Assessing the Green View Index in Chinese Cities: An Example with Data from Eighty Cities

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Abstract: The green view index (GVI) can have a positive impact on residents' health. It can complement the evaluation dimension of urban greening construction, which is essential for urban renewal and development in China. In this study, a total of 56 million street images from 80 national health cities in China were selected to analyze the level and variation of urban greenery in China. The study results show that the average level of GVI in the sample cities is 22.86%, and there is still room for improvement in the construction of urban greening at the spatial level. Although the natural geography of the western region is poor, most of the cities have a high level of GVI. In addition, the study further verifies the critical role of using GVI as an evaluation dimension of urban greening construction by comparing and analyzing GVI with NDVI values. It is hoped that the results of this study can provide data support and reference for the future urban greening construction in China.

Keywords: Green view index (GVI), Full Convolutional Networks (FCN), Normalized Difference Vegetation Index (NDVI), spatial distribution, regional differences

1 Introduction

China's economy and cities have developed at high speed in recent years, and residents' living standards have improved significantly. More and more attention has been paid to the urban environment. The level of urban greening is an essential element in assessing the quality of the urban environment. However, at present, China still considers urban greening quality by two-dimensional quantities of greening, such as green space coverage and park area per capita, ignoring the importance of three-dimensional space. Several studies have shown that giving GVI as an indicator of perceived greenery quality can positively impact human health (THOMAS 2017), and a living environment with higher GVI can have a good promotion effect on both the decrease of obesity rate (KNOBEL 2020). In addition, a study analyzing the degree of depression and several greenness dimensions among the elderly in Beijing pointed out that GVI was effective in mitigating the odds of depression among the elderly rather than NDVI and NDWI (HELBICH 2019). Therefore, GVI as a greening indicator perceived from the subjective perspective of near people should be used as a standard indicator to evaluate urban green spaces and promote urban greening (ZHANG 2018, LI 2016).

The green view index refers to the proportion of green vegetation in the human's field of vision, which can be used to visually feel and measure the greening level of urban space from the perspective of human vision. According to Yoji Aoki's research, people think the surrounding environment is green when the GVI is higher than 25%. The Japanese official documents also recognize this criterion, so the GVI above 25% has become the green construction target in many cities. Based on this, another Japanese scholar, Natsuhi Origahara, has

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refined the range of GVI into five levels: 0-5%, 5-15%, 15-25%, 25-35%, and more than 35%, which in turn indicate that residents' perception of greenness is feeble, poor, average, sound, and very good.

With the development of image processing technology, street maps, and deep learning have become new ways to obtain the green view index, which can achieve fast and batch calculation of GVI (GONG 2018, FARABET 2013). GVI has been applied in various studies (GERRISH 2018, LARKIN 2018). It is found that Full Convolutional Network (FCN) shows excellent performance on semantic segmentation in images (LIN 2017, LONG 2015). The purpose of this paper is to calculate the GVI of Chinese cities by semantic segmentation using FCN for street scenes of 80 Chinese cities, analyze the overall level, spatial characteristics, and urban differences of GVI in Chinese cities. The study can provide data support and reference for relevant departments to reasonably formulate greening construction strategies.

2 Materials and Methods

2.1 Study Area

This study selects 80 cities in China as the sample, involving 27 provinces, covering 550 million people (38.9% of China), and a GDP size of 56.2 trillion (56.7% of China). The 80 cities include 27 central cities, municipalities directly under the central government, provincial capitals, municipalities with separate plans, and 53 prefecture-level cities. All the cities selected are "National Sanitary Cities" awarded by the Chinese government. National Sanitary Cities have clear evaluation criteria in eight areas, including health education and health promotion, urban environmental sanitation, environmental protection, and hygiene of crucial places. The Chinese government recognizes these 80 cities as national cities of sanitary and ecological excellence. Analyzing the overall situation of green vision rate in a sample of great Chinese cities can provide a more intuitive understanding of the current development stage of China's urban greening construction level and offer suggestions for urban renewal and construction.

