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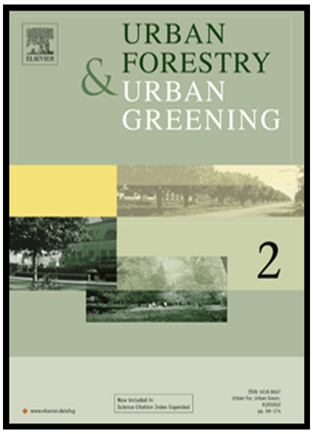

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PII: S1618-8667(24)00016-5

DOI: https://doi.org/10.1016/j.ufug.2024.128219

Reference: UFUG128219

To appear in: *Urban Forestry & Urban Greening*

Received date: 17 July 2023
Revised date: 30 November 2023
Accepted date: 17 January 2024

Please cite this article as: Weiyan Zhang and Hui Zeng, Spatial differentiation characteristics and influencing factors of the green view index in urban areas based on street view images: A case study of Futian District, Shenzhen, China, *Urban Forestry & Urban Greening,* (2024) doi:https://doi.org/10.1016/j.ufug.2024.128219

Spatial differentiation characteristics and influencing factors of the green view index in urban areas based on street view images: A case study of Futian District, Shenzhen, China

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Acknowledgements:

This research was funded by the Shenzhen Fundamental Research Program (No. GXWD20201231165807007-20200812142216001), to which we are very grateful.

Declaration of interests:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abstract: Urban green space provides a variety of benefits, and the green view index (GVI) is regarded as an effective indicator to evaluate the quality of green spaces from a human perspective. To investigate the drivers of the spatial differentiation in GVI in urban areas, the GVI was calculated based on Baidu street view images and semantic segmentation in Futian District, Shenzhen, and its spatial variation characteristics were explored. The dominant influencing factors of GVI were analyzed and screened by applying the Pearson correlation coefficient and optimal parameters-based geographical detector (OPGD). The results showed that the overall GVI was high in the study area, with an average value of approximately 28%. The scale effect of GVI was not obvious, but the spatial heterogeneity was distinct, and the hot spots and cold spots of GVI had an evident clustered distribution. The spatial variation of GVI was influenced by the vegetation cover, landscape pattern, built environment and socioeconomic factors. The normalized difference vegetation index (NDVI) was the most dominant factor affecting the spatial differentiation of GVI, followed by land cover, fractal dimension index, patch area, building density and proximity. Furthermore, the interaction of the influencing factors had a higher degree of explanation than a single factor. In highly urbanized areas, exploring the factors affecting the spatial differentiation of GVI can provide a basis for optimizing the layout and structure of green spaces, contributing to a better perception and quality of urban greening.

Keywords: green view index; influencing factors; landscape pattern; street view image; urban area; optimal parameters-based geographical detector.

1. Introduction

Global urbanization is the megatrend of the 21st century, with the global urban population predicted to increase from 56% in 2021 to 68% by 2050 (UN-Habitat, 2022). In densely populated urban areas, there is a growing interest in improving the quality of the living environment (Li et al., 2021a). Urban green spaces are an essential part of the urban environment and supply multiple ecosystem services, such as sequestrating carbon and releasing oxygen (Saleh et al., 2022; Wang et al., 2021), absorbing air pollutants (Diener and Mudu, 2021; Zhao et al., 2021), reducing noise (Nourmohammadi et al., 2021), regulating climate (Muluneh and Worku, 2022; Richards et al., 2017) and increasing urban biodiversity (Muluneh and Worku, 2022). Urban street greenery is a form of greenery to which urban dwellers are exposed daily, it plays a crucial role in the visual landscape perception (Ma et al., 2021), public health (Labib et al., 2020) and well-being of urban residents

(Du et al., 2021).

In urban areas with tight land use, the expansion of green space is limited and enhancing the quality of urban greening to meet the demands of residents is an issue worth exploring. As a physical measurement reflecting the level of urban greening from a human perspective, the green view index (GVI) means the percentage of green vegetation in the view of people (Aoki, 1987). GVI was incorporated into the Japanese "Landscape Green Three Method" in 2004 and became one of the regular indicators of the green landscape evaluation system (Xiao et al., 2018). Compared to traditional evaluation indicators of urban green spaces, such as greening rate and normalized difference vegetation index (NDVI) (Martinez and Labib, 2023), GVI shifts from being based on satellite remote sensing images to street view images and from a bird's eye view to a human perspective. GVI can estimate the three-dimensional green volume and the human perception of green space, expanding the scope of evaluation of green space from two-dimensional to three-dimensional (Liu et al., 2021). Conventional methods of calculating GVI are often time-consuming and inconvenient through on-site photographs and manual extraction (Falfán et al., 2018; Yang et al., 2009). In recent years, the advent of street view images and machine learning methods has provided a convenient basis for large-scale and quantitative GVI studies. Quite a few scholars have combined street view images (Google, Baidu, Tencent) with semantic segmentation methods (Aikoh et al., 2023; Li et al., 2015b; Xia et al., 2021), and they have compared GVI with other greening evaluation metrics, such as NDVI, green cover (GC), and vegetation structural diversity (VSD), to analyze their correlations and differences (Chen et al., 2019; Falfán et al., 2018; Labib, 2021; Li et al., 2021a; Li et al., 2021b). Research has confirmed that different indicators can capture different aspects of urban greening (Falfán et al., 2018; Helbich et al., 2021), and GVI based on street view images can offer more fine-grained visual perception data for green space research.

