



Understanding multi-perspective urban green space patterns under urban expansion: Evidence from Guangzhou

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ABSTRACT

Urban expansion, a defining process of global urbanization, has profound implications for the distribution and quality of urban green spaces (UGS). This process is often accompanied by competition for land resources between elements of urban morphology and UGS, which in turn can negatively affect ecological sustainability and human well-being. Despite extensive research on the effects of urban growth on UGS, there remains a lack of multi-perspective analyses that integrate both aerial and human-centric perspectives of UGS indicators. Moreover, there is a lack of spatial association analyses between UGS and urban morphology. This study addresses this gap by introducing an innovative methodological framework integrating aerial perspective (Normalized Difference Vegetation Index, NDVI) and human-centric perspective (Green View Index, GVI), urban morphological indicators encompassing building density (BD), road density (RD), and land use mix (LandUSE), as well as socioeconomic housing price (HP) and topographic digital elevation (DE) indicators. This framework is employed to examine the evolving spatial relationships between UGS and urban morphology during different phases of urban expansion in Guangzhou, China. Using high-resolution satellite and street view data, as well as urban morphological data, we reveal that: (1) Significant spatial differences among various UGS metrics, which highlights the necessity of employing a comprehensive multi-perspective metrics approach; (2) UGS and urban morphology typically reflect the trade-offs between built-up growth and green space provision during urban expansion; (3) These relationships are further modulated by land development, urban design, local topography, and planning policies, leading to considerable variation along different urban expansion axes and time periods. Our findings advance the understanding of how urban expansion shapes the dynamics of UGS and provide critical evidence to inform sustainable urban planning and policy-making in rapidly growing cities.

1. Introduction

The global urbanization process has significantly accelerated over the past few decades, and it is projected that urban areas will absorb the majority of the world's population growth in the coming decades. Urban expansion is a universal phenomenon in the change of urban spatial scale, typically referring to the dynamic evolution process of urban outward expansion and diffusion in terms of geographic area (Angel et al., 2011; Zhong et al., 2021). Rapid urban expansion has brought unprecedented economic opportunities, but it has also led to a host of urban issues due to disorderly urban sprawl (Zhang et al., 2025). The theory of urban sprawl posits that expansion patterns characterized by low density, discontinuity, high land consumption, and single land-use

types exacerbate issues such as land resource waste (Wang et al., 2025), social inequality (Wolch et al., 2014) and environmental degradation (Khavarian-Garmsir et al., 2019), thereby affecting urban sustainable development (Hong et al., 2024) and human health (Jia et al., 2023; Markevych et al., 2017). To curb the various problems arising from uncontrolled urban sprawl, Transit-Oriented Development (TOD) has increasingly shaped the urban expansion patterns of global metropolitan areas (Li et al., 2018; Su et al., 2021). However, although this high-intensity development model enhances land use efficiency, it is accompanied by excessive encroachment upon urban green space resources. Urban green space (UGS), as a vital component of the urban environment, is increasingly declining due to uncontrolled urban expansion and high-intensity development models, thereby impeding

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the advancement of sustainable development (Al Hothaufi et al., 2025; Fang et al., 2023). As the largest developing country in the world, China's urbanization rate increased from 36.22% in 2000 to 67.00% in 2024 (Sun et al., 2020). Concurrently, the "green space ratio in the built-up areas" of county-level cities has risen from 12.23% in 1996 to 38.7% in 2021 (Cai et al., 2022). During this process, the distribution and accessibility of UGS have faced significant pressure due to urban expansion (Zhou et al., 2023), resulting in notable negative impacts on ecosystem services (Tzoulas et al., 2007), resource allocation (Su et al., 2024), and human health (Li et al., 2025). The conversion of green space to construction land has become one of the main drivers of global habitat destruction (Hong et al., 2025; Jia et al., 2025). Against this backdrop, to comprehensively assess the developmental changes in green spaces across different urban areas during the urban expansion process, this study employs the Normalized Difference Vegetation Index (NDVI) and the Green View Index (GVI) as key indicators from top-down aerial and human-centered perspectives, respectively (Wang et al., 2021). Exploring the distribution characteristics and evolving trends of UGS across different stages of urban development holds significance implications for unveiling the spatial nexus between urban expansion and diverse green space trajectories, thereby fostering urban ecosystems and sustainable development.

1.1. Multi-perspective assessment of UGS

UGS refers to the collective term for semi-artificial, semi-natural, and natural ecosystems dominated by vegetation in cities, encompassing a variety of types such as parks, gardens, forests, lawns, and nature reserves (Yang et al., 2025; Yao et al., 2026; Zhang et al., 2023). A substantial body of research has confirmed the extensive benefits of UGS for urban development and various aspects of urban residents' lives (Zhang et al., 2025). Traditional studies used diverse UGS metrics including UGS in land use, Net Primary Productivity (Dong et al., 2023), and green coverage rate (Qiu et al., 2019). NDVI, a widely used remote sensing metric in urban studies, is an aerial remote sensing indicator with the advantages of high data precision and broad coverage, making it highly valuable for application. In recent years, with the rise of artificial intelligence semantic segmentation technology and street view images (Yang et al., 2026), GVI quantifies street-level greenery visibility, capturing the human eye-level experience of urban vegetation (Li, 2021).

Previous research on UGS has extensively utilized NDVI and GVI separately. Studies in Europe and North America have begun exploring the integration of NDVI and GVI, highlighting their value in capturing nuanced differences in green space quality and accessibility (Bakhtsiyarava et al., 2024). Several studies have modeled NDVI and GVI separately and conducted correlation analyses, finding that the correlation between the two indices often exhibits substantial variability (Helbich et al., 2019; Huang et al., 2025; Z. Huang et al., 2025; Ye et al., 2019). However, integrated frameworks combining aerial remote sensing with human-centric street-level analysis remain scarce. Moreover, studies such as those mentioned above predominantly employ UGS indicators as key independent variables to discuss their effects on dependent variables, often overlooking the potential discrepancies in results arising from the divergent characteristics of NDVI and GVI. Both indices have their inherent limitations: the aerial remote sensing paradigm of NDVI fails to adequately reflect the true level of human experience and living conditions in urban environments. It is insensitive to low-growing vegetation and vertical greening, and struggles to capture fragmented ecological elements. As for GVI, it is overly reliant on the morphology of the road network, being confined to the assessment of street facade greening and incapable of evaluating the distribution of internal plot green spaces. The subtleties of these differences warrant further exploration. Therefore, relying solely on a single-perspective UGS index may underestimate the true impact of urban expansion on urban ecosystems and human well-being. There is an urgent need to

construct a multi-perspective greening evaluation framework to reveal the co-evolutionary patterns of the "aerial-human" nexus.

1.2. Phases of urban expansion and morphological transformation

Urban expansion is not a homogeneous process, but rather a sequence of distinct morphological transformations driven by evolving socioeconomic, policy, and building environment. Urban morphology refers to the overall "shape + structure" of the urban built environment in two and three dimensions (Wu et al., 2025). It encompasses the planar configuration of elements at various levels, such as streets, blocks, plots, and buildings, as well as three-dimensional features like building height, density, and skyline (He & Zhou, 2024; Wu et al., 2025). Urban expansion typically signifies the growth of the urban built-up area, that is, the expansion of urban morphological elements. In China, the evolution of urban morphology over different periods has been closely linked to historical context and planning priorities.

In the early stage following the founding of the People's Republic of China (1949), limited technological and economic capacity led to slow urban growth. Cities were generally compact, mono-functional, and infrastructure lagged behind, resulting in a relatively static spatial form. Urban expansion accelerated significantly after the reform and opening-up in 1978, ushering in a phase of rapid outward growth. During this period, peripheral expansion and infill development dominated, greatly increasing the built-up area and diversifying urban functions (Yu & Ng, 2007). However, this rapid expansion also brought about extensive encroachment on natural green spaces and increased spatial fragmentation.

Entering the 21st century, the focus of urban development in China shifted from quantity to quality. Urban planning became more comprehensive, with an emphasis on functional improvement and quality of life, rather than unchecked outward sprawl. The TOD paradigm has progressively emerged as a core strategy for reshaping urban morphology, endeavoring to transform dispersed urban sprawl into compact axial growth through the deployment of high-density, mixed-use developments around transit nodes (Li et al., 2018; Li et al., 2020). This high-intensity development paradigm is often accompanied by excessive encroachment upon green spaces surrounding rail transit corridors. Overall, Chinese urban expansion has largely followed a peripheral growth model, yet the specific spatial forms and dynamics have been strongly shaped by both policy shifts and spatial development paradigm (Liu et al., 2016a, 2016b).

These evolving patterns of urban morphology across different expansion phases have had significant and varying impacts on the distribution and quality of UGS. Understanding this spatial differentiation is essential for revealing the spatial associations among different UGS against the backdrop of urban expansion, which will be elaborated in the following sections.

1.3. The relationship between UGS and urban expansion

The adverse effects of urban expansion on UGS are supported by the majority of studies: Urban expansion directly encroaches on green spaces, leading to a reduction in green space area and an increase in fragmentation (Arshad et al., 2022). At the same time, urban expansion indirectly affects green spaces by altering land use patterns. Conversely, the optimized arrangement of urban greening can influence urban expansion by improving urban environmental quality and increasing urban attractiveness, thereby promoting sustainable urban development. For instance, a study encompassing 30 cities revealed higher vegetation cover conversion rates in urban expansion zones, with original vegetation being transformed into other land cover types. Another study focusing on three Southeast Asian cities identified a similar trend, indicating that the continuous expansion of urban built-up areas leads to a persistent reduction in green space area. Research by Liming Jiao et al. demonstrated that as the distance from the city center increases, the

fragmentation of urban built-up areas rises, while correspondingly, the fragmentation of green spaces decreases.

