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Contrasting differences of the green space accessibility utility: a study of 30 major cities in China

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Introduction: Green spaces provision for urban residents is one of the Sustainable Development Goals. However, whether urban residents can readily access green space remains unanswered, both physically and mentally.
Methods: This paper proposes a new indicator—Green Space Accessibility Utility (GSAU) based on three indicators—Green Space Accessibility (GSA), Green Space Accessibility Inequality (GSAI), and Travel Aversion Index (TAI), aiming at revealing green space accessibility and inequality for residents of the 30 major Chinese cities based on both physical and mental attributes.
Results: We found that: (1) GSA of megacities is approximately 1.5 times that of large cities and demonstrates consistent enhancement with increasing walking scale. (2) Although GSA in eastern cities is roughly twice that in western cities, GSAI in the east is about 1.6 times higher than in the west, revealing a distinct inequality paradox, particularly acute within eastern megacities. (3) GSAU in southern cities is about 15% higher than in northern cities, and this regional disparity can be amplified to 30% under seasonal influences, GSAU in northern cities is more susceptible to seasonal fluctuations.
Discussion: These findings contribute to evaluating the effectiveness of urban green space utilization, informing the development of context-appropriate planning strategies, and promoting sustainable urban development.

KEYWORDS
15 min city, green space accessibility, inequality, spatial differentiation, utility

1 Introduction

With the acceleration of urbanization, populations are increasingly concentrating in urban areas. Residents living in cities are inevitably exposed to the urban environment, making human-environment interaction a key topic within the discourse of people-oriented urban planning (Anguluri and Narayanan, 2017). From a perceptual perspective, urban environmental exposure includes aspects that are sensorially perceptible (such as temperature, humidity, color, and sound) and behaviorally perceptible (such as accessibility and social interaction) (Yang et al., 2025). From a state perspective, it can be categorized into dynamic exposure (e.g., walking, strolling) and static exposure (e.g., viewing, contemplation) (Ma and Kwan, 2025). It is noteworthy, however, that the frequency, duration, and intensity of exposure to certain environments—particularly negative ones such as air pollution, noise, and extreme heat—can cause harm to the physical health (e.g., cardiovascular disease, obesity, brain health) and mental wellbeing (e.g., stress, depression) of individuals, especially vulnerable groups like the elderly, children, and pregnant women (Tu et al., 2026; Sander et al., 2025).

Conversely, well-planned urban green space, serving as a critical bridge connecting residents with the natural environment, is widely recognized as a beneficial form of environmental exposure (Pearsall and Eller, 2020; Eldridge et al., 2024; Huang et al., 2017). On the one hand, in terms of sensory perception, in addition to providing aesthetic and landscape value, green spaces can effectively reduce atmospheric particulate concentrations through natural processes such as adsorption, deposition, and dispersion, thereby improving air quality (Park, 2020). Furthermore, studies have demonstrated that green spaces possess significant noise mitigation capabilities (Feng et al., 2024). On the other hand, in terms of behavioral perception, well-designed green spaces can provide venues for neighborhood social activities, offering multiple benefits such as reducing loneliness, enhancing social capital and cohesion, and promoting physical exercise (Veras and Saldiva, 2025). Therefore, green spaces can improve the physical and mental health of individuals exposed to them to varying degrees, offsetting some of the negative effects of other environmental exposures, and consequently becoming ideal destinations for urban residents' leisure and recreation. In light of this, the accessibility and availability of urban green space have emerged as a crucial issue in recent years. The World Health Organization (WHO) has established a baseline of 9 square meters of green space *per capita* for assessing the provision of urban green spaces globally (WHO, 2017). However, the supply of green space in many urban areas falls significantly short of this standard, presenting severe challenges to both the availability and equity of green infrastructure (Olfato-Parojinog et al., 2024). Within this context, the assessment and optimization of the potential of existing urban green spaces are of critical importance.

Urban green space accessibility (GSA) effectively assesses the potential for residents to utilize urban green spaces (Kabisch et al., 2016). Most studies focus on measuring GSA at the scale of single cities or communities (Pearsall and Eller, 2020; Ye et al., 2018; Liu et al., 2021; Badakhshan et al., 2025; Satake et al., 2025; Senetra et al., 2018; Wu et al., 2020; Fan et al., 2017b), and a few studies have focused on the GSA measurement of multiple cities (Chen et al., 2024; Huang et al., 2022; Fan et al., 2017a). For instance, Huang et al. (2022) focused on studying the GSA within a 30 min (with a walking distance of 2500 m) walk for 366 prefecture-level cities in China, and find that less-developed cities always had more GSA than developed cities during 1990–2015. The Huang's work encompassed many cities to summarize GSA's characteristics across different geographical and economic zones, however, it lacks a detailed comparison of GSA differences among major cities in the same period. Simultaneously, it is evident that in fast-paced large cities, urban residents aspire to access urban green spaces within a short time due to limited leisure time (Kabisch et al., 2016; Liu et al., 2022). The "15 min city" is an urban planning concept aimed at creating an ideal environment where residents can meet their daily needs within a 15 min walk or bike ride from their homes, and this entails ensuring that workplaces, shops, schools, healthcare facilities, recreational amenities, and other service facilities are accessible within this radius (Moreno et al., 2021; Khavarian-Garmsir et al., 2023). Equitable access to urban green spaces within a shorter walk distance for urban residents has been proved to contribute to the social justice (Wolch et al., 2014; Jiang et al., 2023). Meanwhile, the current research on the accessibility of pedestrian green spaces in cities is mainly divided based on the concept of a "15 min city", and a distance of 300–1,000 m is taken as a core threshold (Stanners and Bourdeau, 1995; Handley et al., 2003; Roo et al., 2011). Nearly 100 cities around the world have successively carried out the practice of "15 min cities", especially in Paris, the vision of allowing city residents to walk or cycle within a 15 min range has been made into the core strategy for urban greening and emission reduction (Büttner et al., 2024; Moreno et al., 2024). Furthermore, the Chinese government has also proposed the concept of a living walking circle with a service radius of 800–1,000 m and a duration of 15 min (Jiang et al., 2023). Thus, the range of research area in this study focuses on urban residents' GSA within a 15 min walk scale. The GSA assessment primarily employs the Two-Step Floating Catchment Area (2SFCA) method to evaluate residents' potential to use green spaces. This method effectively captures physical accessibility by assessing the spatial interaction between supply and demand, while its assessment of green space equity remains limited (Chen and Jia, 2019; Wang, 2021). Existing research indicates that the Gini index is often used to measure the green space accessibility inequality (GSAI) (Ren and Guan, 2022; Chen B. et al., 2022; Vale and Lopes, 2023). However, the Gini index can only measure the geographical inequality of urban GSA and cannot assess the subjective inequality of urban residents' willingness to travel (Ren and Guan, 2022; Larson et al., 2022). Enjoying time in green spaces, as a non-essential outdoor activity, the resident's travel willingness of that may greatly influenced by the urban outdoor environment (Neuvonen et al., 2007). If the quality of the urban outdoor environment is good, residents are more willing to engage in recreational activities accessing green spaces, conversely, they may lack interest in heading for (Wang et al., 2019; Li et al., 2025). Furthermore, temperature, humidity, and air quality are crucial environmental factors that affect urban residents' willingness to travel (Dong et al., 2019; Giannopoulou et al., 2014). Therefore, it is critical to quantify residents' subjective travel willingness using objective environmental data, as well as to integrate GSA and GSAI, in order to comprehensively evaluate Green Space Accessibility Utility (GSAU).

