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Research article

Towards a Green Equal City: Measuring and matching the supply-demand of green exposure in urban center

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ABSTRACT

Exposure to green environments is crucial for human health. However, urbanization has reduced the contact of urban residents with natural environments, causing a mismatch between the supply and demand for green exposure. Research in this field is hindered by the lack of long-term, reliable data sources and methodologies, leading to insufficient consideration of temporal variations in green exposure. This study presented a comprehensive methodology for assessing green exposure at a fine scale utilizing satellite images for urban tree canopy identification. We conducted a case study in the core area of Beijing from 2010 to 2020 and examined the effects of urban renewal and alleviation efforts. The results revealed a slight decrease in green exposure for the elderly over the decade, with minimal changes in equity. In contrast, green exposure for children has increased, with increasing inequality. Moreover, urban renewal has improved green exposure for nearly half of the low-supply blocks. However, a significant mismatch was observed between supply and demand for blocks with increased demand but limited supply. This study enhances the assessment of green exposure and provides guidance for planning and constructing a “Green Equal City”.

1. Introduction

Urbanization has increased the separation between city-center residents and natural environments (Huang et al., 2022; Turner et al., 2004). This trend has resulted in several issues, including the heat island effect (Deilami et al., 2018), air pollution (Mage et al., 1996), and various health crises (Gong et al., 2012). Moreover, green spaces can considerably alleviate these issues. Studies have shown that urban green spaces provide various ecosystem services, such as a reduction in outdoor temperature (Wong et al., 2021), control of air pollution (Diener and Mudu, 2021), and collection of storm water runoff (Dowtin et al., 2023). Additionally, exposure to green spaces is beneficial for both physical and mental health (de Keijzer et al., 2016; Vanaken and Danckaerts, 2018).

China has undergone rapid urbanization, but this growth has been depended on resources, resulting in numerous environmental issues such as a mismatch between the supply-demand of green exposure (Chen et al., 2019) and significant vegetation degradation in urban expansion areas (Yang et al., 2021). Rapid urbanization has also led to disparities in green exposure between old and new urban areas (Song et al., 2020). In response, the Chinese government introduced the National New-type Urbanization Plan in 2014, aiming to achieve sustainable urbanization (Chen et al., 2018). In Beijing, the local government has implemented a policy of relocating non-capital functions to control urban population growth and undertaken urban renewal projects to improve the environment. Studies have indicated that these strategies and projects have caused population shifts within the core area of Beijing (CAB), leading to changes in the urban environment (Qiang and Hu, 2022; Zheng et al., 2023). These measures collectively increase green exposure and equity for urban residents. However, studies that comprehensively assess this transformation from various perspectives are scarce.

Research on green exposure and its supply-demand can be classified into assessments of the current condition of green spaces and analyses of

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their long-term changes. The predominant method for current assessments involves the use of remote sensing image data to identify green spaces (Gascon et al., 2016; Reid et al., 2018) or the conduction of accessibility analysis on park and green spaces using online maps (Dai, 2011; Xing et al., 2018). Several studies have used more diverse data sources, such as calculating green exposure based on street-view images (Larkin and Hystad, 2019; Li et al., 2015), or analyzing tree contact situations using tree datasets or LiDAR-based crown identification results (Croeser et al., 2020; Nesbitt et al., 2019). Studies on long-term changes have often utilized land use and land cover (LULC) or normalized difference vegetation index (NDVI) data for macroscopic analysis (Chen et al., 2024; Rafiee et al., 2009; Song et al., 2020). On the demand side, numerous studies have utilized typical socio-demographic data and individual perceptions and evaluations of the site (Hegetschweiler et al., 2017).

Different data sources often have advantages and limitations. Remote sensing image data can capture green spaces of all categories, including some that are not publicly accessible, potentially leading to an overestimation of green exposure. Moreover, publicly available LULC and NDVI data have relatively low resolution, posing challenges for studies with high data granularity requirements in urban centers. Accessibility assessments for green spaces mainly prioritize the accessibility of area-based green spaces such as parks, while the green exposure provided by street trees and informal green spaces is often overlooked (Ke et al., 2023). Street-view images can only capture the exposure of street trees, thereby often requiring supplementary data such as NDVI to represent the overall green exposure (Larkin and Hystad, 2019; Lu et al., 2019). Individual tree data can provide flexible measurements of tree exposure at a micro-level, but acquiring these data remains challenging.

The study addressed the challenges related to spatial resolution and variety in traditional green exposure calculations through the development of a method suitable for urban centers. Regarding spatial resolution, high-resolution satellite image data and deep learning techniques were utilized to measure green exposure at the individual tree level. This approach provided a more detailed assessment of green exposure compared with NDVI. Regarding variety, the study considered individual trees as units, including green exposure provided by various types of green spaces such as parks, street trees, and community green areas. This approach addressed the limitations of current studies, which often focus only on specific types of green space based on park boundaries or street view images. This study used CAB as a case study area to assess the green exposure and equity for the elderly and children population in 2010 and 2020 to provide insights for urban planning and policy formulation. This study served three main purposes:

1. To develop a method for assessing green exposure and equity in the city center.
2. To map and analyze the changes in green exposure and supply-demand relationship in the CAB from 2010 to 2020.
3. To provide guidance for the planning and construction of a "Green Equal City" based on the assessment of green exposure in the CAB.

