



Observed inequality in urban greenspace exposure in China

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ABSTRACT

Given the important role of green environments playing in healthy cities, the inequality in urban greenspace exposure has aroused growing attentions. However, few comparative studies are available to quantify this phenomenon for cities with different population sizes across a country, especially for those in the developing world. Besides, commonly used inequality measures are always hindered by the conceptual simplification without accounting for human mobility in greenspace exposure assessments. To fill this knowledge gap, we leverage multi-source geospatial big data and a modified assessment framework to evaluate the inequality in urban greenspace exposure for 303 cities in China. Our findings reveal that the majority of Chinese cities are facing high inequality in greenspace exposure, with 207 cities having a Gini index larger than 0.6. Driven by the spatiotemporal variability of human distribution, the magnitude of inequality varies over different times of the day. We also find that exposure inequality is correlated with low greenspace provision with a statistical significance (p -value < 0.05). The inadequate provision may result from various factors, such as dry cold climate and urbanization patterns. Our study provides evidence and insights for central and local governments in China to implement more effective and sustainable greening programs adjusted to different local circumstances and incorporate the public participatory engagement to achieve a real balance between greenspace supply and demand for developing healthy cities.

1. Introduction

The pressing challenges in the 21st century, such as climate change, population aging, urbanization, and environmental pollution, have enhanced the importance of developing sustainable and healthy living environments (Tonne et al., 2021). The Healthy Cities approach is

therefore becoming one of the key paths for achieving the Sustainable Development Goals (SDGs) of the United Nations, especially Goal 11—Sustainable Cities and Communities (Organization, 2017). A healthy city refers to one that continuously creates and improves its physical and social environments through urban intervention (e.g., health policies, urban design) until population health reaches a

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satisfactory level (Nieuwenhuijsen, 2020). The Healthy Cities movement was originally launched in the 1980s and has been gradually adopted and implemented in many countries worldwide, under the initiative and guidance of the World Health Organization (Tsouros, 2019). It is worth noting that the provision and maintenance of urban natural environments is an indispensable part of these implemented or ongoing healthy cities programmes (Tonne et al., 2021; Yang et al., 2018).

Urban greenspace is considered as one of the key environmental components for a healthy city, which serves as the main area for recreational and social activities, contributing to improving people's physical and mental health (Bauwelinck et al., 2021; Sun et al., 2020). Urban greenspace also greatly promotes urban ecosystems and biodiversity (Kendal et al., 2020) and alleviates numerous environmental issues with adverse effects on health, such as urban heat islands, air and noise pollution, and urban waterlogging (Mueller et al., 2020; Zhang et al., 2020). Nevertheless, rapid urbanization in the past decades, especially in developing countries, not only contributed to massive rural-to-urban migration but also substantially reshaped land cover and land use patterns, thereby dramatically altering both the quality and quantity of urban greenspace (Chen et al., 2017), changing the way people get close to nature (Song et al., 2020a), lowering greenspace generated health benefits (Hunter et al., 2019), and exacerbating environmental and health inequities (Lu et al., 2021). Accordingly, a comprehensive understanding of population greenspace exposure and the corresponding inequality issue has become a prerequisite for supporting the future development of healthy cities, which is gaining growing interest from environmental scientists, public health researchers, urban planners, and authorities (Fan et al., 2020; Mygind et al., 2021).

With a retrospect of existing studies, the assessment of inequality in urban greenspace exposure generally includes the following four steps (Chen et al., 2017; Wüstemann et al., 2017): (1) urban area identification/extraction, (2) greenspace mapping, (3) exposure/accessibility measurement, and (4) inequality assessment. The datasets and methods used in each step will directly affect the accuracy and robustness of final assessment results.

Identifying the extent of urban areas is to ensure that the entire assessment process is focused on urban residents. On the one hand, land cover maps derived from remote sensing images have been widely used to delineate the spatial extent of urban areas, such as ESA-CCL Land Cover (LC) time-series (Santoro et al., 2017) and Global Human Settlement Layer (Pesaresi et al., 2013). However, "urban areas" from these land-cover maps generally refer to impervious surfaces (i.e., built-up areas covered by water-resistant materials), which cannot fully characterize the spatial extent of human activities, thereby excluding places such as green parks, urban forests, and other frequently accessed greenspaces in and around urban fringe areas (Gong et al., 2020). On the other hand, nighttime light (NTL) imagery has been well demonstrated to correlate with the intensity of human and economic activities and has been widely used for identifying human settlements and urban areas (Cai et al., 2017). Also, NTL-based urban area used for greenspace assessment is suggested to be more flexible in the spatial extent, which incorporates not only urbanized regions but also vegetated areas with intensive human activities (Song et al., 2020a).

Remote sensing images have greatly facilitated greenspace mapping by providing spatially explicit and temporally continuous ground truth information (Chen et al., 2017). Nevertheless, some disagreements still exist in remote sensing-based greenspace extraction studies, which can be categorized into two parts according to their potential causes. (1) Different semantic definitions of urban greenspace lead to a part of the disagreements in previous studies (Mears et al., 2020). For example, some works defined urban greenspace narrowly as outdoor areas with significant green vegetation quantities or only considered specific land-use categories (e.g., public gardens or parks) (Boll et al., 2020; Crous-Bou et al., 2020). However, some studies used a broad concept that

regards all areas covered by vegetation as greenspace, which makes the results more comparable among different cities (Mears et al., 2020; Song et al., 2020a). (2) The differences in classification methods and remote sensing data sources contribute to the other part of disagreements (Su et al., 2019). The widely used hard classifiers attempt to classify each pixel to a land-cover category it most closely resembles, yet uncertainties caused by mixed pixel problem are pervasive in urban settings unless high-spatial-resolution (<5 m) but costly data are used (Franke et al., 2009). Soft classifiers, like spectral unmixing models, are suggested to achieve good performance in reducing uncertainties caused by hard classifiers and coarse-resolution remote sensing data (Weng et al., 2004).

Researchers have developed a range of accessibility-based approaches to measure residents' potential exposure to greenspace, including but not limited to gravity-based models, coverage models, container models, and floating catchment area models (Wu et al., 2019). However, these inconsistent measurements and their inherent limitations can lead to quite different results and create challenges in further analyses (Xiao et al., 2019). For one thing, aggregation errors due to various shapes and sizes of the analytical units in some models lead to the modifiable areal unit problem (MAUP) (Su et al., 2019). For another, since dynamic population distribution would cause the change of people's ambient environment, assessment models based on static data are prone to the uncertain geographic context problem (UGCoP) (Kwan, 2012), making these models fail to capture the actual usage of urban greenspace accurately. Therefore, a consistent and advanced exposure measurement considering people's real-time locations should be adopted in a comparative study among different cities in light of the above-mentioned issues.

In terms of inequality assessment, previous studies mainly focus on the disparities in greenspace access for vulnerable groups, such as low-income neighborhoods, less educated people, and minority communities. For instance, the deprived residential areas of Munich, a large German city, were found to have less greenspace provision (Schüle et al., 2017). Other studies in Leicester (UK), Chicago (USA), Pueblo (USA), and Macon (USA) also revealed that people with low socioeconomic positions or who live in minority communities were less likely to enjoy green environments or tended to have access largely to greenspace or parks with poor quality (Comber et al., 2008; Gobster, 2002). In contrast, one case study of Shanghai indicated that the open greenspace accessibility and the policy of promoting open green spaces in the city were more beneficial to vulnerable groups than affluent people (Xiao et al., 2017). Other than disparity measurements by comparing people with different socioeconomic attributes, the Gini index (Gini, 1921) is also a widely used metric to assess the general inequality. By measuring the statistical dispersion to represent inequality level, the Gini index has been successfully applied to evaluate the disparity accessibility of urban greenspace (Wüstemann et al., 2017).

Despite a growing number of studies focusing on the inequality in greenspace exposure, research advances are still limited in the following aspects: (1) The wide range of exposure measurements and evaluation perspectives lead to varying results without a consistent indicator, which makes it challenging for a unified comparison (Xiao et al., 2017). (2) The spatiotemporal variability of population distribution is ignored in greenspace exposure assessment, and the immediate changes in greenspace exposure inequality have rarely been measured in previous studies (Kwan, 2013). (3) A comprehensive understanding of how urban built/natural environments affect the greenspace provision would help alleviate the disparities and promote the sustainable development of the urban environment, but this issue has not been thoroughly discussed in existing studies (Boulton et al., 2018).