Despite the overall increase in green space coverage in Chinese cities over the past two decades, significant transformation of original vegetation cover has occurred in urban expansion areas. Wang et al.'s research (2023) exemplifies that changes in UGS are closely related to urban development priorities and location: in the early stages of urban development, land-based development led to a large amount of natural green space being converted into construction land, causing a noticeable trend of browning. Similarly, Song et al. (2020) found that the green space coverage in new urban areas is usually higher than that in old urban areas, which may be attributed to better natural conditions, lower land development intensity, and policy promotion. Studies by Zhou et al. and Wang et al. further corroborate this conclusion, demonstrating that vegetation cover changes exhibit disparities between newly developed areas and old urban districts. A large number of studies have also demonstrated the importance of UGS in urban expansion research, and the encroachment of UGS can further lead to other urban problems, such as various urban diseases (Markevych et al., 2017), urban pollution (Han et al., 2024), urban heat island (Dai et al., 2025), and urban high-quality economic development (Yang et al., 2022). In conclusion, research on the relationship between UGS and urban expansion helps researchers establish the impact mechanisms between urban expansion and various urban problems.

However, despite the considerable body of research currently focusing on the interplay between urban expansion and the built environment as well as UGS, there remain numerous research gaps. Firstly, many studies rely solely on a single metric to detect the changes in UGS, while neglecting the trend variations of the different metrics at aerial remote sensing perspective (e.g. NDVI) and street human-centric perspective (e.g. GVI), as well as the spatial trend variations of these indicators across different urban development periods. Secondly, existing research also lacks investigation into the associations between urban morphology and different UGS across various expansion periods (Table 1). Addressing these research gaps, this study contributes to urban sustainability theory by explicitly linking multi-perspective green space assessment frameworks with urban morphological transformations. Specifically, this paper seeks to explore the following research questions:

- (1) Do the GVI and NDVI metrics of UGS exhibit spatial distribution differences within the city?
- (2) What are the spatial association patterns between UGS and Morphology across different periods of urban expansion?

To address these research questions, the present study takes Guangzhou City as an example, to systematically analyze the relationship between UGS changes and urban development. A further exploration of policy and geographical factors during different urban expansion periods is followed to explain the differences among these varying UGS metrics and morphological characters, aiming to provide scientific evidence and policy recommendations for relevant researchers and managers.

2. Data and method

This paper systematically analyzes the dynamic relationship between urban expansion and UGS through empirical research, as shown in Fig. 1. First, the study collects UGS and multi-source urban morphological data. By constructing a 500 m × 500 m grid and an 800 m buffer zone around metro stations, these units serve as the basis for subsequent spatial statistical and spatial analyses. The study employed ordinary least squares (OLS) linear regression to separately examine the effects of various factors on NDVI and GVI. Furthermore, univariate and bivariate global spatial autocorrelation Moran's I, as well as Getis-Ord G_i^* hotspot analysis, were utilized to explore spatial disparities between NDVI and

GVI. Data on UGS and urban morphology within an 800 m radius around metro stations along two urban expansion axes are analyzed to investigate the differences in UGS and urban morphology characteristics across different stages of urban expansion.

2.1. Study area

Guangzhou is located in the northern part of the Pearl River Delta in southern China, with a total area of 7238.46 km² and is divided into 11 administrative districts. According to the "Guangzhou Green Space System Plan (2021–2035)," its green space planning focuses on park, protective, plaza, and ancillary green spaces, with regional green spaces also considered. Despite its strong natural resource base and early green space development, Guangzhou still faces issues with green space connectivity, equity, functionality, and distinctiveness (Yang et al., 2022).

This study thus focuses on the central eight districts, excluding Huadu, Conghua, and Zengcheng districts, as these three have relatively smaller urban area and are constrained by natural features like mountains (Fig. 2). We utilize land cover change dataset for China from 1985 to 2023 provided by the China Land Cover Dataset (CLCD), employing the construction land category from its first-level classification to delineate the built-up area boundaries of Guangzhou across different urban expansion periods (Naboureh et al., 2023; Yang & Huang, 2021).

Additionally, in conjunction with the official policy document "Guangzhou Master Plan," Guangzhou's urban expansion has primarily undergone four temporal nodes: 1984–2000, 2001–2010, 2011–2020, and 2021–2035. Based on the aforementioned data and policy documents, this study delineates the urban area prior to 1985 as the historical core district, characterized by early high-density development and neglect of UGS construction, resulting in low UGS and high urban morphological indicators. The area spanning 1985 to 2005 is designated as the development district, where developers emphasized urban spatial quality, yielding high GVI, moderate NDVI resources, and moderate urban morphological indicators. The area from 2005 to the present is classified as the expansion district, where substantial undeveloped land has produced low GVI, high NDVI, and low urban morphological indicators. Based on the above, this study establishes distinct urban expansion periods for Guangzhou (Fig. 3).

Guangzhou's urban development exhibits a cruciform pattern centered on the Yuexiu historic urban area, extending eastward along the Pearl River. The construction of rail transit follows the TOD model. In the old urban area, rail transit construction primarily serves as a posterior functional reinforcement for existing high-density development demands. In the development and expansion zones, rail transit construction further guides the direction of urban development, demonstrating a mutually reinforcing trend with urban expansion to a certain extent. Therefore, to fully capture Guangzhou's cruciform expansion trajectory, this study selects Metro Line 5 and Metro Line 2 as the axes of urban development. Line 5 serves as the east-west transportation backbone of Guangzhou, connecting the primary commercial and residential districts of Liwan, Yuexiu, Tianhe, and Huangpu. Line 2 functions as the north-south transportation backbone, linking Panyu, Haizhu, Yuexiu, and Baiyun districts. The two lines intersect at "Guangzhou Railway Station," the core of the historic urban area, comprehensively encompassing the three phases of Guangzhou's urban expansion.

Drawing upon existing research, within a 10 min walking distance (approximately 800 m), over 80% of pedestrians can reach rail transit stations. Beyond this distance, the proportion of bicycle use and bus transfers increases rapidly, and green space usage intensity declines significantly. The 800 m distance is commonly regarded as a critical threshold for "walking behavior." Consequently, this study establishes 800 m radius buffers centered on each metro station and aggregates all data into 500 m × 500 m grid cells and 800 m buffers around metro stations (van Soest et al., 2020) to ensure spatial consistency and comparability.

Table 1

Literature related to UGS and urban expansion.

Author (year)	Sample	Variables	Method	Results
Jun Yang et al. (2014)	30 cities, China T = 1990, 2000, 2010	• UGC; • BUAs; • PD; • TIUI; • PCGDP	• SVM • MIC	• The average annual increase in UGC across 30 cities was 1.51%, with Beijing and Hangzhou witnessing respective increases of 66.02% and 70.9% between 2000 and 2010. • The built-up areas of all cities expanded significantly, with Nanjing's built-up area expanding by 523.12%. • The conversion rate of vegetation cover in urban expansion areas was relatively high, with original vegetation cover being transformed into other types of land cover.
Amal Najihah M et al. (2017)	Kuala Lumpur, Metro Manila, Jakarta T = 1988, 1999, 2014	• LULC	LCM-Markov Chain models	• From 1989 to 2014, the built-up area of the three cities significantly increased. • During the same period, the green space area decreased. • By 2030, simulation results indicate that the built-up area will further expand. • The green space area is projected to continue diminishing.
Limin Jiao et al. (2017)	Wuhan, China T = 1989, 2001, 2013	• PLAND; • PD; • MESH; • SPLIT; • LPI; • COHESION;	• Correlation analysis • regression modeling	• The study reveals that from 1989 to 2013, the fragmentation of built-up areas exhibited an overall declining trend. • In contrast, the fragmentation of green spaces increased during the same period. • As the distance from the city center increases, the fragmentation of built-up areas rises. • The fragmentation of green spaces decreases with increasing distance from the city center.
Yimeng Song et al. (2020)	290 cities, China T = 1992–2015	• LBS data; • Sentinel-2 satellite imagery; • Nighttime light satellite images.	• Spatial descriptive statistical analysis	• From 1992 to 2015, urban expansion in China was rapid, with new urban areas accounting for 68.09% of the total urban area in 2015. • In 2015, the average green space coverage rate across 290 cities was 45.03%, with new urban areas having a higher green space coverage rate (48.91%) than old urban areas (36.85%). • The average green space exposure level in old urban areas (25.36%) was lower than that in new urban areas (35.63%).
Liquan Sun et al. (2020)	841 cities, World T = 2001–2018	• EVI; • GNI; • Population growth	• Mann-Kendall test	• Megacities in low- and lower-middle-income countries have experienced the most rapid urban population growth. • Cities in upper-middle-income countries have witnessed the fastest rates of urban expansion. • A total of 325 megacities have demonstrated a significant trend in urban greening ($P < 0.05$).
Yiyi Huang et al. (2022)	366 cities, China. T = 1990, 2000, 2010, 2015	• LUCC; • UBUA; • UGS; • UGSA;	• Gaussian-based 2SFCA; • Getis-Ord Gi*; • Global moran's I; • SLM; • SEM; • SDM; • UVCI calculation	• China accounts for 32% of the greening in built-up areas. • Overall, urban green space accessibility in China decreased by 57.23% from 1990 to 2015. • UGSA in the southeast has consistently been lower than that in the northwest. • The eastern region exhibited a declining trend in UGSA • The western region had the highest UGSA but also experienced the fastest rate of decline.
Tianyu Zhou et al. (2023)	388 cities, China. T = 1981 - present	• NDVI	• UVCI calculation	• China has experienced rapid yet uneven urban expansion, with urban areas growing by approximately 556%. • Urbanization has led to a decrease in the greening of urban regions. • Changes in vegetation cover have varied between newly developed areas and old urban districts.
Jie Wang et al. (2023)	Yangtze river delta region, China. T = 2001 - 2019	• NDVI	• PLR model	• During the study period, urban green spaces (UGS) initially decreased and then slightly increased. • Greening trends were primarily observed in the city center.
Yifei Jia et al. (2024)	Shanghai, China. T = 2005, 2020	• UVCI; • LC; • MHB; • LPI; • LSI; • POP; • LD; • FARC;	• GBRT; • SHAP;	• The impact of urban growth on UGS varied across different developmental stages. • The impact of urban expansion on green spaces is multidimensional. • Significant variations in stress factors and effects are observed across different regions. • By identifying key factors and their thresholds, scientific evidence can be provided for urban planning. • This evidence can optimize urban land use and green space layout.
Yang Chen et al. (2025)	106 cities, China. T = 2020	• BGSE; • PGSE; • AI; • LPI; • AWMFDI; • SPLIT;	• Multiple regression model • SLM	• In 106 Chinese cities, green space exposure is primarily concentrated in urban centers. • Average values are 15.04% for Built Green Space Exposure (BGSE) and 27.85% for Public Green Space Exposure (PGSE). • Cities in the south and southeast coastal regions exhibit higher BGSE and PGSE. • Cities in the central and northern regions have lower BGSE and PGSE values. • Urban agglomeration has a positive impact on green space exposure. • Fragmentation exerts a negative influence on green space exposure.