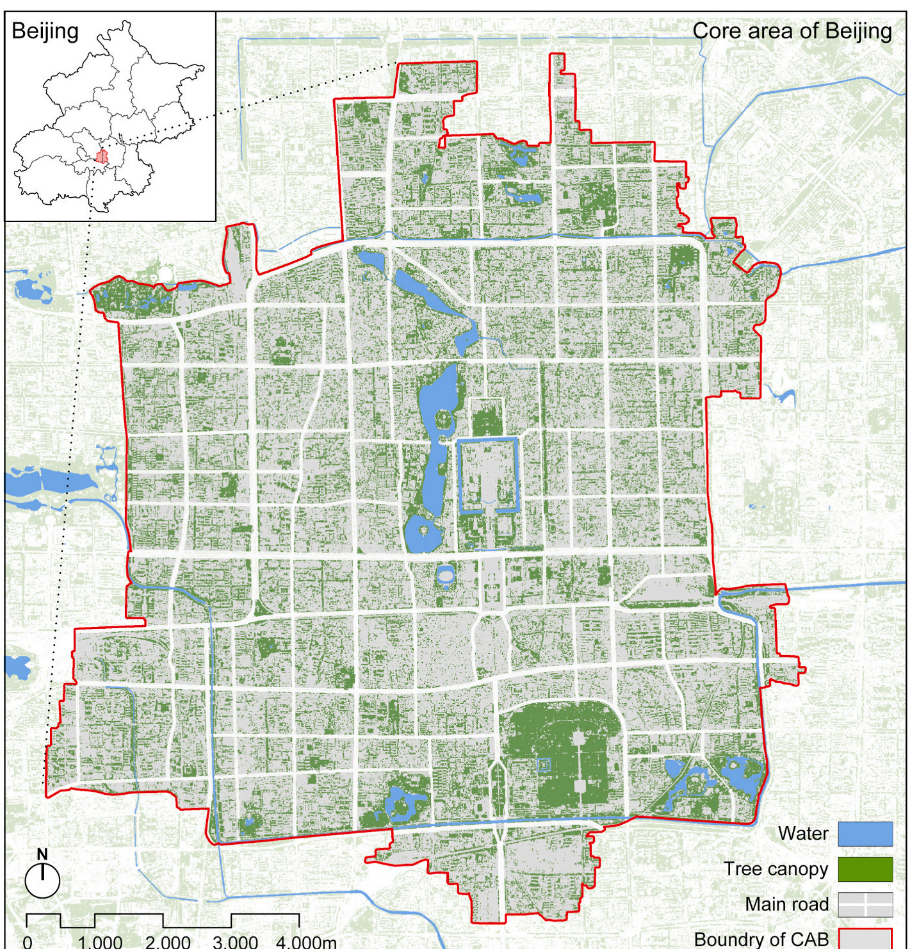

Fig. 1. Distribution of tree canopy within and around CAB.

2. Materials and method

2.1. Case study area

The CAB, comprising the Dongcheng District and Xicheng District of Beijing (Fig. 1), covers a total area of ~92.5 square kilometers and has a resident population of ~1.812 million in 2022. CAB is a focal point for Beijing's urban renewal efforts, including significant ecological spaces such as Jingshan Mountain, Beihai Lake, Tiantan Park, and the zoo.

The Detailed Plan for the Core Area of Beijing (DPCAB) aims to establish a high-quality and pleasant urban environment. Particularly, DPCAB recommends enhancing different types of green spaces, such as parks, micro-green spaces, and ancillary green spaces. Additionally, DPCAB suggests the establishment of a database to preserve old, valuable and large trees to monitor their growth status and improve the tree-growing environment.

CAB, a typical high-density city in China, has recently emerged as the focus of several studies related to environmental equity. For example, Cao et al. (2022)and Wang et al. (2023a) investigated the equity of green space distribution in CAB through different methods. Xu and Zhao (2021)assessed the economic value of ecosystem services provided by green infrastructures in CAB. Zheng et al. (2023) explored individual habits of use and perception of cultural ecosystem services. These studies provide planning strategies for CAB and serve as examples of environmental equity in high-density cities worldwide.

2.2. Research framework

The spatial distribution of urban vegetation plays a crucial role in assessing green exposure and equity, particularly in accessibility (Nesbitt et al., 2018). Therefore, this study utilized the accessibility model proposed by La Rosa (2014), which incorporated factors including origin, destination, and distance. Additionally, considering the features of green exposure in the city center, each component is described as follows:

1. Destination Place: This involved identifying the location and ownership of the tree canopy;
2. Accessibility: This involved determining the walking range from the residential block;
3. Origin Place: This involved estimating the population of the residential block.

With the assessment of green exposure as the central focus, the study framework is illustrated in Fig. 2. Before the assessment of green exposure, data were collected and processed, including satellite images, road network data, and census data. After the assessment of green exposure, the study assessed equity across various demographic groups and walking ranges and evaluated the supply and demand of green exposure for each block.