To address these shortcomings, this study attempts to investigate the dynamic interactions between urban residents and their ambient greenspace from multiple perspectives. Using multi-source geospatial big data and a modified assessment framework, we contribute to the literature by conducting an assessment for 303 cities in China and

answering the following questions: (1) How do urban residents expose to greenspaces when the dynamic population distribution is considered? (2) Are there significant differences in exposure inequalities among different cities, and how do the inequalities change over different temporal periods within a day? (3) Are natural environment factors and socioeconomic features of urban areas associated with greenspace exposure inequalities? A better understanding of the above issues is essential for building a healthy city and facilitating eco-friendly urban development.

2. Methodology

2.1. Study area

The assessments were conducted in 303 cities accounting for 98.45% of the urban population in China (National Bureau of Statistics of China, 2019). We used the urban population size as the criterion to select city samples. Specifically, cities with an urban population greater than 50,000 were selected for urban greenspace assessment. The inclusive cities consisted of 4 municipalities (directly under the central government), 15 sub-provincial cities, 16 provincial capital cities, and 268 prefecture-level cities (Fig. 1). According to their geographic distributions, they also belong to six geographical zones, including southwest China, northeast China, east China, south-central China, northwest China, and southwest China.

2.2. Urban greenspace exposure inequality assessment

To reduce potential uncertainties in inequality assessment and ensure comparable results, we adopted a modified framework consisting of four main steps, including (1) urban area extraction, (2) greenspace mapping, (3) exposure assessment, and (4) Gini-based inequality assessment.

2.2.1. Urban area extraction

Urban areas were extracted for all selected cities by considering the intensity and spatial extent of human activity. The two major datasets used to implement this task were monthly cloud-free NPP-VIIRS NTL images in 2016 (www.ngdc.noaa.gov) and the ESA-CCL LC product in 2016 (www.esa-landcover-cci.org). We adopted a local-threshold-based model to extract an appropriate spatial extent of each city's urban area

from the NTL images (see Section S1 in Supplementary Materials). Particularly, the proposed model considered both the diverse urbanization intensities and physical features among cities, and allowed each city to receive a unique threshold. The extracted urban areas were evaluated via two types of validation datasets (i.e., Amap POI and LC-based “urban area”) (see Section S2 in Supplementary Materials), and achieved a high-level confidence with producer's accuracies >91.32% and overall area-weighted accuracies >94.0%. More importantly, the newly defined urban areas had a more appropriate spatial extent compared with impervious-surface-based “urban area” (Fig. S2), enabling a critical component of frequently visited greenspace in urban fringe areas or big urban forests to be included in the following assessments. Each city's urban areas were further refined by removing all the small (<5 km²) and spatially isolated areas to make subsequent analysis focus on major urban areas.

2.2.2. Greenspace mapping

In this study, greenspace was defined as all areas covered by green vegetation. The data used for greenspace mapping were the full stack of Sentinel-2A imagery in 2016. A three-endmember linear spectral unmixing model (Weng et al., 2004) was employed to unmix the composite image and map subpixel greenspace distribution, with the aim of addressing the inevitable mixed pixel issue in urban land-cover mapping. Detailed information regarding data processing and classification strategies were introduced in Section S3 of the Supplementary Materials. We finally used a set of high-resolution (~0.6 m) greenspace maps (Song et al., 2018) to evaluate the newly derived greenspace maps. The achieved average correlation coefficient of 0.918 verified the reliability of the results (see Section S4 in Supplementary Materials).

2.2.3. Exposure assessment

Tencent location-based services (LBS) data were used to characterize population distribution and assess people's dynamic exposure to green environments. Tencent LBS data were created by recording individuals' real-time locations when they are using Tencent's apps or location-based services (Chen et al., 2020; Xu et al., 2021). As the top Internet service provider for ethnic Chinese in the world, and owing to the extensive use of Tencent's popular apps and services, Tencent recorded 38 billion LBS requests per day on average in 2016 from its 450 million active users around the world (Tencent, 2016). Tencent released this dataset as a grid form with a 1-km resolution per 5 min, excluding any personally

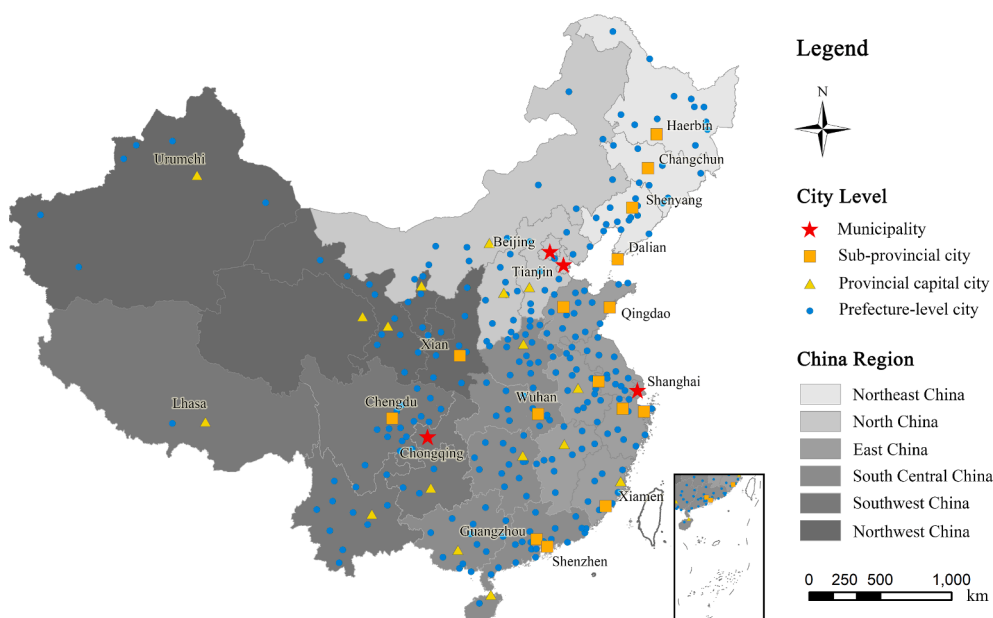


Fig. 1. Distribution of the 303 selected Chinese cities with four administrative levels and six geographical zones.

identifiable and private information. We collected all the data generated in 2016 via the Tencent Location Big Data platform (<https://heat.qq.com>). LBS density maps were then aggregated to characterize the population distribution over the following three periods: daytime (from 06:00 to 18:00), nighttime (from 18:00 to next 06:00), and a whole day (from 00:00 to 24:00).

The extracted greenspace maps and LBS density maps were used jointly to assess residents' average urban greenspace exposure within the urban areas of each city. For the LBS density map, the total number of LBS records in a grid represents the relative population. Given the lack of people's exact locations within the corresponding area of a pixel, we supposed that all the people are in the grid's centroid. A city's greenspace exposure levels during the daytime, nighttime, and a whole day were then measured via Eq. (1) (Song et al., 2018):

$$GE = \frac{\sum_{i=1}^n (p_i \times G_i)}{\sum_{i=1}^n p_i} \quad (1)$$

where GE represents a greenspace exposure level of a city during a pre-set timeframe; p_i denotes the LBS-based relative population within grid- i ; G_i means the green coverage within a specific buffer zone around grid- i 's centroid. Due to the coarse resolution (i.e., 1 km) of LBS-based population maps, we conducted the measurement by using a relatively larger buffer of 1-km around each grid's centroid to ensure that the ambient greenspace of any individual in the each grid can be taken into account.

2.2.4. Gini-based inequality assessment

We used the Gini index to measure the inequality in greenspace exposure of a city. According to the feature of data used in this study, the greenspace exposure Gini index was received by calculating the ratio of the area of A to the total area of A and B (Fig. 2) via a modified equation as Eq. (2). The derivation process of Eq. (2) was provided in Section S5 of Supplementary Materials.

$$Gini = 1 - \frac{2 \times \sum_{i=1}^n \sum_{j=1}^i g_i}{n \times \sum_{i=1}^n g_i} \quad (2)$$

where n is the total population within the urban area of a city during a pre-set timeframe; g_i is the magnitude of individual- i 's greenspace exposure. The $Gini$ ranges from 0 (absolute equality) to 1 (absolute inequality), and a lower $Gini$ means that the amount of greenspace that people are exposed to are more evenly provided. Greenspace exposure inequalities during daytime ($Gini_{\text{daytime}}$), nighttime ($Gini_{\text{nighttime}}$), and a whole day ($Gini_{\text{whole-day}}$) were assessed for all the selected cities, respectively. The received Gini was divided into five ranges: very low inequality (0–0.2), low inequality (0.2–0.4), medium inequality (0.4–0.6), high inequality (0.6–0.8), and very high inequality (0.8–1).