Note: UGC: Urban green coverage; BUAs: Built-up areas; PD: Population density; TIUI: Total investment in urban infrastructure; PCGDP: Per capita gross domestic product; SVM: The supported Vector Machine; MIC: the maximum information coefficients; UGSA: urban green space area; LULC: land use land cover; LCM: Land Change Modeller; PLAND: Percentage of landscape; PD: Patch density; MESH: Effective mesh size; SPLIT: Splitting index; LPI: Largest patch index; COHESION: Patch cohesion index; LBS: location-based services; EVI: Enhanced vegetation index; GNI: gross national income; LUCC: land use and cover change; UBUA: urban built-up area; UGSA: urban green space accessibility; SLM: the spatial lagged model; SEM: the spatial error model; SDM: the spatial durbin model; UVCI: Urbanization-vegetation cover index; LC: built-up land area; MHB: average building height; LPI: maximum patch index change; LSI: landscape shape index; POP: population density; LD: nighttime lighting index; FARC: fractal dimension index; GBRT: Gradient Boosting Regression Trees; SHAP: Shapely additive explanations; BGSE: the share of built-up area; PGSE: the share of population; AI: Aggregation index; LPI: Largest patch index; AWMFDI: Area weighted mean fractal dimension index; SPLIT: Split index.

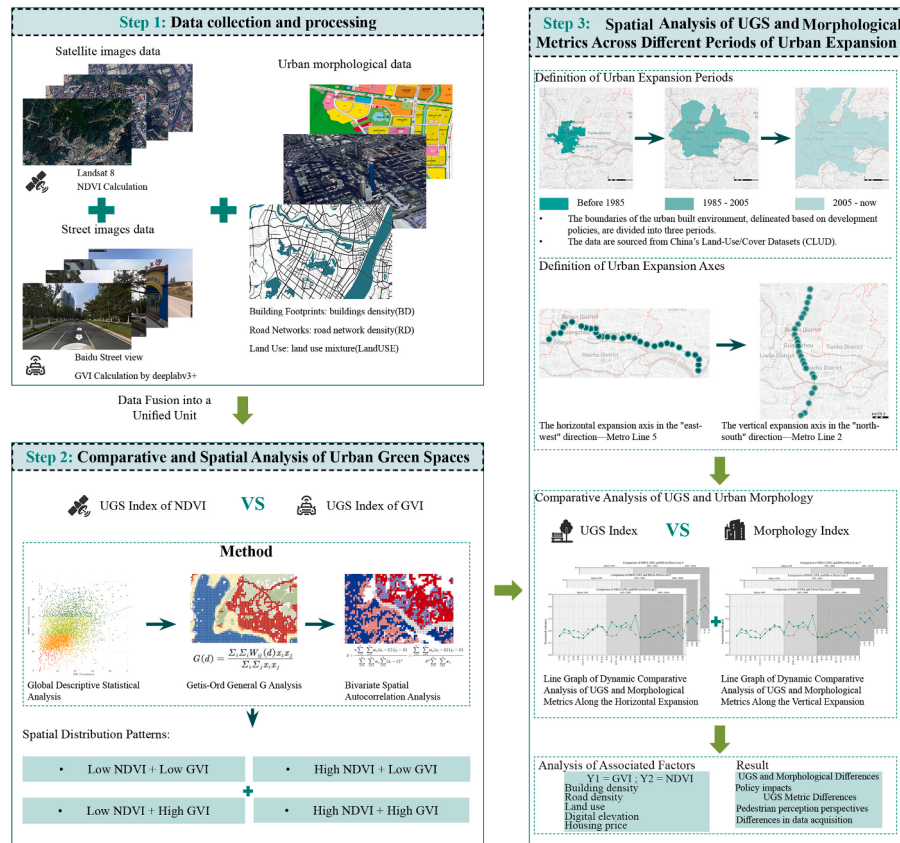


Fig. 1. Research framework.

2.2. Data source

This study employs multi-source data, encompassing two major categories: UGS and urban morphology. The UGS data include two indicators: the Normalized Difference Vegetation Index (NDVI) derived from remote sensing and the Green View Index (GVI) from street view images. The urban morphology data consist of three indicators: building density (BD), road density (RD) and land use mixture (LandUSE). Additionally, housing price (HP) data and topographic digital elevation (DE) data were incorporated as covariates (Tables 2 and 3). Drawing from prior research, it is noted that within a 10 min walking distance (equivalent to 800 m), more than 80% of pedestrians can reach transit stations. Beyond this distance, the proportion of cyclists and those using bus transfers increases rapidly, and the intensity of green space use also declines significantly. The 800 m distance is typically regarded as the critical threshold for "walking behavior." Therefore, All data were aggregated to 500 m × 500 m grid cells and within an 800 m buffer zone (van Soest et al., 2020) around metro stations to ensure spatial consistency and comparability.

2.2.1. UGS data based remote sensing satellites and street view

The remote sensing imagery data utilized in this study were sourced from the National Geospatial Data Cloud Platform (<http://www.gscloud.cn/>), specifically the Landsat 8 image with a 30 m resolution from June 2023. During the data selection process, we prioritized image with cloud cover of less than 1%. Subsequently, the image, which comprised nine bands, were processed using ArcGIS 10.5 to ensure high-quality outputs. In this study, the Normalized Difference Vegetation Index (NDVI) was employed as a macroscopic indicator to measure the degree of urban greening. NDVI is widely used to characterize vegetation density and growth conditions, and its calculation morphology is as follows:

$$NDVI = (NIR - R) / (NIR + R)$$

where *NIR* represents the reflectance of the near-infrared band, and *R* represents the reflectance of the visible red band. The NDVI value ranges from −1 to 1. In practical applications, NDVI values ≤ 0 are typically associated with snow or water bodies, while values ≤ 0.1 often indicate sparse vegetation cover on rocks or sandy areas. Given this, we set all negative NDVI values to 0 in this study to more accurately reflect the vegetation cover in urban spaces. Higher NDVI values imply a richer vegetation cover in urban areas.

To comprehensively evaluate the street view elements in Guangzhou City, this study collected Baidu Panoramic Street View images at 40 m intervals for the year 2023. After excluding street view images with missing data, a total of 250,799 sample points were generated across the street networks of the eight study areas in Guangzhou. The original 360° panoramic images exhibit spherical projection distortion at the four corners. To mitigate the impact of such distortion on segmentation accuracy, this study sampled images in four directions—front, rear, left, and right—at each sampling point, and calculated the average value to represent the authentic human eye-level perception at each sampling point (a total of 988,067 street view images were ultimately collected). This four-direction sampling scheme is extensively applied in urban green view research as a practical and effective approximation of street-level human visual perception. The horizontal visual field of pedestrians can be primarily captured through these four cardinal directions. Li et al. (2015) were the first to propose the use of four-direction images to calculate the green view index, and this method has since been adopted by numerous large-scale urban street greening quantification studies. The calculation formula for GVI is as follows:

