n+1}) are the coordinates of the center of gravity in year n and year $n + 1$.

Sector analysis was employed to quantify the directional characteristics of built-up area expansion. The centroid of the built-up area in 1992 was selected as the reference center to ensure a consistent spatial reference for comparing directional expansion across different periods. Built-up area maps for the 13 cities in 1997, 2002, 2007, 2012, 2017, and 2022 were overlaid to identify expansion patterns over time. Beginning at 22.5° east of north, the study area was divided into eight sectors of equal size (45° each). The area of urban expansion within each sector was then calculated for each study period.

2.3.3. Direct and Indirect Vegetation Effects

The effects of built-up area expansion on vegetation growth were assessed at the 1-km pixel scale. Before analysis, the NDVI was resampled to a 1-km spatial resolution using bilinear interpolation. Following the conceptual framework proposed by Zhao et al. (2016), the effects of urban expansion on vegetation were partitioned into direct and indirect components (Figure 2) [25]. The direct effect represents vegetation change resulting from land-cover conversion associated with increasing impervious surface coverage during urban expansion. Generally, vegetation indices such as NDVI decrease with increasing urbanization intensity. Urbanization intensity (β) was defined as the proportion of impervious surface area within each pixel. If only direct effects are considered, NDVI is expected to decline linearly with increasing β . This relationship defines a theoretical zero-impact line, which represents vegetation conditions in the absence of indirect effects. Based on Equation (6), the theoretical NDVI value (V_{zi}) for each 1-km pixel was calculated as follows:

$$V_{zi} = (1 - \beta)V_v + \beta V_{nv} \quad (6)$$

In Equation (6), V_v represents the mean NDVI of pixels fully covered by vegetation ($\beta = 0$), whereas V_{nv} is the 5th percentile of NDVI values for pixels fully covered by built-up areas ($\beta = 1$) to reduce the influence of extreme values. To construct this homogeneous background area for extracting V_v , background areas were selected according to two criteria: (1) environmental conditions should be comparable to those of the built-up areas, and

(2) anthropogenic disturbance should be minimized. Consequently, the background area could neither be immediately adjacent to nor excessively distant from the built-up area and was required to have similar topographic characteristics. The selection procedure consisted of three steps. First, a 10-km buffer was generated outside the built-up boundary and treated as a transition zone to reduce the influence of land-cover conversion, urban heat island effects, and suburban agricultural activities [37]. Second, an additional buffer extending 5–10 km beyond the transition zone was defined as the candidate background area. Water body pixels were identified from the Global Surface Water dataset using a 75% water occurrence threshold during the study period. These pixels were then excluded together with other built-up areas. Third, the mean elevation of the built-up area was calculated, and candidate areas with elevations within ± 100 m of this value were retained as the final background area. This procedure mitigated topographic and climatic influences on vegetation growth [38].

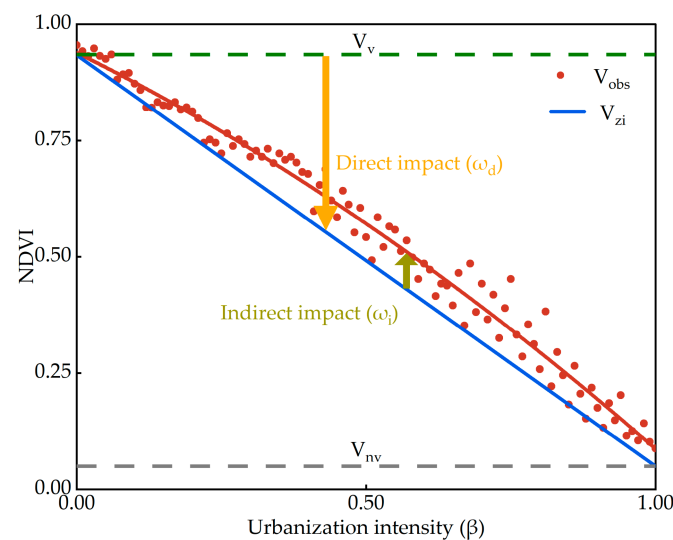


Figure 2. Conceptual framework for quantifying the direct and indirect effects of built-up area expansion on vegetation. Red dots indicate observed NDVI values (V_{obs}), and the red line shows their fitted regression. V_v and V_{nv} denote the NDVI values of rural or potential vegetation and non-vegetated urban surfaces, respectively. The blue line represents the theoretical NDVI along the urbanization gradient in the absence of indirect effects (V_{zi}), referred to as the zero-impact line. Observed NDVI values located above or below this line indicate positive or negative indirect effects of urbanization, respectively.

Based on Equation (7), the relatively direct effect of urbanization on vegetation growth (ω_d) is calculated as follows, and the direct effect is always negative.

$$\omega_d = \frac{V_{zi} - V_v}{V_v} \times 100\% \quad (7)$$

When observed vegetation index values (V_{obs}) are plotted against the urbanization intensity gradient (β), their distribution may deviate from the theoretical zero-impact line, indicating the presence of indirect effects. These effects arise from environmental and management differences between urban and non-urban areas and may either promote or inhibit vegetation growth. Pixels located above the zero-impact line indicate that observed vegetation conditions exceed the theoretical expectation and therefore reflect positive indirect effects. Conversely, pixels below the line indicate negative indirect effects.

Accordingly, the relative indirect effect (ω_i) was quantified as the relative deviation of the observed NDVI from the theoretical value:

$$\omega_i = \frac{V_{obs} - V_{zi}}{V_{zi}} \times 100\% \quad (8)$$

Furthermore, the β distribution was systematically evaluated across all 13 cities to test the applicability of the analytical framework under the 1-km mixed-pixel condition. Results indicate that β consistently spans the full range from 0 to 1, confirming the existence of a complete urbanization gradient in the study area (Figure 3). Although the distribution is right-skewed, high-intensity pixels are consistently observed across all cities, with $\beta \geq 0.75$ accounting for 15.64–36.90%. This confirms that both low- and high-end members are empirically well represented within the observed data space, ensuring that the linear interpolation in Equation (6) is fully supported by observed conditions.

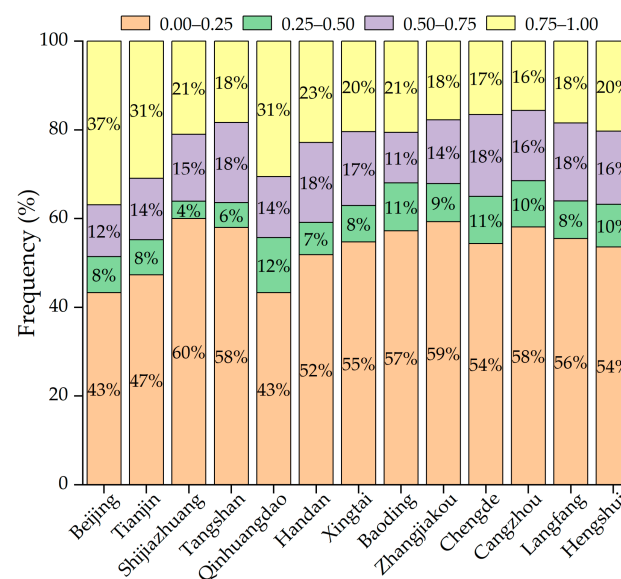


Figure 3. Long-term average composition of urbanization intensity (β) across cities in the BTH region (1999–2022).

2.3.4. GeoDetector Analysis of Expansion Drivers

The GeoDetector model (Detector_2015_Example version) was used to identify the driving forces of built-up area expansion. GeoDetector quantifies the explanatory power of potential driving factors by examining spatial stratified heterogeneity and assesses interactions among factors [34]. In this study, the dependent variable was the city-level built-up area expansion rate from 1992 to 2022. Explanatory variables included socioeconomic factors (GDP per capita, population density, and local fiscal expenditure) and natural environmental factors (annual precipitation, mean temperature, solar radiation, and mean elevation). The analysis was conducted at the city level. Socioeconomic variables were obtained directly from city statistical yearbooks, while natural environmental variables were aggregated from gridded datasets as zonal mean values for each city. Before analysis, all continuous variables were discretized using the natural breaks method. The factor detector is defined as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \quad (9)$$

In Equation (9), L is the number of strata for each factor, N is the total sample size, N_h is the sample size in stratum h , σ^2 is the variance of the dependent variable for all samples,

and σ_h^2 is the variance within stratum h . The q value ranges from 0 to 1. A higher q indicates stronger explanatory power of the factor for the spatial variation in built-up area expansion.

2.3.5. Cluster Analysis

To facilitate the analysis of vegetation responses at the agglomeration scale, the 13 cities were classified according to their built-up area expansion speed during 1992–2022 using the Grouping Analysis tool in ArcGIS 10.6. The number of groups was predefined as three according to the study objective of distinguishing rapidly, moderately, and slowly expanding cities for subsequent comparative analyses. Similarity among observations was measured using Euclidean distance. A K-NEAREST NEIGHBORS spatial constraint was applied to preserve the spatial continuity of neighboring cities, thereby generating geographically coherent groups for subsequent agglomeration-scale comparisons. To evaluate the robustness of the grouping results, additional analyses were performed using the CONTIGUITY EDGES ONLY and CONTIGUITY EDGES CORNERS spatial constraint settings while keeping all other parameters unchanged.