We further used the local Moran's I-based cluster and outlier analysis

tool (Anselin, 1995) to identify the spatial pattern of $Gini_{\text{whole-day}}$, including the hot spots, cold spots and spatial outliers. Specifically, a hot spot (high-high cluster) or cold spot (low-low cluster) means a group of geographically adjacent cities have statistically significant high/low $Gini_{\text{whole-day}}$ compared to their neighbors. A spatial outlier means one city with high $Gini_{\text{whole-day}}$ is surrounded primarily by cities with low $Gini_{\text{whole-day}}$ (high-low outlier), or one city with low $Gini_{\text{whole-day}}$ is surrounded primarily by cities with high $Gini_{\text{whole-day}}$ (low-high outlier).

2.3. Exploring the association between urban factors and exposure inequality

We collected a range of variables to explore the linkage between $Gini_{\text{whole-day}}$ and urban areas' physical and socioeconomic features. Spearman correlation analysis was first used to remove all variables that have no significant correlations with $Gini_{\text{whole-day}}$. As shown in Table 1, the nine finally selected variables were classified into four categories. In particular, geographical variable (i.e., C1: variable 1) was the six geographical regions of China introduced in Section 2.1, which provided geospatial information of the selected cities. The distance between spatial attribute weighted centroid (i.e., C2: variables 2–4) represented the difference between two factors in terms of spatial distribution pattern. These factors can be either socioeconomic or physical features of urban areas. Climate and environmental variables (i.e., C3: variables 5–8) and the socioeconomic variable (i.e., C4: variable 9) were used to uncover how environmental or socioeconomic factors associate with the

Table 1
Descriptions of urban factors.

Category	No.	Code	Name (Unit) of urban factor
C1: Geographical factor	1	GR	Geographical region in China
C2: Distance between spatial attribute weighted centroid	2	CDpg	Distance between population density centroid and greenspace distribution centroid (km ²)
	3	CDgg	Distance between gross domestic product (GDP) centroid and greenspace distribution centroid (km ²)
	4	CDrg	Distance between road density centroid and greenspace distribution centroid (km ²)
C3: Climate and environmental factor	5	GCR	Greenspace coverage rate within urban area (%)
	6	PPTN	Annual precipitation (mm/year)
	7	Temp	Annual mean temperature (°C)
	8	TempD	Difference in temperature between day and night (°C)
C4: Socioeconomic factor	9	PopD	Population density within urban areas (pop/m ²)

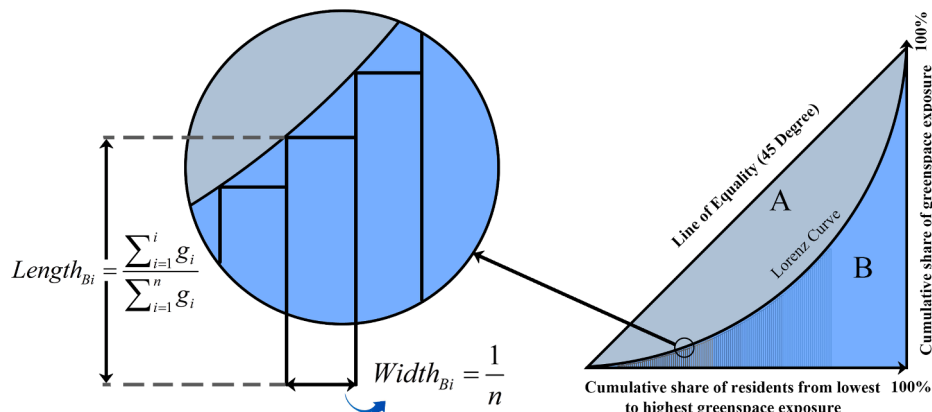


Fig. 2. Illustrative diagram of the Gini index to assess greenspace exposure inequality.

inequality in greenspace exposure. The detailed information regarding data sources and data processing of these variables were provided in Section S6 of the Supplementary Materials.

Geographical detector models from the spatial stratified heterogeneity (SSH) analysis framework (Song et al., 2020b) were used to explore the association between greenspace exposure inequality and urban factors. The two geographical detectors used in this paper were the factor detector model and the interaction detector model. Specifically, the factor detector model can help detect the spatial heterogeneity of response variables (i.e., the Gini index of greenspace exposure) and explain the relative importance of explanatory variables in determining the spatial heterogeneity of the response variable. The factor detector model uses a Q value ($0 \leq Q \leq 1$) as a metric, where a higher Q value suggests that the associations between $Gini_{whole-day}$ and the urban factor are stronger. The interaction detector was used to identify the co-effect from urban factors on $Gini_{whole-day}$. By comparing the importance (i.e., Q value) of two combined variables with each independent's importance, the interaction detector can uncover how explanatory variables interact with the response variable. Details of the analysis procedure are provided in section S7 in Supplementary Materials.

3. Results

3.1. Greenspace exposure in Chinese cities

As shown in Fig. 3a, the colored circles (from green to red) represent the magnitude of cities' GCR (from high to low); the circle scale indicates the level of $GE_{whole-day}$, with larger circles representing greater $GE_{whole-day}$ levels. Note that high-GCR cities always have relatively high $GE_{whole-day}$ levels. However, 298 of the 303 cities have a higher value of GCR than $GE_{whole-day}$, and the average GCR and $GE_{whole-day}$ of all cities are 26.69% and 13.15%, respectively, which highlights that a metric like GCR tends to overestimate the amount of available greenspace enjoyed by people during daily lives.

We find considerable differences in greenspace exposure among cities in different regions and administrative levels. The geographical zones of cities having the top three highest average GCR are northeast China (36.48%), southwest China (29.08%), and east China (27.4%)

(Fig. 3b). However, the highest average $GE_{whole-day}$ (19.4%) is found in southwest China, followed by northeast China (15.24%) and east China (14.45%). Cities in Northwest China have both the lowest GCR (15.93%) and $GE_{whole-day}$ (6.62%). For cities with different administrative levels (Fig. 3c), sub-provincial cities have the highest average GCR (29.77%), followed by municipalities (27.09%), prefecture-level cities (26.87%), and provincial capital cities (20.67%). However, the highest average $GE_{whole-day}$ belongs to municipalities (16.86%), followed by sub-provincial cities (14.77%), prefecture-level cities (13.2%), and provincial capital cities (9.85%).

Moreover, the difference between daytime and nighttime greenspace exposure ($GE_{daytime} - GE_{nighttime}$) (Fig. S3 in Supplementary Materials) illustrates that the population distribution change leads to noticeable variation in their ambient green environment.

3.2. Inequality in greenspace exposure

The average $Gini_{whole-day}$ of all the selected cities is up to 0.669, indicating that greenspace exposure is at a high inequality level in urban China. We identify a substantial difference in $Gini_{whole-day}$ among cities (Fig. 4). Specifically, the top three cities with the lowest $Gini_{whole-day}$ are Panzhihua (0.146), Rizhao (0.150), and Dongying (0.154), while the top three cities with the highest $Gini_{whole-day}$ are Kashgar (0.982), Shigatse (0.978), and Yuncheng (0.974). We also find that the distribution of $Gini_{whole-day}$ is characterized by obvious spatial heterogeneities. As shown in Fig. 4, more than 66% of cities' $Gini_{whole-day}$ in northwest China are greater than 0.8, illustrating that very high inequality of greenspace exposure is prevalent in this region. By contrast, the situation is much better in southwest China where only 30% of cities having very high inequality ($Gini_{whole-day} \geq 0.8$), and more than 29% of cities having low or very low inequality ($Gini_{whole-day} < 0.4$). Statistically, cities in northwest China, north China, and south-central China are the top three groups of cities with a high average $Gini_{whole-day}$ of 0.804 and 0.763, and 0.673, respectively, followed by east China (0.642), northeast China (0.639), and southwest China (0.528). As for cities with different administrative levels, municipalities have the lowest average $Gini_{whole-day}$ (0.546), followed by sub-provincial cities (0.639), the prefecture-level cities (0.669), and provincial capital cities (0.721).

