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Interpreting differences in access and accessibility to urban greenspace through geospatial analysis

Gang Lin [a], Yongze Song [b,*], Dong Xu [c], Mohammad Shahidul Hasan Swapan [b], Peng Wu [b], Weitao Hou [b,d], Zhuoyao Xiao [b,e]

[a] School of Electrical Engineering, Computing and Mathematical Sciences, Curtin University, Perth, WA 6845, Australia
[b] School of Design and the Built Environment, Curtin University, Perth, WA 6845, Australia
[c] Department of Geography, National University of Singapore, Singapore
[d] Department of Biological Sciences, National University of Singapore, Singapore
[e] School of Geography, University College Dublin, Ireland

A R T I C L E I N F O

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Spatial morphology
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A B S T R A C T

Access to urban greenspace is a fundamental requirement in providing critical ecosystem services, improving health and well-being across all ages, fostering social cohesion, and addressing prevalent health disparities in an increasingly urbanised society. Access refers to the availability of urban greenspace, while accessibility indicates the ease of reaching and enjoying these greenspaces and the quality of greenspace services. However, quantitative studies to interpret such difference between accessibility and access are limited. To contribute to this gap, this study developed a Spatial Delta Model (SDM) to quantify the difference between accessibility and access to greenspace and assess its spatial characteristics. The study examines the block-level access, accessibility, and their difference in Perth, Australia, using the SDM with a series of high-resolution greenspace and socio-economic spatial data. Access was calculated as the total greenspace near residential blocks and accessibility was derived using a modified Gaussian two-step floating catchment area (MG2SFCA) approach. Once they were quantified, a set of residential, morphological, and greenspace related factors were utilised to explain the spatial patterns of the difference between accessibility and access using a machine learning geographical detector model. The findings on the measure of the greenspace usability and the user experience further contribute to develop a green city classification system (GCCS), which is useful to informing urban planning and greenspace management.

1. Introduction

Urban greenspace provides essential ecosystem and cultural services, enhancing physical, mental, and social health, and human well-being across different age groups (Anguelovski et al., 2022; Chen et al., 2022; Reyes-Riveros et al., 2021; Enssle and Kabisch, 2020). As more than half of the global population live in cities, urban greenspace directly links with the quality of life of urban residents (Wendel et al., 2012). However, greenspace access contains significant regional difference, leading to social group variations and the consequential health disparities (Schüle et al., 2019). Thus, understanding and addressing the inequality in greenspace access is a key concern in the healthy, cohesive, and sustainable development (Song et al., 2021).

In the studies about greenspace access, there are two critical concepts: access and accessibility. Access to urban greenspace refers to the measure of the physical presence and availability of green areas within urban areas (Coombes et al., 2010). This means that the access to urban greenspace can be calculated as the area of available green space within a certain distance to the residents. Studies of access to greenspace aim at quantitatively assessing the distribution of green areas to the urban residents, which can be used to inform urban planning, health initiatives, and social policies (Wolch et al., 2014; Kabisch et al., 2015). Accessibility, on the other hand, to urban greenspace indicates the ease of reaching green areas and the quality of services they provide (Žlender and Thompson, 2017; Tannous et al., 2021). It expands the physical proximity to consider factors such as greenspace size, distance to residential areas, and socio-economic conditions affecting usage (Wendel et al., 2012; Reyes et al., 2014). For instance, studies in Seoul and Athens used metrics of park area per capita and greenspace indices to reveal socio-economic influences on greenspace accessibility (Koliotsis and Papadopoulou, 2020; Heo et al., 2021).

* Corresponding author.
E-mail address: yongze.song@curtin.edu.au (Y. Song).