3. Results

3.1. Spatiotemporal Dynamics of Built-Up Area Expansion

3.1.1. Overall Expansion Patterns

From 1992 to 2022, built-up area expansion in the BTH region followed four distinct spatial patterns (Figure 4). The first was concentric outward growth, observed in Beijing and Shijiazhuang, with radial outward extension generating satellite urban areas. The second was dual-core growth, exemplified by Tianjin, where the central urban area and Binhai New Area expanded and coalesced. Baoding and Langfang showed similar dual-core patterns. The third was leapfrog and dispersed growth, occurring in Tangshan, Qinhuangdao, Handan, Xingtai, Cangzhou, and Hengshui, where new development patches emerged on the periphery of the existing urban core. The fourth was restricted growth, characteristic of Zhangjiakou and Chengde, where urban expansion was constrained by topographic limitations and ecological protection policies. Overall, the expansion pattern encompassed concentric growth in Beijing, dual-core growth in Tianjin and adjacent cities, dispersed leapfrog development in eastern and southern Hebei, and constrained expansion in mountainous areas.

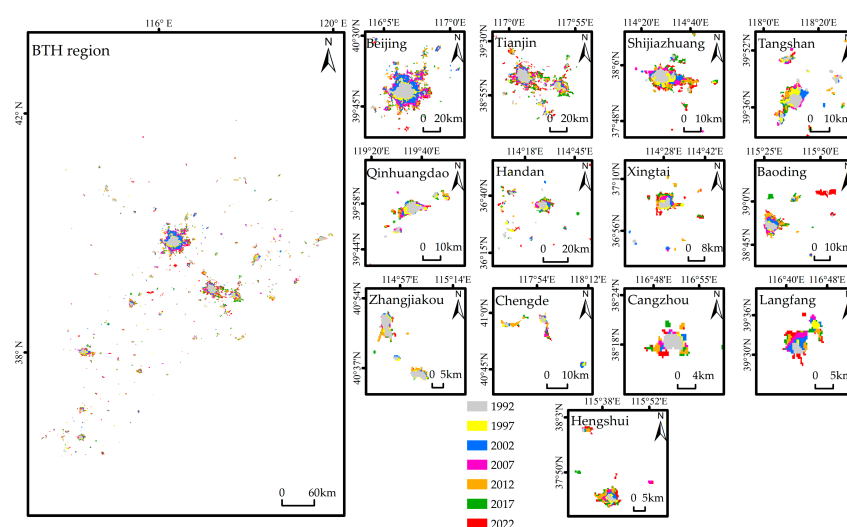


Figure 4. Spatial distribution of built-up areas in the BTH region, 1992–2022.

3.1.2. Expansion Speed, Intensity and Compactness

Cities varied substantially in expansion speed, intensity, and compactness over 1992–2022 (Figure 5). Beijing (35.23 km²/yr) and Tianjin (30.54 km²/yr) maintained the highest expansion rates throughout the study period, far exceeding those of other cities. By contrast, Zhangjiakou (1.10 km²/yr), Chengde (1.58 km²/yr), and Cangzhou (1.80 km²/yr) showed markedly lower rates. Urban expansion varied markedly across stages. Beijing experienced its most rapid expansion during 1997–2002, peaking at 105.66 km²/yr. Relatively high growth continued during 2002–2007; meanwhile, Tianjin began to accelerate. Tianjin peaked at 73.52 km²/yr during 2012–2017, becoming the principal growth center in the later stages. Most Hebei cities accelerated intermittently after 2002, though their overall expansion remained well below that of Beijing and Tianjin.

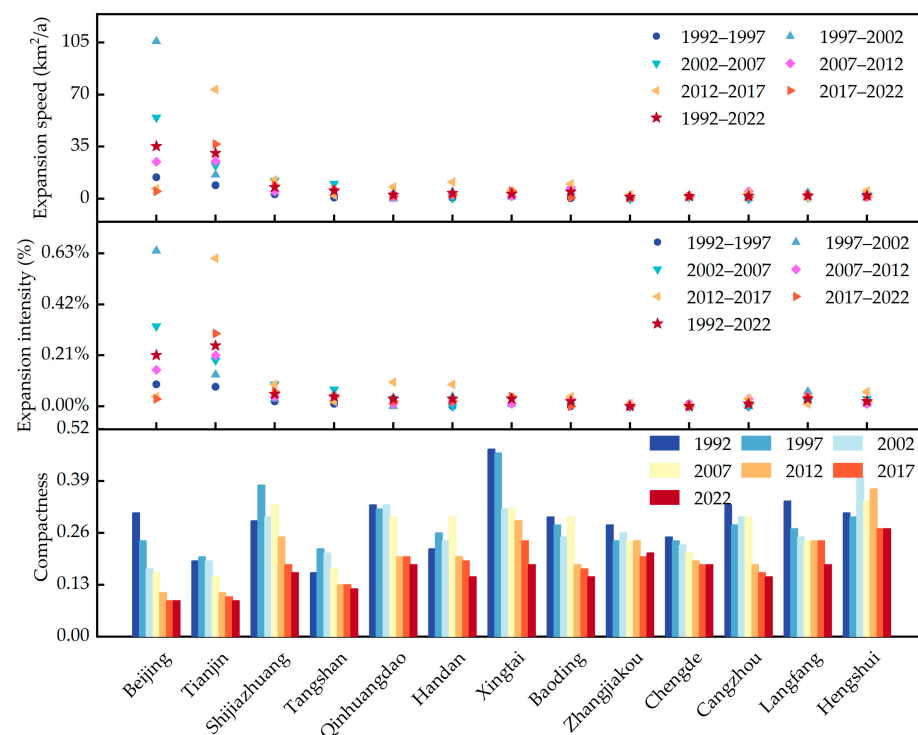


Figure 5. Expansion speed, intensity, and compactness of built-up areas in the BTH region, 1992–2022.

Expansion intensity largely mirrored expansion speed. Tianjin showed a marginally higher mean intensity (0.25%) than Beijing (0.21%). Beijing registered the highest intensity during 1997–2002 (0.64%), whereas the peak later shifted to Tianjin during 2012–2017 (0.61%). Northern cities with important ecological functions, such as Zhangjiakou and Chengde, showed intensities consistently below 0.01%.

Compactness declined across most cities during the study period. In 1992, compactness varied markedly among cities; Xingtai, Hengshui, and Shijiazhuang showed relatively high values, while Beijing and Tangshan showed lower values. By 2022, compactness values converged within a narrower range (0.09–0.18). Beijing and Tianjin showed the most pronounced declines. In contrast, Zhangjiakou and Chengde showed only limited changes. Overall, expansion speed and intensity showed similar patterns, with Beijing and Tianjin exhibiting the highest expansion rates and intensities. However, rapid expansion did not always lead to greater compactness declines, as slower-expanding cities such as Xingtai also experienced substantial compactness reductions. This indicates that urban morphology changes were influenced by both expansion magnitude and spatial development patterns.

3.1.3. Centroid Shift in Built-Up Areas

From 1992 to 2022, centroid shifts in built-up areas in the BTH region followed a distinct temporal pattern, with rapid adjustment early on, pronounced divergence during the middle period, and gradual stabilization toward the end (Figure 6). Overall, the two municipalities displayed relatively stable trajectories, whereas cities in Hebei Province experienced greater fluctuations. The largest shifts occurred in coastal cities and those adjacent to Beijing.

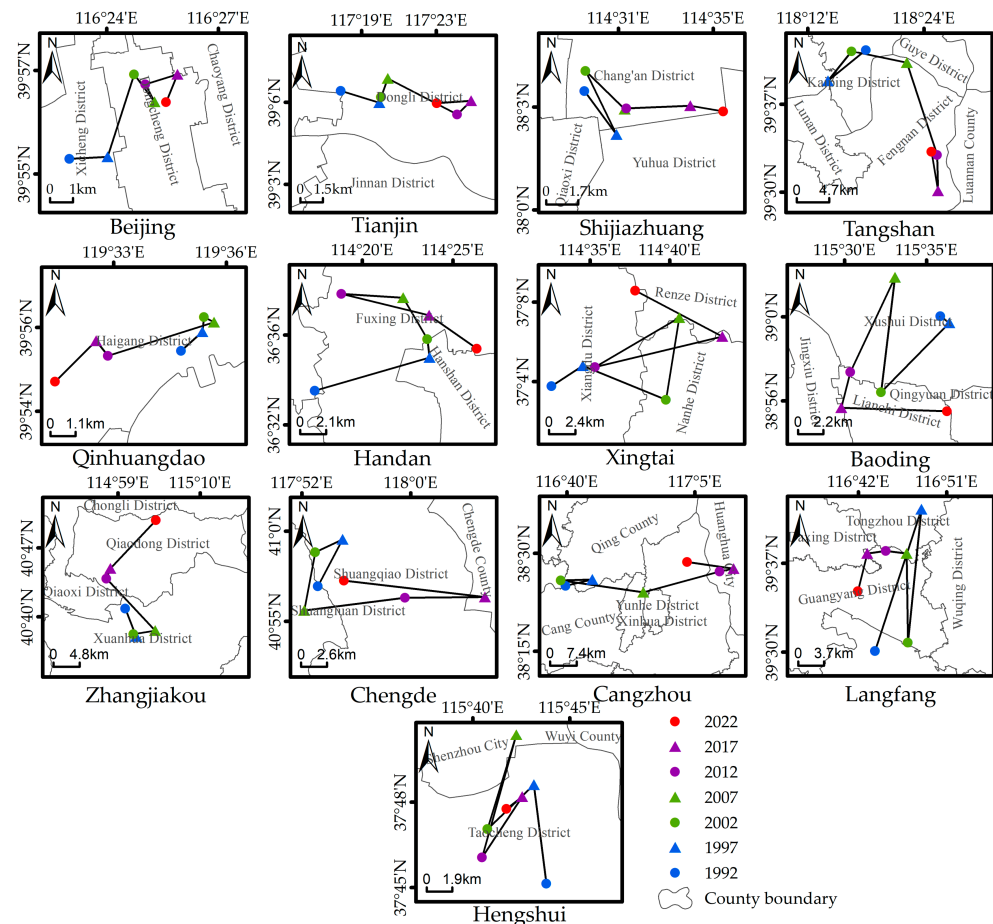


Figure 6. Center of gravity shift in urban built-up areas in the BTH region, 1992–2022.