To address the challenges outlined above, this paper employs 1 m resolution green space data about 30 major cities in China, the precise residential area locations and household data from the Anjuke website intend to provide a detailed comparison of GSA, GSAI and GSAU among major cities in China. Based on the 15 min city concept, and for ease of interpretation, we define green space access in this study using the 5-, 10-, and 15- min walking scales. We also calculate the travel aversion index (TAI) based on three indicators-temperature, humidity, and air quality, using the entropy weight method (EWM) (He et al., 2016). The TAI is similar to the risk aversion index in the financial investment industry, which reflects the degree to which investors dislike risk. A higher risk aversion index indicates a greater aversion to risk for investors. Similarly, the TAI indicates residents' degree of aversion to travel. A higher TAI indicates a greater aversion to access to green space by urban residents (Pratt, 1978). Furthermore, utility functions are often mentioned alongside the risk aversion index in financial investment industry literature, which are commonly used to objectively select a balanced investment utility portfolio by

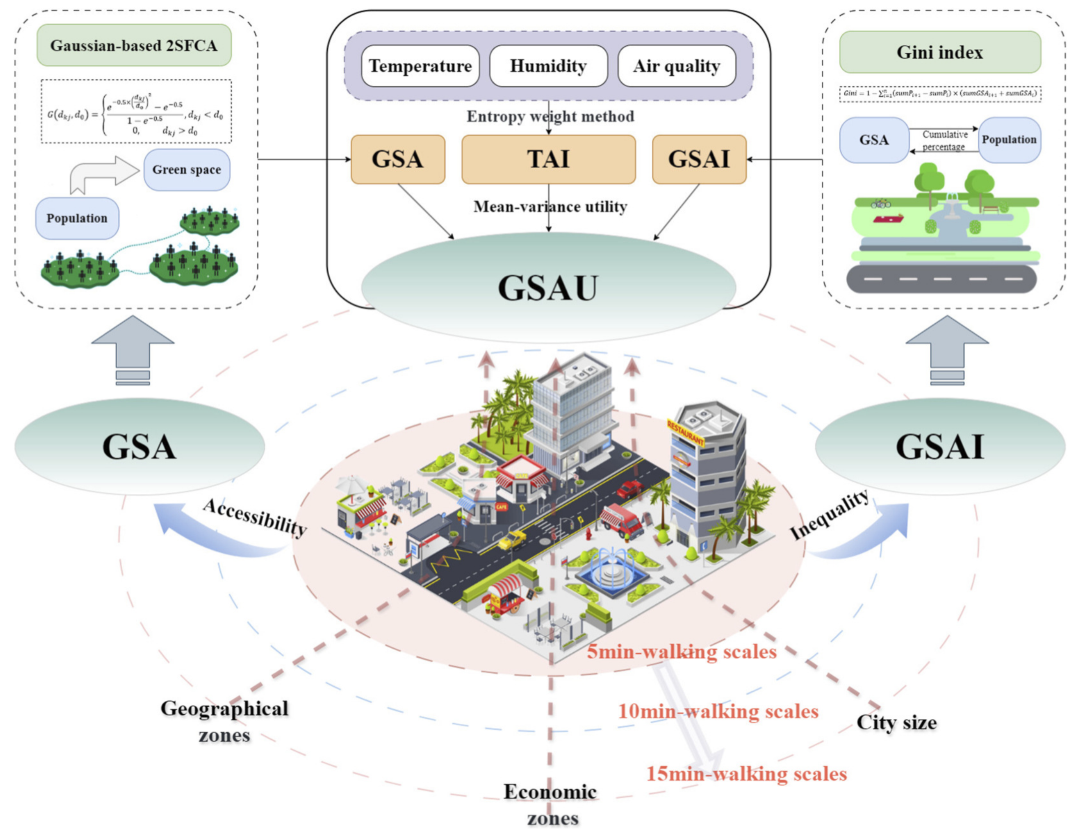

FIGURE 1
The flowchart of research design.

combining investors' subjective risk aversion levels with the objective stock expected value variance in a quantitative manner (Pratt, 1978). Thus, we combined the subjective aversion to travel in cities with GSA and GSAI forms GSAU. During this process, the mean-variance utility function is commonly used, so we draw on Markowitz's mean-variance utility function to calculate the GSAU in 30 major cities (Markowitz, 1952). Specifically, we addressed the following three questions. (1) What are the spatial distribution differences in green space accessibility (GSA), green space inequality (GSAI), and green space accessibility utility (GSAU) among 30 major cities in China? (2) At different walking scales, what are the characteristics of GSAU in 30 major cities in China? (3) Will seasonal changes affect the accessibility of green spaces? What extent differences it is?

2 Materials and methods

2.1 Study design and area

A flowchart outlining the entire research design is shown in Figure 1. We combined 1 m resolution green space data, Anjuke residential area locations, and household data of 2023 to calculate green space accessibility and inequality for 30 major cities in China, including 4 municipalities directly under the central government (Beijing, Shanghai, Tianjin, Chongqing) and 26 provincial capital cities, then we conducted a comparative analysis (Figure 2). Meanwhile, a comprehensive evaluation and comparison of GSAU for the 30 cities were performed. For comparative research, cities were divided into southern and northern cities based on geographical zones, and into eastern, central, northeastern, and western cities based on economic zones, and megacities, metropolises, and large cities based on city size (Hou et al., 2023). The classification of major cities was shown in Table 1.

2.2 Assessment of urban green space accessibility (GSA)

This study examined the urban green space accessibility by the Gaussian-based 2SFCA method. For each green space j, all population locations k within the threshold travel distance d_0 starting from j are identified to calculate the catchment area of green space j. The population at k is weighted using a Gaussian function G, which characterizes friction-of-distance as follows Equation 1:

$$G\left(d_{kj}, d_0\right) = \begin{cases} \dfrac{e^{-0.5\times\left(\frac{d_{kj}}{d_0}\right)^2} - e^{-0.5}}{1 - e^{-0.5}}, d_{kj} < d_0 \\ 0, \qquad d_{kj} > d_0 \end{cases} \tag{1}$$

where d_{kj} is the travel distance from the population at k to the green space j. The weighted population within the catchment of j is

FIGURE 2
Study area. Note: The map is created based on the standard map with figure number GS (2024) 0650, and the base map is unaltered. Due to the unavailability of data, Lhasa and Taipei were excluded.

TABLE 1 Classification of major cities.