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Studies about the access or accessibility to greenspace can be classified into three categories. The first category is to assess the influence of greenspace access on health and well-being. For instance, studies have shown a correlation between access to greenspace and health outcomes, reduction in stress, and adolescent mental well-being (Mueller and Flouri, 2021). In Greater London, high-quality greenspaces, rather than just open spaces, have been found to enhance life satisfaction and subjective well-being (Knight et al., 2022). A Puerto Rican study highlights the contribution of greenspace to improving human well-being, especially in education, health, and economic and social services (Yee, 2020). The second category is about the inequality in greenspace access, including disparities among different regional, socio-economic, racial, and ethnic groups. Studies in China reveal a high inequality in greenspace exposure across cities, which is influenced by human distribution and greenspace provision (Song et al., 2021; Chen et al., 2022). Similarly, in Sheffield, UK, findings suggest that while greenspace accessibility favours more deprived areas, the greenspace is not evenly distributed, and the needs of different residents should be considered for greenspace planning, such as spaces for culture, play, and ease to reach these areas (Mears et al., 2019). The last but not least category is about planning and policy for improving greenspace access, such as urban design and policy interventions. Studies show that while strategic planning recognises the benefits of urban greenspace, such as in Brisbane, Australia, there is still a gap between policy objectives and actual outcomes (Osborne et al., 2020). For instance, actions are not always consistent with policy intent, indicating the need of effective assessment benchmarks and improved policy evaluation (Osborne et al., 2020). Studies also show that despite increased global urban populations and pressures on land resources, people focus more on greenspace demand than supply, thus effective urban green area management is increasingly required for supplying greenspace with various ecosystem functions (Boulton et al., 2018).

The relationship between accessibility and access can reveal essential information of the association between residents and greenspaces. However, quantitative studies about the difference between accessibility and access are limited. The difference between accessibility and access means the quality of service facilities to access greenspaces, greenspace usability, and user experience. A high positive difference shows the resilient greenspace service facilities and high greenspace usability. A significant negative difference may indicate that, despite the physical proximity of greenspace, the accessibility still cannot satisfy the residents' requirements to access greenspace, which may be related to the quality of service facilities and infrastructure, and high population density. A difference value near zero demonstrates the consistency between accessibility and access to greenspace. Therefore, understanding the difference between accessibility and access can provide valuable information for optimising the use and management of urban greenspace.

This study develops a Spatial Delta Model (SDM) to quantify the difference between accessibility and access to greenspace and assess its spatial characteristics. The study examines block-level access, accessibility, and their difference in Perth, Australia, using the SDM with high-resolution geospatial data related to greenspace and socio-economic factors. First, access and accessibility to greenspace were first computed, respectively, where access was calculated as the total greenspace near residential blocks, accessibility was derived using a modified Gaussian two-step floating catchment area (MG2SFCA) approach. Next, both indicators were standardised for their comparative analysis, examination at different spatial scales, and the computation of their difference. Third, relationships among access, accessibility, and their difference were then quantified. Finally, spatial statistical inference based on the characteristics and relationships of spatial distribution patterns is essential for exploring potential determinants and predicting greenspace performance (Song, 2022, 2023). Thus, a set of residential, morphological, and greenspace related factors and their geocomplexities were collected to explain the spatial patterns of the difference between accessibility and access, as estimated using a machine learning geographical detector model.

2. Study area and data

2.1. Study area

The study contains nine regions in Perth, Australia, including Bayswater-Bassendean, Belmont-Victoria Park, Canning, Cottesloe-Claremont, Fremantle, Melville, Perth City, South Perth, and Stirling (Fig. 1). These regions have a total population of 824,891 residents, with a population density of approximately 1719 persons/km^2. The study area contains 8259 residential blocks, which vary significantly in size, with a minimum area of 904.6 m^2, a maximum area of 0.83 km^2, and an average area of 0.032 km^2. Each block is estimated to have around 100 persons on average. From the perspective of greenspace, the regions contains a total of 1170 greenspaces that cover 90.0 km^2, which constitutes 18.8% of the total land area within the study area.