As a beneficial tool to quantify visible greenery at the eye level, GVI is not equally distributed (Li et al., 2015a; Li et al., 2021b; Wang et al., 2022). A higher GVI has a positive effect on the urban thermal environment (Zhou et al., 2021; Zhou et al., 2023) and is helpful for physical and mental health (Huang et al., 2022; Helbich et al., 2019; Zhang et al., 2021). GVI is closely related to various factors, including the surrounding environment (Hao and Long, 2017; Wang et al., 2022; Zhu et al., 2022b), sociodemographic and economic levels (Chen et al., 2020; Pham et al., 2017), and building layout and density (Chen et al., 2020; Xiao, 2021). Existing studies have mainly focused on specific physical and biological features, such as the class, width, and slope of roads (Hao and Long, 2017; Wang et al., 2022; Wu et al., 2009) and the type, quantity, size, morphology, seasonal variation, and disposal of plants (Li et al., 2021; Wang et al., 2022; Yang et al., 2009; Zhu et al., 2022a; Zhu et al., 2022b). However, there is a lack of research on the interactions of multifarious influencing factors, and the identification of dominant driving factors needs further study. In addition, the influence of landscape patterns has received little attention, and there is evidence that urban thermal environments and ecosystem services are influenced by the landscape patterns of green spaces (Guo et al., 2021; Liu and Russo, 2021). Are there links between landscape patterns and GVI? Which factors play the dominant role among the various influences? How can we enhance the visibility of greenery in the future?

To answer the above questions, the objectives of this study are as follows: 1) Characterize the spatial differentiation of the GVI and landscape patterns. Taking the Futian District of Shenzhen as an example, we calculated the GVI based on Baidu street view images and semantic segmentation. 2) Explore the potential influencing factors in the spatial differentiation of GVI. We thoroughly discussed the vegetation cover, landscape pattern, built environment, and socio-economic variables simultaneously. This comprehensive approach contributed to analyzing the complex drivers of GVI. And we considered the landscape pattern factors, which would deepen our understanding of how the spatial differentiation of GVI is influenced by the attributes and distribution of green space patches. 3) Identify the key factors, quantify the relative contributions, and analyze their interactions. We adopted the Optimal Parameters-based Geographical Detector (OPGD), an innovative analytical tool that elucidates the driving forces behind the spatial divergence of the GVI. Additionally, the OPGD model can reveal the intricate relationships between influences, providing valuable insights for urban planners and managers. In urban areas with high building density, concentrated population and tight land use, the expansion of green space is limited. To improve greenery quality, it is crucial to advance the spatial configuration of green space by identifying the influencing factors of GVI. Our research could provide a new perspective for exploring the spatial variation drivers of GVI and a scientific basis for the planning and management of urban green space.

2. Materials and methods

2.1. Study area

As one of China's special economic zones, Shenzhen is a sub-provincial city in Guangdong Province. Futian District is situated in the south-central part of Shenzhen (22°30'-22°36'N, 113°59'-114°06'E), covering an area of approximately 78.66 km^2 (Fig. 1). Futian District is in the subtropical maritime climate zone with a mild climate and abundant sunshine. The average annual temperature in Futian District is 24 °C with an average annual rainfall of about 1950 mm. As of August 2022, the permanent population of the district was approximately 1.56 million; the regional GDP in 2021 reached RMB 531.819 billion. The district has a forest coverage rate of 35%, a per capita park green area of 21.66 m^2 and a greening coverage rate of 43%. Futian is the central urban area of Shenzhen, which is constrained by its spatial area and is one of the typical areas of rapid three-dimensional urbanization (Fu et al., 2019), making it suitable for spatial green view index research.

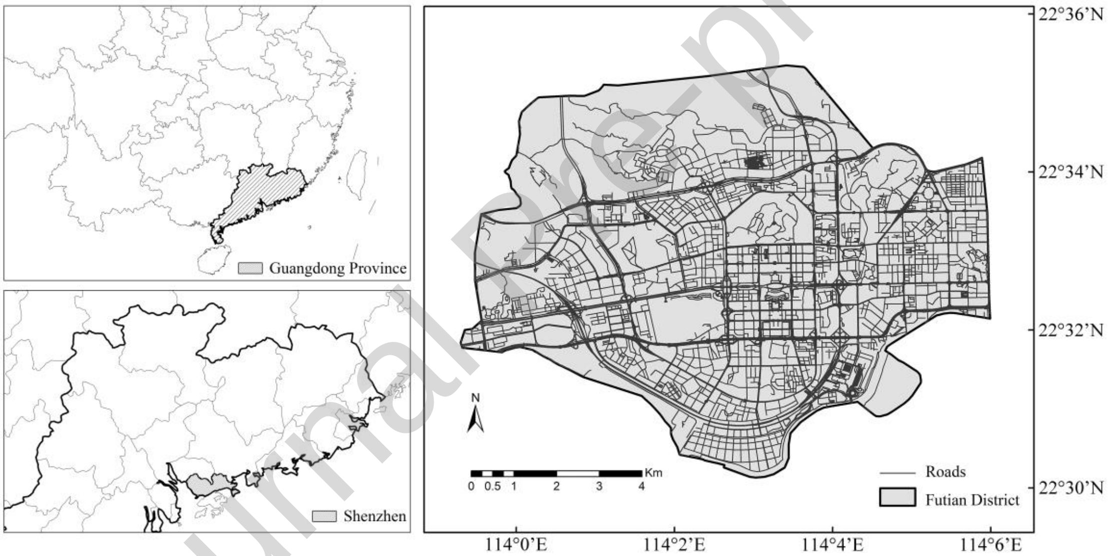

Fig. 1. The location of study area (not including Nei Lingding Island).

2.2. Data source

In this study, multisource data were used, including the following: (1) Urban road network data were downloaded from the OpenStreetMap platform; (2) Street view images were from the Baidu Street View Map, obtained by batch crawling through the Python program; (3) Urban green space cover data were from the European Space Agency 2020 global land cover data with the spatial resolution of 10 m; (4) NDVI was calculated from 2020 Sentinel-2 satellite images from the Google Earth Engine platform with a spatial resolution of 10 m; (5) Park and residential POI data were obtained from Amap; (6) Housing price and housing age data were from the Anjuke real estate website; and (7) Population density data were obtained from the WorldPop platform with a spatial resolution of 100 m.