During 1992–2002, centroids underwent rapid movement. Most cities showed substantial displacement, though expansion directions remained variable. Beijing showed a distinct eastward shift, totaling 3.92 km during 1997–2002. Over the same period, Langfang shifted by more than 19 km, reflecting its early role in accommodating functions transferred from the regional core. Coastal cities also experienced substantial adjustments, producing more stable expansion directions in subsequent years.

The period from 2002 to 2012 saw the most active phase of centroid shifts, along with increasingly pronounced regional disparities. Tianjin shifted 5.35 km during 2007–2012, and maintained a southeastward trajectory largely associated with the development of the Binhai New Area. Coastal and resource-oriented cities in Hebei exhibited particularly marked spatial shifts. Tangshan displaced 14.51 km during 2007–2012, whereas Cangzhou experienced even larger shifts of 23.92 km during 2002–2007 and 22.70 km during 2007–2012.

From 2012 to 2022, the magnitude of centroid shifts generally declined across the region. Shift distances in Beijing and Tianjin decreased markedly, and most single-period shifts remained below 2.4 km. Most cities across Hebei Province showed a comparable de-

cline. Qinhuangdao and Shijiazhuang maintained relatively stable trajectories, suggesting a gradual consolidation of the regional spatial structure.

3.1.4. Directional Patterns of Urban Expansion

Between 1992 and 2022, directional expansion of built-up areas in the BTH region shifted from a relatively dispersed pattern to one concentrated along several dominant directions (Figure 7). In the later period, overall expansion intensity weakened, and dominant expansion directions narrowed.

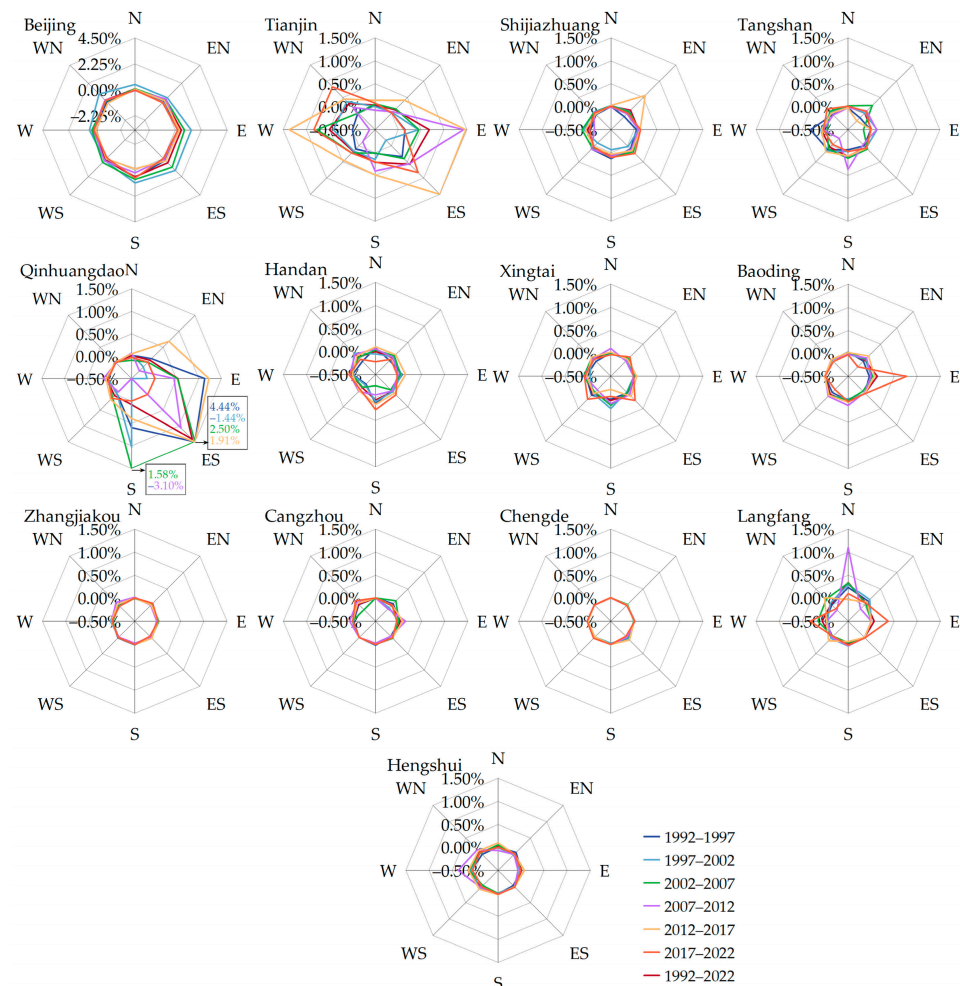


Figure 7. Directional expansion intensity in the eight sectors of the BTH region from 1992 to 2022. The radial axis was standardized to a common range of -0.50% to $+1.50\%$ for all cities to facilitate cross-city comparison. Values exceeding this range are indicated by arrows, with their actual values labeled.

During 1992–2002, urban expansion intensity remained relatively low, with limited directional differences. Beijing was the first city to exhibit clear directional preferences, as expansion concentrated toward the east, southeast, and south. During 1997–2002, expansion intensities reached 1.37% eastward and 1.47% southeastward. By contrast, Tianjin and most cities in Hebei experienced relatively limited expansion and showed no obvious directional concentration.

From 2002 to 2012, expansion intensity increased substantially, and directional differentiation became more pronounced. Beijing continued to expand primarily toward the east, southeast, and south, despite a slight decrease in overall intensity. Expansion in Tianjin became increasingly concentrated in the east and southeast, with eastward intensity exceeding 1.40% during 2007–2012. Among coastal cities, Qinhuangdao exhibited a brief

southeastward expansion peak (2.50% during 2002–2007) before later contracting toward the south.

During 2012–2022, expansion intensity declined substantially across the region. In Beijing, several directions shifted from positive growth to weak expansion or even contraction. Tianjin maintained positive growth only toward the east and southeast, albeit at considerably lower rates. Most Hebei cities showed limited expansion activity, while Zhangjiakou and Chengde exhibited near-zero growth, with only localized growth in Baoding and Langfang.

3.2. Drivers of Built-Up Area Expansion

To identify the key drivers of built-up area expansion across cities in the BTH region from 1992 to 2022, we employed the GeoDetector model. Seven potential factors—three socioeconomic (GDP per capita, X1; population density, X2; local general public budget expenditure, X3) and four natural (precipitation, X4; temperature, X5; solar radiation, X6; elevation, X7)—were examined.

The factor detector results (Figure 8a) revealed that local general public budget expenditure (X3) had the highest explanatory power ($q = 0.97$, $p < 0.05$), far exceeding all other factors. However, this high q value should be interpreted cautiously due to the limited sample size and potential correlations among socioeconomic factors. GDP per capita (X1) also showed a significant but lower explanatory power ($q = 0.64$, $p < 0.05$). In contrast, none of the natural factors (X4–X7) reached statistical significance ($p > 0.05$), with q values below 0.15, indicating that natural conditions acted only as background constraints rather than direct drivers of expansion intensity at the city scale.

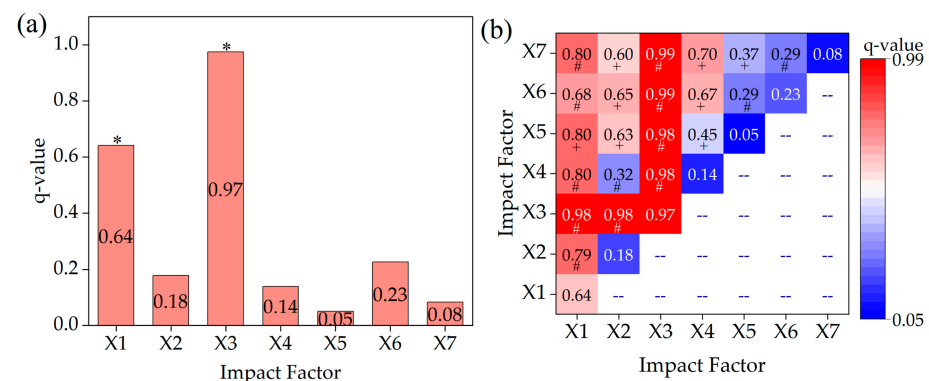


Figure 8. Driving factors of built-up area expansion rate in the BTH region from 1992 to 2022. X1: GDP per capita; X2: population density; X3: local general public budget expenditure; X4: precipitation; X5: temperature; X6: solar radiation; X7: elevation. (a) Explanatory power of individual factors on the expansion rate. * indicates $p < 0.05$. (b) Interaction detection between driving factors of the expansion rate. # denotes bivariate enhancement, and + denotes non-linear enhancement.

