The inequalities of different dimensions of visible street urban green space provision: A machine learning approach

ABSTRACT

Awareness is growing that the uneven provision of street urban green space (UGS) may lead to environmental injustice. Most previous studies have focused on the over-head perspective of street UGS provision. However, only a few studies have evaluated the disparities in visible street UGS provision. While a plethora of studies have focused on a single dimension of visible UGS provision, no previous studies have developed a framework for systematically evaluating visible street UGS provision. This study therefore proposes a novel 4 ‘A’ framework, and aims to assess different dimensions (namely: availability; accessibility; attractiveness; and aesthetics) of visible street UGS provision, using Beijing as a case study. It investigates inequities in different dimensions of visible street UGS provision. In addition, it also explores the extent to which a neighbourhood’s economic level is associated with different dimensions of visible street UGS. Our results show that, in Beijing, the four chosen dimensions of visible street UGS provision significantly differ in terms of spatial distribution and the association between them. Furthermore, we found that the value of the Gini index and Moran’s I index for attractiveness and aesthetics are higher than those for availability and accessibility, which indicates a more unequal distribution of visible street UGS from a qualitative perspective. We also found that a community’s economic level is positively associated with attractiveness and aesthetics, while no evidence was found to support the claim that the economic level of a community associated with availability and accessibility. This study suggests that visible street UGS provision is unequal; therefore, urban planning policy should pay more attention to disparities in visible street UGS provision, particularly in urban areas.

Keywords: 4 ‘A’ framework; Disparity; Visible street urban green space; Street view data; Machine learning; Beijing

1. Introduction

Urban green space (UGS) is one of the most important amenities for urban residents, since it not only fulfils crucial ecosystem functions, but also contributes to the improvement of public health (Bratman et al., 2019). Previous studies have indicated that UGS can mitigate environmental hazards, such as reducing air pollution (Wang et al., 2020) and urban heatwaves (Yang, Sun, Ge, & Li, 2017). In addition, UGS contributes to public health by encouraging physical activity (Wang et al., 2019), promoting social cohesion (Liu et al., 2020), fostering a sense of well-being and reducing stress among residents (Wang et al., 2019). Due to rapid urbanization, the amount of contact that most people have with large-scale UGS has decreased in the last two decades, in China, among other countries (Song, Chen, & Kwan, 2020). Compared with large green infrastructure (e.g., urban parks), street-level UGS (e.g., trees, grass, and vegetation) takes less space and is more economical, so it can be planned in compact and urbanized area to increase people's contact with nature (Donovan & Butry, 2010; Mullaney et al., 2015). Hence, street UGS is important for the whole urban system (Seamans, 2013). For example, Wang and Akbari. (2016) found street trees are necessary for mitigating the effect of urban heat island in Montreal. Wood and Esaian. (2020) pointed out that street vegetation can increase the richness of urban avifauna in Greater Los Angeles, which is important for urban ecology system. Therefore, street-level UGS has attracted attention in recent years and has become a popular means of intervention for meeting the public demand for greater engagement with green space (Kondo et al., 2020).

Disparities in UGS provision on the basis of socio-economic status (SES) have become an important social issue and green justice globally (Liu et al., 2022; Wolch, Byrne, & Newell, 2014). Social groups with a lower SES are more likely to have limited access to UGS, as they may be not able to afford to live near the main UGS locations (Hughey et al., 2016; Li et al., 2021; Rigolon, 2016; Wolch, Wilson, & Fehrenbach, 2005; Xu et al., 2019). In addition, socio-economically disadvantaged groups have fewer political resources and less support, which may restrict the extent to which they can engage with the decision-making processes involved in urban planning (Hughey et al., 2016; Rigolon, 2016; Wolch et al., 2005). However, findings regarding the association between SES and UGS provision are inconsistent in the case of some developed countries, such as Japan and the United States (Boone, Buckley, Grove, & Sister, 2009; Comer & Skraastad-Jurney, 2008; Cutts, Darby, Boone, & Brewis, 2009; Dai, 2011; Hughey et al., 2016; Rigolon & Flohr, 2014; Yasumoto, Jones, & Shimizu, 2014; Zhou & Kim, 2013). On the one hand, some studies have found that social groups with a higher SES have better access to UGS (Dai, 2011; Hughey et al., 2016; Yasumoto et al., 2014). For example, Yasumoto et al. (2014) found that park accessibility is positively associated with neighbourhood SES, and new parks are more likely to be built in affluent communities in Japanese cities. Hughey et al. (2016) showed that the quality of parks in areas where socio-economically disadvantaged groups live is likely to be poorer in southeastern US counties. Dai (2011) also pointed out that socio-economically disadvantaged groups, such as African Americans, have more limited access to green spaces in metropolitan Atlanta, Georgia. However, other studies from the existing literature have found that socio-economically disadvantaged groups tend to have better access to UGS (Boone et al., 2009; Comer & Skraastad-Jurney, 2008; Cutts et al., 2009). For instance, Boone et al. (2009) found that some African Americans have a relatively higher level of accessibility to parks compared to white people in Baltimore, Maryland. Comer et al. (2008) found that Hispanics and other social groups with lower incomes in fact have a higher level of accessibility to parks in Oklahoma City. Finally, Cutts et al. (2009) found that African Americans and Hispanics have better pedestrian access to neighbouring parks in Phoenix, Arizona.