2.3. Methods

We chose GVI as the primary indicator to quantify the urban greening level from the vertical scale in this study. The GVI was calculated using Baidu street view images and semantic segmentation, and its spatial distribution characteristics in Futian District were evaluated by hotspot analysis. The landscape pattern characteristics of green space were analyzed through the landscape indices. The effects of vegetation cover factors, landscape pattern factors, built environment factors and socioeconomic factors on the spatial differentiation of GVI were also discussed. Furthermore, the dominant influencing factors of GVI were explored through the Pearson correlation coefficient and optimal parameters-based geographical detector. Fig. 2 shows the framework of the study.

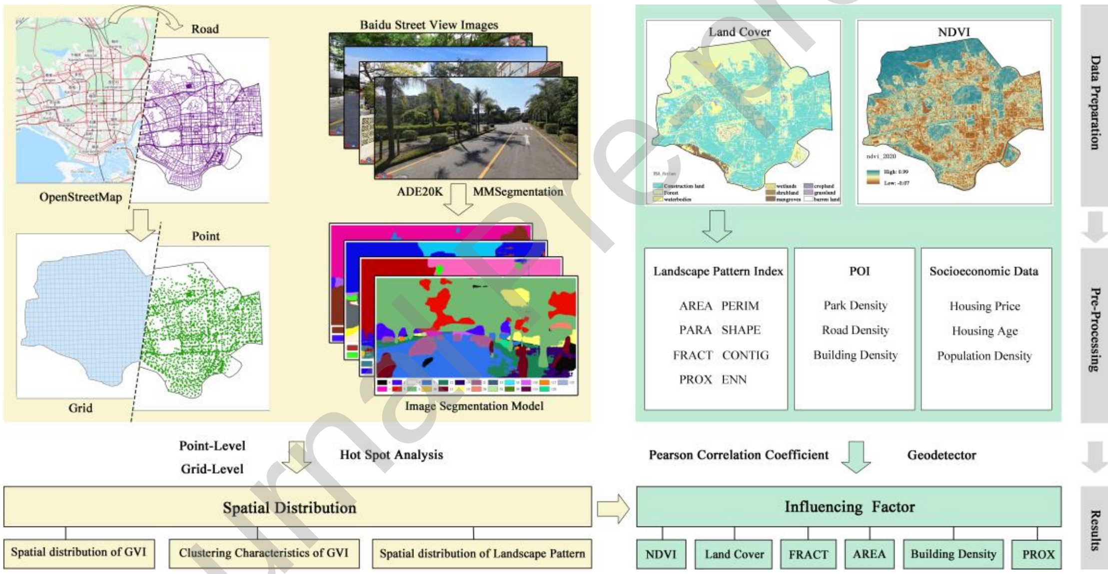

Fig. 2. Research Framework.

2.3.1. GVI calculation

(1) Identify sample points and grids

The OSM road network data were topologically corrected and then used to generate sample points every 300 m along the road using the constructed point tool, generating a total of 3373 sample points and calculating their latitude and longitude as parameters for collecting street view data. To enable direct comparison between the GVI and the landscape pattern index, the two were matched using the grid method (Xiao, 2021), with a grid scale of 300 m × 300 m (Chen et al., 2020). We used the average of all sample points in a grid to represent the indicators of the grid.

(2) Crawling and semantic segmentation of street view images

In total, 13,124 Baidu street view images of Futian District were captured from 3281 sample points by the Python program. The size of the street view images was 1024 × 512 pixels, the vertical angle was set to 0 degrees, and for each sample point, the images were acquired in four directions (heading= 0, 90, 180, 270): front, back, left and right (Fig. S1).

We used the ADE20K dataset and MMSegmentation semantic segmentation to automatically extract the green elements in the street view images. The ADE20K dataset is a scene parsing dataset with more than 20,000 images and 150 category annotations, covering outdoor, indoor and natural scenes, which can be applied to scene perception, parsing, segmentation as well as semantic understanding (Zhou et al., 2019). The ADE20K dataset was released by the MIT CSAIL research group in 2017, with abundant scenes and high recognition accuracy. We calculated trees, grass and shrubs together as green pixels, and the segmentation results are shown in Fig. S2.

(3) Calculation of GVI

After the above processing, we calculated the GVI of each sample point according to the following formula (Dong et al., 2018):

$$GVI = \frac{Area_g}{Area_t} = \frac{\sum_{i=1}^{4} Area_{g\_i}}{\sum_{i=1}^{4} Area_{t\_i}} \times 100\% \tag{1}$$

where $Area_{g\_i}$ is the total number of green vegetation pixels in direction i in the street view image. $Area_{t\_i}$ represents the total number of pixels in direction i in that image. The grid GVI was represented by the average of the GVI of all points in the grid.

2.3.2. Landscape pattern analysis of urban green spaces

Forest, shrubland, grassland and mangroves were extracted from the ESA land cover data as urban green space in Futian District, and cropland, construction land, barren land, waterbodies and wetlands were non-green space.

Landscape indices are widely used to measure urban green space patterns. They are quantitative indicators that indicate the spatial configuration and structural composition of the landscape pattern (Chen et al., 2002). In this study, the patch area (AREA), perimeter area ratio (PARA), patch perimeter (PERIM), fractal dimension index (FRACT), shape index (SHAPE), contiguity index (CONTIG), Euclidean nearest neighbor distance (ENN) and proximity (PROX) indices were selected to analyze the spatial characteristics of green space patches in terms of area, shape, boundary, location and connectivity. The calculation formulas and descriptions of these landscape indices are shown in Table S1. We calculated these landscape pattern indices to analyze the spatial pattern of urban green space based on Fragstats 4.2.1.

2.3.3. Pearson correlation coefficient

As a linear correlation coefficient, the Pearson correlation coefficient is suitable for reflecting the linear correlation statistics of two variables (Li et al., 2021b). This study was based on SPSS 26 to calculate Pearson's correlation coefficient between the GVI and landscape pattern index and between all influencing factors to analyze the correlation between factors and to eliminate multicollinearity.