The interaction detector (Figure 8b) further revealed pronounced synergistic amplification effects. All factor pairs exhibited either bivariate or nonlinear enhancement. Notably, the interaction between local general public budget expenditure (X3) and any natural factor yielded a joint q value exceeding 0.98, suggesting that strong fiscal and policy drivers can substantially override the constraints imposed by natural conditions.

3.3. Effects of Built-Up Area Expansion on Vegetation

3.3.1. Vegetation Effects at the Agglomeration Scale

Based on built-up area expansion speed during 1992–2022, the 13 cities were classified into three groups using cluster analysis (Table 3): rapidly expanding agglomerations (Beijing and Tianjin), moderately expanding agglomerations (Shijiazhuang, Tangshan, and

Baoding), and slowly expanding agglomerations (the remaining eight cities). The grouping results remained identical under three different spatial constraint settings (K-NEAREST NEIGHBORS, CONTIGUITY EDGES ONLY, and CONTIGUITY EDGES CORNERS), confirming the robustness of the classification. Based on this classification, vegetation effects at the agglomeration scale exhibited clear stage-dependent patterns (Figure 9).

Table 3. Cluster assignment of the 13 cities based on built-up area expansion speed during 1992–2022.

Agglomeration Group	Number of Cities	Cities
Rapidly expanding agglomerations	2	Beijing, Tianjin
Moderately expanding agglomerations	3	Shijiazhuang, Tangshan, Baoding
Slowly expanding agglomerations	8	Qinhuangdao, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Xingtai, Handan

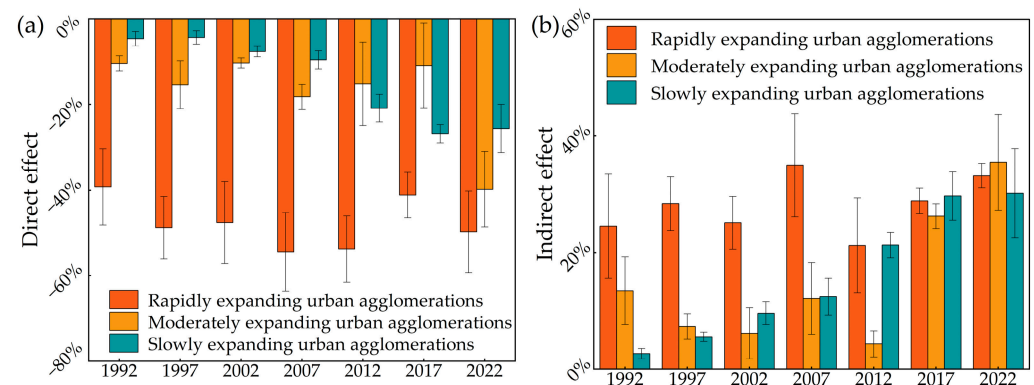


Figure 9. Mean and standard deviation of the direct (a) and indirect (b) effects of built-up area expansion on vegetation at the urban agglomeration scale during different study periods.

During 1992–2002, rapidly expanding agglomerations showed strengthening direct negative effects (−39.27% to −47.63%) and stable indirect effects (24–29%). Moderately and slowly expanding agglomerations showed weaker direct effects and limited indirect compensation (2.64% in slowly expanding agglomerations in 1992). This pattern reflects an early development stage dominated by concentrated urban land conversion in core metropolitan areas, while most peripheral cities still retained substantial vegetated land.

During 2002–2012, both direct (−54.47%) and indirect (34.96%) effects peaked in 2007 in rapidly expanding agglomerations. Slowly expanding agglomerations recorded >10% increases in both effects, whereas moderately expanding agglomerations showed smaller fluctuations. This indicates a period of accelerated regional urban expansion, during which land conversion intensified and ecological enhancement measures began to increase but remained spatially uneven.

During 2012–2022, direct effects in rapidly expanding agglomerations weakened around 2017 before recovering (Figure 9a). In slowly expanding agglomerations, direct negative effects deepened (−20.86% to −25.62%). This reflects a shift toward land saturation in core cities and continued expansion pressure in peripheral cities. Indirect effects increased markedly after 2012 across most agglomerations, with moderately expanding agglomerations recording the highest indirect effects by 2022 (35.46%), exceeding rapidly expanding agglomerations for the first time (Figure 9b). This suggests that ecological restoration and greening measures became more effective in cities where sufficient residual vegetated land remained available. In addition, the standard deviations shown in Figure 9 indicate that vegetation responses differed in their within-group variability among the three agglomeration groups, with rapidly expanding agglomerations exhibiting greater heterogeneity, whereas slowly expanding agglomerations showed more consistent responses.

3.3.2. Vegetation Effects at the City Scale

At the individual city scale, direct and indirect effects showed significant spatial imbalances across periods (Figure 10). From 1992 to 2002, direct effects were strongly polarized (Figure 10a). As early expansion centers, Beijing, Tianjin, and Qinhuangdao all recorded direct effects exceeding -30% , with Tianjin reaching -55.27% in 2002. For most other cities, direct negative effects remained around -10% . This pattern reflects the concentration of early urban expansion in core cities, while other cities experienced relatively limited land conversion. Indirect effects were mostly below 10% , except in Beijing (32.32–41.69%) and Qinhuangdao (35.48–48.94%) (Figure 10b).

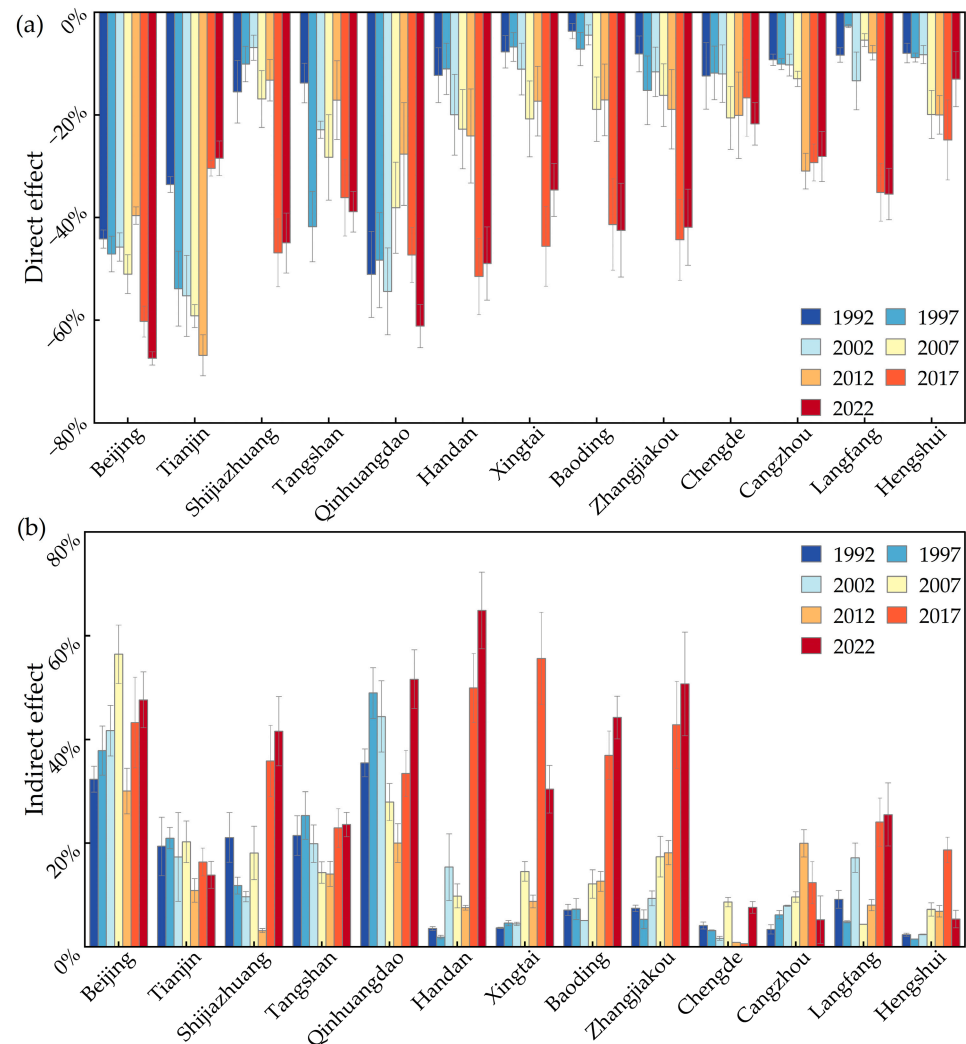


Figure 10. Mean and standard deviation of the direct (a) and indirect (b) effects of built-up area expansion on vegetation at the individual city scale during different study periods.

During 2002–2012, direct negative effects intensified in most cities (Figure 10a). Tianjin reached -66.86% in 2007, while previously less affected cities deepened to approximately -25% to -31% by 2012. Meanwhile, indirect effects increased rapidly across the region, roughly doubling from the previous stage in several cities (Figure 10b).

During 2012–2022, direct and indirect effects diverged sharply. Direct effects ranged from -30% to -65% (Figure 10a). In Beijing, direct effects fell from -60.26% in 2017 to -67.43% in 2022, the lowest value in the study period; Qinhuangdao also reached -61.12% in 2022. This indicates persistent high land conversion pressure in core cities due to limited available space. Meanwhile, indirect effects strengthened markedly (Figure 10b).