	Economic zones			
	Western	Central	Eastern	Northeastern
Megacities	Chengdu Chongqing		Beijing* Tianjin* Shanghai Guangzhou	
Metropolises	Xi'an* Kunming	Zhengzhou* Wuhan Changsha	Jinan* Nanjing Hangzhou	Changchun*
Large cities	Wulumuqi* Xining* Lanzhou* Yichuan* Huhehaote* Guiyang Nanning	Hefei Nanchang Taiyuan*	Shijiazhuang* Fuzhou Haikou	Shenyang* Haerbin*

Those marked with "*" belong to the northern cities, while the rest are southern cities.

summed up as potential users of green space j. The ratio of green space to populations R_j is expressed as follows Equation 2:

$$R_j = \frac{S_j}{\sum_{k\in\{d_{kj} < d_0\}} G\left(d_{kj}, d_0\right) P_k} \tag{2}$$

where P_k is the population at location k whose centroid lies in the catchment ($d_{kj} \le d_0$) from green space j; S_j is the capacity of green space at j. The value of R_j represents the *per capita* green area that the potential users of green space j can obtain.

Step 2. For each population location i, search all green spaces l within the threshold travel distance d_0 from i, thus establishing the catchment for the population at i. R_l is weighted using a Gaussian function G. Sum up weighted R_l within the catchment area of green spaces i to obtain the spatial accessibility at population location i as follows Equation 3:

$$A_i = \sum\nolimits_{l \in \{d_{il} < d_0\}} G(d_{il}, d_0) R_j \tag{3}$$

where l denotes all green spaces within the catchment of population location i. A_i is the accessibility score, which represents the amounts of green spaces every nearby resident can access. A larger R_j value denotes that each potential resident can access more green space.

2.3 Measurement of green space accessibility inequality (GSAI)

The *Gini* index is a widely used measure of inequality, defined as the ratio of the area between the Lorenz curve and the line of perfect equality to the total area under the line of ideal equality (Raileanu and Stoffel, 2004). The *Gini* index is calculated as follows Equation 4:

$$Gini = 1 - \sum_{i=1}^{n} (sumP_{i+1} - sumP_i) \times (sumGSA_{i+1} + sumGSA_i) \tag{4}$$

where $sumGSA_i$ represents the cumulative percentage of the total accessibility of each district i within the city, sorted by rank; $sumP_i$ represents the corresponding cumulative percentage of the total population in each district i within the city. In this article, GSAI is represented by the *Gini* index, and the *Gini* index ranges between 0 and 1.

2.4 Measurement of green space accessibility utility (GSAU)

The mean-variance utility function provides a basis for quantifying decision-making under risk and uncertainty (Markowitz, 1952; Zakamouline and Koekebakker, 2009). This article combined accessibility, inequality, and TAI using the mean-variance utility function to quantify the GSAU of 30 major cities. Firstly, the ideal urban GSAU is calculated by assuming that the travel level of residents in all cities is in an ideal state. Secondly, the TAI is obtained by weighting urban temperature, humidity, and air quality data using the entropy weight method, which is a common weighting method. The entropy weight method ensures the objectivity of the weights (Delgado and Romero, 2016). When TAI is equal to 1, it indicates an ideal GSAU. The annual TAI is calculated by weighting the annual temperature, humidity, and air quality data from January to December, thereby determining the annual GSAU. Similarly, the winter GSAU is calculated by weighting the temperature, humidity, and air quality data from December, January, and February. The summer GSAU is calculated by weighting the temperature, humidity, and air quality data from June, July, and August. The formula is as follows Equations 5, 6:

$$GSAU = GSA - \frac{TAI}{2} \times (GSAI)^2 \tag{5}$$

$$TAI = a_1 TSI + a_2 HSI + a_3 AQI \tag{6}$$

Where the $GSAU$ represents the utility of urban green spaces, indicating the extent to which residents utilize these spaces. GSA means urban green space accessibility, representing the degree of difficulty the residents go to specified spaces under different conditions. TAI refers to the Travel Aversion Index, which measures the level of discomfort during the travel process. $GSAI$ indicates the inequality in green space accessibility, highlighting disparities among different groups or areas in accessing urban green spaces. TSI and HSI represent the temperature and humidity indices, respectively, used to describe environmental warmth and moisture levels, the index is represented by the absolute value of the difference between the average temperature (humidity) within a specific time range and the most suitable travel temperature (humidity). Here, based on previous studies, the ideal travel temperature is defined as 20 °C and the ideal humidity as 0.5 (Liu et al., 2024). AQI stands for the air quality index, assessing levels of air pollution. Symbols a_1, a_2, and a_3 represent weighting coefficients for temperature, humidity, and air quality, respectively, adjusting their importance in comprehensive evaluations. The values of a_1, a_2, and a_3 are calculated using the entropy weight method, which yields 0.31, 0.29, and 0.40, respectively.

2.5 Data resource

As shown in Table 2, the data used in this study are collected from the following sources: the map of China originates from the National Standard Map Service System of the Ministry of Natural Resources. Residential community addresses and household data within urban areas are sourced from the Anjuke website (https://www.anjuke.com). Urban green space data is obtained from the UGS-1m dataset (Shi et al., 2022), and green spaces are primarily classified into parks, green buffers, square green spaces, attached green spaces, and other green spaces, all of which are located within global urban boundaries. Temperature and humidity data are sourced from the China Meteorological Administration's National Meteorological Science Data Center (https://data.cma.cn/). Air quality data is derived from the monthly report on urban air quality conditions by the Ministry of Ecology and Environment of the People's Republic of China (https://www.mee.gov.cn/).

3 Results

3.1 The comparation of GSA in major cities in China

We leveraged fine-resolution global green space and population of residential areas in 2023 to compare GSA in the 30 major cities, within 5-, 10-, and 15- min walking scales (Figures 3a–c). We observe the number of cities with a GSA above 30m^2/person gradually increases from different walking scales, and cities with relative high GSA (above 30m^2/person) are primarily located in the eastern region.

At the level of different geographical regions (Figure 3d), we find that the GSA in southern cities is slightly higher than the GSA in northern cities within different walking scales. As the walking scale increases, the mean GSA in southern cities gradually rises to approximately 0.12, whereas in northern cities, it shows a marked increase from 0.08 to 0.28. This trend suggests that the potential for residents to access urban green space is more stable in southern cities than in northern ones across the 5-, 10-, and 15- min walking scales. Meanwhile, the cities in various economic zones show obvious differences of GSA (Figure 3e), especially the cities between the eastern and western zones. The mean GSA of eastern

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TABLE 2 Information on datasets used in this study.

Category	Indicator	Unit	Dataset
Residential data	Community addresses Per capita GDP	— CNY *per capita*	Anjuke website (https://www.anjuke.com) China statistical yearbook (https://www.stats.gov.cn/)
Green space data	Green land cover Proportion	Raster data (1 m)	UGS-1m (Shi et al., 2022)
Meteorological data	Ambient temperature Relative humidity	°C %	The China meteorological Administration's national meteorological science data center (https://data.cma.cn/)
Air quality data	Air quality index (AQI)	—	The ministry of ecology and environment of the People's republic of China (https://www.mee.gov.cn/)

According to the "Urban Residential Area Planning and Design Code" (GB, 50180–93) issued by the Chinese government, the average family size is defined as 3.2.