2.2 Data Source

The study used open-source image data of urban street view (street view from Baidu Maps). Constrained by means of Baidu Street View acquisition, the selected street view images have a view height of about 2.3 m and a 15° elevation angle. The obtained image size is 600 pixels, 480 pixels. In this study, all image acquisition points along the target city road are downloaded by acquiring a sampling point every 50 meters. The horizontal view parameters are set to 0°, 120°, and 240°, and each point contains three street view images. This study acquired 56 million street view images from 80 cities in June 2019. The city with the highest number of street view images was Shanghai with 541,263 images, and the lowest was Xining with 132,684 images.

2.3 Methods

2.3.1 Semantic Segmentation Using Full Convolutional Networks (FCN)

Full pixel semantic segmentation was performed after capturing the street view image of each city. The method selected for this study was applied by YAO's team, using the FCN trained by the ADE-20K1 dataset to semantically segment the features in each street view photo and obtain the area ratio of each semantic object (Yao 2019). The network was tested to have a pixel contrast accuracy of 0.81 on the training dataset and 0.67 on the test dataset, allowing for fast and efficient evaluation of local city perceptions in Chinese cities. Each ID within the segmented PNG image file output by the above method corresponds to a class of objects containing 150 IDs, including sky, road, building, tree, lawn, car, bus, and so on. Taking a sampling point in Beijing as an example, a semantic cut was performed on the street scene image from three angles. The output PNG image after the cut was superimposed on the original image, as shown in Figure 1.

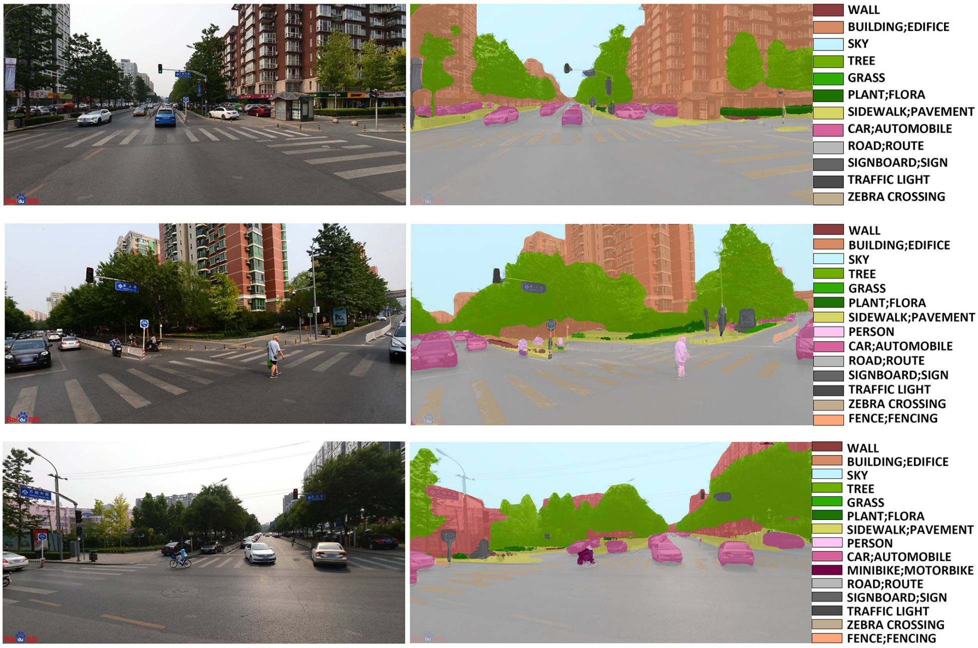


Fig. 1: The output PNG image after the cut was superimposed on the original image (From the top to the bottom of the picture, the viewing angle is 0°, 120°, and 240° in order)

2.3.2 Green View Index (GVI) Calculation

The area ratio of green vegetation pixels in the semantically cut image was considered as the GVI of the image. The GVI in each city is divided into 20 groups based on a 5% grouping interval (0%-5%, 5%-10%, ..., 90%-95%, 95%-100%). The weighted average was calculated using the median of each group interval as the weight for that group. The results were calculated as the GVI. The distribution of the number of images within the GVI grouping interval for each district in Beijing is shown in Figure 2. Due to many street images studied and the focus of the study is on discussing differences in the average GVI across cities, rather than for each observation point on each city street. Therefore, we did not use the traditional average GVI of six directional images.