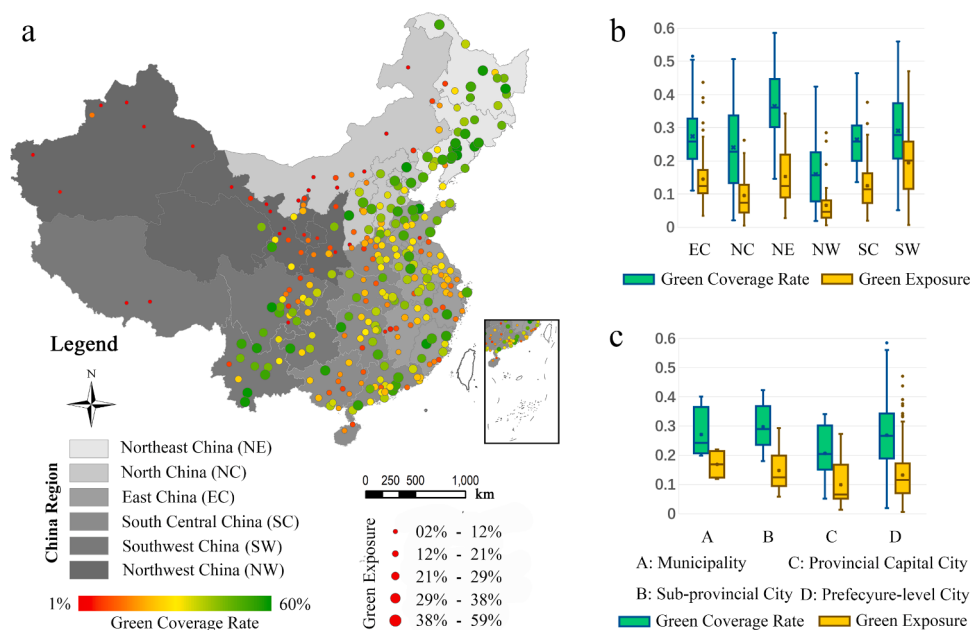


Fig. 3. (a) Greenspace coverage rate (GCR) and greenspace exposure ($GE_{whole-day}$) of 303 Chinese cities; (b) comparison of GCR and $GE_{whole-day}$ among cities in different geographical zones; (c) comparison of GCR and $GE_{whole-day}$ among cities in different administrative levels.

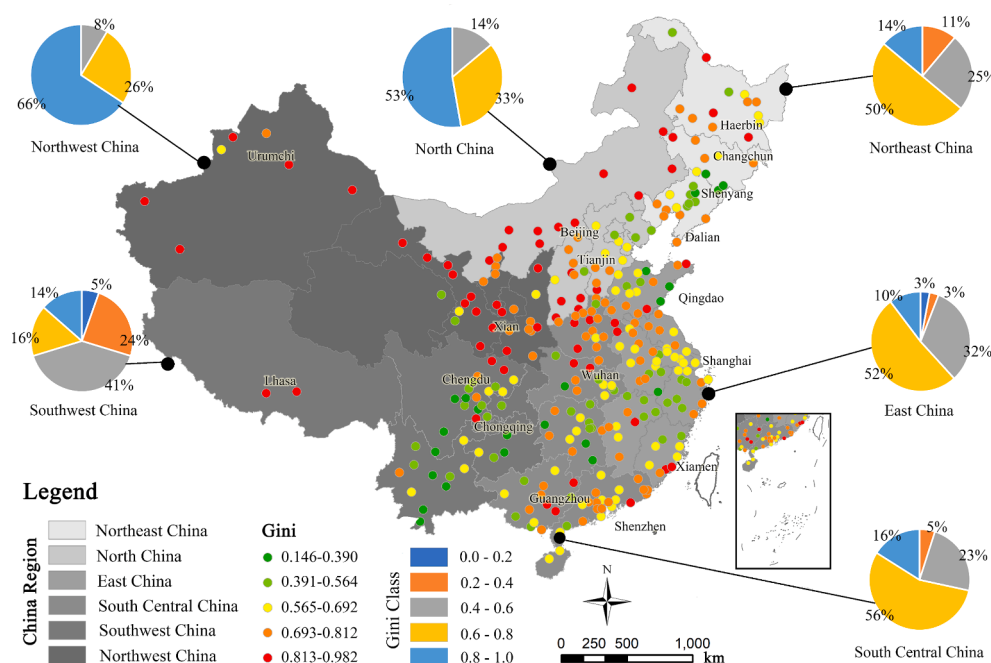


Fig. 4. Greenspace exposure inequality ($Gini_{\text{whole-day}}$) of Chinese cities and its spatial heterogeneity.

Overall, 207 out of the 303 cities have a $Gini_{\text{whole-day}}$ greater than 0.6, indicating that high and very high inequality in greenspace exposure is dominant among Chinese cities.

Fig. 5 presents the identified hot spots (cities colored in pink) and cold spots (cities colored in nattier blue) of $Gini_{\text{whole-day}}$. The hotspot cities are primarily located in north and northwest China, including cities belonging to provinces of Inner Mongolia, Gansu, Ningxia, Shaanxi, and Henan. Some other major hot spots can also be found in the west of Xinjiang, north of Inner Mongolia, and Tibet. The cities of cold-spots are generally distributed as a belt along the Yangtze River, and cities belong to Yunnan province. Besides, some cities located in the area between Liaoning and Jilin provinces also form other cold spots.

3.3. Difference in greenspace exposure inequality between daytime and nighttime

The statistical difference in greenspace exposure between daytime and nighttime highlights that the rhythmic variability of population distribution causes the change of their ambient environment. It is, therefore, necessary to evaluate the inequality in greenspace exposure as a function of time. Fig. 6 shows the difference in exposure inequality between daytime and nighttime using $Gini_{\text{daytime}} - Gini_{\text{nighttime}}$. A blue/red circle represents that $Gini_{\text{daytime}}$ is smaller/larger than $Gini_{\text{nighttime}}$, and the circle size indicates the magnitude of the absolute difference. We find that the difference between daytime and nighttime is obvious, as 112 cities' absolute values of $Gini_{\text{daytime}} - Gini_{\text{nighttime}}$ are larger than 0.01. In Daxinganling, for example, the $Gini_{\text{daytime}}$ is 0.478, but the

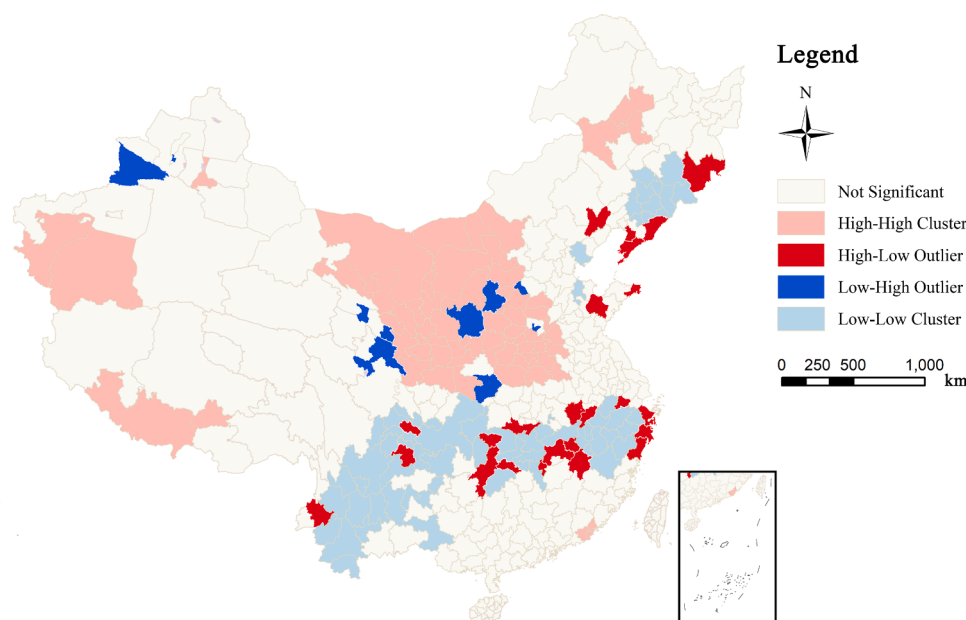


Fig 5. The spatial pattern of greenspace exposure inequality among Chinese cities.

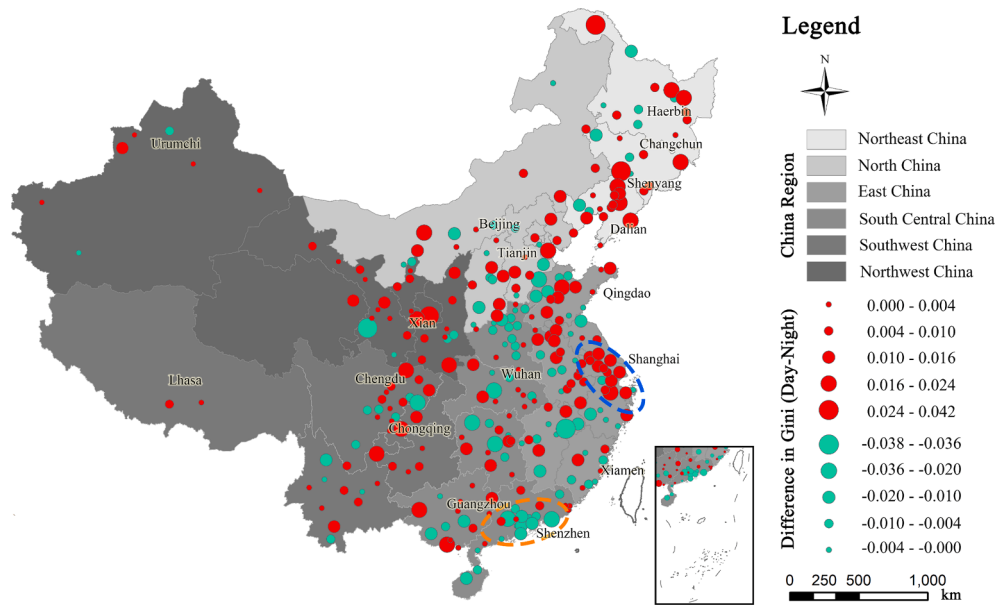


Fig. 6. Difference in greenspace exposure inequality between daytime and nighttime.