Empirical evidence regarding green justice in the Chinese context is still relatively scant. Most existing studies conducted in China have confirmed the existence of SES disparities in UGS provisions (Guo et al., 2019; H. Li & Liu, 2016; Shen, Sun, & Che, 2017; Xu, Xin, Su, Weng, & Cai, 2017; You, 2016; J. Zhang et al., 2020). For example, You (2016) found that district disadvantage degree of income, occupation and housing are all negatively associated with the quantity of UGS in Shenzhen. Guo et al. (2019) demonstrated that areas with higher housing prices also have higher levels of accessibility to parks in Beijing. However, two recent studies conducted in Shanghai showed that socio-economically disadvantaged groups, such as migrants and older adults, have better accessibility to parks (Xiao, Wang, & Fang, 2019; Xiao, Wang, Li, & Tang, 2017). Compared with large-scale UGS (e.g., parks), SES-related disparities in the provision of street-level visible UGS (e.g., trees) have received less attention, particularly in the Chinese context. Previous studies involving developed countries have shown that SES-related disparities in the provision of street-level visible UGS may be more significant than that of large-scale UGS (Li, Zhang, Li, & Kuzovkina, 2016; Li, Zhang, Li, Kuzovkina, & Weiner, 2015). For example, Li et al. (2016) found that neighbourhoods with higher levels of both income and educational attainment have more street-level visible UGS in Hartford, Connecticut; however, the same association was not observed for proximity to urban parks. One possible explanation for this difference could be that the provision and maintenance of visible street UGS may be more costly and labour-intensive than the provision and maintenance of parks (Li et al., 2016; Li et al., 2015). However, only two recent studies carried out in Guangzhou have focused on SES-related disparities in the provision of visible street UGS in China, and they have yielded similar results to those found in the existing literature for some developed countries (Chen, Zhou, & Li, 2020; Wang et al., 2021).

Although the provision of visible street UGS has attracted considerable attention, there is currently no systematic framework for assessing it. While an increasing amount of scholarly attention has been paid specifically to the uneven provision of UGS, there has been surprisingly little empirical research on the disparities in visible street UGS provision. A handful of studies have examined the uneven provision of visible street UGS in developed countries, such as the United States (Li et al., 2016; Li et al., 2015), the United Kingdom (Labib, Huck, & Lindley, 2021) and Finland (Toikka, Willberg, Mäkinen, Toivonen, & Oksanen, 2020). However, the findings from these studies may differ from those for developing countries due to cultural and contextual differences. Moreover, previous studies conducted in China have mainly concentrated on the methodological aspect of developing different indices for assessing visible street UGS (Chen, Meng, Hu, Zhang, & Yang, 2019; Dong, Zhang, & Zhao, 2018; Long & Liu, 2017; Yu, Zhao, Chang, Yuan, & Heng, 2019), while only two existing studies have focused on SES-related disparities in visible street UGS provision (Chen et al., 2020; Wang et al., 2021). However, they are based either on the district or neighbourhood level (juweihui). To the best of our knowledge, no previous studies have evaluated the socio-economic disparities in visible street UGS provision in China at a community level (juzhuxiaoqu).

2. Theoretical framework

Based on the above review, this study therefore aims to develop a 4 'A' framework (namely: availability; accessibility; attractiveness; and aesthetics) (Fig. 1) for assessing visible street UGS using street view data collected from Beijing. It investigates inequities in different dimensions of visible street UGS provision. In addition, it also explores the extent to which a neighbourhood's economic level is associated with different dimensions of visible street UGS.

First, existing studies usually classified UGS into objective and subjective dimension (Kronenberg et al., 2020; Stoltz & Grahn, 2021). Objective dimension reflects how easily people can get access to UGS, while subjective dimension measures whether people are willing to get access to UGS (Kronenberg et al., 2020; Stoltz & Grahn, 2021). Second, both objective and subjective dimension of UGS may interact and integrate with each other, which finally forms people's overall impression of a certain UGS (Kronenberg et al., 2020; Stoltz & Grahn, 2021). Therefore, as shown in Fig 1, we classified visible street UGS into two dimensions (objective and subjective) and four perspectives (quantity, proximity, quality and diversity).

This study extends previous research in several respects. First, it enhances our knowledge of different dimensions of visible street UGS in China by proposing a novel 4 'A' framework. Second, it investigates the inequalities based on different dimensions of visible street UGS provision. Third, it further explores the extent to which neighbourhood socio-economic level is associated with different dimensions of visible street UGS.