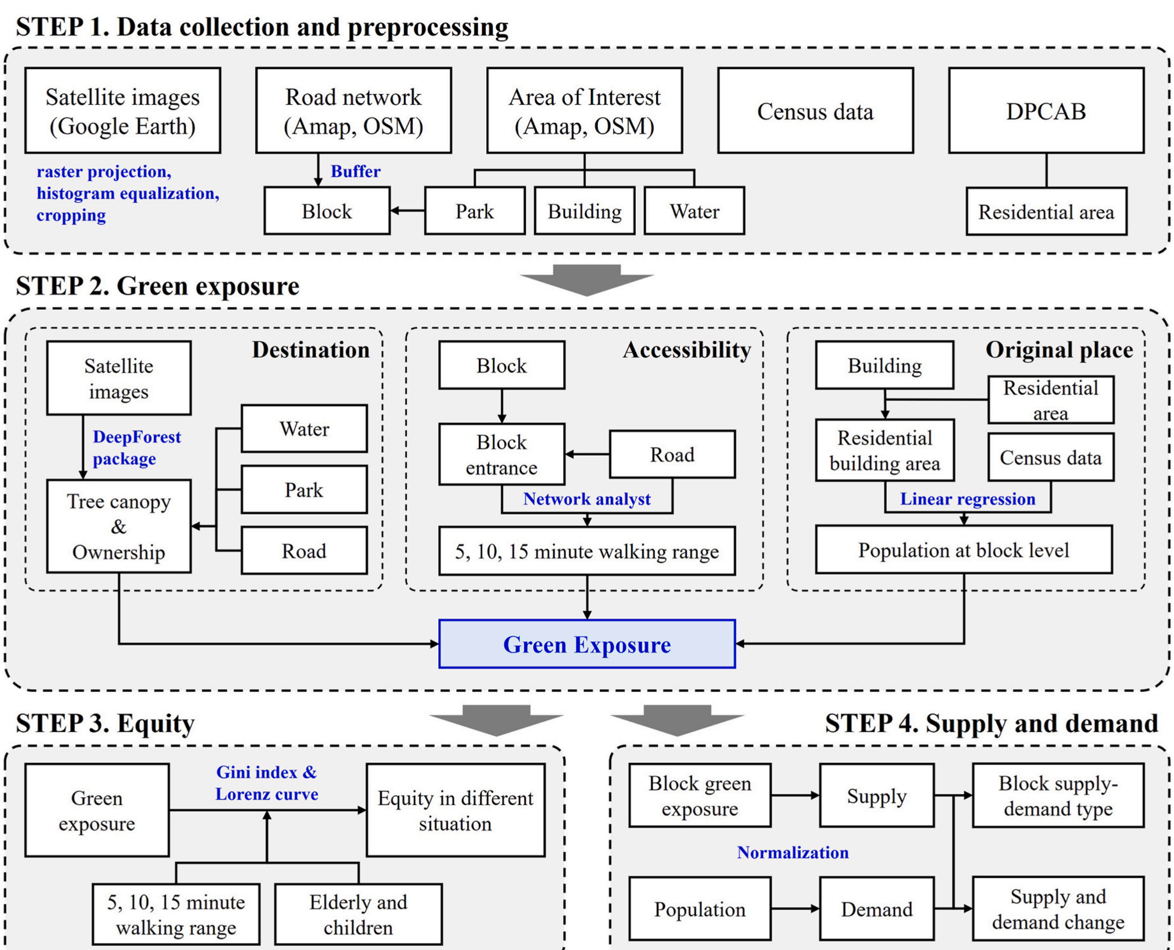

Fig. 2. Framework for assessing green exposure and equity. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2.3. Data collection and preprocessing

The data and sources utilized in the study are presented in Table 1. RGB satellite image data from Google Earth (September 18, 2020, and September 27, 2010) underwent raster projection, histogram equalization, and cropping of the raw images. The cropping range included the study area and its surrounding area to mitigate the "edge effect".

Road network, building, and Area of Interest (AOI) data were obtained from Amap, a famous navigation software in China. However, Amap lacked relevant data for the year 2010. Therefore, the 2010 road network and some AOI data were modified using previous files from OpenStreetMap (OSM). Moreover, building data were supplemented and manually drawn based on satellite image data.

We implemented the road buffer and water-based delineation method proposed by Liu and Long (2016) and integrated to the road buffer class and radius settings recommended by Zhang et al. (2019) into the initial delineation of the block. Additionally, we included railroads and internal fences within the blocks to further subdivide them.

Although several studies have used Point of Interest (POI) to classify land use (Liu and Long, 2016), this method is mainly used for rapidly delineating numerous city blocks, resulting in relatively low accuracy when applied to specific city blocks. In this study, residential blocks were identified based on the current land use in DPCAB, AOI from Amap and OSM, and satellite images. DPCAB, established in 2018, effectively represented the distribution of residential land use in 2020 owing to minimal changes in land use within CAB. This current land use map was aligned with other data sources using the Georeferencing tool in ArcMap 10.8.

2.4. Green exposure calculation

2.4.1. Destination Place

We used DeepForest to train and classify the images described in Section 2.3 for canopy identification. DeepForest is a Python package designed to detect individual tree canopies from RGB images. Additionally, DeepForest provides pre-trained models and annotations to enhance the performance of the models through further training. The selected area, covering a range of ~100 ha in the southern region of the CAB, was designed for manual annotation and training. This area comprised tree arrays, irregular bushes, street trees, and water surfaces with multiple clusters of trees, which effectively captured tree characteristics of the study area. Owing to the limitation of RGB images in detecting trees in the shadows of buildings, we manually added trees in these areas using street view maps, compared images from different periods, and manually identified the misclassified tree.

The impact of ownership on green exposure depended on the level of public accessibility. For example, trees along roadsides and in parks were typically accessible to all residents, while trees in gated communities were mainly accessible to residents within their respective blocks. According to different tree ownership, this study categorized trees into public, semi-public, and non-public groups. These classifications were established using Amap road network data, AOI, water surface, satellite images, and DPCAB (Supplementary Material 1).

Table 1
Main data and sources.

Feature	Data format	Year	Source
Population	Tabular	2010	the Sixth Population Census of China (https://nj.tjj.beijing.gov.cn/tjnj/rkpc-2010/e/left.htm)
		2020	the Seventh Population Census of China (https://nj.tjj.beijing.gov.cn/tjnj/rkpc-2020/indexch.htm)
Road network	Polyline	2010,	OpenStreetMap older files (china-140101-free) (http://download.geofabrik.de/asia/china.html#)
		2020	Amap (https://ditu.amap.com/)
Satellite images	Raster	2010	Google Earth (September 18, 2020)
		2020	Google Earth (September 27, 2010)
Land use	Raster	2010, 2020	DPCAB current land use map (https://www.beijing.gov.cn/zhengce/zhengcefagui/202008/t20200828_1992592.html)
	Polygon		OpenStreetMap older files (china-140101-free) (http://download.geofabrik.de/asia/china.html#) Amap (https://ditu.amap.com/)
Building	Polygon	2020	Amap (https://ditu.amap.com/)

2.4.2. Accessibility

Owing to the exclusion of large parks from the block scope, counting trees only within block boundaries could not capture the real extent of green exposure. Previous studies have used buffer zones with different radii to evaluate greenspace accessibility at the block level. However, the actual accessibility to green spaces in the city varied based on the configuration of the road network (Chen et al., 2022). Therefore, we assessed the accessibility of residential blocks by considering the entrances and exits of residential blocks and the configuration of the road network.