2.2. Data for measuring access and accessibility

Table 1 provides a statistical summary of greenspace distribution across the nine regions of Perth, Australia. The block-level greenspace and population data are sourced from the Australian Statistical Geography Standard (ASGS) Edition 3 (Australian Bureau of Statistics, 2021a). The table summarises the greenspace from three aspects: area, population-greenspace relation, and size distribution. First, the table shows the total area and proportion of greenspace within each region. The largest greenspace area is in Stirling, with 21.30 km^2, accounting for 21.4% of the region's land area. Although Cottesloe-Claremont has a lesser total greenspace area (16.49 km^2), it has the highest greenspace ratio, with 33.8% of its land used for greenspace. Fremantle has the smallest greenspace area at 3.51 km^2, which is 8.4% of its land area. Second, population density and the amount of greenspace per person are assessed. Perth City is the most densely populated region, with a population density of 2462.10/km^2. However, Perth City is in the moderate position in terms of the greenspace-population ratio, providing approximately 97.95 m^2 of greenspace per person. The region with the most greenspace per person is Cottesloe-Claremont, where each individual has access to 241.33 m^2 of greenspace on average. Finally, the size distribution of greenspace is evaluated by classifying size into four groups according to quartile values: small (smaller than 0.010 km^2), medium-small (between 0.010 and 0.024 km^2), medium–large (between 0.024 and 0.062 km^2), and large (larger than 0.062 km^2). Stirling has the most greenspaces, with a total of 234. Regions with the more small and medium-small greenspaces include Bayswater-Bassendean, Belmont-Victoria Park, Canning, Fremantle, and Melville, and regions with more large and medium large greenspaces consist of Cottesloe-Claremont, Perth City, South Perth, and Stirling. Among the regions, Canning has the most number of small greenspaces (59), and Cottesloe-Claremont has the most number of large greenspaces (48).

2.3. Data of explanatory variables

In the study, three categories of geospatial variables were collected to explain the spatial patterns of the difference between accessibility and access, including residential, morphological, and greenspace related variables. First, residential variables, consisting of block-level population and dwelling densities, were calculated using high-resolution population data sourced from the Australian census mesh block counts dataset (Australian Bureau of Statistics, 2021b). Second, spatial morphological variables include shape factor and compact ratio of blocks, calculated using the methods of Song et al. (2018a). The shape factor is calculated as a ratio of block area to the area of its circumscribed circle (Haggett et al., 1977):

$$\zeta = \frac{A}{A_c} \tag{1}$$

where ζ is shape factor, A is the block area, and A_c is the area of block's circumscribed circle. A smaller shape factor indicates an