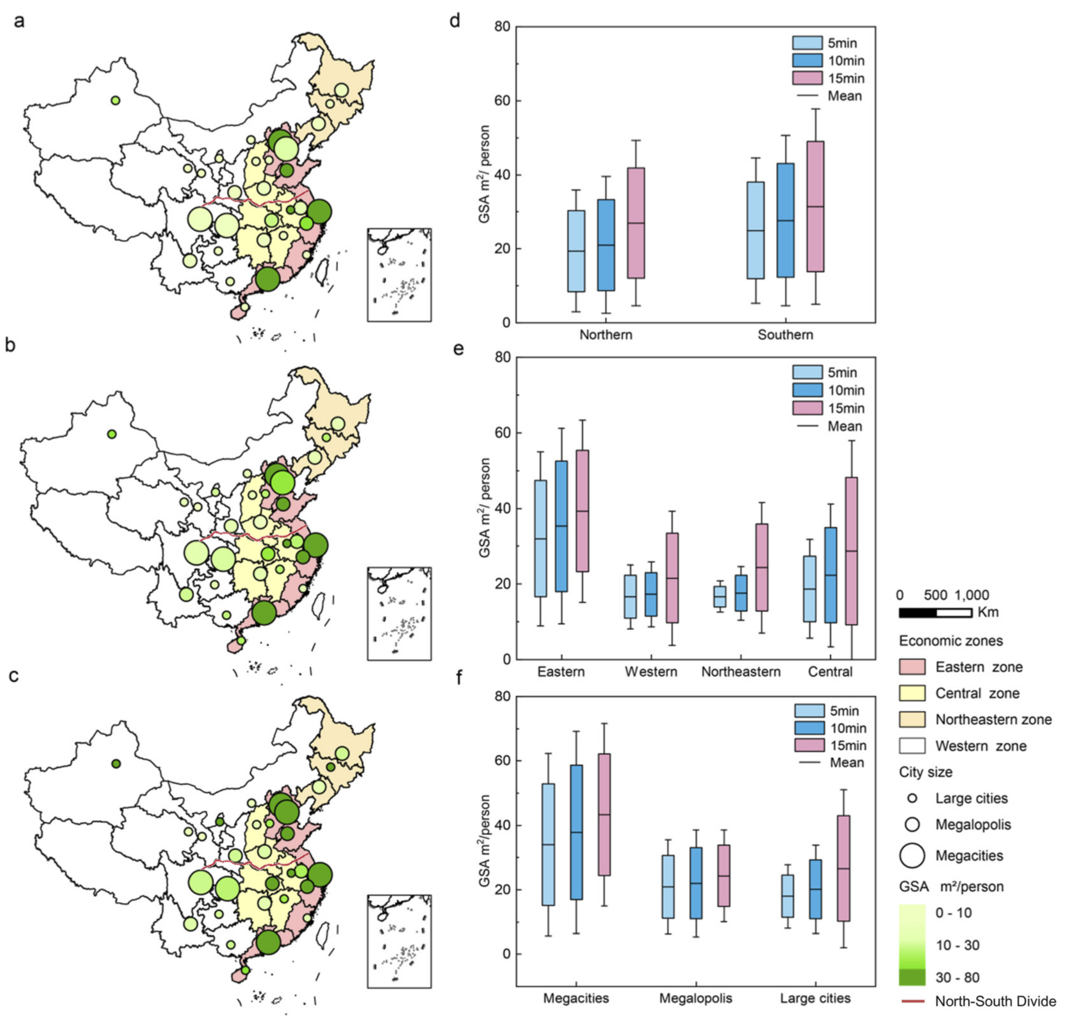

FIGURE 3
Distribution of GSA in 30 major cities in China. **(a–c)** GSA at 5-, 10-, and 15- min walking scales, respectively, where darker and lighter shades of green represent higher and lower levels of GSA; **(d)** Differences in GSA by geographic zones at 5-, 10-, and 15- min walking scales; **(e)** Differences in GSA by economic zones; **(f)** Differences in GSA by city size.

cities is approximately twice than that of western cities at different walk levels. From 5- to 10- and 10- to 15- min walk scales, the GSA in eastern cities shows a steady growth ratio (10%, 11%) with the expansion of pedestrian distance, and the GSA in western cities shows a turbulent growth ratio (4%, 25%). This implies that residents of cities in the western region have a lower potential for utilizing green spaces within shorter walking distances, the GSA at the 5- and 10- min walk scales in the western zone needs to be enhanced. In terms of city size (Figure 3f), there are two special differences of GSA among the major cities. On the one hand, the

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TABLE 3 Analysis of the correlation between *per capita* GDP and urban GSA.

Correlation factor	GSA-5min	GSA-10min	GSA-15min
Correlation coefficient	0.511	0.443	0.336
p-value	0.004***	0.014**	0.070*

* means p < 0.1, ** means p < 0.05, *** means p < 0.01.