$Gini_{nighttime}$ becomes 0.436, resulting in a relatively large difference of 0.042. Also, cities located in the Yangtze River delta (the blue dotted circle in Fig. 6) generally have a higher $Gini_{daytime}$ than $Gini_{nighttime}$. Opposite situations are identified in most Pearl River Delta cities (the orange dotted circle in Fig. 6). Statistically, 185 out of 303 cities' $Gini_{daytime}$ is greater than their $Gini_{nighttime}$.

3.4. Association between urban factors and exposure inequality

Fig. 7a shows the single factor's Q value derived from the factor detector model, excluding factors without a significant Q value ($p < 0.05$). Overall, the factors from climate and environmental factors (C3) and geographical factors (C1) are found to have stronger linkages with $Gini_{whole-day}$, compared to the distance of spatial attribute weighted centroids (C2) and socioeconomic factors (C4). Three of the four factors belonging to the category of climate & environment factors are identified to have greater and significant Q values. Particularly, GCR (greenspace coverage rate, $Q = 0.47$ and PPTN (annual precipitation, $Q = 0.24$) are the top two factors with the strongest associations with $Gini_{whole-day}$, followed by GR (geographical region, $Q = 0.21$), Temp (Temperature, $Q = 0.14$), and CDrg (distance between road density centroid and greenspace distribution centroid, $Q = 0.05$).

The association between $Gini_{whole-day}$ and a pair of factors' interaction effect are presented in Fig. 7b. Red/yellow circles represent that the

association is nonlinear-/bi-enhanced by the interaction. Specifically, a nonlinear-enhanced effect means the explanatory power (i.e., linkage with $Gini_{whole-day}$) of the interaction of two factors is greater than the sum of two single factors' power; a bi-enhanced effect means that the interaction enhances the explanatory power of any single factor, but not greater than their sum (see Section S7 in Supplementary Material). Finally, the interaction of greenspace coverage rate and temperature ($GCR \cap Temp$) is found to have the strongest and nonlinearly enhanced association with $Gini_{whole-day}$ (Q value = 0.63), indicating that the high inequality is more likely to be found in cities with both low greenspace coverage and low temperature. Besides, the interactions that have second and third strongest linkages with $Gini_{whole-day}$ are greenspace coverage rate and geographical region ($GCR \cap GR$: $Q = 0.62$), and greenspace coverage rate and annual precipitation ($GCR \cap PPTN$: $Q = 0.59$).

4. Discussions

Using a modified assessment framework, we evaluated the inequality in greenspace exposure and their diurnal variations. Unlike most existing works that examine a specific city/region's inequality issue among vulnerable groups, this study conducts a general and comparative assessment for 303 Chinese cities, and provide evidence reflecting the inequality problems in existing urban greenspace arrangement across

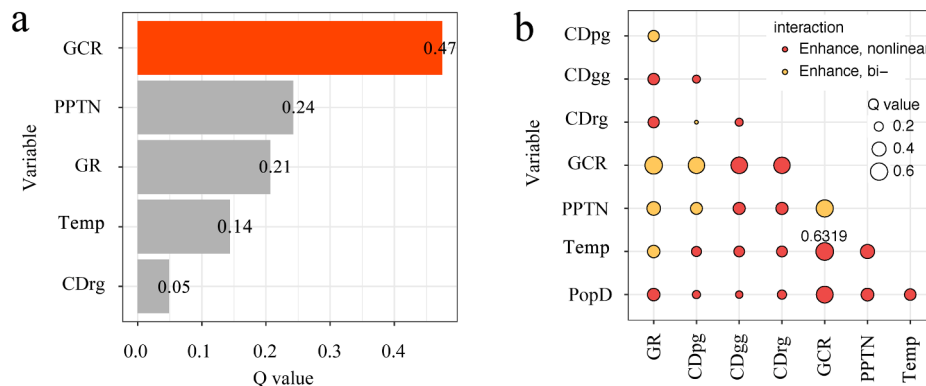


Fig. 7. Association between urban factors (and their interactions) with $Gini_{whole-day}$: (a) Q values measured by factor detector model; (b) Q values measured by interaction detector model.

China's cities.

4.1. The contradiction between quantity and equality in urban China

As an essential public natural resource, urban greenspace is expected to be utilized abundantly and equally. However, our findings reveal an unpleasant fact that, in many Chinese cities at different administrative levels, the scarcely available greenspace is mostly enjoyed by limited people, resulting in a disproportionately high inequality in greenspace exposure. Given that greenspace is suggested to positively affect people's health and social benefits, the great greenspace injustice issue in Chinese cities is more likely to exacerbate residents' health and social inequality (Lu et al., 2021). In fact, the Chinese government has been making efforts to improve the urban green environment over recent decades. In 1992, the Ministry of Housing and Urban-Rural Development of China launched an incentive scheme and started to grant the title of "National Garden City" to cities with increased greenspace to meet specific national standards (Wolch et al., 2014). From 1992 to 2019, 235 of the 303 selected cities in this study have met the established standards (<http://dwz.date/cHsf>). Nevertheless, as 156 out of the 235 "National Garden City" have a $Gini_{whole-day}$ larger than 0.6, it is clear that they have not fully resolved the issues of usability and equity in the context of securing the growth of greenspace supply. Therefore, a balance between quantity and equality of urban greenspace is still required in the future development of healthy cities in China (Yang et al., 2018).

4.2. Greenspace exposure and inequality changes over time

Suppose people are in their workplaces during the daytime and go back to their residences during the nighttime, the comparison of exposure ($GE_{daytime} - GE_{nighttime}$) or inequality ($Gini_{daytime} - Gini_{nighttime}$) could be regarded as the difference in greenspace exposure or inequality of people's work and residential locations (Song et al., 2018). Specifically, a lower daytime inequality, for example, the cluster of cities located in the Pearl River Delta, means that people are experiencing a relatively similar greenspace supply around workplaces. The higher exposure values at nighttime can be interpreted as a result from either a relatively better greenspace environment around residences, or residents' more active proximity to greenspace environments during leisure time at night (Shan, 2020). In addition, given the different socio-environmental benefits and impacts from greenspace at different times of the day, the identified variations in greenspace exposure and inequality can also shed lights on interpreting urban microclimates, for example, the cooling effect from green environments during daytime (Hu and Li, 2020), and urban safety issues, for example, the safety risk caused by poorly-lit greenspace during the nighttime for some vulnerable people such as women and children (Bauwelink et al., 2021). These comparisons between greenspace exposure and inequality in different times and real-world scenarios would provide urban planners and designers multi-dimensional information of greenspace in both spatial and temporal contexts to support eco-friendly and user-friendly healthy city developments.

4.3. Geo-climatic features and limited greenspace provision

Our results also reveal that the spatial distribution of greenspace exposure inequality presents obvious geographical heterogeneity. In general, cities located in the northwest region and the north region of China tend to have very high $Gini_{whole-day}$. Note that these regions' geo-climatic characteristics are mainly characterized by desert, arid and semi-arid climates, with low and uneven rainfall, low average temperature (long winter), and large daily/seasonal temperature differences (Shi et al., 2020). In Yinchuan (capital of Ningxia), for example, the average annual precipitation from 1986 to 2015 is only 189.8 mm (30.2% of the national average precipitation), and the average annual temperature is as low as 7.6 °C (www.cma.gov.cn). Such climates make

these regions unsuitable for the growth of green vegetation, which increases the cost of urban greenspace provision and maintenance (Wen et al., 2019). Therefore, limited greenspace may be available only in some certain communities, which increases the likelihood of unequal greenspace arrangements. This interpretation is also statistically supported by the linkages explored through geographical detector models, as serious exposure inequality is more common in cities with low greenspace provision (i.e., coverage rate), low annual precipitation, and low temperature. Thus, innovative strategies are urgently required to addressing provision issues in cities located in arid and ecologically vulnerable areas. The efficient use of water resources is the key to ensuring greenspace provision for cities with water shortages, and specific measures may include irrigating with reclaimed water, developing water-efficient greenspace irrigation systems, and planting various types of drought-resistant vegetation (Shi et al., 2020).