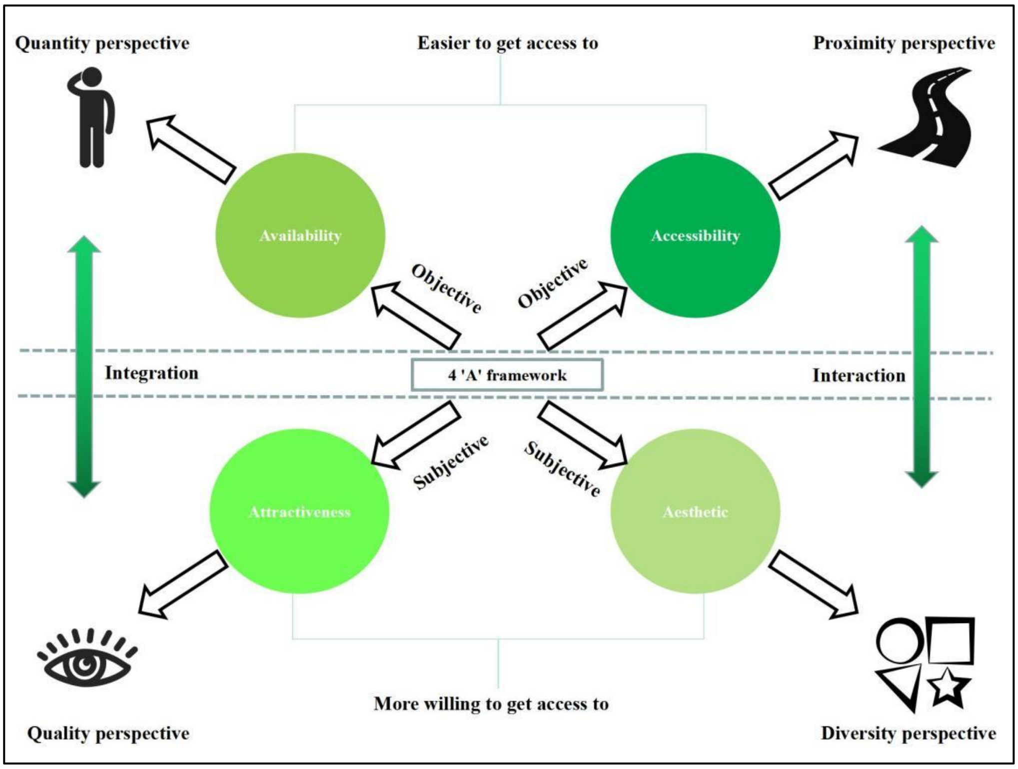

Fig 1. 4 'A' framework for evaluating visible street UGS.

3. Methodology

3.1 Research area

As the capital and one of the most unbanised areas of China, Beijing was chosen as the research area for our study. In 2020, 86.6% of the city was urbanised. We selected the central urban area (the area within the Fifth Ring Road) of Bejing city as the main research area (Fig. 2). In total, 5,180 residential communities (*juzhuxiaoqu*) were included in the study (516 residential communities were excluded due to the limitation of data availability). The average area of the sampled communities was 0.166 km^2 (SD= ± 0.227 km^2), while the average residential population was 1,487 persons (SD= ± 2101 persons). The visible UGS assessed in this study mainly refers to street-level vegetation, which can be viewed by pedestrians.

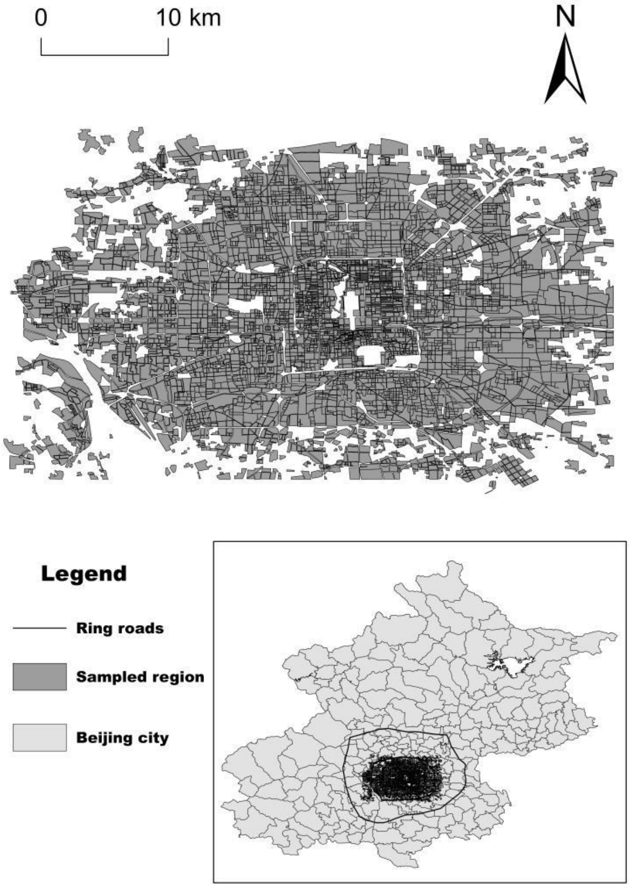

Fig 2. The research area in Beijing city, China

3.2 Data

Street view

We used street view images from Tencent Map (https://map.qq.com/) to estimate visible street UGS. Tencent Map is the most comprehensive online mapping website available, and has been used for a wide range of urban studies in China (see Long & Liu, 2017). We constructed sampling points along the road network based on OpenStreetMap (Haklay & Weber, 2008). Following the approach used in previous studies (Wang et al., 2021; Wang et al., 2019), street view images from the four cardinal directions (0, 90, 180, and 270 degrees) were retrieved for each sampling point. In total, 222,868 images were obtained.

Similarly to previous studies (Wang et al., 2021; Wang et al., 2019), we used a machine learning approach to extract ground-level objects from street view images. We applied a fully convolutional neural network for semantic segmentation (FCN-8s) (Long, Shelhamer, & Darrell, 2015), which segments the images into the different ground-level objects that are visible along the streetscape. We trained our FCN-8s model based on the ADE20K scene parsing and segmentation databases (Zhou et al., 2019). The accuracy of our model was higher than 85% for both the testing and trained data. After the image segmentation process had been completed, the ratio of different ground-level objects was calculated for each image at each sampling point. Since the street view images were collected along the street with precise location information, they can be used to measured how pedestrians are exposed to visible street UGS for each of the sampling point.