$$GVI = \frac{\text{vegetation pixels}}{\text{image pixels}} \times 100\%$$

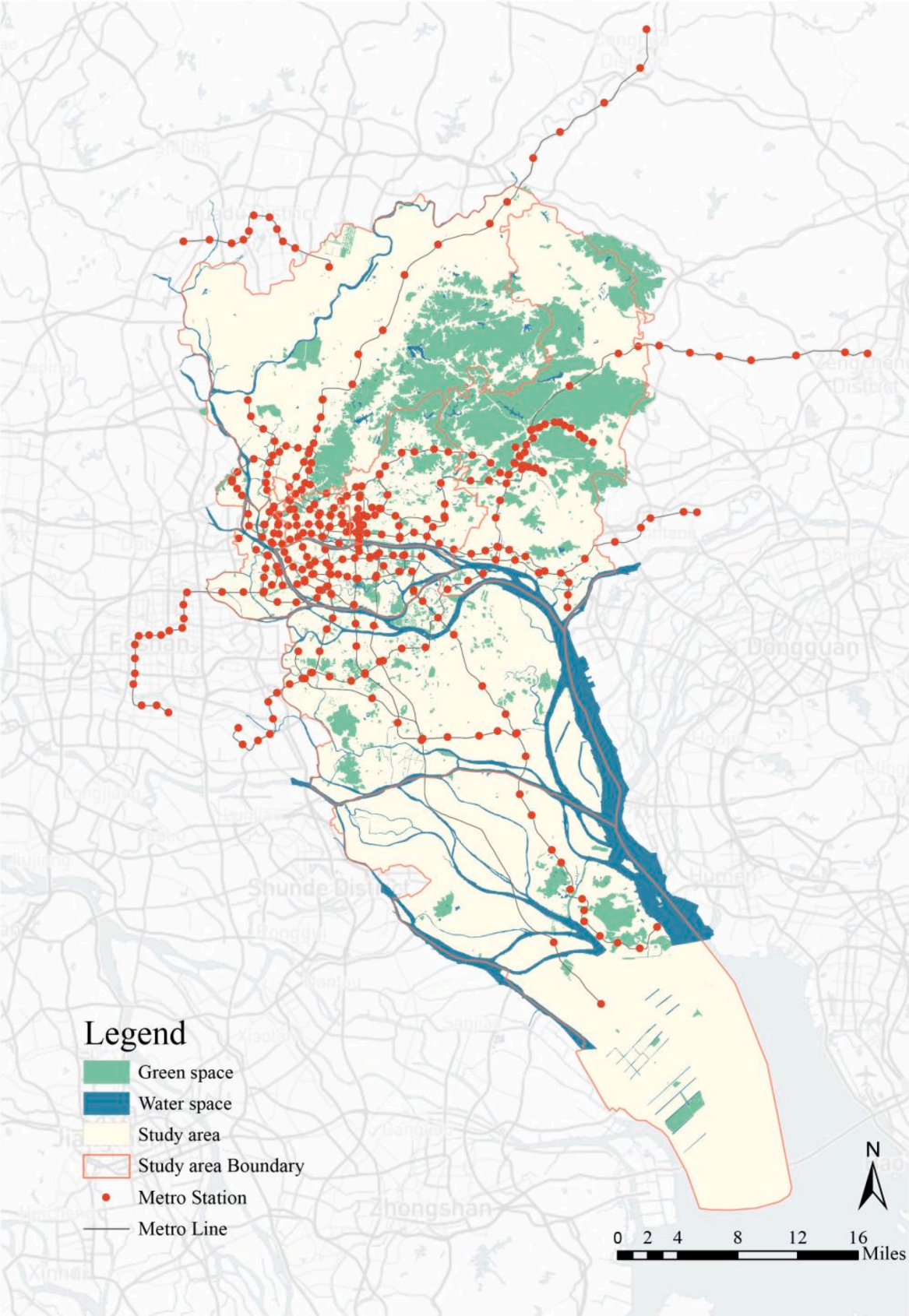


Fig. 2. Study area.

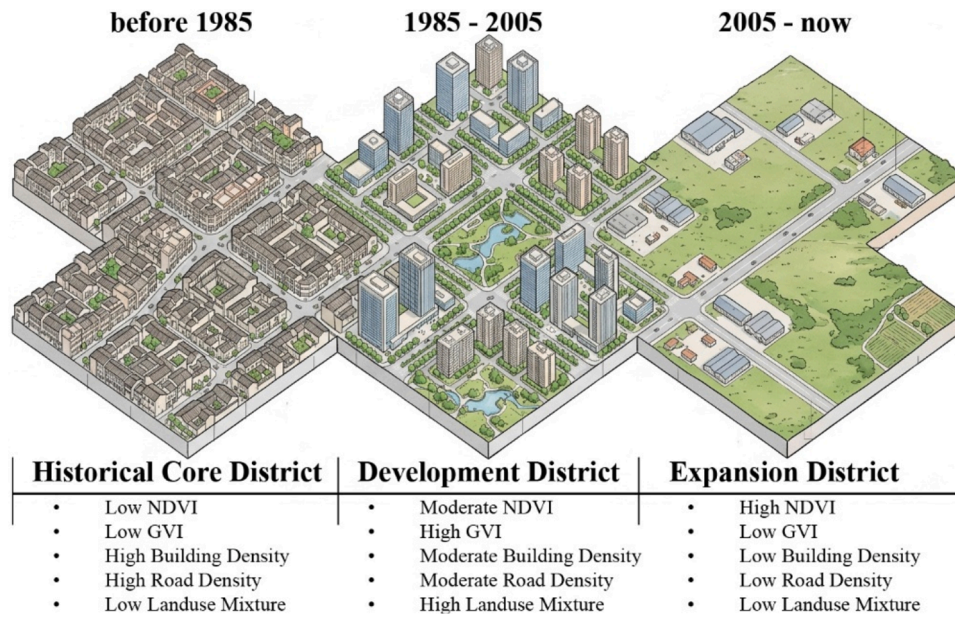


Fig. 3. Conceptual diagram of different urban expansion period.

Table 2

Data sources used in this study.

Main	Secondary	Code	Definition	Data Source
Urban green space	Green View Index	GVI	The ratio of vegetation among the objects seen in the current visual field	Baidu Map (http://lbsyun.baidu.com/)
	NDVI	NDVI	/	Semantic segmentation of street view images using deeplabv3+ National Earth System Science Data Center (http://www.geodata.cn/) Geospatial Data Cloud (http://www.gscloud.cn/)
Urban morphology	Building Density	BD	The total area of building bases within the current grid divided by the grid area	Peng Cheng Laboratory (https://data-starcloud.pcl.ac.cn/zh/resource/14)
	Road Density	RD	the total length of roads within the current grid divided by the grid area	Open Street Map (OSM)
Covariate	Land Use Mixture	LandUSE	Calculated using the Shannon entropy formula	Peng Cheng Laboratory (https://data-starcloud.pcl.ac.cn/zh/resource/14)
	Housing Price	HP	Unit price of residential housing (CNY/m ²)	Anjuke (https://guangzhou.anjuke.com/)
	Digital Elevation	DE	Current elevation (m)	NASA Earth Science Data (https://nasadaacs.eos.nasa.gov/)

Table 3

Descriptive statistics of selected variables.

Variable	N	min	max	mean	Std.	Var.
GVI	5924	0.000	63.315	18.125	9.612	92.395
NDVI	5924	0.002	0.401	0.176	0.0629	0.004
BD	5924	0.000	0.624	0.138	0.108	0.012
RD	5924	11.588	13253.671	2554.003	1540.433	2372934.621
LandUSE	5924	0.000	0.653	0.152	0.133	0.018
HP	5924	4978.000	185437.000	36277.553	20366.841	414808242.000
DE	5924	-10.000	230.000	15.0663	24.413	595.998

where *vegetation pixels* represents the number of pixels occupied by vegetation in the current street view image, and *image pixels* denotes the total number of pixels in the current street view image.

This study employed the DeepLabv3+ deep learning semantic segmentation network on the TensorFlow open-source machine learning framework, using Python 3.7 programming software, to perform semantic segmentation and feature extraction on street view images. The DeepLab network model inherits the advantages of Fully Convolutional Networks (FCN) and introduces improvements such as dilated convolutions and pyramid pooling. As the latest improved version of this network model (Chen et al., 2018), DeepLabv3+ combines the benefits

of an encoder-decoder structure and multi-scale pyramid pooling, significantly enhancing the model's segmentation accuracy to 89%, making it one of the most mature semantic segmentation networks in the world. A substantial body of urban research has adopted this deep learning semantic segmentation framework. The dataset used was the ADE20K open-source dataset (<https://groups.csail.mit.edu/vision/datasets/ADE20K/index.html>), which contains over 27,000 images, each with dense label annotations, covering most urban scenes and is considered a mainstream dataset in the field of street view image semantic segmentation alongside the Cityscapes dataset. In the segmentation samples, this study extracted grass and trees as indicators of the

Green View Index (GVI). By comparing manual Photoshop segmentation results with semantic segmentation results from 200 sample images, the accuracy was found to be 81%.

2.2.2. Urban morphological data

To measure the dynamic association between the built environment and UGS during different urban development periods, the study employed a variety of urban morphology indicators, utilizing three types of data: buildings, roads, and functions. Building data were sourced from the global building dataset (<https://data-starcloud.pcl.ac.cn/zh/source/14>). The building density (BD) was calculated using the morphology: building footprint area divided by land area. Road network data were obtained from the OpenStreetMap (OSM) dataset, with road density (RD) calculated as road network length divided by land area. Functional metrics were assessed through the calculation of land use mixture based on the Shannon entropy formula. Land use data were based on land use dataset of Peng Cheng Laboratory (Li et al., 2020).

As illustrated in Fig. 4, the spatial statistics of the indicators reveal a pronounced decreasing trend in the building morphological metric BD (m^2/m^2) from the historical urban area to the expansion area. The road metric RD (m/m^2) also exhibits a decreasing trend from the historical core area to the expansion area, although this trend is not significant. The functional diversity metric LandUSE shows a fragmented spatial pattern, with no evident spatial clustering.

2.2.3. Covariates

In addition to urban morphology, the study controlled for the effects of socioeconomic and topographic factors on UGS. Socioeconomic indicators primarily utilized housing price data (CNY/ m^2), sourced from the Anjuke website in 2023. Topographic data employed the digital elevation model data for Guangzhou. All data were ultimately aggregated into 500 m grids for subsequent analysis.

2.3. Spatial analysis

This study employs descriptive statistical, OLS linear regression and spatial econometric analysis methods to compare the spatial distribution differences of UGS and various urban morphological metrics across the entire Guangzhou urban area. It also examines the changes in UGS over different periods and the differences in other urban morphological factors. Prior to the analysis, each indicator's values were subjected to min-max normalization to ensure comparability across different metrics on a consistent scale. In the global OLS analysis, the study examines how

various indicators influence NDVI and GVI. The local spatial analysis utilizes global univariate and bivariate spatial autocorrelation analyses, as well as Getis-Ord Gi hotspot analysis (Bivand & Wong, 2018), to explore the spatial patterns of differences between NDVI and GVI. The bivariate local spatial autocorrelation index (Local Indicators of Spatial Association, LISA) can reflect the correlation and spatial clustering degree of NDVI in a certain spatial unit with GVI in its adjacent spatial units. The Getis-Ord Gi statistical method, widely used for revealing local spatial clustering patterns, can precisely identify hotspots and cold spots where NDVI is significantly higher or lower than GVI. Specifically, the spatial statistical analysis was conducted using GeoDa 1.20 and ArcGIS 10.5. During the analysis, the conceptualization of spatial relationships was set to the inverse of the squared distance, and the Euclidean distance method was employed for calculations.