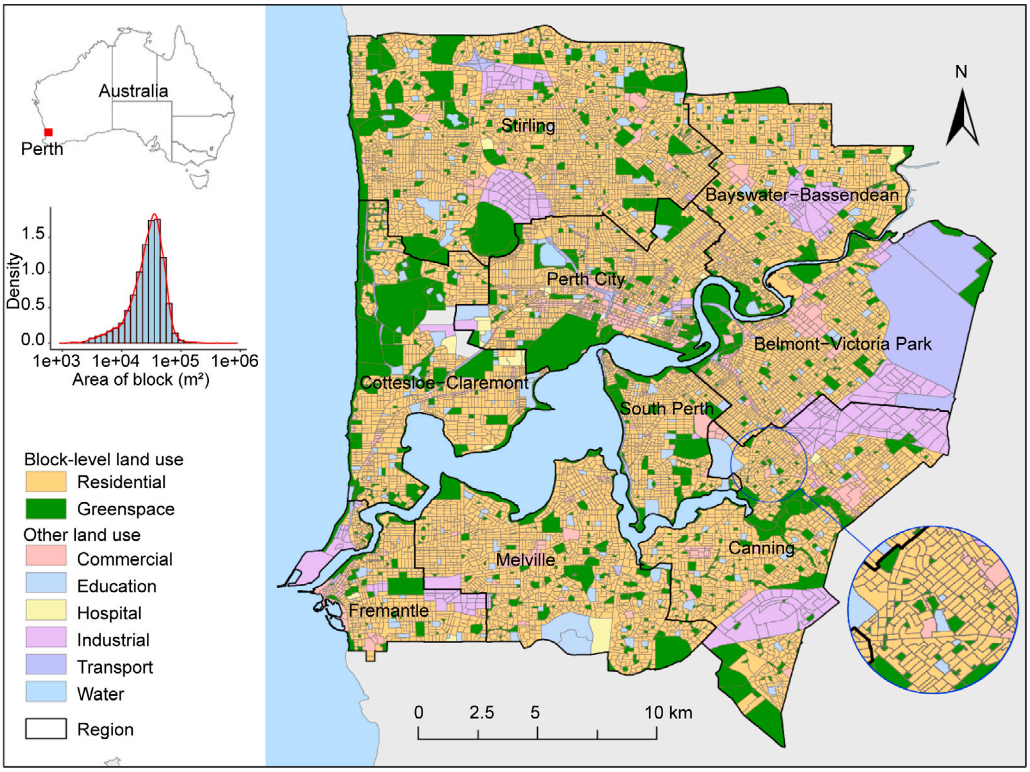

Fig. 1. Study area and spatial distributions of block-level residential areas and greenspace.

Table 1
Statistical summary of greenspace in the study area.

Region	Greenspace area (km^2)	Greenspace ratio	Population density (/km^2)	Greenspace per person (m^2)	Number of greenspace by size				
					Total	Small	Medium-small	Medium-large	Large
Bayswater-Bassendean	6.29	14.1%	1882.62	74.83	128	26	**34**	42	26
Belmont-Victoria Park	7.35	12.2%	1239.70	98.68	109	**38**	15	25	31
Canning	11.66	17.1%	1442.38	118.57	186	**59**	50	43	34
Cottesloe-Claremont	16.49	33.8%	1402.23	241.33	145	28	30	39	**48**
Fremantle	3.51	8.4%	919.97	91.61	66	16	**23**	14	13
Melville	7.96	14.9%	1954.28	76.25	142	38	**47**	23	34
Perth City	10.50	24.1%	2462.10	97.95	94	23	15	23	**33**
South Perth	4.97	24.5%	2103.23	116.45	66	16	16	15	**19**
Stirling	21.30	21.4%	2083.35	102.94	234	49	62	**69**	54

anisotropic urban form, diverse distribution of urban functions, and multiple centres of development. The compact ratio was computed as (Liu et al., 2003):

$$\gamma = \frac{4\pi A}{P^2} \tag{2}$$

where γ is compact ratio, and P is the perimeter of the block. A higher compact ratio value indicates a compact and circular urban form, while a lower value shows a narrow and elongated urban structure. Finally, greenspace related variables consist of the distance from blocks to the nearest greenspace, as well as the area of this near greenspace. The area of near greenspace is used to understand if the size of the greenspace is related to the difference between accessibility and access. Fig. 2 presents the spatial distributions of these six geospatial variables.

The spatial distributions of variables shown in Fig. 2 demonstrate the complex local patterns of variables. As such, the geocomplexities (i.e., spatial local complexity) of these variables were calculated to measure the complex local spatial patterns of variables and to improve modelling accuracy and reduce modelling spatial errors (Zhang et al., 2023b). In this study, the local indicator of spatial association (LISA) (Anselin, 1995) was employed as a proxy variable for geocomplexity, as it provides a simple but effective indicator of spatial local complexity (Zhang et al., 2023b).

3. Methods

This study developed a Spatial Delta Model (SDM) to quantify the difference between accessibility and access to greenspace and assess its spatial characteristics. SDM includes four steps: (i) assessing access and accessibility to greenspace, respectively; (ii) computing the difference between accessibility and access; (iii) identifying relationships among access, accessibility, and their difference, for developing a green city classification system considering the relationships; and (iv) exploring geospatial factors affecting the difference between accessibility and access. The detailed methods for modelling are presented below.