Tencent mobile phone big data

Again, following the method used in previous studies (Liu, Wu, Thakuriah, & Wang, 2020), we obtained Tencent mobile phone data from the Tencent Big Data Centre (http://data.qq.com/) through the Institute of Geographic Science and Natural Resources Research Centre, at the Chinese Academy of Sciences from 2015. Tencent mobile phone big data mainly records the location information of WeChat users, which is representative of smart phone users in China (Economist, 2016). The data consisted of the location information for each user and the spatial resolution of this data was 100-m.

Night-time light data

2013 VIIRS night-time light data for Beijing was downloaded from the WorldPop website (https://www.worldpop.org/). The spatial resolution of this data was 100-m.

3.3 Variables

3.3.1 Objective perspective

Street view greenness (SVG) per sampling point was calculated by the ratio of the number of greenness pixels per image summed over the four cardinal directions to the total number of pixels per image summed over the four cardinal directions.

Availability

Availability reflects whether people have access to UGS (Kronenberg et al., 2020), so we calculated the availability of visible UGS by weighting SVG based on Tencent mobile phone data. The following formula was used:

$$Availability_j = \sum_{p=1}^{n} SVG_{pj} \cdot \frac{Pop_{pj}}{\sum_{p=1}^{n} Pop_{pj}} \qquad (1)$$

Where SVG_{pj} is the value of street view greenness for sampling point p in community j; Pop_{pj} is the value of the Tencent mobile phone population for sampling point p in community j; n is the total number of sampling points within community j.

Accessibility

Accessibility is an indicator of how easily people can travel to UGS in their locality (Kronenberg et al., 2020), so we calculated the accessibility of visible UGS by weighting SVG based on travel distance. The formula used was as follows:

$$Accessibility_j = \sum_{p=1}^{n} SVG_{pj} \cdot \frac{Dis_{pj}}{\sum_{p=1}^{n} Dis_{pj}} \qquad (2)$$

Where SVG_{pj} is the value of street view greenness for sampling point p in community j; Dis_{pj} is the distance between the community geometric centroid and sampling point p in community j; n is the total number of sampling points within community j.

3.3.2 Subjective perspective

Attractiveness

Attractiveness reflects the general quality of UGS (Kronenberg et al., 2020), so we calculated the attractiveness of visible UGS using the method proposed by Wang et al. (2021). First, 2,000 images were randomly selected and rated based on a UGS quality scale (0 to 10). The scale included the following items: maintenance (very bad-very good), naturalness (very unnatural-very natural), colourfulness (very dull-very colourful), clear arrangement (very difficult to survey-very surveyable), shelter (very enclosed-very open), absence of litter (a lot of litter-very little litter), and safety (very unsafe-very safe). This scale has been widely used by previous studies (De Vries et al., 2013; Lu, 2019; Van Dillen et al., 2012), which aims to reflect people's general perception of the green space quality. It measures various aspects of green space quality. For example, maintenance mainly reflects whether the green space is regularly and well maintained by the government sector, while the naturalness reflects whether the green space is with higher level of biodiversity (e.g., with bird or other creatures) but without too many artificial decorative objects. Second, based on those 2,000 images, a random forest (RF) model (Breiman, 2001) was trained by the proportion of different ground-level objects (from the results of the image segmentations) to predict the UGS quality scale. Finally, the trained random forest (RF) model was used to score all of the street view images for UGS quality. The attractiveness of each sampling point was calculated by the average score on the UGS quality scale (7 items)/10. The following formula was used:

$$Attractiveness_j = \sum_{p=1}^{n} Q_{pj} \cdot \frac{1}{n} \qquad (3)$$

Where Q_{pj} is the value of the street view greenness attractiveness for sampling point p in community j; n is the total number of sampling points within community j.

Aesthetics

Aesthetics is a measure of how people perceive the beauty and tastefulness of UGS and it is comprised of multiple dimensions (Stoltz & Grahn, 2021). We calculated the aesthetics of visible UGS based on the diversity dimension proposed by Stoltz and Grahn (2021). The more mixed the elements are, the more aesthetically pleasing the UGS is considered to be. Since there is a wide variety of man-made elements, and natural elements is more related to the restorative effect of green space (Stoltz & Grahn, 2021), we only focused on natural elements in this study. Therefore, we calculated the aesthetics of visible UGS by generating the entropy of natural elements (bodies of water, greenness and living creatures).

The formula used was as follows:

$$Aesthetic_j = \sum_{p=1}^{n} \frac{-\left(\sum_{l=1}^{3} G_{lpj} \cdot \ln G_{lpj}\right)}{\ln 3} \cdot \frac{1}{n} \qquad (4)$$

Where G_{lpj} is the value of a given street view natural element l (body of water, greenness or living creatures) for sampling point p in community j; n is the total number of sampling points within community j.

3.3.3 Community population density and economic level

Community population density was calculated based on Tencent mobile phone data. We aggregated the amount of Tencent mobile phone users at a community level, and then calculated the population density for each community selected. Community economic level was calculated based on VIIRS night-time light data. Previous studies have shown that the pixel values (brightness) of night-time light data can reflect the economic level of a region (Li, Xu, Chen, & Li, 2013; Wu, Yang, Dong, Zhang, & Xia, 2018). Thusm we calculated the average pixel values of night-time light data for each community and took this value as the proxy for the economic level of the community.