3. Result

3.1. Spatial variations of UGS metrics

Combining NDVI and GVI in spatial analyses provides a more comprehensive understanding of green space quality and accessibility. From a global perspective, the proportions of NDVI and GVI increase progressively from the historical core areas to the urban expansion areas and then to the undeveloped urban areas. Despite this, the spatial distributions of the two indicators exhibit significant differences. The spatial distribution of NDVI is relatively concentrated, while that of GVI is more dispersed. To more accurately compare the spatial distribution differences between NDVI and GVI, further spatial autocorrelation Moran's I and Getis-Ord Gi* hotspot analyses were conducted. The global Moran's I values for NDVI and GVI were 0.306 ($Z = 284.673$, $P < 0.001$) and 0.132 ($Z = 123.024$, $P < 0.001$), respectively, indicating that both exhibit spatial clustering characteristics, with NDVI demonstrating a higher degree of clustering than GVI. As illustrated in Fig. 5, consistent with existing research, NDVI and GVI display significant spatial distribution disparities. The hotspot analysis reveals that the cold and hotspot distributions of NDVI are relatively concentrated: hotspots are clustered around natural scenic areas in the north, while cold spots more prominently reflect Guangzhou's "cruciform" urban expansion pattern, indicating the excessive encroachment on urban green spaces under the TOD model. In contrast, the cold and hotspot distributions of GVI are more dispersed: hotspots are scattered across various urban areas, while cold spots are concentrated in Baiyun District in the northern part of the city.

The study employed bivariate spatial autocorrelation analysis to

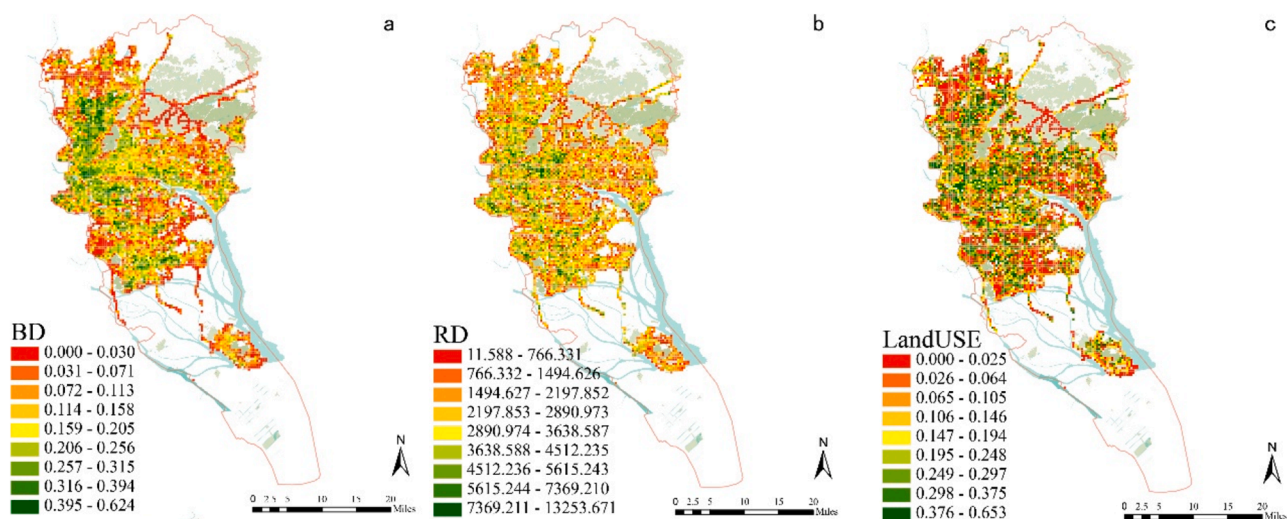


Fig. 4. The spatial pattern of selected morphological variables at the 500×500 grid level. (a. Descriptive statistics of Building Density (BD). b. Descriptive statistics of Road Density (RD). c. Descriptive statistics of Land Use Mixture (LandUSE).).

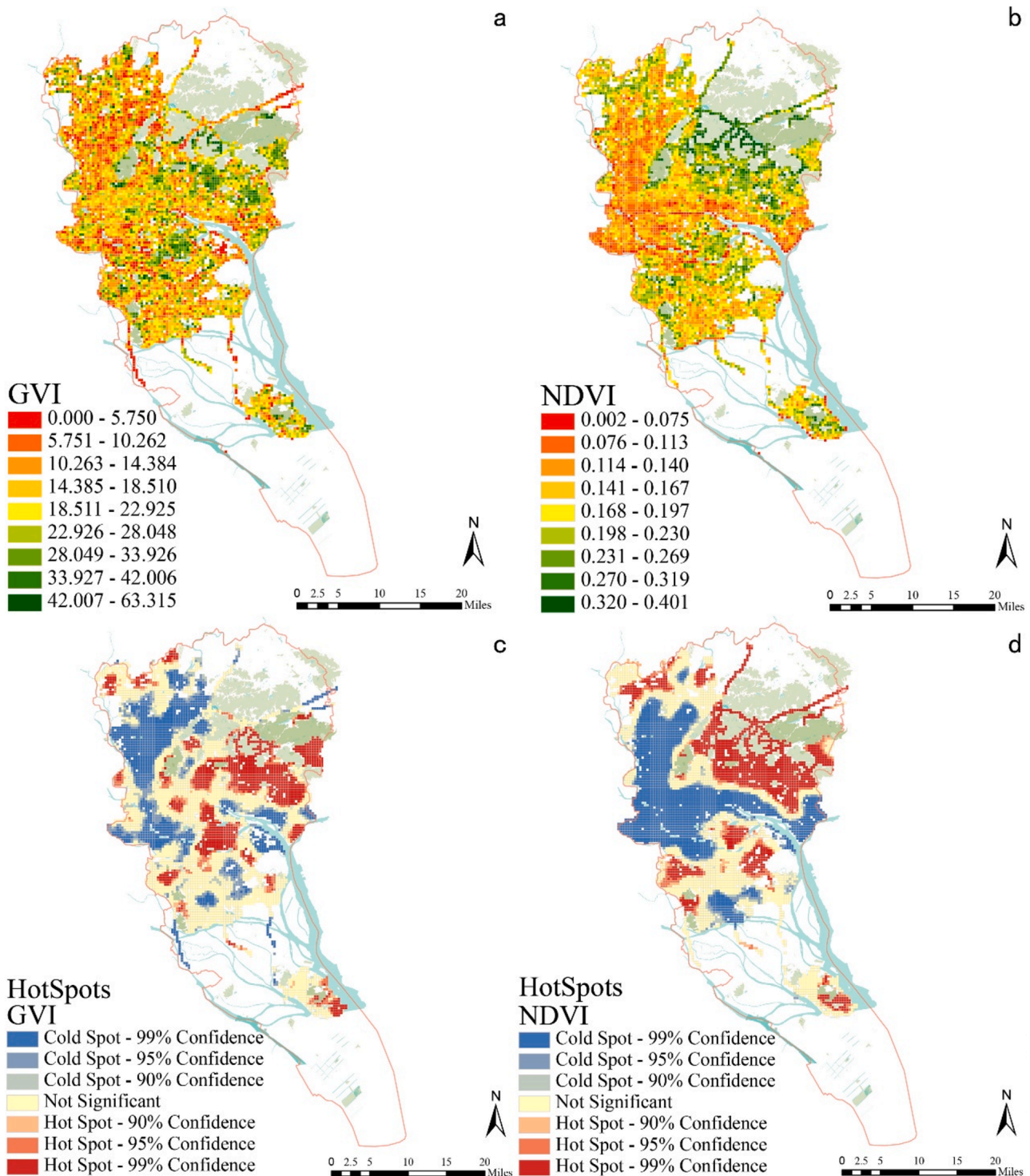


Fig. 5. Spatial analysis results of UGS. (a. Descriptive statistics of GVI. b. Descriptive statistics of NDVI. c. Hotspot analysis of GVI. d. Hotspot analysis of NDVI.).

explore the spatial distribution disparities between NDVI and GVI. The bivariate global Moran's I value was 0.099 ($Z = 143.534$, $p < 0.001$), indicating a positive spatial correlation between the two (Fig. 6). Local bivariate spatial autocorrelation analysis was further conducted, with results categorized into four characteristic regions: low NDVI and low GVI values, high NDVI and high GVI values, high NDVI and low GVI values, and low NDVI and high GVI values. Areas with low NDVI and low GVI values are primarily concentrated in the historical urban core. These areas are characterized by high-density urban development, exhibiting urban morphology with high building density, road network density,

and functional diversity. Streets and public spaces are often encroached upon by various urban morphological elements, neglecting the overall creation of green spaces. Regions with high NDVI and high GVI values are mostly found in suburban areas near natural mountains. These areas have lower urban morphological metrics. Despite higher local building density in some spaces, the overall floor area ratio generally exhibits lower values. This is because the urban morphology in these areas has made concessions to the preservation of UGS resources. Areas with high NDVI and low GVI values are mainly found in undeveloped regions in the peripheral of the city. The urban morphology in these areas is