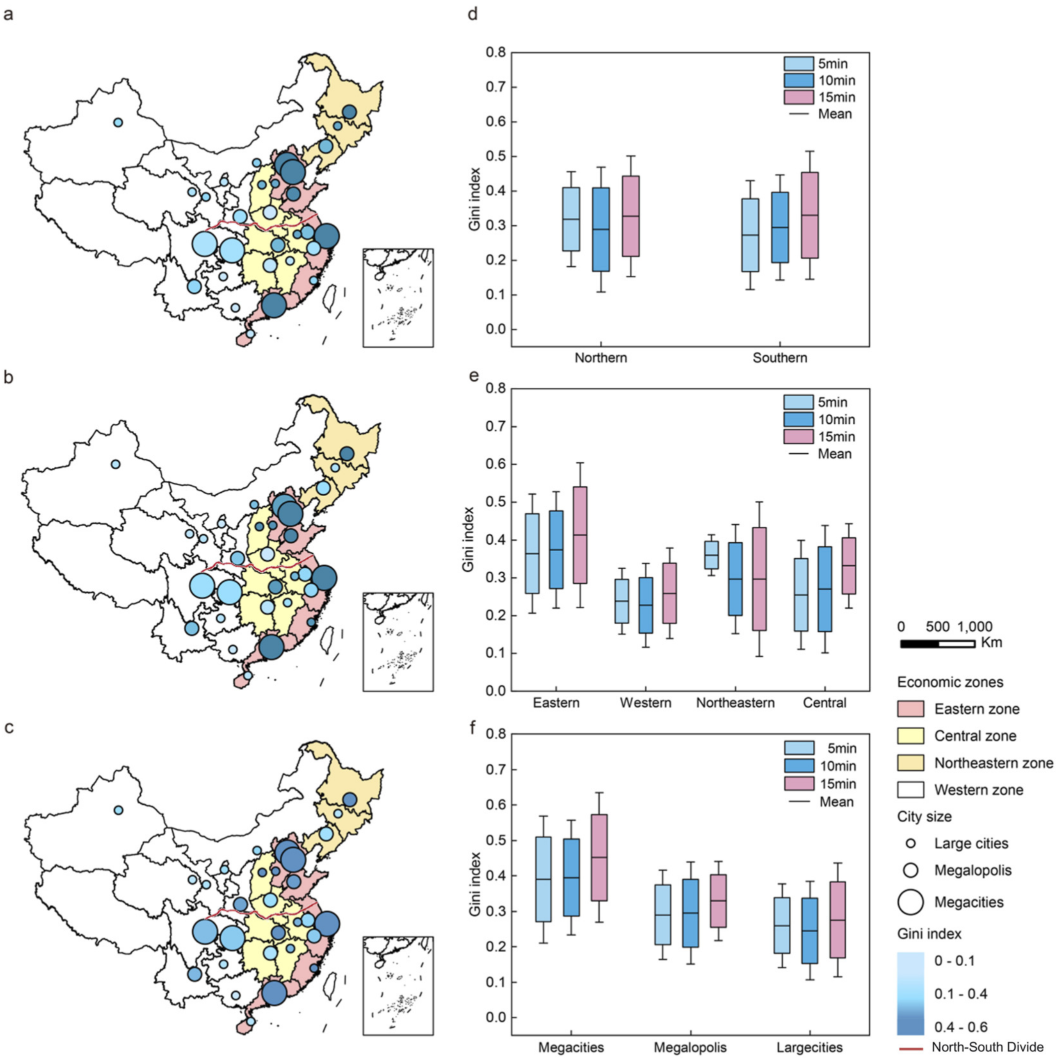

FIGURE 4
Distribution characteristics of GSAI in 30 major cities in China. **(a–c)** GSAI at 5-, 10-, and 15- min walking scales, respectively, where darker and lighter shades of green represent higher and lower levels of GSAI; **(d)** Differences of GSAI by geographic zones at 5-, 10-, and 15- min walking scales; **(e)** Differences in GSAI by economic zones; **(f)** Differences in GSAI by city size.

GSA of megacities is approximately 1.5 times that of large cities. On the other hand, the mean GSA of megalopolis cities increased smoothly from 17.68 to 18.16 and finally to 20.25, but the mean GSA of megacities and large cities grew dramatically. As mentioned above, it can be deduced that megacities in the eastern region possess higher GSA, which consistently improves with the growth of walking distances. For example, major megacities in the eastern zone, such as Guangzhou, Shanghai, and Beijing, rank in the top three in GSA among the 30 major cities. This pattern may be attributed to more substantial funding for urban green space construction in economically developed cities. To test this hypothesis, we examined the correlation between GSA at different walking scales and *per capita* GDP of cities. The results reveal a statistically significant positive correlation at the 5- and 10-min walking scales, with correlation coefficients of 0.511 (p < 0.01) and 0.443 (p < 0.05), respectively (Table 3). This indicates that a city's economic development level is, to some extent, a positive predictor of its residents' GSA.

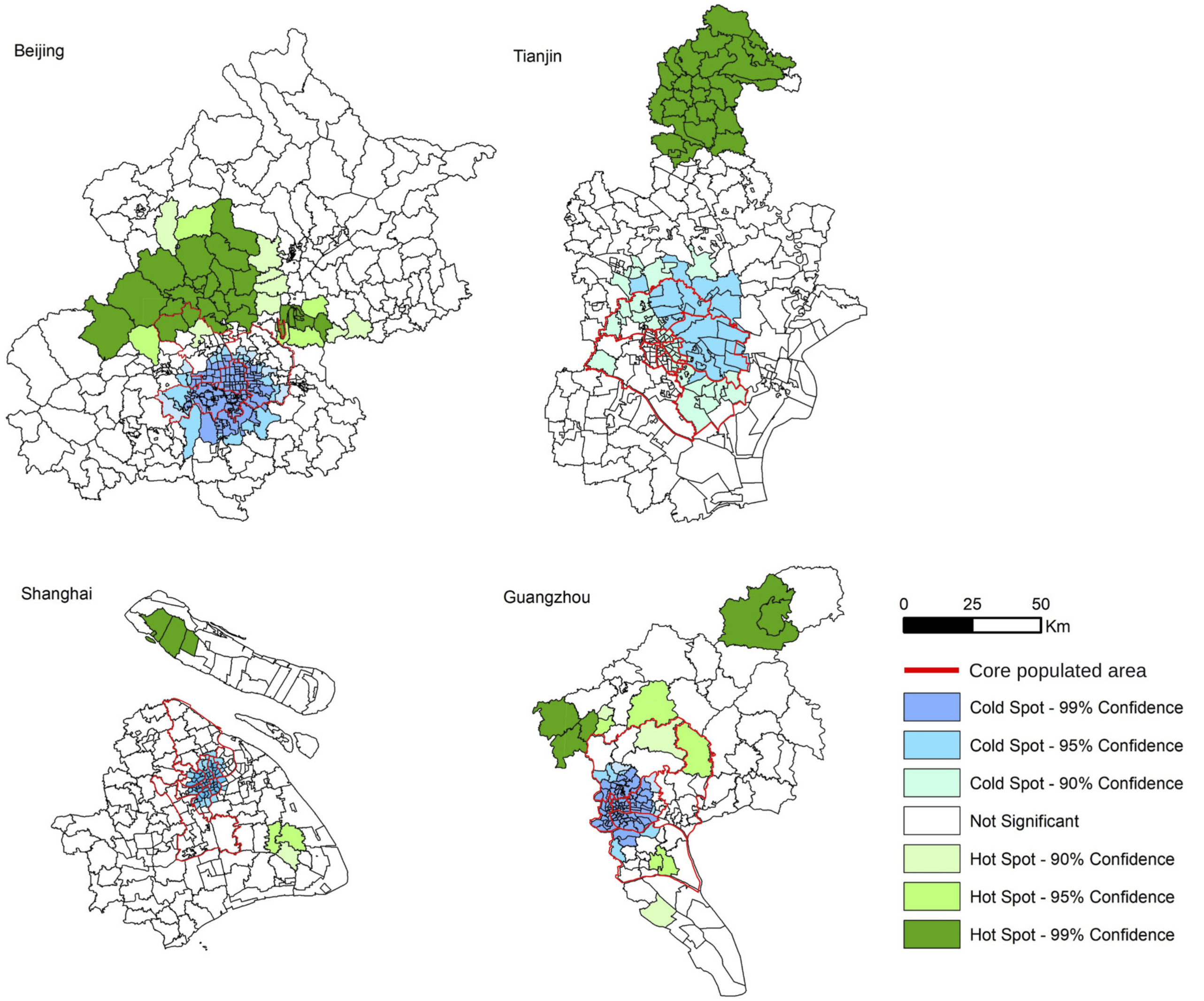

FIGURE 5
Analysis of accessibility hot spots and cold spots in megacities of the eastern region.

3.2 The comparation of GSAI in major cities in China

Our analysis of the Gini index reveals that pronounced GSAI is characterized by its concentration in the eastern zone. Among the 30 major Chinese cities, only a few exhibit a high Gini index (>0.4) at the 5-, 10-, and 15- min walking scales (Figures 4a–c). The cities with the highest inequality—Shanghai, Tianjin, and Beijing at the 5-min scale, and Shanghai, Tianjin, Guangzhou, or Tianjin, Shanghai, Guangzhou at the longer scales—are all eastern megacities. This consistent pattern strongly indicates a systematically higher level of green space inequality within the eastern region.