2.3.4. Optimal Parameters-based Geographical Detector (OPGD)

Geodetectors are a set of statistical approaches for detecting spatial heterogeneity and identifying the driving factors, which are able to detect the geospatial variation of variables and recognize the key influencing factors and interactions between them (Wang et al., 2017). Traditional geographical detectors suffer from subjectivity and inadequate discretization, requiring manual adjustments for the discretization of continuous variables. Hence, we chose the OPGD model in this research, which is an innovative analytical tool that surpasses conventional discretization methods (Song et al., 2020). In recent years, the OPGD model has been effectively applied to the research on spatial heterogeneity. This method can quantify the relative contributions of individual factors, identify dominant drivers, and reveal complex relationships among factors (Gao et al., 2023; He et al., 2023; Wang et al., 2023). The analysis of the factor detector and interaction detector was implemented based on the GD package in R. For each factor, the GD package can automatically determine the optimal discretization method and the number of discretizations, using the most influential among equal breaks, natural breaks, quantile breaks, geometric breaks and standard deviation breaks. In this research, we chose the most influential of 5-7 discretized divisions as the number of discretizations.

3. Results

3.1. Spatial differentiation of GVI and landscape patterns

The GVI statistics at the sample point and grid level in Futian District are shown in Table 1, with average GVI values of 27.81% ± 15.33% and 28.60% ± 11.96%, respectively. The GVI values were classified into five levels: extremely high, high, medium, low and very low, according to Orihara's five levels of evaluation: over 35% is good greening, 25% to 35% is more greening, 15%

Corrrect Citations for Geodetector q:
[1] Wang JF, Li XH, Christakos G, Liao YL, Zhang T, Gu X & Zheng XY. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. International Journal of Geographical Information Science 24(1): 107-127.
[2] Wang JF, Zhang TL, Fu BJ. 2016. A measure of spatial stratified heterogeneity. Ecological Indicators 67: 250-256.

to 25% is some greening, 5% to 15% is poor perception and less than 5% is very poor perception of greenness (Orihara, 2006). The proportion of GVI values greater than 35% gradually decreased at different levels, with the overall level performing consistently.

For the spatial distribution of GVI, the differentiation characteristics at the point level and grid level were similar, the scale effect was not obvious, but the spatial variation was significant, and the overall trend was higher in the central and western parts while lower in the east. Hot spots and cold spots with statistical significance were identified by ArcGIS hotspot analysis and were prominently distributed in clusters. The hot spots at the point level accounted for 26.36% and 14.07% at the grid level, which were mainly distributed in the north-central part of Futian District and were located around the city park. The cold spots at the point level accounted for 25.62% and 16.22% at the grid level, which were more extended and mainly distributed in the south-central part and were located around the city government and the commercial center (Fig. 3 a-d). Statistical descriptions for hotspot analysis are displayed in Table S2, and typical areas are shown in Fig. S3.

The landscape pattern index of green space patches in the study area calculated based on Fragstats is displayed in Table S3. The maximum value of FRACT was only 1.34, indicating that the overall shape of green space patches was relatively regular and the complexity was not high; the maximum value of CONTIG was close to 1, and the mean value was 0.61, which indicated that the spatial connectivity of green space patches was good. The spatial differentiation of the landscape pattern index was significant, with a skewed distribution pattern of the AREA, PERIM and PROX, which had high values in the northwest and low values in the southeast; a transitional distribution pattern of the SHAPE and ENN, which gradually varied from northwest to southeast; and a uniform distribution pattern of the PARA, FRACT and CONTIG (Fig. 3 e-l).

Table 1 The statistics of GVI.

Level	Number	Max. (%)	Min. (%)	Mean (%)	Std. (%)	Green View Index (%)				
						<5.0	5.0 - 15.0	15.0 - 25.0	25.0 - 35.0	>35.0
Point level	3281	77.51	0.001	27.81	15.33	7.89	14.86	20.45	24.21	32.59
Grid level	604	70.66	0.07	28.60	11.96	2.48	11.60	23.01	33.28	29.63