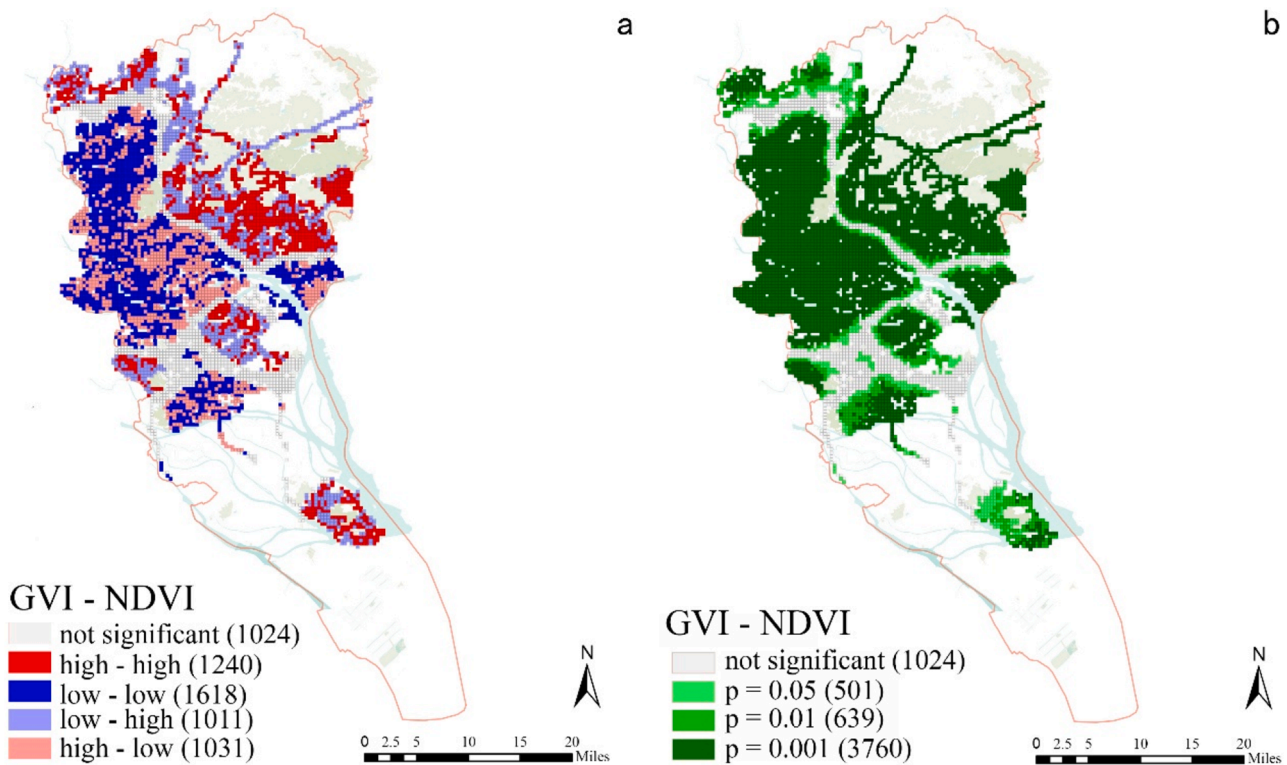


Fig. 6. Comparison of NDVI and GVI based on bivariate spatial autocorrelation. (The number of grids is indicated within parentheses. **a.** Bivariate spatial autocorrelation results. **b.** Significance results of bivariate spatial autocorrelation.).

dominated by large, single green spaces. Due to the lack of overall green space planning and the absence of various types of infrastructure planning, these areas, despite having abundant green space resources, are not accessible to urban residents. Lastly, zones with low NDVI and high GVI values are concentrated in new urban development areas. Planning strategies in these areas typically focus on the design of local micro-spaces, resulting in higher street walkability. Meanwhile, building morphological metrics are at a medium level, achieving a dynamic balance with UGS metrics. Based on the aforementioned findings, although NDVI and GVI within the city generally exhibit similar spatial distribution trends, significant local spatial distribution differences exist. Given that these two indices are subject to differences in human perceptual perspectives, it is essential for the study to complement aerial remote sensing with human-centric street-level perspectives.

3.2. Spatial character of UGS and urban morphology under urban expansion

Constrained by the topography of mountains, the urban development of Guangzhou essentially follows a cruciform pattern, extending in the east–west and south–north directions. This study employs two time axes, represented by Metro Line 5 (east–west) and Line 2 (south–north), to analyze the UGS and morphological characteristics during different periods of urban expansion. Line 5 generally exhibits a trend of urban expansion from west to east, with the city sprawling in a linear, ribbon-like pattern. In contrast, Line 2, limited by the Pearl River water system to the south and the terrain of Baiyun Mountain to the north, demonstrates a pattern of expansion from the center to both the northern and southern ends. This study delineates three periods of urban expansion: the historical urban core before 1985, the development area from 1985 to 2005, and the expansion area from 2005 to the present (Fig. 7).

Regarding the urban expansion axis of Metro Line 5, The historical urban core is characterized by high-density buildings, high-density road networks, and single land use functions, with relatively low NDVI and

GVI metrics, indicating a severe shortage of UGS. The development area exhibits medium-density buildings, medium-density road networks, and complex land use patterns, with relatively high NDVI and GVI metrics, where the GVI metric is significantly higher than the NDVI metric. The expansion area features medium-density buildings, low-density road networks, and a coexistence of single and complex land use functions, with considerable fluctuations in NDVI and GVI metrics influenced by different types of land use and land use policies. The results indicate that excessively high urban morphological metrics can encroach upon the spatial distribution of UGS. In the historical urban core, increases in building density typically come at the direct expense of natural vegetation. The high-density and highly concentrated development pattern has led to the replacement of original green spaces by impervious surfaces such as buildings and roads, resulting in a sharp decline in green space. During the phase of urban development, planning interventions or resident demands may drive the "re-implantation" of green spaces, such as street greening or pocket parks, leading to a spatial reconfiguration of the "built environment - green space" relationship. The expansion area contains a large number of undeveloped and single-function lands, exacerbating the fragmentation of UGS and reducing the efficiency of UGS utilization (Fig. 8).

The north–south and east–west axes exhibit distinct urban development characteristics. Regarding the north–south development axis (Metro Line 2), urban expansion is more susceptible to the influence of natural topography. The expansion areas at both ends of this axis have relatively higher NDVI and GVI values but display different UGS patterns. The southern section (from Guangzhou South Railway Station to Nanpu), originally consisting of large tracts of farmland, has been newly planned with ample green space, resulting in synchronous increases in both GVI and NDVI. In contrast, the northern section (from Baiyun to Jiahe Wanggang), constrained by the ecological limitations of Baiyun Mountain, has experienced restricted expansion. The green space in this area follows a pattern of "high-density preservation + low-density development," characterized by high NDVI but relatively low GVI. As

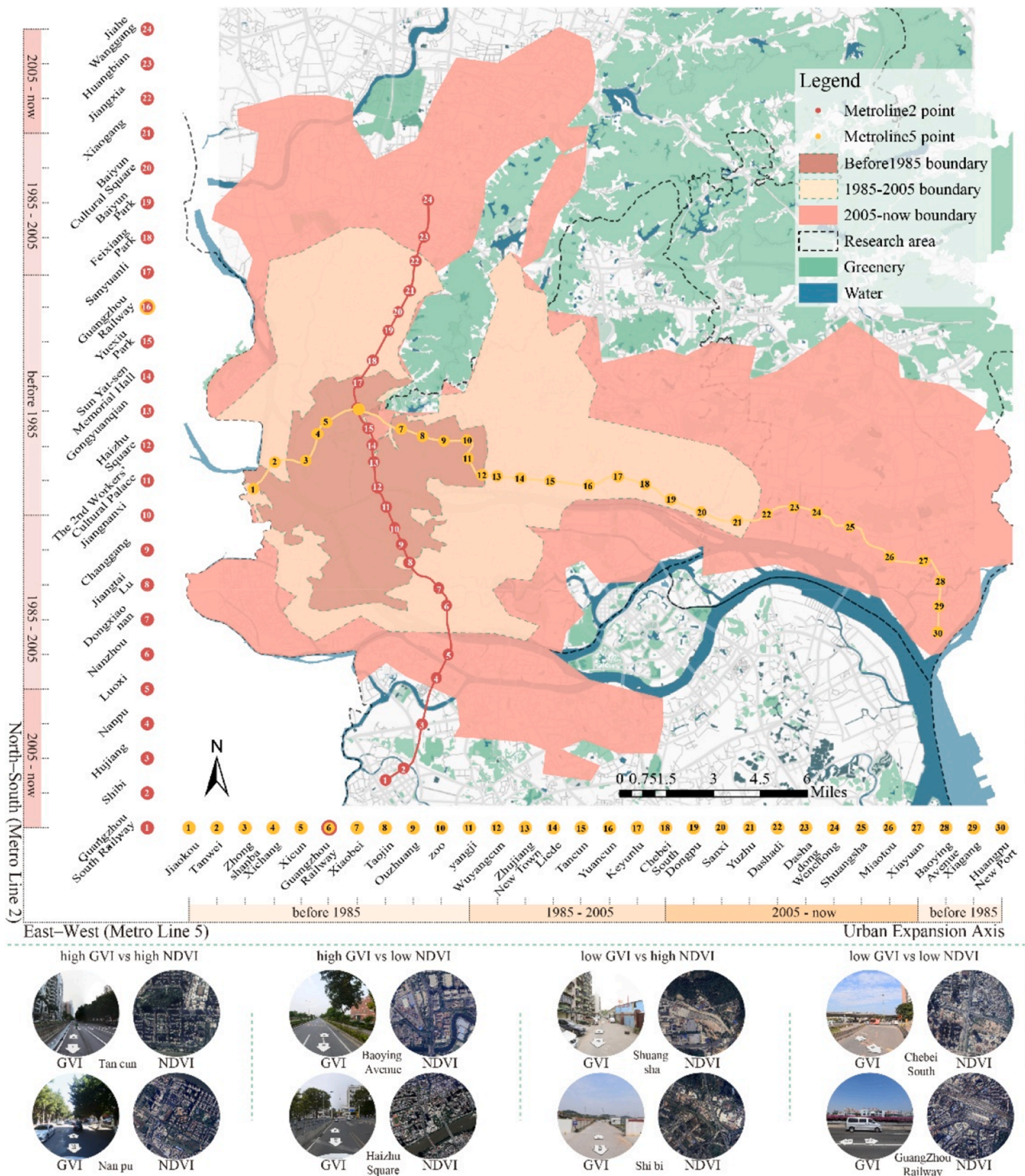


Fig. 7. Metro stations along Lines 2 and 5 across different expansion periods.

for the east-west axis (Metro Line 5), urban development exhibits a linear characteristic, extending from west to east along the Pearl River.