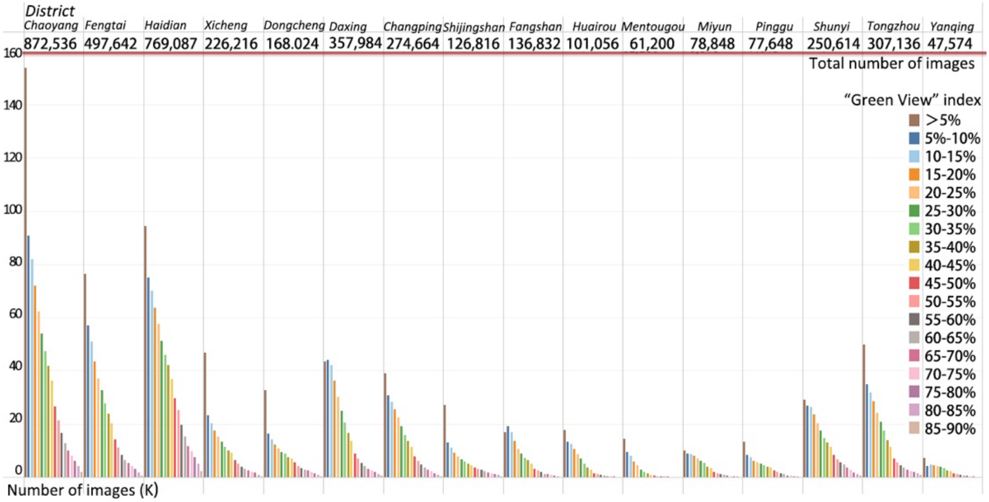


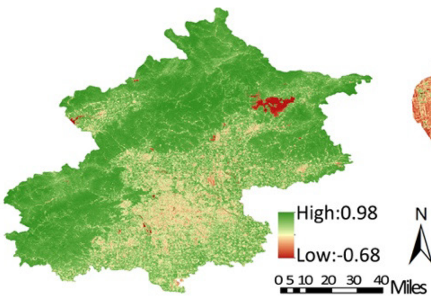
Fig. 2: The distribution of the number of images within the GVI grouping interval for each district in Beijing

2.3.3 Normalized Difference Vegetation Index (NDVI) Calculation

The remote sensing data used in this paper were obtained from the USGS website (http://www.gscloud.cn/), and the data were selected from Landsat-8 OLI data dated June 2019. The stitched images were cropped using Chinese urban boundary vector data. The following equation performed the calculation of NDVI values:

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red})$$

Where ρ_{nir} was the NIR band reflectance in the image data and ρ_{red} was the red band reflectance in the image data. The spatial distribution of NDVI for Beijing and Shenzhen is shown in Figure 3.