3.1. Access and accessibility

Access (α) is measured by the total area of greenspace available within a set of travel time or distance. This study utilises a range of walking times along with their corresponding estimated average distances as spatial scales to calculate the access of block residences to greenspace. With an average pedestrian walking speed set at 5 km/h (Cronin et al., 2009; Chow et al., 2017), the distances within various times can be calculated as shown in Table 2. Thus, access is

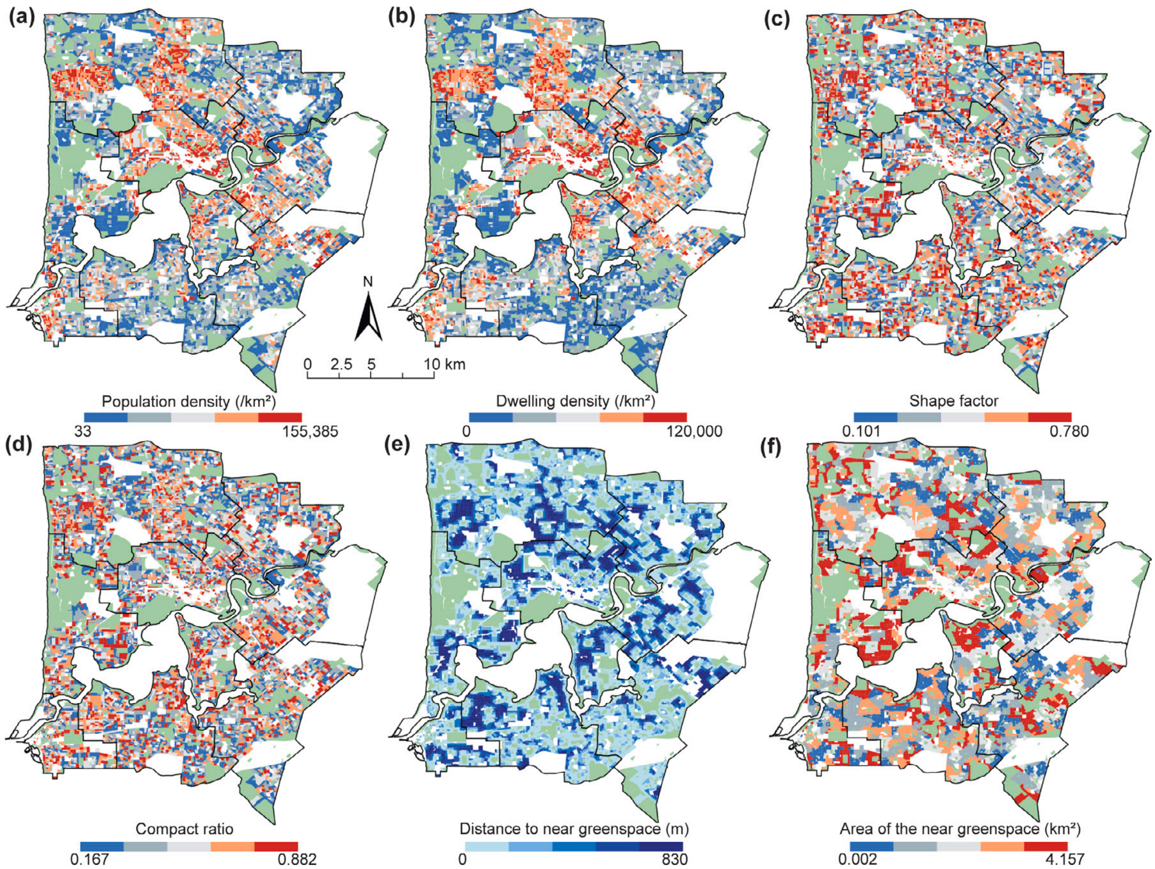

Fig. 2. Spatial distributions of variables for explaining the difference between accessibility and access. (a) Population density, (b) dwelling density, (c) shape factor, (d) compact ratio, (e) distance to near greenspace, and (f) area of the near greenspace.