We further explore the disparities in urban green space equality from three perspectives: geographical zone, economic zone, and city size. There is no significant difference in the mean Gini index between cities in the northern and southern zones. The Gini index in southern cities gradually increases keeping the growth rate steadily improving (8%, 12%) with the expansion of the walk distance (Figure 4d), and the northern cities have no growth trend. This implies that the GSAI in southern cities increases with the expansion of walking distance. From the perspective of economic zones (Figure 4e), the mean Gini index is highest in eastern cities (mean: 0.38), lowest in western cities (mean: 0.23), and intermediate in central (mean: 0.28) and northern (mean: 0.31) cities within three different walk distance. The Gini index of cities in the eastern region is approximately 1.6 times that of the western region. Nearly half of the cities in the eastern zone have a Gini index exceeding 0.4, while all cities in the western zone have a Gini index below 0.4. This indicates higher GSAI in the eastern zone and highlights the urgent need for green space planning for health and wellbeing in eastern cities of China. Based on city size, the GSAI is highest in megacities (mean: 0.41), followed by metropolis (mean: 0.30), and lowest in large cities (mean: 0.25). The Gini index of megacities is about 1.6 times that of large cities, indicating severe inequality within eastern megacities. This disparity may be attributed to the high population concentration in central urban areas of megacities and significant intra-city zonal population variations, which adversely affect the equality of green space access. To explore this further, a

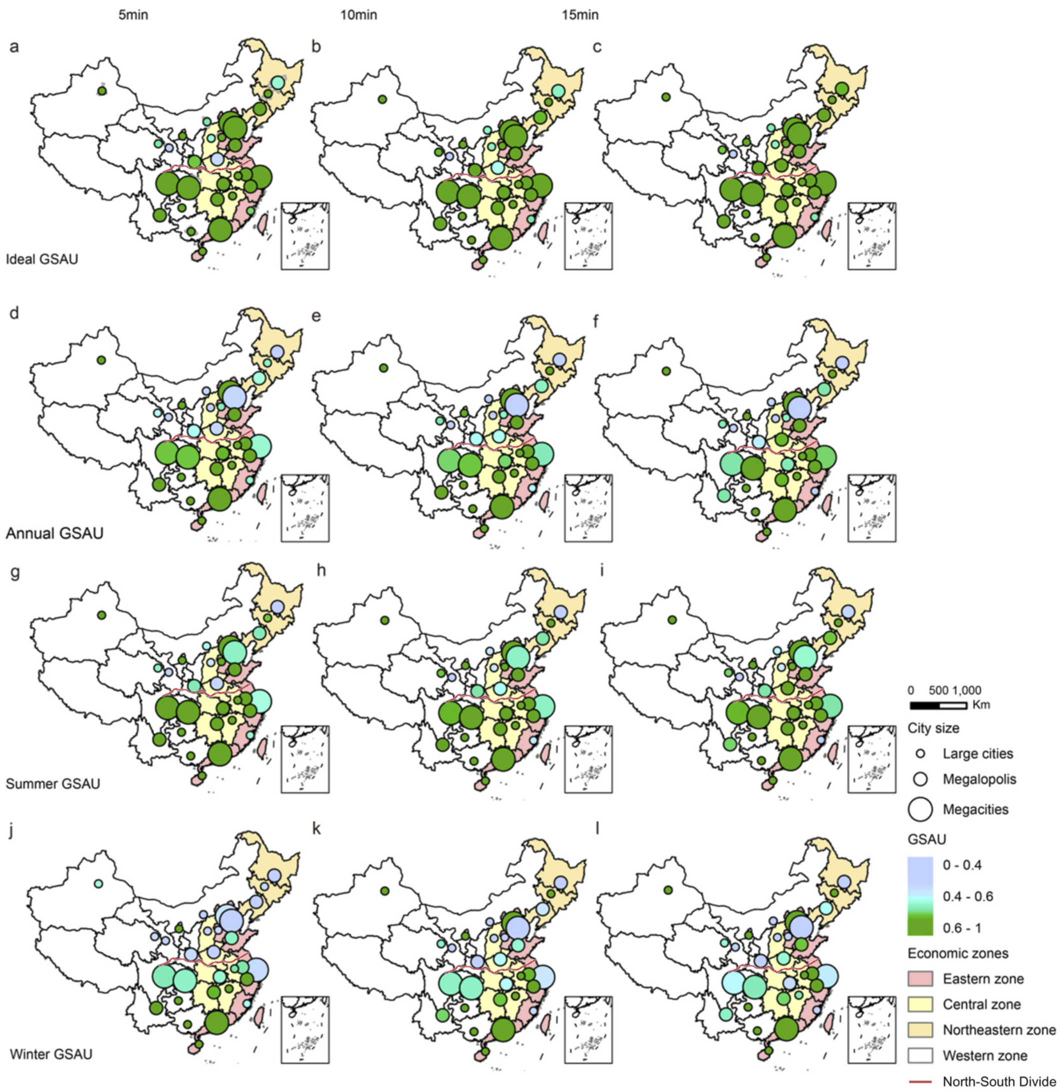

FIGURE 6
Distribution characteristics of GSAU in 30 major cities in China at 5-, 10-, and 15-min walking scales, where darker and lighter shades of green represent higher and lower levels of GSAI. **(a–c)** Ideal GSAU; **(d–f)** Annual GSAU; **(g–i)** Summer GSAU; **(j–l)** Winter GSAU.

hotspot analysis was conducted for the four high-Gini cities. The results (Figure 5) reveal that high-population-density areas in these megacities consistently coincide with cold spots of GSA, suggesting that population density is a key factor influencing intra-city GSAI.

3.3 The heterogeneity analysis of GSAU in major cities in China

We analyzed the differences in GSAU under ideal, annual, summer, and winter scenarios across different walking scales in major Chinese cities (Figure 6). The number of cities with a GSAU above 0.6 showed little variation across the three walking scales. However, significant disparities were observed among the ideal, annual, summer, and winter GSAU values within the same city. For a detailed comparison, we focused on the 15 min walking scale. At this level, the number of cities with an ideal GSAU above 0.6 is greater than those under annual, summer, or winter scenarios, and the number of cities with an ideal GSAU exceeding 0.6 is approximately 1.5 times that of cities with annual GSAU. Moreover, the quantity of cities with summer GSAU above 0.6 is roughly 1.7 times that of cities in winter. That indicates that outdoor environmental quality significantly influences the GSAU, emphasizing the necessity of considering the impact of outdoor environmental quality on residents' travel, and also showing the impact of season differences on easy access to green spaces.