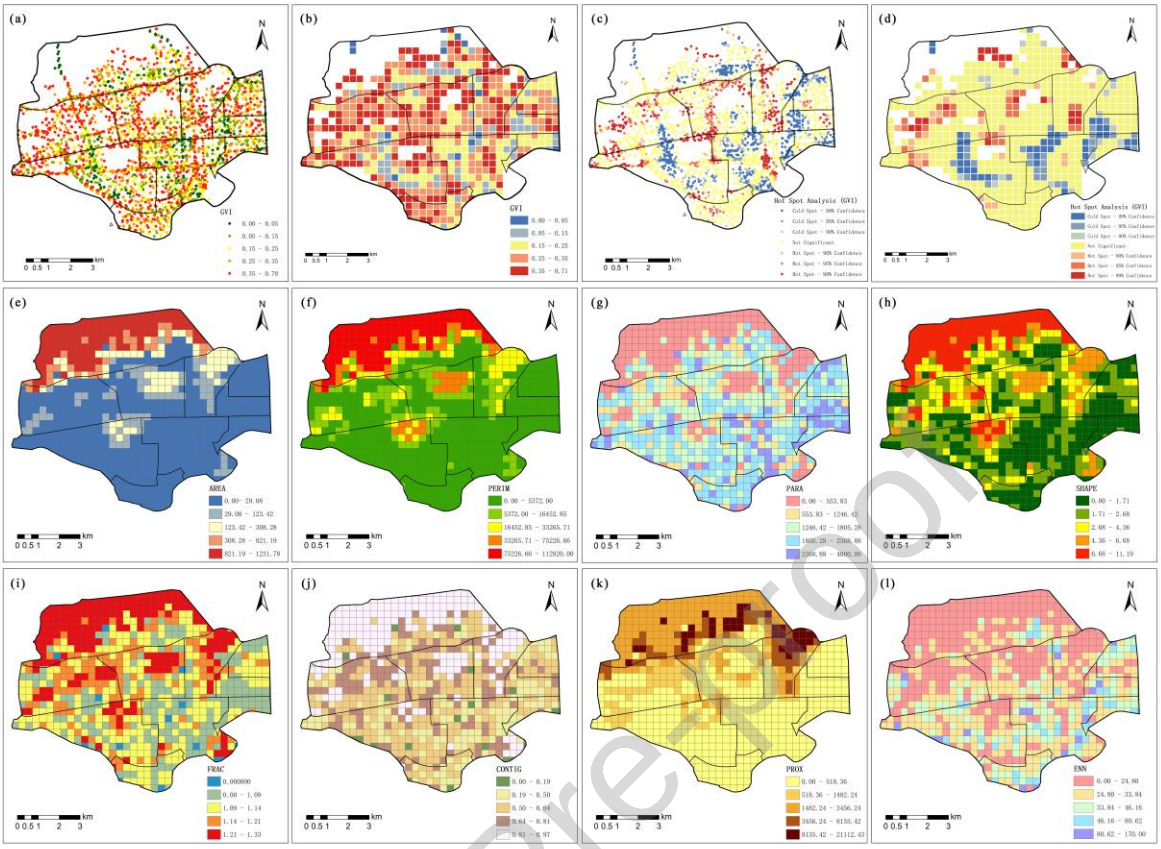

Fig. 3. Spatial distribution of GVI and landscape pattern: (a) GVI of all sample points; (b) GVI of all grids; (c) hot pot analysis result of sample point level; (d) hot pot analysis result of grid level; （e）AREA;（f）PERIM;（g）PARA;（h）SHAPE;（i）FRACT;（g）CONTIG;（k）PROX;（l）ENN.

3.2. Analysis of categorized influencing factors

To investigate the driving factors of GVI spatial differentiation in Futian District, the distribution features of GVI at the sample point level were analyzed in terms of four factors: built environment factors, socioeconomic factors, vegetation cover factors and landscape pattern factors.

(1) Vegetation cover factors

NDVI was applied to represent the vegetation cover, and the results showed an obvious positive correlation between the NDVI and GVI (Fig. 4e).

(2) Landscape pattern factors

The GVI at the grid level was matched to the greenspace landscape pattern index, and the correlation between them was expressed by the Pearson correlation coefficient. Our results indicated that GVI had an obvious positive correlation with green space patch AREA and less significant positive correlations with PERIM, SHAPE, FRAC and CONTIG, while GVI had slightly negative correlations with PARA and ENN (Table 2).

Table 2 Pearson correlation coefficient between GVI and landscape pattern index

		GVI			GVI
AREA	Correlation coefficient	0.526**	FRAC	Correlation coefficient	0.451**
	p-value	0.000		p-value	0.001
PERIM	Correlation coefficient	0.465**	CONTIG	Correlation coefficient	0.359*
	p-value	0.001		p-value	0.010
PARA	Correlation coefficient	-0.315*	PROX	Correlation coefficient	0.406**
	p-value	0.026		p-value	0.003
SHAPE	Correlation coefficient	0.442**	ENN	Correlation coefficient	-0.280*
	p-value	0.001		p-value	0.049

** Correlation is significant at the 0.01 level (two-tailed).

(3) Built Environment Factors

The GVI varied significantly with different land cover types: forest, mangrove and grassland had the highest GVI values, followed by bare land and cropland, and construction land had the lowest GVI values (Fig. 4a). Park density (Fig. 4c) and road density (Fig. 4d) indicated a weak positive correlation with GVI; however, building density (Fig. 4b) showed a more significant negative correlation with GVI.

(4) Socioeconomic factors

Domestic housing prices can indirectly reflect the income level of residents and have been widely used as a socioeconomic variable to measure urban greening drivers (Wang et al., 2015; Zhu et al., 2019), so housing price and housing age were selected as two of the influencing factors. The results indicated that there is a favorable correlation between housing prices and GVI (Fig. 4f); the GVI value was highest within 13 years of housing age, but there was no significant trend in the GVI value with increasing housing age (Fig. 4g). Population density had no notable effect on GVI (Fig. 4h).