We used the road network described in Section 2.3 as the transportation network for measuring walking accessibility. We used the residential area and road network to identify the roads in the residential block and designated the intersections of the residential block as the entry and exit points. Moreover, according to existing studies, the walking speed was set at 5 km/h (Millward et al., 2013), and the walking ranges were determined using 5, 10, and 15-min travel times. The Network Analyst tool in ArcMap 10.8 was used to measure the accessibility of the block.

2.4.3. Origin place

Traditional population studies have often relied on census data, but China's census data is available only at the sub-district level, making it challenging to reflect population figures at the block level. Because CAB comprised only 32 sub-districts, the results may lack statistical significance. However, Zhou et al. (2021)used block floor area data to reflect population distribution. We conducted a linear regression of residential floor area on census population for both 2010 and 2020 at the sub-district level. The R-squared values for both years exceeded 0.8. The age composition of each block was derived from the census data of the corresponding sub-district. According to the Chinese population census standards, individuals aged 65 and above were classified as the elderly group, while those aged 14 and below were categorized as the children group.

To validate the age composition estimates, this study used data from the 2010 1% population sample survey, which included information such as birth year, gender, and neighborhood (between sub-district and block). However, within CAB, only the Shichahai and Desheng sub-districts have officially disclosed neighborhood boundaries. Therefore, validation was conducted using these two sub-districts, which comprised a total of 42 neighborhoods and 774 individual samples. A one-sample *t*-test was performed on the proportions of elderly and children in each neighborhood, with the proportions of elderly and children in the sub-districts serving as the test values. The results revealed that all p-values exceeded 0.05, indicating no significant difference in the age composition between the sub-district level and the finer scale.

The linear regression results between the neighborhood samples and the previously estimated numbers of elderly and children yielded an R-squared value of ~0.3, with p-values below 0.05. This indicates that residential building areas significantly influenced the estimation of the numbers of children and elderly. However, owing to the small population in some neighborhoods, the sampled numbers of children and elderly were zero, leading to significant heterogeneity in population distribution between neighborhoods. Consequently, the R-squared value at the neighborhood level was lower than that at the sub-district level. Nevertheless, the prediction results can still considerably capture the population distribution of children and the elderly.

2.4.4. Green exposure

This study defined green exposure as the probability of encountering trees while walking from a block. The study considered semi-public trees within the block and public trees within the walking range. The green exposure values for each block are presented in equations (1)–(3):

$$GE_{ij} = \frac{N_{ij}}{Pop_i} \tag{1}$$

$$GE_i = \frac{\sum_{j=0}^{j=15} d_j \times N_{ij}}{Pop_i} \tag{2}$$

$$d_j = \begin{cases} 0.4, if, j = 0 \\ 0.3, if, j = 5 \\ 0.2, if, j = 10 \\ 0.1, if, j = 15 \end{cases} \tag{3}$$

where GE_{ij} represents the green exposure for block i within a j min walking range. N_{ij} represents the number of trees encountered by block i within the j-minute walking range. Pop_i denotes the population of block i. GE_i indicates the green exposure for block i under distance decay weighting. d_j represents the decay coefficient, while $j = 0$ indicates the coefficient corresponding to the green exposure within the block, and $j = 5, 10, 15$ reflects the coefficients for 5, 10, and 15-min walking ranges, respectively.

2.5. Equity assessment

The Lorenz curve and the Gini index (GI) are widely used in measuring inequity in environmental justice (Song et al., 2021; Yu et al., 2023). The Lorenz curve, originally developed to measure wealth concentration, is used to plot the cumulative percentage of the population (arranged from the poorest to the richest) on one axis against the cumulative percentage of total wealth held by these population segments on the other axis. This graphical representation is instrumental in analyzing income or wealth distribution within a population (Lorenz, 1905). In this study, we sorted the data and calculated the percentages by comparing the predicted number of individuals in each block with the number of trees accessible per capita. Additionally, the Lorenz curve was plotted in RStudio using x- and y-axes for the cumulative percentage of the population and the accessible trees, respectively. The Gini index was calculated based on the area between the Lorenz curve and the line of absolute equity.

2.6. Block supply and demand

This study assessed the supply and demand by normalizing data on the green exposure and population. The classification of blocks was determined using the relative values of supply and demand. The calculations for supply and demand are presented in equations (4) and (5):

$$S_i = \frac{\log_{10} \sum_{j=0}^{j=15} d_j \times N_{ij}}{\log_{10} \max_n \sum_{j=0}^{j=15} d_j \times N_{ij}} \tag{4}$$

$$D_i = \frac{\log_{10} Pop_i}{\log_{10} \max_n Pop_i} \tag{5}$$

where S_i and D_i represents the supply and demand state of block i. n represents the total number of blocks. According to the average values of supply and demand for each block in CAB, the blocks were categorized into high supply-low demand (HSLD), high supply-high demand (HSHD), low supply-low demand (LSLD), and low supply-high demand (LSHD). Among these groups, LSHD indicated that the demand for green exposure exceeded the supply. HSLD signified an excess supply of green exposure. HSHD and LSLD indicated a relatively balanced match between supply and demand for green exposure.

3. Results

3.1. Data foundation

According to the final results of tree identification in the southern region of CAB, covering ~100 ha, we re-examined the data for reliability and accuracy. The tree identification process was evaluated using the original DeepForest metric with an IoU of 0.4. The identification achieved a precision of 0.6164, a recall of 0.7302, and an F1 score of 0.6685, indicating reasonable performance.