The study selected eight typical metro stations for analysis based on the comparison of NDVI and GVI indices at metro stations. High NDVI and high GVI are present at Tancun Station on Line 5 and Nanpu Station on Line 2, which are located in the urban development area and the urban expansion area, respectively. Tancun is surrounded by high-quality streets and urban parks with diverse functions, while Nanpu is adjacent to some undeveloped green spaces. High GVI but low NDVI are found at Baoying Avenue Station on Line 5 and Haizhu Square Station on

Line 2. The area surrounding Baoying Avenue is primarily industrial land, and the monolithic land use pattern results in a lack of large green spaces in the region. Although Haizhu Square has its own green space planning, it is surrounded by a large number of urban villages and high-density residential areas. Low GVI but high NDVI are present at Shuangsha Station on Line 5 and Shibi Station on Line 2. Both stations are located in urban expansion areas with abundant natural green spaces, but these areas also lack planning and development. Low GVI and low NDVI are found at Guangzhou Railway Station, which is an interchange station for Lines 5 and 2. Located in the heart of the

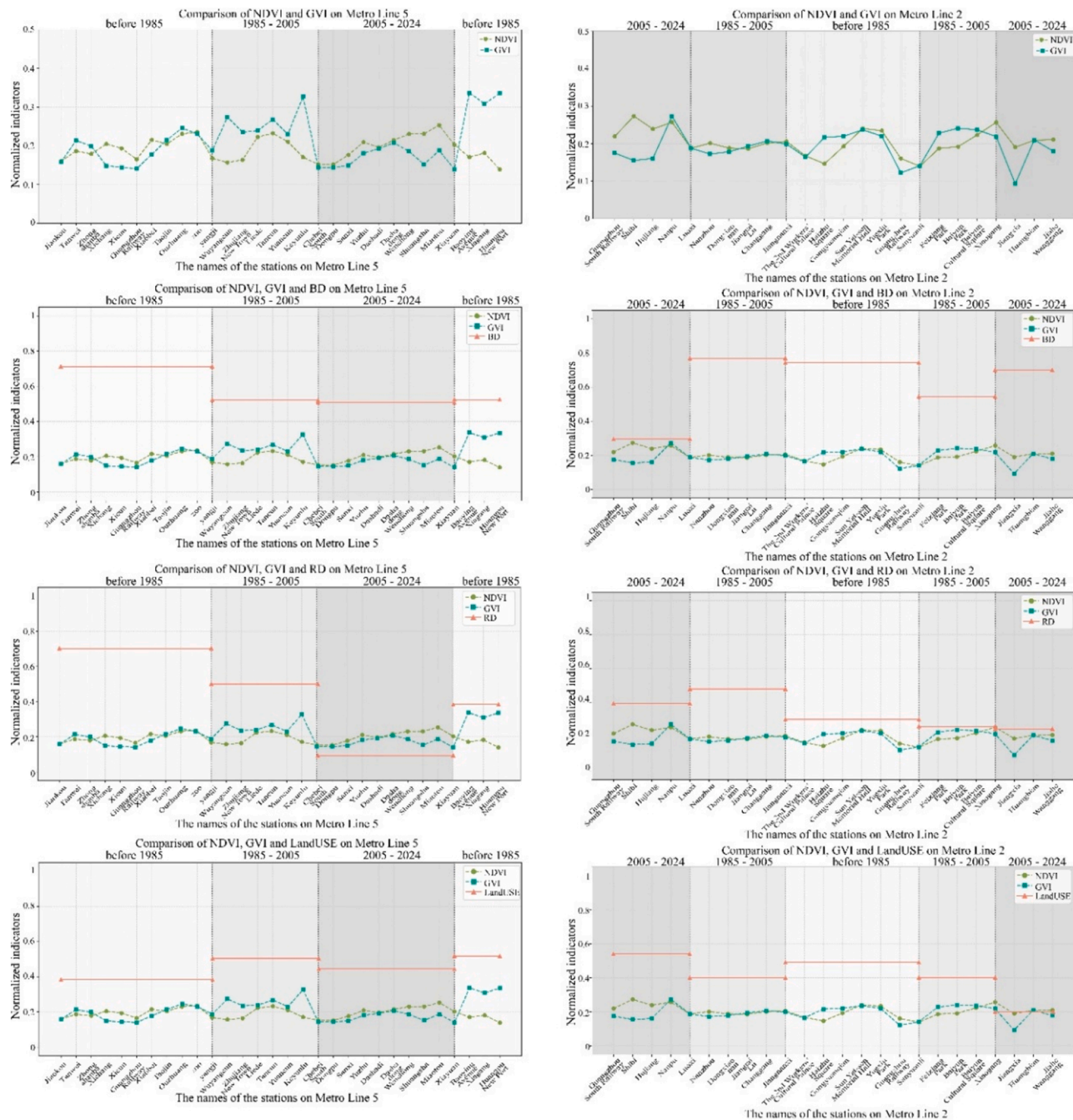


Fig. 8. Comparative changes in NDVI, GVI, and morphological indicators along metro lines 2 and 5 across different expansion periods.

historical core area, the high-density built environment leads to a severe shortage of public green spaces. The above comparative results indicate that the overall trend of UGS indicators around different metro stations is associated with the trend of urban expansion, and there are significant differences in the indices between the stations.

3.3. Analysis of factors influencing UGS

To explore how urban morphology, socioeconomic factors, and topography influence UGS, the study established OLS models with NDVI and GVI as dependent variables, respectively. The variance inflation factor (VIF) values for all variables in the models were below 3, indicating no multicollinearity (Tables 4 and 5).

In Models 1 and 2, the results indicate that among urban morphological indicators, POI density (Model 1: $\beta = -0.066, p = 0.008$; Model

Table 4
Estimation results of the global OLS Models-1 (Y = GVI).

Models-1 (GVI)	Estimate	Std.Error	Pr(> z)	VIF
(Intercept)	−0.131	0.039	0.001***	
BD	−0.066	0.025	0.008**	2.195
RD	−0.051	0.022	0.020*	1.146
LandUSE	−0.115	0.028	0.000***	2.142
DE	0.139	0.033	0.000***	1.022
HP	0.152	0.021	0.000***	1.047

$R = 0.325, R^2 = 0.106, \text{adj } R^2 = 0.103.$
*** Significant at 0.001 level; **Significant at 0.01 level; *Significant at 0.05 level.

2: $\beta = -0.131, p < 0.001$) and LandUSE (Model 1: $\beta = -0.115, p <$

Table 5

Estimation results of the global OLS Models-2 (Y = NDVI).

Models-2 (NDVI)	Estimate	Std.Error	Pr(> z)	VIF
(Intercept)	-0.125	0.030	0.000***	
BD	-0.131	0.019	0.000***	2.195
RD	-0.014	0.017	0.399	1.146
LandUSE	-0.187	0.021	0.000***	2.142
DE	0.603	0.025	0.000***	1.022
HP	0.033	0.016	0.034*	1.047

R = 0.670, R² = 0.449, adj R² = 0.447.

*** Significant at 0.001 level; **Significant at 0.01 level; *Significant at 0.05 level.

0.001; Model 2: $\beta = -0.187$, $p < 0.001$) exert negative effects on both green space indicators, reflecting the encroachment of green space resources by built-up land development during urban expansion. The effect of RD (Model 2: $\beta = -0.014$, $p = 0.399$) on NDVI was not significant. Housing price and elevation demonstrate significant positive effects on both GVI and NDVI, with housing price having a stronger positive effect on GVI (Model 1: $\beta = 0.152$, $p < 0.001$) and a weaker effect on NDVI (Model 2: $\beta = 0.033$, $p < 0.001$), while elevation has a weaker positive effect on GVI (Model 1: $\beta = 0.139$, $p < 0.001$) and a stronger effect on NDVI (Model 2: $\beta = 0.603$, $p < 0.001$).

In summary, through the spatial association analysis between UGS and urban morphology across different periods of urban expansion, this study finds that UGS and urban morphology exhibit a significant negative spatial correlation. Urban morphology tends to weaken and encroach upon UGS during the process of urban expansion, further exacerbating green space fragmentation in urban expansion areas.

4. Discussion

4.1. Spatial differences in urban green space metrics

This study has identified significant spatial differences in the measurement of UGS using NDVI and GVI. Specifically, lower NDVI does not necessarily correlate with lower GVI, particularly in historical urban cores. In these areas, early-stage urban development lacked systematic planning, resulting in limited green spaces. The urban morphology characterized by high-density buildings and dense road networks constrained large-scale green space construction, prompting urban design efforts to pivot toward creating "pocket parks" and smaller street-level micro-green spaces. Micro-renewal initiatives in historic districts have also focused on local landscape feature design and façade greening updates. These localized greening measures effectively enhance street-level greenery (captured by GVI) without substantially altering aerial-level vegetation coverage (NDVI).

Residential spatial design patterns also influence these indicators. Post-2000 residential development in China has been predominantly gated, typically accompanied by concentrated internal private green space landscapes within communities. Although these internal green spaces significantly elevate NDVI, the presence of access restrictions impedes improvements in street-level GVI, reflecting the segregation between internal community green spaces and public street greenery. Gated community residents, through the payment of property fees, demonstrate a stronger preference for the cultivation and professional maintenance of internal private green space landscapes. Conversely, external public street greenery relies more heavily on government management, where constraints in administrative attention and scope often result in the neglect of street greening quality.

This further enriches existing research on "green gentrification" (Anguelovski et al., 2018). With the implementation of landscape design and green infrastructure projects (such as small-scale decorative elements) within gated communities, internal environmental quality improves, leading to escalated housing and land prices (Chen et al., 2025). The significant positive correlation between UGS indicators and housing

prices in our results further corroborates this phenomenon. This ultimately results in the displacement of low-income residents by middle- and high-income groups, with social networks being reconstituted, representing a spatial redistribution of class. "Green gentrification" further exacerbates the imbalance in urban green space resource distribution, reinforcing the privilege of high-income urban residents in accessing high-quality environments (Cao et al., 2024). A substantial body of scholarly research has substantiated the conclusions regarding green gentrification, such as the significant positive correlation between new green space investment and the displacement of low-income residents, and the accompaniment of greening improvements in peripheral urban communities by soaring housing prices and the replacement of original inhabitants (Pearsall & Eller, 2020). Sustainable greening projects often attract capital through environmental quality enhancements, triggering a gentrification chain of "environmental improvement → rent escalation → vulnerable group outmigration." This reduces the efficacy of urban green space infrastructure construction to a superficial level and undermines the credibility of urban governance.