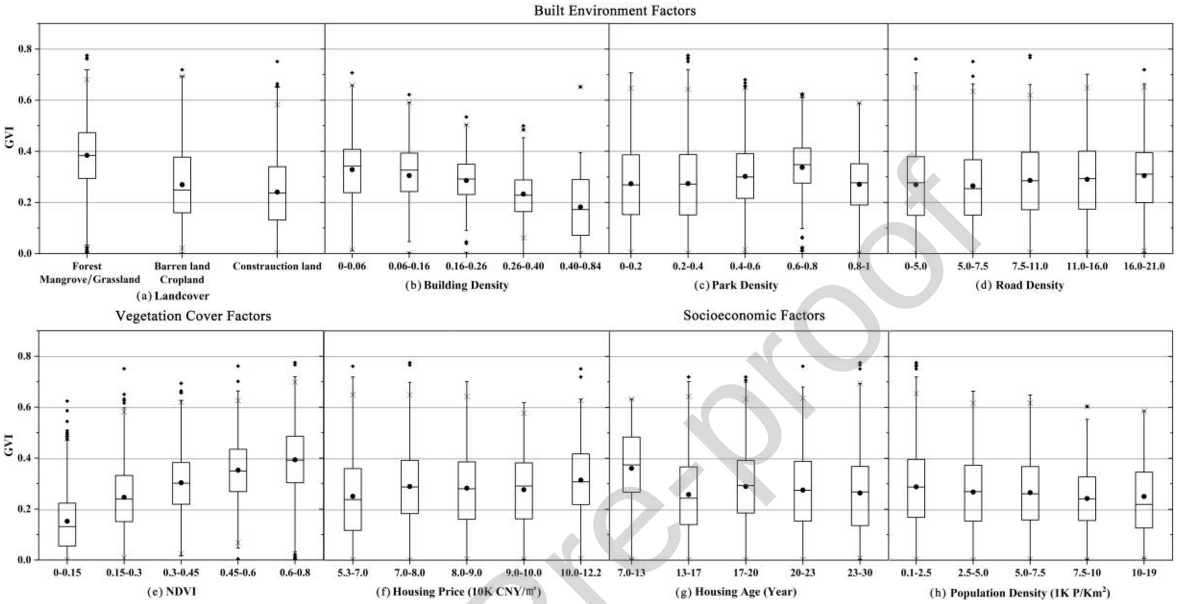

Fig. 4. The influencing factors of GVI: (a) land cover; (b) building density; (c) park density; (d) road density; (e) NDVI; (f) housing prices; (g) housing age; (h) population density.

3.3. Screening and ranking of dominant influencing factors

3.3.1. Correlation analysis of all influencing factors

Correlations between all influencing factors were analyzed using Pearson correlation coefficients to eliminate multicollinearity between the data and to make a dominant factor screening. The results suggested that there was a high correlation between landscape pattern indices, building density and housing age (Fig. 5). Therefore, AREA, FRACT and PROX, as well as land cover, NDVI, building density, road density, park density and housing price, were selected as the nine key influencing factors.

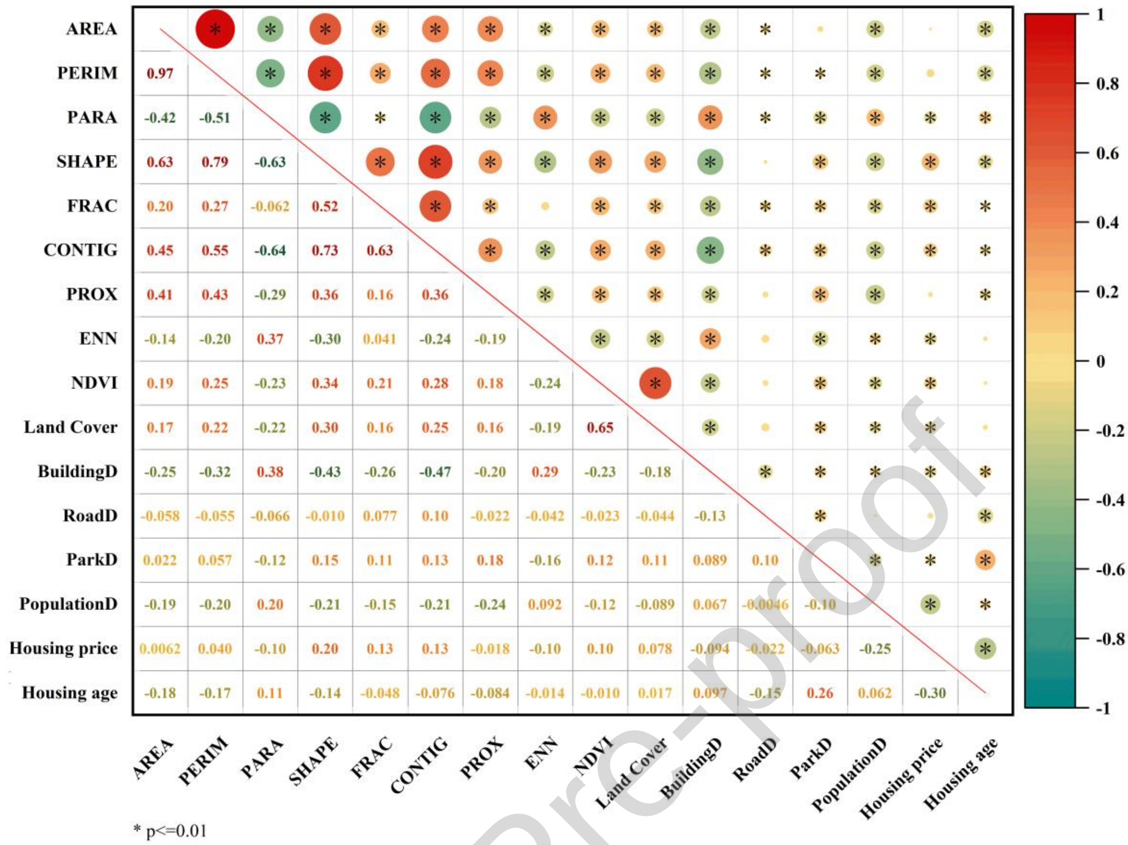

Fig. 5. Correlation matrix of influencing factors.

3.3.2. Dominant influencing factors

Geodetector analysis was performed using the discretization and classification method with the highest Q value (Fig. S4, Fig. S5). According to the results of the factor detection, NDVI had the highest Q value and the greatest degree of explanation, revealing that NDVI was the most dominant factor in determining the spatial differentiation of GVI among the nine factors. Next, land cover, FRACT, AREA, building density, and PROX were also the main influencing factors. Park density, house prices and road density were the least important in comparison (Fig. 6a).

The interaction detection showed that the interaction between the factors mainly presented binary enhancement and nonlinear enhancement, the interaction of any two factors on the spatial variation of GVI was greater than that of one factor alone, and the degree of explanation was enhanced by the interaction of the influencing factors (Fig. 6b). This reflected the complexity of the spatial variation in the green eyesight rate in relation to various influencing factors.