By 2022, indirect effects exceeded 40% in multiple cities, peaking at 64.85% in Handan. This pronounced enhancement in Handan may be related to its favorable climatic conditions, ecological location, and recent restoration efforts. Overall, core cities such as Beijing and Tianjin maintained persistently strong direct negative effects, while most cities showed stronger indirect effects during the later expansion stage.

4. Discussion

4.1. Diverse Expansion Trajectories and Their Policy Origins

We identified four distinct urban expansion patterns across the BTH region between 1992 and 2022: concentric outward growth in Beijing and Shijiazhuang, dual-core growth in Tianjin, Baoding, and Langfang, leapfrog and dispersed growth in eastern and southern Hebei cities, and topographically constrained growth in Zhangjiakou and Chengde. These patterns challenge the simple core-periphery diffusion model often applied to urban agglomerations [39,40]. Instead, local policy interventions appear to have generated secondary growth poles that reshape regional spatial structures without exclusive dependence on the primary core. The development of Tianjin's Binhai New Area and Hebei's Xiong'an New Area exemplifies this process. Importantly, these policies did not exert uniform effects across the region because they were designed to achieve different development objectives. The Binhai New Area strategy prioritized port-oriented industrialization, manufacturing expansion, and transport infrastructure construction [41], thereby creating a strong eastern growth pole that reinforced Tianjin's dual-core expansion pattern. In contrast, the establishment of Xiong'an New Area was intended primarily to absorb Beijing's non-capital functions and redistribute regional development resources [42], promoting a new growth center in central Hebei rather than simple outward expansion from the metropolitan core. Consequently, these policy interventions not only accelerated urban expansion but also reshaped its spatial configuration, resulting in distinct urban expansion trajectories across cities.

Another notable finding is the widespread decline in urban compactness across most cities, indicating a general transition toward more dispersed urban forms during the study period. This pattern is likely associated with rapid outward expansion driven by development zones, industrial parks, transportation corridors, and satellite towns [43,44], which increased the spatial fragmentation of built-up areas. The most pronounced declines occurred in Beijing and Tianjin, reflecting their sustained large-scale suburban expansion and multi-directional urban growth. In contrast, compactness remained relatively stable in Zhangjiakou and Chengde, where mountainous terrain and ecological protection policies constrained outward development. Declining compactness is not only a morphological characteristic of urban expansion but also an indicator of increasing urban sprawl, which may intensify landscape fragmentation, infrastructure demand, and ecological pressure [45].

After 2012, Beijing and Tianjin maintained relatively stable centroid trajectories, whereas Hebei cities had experienced large fluctuations during the preceding decade (2002–2012). This contrast signals a regional shift from rapid outward sprawl toward more stable, policy-guided consolidation. The 2015 Outline of the Beijing–Tianjin–Hebei Coordinated Development Plan is likely to have gradually redirected expansion from uncoordinated leapfrog development toward corridor-based, multi-center integration [46–48].

The GeoDetector results are consistent with this interpretation. Local fiscal expenditure ($q = 0.97$) emerged as the single most powerful driver of built-up expansion, whereas natural factors were statistically insignificant as independent drivers. This strong explanatory power supports Hypothesis 3, indicating that socioeconomic factors exert a stronger influence than natural factors. This is consistent with the argument that in highly managed urban agglomerations, biophysical constraints primarily define the potential ex-

pansion boundary, while socioeconomic and political forces determine the actual rate and trajectory [49]. However, the relative importance of socioeconomic factors is mainly reflected at the city scale; at finer spatial scales, natural factors such as topography and climate may exert more pronounced constraints by influencing the suitability and spatial configuration of local urban expansion [50]. Nevertheless, this result should be interpreted within the context of the present study. Because the analysis was conducted at the prefecture-city level using only 13 cities, the estimated explanatory power of individual factors is subject to greater uncertainty, and the exceptionally high q value may also reflect correlations among socioeconomic variables. Therefore, greater emphasis should be placed on the interaction detector, which provides a more comprehensive representation of the joint effects of multiple drivers. The interaction between local fiscal expenditure and elevation or precipitation yielded q values exceeding 0.98, suggesting that government investment influences urban expansion through interactions with the natural environment rather than operating independently. This interpretation is consistent with the constrained expansion observed in Zhangjiakou and Chengde, where ecological protection policies in the Taihang–Yanshan Mountains have limited the conversion of forest and grassland [51]. Together, these results indicate that urban expansion in the BTH region is governed by the combined effects of policy intervention and environmental constraints, thereby creating divergent contexts for subsequent vegetation responses.

4.2. Direct Effects as Physical Displacement

Direct negative effects represent the physical replacement of vegetated surfaces by impervious cover. In the BTH region, these effects deepened over the study period, reaching -67.43% in Beijing by 2022. This aligns with previous evidence from China that impervious surface expansion causes irreversible local vegetation loss [25]. Yet the magnitude observed in Beijing exceeds that reported for some U.S. cities [52], which likely reflects the higher population density and floor area ratio typical of Chinese urban cores.

At the agglomeration scale, rapidly expanding cities consistently showed the strongest direct effects (-39.27% to -54.47%), a consequence of extreme vegetative space compression by large-scale surface sealing. This physical displacement effect is irreversible: once land is sealed, primary productivity is fundamentally suppressed [33,53]. Core cities such as Beijing and Tianjin maintained persistently high direct negative effects across all periods, suggesting that robust fiscal support and early ecological awareness cannot overcome the fundamental constraint of finite physical space. These findings are consistent with Hypothesis 1, which suggests that rapidly expanding cities experience stronger direct negative effects due to intensified vegetation conversion.

Spatial heterogeneity in direct effects across cities is primarily controlled by differences in urban expansion intensity, urban spatial morphology, and long-term land-use lock-in processes. Cities with higher population density, more compact urban forms, and earlier onset of irreversible urban sealing tend to exhibit persistently stronger vegetation loss, whereas cities with lower sealing intensity or more dispersed urban development patterns show relatively weaker direct effects.

Our city-scale analysis masks substantial within-city variation. Beijing's aggregate value of -67.43% conceals near-complete vegetation loss in the central urban core alongside enhanced vegetation in the greenbelt and Olympic forest zones. Future work should adopt a gradient or landscape-patch approach to disentangle this intra-urban heterogeneity [54–56]. Nonetheless, the aggregate direct effect serves as a reliable indicator of the overall physical pressure on vegetation, and it sets the baseline relative to which indirect effects are evaluated.

4.3. Indirect Effects: The 2012 Threshold and a Hypothesized Land-Release Effect

Indirect positive effects showed a clear temporal threshold around 2012. These effects are most likely primarily associated with urban greening and afforestation activities, which directly increase vegetated surface coverage and biomass within urban and peri-urban areas [57]. In addition, irrigation and water supply regulation may have played a supporting role by improving vegetation water availability [58], while fertilization and agricultural land management in surrounding areas likely contributed to enhanced vegetation productivity at the regional scale. Ecological restoration projects, such as mining-area rehabilitation and land reclamation, may further amplify these effects in specific locations.

Before 2012, indirect effects remained modest (<10%) in most Hebei cities and fluctuated without a clear trend. After 2012, they rose sharply across all city types, hitting 64.85% in Handan by 2022. This 2012 inflection point aligns with two major policy shifts. First, the 2008 Beijing Olympics triggered large-scale greening investments that matured after a lag of several years [59]. Second, the post-2012 coordinated development agenda introduced ecological compensation mechanisms that channelled greening resources from core cities to peripheral areas. This pronounced temporal shift and the subsequent surge in indirect enhancement are consistent with Hypothesis 2, suggesting that the cumulative benefits of persistent regional greening investments and intensified urban management tend to increase over time. Although the estimated indirect effect in Handan was exceptionally high, it can be attributed to the combined influence of three regional factors. First, its location in the southern BTH region results in higher temperature and longer growing seasons, enhancing vegetation responsiveness to urban-induced microclimatic and irrigation effects. Second, its position at the Taihang Mountains–North China Plain transition zone exposes it to ecological spillover from large-scale post-2012 afforestation programs. Third, intensive post-2012 ecological restoration of mining-subsidence areas and associated water reallocation significantly strengthened local vegetation recovery [60]. These interacting climatic, geomorphological, and management conditions jointly amplify vegetation enhancement, explaining why Handan exhibits the highest indirect effect among all cities. Similar studies using the same framework have reported indirect effects ranging from 50–100% [61] and exceeding 200% in some cases [25], supporting consistency with previous findings.

Why did moderately and slowly expanding cities eventually overtake Beijing and Tianjin in indirect effects by 2022? We hypothesize a “land-release effect”. One possible explanation is that moderate urban expansion retains a larger proportion of vegetated land and unsealed surfaces than rapidly expanding cities. This provides greater opportunities for ecological restoration, afforestation, irrigation, and other vegetation management practices to enhance vegetation growth [62,63]. By contrast, extensive surface sealing in rapidly expanding cities substantially reduces the remaining ecological substrate available for subsequent vegetation recovery [26]. Consequently, the effectiveness of ecological management may depend not only on investment intensity but also on the amount of residual vegetated land available for restoration. This interpretation is consistent with previous studies showing that vegetation recovery in urban and peri-urban areas is strongly constrained by the availability of remnant vegetation and landscape conditions [64]. In Handan and similar cities, relatively lower sealing pressure may therefore have allowed existing vegetation to respond more effectively to improved water availability, favorable microclimatic conditions, and sustained ecological management after 2012.