3.3.4 Statistical analysis

To assess the inequalities between different dimensions of visible UGS, we used spatial analysis, inequality indices and linear regressions. First, to identify general inequalities in visible UGS, we calculated the Gini index (Gini, 1921) for the four visible UGS measures. In addition, we used the Global Moran's I (Moran, 1950) to examine the global spatial autocorrelation (inequality) of visible UGS at the community level. Second, we further calculated the Local Moran's I (Anselin, 1995) value in order to assess the spatial relevance of visible UGS in each community to its neighbours. The Local Moran's I measures the degree of spatial autocorrelation (inequality) between the visible UGS within each community and its surrounding communities. LISA (Local Indicators of Spatial Association) cluster maps of distribution of the visible UGS at the community level were used to visually represent the results. Lastly, to examine whether there were any socio-economic disparities in visible UGS provision at the community level, we regressed the community population density and economic level for the four measures of visible UGS. The analyses were carried out with ArcGIS 10.8.1 (Esri Inc., College Station, Aylesbury, UK) and Stata 15.1 (StataCorp., College Station, TX, USA) using the 'reg' commands.

4. Results

Fig. 3 shows the spatial distribution of visible UGS at a community level from the perspective of availability (Fig. 2a), accessibility (Fig. 2b), attractiveness (Fig. 2c) and aesthetics (Fig. 2d), respectively. We found that visible UGS was generally unevenly distributed in Beijing based on our 4-A framework at the community level. From a quantitative perspective (i.e., availability and accessibility), residential communities with higher values of visible UGS were mainly located in the northern and western part of the research area. Additionally, there were more residential communities with higher values of visible UGS in the outer area (urban periphery) than in the inner area. Residential communities with lower values of visible UGS were relatively evenly distributed.

From a qualitative perspective (i.e., aesthetics and attractiveness), residential communities with higher values of visible UGS were mainly located in the western part of the research area. In addition, residential communities with higher values of visible UGS were relatively evenly distributed in both the inner and outer areas. However, compared with the inner area, there were more residential communities with lower values of visible UGS in the outer area (urban periphery).

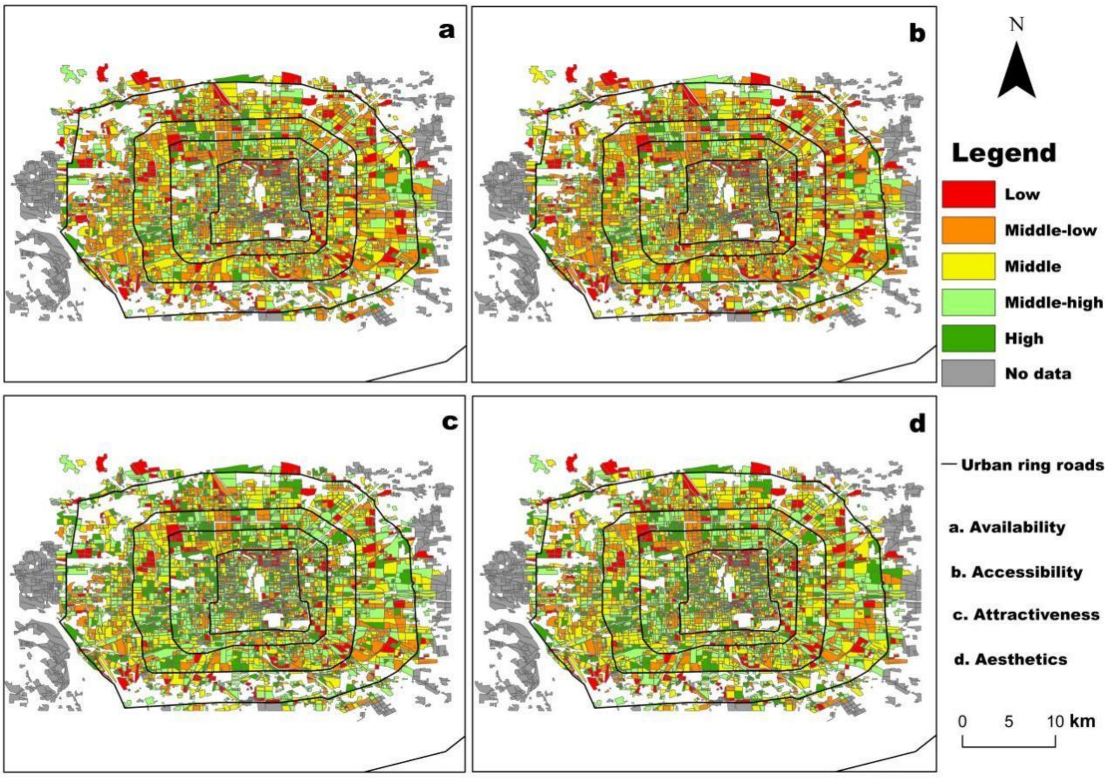

Fig 3. The distribution of visible UGS at the community level (Natural Breaks): (a)Availability; (b)Accessibility; (c)Attractiveness; (d)Aesthetics

Table 1 shows the results of the inequality indicators for different visible UGS measures. The Gini index measures the general inequalities in the provision of visible UGS, while Moran's I index measures spatial inequality of the visible UGS provision. From a quantitative perspective (availability and accessibility), the Gini index of visible UGS was lower than the Gini index of visible UGS from a qualitative perspective (aesthetics and attractiveness), which indicates there are generally more striking inequalities in the qualitative (aesthetic and attractiveness) provision of visible UGS. In addition, from a quantitative perspective (availability and accessibility), the Moran's I index of visible UGS was lower than that from a qualitative perspective (aesthetics and attractiveness), which suggests there is a more obvious spatial autocorrelation from a qualitative perspective (aesthetics and attractiveness) in terms of the provision of visible UGS.