Table 2 illustrates the changes in both the quantity and types of trees and population from 2010 to 2020, while Fig. 3 shows the spatial distribution. Over the past decade, the most significant change in tree composition has been the remarkable increase in public trees. This increase mainly resulted from three initiatives: the establishment of new pocket parks, the planting of new street trees along specific roads, and the transformation of the defunct Beijing amusement park into a public park. This comprehensive strategy indicated a multifaceted approach to urban greening and the enhancement of public spaces. The increase in semi-public trees was mainly attributed to tree planting within residential areas result from real estate development activities. However, this increase has caused significant changes in the original distribution of trees. Moreover, Beijing's population has decreased owing to the alleviating policies of the city. Additionally, both the elderly and children populations have increased. The increase in the children population can be partly attributed to the high-quality education in CAB and school district policies, which have attracted external families seeking better educational opportunities (Han et al., 2021). The increase in the elderly population indicated broader aging trends in the city.

3.2. Green exposure and equity

The results revealed that as walking range increased, the levels of green exposure also increased. However, within the same walking range, minimal variation was observed in green exposure between 2010 and 2020 (Fig. 4-A). Regarding different age groups, a slight decrease in green exposure for the elderly has been observed over the past decade, while children have exhibited a significant increase in green exposure (Fig. 4-B).

Regarding equity, the overall GI has increased over the past decade, indicating a widening gap in green exposure among blocks. Additionally, across different walking ranges, GI increased with larger walking ranges, suggesting that green exposure became increasingly unequal at larger radii. Regarding different age groups, the GI for the elderly slightly differed compared with the overall age range, while the GI for

Table 2
Changes in trees and population.

Trees and Population		2010	2020
Trees		530,661	550,283
	Public trees	236,538	250,333
	Semi-public trees	275,454	282,825
	Non-public trees	18,669	17,125
Population		2,151,010	1,815,043
	0–14 years old	163,842	256,202
	15–64 years old	1,717,705	1,228,560
	65 years old and over	270,463	330,281

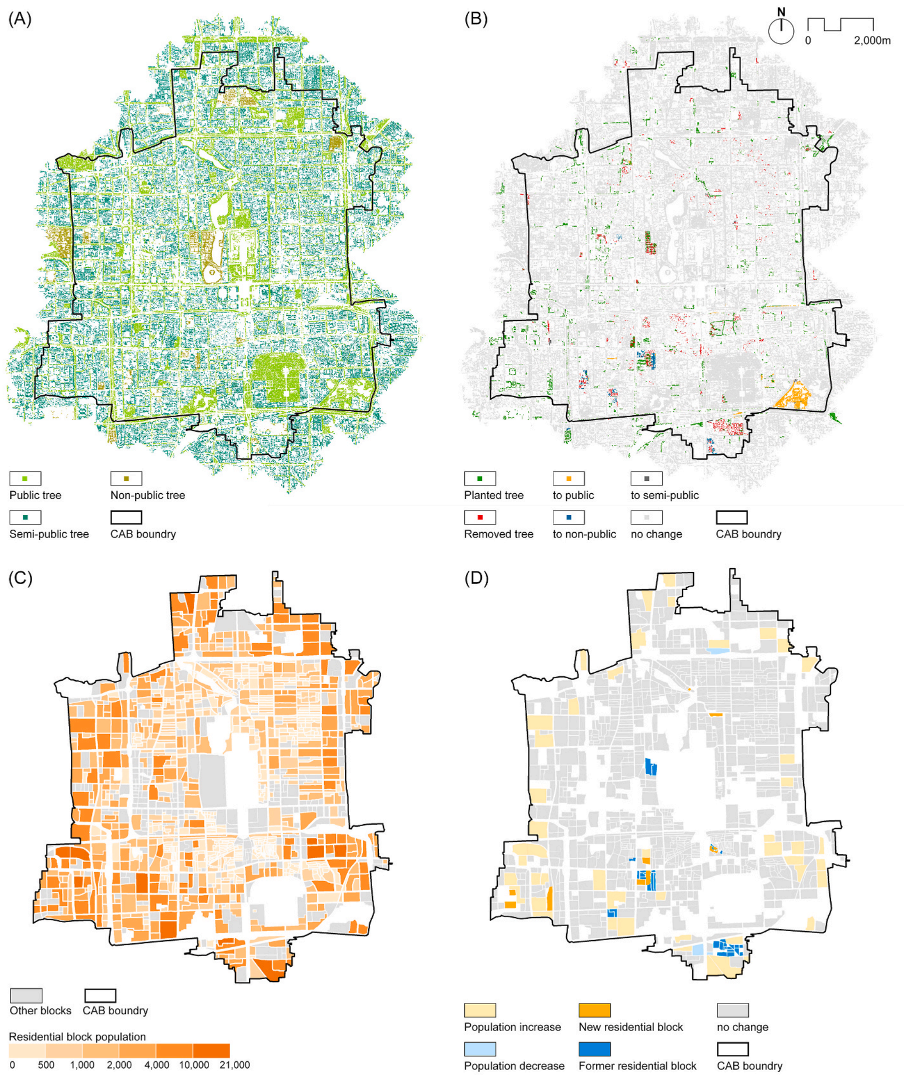

Fig. 3. Distribution of tree locations and block population. (A) Tree type in 2020; (B) Changes in trees between 2010 and 2020; (C) Block population in 2020; (D) Changes in block between 2010 and 2020.