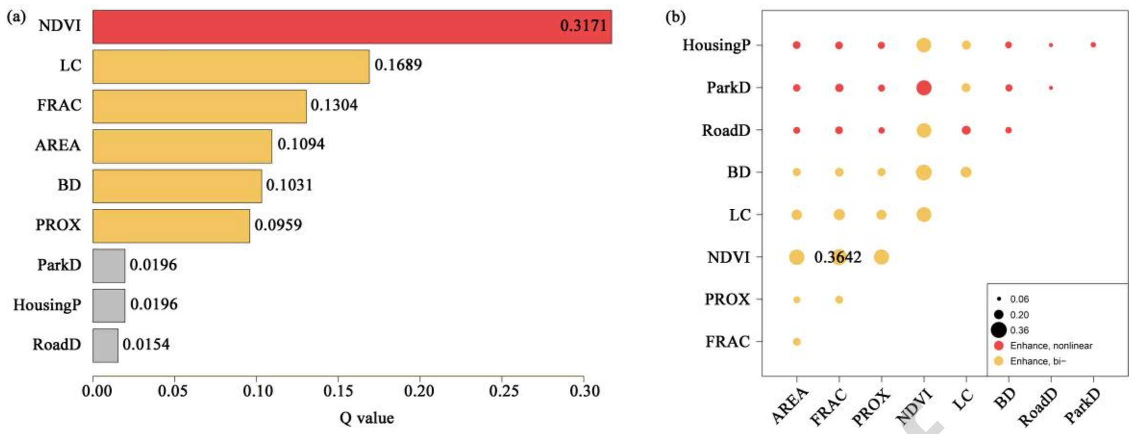

Fig. 6. Detection and interactions of influencing factors: (a) Factor detection; (b) Interaction detection

4. Discussion

In Futian District, the general greening was in good condition, with average GVI values ranging from 27% to 29% at different levels (Table 1). It was well above the global average of 19% (Cui et al., 2018) and slightly higher than some developed countries and regions, such as Hartford, Connecticut, USA (22.8%) (Li et al., 2015a) and Singapore (21%) (Ye et al., 2019). However, our results were below the GVI average of 35%, which is considered to be the threshold of superior greening (Orihara, 2006), so there is still room for improvement. The spatial variation in GVI in Futian was significant (Fig. 3a-d). The high value hotspots were mainly located around large green spaces such as parks, while low value clusters were mainly concentrated around the city center and commercial centers, where the green spaces were small and fragmented.

GVI is influenced by multifarious factors. Subjective factors include viewer behavior (Ki et al., 2021; Wu et al., 2009) and photographic parameters (Meng et al., 2020). Objective factors include the spatial layout and morphological structural features of green spaces (Li et al., 2021a; Wang et al., 2022; Yang et al., 2009; Zhu et al., 2022a), street attribution (Chen et al., 2019; Dong et al., 2018; Hao and Long, 2017; Wang et al., 2022; Wu et al., 2009), characteristics of the surrounding environment (land use, functional zones, building density and street enclosure) (Chen et al., 2020; Hao and Long, 2017; Li et al., 2021a; Wang et al., 2022; Xiao, 2021) and socioeconomic properties (Chen et al., 2020; Pham et al., 2017). At larger scales, such as between different cities, GVI is also related to natural environmental factors (temperature, precipitation, soil properties, topography, rivers) (Xiao, 2021). For a highly urbanized area such as Futian District, we found that GVI spatial differentiation was influenced by a combination of vegetation cover, landscape pattern, built environment and socioeconomic factors.

4.1. Influence of vegetation cover factors and landscape pattern factors

It has been demonstrated that GVI is affected by NDVI, and there were also findings that the correlation between NDVI and tree GVI was strong, while the correlation with grass GVI was weak (Yu et al., 2021). Our study showed that the NDVI had a significant positive impact on the heterogeneity of the GVI (Fig. 4e). This result suggested that more greenery could be caught by eyes in areas with better vegetation cover, and the GVI tended to be relatively high. However, the NDVI could only explain 31.7% of the differentiation (Fig. 6a). It also demonstrated that the GVI focused on the vertical section of urban greening, whereas the NDVI hardly reflected the greenery perception at eye level (Helbich et al., 2019). Consequently, GVI could be applied together with other two-dimensional green space indicators to enrich and advance the greening evaluation system (Falfán et al., 2018).

It is worth mentioning that we discovered that GVI was closely related to some landscape pattern features. The GVI had an apparent positive correlation with AREA and a slight positive correlation with PERIM, SHAPE, FRACT and CONTIG (Table 2). Our work indicated that the larger area and perimeter, more complex shape and higher connectivity of green spaces led to a higher GVI. This revealed that large and concentrated green spaces with high continuity result in a high level of GVI. Similarly, Xiao (2020) found the total area (TA) and edge density (ED) were the main factors affecting GVI, and the patch density (PD), landscape shape index (LSI), and landscape division index (DIVISION) showed significant positive correlations, which also implied that green spaces with large areas and complex shapes provide more visual greenery. Therefore, we discovered that there were two types of landscape indices affecting GVI: one representing the scale and shape of green space patches (AREA, PERIM, SHAPE, FRACT), and the other indicating the spatial distribution (CONTIG, ENN, ED). These indices led to the spatial differentiation of GVI by influencing the visibility of green spaces and thus showed a strong correlation with GVI.

Accordingly, in the future management of green space, the landscape pattern index could be given more consideration rather than simply increasing the amount of greenery. We could do much through planning and design, such as protecting green patches with concentrated areas and enriching the boundary as much as possible. To enhance landscape continuity, it would also be advantageous to set up continuous greenways and link adjacent green spaces appropriately. By optimizing the two-dimensional plant configuration, the three-dimensional green volume could also be increased, allowing for more efficient and intensive utilization of green space resources, as well as enhancing the ecological and health benefits (Li et al., 2021a).