Table 1

Results of inequality indicators for the four visible UGS measures.

	Availability	Accessibility	Aesthetic	Attractiveness
Gini index	0.103	0.109	0.129	0.243
Moran's I index	0.047***	0.045***	0.049***	0.055***

*p < 0.10, **p < 0.05, ***p < 0.01.

Fig. 4 displays the local Moran's I values in relation to the four visible UGS measures. Fig. 4a and 4b show the LISA (Local Indicators of Spatial Association) cluster maps of visible UGS from a quantitative perspective (availability and accessibility). We only focused on the HH (high-high) and LL (low-low) clusters, because the HL and LH clusters only make up a small proportion of visible UGS from a quantitative perspective. The HH clusters were mainly located in the northern and western part of the research area, while the LL clusters were largely located in the outer area (urban periphery). Fig. 4c shows the LISA cluster map of visible UGS from an attractiveness perspective. We only focused on the HH and HL clusters, as the LL and LH clusters comprised only a small proportion of visible UGS in terms of attractiveness. The HH and HL clusters were primarily located in the western part of the research area and the inner area. Fig. 4d shows the LISA cluster map of visible UGS from an aesthetic perspective. Again, we only focused on the HH and LL clusters, due to the HL and LH clusters comprising just a small part of visible UGS from an aesthetic perspective. The HH clusters were mainly located in the northern and western part of the research area, while the LL clusters were primarily found in the northern and inner parts of the research area.

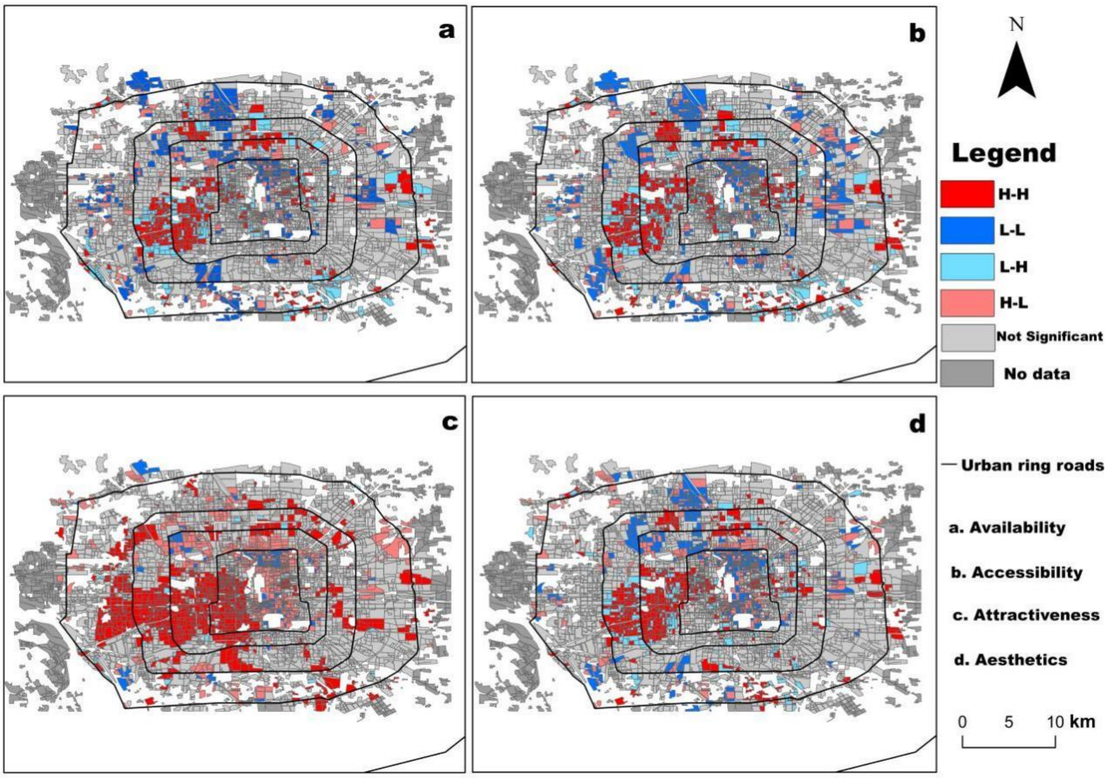

Fig 4. LISA (Local Indicators of Spatial Association) cluster map of distribution of visible UGS at the community level: (a)Availability; (b)Accessibility; (c)Attractiveness; (d)Aesthetics

Table 2 shows the relationship between the four measures of visible UGS and community population density and economic level using the OLS (ordinary least squares) method. The results show that community population density was positively associated with all four measures of visible UGS, when the other variables remained constant. The economic level of a community was positively associated with visible UGS from a qualitative (aesthetics and attractiveness) dimension. However, there was no statistical evidence to support an association between a community's economic level and the quantity (availability and accessibility) of visible UGS.

Table 2

Regression models of visible UGS at the community level in Beijing.

	Model 1 (Availability)	Model 2 (Accessibility)	Model 3 (Aesthetics)	Model 4 (Attractiveness)
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Population density	0.008***(0.001)	0.007***(0.001)	0.004***(0.001)	0.003***(0.001)
Economic level	0.002*(0.002)	-0.002(0.002)	0.003**(0.001)	0.002***(0.000)
Constant	0.054***(0.016)	0.068***(0.017)	0.131***(0.012)	0.537***(0.007)
AIC	-15018.99	-14182.19	-17511.38	-23462.25

Note: Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01.