4.4. Urbanization and greenspace provision disparity

In addition to climate factors, urbanization patterns may be another factor that affects the equity of greenspace exposure. Particularly, the increasing urban population, along with a growing awareness of farmland and environment preservation in recent years, make China's urbanization process gradually shift from expansion to a pattern that combines expansion and infill (e.g., urban densification) (He et al., 2019). Despite the benefits of effective land use during densification, the infill development was confirmed to pose a threat to greenspace, causing a dramatic decline in inner urban areas (Tonne et al., 2021). As a result, a disparity in greenspace provision (i.e., coverage rate) may arise between the densified areas (inner urban areas) and newly developed areas at the periphery of a city, which leads to inequality in residents' greenspace exposure (Song et al., 2020a). This partly explains why the $Gini_{whole-day}$ in some highly urbanized or compact cities is relatively high, although they are located in areas with moderate temperatures and abundant rainfall, such as Xiamen, and cities in Pearl River Delta. This fact also reminds the local municipalities to use smart strategies in densified areas' future greenspace planning and management. Specifically, semi-natural greenspace should be preserved so as to ensure the supply of quality greenspace is not diminished during the subsequent urbanization of inner urban areas (Zlender and Ward Thompson, 2017). Adding greenery to renovated sites and other less-green sites (e.g., narrow streets) are also feasible ways to increase greenspace provision in inner urban areas and reduce inequality in greenspace exposure of a city (Wolch et al., 2014).

4.5. Balancing supply and demand to eliminate inequality

Although the Gini index reveals the inequality of urban greenspace provision in a spatial perspective, simply relying on increasing the supply of greenspace to reduce the Gini index is not the way to address inequality. It is important to note that residents' demand for greenspace is not only in terms of quantity but also quality (Knobel et al., 2021). The quality of urban greenspace can be understood as the factors influencing people's greenspace usage, such as size, location, facilities, maintenance, safety, design and accessibility (Knobel et al., 2021). Helping the public achieve a balance between supply and demand of greenspace (including quantity and quality) is therefore the ultimate goal of eliminating inequality issues (Wolch et al., 2014). A well-developed standard that encompasses a breadth of factors is a necessary prerequisite, such as the Natural England's accessible green space standards (ANGSt) implemented in cities like Manchester (naturegreatermanchester.co.uk). Besides, due to the difference in climate, geography, and cultural characteristics among Chinese cities, and the diversity of socio-economic attributes of communities within a city, it is more than challenging to achieve such a balance by using one or two standardised ways. Consequently, in addition to implementing sound planning and policy support tailored to local conditions, in-depth public participatory

engagement should be put in place, which is beneficial in reducing irrationalities of greenspace design and enables greenspace to be located where it is needed (Li et al., 2021).

4.6. Advantages and limitations

The assessment in this study was conducted for the vast majority of Chinese cities, from small cities with an urban population of just 50,000 to metropolises with more than 10 million urban residents, which addresses the biases in existing published urban nature-related literature that do not adequately represent the urban population in small cities and the developing world (Kendal et al., 2020). Given healthy cities are also under construction in developing countries in Africa and South America (De Leeuw and Simos, 2017), we believe the findings in China can be used as a reference for the urban natural environment development in these countries. Besides, compared with the previous widely used exposure assessment models, the modified assessment framework plays an important role in explicitly uncovering the interactions between urban residents and their ambient green environment by considering the spatial extent of human activity, uncertainty in greenspace mapping, and spatiotemporal variability of population distribution. When fine-scale population maps (e.g., with a 10-m resolution) or individual-scale data are available, the study's proposed methods and framework can be leveraged to derive city- and even community-scale assessments and provide spatially explicit evidence and pathways for strategizing urban policy and planning. In addition to greenspace, the assessment framework can be extended to assess exposure to other environmental factors, including but not limited to air pollution, blue space, noise, nighttime light, and heatwave (Chen et al., 2018b; Song et al., 2019).

Nevertheless, some limitations in this study should be pointed out. First, the quality of urban greenspaces is not considered in the assessment of this study. Urban greenspace is notoriously heterogeneous in size, vegetation type, phenological characteristic, range of facilities, park congestion, and safety to its users, making it a challenge to reasonably measure the quality characteristic of greenspace. Still, as different types of greenspace will have various benefits to public health and wellbeing, quality is often at least as important as quantity (Knobel et al., 2021). Therefore, considering quality would make the greenspace assessment much sounder. Second, the assessed exposure levels of cities only considered the greenspaces just around people, but proximity-based greenspace exposure was not measured in this study, such as the shortest distance to a special kind of greenspace (e.g., more than 2 ha in size). Given the important role which the accessibility of greenspace plays for the residents' physical activity and health (Xiao et al., 2017), proximity-based greenspace exposure assessment will be the direction of our further research. Third, although the usage of the LBS-based population maps provides rich information on characterizing real-time population distributions and reduces some uncertainties in static-data based models as defined in UGCoP (Kwan, 2013), MAUP still exists in the proposed assessment model. Specifically, the coarse resolution of LBS-based population and the 1-km buffer used in the model contribute to a large area of aggregation, which will diminish the variance and heterogeneity in exposure and make the relations with other variables more significant (Dark and Bram, 2007; Jelinski and Wu, 1996). For greenspace and physical health studies, the large aggregation (i.e., large buffer distance) tends to result in significant but inconstant effect sizes (Browning and Lee, 2017) as well as reducing the effect size (Wolch et al., 2011). Therefore, localized effect and spatial heterogeneity need to be taken into account when using our methodology and results to develop community planning and policy options. Additionally, how to incorporate multi-source population data and advanced models to derive dynamic population distributions with fine resolutions will be another open topic in our future research. Finally, although LBS data from mobile phones have been demonstrated to have good performance in characterizing real-time population distribution (Dunkel, 2015), they

are still considered as non-representative data, as some parts of society appear to be excluded, such as vulnerable citizens including the elderly, children, and poor (Chen et al., 2018a; Kwan, 2016). Therefore, we should be cautious about interpreting the results derived from these datasets in practical applications.

5. Conclusions

Leveraging multi-source geospatial big data and a modified urban greenspace exposure inequality assessment framework, this study conducts an evaluation of spatial inequality in greenspace exposure for 303 major Chinese cities, with the aim to better understand the role and pressing challenges of urban greenspace settings for healthy city development in China. The results reveal that urban residents in most Chinese cities experience severe inequality in terms of greenspace exposure. The exposure and inequality levels also change over different times, as people engage with different activities and change their locations (e.g., workplaces and residences). The distribution of city-level inequality presents prominent spatial heterogeneity, as cities located in north and northwest China tend to have higher greenspace exposure inequality. Moreover, serious inequality is highly correlated with low greenspace provision, and the inadequate provision may be caused by various reasons, such as dry cold climate and urbanization patterns (e.g., infill development). The findings in this study provide evidence of the inequalities in natural environment faced by urban dwellers in China, but the promotion and optimization of greenspace exposure in the context of healthy cities cannot be accomplished by simply increasing greenspace supply to reduce these inequalities. We suggest that the local municipalities in China should implement more effective and sustainable greening programs adjusted to different local circumstances and incorporate public engagement to achieve a real balance between greenspace supply and demand for developing healthy cities.

CRedit authorship contribution statement

Yimeng Song: Conceptualization, Data curation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Bin Chen:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Hung Chak Ho:** Writing – review & editing. **Mei-Po Kwan:** Writing – review & editing. **Dong Liu:** Writing – review & editing. **Fei Wang:** Writing – review & editing. **Jionghua Wang:** Writing – review & editing. **Jixuan Cai:** Writing – review & editing. **Xijing Li:** Writing – review & editing. **Yong Xu:** Writing – review & editing. **Qingqing He:** Writing – review & editing. **Hongzhi Wang:** Writing – review & editing. **Qiyang Xu:** Writing – review & editing. **Yongze Song:** Methodology, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