However, the proposed land-release effect should be regarded as a plausible explanatory hypothesis rather than direct evidence of causality. The exceptionally high indirect effect estimated for Handan should still be interpreted with appropriate caution. Part of its magnitude may be influenced by the relatively coarse spatial resolution of the NDVI

dataset, the differential sensitivity of NDVI to land-cover characteristics such as leaf water content and phenological variation across cities, and the theoretical zero-impact line assumption used to infer indirect effects. Future studies using higher-resolution land-use and vegetation datasets are needed to reduce methodological uncertainty and to further validate the magnitude of indirect effects at finer spatial scales.

This hypothesized land-release effect implies that indirect vegetation recovery is not simply a function of policy investment or ecological awareness. Rather, it may depend critically on the residual stock of natural vegetation at the time of intervention. Cities that have already sealed most of their surfaces may face a much lower ecological recovery ceiling, regardless of subsequent greening expenditure [65,66]. If confirmed, this hypothesis would carry immediate planning implications: the window for cost-effective ecological enhancement may narrow as horizontal expansion proceeds.

4.4. A Stage-Dependent Trade-Off Framework

Taken together, our findings suggest that urbanization does not degrade vegetation in a linear fashion. Instead, its net ecological outcome appears to reflect a dynamic trade-off between direct displacement (negative) and indirect enhancement (positive), with the balance shifting systematically across urbanization stages. Although these pathways could be combined into a net effect, we retain their separate evaluation to distinguish the mechanisms of vegetation loss and compensation. We tentatively propose a three-stage framework for the BTH region.

During 1992–2002, direct effects dominated and indirect effects were minimal. Urbanization was driven by infrastructure construction and industrial land demand, with little coordinated ecological investment [67,68]. The net vegetation impact was strongly negative. During 2002–2012, direct effects peaked while indirect effects began to rise. The 2008 Olympics catalyzed regional greening initiatives, and direct and indirect effects moved in parallel rather than in opposition [69]. During 2012–2022, indirect effects increased markedly and began to offset direct losses in moderately and slowly expanding cities. By 2022, indirect effects exceeded 40% in multiple cities, and moderately expanding agglomerations recorded higher indirect effects than rapidly expanding ones for the first time.

Most notably, the period 2012–2022 is characterized by a clear divergence between direct and indirect effects, indicating a structural shift in urban vegetation dynamics. This divergence suggests that urbanization impacts are no longer governed by a single coupled response, but instead by two distinct pathways. Direct effects remain constrained by irreversible land conversion, exhibiting a persistent “lock-in” behavior with limited temporal reversibility. In contrast, indirect effects follow a cumulative enhancement pathway driven by long-term ecological management and environmental regulation, resulting in progressively increasing vegetation gains after 2012. Together, these two pathways indicate a partial decoupling of urban vegetation dynamics after 2012, in which physical land conversion establishes a stable negative baseline, while ecological interventions increasingly determine deviations above this baseline.

This framework offers a perspective that reframes the urbanization-ecosystem debate from a narrative of inevitable degradation to one of managed trade-offs. The key variable may not be urbanization per se, but rather the trajectory and speed of expansion. Fast, high-intensity sealing exhausts the land-release potential early, locking cities into a high-direct-effect regime [70]. Moderate expansion preserves the ecological substrate needed for indirect effects to mature. For regional planners, this means that ecological compensation should prioritize cities in the moderate-expansion category, where the marginal return on greening investment is highest.

4.5. Limitations, Policy Implications and Future Outlook

Several limitations warrant mention. The nighttime light data used to extract built-up areas are affected by mixed-pixel effects in urban–rural transition zones and radiometric saturation in highly urbanized cores [71,72], which may lead to overestimation of peri-urban expansion intensity and underestimation of built-up extent in dense urban areas. Although the extraction thresholds were calibrated using official statistical records and achieved acceptable accuracy, residual uncertainties remain due to sensor limitations and cross-resolution inconsistencies with reference datasets. The NDVI dataset also introduces scale-related uncertainty. Although resampling was applied, the original coarse resolution (~8 km) cannot be improved, which may smooth fine-scale vegetation heterogeneity and weaken the detection of localized ecological responses to urban expansion gradients. In addition, the sector-based analysis relies on a fixed centroid (1992) to ensure temporal comparability, but does not account for centroid migration during long-term urban expansion. Although the compactness index provides an intuitive measure of urban form, additional landscape metrics (e.g., Aggregation Index and Fractal Dimension) could provide a more comprehensive characterization of urban morphology. Moreover, the assumption of a linear relationship between impervious surface expansion and NDVI-based vegetation responses, although widely used [7,25,73], may oversimplify potentially nonlinear urban ecological processes. At the statistical level, the relatively small number of cities in the GeoDetector analysis limits cross-city inferential robustness, and the results should therefore be interpreted as indicative rather than strictly generalizable. Finally, the absence of explicit future scenario modeling and cross-regional comparison (e.g., with the Yangtze River Delta and Pearl River Delta) constrains the extrapolation of findings beyond the Beijing–Tianjin–Hebei region. In addition, some socioeconomic drivers such as policy shifts, migration dynamics, and industrial restructuring were not explicitly incorporated, which may introduce unobserved heterogeneity. Future studies should address these limitations by integrating higher-resolution satellite observations (e.g., Landsat, Sentinel-2), nonlinear modeling frameworks, and multi-regional comparative designs.

These limitations do not undermine the central message. Our results demonstrate that the BTH region has entered a post-2012 phase where indirect vegetation enhancement is increasingly compensating for direct losses, particularly in cities that have not yet exhausted their residual green space. This offers cautious optimism that coordinated regional planning and well-designed ecological compensation can mitigate the vegetation impacts of continued urban growth. However, the persistently high direct effects in megacities such as Beijing underscore an irreversible physical constraint. Future urbanization in the BTH region must therefore prioritize vertical and infill development over horizontal expansion to preserve the remaining vegetated surfaces that sustain indirect recovery.

5. Conclusions

Using nighttime light data and statistical yearbooks, we mapped built-up areas in the Beijing–Tianjin–Hebei (BTH) region from 1992 to 2022. We then characterized their expansion across five dimensions: speed, intensity, compactness, centroid shift, and directional bias. We further separated the direct and indirect effects of this expansion on vegetation growth at both the agglomeration level and the individual city level. The main findings are summarized as follows:

- (1) Four distinct patterns of urban expansion emerged. Beijing expanded in concentric rings, Tianjin developed as a dual-core city, cities in eastern and southern Hebei followed leapfrog trajectories, and Zhangjiakou and Chengde in the northwest exhibited topography-constrained expansion. Beijing and Tianjin sustained high-intensity growth throughout the study period, with peak expansion rates exceeding

70 km²·yr^{−1}. In contrast, cities in northern and western Hebei expanded at rates below 5 km²·yr^{−1}.

- (2) The ecological responses of vegetation exhibited a profound divergence between direct effects and indirect effects. Rapidly expanding agglomerations showed persistently strong direct negative effects. These peaked at −54.47% at the agglomeration scale in 2007 and reached −67.43% at the city scale in Beijing by 2022. By contrast, moderately and slowly expanding cities developed pronounced positive indirect effects after 2012, the highest of which reached 64.85% in Handan in 2022.
- (3) The contrasting vegetation responses support the proposed land-release effect: moderate expansion leaves behind remnant vegetated patches that may complement artificial greening, whereas rapid surface sealing risks exhausting this ecological buffer prematurely. Thus, the net effect of urbanization on vegetation depends less on expansion intensity alone than on the growth trajectory and on how much green space survives the expansion process.

From a management perspective, our findings suggest that the ecological redline policy in the BTH region should be further refined to account for the spatial heterogeneity of indirect vegetation effects, particularly in cities where positive indirect effects are strongest. Such differentiated ecological management may help maximize the ecological benefits of urban greening while minimizing vegetation loss associated with rapid urban expansion. Future studies should integrate higher-resolution long-term NDVI datasets to better capture vegetation dynamics in heterogeneous urban environments. In addition, further investigation of the ecological mechanisms underlying indirect vegetation effects is needed to improve our understanding of vegetation responses under different urban expansion trajectories.