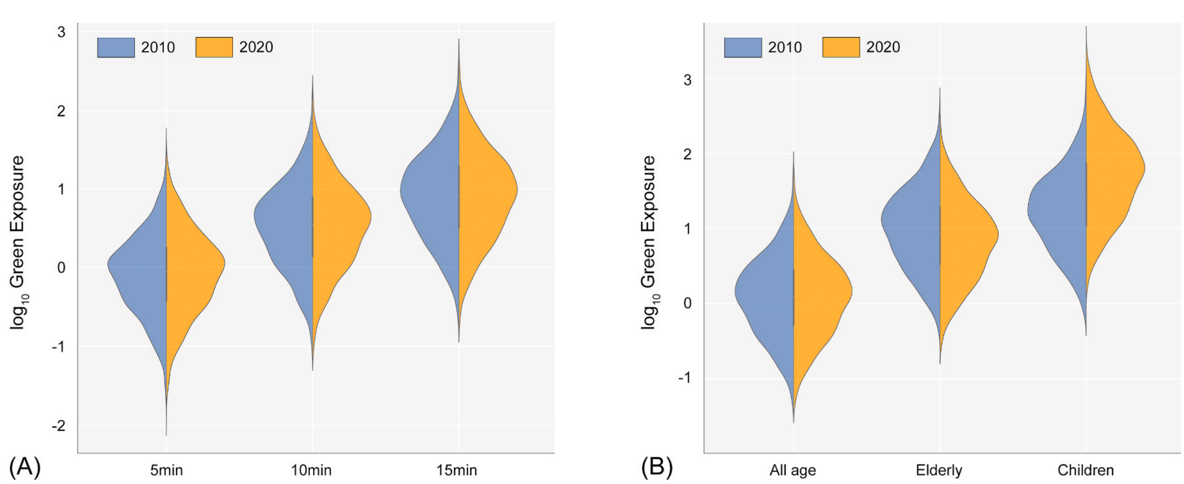

Fig. 4. Changes in green exposure across different walking ranges and groups. (A) Green exposure in different walking ranges; (B) in different age groups. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

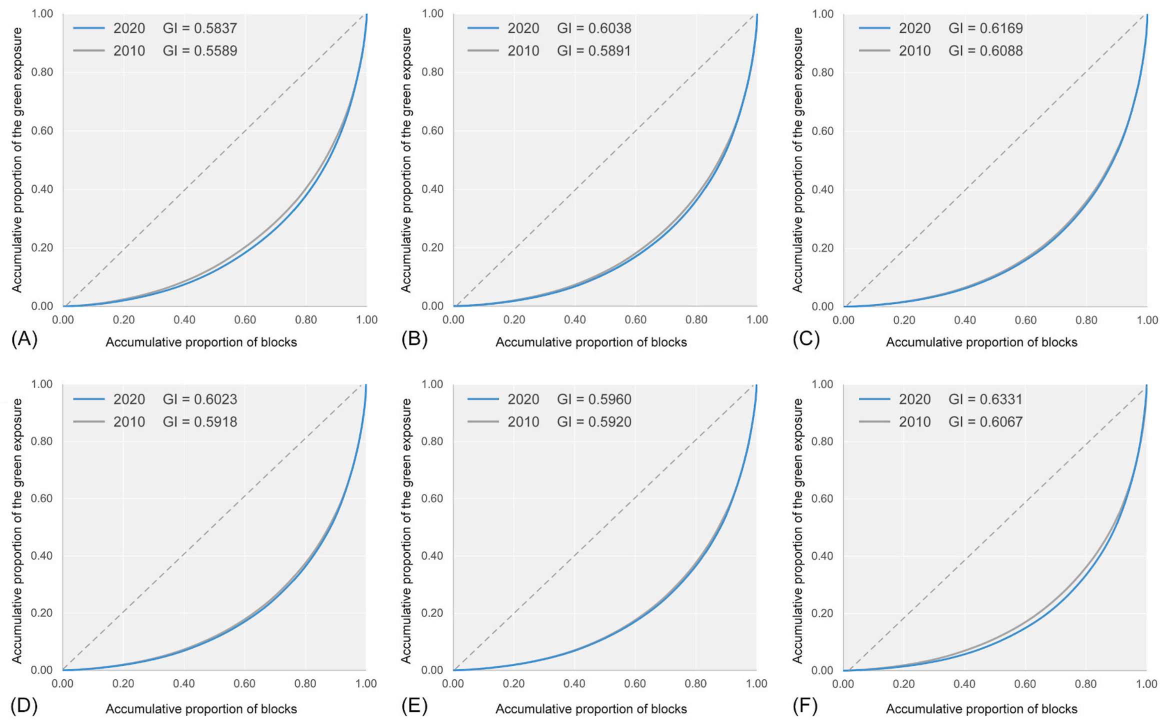

Fig. 5. Lorenz curve in different walking ranges and groups. (A) 5-min walking range; (B) 10-min walking range; (C) 15-min walking range; (D) all age groups; (E) elderly; (F) children.