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References

- Anselin, L., 1995. Local Indicators of Spatial Association—LISA. *Geograph. Anal.* 27 (2), 93–115.
- Bauwelinck, M., Casas, L., Nawrot, T.S., Nemery, B., Trabelsi, S., Thomas, I., Aerts, R., Lefebvre, W., Vanpoucke, C., Van Nieuwenhuysse, A., Deboosere, P., Vandenheede, H., 2021. Residing in urban areas with higher green space is associated with lower mortality risk: A census-based cohort study with ten years of follow-up. *Environ. Int.* 148, 106365. <https://doi.org/10.1016/j.envint.2020.106365>.
- Boll, L.M., Khamirchi, R., Alonso, L., Llurba, E., Pozo, Ó.J., Miri, M., Dadvand, P., 2020. Prenatal greenspace exposure and cord blood cortisol levels: A cross-sectional study in a middle-income country. *Environ. Int.* 144, 106047. <https://doi.org/10.1016/j.envint.2020.106047>.
- Boulton, C., Dedekorkut-Howes, A., Byrne, J., 2018. Factors shaping urban greenspace provision: A systematic review of the literature. *Landscape Urban Plann.* 178, 82–101.
- Browning, M., Lee, K., 2017. Within What Distance Does “Greenness” Best Predict Physical Health? A Systematic Review of Articles with GIS Buffer Analyses across the Lifespan. *Int. J. Environ. Res. Public Health* 14 (7), 675. <https://doi.org/10.3390/ijerph14070675>.
- Cai, J., Huang, B.o., Song, Y., 2017. Using multi-source geospatial big data to identify the structure of polycentric cities. *Remote Sens. Environ.* 202, 210–221.
- Chen, B., Nie, Z., Chen, Z., Xu, B., 2017. Quantitative estimation of 21st-century urban greenspace changes in Chinese populous cities. *Sci. Total Environ.* 609, 956–965.
- Chen, B., Song, Y., Huang, B.o., Xu, B., 2020. A novel method to extract urban human settlements by integrating remote sensing and mobile phone locations. *Sci. Remote Sens.* 1, 100003. <https://doi.org/10.1016/j.srs.2020.100003>.
- Chen, B., Song, Y., Jiang, T., Chen, Z., Huang, B.o., Xu, B., 2018a. Real-Time Estimation of Population Exposure to PM2.5 Using Mobile- and Station-Based Big Data. *Int. J. Environ. Res. Public Health* 15 (4), 573. <https://doi.org/10.3390/ijerph15040573>.
- Chen, B., Song, Y., Kwan, M.-P., Huang, B.o., Xu, B., 2018b. How do people in different places experience different levels of air pollution? Using worldwide Chinese as a lens. *Environ. Pollut.* 238, 874–883.
- Comber, A., Brunson, C., Green, E., 2008. Using a GIS-based network analysis to determine urban greenspace accessibility for different ethnic and religious groups. *Landscape Urban Plann.* 86 (1), 103–114.
- Crous-Bou, M., Gascon, M., Gispert, J.D., Cirach, M., Sánchez-Benavides, G., Falcon, C., Arenaza-Urquijo, E.M., Gotsens, X., Fauria, K., Sunyer, J., Nieuwenhuijsen, M.J., Luis Molinuevo, J., 2020. Impact of urban environmental exposures on cognitive performance and brain structure of healthy individuals at risk for Alzheimer's dementia. *Environ. Int.* 138, 105546. <https://doi.org/10.1016/j.envint.2020.105546>.
- Dark, S.J., Bram, D., 2007. The modifiable areal unit problem (MAUP) in physical geography. *Prog. Phys. Geogr.* 31 (5), 471–479.
- De Leeuw, E., Simos, J., 2017. Healthy cities: the theory, policy, and practice of value-based urban planning. Springer.
- Dunkel, A., 2015. Visualizing the perceived environment using crowdsourced photo geodata. *Landscape Urban Plann.* 142, 173–186.
- Fan, J., Guo, Y., Cao, Z., Cong, S., Wang, N., Lin, H., Wang, C., Bao, H., Lv, X., Wang, B., Gao, Y.i., Chen, Y., Yang, T., Wang, L., Wang, C., Ruan, Z., Fang, L., 2020. Neighborhood greenness associated with chronic obstructive pulmonary disease: A nationwide cross-sectional study in China. *Environ. Int.* 144, 106042. <https://doi.org/10.1016/j.envint.2020.106042>.
- Franke, J., Roberts, D.A., Halligan, K., Menz, G., 2009. Hierarchical Multiple Endmember Spectral Mixture Analysis (MESMA) of hyperspectral imagery for urban environments. *Remote Sens. Environ.* 113 (8), 1712–1723.
- Gini, C., 1921. Measurement of inequality of incomes. *Econ. J.* 31 (121), 124. <https://doi.org/10.2307/2223319>.
- Gobster, P.H., 2002. Managing Urban Parks for a Racially and Ethnically Diverse Clientele. *Leisure Sci.* 24 (2), 143–159.
- Gong, P., Chen, B., Li, X., Liu, H., Wang, J., Bai, Y., Chen, J., Chen, X.i., Fang, L., Feng, S., Feng, Y., Gong, Y., Gu, H., Huang, H., Huang, X., Jiao, H., Kang, Y., Lei, G., Li, A., Li, X., Li, X., Li, Y., Li, Z., Liu, C., Liu, C., Liu, M., Liu, S., Mao, W., Miao, C., Ni, H., Pan, Q., Qi, S., Ren, Z., Shan, Z., Shen, S., Shi, M., Song, Y., Su, M.o., Ping Suen, H., Sun, B.o., Sun, F., Sun, J., Sun, L., Sun, W., Tian, T., Tong, X., Tseng, Y., Tu, Y., Wang, H., Wang, L., Wang, X.i., Wang, Z., Wu, T., Xie, Y., Yang, J., Yang, J., Yuan, M., Yue, W., Zeng, H., Zhang, K., Zhang, N., Zhang, T., Zhang, Y.u., Zhao, F., Zheng, Y., Zhou, Q., Clinton, N., Zhu, Z., Xu, B., 2020. Mapping essential urban land use categories in China (EULUC-China): preliminary results for 2018. *Sci. Bull.* 65 (3), 182–187.
- He, Q., Zeng, C., Xie, P., Tan, S., Wu, J., 2019. Comparison of urban growth patterns and changes between three urban agglomerations in China and three metropolises in the USA from 1995 to 2015. *Sustain. Cities Soc.* 50, 101649. <https://doi.org/10.1016/j.scs.2019.101649>.
- Hu, L., Li, Q.i., 2020. Greenspace, bluespace, and their interactive influence on urban thermal environments. *Environ. Res. Lett.* 15 (3), 034041. <https://doi.org/10.1088/1748-9326/ab6c30>.
- Hunter, R.F., Cleland, C., Cleary, A., Droomers, M., Wheeler, B.W., Sinnett, D., Nieuwenhuijsen, M.J., Braubach, M., 2019. Environmental, health, wellbeing, social and equity effects of urban green space interventions: A meta-narrative evidence synthesis. *Environ. Int.* 130, 104923. <https://doi.org/10.1016/j.envint.2019.104923>.
- Jelinski, D.E., Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecol.* 11 (3), 129–140.
- Kendal, D., Egerer, M., Byrne, J.A., Jones, P.J., Marsh, P., Threlfall, C.G., Allegretto, G., Kaplan, H., Nguyen, H.K.D., Pearson, S., Wright, A., Flies, E.J., 2020. City-size bias in knowledge on the effects of urban nature on people and biodiversity. *Environ. Res. Lett.* 15 (12), 124035. <https://doi.org/10.1088/1748-9326/abc5e4>.
- Knobel, P., Maneja, R., Bartoll, X., Alonso, L., Bauwelinck, M., Valentin, A., Zijlema, W., Borrell, C., Nieuwenhuijsen, M., Dadvand, P., 2021. Quality of urban green spaces influences residents' use of these spaces, physical activity, and overweight/obesity. *Environ. Pollut.* 271, 116393. <https://doi.org/10.1016/j.envpol.2020.116393>.
- Kwan, M.-P., 2012. The Uncertain Geographic Context Problem. *Ann. Assoc. Am. Geogr.* 102 (5), 958–968.
- Kwan, M.-P., 2013. Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility. *Ann. Assoc. Am. Geogr.* 103 (5), 1078–1086.
- Kwan, M.-P., 2016. Algorithmic Geographies: Big Data, Algorithmic Uncertainty, and the Production of Geographic Knowledge. *Ann. Assoc. Am. Geogr.* 106, 274–282.
- Li, X., Ma, X., Hu, Z., Li, S., 2021. Investigation of urban green space equity at the city level and relevant strategies for improving the provisioning in China. *Land Use Policy* 101, 105144. <https://doi.org/10.1016/j.landusepol.2020.105144>.
- Lu, Y.i., Chen, L., Liu, X., Yang, Y., Sullivan, W.C., Xu, W., Webster, C., Jiang, B., 2021. Green spaces mitigate racial disparity of health: A higher ratio of green spaces indicates a lower racial disparity in SARS-CoV-2 infection rates in the USA. *Environ. Int.* 152, 106465. <https://doi.org/10.1016/j.envint.2021.106465>.
- Mears, M., Brindley, P., Jorgensen, A., Maheswaran, R., 2020. Population-level linkages between urban greenspace and health inequality: The case for using multiple indicators of neighbourhood greenspace. *Health Place* 62, 102284. <https://doi.org/10.1016/j.healthplace.2020.102284>.
- Mueller, N., Rojas-Rueda, D., Khreis, H., Cirach, M., Andrés, D., Ballester, J., Bartoll, X., Daher, C., Deluca, A., Echave, C., Milà, C., Márquez, S., Palou, J., Pérez, K., Tonne, C., Stevenson, M., Rueda, S., Nieuwenhuijsen, M., 2020. Changing the urban design of cities for health: The superblock model. *Environ. Int.* 134, 105132. <https://doi.org/10.1016/j.envint.2019.105132>.
- Mygind, L., Kurtzals, M., Nowell, C., Melby, P.S., Stevenson, M.P., Nieuwenhuijsen, M., Lum, J.A.G., Flensburg-Madsen, T., Bentsen, P., Enticott, P.G., 2021. Landscapes of becoming social: A systematic review of evidence for associations and pathways between interactions with nature and socioemotional development in children. *Environ. Int.* 146, 106238. <https://doi.org/10.1016/j.envint.2020.106238>.
- National Bureau of Statistics of China, 2019. China city statistical yearbook. China Statistics Press, Beijing.
- Nieuwenhuijsen, M.J., 2020. Urban and transport planning pathways to carbon neutral, liveable and healthy cities: A review of the current evidence. *Environ. Int.* 140, 105661. <https://doi.org/10.1016/j.envint.2020.105661>.
- Organization, W.H., 2017. Shanghai Consensus on Healthy Cities 2016. *Health Promot. Int.* 32, 603–605.
- Pesaresi, M., Huadong, G., Blaes, X., Ehrlich, D., Ferri, S., Gueguen, L., Halkia, M., Kauffmann, M., Kemper, T., Lu, L., Marin-Herrera, M.A., Ouzounis, G.K., Scavazon, M., Soille, P., Syrris, V., Zanchetta, L., 2013. A Global Human Settlement Layer From Optical HR/VHR RS Data: Concept and First Results. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 6 (5), 2102–2131.
- Santoro, M., Kirches, G., Wevers, J., Boettcher, M., Brockmann, C., Lamarche, C., Defourny, P., 2017. Land Cover CCI: Product User Guide Version 2.0. Climate Change Initiative Belgium.
- Schüle, S.A., Gabriel, K.M.A., Bolte, G., 2017. Relationship between neighbourhood socioeconomic position and neighbourhood public green space availability: An environmental inequality analysis in a large German city applying generalized linear models. *Int. J. Hyg. Environ. Health* 220 (4), 711–718.
- Shan, X.-Z., 2020. Association between the time patterns of urban green space visitations and visitor characteristics in a high-density, subtropical city. *Cities* 97, 102562. <https://doi.org/10.1016/j.cities.2019.102562>.
- Shi, L., Halik, Ü., Abliz, A., Mamat, Z., Welp, M., 2020. Urban Green Space Accessibility and Distribution Equity in an Arid Oasis City: Urumqi, China. *Forests* 11 (6), 690. <https://doi.org/10.3390/f11060690>.
- Song, Y., Chen, B., Kwan, M.-P., 2020a. How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities. *J. Clean. Prod.* 246, 119018. <https://doi.org/10.1016/j.jclepro.2019.119018>.
- Song, Y., Huang, B.o., Cai, J., Chen, B., 2018. Dynamic assessments of population exposure to urban greenspace using multi-source big data. *Sci. Total Environ.* 634, 1315–1325.
- Song, Y., Huang, B.o., He, Q., Chen, B., Wei, J., Mahmood, R., 2019. Dynamic assessment of PM2.5 exposure and health risk using remote sensing and geo-spatial big data. *Environ. Pollut.* 253, 288–296.