5. Discussion

This study extends previous research on inequities in UGS provision in several respects. First, it aims to be the first to propose and apply the 4 'A' framework previously described, in order to assess visible UGS based on street view data. Second, it systematically explores the inequalities in different dimensions of visible UGS provision in Beijing. Third, it further investigates the extent to which a neighbourhood's economical level is statistically associated with different dimensions of visible UGS.

5.1 Evaluating the inequalities in different dimensions of visible UGS provision

Our results show that, in quantitative terms (availability and accessibility), visible UGS is relatively high in the outer areas, but low in the inner areas (within the Fifth Ring Road) of Beijing. This finding is consistent with previous research using different measures of UGS, such as land cover data, NDVI (normalised difference vegetation index) (Qian, Zhou, Li, & Han, 2015; Qian, Zhou, Yu, & Pickett, 2015; Yan, Zhou, Zheng, Wang, & Tian, 2020; Yin et al., 2019; Zhou et al., 2018) and public parks data (Guo et al., 2019; J. Wu, He, Chen, Lin, & Wang, 2020). For example, Guo et al. (2019) found that park accessibility was higher in the outer areas of Beijing than in the inner areas. Li et al. (2021) found that the NDVI value was relatively low within the Third Ring Road, but high in outer areas of the city. In addition, two recent studies conducted in Beijing confirmed a similar spatial pattern for the green view index (GVI) using street view data at both road and country level (Dong et al., 2018; Li et al., 2021). One possible explanation is that the inner areas were developed and urbanised earlier than the outer areas; therefore, the building density is higher in the inner areas, resulting in less land being available for the building new visible green infrastructure (Wu, Li, & Yu, 2016). In addition, there are many historic sites within the inner areas, which may restrict the expansion of existing visible UGS (Li et al., 2021). By contrast, in qualitative terms (aesthetics and attractiveness), visible UGS is plentiful in the inner areas, but sparser in the outer areas. Previous studies have demonstrated that the government has spent more on maintaining the historic sites and the surrounding environs in the inner areas (Dou, Zhen, De Groot, Du, & Yu, 2017). This may also have had the effect of increasing the quality (aesthetics and attractiveness) of visible UGS in the inner areas. Hence, housing prices are higher in the inner areas, which may also encourage local residents to maintain the quality of visible UGS (Zhang & Dong, 2018).

Our results also imply that visible UGS is less equally distributed from a qualitative perspective (aesthetics and attractiveness) than from a quantitative perspective (availability and accessibility). With regard to quantity, there are laws and standards in place to ensure the provision of greenspace in the Chinese context, such as the Urban and Rural Planning Law of the People's Republic of China (Standing Committee of the Tenth National People's Congress of the People's Republic of China, 2007), the Assessment Standard for Healthy Communities (China Association for Engineering Construction Standardization, 2021b) and the Assessment Standard for Elderly-oriented Function of Urban Communities (China Association for Engineering Construction Standardization, 2021a). Therefore, from a quantitative viewpoint, visible UGS is regulated by macroscopic policy, which has resulted in relatively equal distribution. However, due to difficulties in measuring and regulating the quality of visible UGS, its distribution is less equal from this perspective. First, the quality of UGS is a relatively subjective notion, so it is difficult for it to be precisely defined and regulated via laws or standards. For example, Knobel et al. (2021) included safety as one of the measures in their green space quality assessment tool, while Gidlow et al. (2012) did not. Second, there are multiple sub-categories that can be used for measuring the quality of visible UGS, which means that assessment and regulation will be time-consuming, labour-intensive and expensive (Wang et al., 2021). Lastly, although the quality of visible UGS may be more directly related to health outcomes (Feng & Astell-Burt, 2017), its quantity can be linked to a wider range of ecological functions such as reducing heatwaves (Maimaitiyiming et al., 2014), mitigating air pollution (Wang et al., 2020) and increasing biodiversity by providing a habitat for wildlife (Karuppannan, Baharuddin, Sivam, & Daniels, 2014). Therefore, in order to improve the overall well-being of a city, it is more economical and feasible for the government set standards or legislate on the basis of quantity rather than the quality of UGS.

Our results also show that there is a positive association between a community's economic level and the quality of UGS, although there is no evidence of a similar association with regard to the quantity of UGS, which is consistent with previous studies, such as Wang et al.'s (2021) research in Guangzhou. This means that SES-related disparities are more significant in terms of the provision of visible UGS from a qualitative than a quantitative perspective. There are several explanations for this finding. First, although most UGS in China is provided by the government, it is maintained via local public finance, which is closely related to the economic level of the local community (You, 2016). Therefore, communities with a higher SES are more likely to be able to afford the maintenance charges or even to pay more to improve the surrounding environment, so that local residents can enjoy a better quality of public open space (Wang et al., 2021). Second, people living in communities with a higher SES are also more likely to demand better quality UGS and be willing to pay for it (Xiao, Lu, Guo, & Yuan, 2017). Previous studies have shown that UGS can function as a public good and is positively related to housing prices, so local residents living in wealthier communities may be willing to pay to improve the quality of UGS in order to maintain the value of their properties (Xiao, Li, & Webster, 2016; Xiao, Lu, et al., 2017). Additionally, people living in wealthier communities may have more spare time and higher requirements for engaging with the open space environment, so they are more likely to be willing to fund it (Xiao, Wang, et al., 2017). Lastly, as previously mentioned, there are national laws and standards to ensure the provision of UGS in China, so the quantity of visible UGS is less influenced by a community's economic level. However, the omission of a qualitative perspective from the laws and standards relating to UGS may make its provision more market-based, and thus more influenced by the economic level of a community. Therefore, Zhang et al. (2021) argued that to ensure social equality, more attention should be paid to the qualitative perspective of UGS, instead of excessively pursuing the promotion of its quantity. Although previous studies in China found that labour and capital are the main driving forces of UGS, there were still spatial variations for that (Xu et al., 2019). For example, Xu et al. (2019) pointed out that the positive association between capital and UGS provision was weaker in Eastern District such as Beijing than other regions.