4.2. Influence of built environment factors

In urban environments, the distribution of land cover, buildings, parks, roads and other elements can directly affect the amount of greenery that can be captured by eyes. Little attention has been given to the relationship between GVI and land cover types, with only Yang et al. (2009) analyzing the correlation between Green View and the percentages of different land cover types. They found a strong positive correlation between GVI and the cover of trees and shrubs. Similarly, we discovered that the land cover had considerable influence: forest, mangroves and grassland had the highest GVI values, while construction land had the lowest (Fig. 4a). It means that the land with better vegetation cover had higher green visibility, while built-up areas had a negative effect on GVI through the modification of vegetation cover. It also reflected the adverse effect of urbanization on vegetation cover in general. However, as the level of urbanization continues to progress, the negative impact may gradually diminish or even disappear, which is related to the increasing emphasis on the construction of urban green spaces (Du et al., 2019; Wang et al., 2017; Zhou et al., 2023). In addition, researchers have noted that the GVI is influenced by land use and urban functional areas (Hao and Long, 2017; Li et al., 2021b; Zhu et al., 2022b), which also reflects the importance of balancing urban development against greening needs.

Our work verified that building density exhibited a negative role in GVI (Fig. 4b), which was probably due to the buildings crowding out green space. In addition, buildings and external walls could also block views of vegetation (Li et al., 2021a; Zhu et al., 2022b). Therefore, in areas with high building density, GVI could be raised in three ways. First, maximize the continuity and permeability of green spaces as mentioned above. Second, transform the layout of buildings to leave view corridors. Third, vertical greenery could be developed using building facades. As opposed to building density, park density initially exerted a positive effect on GVI, but after the density reached a certain threshold value, it triggered a decrease in GVI (Fig. 4c). The positive effect of parks on GVI was consistent with the studies of Wang et al. (2022) and Zhu et al. (2022b), where parks tended to have large green areas, so the GVI was usually higher in the surrounding areas. However, our results implied that there was a certain range of parks' positive effects and that GVI was also influenced by other factors. For the phenomenon that higher park density triggered a decrease in GVI after reaching a certain threshold, it is speculated that it may be related to the error caused by fewer sampling points within the park. The negative impact of excessive park density may be due to sample error caused by insufficient sampling points within the park (the sampling points were mainly located on roads). This could also explain the slight positive effect of road density on GVI (Fig. 4d), which may be related to the favorable street landscape as well.

4.3. Influence of socioeconomic factors

In terms of socioeconomic factors, residents with higher per capita income are inclined to live in greener areas (Li et al. 2015a). This study used housing prices to reflect dwellers' income, and the results demonstrated that GVI tended to increase with higher housing prices (Fig. 4f), which was consistent with the findings of Xiao (2021). For individuals, those with higher incomes are willing to spend more to choose or improve their living environment, having more access to higher visible greenery (Li et al., 2015a). For governments, more investment in green space could lead to GVI (Chen et al., 2020). In addition, we found that GVI was highest with 13 years of housing age, but no apparent change since that housing age (Fig. 4g). It could be speculated that neighborhoods built in recent years may be more focused on creating a green environment than older neighborhoods.

4.4. Interaction between factors

We discovered that NDVI had the greatest explanation for the spatial distribution differences in GVI and was the most dominant positive factor, followed by land cover, FRACT, AREA, building density and PROX (Fig. 6a). The variation in GVI was better explained by the interaction of the influencing factors (Fig. 6b), reflecting the complexity of the driving mechanism. The complicated correlations between different factors deserve further research.

The high average GVI in Futian District was the consequence of the interaction of multiple factors. On the one hand, it was due to the importance the government attached to the ecological environment and the support of the economic base. Shenzhen is the "City of a Thousand Parks", with 1,260 parks built up to the end of 2022, preserving plenty of concentrated green spaces. There is an abundance of vegetation on both sides of the city roads and in the median barrier, thus contributing to high green coverage and a relatively continuous green interface, which provides a good foundation for green space perception. On the other hand, there are advantages of climate and vegetation. The climate is mild and humid and suitable for plant growth. The native vegetation is subtropical evergreen plants, which are tall and have large leaves. Therefore, foliage can occupy a large proportion of the longitudinal section captured by eyes. Moreover, evergreen trees are less affected by the seasons than deciduous trees, which is conducive to maintaining a more stable level of GVI throughout the year. For similar highly urbanized areas, devoting more attention to landscape pattern features and optimizing the spatial layout of green spaces could become an effective way to further improve the GVI.

4.5. Limitations

This study has several limitations. First, the GVI varies with the growth of the plant in different seasons, and the collected street view images only represent one period of time. Now there is a new feature called "Time Machine", which lets users view images from historical periods. This makes it possible to explore the dynamic change of GVI over time in the future. Second, our study in Shenzhen and the evidence from Harbin and Changchun suggest that GVI was driven by landscape patterns of urban green spaces (Xiao, 2020), but its generality needs to be verified in more countries and regions. Third, this study analyzed the influences of GVI from four aspects: the vegetation cover, landscape pattern, built environment, and socioeconomic factors, but other factors may still be omitted. Future studies can further improve the conceptual framework to reveal the driving mechanism of GVI.

5. Conclusion

This study explored the spatial differentiation characteristics and influencing factors of GVI in urban areas by taking the Futian District of Shenzhen as an example. The following conclusions were obtained:

1) The average GVI in Futian District was relatively high overall. The scale effect of GVI was not obvious, but the spatial heterogeneity was evident, and the hot spots and cold spots had apparent clustered distributions. The spatial divergence of landscape patterns was significant, with deviated, transitional, and homogeneous distribution patterns.

2) The impact of certain landscape pattern features and land cover cannot be ignored. The landscape indices indicating the scale, shape, and spatial configuration of green space patches led to the spatial differentiation of GVI by influencing the visibility of the green spaces. In urban areas, construction land had a negative effect on GVI through the modification of vegetation cover.

3) The interaction of multifarious factors resulted in the spatial differentiation of GVI,

including the vegetation cover, landscape patterns, built environment, and socioeconomic factors. We recognized NDVI as the most dominant factor, and the interaction of various factors explained better than a single factor.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Highlights:

- The spatial heterogeneity of the GVI was distinct in the study area.
- The land cover and landscape pattern features were key influencing factors.
- There were enhanced interactions between the influencing factors.
- Improving GVI by optimizing the layout of green spaces could be a good way.