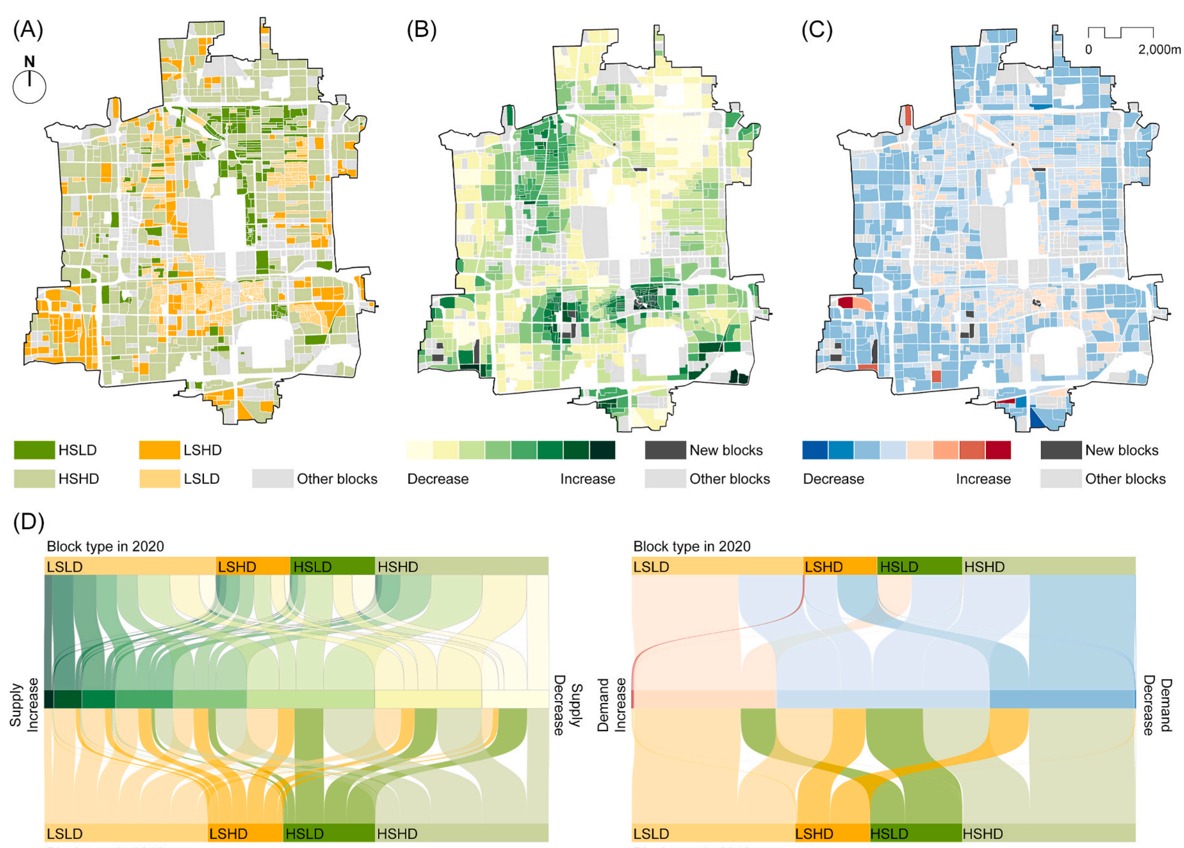

Fig. 6. Dynamics of supply and demand in blocks. (A) Block supply-demand type in 2020; (B) Changes in green exposure supply; (C) Changes in block green exposure demand; (D) Changes in block supply-demand type. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the children was relatively higher. This indicates that children faced a relatively more significant disparity in green exposure (Fig. 5).

3.3. Block demand and supply

Fig. 6-A illustrates the supply and demand types of each block in 2020. HSLD blocks were mainly concentrated around parks, representing traditional low-density residential areas. HSHD blocks were widely distributed on the outskirts of CAB and mainly consisted of medium-density residential blocks built during the 1950s–1980s. LSHD blocks clustered in the southwest region of CAB mainly comprised high-density residential blocks built after the 1990s, characterized by limited public green spaces. LSLD blocks were concentrated in the central areas of CAB, particularly in the Qianmen and Dashila sub-districts. This region constituted a traditional hutong preservation zone in Beijing, with only a few pocket parks, resulting in a limited supply of green exposure.

Fig. 6-B and 6-C illustrate the changes in the supply and demand of green exposure over the past decade, with the values categorized using the Jenks natural breaks. The central area of CAB has exhibited a significant increase in the supply of green spaces owing to the construction of two new parks as part of urban renewal projects (Guangyanggu Urban Forest and Qianmen Sanlihe Park). Additionally, the development of pocket parks and the increase in street trees have contributed to the overall improvement in green exposure in the northwest region of CAB. The demand for most blocks has remained relatively stable, with a slight decrease observed in demand for numerous blocks on the outskirts of CAB, possibly related to a decline in population. Moreover, only a few blocks near the CAB boundary have shown an increased demand owing to real estate development.

Fig. 6-D illustrates the changes in supply and demand across various block types. Over the decade, the LSLD block has shown the most significant increase in supply. This suggests a considerable enhancement in green exposure for the traditional hutong blocks within CAB. Despite the highest demand for supply in LSHD blocks, less than half of the blocks exhibited an increase in green exposure. Regarding changes in demand, most blocks exhibited minor fluctuations, while LSHD and HSHD blocks displayed a slight decrease in demand. Notably, only a few blocks exhibited significant increases or decreases in demand, indicating a prevailing issue of supply-demand mismatch in blocks undergoing renovations throughout the decade.

4. Discussion

4.1. Comparison with other green exposure and equity measures

As previously mentioned, accessibility models comprised three variables: destination, distance, and original place (La Rosa, 2014). Regarding the destination variable, current research on urban environmental justice mainly focuses on park green spaces (Ekkel and de Vries, 2017; Rigolon, 2016). Although research on urban trees often involves identifying canopy coverage ratios and counting the number of trees within the research area (Flocks et al., 2011; Nesbitt et al., 2019), less attention has focus on tree accessibility. However, this lck of emphasis does not indicate that tree accessibility is insignificant, rather exposure to trees has significantly enhanced the health of residents (Moreira et al., 2020). The scarcity of related research may be attributed to the complex computations involved with numerous urban trees, particularly when each tree is when tree is treated as a distinct destination. In our study, we simplified the calculation of accessibility by defining the walking range for blocks and focusing on green exposure from the perspective of individual trees. This approach streamlined the analysis, making it more manageable assess of green exposure in urban settings.

Regarding the origin variable, the origin place should ideally align with the population distribution (Apparicio et al., 2008). In several studies conducted in the United States, the central points of census block groups or census tracts served as the origin for accessibility calculations (Beyer et al., 2014; Greene et al., 2018; Heckert, 2013). However, China's population census only publicly disclosed information at the sub-district level, limiting research to a fine scale. Therefore, several studies have resorted to using residence points obtained from online maps and housing transaction websites as the origin for analysis (Wang et al., 2023a; Yu et al., 2023). The extensive existing data, often lacks validation and fails to annotate informal settlements such as urban villages, or neglects low-income groups. To address this issue, our study incorporated residential land use data from DPCAB, building area, and population census data to accurately estimate block-specific populations.