Historical policy frameworks have significantly shaped these differences. The first comprehensive green space policy in Guangzhou emerged only recently, in 2021, highlighting a prior era of unplanned urban expansion which neglected systematic allocation of UGS, thus leading to the encroachment and loss of larger green areas. Subsequent green space improvements have predominantly been retroactive and focused on micro-scale interventions, exacerbating disparities between aerial remote sensing perspective NDVI and human-centric perspective GVI measurements. The natural conditions of a city also play a significant role in causing differences between the NDVI and GVI indices. Although the northern Baiyun Mountain area is rich in green space resources, its high elevation and complex terrain have led to the fragmentation of the mountain by winding mountain roads, footpaths, and access control systems. The inability of street view collection to access these areas results in a relatively low GVI in the northern section of Line 2.

Moreover, perspective limitations and accessibility constraints affect GVI measurements. Large, inaccessible green spaces or those obscured by infrastructure, such as parks, schools, private gardens, and areas beneath overpasses, contribute to discrepancies between NDVI and GVI. For instance, street-level greenery beneath overpasses is effectively captured by GVI but missed by NDVI due to its two-dimensional top-down perspective. The current comparison of different UGS indicators is limited to NDVI and GVI. In the future, LiDAR and drone imagery will be integrated to construct a three-dimensional green volume index for further analysis. The temporal span of this study is limited by its annual granularity, which is relatively coarse. Subsequent research is anticipated to employ more refined quarterly data on urban expansion and urban green spaces to conduct in-depth causal analyses.

4.2. Spatial variations in urban green space and urban morphology

The findings of this study confirm that early urban expansion weakened and even encroached upon existing UGS resources. The disorderly sprawl of urban suburbs further exacerbated the fragmentation of UGS, consistent with prior research. The dynamic relationship between urban morphology and UGS during different periods of urban expansion in China is strongly correlated with policy and spatial contexts. Following the founding of the People's Republic of China in 1949, extensive urban construction was required to boost the post-war economy. Consequently, natural woodlands, grasslands, and other green spaces at the urban periphery were cleared to make way for large-scale industrial parks. UGS in historical core areas were largely confined to historical conservation zones (e.g., the Shamian Concession area in Guangzhou). It was not until the reform and opening up that UGS construction gradually became an indicator of urban competitiveness, exemplified by Hangzhou's "one core, two belts, multiple points, and multi-level" strategy. However, the current Chinese planning strategy of

"emphasizing the core and neglecting the suburbs" has led to uncontrolled suburban sprawl, worsening green space fragmentation (Li et al., 2019). Although the expansion areas have abundant green space resources, these haven't been reasonably developed and utilized. The exposure to green space in the expansion areas is significantly lower than that in the developed areas, thereby exacerbating green space exposure inequality. This has led to increased difficulty for residents in accessing natural resources and a false sense of green space prosperity (He et al., 2023).

As a paradigmatic city following the TOD model, Guangzhou exhibits a progressively widening divergence between GVI and NDVI as transit stations extend toward peripheral expansion zones. This reflects that while the TOD model promotes compact urban expansion, it may do so at the expense of human-scale street-level green visibility experiences. This finding raises a cautionary note for sustainable urban design: within high-density TOD development frameworks, mandatory street tree canopy coverage standards and three-dimensional greening visibility design guidelines are imperative to mitigate perceived green space deprivation along expansion axes. Furthermore, substantial green spaces in urban peripheral expansion zones remain in a pre-development state. Vigilance is required regarding the "browning" effect that high-intensity land use development under the TOD model may exert on existing green space systems. Although the TOD model has curbed the trend of uncontrolled urban sprawl, it often neglects the value of suburban green spaces. Existing research indicates that rail transit not only enhances land use development intensity in suburban areas but also induces transformations in land use functions and characteristics. Such transformations typically occur at the cost of green space fragmentation, undermining the positive benefits that natural environments confer upon cities. GVI distribution in the historical urban core exceeds that of NDVI. This discrepancy stems from the early local government's expansion logic driven by "land finance," which prioritized the provision of sellable land over public green spaces (Tong et al., 2023). Consequently, improvements in local micro-scale green spaces often lag behind the loss of macro-scale green spaces. Such ex post remedial approaches typically prove insufficient for meaningful green space enhancement.

The constraints imposed by natural conditions further amplify the spatial disparities between urban morphology and UGS under urban expansion (Li et al., 2018). Taking Line 2 as an example, the northern Baiyun Mountain and the southern wetlands provide a high "NDVI" foundation for UGS. However, these natural features also restrict the availability of construction land resources. Urban development inevitably focuses on the construction of various built environment infrastructures. For instance, the high-intensity TOD around major overpasses and transportation hubs (such as Guangzhou South Railway Station) operates through three mechanisms: "obstruction, fragmentation, and edge adherence (Park et al., 2020)." These mechanisms break the continuous UGS space into isolated islands and lack localized greening efforts. Ultimately, this results in a dislocation between different green space areas. Based on extant research, this research underscores the necessity of adopting comprehensive, multi-perspective evaluation frameworks when assessing UGS to avoid biases that could misinform urban planning decisions. Over-reliance on single metrics may lead planners to underestimate or overlook important spatial dynamics and accessibility considerations. However, this study's exclusive focus on Metro Lines 2 and 5 cannot fully capture the spatial disparities of green spaces in other clustered areas beyond Guangzhou's cruciform expansion pattern (e.g., the Nansha sub-center). Urban expansion constitutes a multi-dimensional and complex process, which may lead to insufficient understanding of UGS and urban development models in such regions. Future research needs to be extended to other cities and regions, as not all urban expansion patterns follow a cruciform trajectory. Whether similar conclusions can be drawn under polycentric clustered or peripheral expansion modes remains to be further validated.

4.3. Policy implications

Urban policy and planning should adhere to the framework of "UGS (multi-perspective representation) — Morphology (built environment) — Spatiotemporal Context (urban expansion boundaries)" to strategically respond to different historical and spatial contexts. In historical urban cores, prioritizing micro-scale interventions such as pocket parks and street-level greenery enhancement can effectively address limited space constraints. Particular attention should be given to the greening transformation of micro-spaces perceived by individuals, such as building setbacks, irregular parcels of land, and spaces under bridges, to ensure that residents can directly benefit from green space entitlements. Additionally, urban renewal strategies could be integrated to implement "demolition for greening" measures in areas such as urban villages, thereby further transforming UGS (Zhou et al., 2024). In development zones, continued investment in integrated green space planning can further optimize balance between urban morphology and green coverage. Emphasis should be placed on the maintenance of existing UGS, enhancement of the quality of street-level micro-green spaces, and the opening up of some gated communities to facilitate accessibility for residents and reduce existing green space exposure inequality (Wu et al., 2020). For contemporary urban expansion areas, policy interventions should aim at reducing fragmentation and enhancing the connectivity and accessibility of green spaces. Based on marginal rivers, forest belts, and road networks, high-quality suburban green parks should be created through the reconstruction of ecological networks, with rational utilization of every piece of construction land.

When formulating subsequent "Green Space System Plans or Regulations," governments should mandate a ratio between floor area ratio and UGS provision, stipulating that higher floor area ratios must be accompanied by higher UGS proportions. During suburban development, the proportion of UGS land should be guaranteed to achieve regional ecological balance. Furthermore, a "renewal + green space" public-private partnership model for urban renewal and ecological restoration should be established: for instance, government-led collaborations with real estate developers and landscape enterprises to implement participatory green space maintenance in UGS-deficient areas—developers construct station parks in exchange for government incentives, professional landscape companies assume subsequent maintenance responsibilities, and government subsidies support greening maintenance costs in older communities and public spaces, thereby preventing UGS degradation due to insufficient maintenance funding. It should be noted that the policy recommendations in this study are primarily targeted suggestions for UGS improvement based on the results. More specific policies should be grounded in causal inference methods to explore the causal mechanisms of specific land policies on UGS land use changes. Furthermore, this study focuses exclusively on Guangzhou, China, and the conclusions drawn require further validation in cold and arid cities in northern China. The discussion of research findings is primarily based on China's development context, and whether similar results can be obtained in foreign cities remains to be verified.

5. Conclusion

By integrating aerial remote sensing (NDVI) with human-centric street-level metrics (GVI), this study constructs a multi-perspective analytical framework that deepens the understanding of the dynamic relationship between UGS and urban morphology under the context of urban expansion. The study reveals that the disparities between NDVI and GVI indicators are primarily manifested in land development, urban design, land policy, topographic constraints, data acquisition perspectives, and accessibility. Under the high-intensity development model dominated by TOD, increases in urban morphological indicators typically lead to reduced green space availability and intensified green space fragmentation. The historical urban core, characterized by dense built

environments and lack of planning, exhibits green space scarcity, posing challenges to sustainability. In contrast, planned expansion areas achieve a more balanced integration of urban morphological and greening, highlighting the importance of deliberate planning. The fragmentation of green spaces in recently developed areas results in spatial discrepancies between NDVI and GVI metrics, weakening the ecological functions of green spaces and underscoring the necessity for comprehensive spatial policies. This paper emphasizes the need for targeted interventions tailored to different urban contexts, such as enhancing micro-scale green spaces in historical cores, maintaining integrated greening in development areas, and addressing fragmentation in contemporary expansion areas through frameworks like urban growth boundaries and land use quotas. Overall, multi-perspective urban greening assessments are crucial for shaping sustainable urban growth and provide valuable insights for urban planners and policymakers.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Qiming Liu: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shaoqing Dai:** Writing – review & editing, Supervision, Methodology. **Guosheng Yang:** Writing – review & editing, Visualization. **Cai Wu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

None.

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Data availability

Data will be made available on request.

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