- Song, Y., Wang, J., Ge, Y., Xu, C., 2020b. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. *GISci. Remote Sens.* 57 (5), 593–610.
- Su, J.G., Dadvand, P., Nieuwenhuijsen, M.J., Bartoll, X., Jerrett, M., 2019. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. *Environ. Int.* 126, 162–170.
- Sun, Y.i., Sheridan, P., Laurent, O., Li, J., Sacks, D.A., Fischer, H., Qiu, Y., Jiang, Y.u., Yim, I.S., Jiang, L.-H., Molitor, J., Chen, J.-C., Benmarhnia, T., Lawrence, J.M., Wu, J., 2020. Associations between green space and preterm birth: Windows of susceptibility and interaction with air pollution. *Environ. Int.* 142, 105804. <https://doi.org/10.1016/j.envint.2020.105804>.
- Tonne, C., Adair, L., Adlakha, D., Anguelovski, I., Belesova, K., Berger, M., Brelsford, C., Dadvand, P., Dimitrova, A., Giles-Corti, B., Heinz, A., Mehran, N., Nieuwenhuijsen, M., Pelletier, F., Ranzani, O., Rodenstein, M., Rybski, D., Samavati, S., Satterthwaite, D., Schöndorf, J., Schreckenberger, D., Stollmann, J., Taubenböck, H., Tiwari, G., van Wee, B., Adli, M., 2021. Defining pathways to healthy sustainable urban development. *Environ. Int.* 146, 106236. <https://doi.org/10.1016/j.envint.2020.106236>.
- Tsouros, A.D., 2019. The healthy cities movement. In: Tsouros, A.D. (Ed.), *Urban HealthUrban Health*. Oxford University Press, New York, pp. 285–292. <https://doi.org/10.1093/oso/9780190915858.003.0030>.
- Wen, X., Deng, X., Zhang, F., 2019. Scale effects of vegetation restoration on soil and water conservation in a semi-arid region in China: Resources conservation and sustainable management. *Resour. Conserv. Recycl.* 151, 104474. <https://doi.org/10.1016/j.resconrec.2019.104474>.
- Weng, Q., Lu, D., Schubring, J., 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sens. Environ.* 89 (4), 467–483.
- Wolch, J., Jerrett, M., Reynolds, K., McConnell, R., Chang, R., Dahmann, N., Brady, K., Gilliland, F., Su, J.G., Berhane, K., 2011. Childhood obesity and proximity to urban parks and recreational resources: A longitudinal cohort study. *Health Place* 17 (1), 207–214.
- Wolch, J.R., Byrne, J., Newell, J.P., 2014. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape Urban Plann.* 125, 234–244.
- Wu, J., Feng, Z., Peng, Y., Liu, Q., He, Q., 2019. Neglected green street landscapes: A re-evaluation method of green justice. *Urban For. Urban Green.* 41, 344–353.
- Wüstemann, H., Kalisch, D., Kolbe, J., 2017. Access to urban green space and environmental inequalities in Germany. *Landscape Urban Plann.* 164, 124–131.
- Xiao, Y., Wang, D.e., Fang, J., 2019. Exploring the disparities in park access through mobile phone data: Evidence from Shanghai, China. *Landscape Urban Plann.* 181, 80–91.
- Xiao, Y., Wang, Z., Li, Z., Tang, Z., 2017. An assessment of urban park access in Shanghai – Implications for the social equity in urban China. *Landscape Urban Plann.* 157, 383–393.
- Xu, Y., Song, Y., Cai, J., Zhu, H., 2021. Population mapping in China with Tencent social user and remote sensing data. *Appl. Geogr.* 130, 102450. <https://doi.org/10.1016/j.apgeog.2021.102450>.
- Yang, J., Siri, J.G., Remais, J.V., Cheng, Q.u., Zhang, H., Chan, K.K.Y., Sun, Z., Zhao, Y., Cong, N.a., Li, X., Zhang, W., Bai, Y., Bi, J., Cai, W., Chan, E.Y.Y., Chen, W., Fan, W., Fu, H., He, J., Huang, H., Ji, J.S., Jia, P., Jiang, X., Kwan, M.-P., Li, T., Li, X., Liang, S., Liang, X., Liang, L.u., Liu, Q., Lu, Y., Luo, Y., Ma, X., Schwartländer, B., Shen, Z., Shi, P., Su, J., Wu, T., Yang, C., Yin, Y., Zhang, Q., Zhang, Y., Zhang, Y., Xu, B., Gong, P., 2018. The Tsinghua-Lancet Commission on Healthy Cities in China: unlocking the power of cities for a healthy China. *Lancet* 391 (10135), 2140–2184.
- Zhang, W., Kinney, P.L., Rich, D.Q., Sheridan, S.C., Romeiko, X.X., Dong, G., Stern, E.K., Du, Z., Xiao, J., Lawrence, W.R., Lin, Z., Hao, Y., Lin, S., 2020. How community vulnerability factors jointly affect multiple health outcomes after catastrophic storms. *Environ. Int.* 134, 105285. <https://doi.org/10.1016/j.envint.2019.105285>.
- Žlender, V., Ward Thompson, C., 2017. Accessibility and use of peri-urban green space for inner-city dwellers: A comparative study. *Landscape Urban Plann.* 165, 193–205.