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References

1. National Bureau of Statistics of China. *China Statistical Yearbook 2023*; China Statistics Press: Beijing, China, 2023.
2. Chatti, W.; Majeed, M.T. Information communication technology (ICT), smart urbanization, and environmental quality: Evidence from a panel of developing and developed economies. *J. Clean. Prod.* **2022**, *366*, 132925. [[CrossRef](#)]
3. Liang, L.; Chen, M.; Lu, D. Revisiting the relationship between urbanization and economic development in China since the reform and opening-up. *Chin. Geogr. Sci.* **2022**, *32*, 1–15. [[CrossRef](#)]
4. Zhou, W.; Yu, W.; Qian, Y.; Han, L.; Pickett, S.T.; Wang, J.; Li, W.; Ouyang, Z. Beyond city expansion: Multi-scale environmental impacts of urban megaregion formation in China. *Natl. Sci. Rev.* **2022**, *9*, nwab107. [[CrossRef](#)] [[PubMed](#)]
5. Rakshit, B.; Jain, P.; Sharma, R.; Bardhan, S. An empirical investigation of the effects of poverty and urbanization on environmental degradation: The case of sub-Saharan Africa. *Environ. Sci. Pollut. Res.* **2023**, *30*, 51887–51905. [[CrossRef](#)] [[PubMed](#)]
6. Warsame, A.A.; Abdi, A.H.; Amir, A.Y.; Azman-Saini, W. Towards sustainable environment in Somalia: The role of conflicts, urbanization, and globalization on environmental degradation and emissions. *J. Clean. Prod.* **2023**, *406*, 136856. [[CrossRef](#)]

7. Zhang, L.; Yang, L.; Zohner, C.M.; Crowther, T.W.; Li, M.; Shen, F.; Guo, M.; Qin, J.; Yao, L.; Zhou, C. Direct and indirect impacts of urbanization on vegetation growth across the world's cities. *Sci. Adv.* **2022**, *8*, eabo0095. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Yang, Y.; Liu, Y.; Li, Y.; Du, G. Quantifying spatio-temporal patterns of urban expansion in Beijing during 1985–2013 with rural-urban development transformation. *Land Use Policy* **2018**, *74*, 220–230. [\[CrossRef\]](#)
9. Liu, X.; Zhang, X.; Shu, Q.; Yao, Z.; Wu, H.; Gao, S. Effects of Urbanization-Induced Land Use Changes on Ecosystem Services: A Case Study of the Anhui Province, China. *Land* **2025**, *14*, 1238. [\[CrossRef\]](#)
10. Asabere, S.B.; Acheampong, R.A.; Ashiagbor, G.; Beckers, S.C.; Keck, M.; Erasmi, S.; Schanze, J.; Sauer, D. Urbanization, land use transformation and spatio-environmental impacts: Analyses of trends and implications in major metropolitan regions of Ghana. *Land Use Policy* **2020**, *96*, 104707. [\[CrossRef\]](#)
11. Sarker, T.; Fan, P.; Messina, J.P.; Mujahid, N.; Aldrian, E.; Chen, J. Impact of Urban built-up volume on Urban environment: A Case of Jakarta. *Sustain. Cities Soc.* **2024**, *105*, 105346. [\[CrossRef\]](#)
12. Talukdar, S.; Naikoo, M.W.; Rahman, A. Urban expansion and vegetation dynamics: The role of protected areas in preventing vegetation loss in a growing mega city. *Habitat Int.* **2024**, *150*, 103129. [\[CrossRef\]](#)
13. Han, W.; Tao, Z.; Li, Z.; Cheng, M.; Fan, H.; Cribb, M.; Wang, Q. Effect of urban built-up area expansion on the urban heat islands in different seasons in 34 metropolitan regions across China. *Remote Sens.* **2022**, *15*, 248. [\[CrossRef\]](#)
14. Gu, T.; Huang, Q.; Chen, M.; He, C.; Zhu, G.; Hou, Y.; Zhou, Y.; Yue, K.; Zhang, M.; Zhang, S.; et al. Does people oriented urbanization catch up with land and population urbanization. *npj Urban Sustain.* **2025**, *5*, 61. [\[CrossRef\]](#)
15. Jia, M.; Zhang, H.; Yang, Z. Compactness or sprawl: Multi-dimensional approach to understanding the urban growth patterns in Beijing-Tianjin-Hebei region, China. *Ecol. Indic.* **2022**, *138*, 108816. [\[CrossRef\]](#)
16. Wang, K.; Wang, W.; Zha, N.; Feng, Y.; Qiu, C.; Zhang, Y.; Ma, J.; Zhang, R. Spatially heterogeneity response of critical ecosystem service capacity to address regional development risks to rapid urbanization: The case of Beijing-Tianjin-Hebei urban agglomeration in China. *Sustainability* **2022**, *14*, 7198. [\[CrossRef\]](#)
17. Seto, K.C.; Fragkias, M. Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. *Landsc. Ecol.* **2005**, *20*, 871–888. [\[CrossRef\]](#)
18. Quigley, M.F. Street trees and rural conspecifics: Will long-lived trees reach full size in urban conditions? *Urban Ecosyst.* **2004**, *7*, 29–39. [\[CrossRef\]](#)
19. Zhou, Y.; Xing, B.; Ju, W. Assessing the impact of urban sprawl on net primary productivity of terrestrial ecosystems using a process-based model—A case study in Nanjing, China. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 2318–2331. [\[CrossRef\]](#)
20. Zhu, Z.; Fu, Y.; Woodcock, C.E.; Olofsson, P.; Vogelmann, J.E.; Holden, C.; Wang, M.; Dai, S.; Yu, Y. Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). *Remote Sens. Environ.* **2016**, *185*, 243–257. [\[CrossRef\]](#)
21. Sandel, B.; Svenning, J.-C. Human impacts drive a global topographic signature in tree cover. *Nat. Commun.* **2013**, *4*, 2474. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Du, J.; Fu, Q.; Fang, S.; Wu, J.; He, P.; Quan, Z. Effects of rapid urbanization on vegetation cover in the metropolises of China over the last four decades. *Ecol. Indic.* **2019**, *107*, 105458. [\[CrossRef\]](#)
23. Zhong, Q.; Ma, J.; Zhao, B.; Wang, X.; Zong, J.; Xiao, X. Assessing spatial-temporal dynamics of urban expansion, vegetation greenness and photosynthesis in megacity Shanghai, China during 2000–2016. *Remote Sens. Environ.* **2019**, *233*, 111374. [\[CrossRef\]](#)
24. Wang, S.; Ju, W.; Peñuelas, J.; Cescatti, A.; Zhou, Y.; Fu, Y.; Huete, A.; Liu, M.; Zhang, Y. Urban–rural gradients reveal joint control of elevated CO₂ and temperature on extended photosynthetic seasons. *Nat. Ecol. Evol.* **2019**, *3*, 1076–1085. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Zhao, S.; Liu, S.; Zhou, D. Prevalent vegetation growth enhancement in urban environment. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 6313–6318. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Peng, L.; Huang, K.; Zhang, H.; Sun, W. Exploring the impacts of urbanization on vegetation growth from the perspective of urban expansion patterns and maturity: A case study on 40 large cities in China. *Sustain. Cities Soc.* **2024**, *115*, 105841. [\[CrossRef\]](#)
27. You, Y.-J.; Liu, M.; Ni, H.-G. Dynamic indirect impacts of urbanization on vegetation growth in Chinese cities. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *131*, 103974. [\[CrossRef\]](#)
28. Chen, X.; Wang, Z.; Zhang, F.; Shen, G.; Chen, Q. A global annual simulated VIIRS nighttime light dataset from 1992 to 2023. *Sci. Data* **2024**, *11*, 1380. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Li, M.; Cao, S.; Zhu, Z.; Wang, Z.; Myneni, R.B.; Piao, S. Spatiotemporally consistent global dataset of the GIMMS Normalized Difference Vegetation Index (PKU GIMMS NDVI) from 1982 to 2022. *Earth Syst. Sci. Data* **2023**, *15*, 4181–4203. [\[CrossRef\]](#)
30. Luo, Y.; Ma, N.; Zhang, Y. Divergent vegetation greening's direct impacts on land-atmosphere water and carbon exchanges in the northeastern Tibetan Plateau. *Glob. Planet. Change* **2025**, *251*, 104825. [\[CrossRef\]](#)
31. Sun, Z.; An, Y.; Kong, J.; Zhao, J.; Cui, W.; Nie, T.; Zhang, T.; Liu, W.; Wu, L. Exploring the spatio-temporal patterns of global mangrove gross primary production and quantifying the factors affecting its estimation, 1996–2020. *Sci. Total Environ.* **2024**, *908*, 168262. [\[CrossRef\]](#) [\[PubMed\]](#)