By comparing the geographical differences between ideal and annual GSAU (Figure 6a), we find the ideal GSAU in southern cities (mean: 0.70) is approximately 10% higher than that in northern cities (mean: 0.63), the number of cities in the south with an ideal GSAU above 0.6 approximately 1.3 times that of northern cities (Figure 6c). The mean annual GSAU in the southern zone (mean: 0.62) is approximately 15% higher than the northern zone (mean: 0.53) at different walk scales, and the proportion of cities in the southern zone (70%) with GSAU above 0.6 is more than twice that of northern cities (30%) (Figure 6d). Furthermore, the ideal GSAU

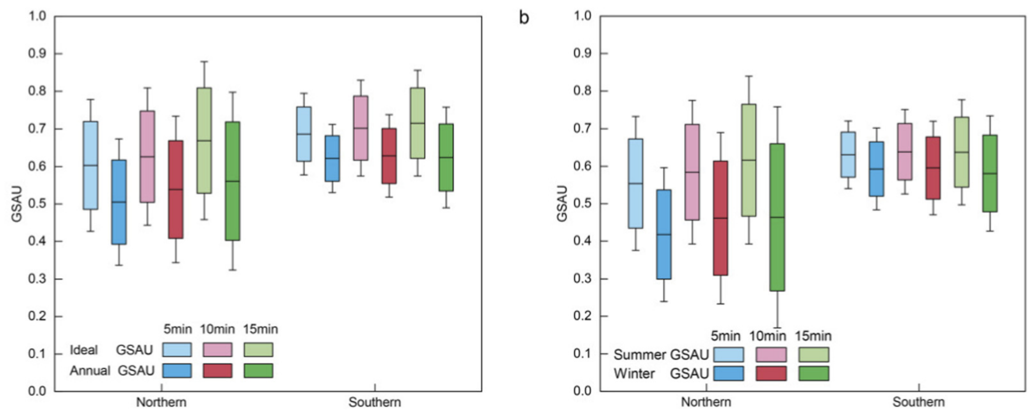

FIGURE 7
Comparison of ideal GSAU and annual GSAU, summer GSAU, and winter GSAU in 30 major cities. **(a)** Comparison of ideal GSAU and annual GSAU between the cities of the North and the South at 5-, 10-, and 15-min walking scales; **(b)** Comparison of summer GSAU and winter GSAU between the cities of the North and the South at 5-, 10-, and 15-min walking scales.

exceeds the annual GSAU by approximately 20% in northern cities, whereas the ideal GSAU exceeds the annual GSAU by about 10% in southern cities. Our analysis reveals that the disparity in environmental quality (temperature, humidity, air quality) between northern and southern regions has exacerbated the gap in GSAU, highlighting the critical importance of considering green space planning and environmental governance together in northern cities for residents' easy access to green spaces.

By comparing the differences in GSAU across the summer and winter seasons between southern and northern cities (Figures 7a,b), we found that the summer GSAU in southern cities (mean: 0.63) is approximately 10% higher than in northern cities (mean: 0.58), and the winter GSAU is about 30% higher in southern cities (mean: 0.59) than in northern cities (mean: 0.44). The proportion of southern cities with summer GSAU above 0.6 (85%) is more than twice that of northern cities (40%) (Figure 6i), with winter GSAU above 0.6 (45%) is more than twice that of northern cities (20%) (Figure 6l). In southern cities, the GSAU during the summer is approximately 8% higher than in the winter, whereas in northern cities, the summer GSAU exceeds the winter GSAU by about 30%. These indicate significant geographical variations in both winter and summer GSAU of China's major cities, and the GSAU of northern cities is greatly influenced by the season. Consequently, while the temperature gap driven by latitude is fixed, the significant role of air quality in this seasonal slump presents a tangible opportunity for intervention. Improving urban air quality through ecological controls could thus be a key strategy for mitigating the severe wintertime decline in green space accessibility in northern China.

4 Discussion

Geographical location, economic development, and city size, among other varying factors, contribute to the uniqueness of each city, including its green space accessibility. Previous research has conducted modeling and exploration at the level of individual cities worldwide or across multiple cities. At the urban scale, evidence from cities such as Osaka, Japan; Vienna, Austria; Tehran, Iran; and Tczew, Poland indicates a connection between the accessibility of green infrastructure and socioeconomic factors (Badakhshan et al., 2025; Satake et al., 2025; Senetra et al., 2018; Liu et al., 2021). For example, studies in Vienna have shown a significant positive correlation between the average accessibility of infrastructure and socioeconomic status (Riepl et al., 2025). Meanwhile, evidence from Barcelona and Shanghai, based on the spatiotemporal changes in urban green spaces, further supports this conclusion (Fan et al., 2017a). Additionally, a study of 1,039 medium and large cities globally found that cities in high-income countries generally have higher green space coverage and better accessibility compared to those in low-income countries (Huang C. et al., 2021).

It is noteworthy that some studies have found that city size and administrative rank also significantly influence green space accessibility (Xu et al., 2019; Chen et al., 2024). For instance, research on 283 Chinese cities revealed a positive correlation between a city's administrative level and its green space accessibility, which may be attributed to greater policy support and systematic planning in larger cities (Chen et al., 2024). Another study focusing on the same sample reached a similar conclusion, showing that provincial capitals had a significantly higher positive correlation with GSA than non-capital cities (Huang et al., 2023). Furthermore, despite a declining trend of GSA happened in megacities, another study noted that megacities still maintained higher overall GSA (Huang et al., 2022; Huang Y. et al., 2021). Beyond economic and size-related factors, the natural conditions, climate, and urbanization patterns of cities in different geographical regions may also play a role (Song et al., 2021). For example, some research suggests that southeastern China has lower urban green space stock coverage compared to the northwestern region, and GSA in the southeast has consistently been lower than in the northwest, with a declining trend observed in the eastern regions (Huang C. et al., 2021).

We conducted a systematic, multi-scale assessment of GSA, GSAI, and GSAU across 30 major Chinese cities, comparing differences based on geographical location, economic development level, and city size. The findings align with some of the aforementioned research while also revealing distinct conclusions. Firstly, although previous studies have addressed the distributional differences and temporal changes in green spaces across cities in terms of geography, economic development, and city size, seasonal variations have seldom been discussed. One of the most important findings of this paper is the clear disadvantage of northern cities that had not only lower annual GSA but also more severe seasonal decline of GSAU than the south. This broadens the results of works on individual northern cities (Pei et al., 2022) with the quantification of a systematic regional climate disadvantage. Though the idea of annual variation is accepted in literature of parks usage, the severity in which its effect on reducing actual accessibility in the North China—a 30% reduction in winter—has not before been brought up in this scale, and indicates that the more conventional climate agnostic GSA studies, may greatly over-estimate accessible green area in harsh season areas in temperate regions, an interesting consideration to planners of temperate zones around the world. Meanwhile, Chen Y. et al. (2022) believe that the inequality of *per capita* green space ecosystem services is negatively correlated with the size of cities measured by population and GDP. However, we detected an "inequality paradox" among the economically developed eastern megacities. Although their high GSA is consistent with the positive association between us and others (e.g., Huang et al., 2022) of the relationship between GDP and green space supply, their simultaneity with the high Gini indices indicates that it is unable to bridge between economic wealth and social justice. The findings are further puzzling as the three megacities where GSA is largest are also the leading cities in Gini (i.e. Shanghai, Beijing and Shenzhen), as well as many other Chinese cities (Huang et al., 2022; Li et al., 2022). That could be attributed to the "green space paradox" phenomenon, where newly built or restored green spaces promote environmental gentrification. While the community environment improves, the increase in property values and community living costs may lead to the migration and marginalization of low-income residents (Wolch et al., 2014; Immergluck and Balan, 2018; Pearsall and Eller, 2020). On the other hand, although the green spaces in leading economic cities have more abundant policy and financial support to increase the capacity, the newly built green spaces are usually located near upscale communities and attract groups with high socioeconomic status, which exacerbates the unfairness in green space accessibility (Yasumoto et al., 2014; Yutian et al., 2024). This suggests the observation that growth in wealth does not necessarily lead to growth in environmental equality. And this is further corroborated and generalized in scope from the intra-urban inequities documented in the case studies (Ou et al., 2021) to a regional level, which also indicates that the spatial gap between population and green resources is a ubiquitous characteristic of China's emerging megacities.