The scalability of using this method across different cities, scales, and periods depended on the availability of required data. Owing to China's relatively strict air traffic control, fewer studies have used LiDAR data to construct databases for urban ecological elements at the city level (Wang et al., 2018). However, deep learning technology has significantly increased the speed, scale, and cost of individual tree canopy identification (Weinstein et al., 2021). This method utilized remote sensing data on 100 million tree canopies from the National Ecological Observation Network and employed the DeepForest package for tree crown identification (Weinstein et al., 2021). The effectiveness of the package was further confirmed by successful applications in other urban studies (Velasquez-Camacho et al., 2023).

4.2. Implication for Green Equal City

Urban green equity comprises two key aspects: the spatial distribution of vegetation and recognition in decision-making (Nesbitt et al., 2018). This principle is reflected in the DPCAB planning documents, which introduce requirements, such as expanding the size of green spaces and establishing mechanisms for public participation. This study focused on analyzing the spatial distribution dimension of green equity. Through the assessment of green exposure, the study provides guidance for achieving a "Green Equal City".

Studies indicated that specific groups, particularly the elderly and children, are vulnerable in urban environments (Sikorska et al., 2020). The analysis of different age groups in CAB revealed a decrease in green exposure for the elderly, with relatively minimal changes in equity. In contrast, green exposure for children has significantly increased, with increasing equity. This change resulted from the combined impact of urban renewal projects and shifts in population structures. Particularly, the Tiantan and Tianqiao sub-districts, located in the southern region of CAB, exhibited the highest proportion of elderly residents (both exceeding 20%). Over a decade, the elderly population in these areas has increased by over 6%. However, these regions were characterized by only a few planted trees and newly constructed parks. Wang et al. (2020) also indicated similar results, suggesting insufficient resources for the elderly in old Beijing city and significant disparities in the provision of facilities across different communities.

Recognizing potential mismatches between supply and demand provides detailed insights into areas requiring intervention or investment (Keeler et al., 2019). In this study, the construction of Guangyanggu Urban Forestry and Sanlihe Park in the central CAB addressed the supply-demand mismatch, leading to a significant increase in green exposure in surrounding low-supply blocks. This trend can be attributed to Beijing's numerous small-scale urban renewal projects from 2011 to 2020, a period characterized by organic renewal (Wang et al., 2023b). However, the construction of Sanlihe Park involved the displacement of indigenous residents, leading to an increase in rents. This trend in environmental gentrification may result in more severe inequities (Krings and Schusler, 2020). Therefore, as the available space for large green spaces in the urban center decreases, it is recommended to address the mismatch in supply and demand within specific blocks. This can be achieved through the implementation of strategies such as constructing pocket parks and incorporating vertical greening to improve green exposure.

4.3. Limitations and future research

This study presented a method to assess tree accessibility and equity in the city center, but certain limitations persisted. First, the assessment of green exposure depended on the residential research paradigm, potentially leading to the uncertain geographic context problem (Liu et al., 2023). Adopting a mobility-oriented approach in green exposure research can provide valuable insights for future studies.

Second, this study assessed green exposure based on tree location and type. However, research has suggested that green exposure can be influenced by individual usage behaviors and travel preferences, and the green space area may not necessarily correlate with green exposure (Chen et al., 2020; Xie et al., 2023). Therefore, we recommend that future research consider integrating street-level images with survey results to achieve a more comprehensive assessment of green exposure.

Additionally, owing to the accessibility of the required data, we anticipated the future application of this method in the comparative assessment of tree accessibility and inequity across different scales and cities. For example, in the comparative assessment of tree accessibility at the city level, the analysis could be conducted at the sub-district level, considering the accessible areas for various modes of transport. On a smaller scale, such as the community level, the analysis could focus on the building level and examine tree accessibility for residents in different locations and on various floors.

5. Conclusion

In urban centers, the health of residents can be significantly influenced by their exposure to green environments. The green exposure in city centers was shaped by various factors, including urban renewal and park construction, the aging population and urban policies. This study established a method for assessing urban green exposure and equity, characterized by the following features.

(1) RGB satellite images were used to identify features through a deep learning method, enabling the measurement of urban green exposure across different periods.
(2) The use of multiple data sources for urban feature recognition ensured precision and comprehensive assessments of equity from various perspectives.
(3) This method can enable the assessment of past development and serve as a basis for future planning policies based on the supply and demand of green exposure for each block.

The conclusions drawn from a case study conducted in CAB between 2010 and 2020 are as follows:

(1) The number of public and semi-public trees in CAB has increased, while non-public trees have decreased. Despite the overall decrease in the population of CAB, the numbers of children and elderly have increased.
(2) Over time, the inequity in green exposure has increased. While green exposure for the elderly has decreased, the overall equity has remained relatively stable. Additionally, green exposure for children has significantly increased, with increasing inequity.
(3) The construction of parks has improved green exposure for nearly half of the low-supply blocks. However, a significant mismatch was observed between supply and demand for blocks with increased demand but limited supply.

CRediT authorship contribution statement

Chaoyang Zhu: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Shanwen Zheng:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Shengjie Yang:** Writing – review & editing, Validation, Investigation, Formal analysis. **Jun Dong:** Investigation, Formal analysis. **Moheng Ma:** Validation, Investigation. **Shanshan Zhang:** Investigation. **Shengnan Liu:** Investigation. **Xinyu Liu:** Writing – review & editing. **Yifeng Yao:** Writing – review & editing, Validation. **Baolong Han:** Validation, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shanwen Zheng reports financial support was provided by National Natural Science Foundation of China (Project No. NSFC51908004). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.121510.

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