32. Xu, Y.; Hao, S.; Cui, Y.; Li, P.; Sheng, L.; Liao, C. Analysis of the spatiotemporal expansion and pattern evolution of urban areas in Anhui Province, China, based on nighttime light data. *Ecol. Indic.* **2023**, *157*, 111283. [\[CrossRef\]](#)
33. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [\[CrossRef\]](#)
34. Yin, C.; Meng, F.; Yang, X.; Yang, F.; Fu, P.; Yao, G.; Chen, R. Spatio-temporal evolution of urban built-up areas and analysis of driving factors—A comparison of typical cities in north and south China. *Land Use Policy* **2022**, *117*, 106114. [\[CrossRef\]](#)
35. Xiao, J.; Shen, Y.; Ge, J.; Tateishi, R.; Tang, C.; Liang, Y.; Huang, Z. Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. *Landsc. Urban Plan.* **2006**, *75*, 69–80. [\[CrossRef\]](#)
36. Shi, L.; Zhang, Z.; Liu, F.; Zhao, X.; Liu, B.; Xu, J.; Hu, S. Spatial expansion remote sensing monitoring of special economic zones from 1973 to 2013. *J. Remote Sens.* **2015**, *19*, 1030–1039. [\[CrossRef\]](#)
37. Xin, J.; Yang, J.; Wang, L.; Jin, C.; Xiao, X.; Xia, J. Seasonal differences in the dominant factors of surface urban heat islands along the urban-rural gradient. *Front. Environ. Sci.* **2022**, *10*, 974811. [\[CrossRef\]](#)
38. Dong, C.W.; Cao, Y.; Tan, Y.Z. Urban expansion and vegetation changes in Hangzhou Bay area using night-light data. *Ying Yong Sheng Tai Xue Bao = J. Appl. Ecol.* **2017**, *28*, 231–238. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Li, W.; Cui, Y.; Qin, Y.; Qin, H.; Dong, J. Construction land allocation in Beijing-Tianjin-Hebei and Yangtze River Delta urban agglomerations. *J. Geogr. Sci.* **2025**, *35*, 501–520. [\[CrossRef\]](#)
40. Zhang, Z.; Li, N.; Wang, X.; Liu, F.; Yang, L. A comparative study of urban expansion in Beijing, Tianjin and Tangshan from the 1970s to 2013. *Remote Sens.* **2016**, *8*, 496. [\[CrossRef\]](#)
41. Li, X.; Deng, X.; Huang, S. Evolution of land use policies and its effects on wetlands change in Tianjin Binhai New Area, China. *Procedia Environ. Sci.* **2010**, *2*, 945–952. [\[CrossRef\]](#)
42. Zou, Y.; Zhao, W. Making a new area in Xiong'an: Incentives and challenges of China's "Millennium Plan". *Geoforum* **2018**, *88*, 45–48. [\[CrossRef\]](#)
43. Yue, W.; Liu, Y.; Fan, P. Measuring urban sprawl and its drivers in large Chinese cities: The case of Hangzhou. *Land Use Policy* **2013**, *31*, 358–370. [\[CrossRef\]](#)
44. Deng, F.F.; Huang, Y. Uneven land reform and urban sprawl in China: The case of Beijing. *Prog. Plan.* **2004**, *61*, 211–236. [\[CrossRef\]](#)
45. Rao, Y.; Dai, J.; Dai, D.; He, Q.; Wang, H. Effect of compactness of urban growth on regional landscape ecological security. *Land* **2021**, *10*, 848. [\[CrossRef\]](#)
46. Kuang, W.; Yang, T.; Yan, F. Examining urban land-cover characteristics and ecological regulation during the construction of Xiong'an New District, Hebei Province, China. *J. Geogr. Sci.* **2018**, *28*, 109–123. [\[CrossRef\]](#)
47. Daunt, A.B.P.; Silva, T.S.F.; Bürgi, M.; Hersperger, A.M. Urban expansion and forest reserves: Drivers of change and persistence on the coast of São Paulo State (Brazil). *Land Use Policy* **2021**, *101*, 105189. [\[CrossRef\]](#)
48. He, Z.; Zhao, C.; Fürst, C.; Hersperger, A.M. Closer to causality: How effective is spatial planning in governing built-up land expansion in Fujian Province, China? *Land Use Policy* **2021**, *108*, 105562. [\[CrossRef\]](#)
49. Liu, X.; Li, Y.; Zhang, S.; Niu, Q. Spatiotemporal patterns, driving mechanism, and multi-scenario simulation of urban expansion in Min Delta Region, China. *Ecol. Indic.* **2024**, *158*, 111312. [\[CrossRef\]](#)
50. Ceola, S.; Grandi, G.; Bertuzzo, E. Geomorphology and hydroclimate control regional urban expansion. *Earth's Future* **2025**, *13*, e2024EF005652. [\[CrossRef\]](#)
51. Tang, Z.; Zhang, Z.; Zuo, L.; Wang, X.; Zhao, X.; Liu, F.; Hu, S.; Yi, L.; Xu, J. Spatial evolution of urban expansion in the Beijing-Tianjin-Hebei coordinated development region. *Sustainability* **2021**, *13*, 1579. [\[CrossRef\]](#)
52. Imhoff, M.L.; Bounoua, L.; DeFries, R.; Lawrence, W.T.; Stutzer, D.; Tucker, C.J.; Ricketts, T. The consequences of urban land transformation on net primary productivity in the United States. *Remote Sens. Environ.* **2004**, *89*, 434–443. [\[CrossRef\]](#)
53. Zhao, A.; Tian, X.; Jin, Z.; Zhang, A. The imprint of urbanization on vegetation in the ecologically fragile area: A case study from China's Loess Plateau. *Ecol. Indic.* **2023**, *154*, 110791. [\[CrossRef\]](#)
54. Diksha; Mishra, V.N.; Kumar, D.; Kumari, M.; Bashir, B.; Pramanik, M.; Zhran, M. Dynamic quantification and characterization of Spatial heterogeneity in Mid-Sized urban landscape of India. *Land* **2024**, *13*, 1989. [\[CrossRef\]](#)
55. Rahimi, E.; Barghjelveh, S.; Dong, P. Quantifying how urban landscape heterogeneity affects land surface temperature at multiple scales. *J. Ecol. Environ.* **2021**, *45*, 22. [\[CrossRef\]](#)
56. Han, J.; Zhao, X.; Zhang, H.; Liu, Y. Analyzing the spatial heterogeneity of the built environment and its impact on the urban thermal environment—Case study of downtown Shanghai. *Sustainability* **2021**, *13*, 11302. [\[CrossRef\]](#)
57. Wang, C.; Jin, J.; Davies, C.; Chen, W.Y. Urban forests as nature-based solutions: A comprehensive overview of the national forest city action in China. *Curr. For. Rep.* **2024**, *10*, 119–132. [\[CrossRef\]](#)
58. Li, P.; Wang, Z.-H.; Wang, C. The potential of urban irrigation for counteracting carbon-climate feedback. *Nat. Commun.* **2024**, *15*, 2437. [\[CrossRef\]](#) [\[PubMed\]](#)
59. Tu, Y.; Chen, B.; Yang, J.; Xu, B. Olympic effects on reshaping urban greenspace of host cities. *Landsc. Urban Plan.* **2023**, *230*, 104615. [\[CrossRef\]](#)

60. Xu, W.; Cai, Z.; Tian, X.; Zhu, Q.; Yang, Z.; Li, S. Spatiotemporal Evolution Characteristics of Groundwater Level in the Hebei Plain During the Past Six Decades. *Sustainability* **2026**, *18*, 788. [[CrossRef](#)]
61. Zhao, Y.; Chen, H.; Ge, W.; Shi, S.; Li, R.; Sinore, T.; Wang, F. Examining the direct and indirect impacts of urbanization on vegetation net primary productivity across Chinese cities. *Agr. For. Meteorol.* **2025**, *374*, 110815. [[CrossRef](#)]
62. Kong, D.; Wang, K.; Dong, L.; Yang, J.; Gao, Z.; Liang, H. Anthropogenic Drivers of Small-Island Effects in Urban Remnant Woody Plants. *Plants* **2024**, *13*, 3522. [[CrossRef](#)] [[PubMed](#)]
63. He, M.; Yang, J.; Zhang, B.; Guo, M.; Zhou, L.; Yin, J. Effects of habitat fragmentation on multiple ecosystem functions in urban remnant forests. *For. Ecosyst.* **2026**, *15*, 100432. [[CrossRef](#)]
64. Shen, Y.; Wang, N.; Du, Y.; Yi, J.; Huang, S.; Tu, W.; Luo, P.; Xu, R.; Hu, D. Critical thresholds in urbanization-vegetation dynamics: Multiscale remote sensing evidence from Chinese cities. *J. Environ. Manag.* **2026**, *405*, 129721. [[CrossRef](#)] [[PubMed](#)]
65. Klaus, V.H.; Kiehl, K. A conceptual framework for urban ecological restoration and rehabilitation. *Basic Appl. Ecol.* **2021**, *52*, 82–94. [[CrossRef](#)]
66. De Bell, S.; Graham, H.; White, P.C. Evaluating dual ecological and well-being benefits from an urban restoration project. *Sustainability* **2020**, *12*, 695. [[CrossRef](#)]
67. Yang, Y.; Bao, W.; Li, Y.; Wang, Y.; Chen, Z. Land use transition and its eco-environmental effects in the Beijing–Tianjin–Hebei urban agglomeration: A production–living–ecological perspective. *Land* **2020**, *9*, 285. [[CrossRef](#)]
68. Xu, Z.-Y.; Sun, Z.-Y.; Zhu, X.; Xu, D. Spatiotemporal coordination and imbalance between urbanization and eco-environmental quality: A global remote sensing perspective. *GISci. Remote Sens.* **2025**, *62*, 2564537. [[CrossRef](#)]
69. He, G.; Zhang, Q.; Lü, Y. Eco-environmental impacts of the Winter Olympic Games on host cities: A critical review. *Acta Ecol. Sin.* **2020**, *40*, 1129–1139. [[CrossRef](#)]
70. Liang, J.; Li, H.; Jiao, A.; Lv, H.; Feng, Z. Urban Expansion-Driven Cropland NPP Change in the Beijing-Tianjin-Hebei Region, China (2001–2020): Spatiotemporal Patterns, Ecological Selectivity, and Spatially Varying Driver Effects. *Remote Sens.* **2026**, *18*, 933. [[CrossRef](#)]
71. Small, C.; Pozzi, F.; Elvidge, C.D. Spatial analysis of global urban extent from DMSP-OLS night lights. *Remote Sens. Environ.* **2005**, *96*, 277–291. [[CrossRef](#)]
72. Tong, L.; Hu, S.; Frazier, A.E. Mixed accuracy of nighttime lights (NTL)-based urban land identification using thresholds: Evidence from a hierarchical analysis in Wuhan Metropolis, China. *Appl. Geogr.* **2018**, *98*, 201–214. [[CrossRef](#)]
73. Liu, M.; Luo, Q.; Huang, R.; Wu, Y.; Zhou, J. Dynamic impacts of urban expansion on vegetation growth in urban environments: A sustainable land management framework. *Land Use Policy* **2025**, *153*, 107541. [[CrossRef](#)]

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