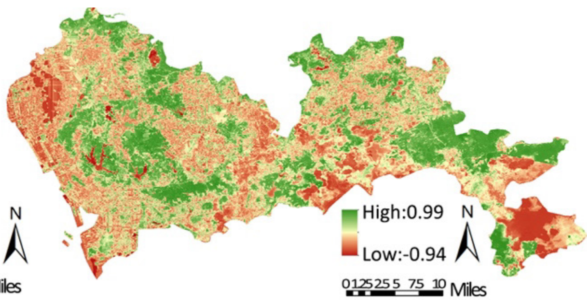


Fig. 3a: NDVI of Beijing **Fig. 3b:** NDVI of Shenzhen

3 Results

3.1 Characteristics of GVI in Chinese Cities

The selected 80 Chinese cities with excellent environment and sanitation have an average green vision rate of 22.86%, where residents perceive some greenery in their daily lives but do not meet the official Japanese government standard of 25% city construction. Of the cities evaluated, 65% of the sample cities had a GVI between 15% and 25%, with 25 cities having a GVI above 25%, just one-third of the total. Since the selected cities are already among the top in China in terms of sanitation and environmental construction, it is assumed that the overall situation of GVI in Chinese cities is relatively average, and urban greening needs to be improved at the spatial level of construction. In addition, as can be seen in Figure 4, cities in the Pearl River Delta and south, most cities in the northwest, and some cities in the Yangtze River Delta in China have GVI higher than 25%, which is a top-level compared with other cities. Residents will have the feeling that their surroundings are better greened.

Fig. 4: Spatial Distribution Characteristics of GVI in China

From the city level, the average GVI of central cities is 24.04%, which is slightly higher than the average of 22.40% for prefecture-level cities. As seen in Figure 5(a), all 27 central cities have a GVI level higher than 15%, and 10 of them have a GVI of more than 25%, with Nanjing having the highest at 29.21%. Among the 53 prefecture-level cities, there are 15 cities with GVI over 25%, among which Baoji ranks first in the country with 30.23%. There are three cities with GVI below 15%, all of which are general prefecture-level cities. The overall green vision rate construction in central cities is relatively good.

From Figure 5(b), the green vision rate in central cities is concentrated between 18% and 30%. At the same time, the green vision rate in general prefecture-level cities also lies within this range in most cities, but there are six cities below 18% and two cities above 30%. This indicates that the general prefecture-level cities have uneven development in terms of GVI construction compared with the central cities.

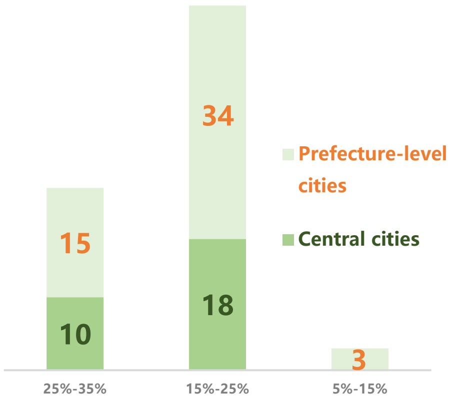


Fig. 5a:
Overall GVI for different cities

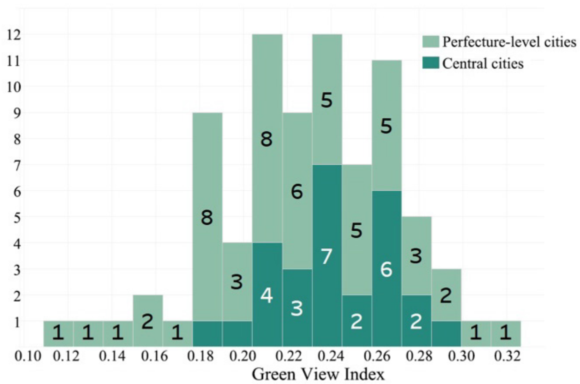


Fig. 5b:
The GVI values of different cities

3.2 Analysis of the Differences in GVI of Different Areas in Each City

The difference between the highest and lowest GVI values in different administrative regions of each city is shown in Table 1, which can reflect the development differences of urban green vision rate construction. The average value of GVI difference in the western region is 11.76%, which ranks the top of the four areas. 13 out of 20 cities in the west have a difference of GVI of more than 10%, and the development of different regions within the cities in the western part is more uneven. The mean values of GVI differences in the central and eastern areas are the same, at 9% and 8.99%, respectively. The mean value of GVI differences among administrative regions within cities in the northeast region is relatively small, 7.06%.