Given the pace of urbanization, the disproportionate allocation of urban greenspace has become one of key concerns for social justice in research in this area. A wide range of papers also apply different techniques to measure the inequity in green spaces from different angles, such as Xu et al. (2024) using the Theil index to measure inequity in access and availability of greenspace within and among urban villages and formal residential zones of Shenzhen. On a national scale, Chen B. et al. (2022) used the Gini coefficient to quantify the inequalities of green space exposure across the globe. Continuing to refine the idea of equity, Jiang et al. (2023) developed green space equity in the Qingdao city according to both distributive and perceptual equity aspects. Likewise, Li et al. (2022) propose a multiscale general equity evaluation index considering accessibility (Ai), diversity (Di), convenience (Ci) and satisfaction (Si). Also, there is a new evaluation method from social, economics, and geography aspects is added by Cao et al. (2024) to the central area West Bank in Changsha. Despite these meaningful efforts, a typical gap exists in these existing studies: objective equity facets, such as spatial allocation and spatial proximity, have received much more attention than subjective equity factors including travelers' perceptions, satisfaction, and intent to visit. In addition, we find no existing framework has achieved the objective of taking both subjective and objective evaluations together as a comprehensive indicator of the quality of urban public green space equity. In our paper, we fill this gap with the introduction of the TAI–a representative index that indicates the urban residents' subjective aversion to the outdoor space of public green under different temperatures. TAI measures travelers' preference differences of travelling willingness with respect to different quality environments between Chinese cities, which has rectified the shortcoming of only considering geographic equity in traditional GSA evaluation. Nevertheless, we want to make sure readers understand the limitations of the methods used in this study. The reason we have selected temperature, humidity, and AQI as the environmental factors is we can only access these data. Moving forward, more detailed and granular indicators—such as the acoustic ambient, perceived safety and aesthetics quality—may be incorporated to further enrich the robustness of such equity evaluation and completeness of the evaluations.

Mean-variance utility function is one of the core concepts of asset allocation theory in business economics to help the investors make an optimal risk-return trade-off by allocating different types of assets (Markowitz, 1952). Similarly, we creatively apply mean-variance utility function to study urban green space access in this paper and hypothesize that it will help the residents to strike an optimal risk-return trade-off between their negative perceptions of the travel and "rewards" or positive outcomes of the travel. Although utility functions have not been used very much in making travel choices, for example Zhang et al. (2016) calculated tourist destination utility based on the mean-variance utility, Zhang et al. (2024) posited that individual green space preference can be represented by utility functions, and that there is still an important gap in their use to model residents' green space travel decisions in variable environmental contexts. We offer a new framework for assessing the optimal urban green space destination by incorporating residents' travel willingness (derived from environmental quality), GSA, and GSAI. A critical result is the significant gap between optimal and annual GSAU. Under the ideal environment condition (i.e. TAF = 1), 30 major Chinese cities have higher GSAU. The 30 cities have significantly lower annual GSAU, computed through the year-long TAI fitted with temperature, humidity, and air quality during the year. The "utility gap" highlights the very real consequence of real environmental quality on effective access that has arguably never been this important a factor given climate change and globalization.

For future study, our work can be scaled further. If enough data are collected, GSAU assessment on a regional (countrywide or worldwide) scale would be more feasible with a "world map of green space utility" exhibiting global-level pattern. On the other hand, we identified contrasting winter and summer GSAU in northern and southern Chinese cities respectively; the similar north-south and winter-summer differences in other hemispheres or other countries/cities should also be examined. In future, researchers need to take the green area quality, traffic quality and other related influencing factors, and the residents' thematic preference into account to study GSAU differences between inner areas.

Our work in this paper can be looked upon as first step towards quantifying the realized utility of the urban green spaces. We claim that it cannot be captured only by physical distance or distributional fairness. The urban ecosystem is a co-evolving holistic entity and human-green interaction happens along a continuum of mediating environmental variables. While more focus on the drastic influence of external environmental quality on travel willingness, the quantification of feasible green space utility will gain significance to build actual livable cities and cities for all.

5 Conclusion and recommendations

This paper shows that equal and efficient green space access in urban Chinese megacities is a complicated issue. It has been found that the GSAs' spatially inhomogeneous distribution is closely related to urban economic levels and the higher GSAI is surprisingly discovered in economically developed eastern megacities such as Shanghai and Beijing. Finally, GSAU index shows the difference in ideal and real utility that also impacted by seasonal and climate differences strongly in northern cities and shows that merely physical distance is not enough for considering in wellbeing of residents. Notably, as the seasonal and climatic attributes of nature are difficult to intervene in, policymakers should focus on optimizing GSA and GSAI, taking into account the geographical characteristics, economic development levels, and scale differences of cities for adaptive improvement and planning. For example, from a geographical perspective, for eastern megacities with high economic levels, it is necessary to enhance regional greenway networks, ensure equitable distribution of green space through pocket parks and green networks, and pay attention to the needs of "new urban residents," focusing on green space provision in remote industrial parks and affordable housing areas. For expanding cities in the central region, ecological corridors and structural green spaces should be preemptively reserved during urban expansion planning, ensuring the protection of existing green spaces while improving green space coverage and accessibility. For cities in ecologically fragile western regions, the priority should be protection, with green space construction avoiding damage to ecologically sensitive areas. From a climatic perspective, given the seasonal variations in green space utility between northern and southern cities, "season-adaptive planning" should be implemented, especially in northern cities. To address extreme low temperatures, cold-resistant vegetation can be selected for outdoor greening, and greenhouse gardens can be promoted, combined with sustainable energy sources to enhance residents' potential access to greenery. Furthermore, for cities with sufficient green coverage but low GSAU, improving transportation infrastructure is a crucial step in enhancing green space accessibility and equity. Finally, urban planners should also focus on the quality and management of green infrastructure. For instance, artificial intelligence and big data technologies can be utilized to analyze and provide feedback on the basic conditions of green spaces, continuously optimizing green space management to minimize variations in usability and promote sustainable green urban development.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YZ: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review and editing. CX: Conceptualization, Data curation, Methodology, Visualization, Writing – original draft. LS: Funding acquisition, Supervision, Writing – review and editing, Formal Analysis. JZ: Data curation, Investigation, Writing – review and editing. YZ: Data curation, Writing – review and editing, Software. YX: Validation, Writing – review and editing. WF: Supervision, Writing – review and editing. TZ: Supervision, Writing – review and editing. CZ: Supervision, Writing – review and editing, Funding acquisition.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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