5.2 Implications for urban planning and policy

Assessing the disparities in community-level visible UGS provision in Beijing has implications for urban planning and policy. First, although the system used in China for planning green space has specific rules for the general provision of UGS (Zhou et al., 2021), scant attention has been paid specifically to visible UGS provision. Therefore, the latter should be taken into consideration in the planning process. Second, our proposed framework for assessing visible UGS provision, which provides a systematic understanding of visible UGS provision, could be used to guide the future planning of green space. In addition, remote-sensing data and land use data were included in the national dataset used in this study, so they could easily be used by policy makers to assess UGS provision from an overhead perspective. However, there are currently no data that policymakers could use to assess visible UGS provision, so the government should invest in creating an appropriate dataset. For example, currently, street view data is mainly collected by commercial corporations, so it cannot be updated annually due to the high level of investment required. Therefore, the government could collaborate with these companies to create a dataset for assessing changes in visible UGS which would then be updated on an annual basis. Third, our results indicate that the four different dimensions of visible UGS provision significantly differ in terms of their spatial distribution and the association between them in Beijing. Therefore, urban planning policy should pay attention to the spatial heterogeneity of different dimensions of visible UGS provision. For example, the availability and accessibility of visible UGS are relatively low in the inner area of Beijing, while the attractiveness and aesthetics of visible UGS are relatively high in the same area. Therefore, urban planning policy should focus more on improving the availability and accessibility of visible UGS in the city's inner area. Fourth, inequity indices (e.g., Gini index) relating to different dimensions of visible UGS provision should be considered as a crucial indicator for urban planning policy. For example, the China Association for Engineering Construction has published 'Assessment Standards for Healthy Communities' (Standardization, 2021b), which highlights the importance of green justice, but contains no specific indicators for measuring inequalities in the provision of visible UGS. Therefore, inequality indices relating to different dimensions of visible UGS provision could be added to the revised version of the standards. Last but not least, we have identified that economically disadvantaged communities have less visible UGS (from a qualitative perspective), so their maintenance allocations for UGS should be increased to provide for the upkeep of their visible UGS.

5.3 Limitations

It should be noted that this study has the following limitations. First, our proposed framework may not be comprehensive enough. For example, there are different aspects of aesthetics, but we have only focused on aesthetics from a diversity perspective. Second, street view data are collected over a set period of time, so they may not fully reflect seasonal variations in greenery. Third, there are some gated communities in Beijing, so the street view data may only contain information about the visible UGS outside the boundaries of these communities. Fourth, we only had access to cross-sectional street view data, which meant our study was unable to take changes in visible UGS into account, nor were we able to make inferences about the causality between the economic level of communities and visible UGS provision. Fifth, communities were identified on the basis of the administrative boundaries, which may have led to a modifiable areal unit problem (MAUP) due to the differences in scale between the geographical units (Fotheringham & Wong, 1991). Sixth, census data is usually aggregated at neighbourhood level (*juweihui*), so it does not provide detailed socio-economic and demographic covariates (only population density was included). Seventh, street view data offer only two dimensions of visible street UGS, but other two dimension information such as the size of street trees and spacing between the trees also matter (Zhu et al., 2021). Last, the factors for measuring SVG attractiveness may be contradictory in some area. For example, if an area is of high naturalness, it is possible that both maintenance and safety can only achieve a relatively low level, since a sense of naturalness is associated with higher degree of re-wilding (Hoyle et al., 2019). Hence, we did not consider man-made elements when calculating SVG aesthetics, and this may lead to potential measurement bias.

6. Conclusions

This study constitutes the first attempt to propose a systematic framework for assessing visible street UGS provision. Based on Beijing street view data, it explored inequalities in four different dimensions of visible street UGS provision and the extent to which a neighbourhood's economic level is associated with these different dimensions of visible street UGS. Based on the empirical study of Beijing, this paper draws the following conclusions.

(1) We found that the value of the Gini index and Moran's I index for attractiveness and aesthetics are higher than those for availability and accessibility, which indicates that there is a more unequal distribution of visible street UGS from a qualitative perspective.

(2) The results showed that there are differences in the spatial distribution and clustered pattern between qualitative and quantitative perspective of UGS in Beijing.

(3) We also found that a community's economic level is positively associated with attractiveness and aesthetics, while no evidence was found to support the claim that the economic level of a community associated with availability and accessibility. Such a result indicated that a community's economic level is only associated with the qualitative aspects of visible street UGS, which suggests that there are socio-economic disparities in the qualitative provision of visible street UGS.

Therefore, to help achieve the goal of green justice through urban planning and design, policymakers and urban planners should pay more attention to visible street UGS provision.

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