Table 1: The difference between the highest and lowest GVI values in different administrative regions of each city

City	GVI difference	City	GVI difference	City	GVI difference	City	GVI difference
Eastern areas (Average: 8.99%)							
Guilin	21.01%	Wuxi	10.97%	Linyi	7.16%	Jining	5.60%
Nanning	17.85%	Yantai	10.69%	Wenzhou	7.14%	Weifang	5.50%
Shenzhen	16.50%	Taizhou	10.37%	Shaoxing	6.88%	Jiaxing	4.53%
Fuzhou	16.29%	Quanzhou	10.05%	Zhenjiang	6.75%	Xiamen	4.29%
Tianjin	14.35%	Nanjing	9.70%	Maanshan	6.53%	Suzhou	4.26%
Beijing	13.64%	Qingdao	9.35%	Nantong	6.38%	Haikou	4.12%
Hangzhou	12.78%	Sanya	9.05%	Ningbo	6.35%	Weihai	3.93%
Jinan	12.53%	Zhuhai	8.92%	Shanghai	6.17%	Foshan	3.79%
Guangzhou	11.24%	Jinhua	8.02%	Xuzhou	5.60%	Changzhou	3.29%
Zhangzhou	11.01%						
Middle areas (Average: 9.00%)							
Luoyang	17.26%	Jincheng	11.18%	Zhengzhou	9.97%	Ordos	4.79%
Zhuzhou	16.25%	Wuhan	11.18%	Xiangyang	9.35%	Tongling	3.74%
Baotou	15.99%	Yichang	10.60%	Changde	7.46%	Nanchang	1.83%
Ji'an	12.99%	Xuchang	10.26%	Yueyang	6.01%	Nanyang	1.27%
Xinxiang	11.92%						
Western areas (Average: 11.76%)							
Jinchang	20.57%	Xi 'An	15.30%	Zhunyi	12.06%	Liupanshui	6.29%
Chengdu	20.12%	Mianyang	14.89%	Xining	10.17%	Yinchuan	6.21%
Chongqing	18.98%	Baoji	14.48%	Shizuishan	10.02%	Guiyang	6.00%
Yuxi	18.18%	Xianyang	12.70%	Kunming	8.98%	Karamay	4.80%
Yulin	15.32%	Luzhou	12.16%	Qujing	7.72%	Yibin	0.20%
Northeast areas (Average: 7.06%)							
Changchun	12.45%	Shenyang	7.96%	Dalian	4.58%	Siping	1.53%
Anshan	8.79%						

3.3 Comparison Analysis of GVI and NDVI

As shown in Figure 6, the scattered distribution of cities, the horizontal axis is NDVI, and the vertical axis is GVI. Although the trend of GVI changes with NDVI for different economic levels is different, it presents the tendency that the GVI of cities becomes larger as NDVI increases because the slope of each trend line is slight. Among the cities with the same NDVI, the more advanced the economic level is, the higher the urban GVI is.

However, Karamay and Jinchang have the lowest urban vegetation index, but the urban street greenness rate is relatively good. This can reflect the level of cities in terms of street greenery and landscape. Both Karamay and Jinchang are typical resource-based cities with average natural background conditions city but attach great importance to street greening construction.

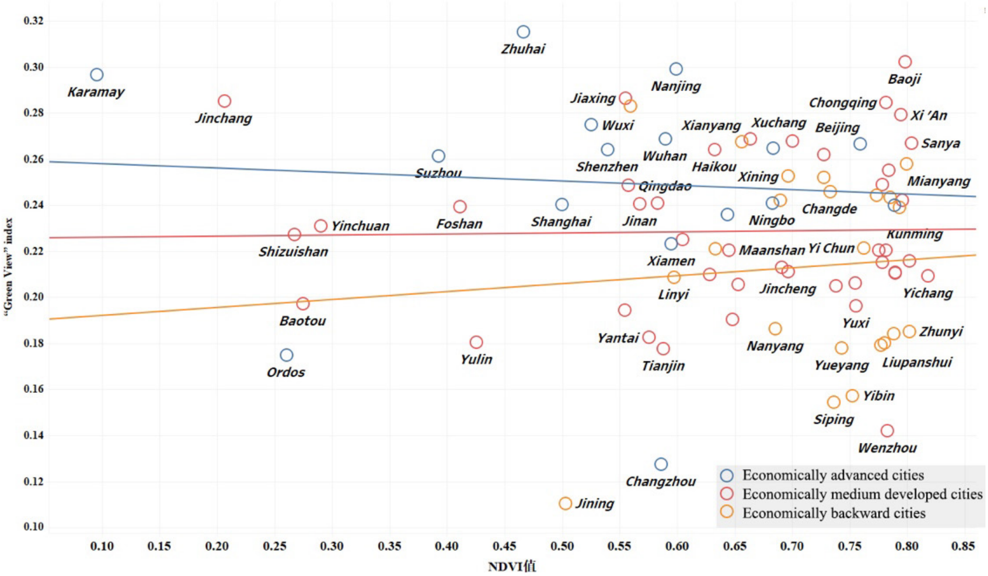


Fig. 6: Comparison analysis of GVI and NDVI

4 Discussion

By analyzing the GVI and NDVI of 80 cities in China, this paper provides an overall knowledge of urban greenery construction in China. It offers large-scale data support for inter-regional differences, inter-city differences, and other regional differences within cities. Most of the study results are also consistent with China's urban conditions and development laws at this stage. For example, the southern cities such as Yangtze River Delta and Pearl River Delta have better greenery construction based on their natural ecological environment and urban economic level. This can be considered well known in China because these regions have more native plants, suitable climatic conditions for plant growth, and a higher urban construction level. However, it is essential to discuss that the green vision situation in some cities in Northwest China differs in many ways from the general perception. Northwest China is in a temperate continental semi-arid and arid climate zone with scarce precipitation and widespread desert distribution, which is not conducive to plant growth. However, northwestern cities such as Baoji, Karamay, and Jinchang have outstanding performance with GVI of over 28.5%.

In recent years, despite the unfavourable natural conditions, the governments of cities in northwest China have attached great importance to street greening construction and increased investment in vegetation maintenance, achieving remarkable results worthy of reference for other cities. Karamay city has more differences in GVI and NDV development, is located in the alluvial fan formerly tilted plain zone at the northwest edge of the Junggar Basin, with a single landform, mostly a broad and flat Gobi. Moreover, the city of Karamay has a temperate continental arid desert climate with hot summers, severely cold winters, drought and little rain, evaporation, and much sand and wind with high intensity. However, the government of

Karamay has actively reversed the disadvantage of local conditions in recent years and established five strategic goals to realize the construction of a national model city of environmental protection, national ecological garden city, national habitat city, and the city with the best ecological and environmental quality in Xinjiang. In addition, it has significantly strengthened the ecological environment in urban construction and vigorously implemented a series of environmental protection projects such as afforestation and emission reduction. The city's greening coverage and air quality rates have climbed significantly.

5 Conclusion

This paper assesses the GVI and NDVI levels in 80 cities in China and has the following main findings. 1) The GVI of Chinese cities is currently at an average level, and urban greening still needs to be improved at the spatial level. 2) The overall GVI construction of central cities is relatively good, while the development of general prefecture-level cities is uneven in terms of GVI construction. 3) Most cities in the western region have a high level of GVI. Still, the development is more uneven between different regions within each city. 4) The more advanced the economic level is, the higher the urban GVI is, in terms of cities with the same NDVI. This study analyzes the greening level of China from the perspective of GVI and discovers typical cities by comparing with NDVI, hoping that it can provide data support and reference for the future urban greening construction in China. The study has only investigated and researched in the field of GVI and NDVI so far, which cannot fully surface the level of urban greening quality. It should also be added to continue in-depth research on park areas, urban heat islands, and other perspectives.

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