Table 2
General relationships between walking time and distance.

Walking time (min)	Distance (km)
3	0.250
5	0.417
10	0.833
15	1.250
20	1.667
30	2.500

computed at the spatial scales equivalent to walking times of 3 min, 5 min, 10 min, 15 min, 20 min, and 30 min.

Accessibility (β) is assessed using a Modified Gaussian Two-Step Floating Catchment Area (MG2SFCA) model for the same set of walking times. The MG2SFCA model, which is an integration of the widely used Modified Two-Step Floating Catchment Area (M2SFCA) model and a continuous Gaussian function for weighting decay distance, provides an estimate of spatial accessibility (Song et al., 2018b). The formula for the calculation of spatial accessibility based on MG2SFCA is:

$$\beta_i = \sum_{j,j\in[d_{ij}\le d0]} \frac{G_j f(d_{ij}) f(d_{ij})}{\sum_{k,k\in[d_{jk}\le d0]} P_k f(d_{kj})} \tag{3}$$

where β_i is the accessibility measure at block i, G_j is the supply of jth greenspace, P_k is the population at block k, d_{ij} is the distance from block i to greenspace j, d_{jk} is the distance from greenspace j to block k, $d0$ is the maximum distance threshold for considering accessibility (as shown in Table 2), and $f(d_{ij})$ is a continuous Gaussian function providing a weight to the distance d_{ij}. The Gaussian distance decay function is calculated as (Tao et al., 2020):

$$f(d_{ij}) = \begin{cases} \dfrac{e^{-\frac{1}{2}\left(\frac{d_{ij}}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}} & \text{if } d_{ij} \le d_0 \\ 0 & \text{if } d_{ij} > d_0 \end{cases} \tag{4}$$

The function $f(d_{ij})$ decreases as d_{ij} increases, which implies that the influence of a greenspace on a block decreases as the distance from the greenspace increases. Both indicators of access and accessibility are standardised for their comparative analysis, examination at different spatial scales, and the computation of their difference.

3.2. Difference between accessibility and access

The difference between accessibility and access can reveal the quality of greenspace service facilities and infrastructure, greenspace usability, and user experience. In SDM, the difference is calculates as:

$$\delta = \beta - \alpha \tag{5}$$

where δ is the difference between standardised accessibility and standardised access. Table 3 shows meanings and descriptions of different types of δ values. If $\delta > 0$, the accessibility is higher than the access to greenspace, indicating a well-designed urban environment that encourages human-nature interaction, high-quality greenspace service facilities and infrastructure, and high usability. If $\delta = 0$, the accessibility is equivalent to the access to greenspace, meaning that while the greenspace is well integrated into residential areas, emphasis on the user experience and the greenspace usability is lacking. If $\delta < 0$, the accessibility is lower than the access to greenspace, suggesting that while greenspace may be available and close to residents, it is not easy to use. This may be due to a lack of service facilities and infrastructure or a high population density that shares the available greenspace.

Table 3
Types and descriptions of the difference between accessibility and access.

Type of difference (δ)	Description
$\delta > 0$ ($\beta > \alpha$)	Accessibility is higher than the access to greenspace. Greenspace is designed to encourage the use and make the human-nature interaction effortless. The well-planned urban environment and enhanced accessibility also indicate the high quality of greenspace service facilities and infrastructure development.
$\delta = 0$ ($\beta = \alpha$)	Accessibility is roughly equivalent to the access to greenspace. Greenspace is well integrated into residential areas, but user experience and usability of these spaces are not emphasised.
$\delta < 0$ ($\beta < \alpha$)	Accessibility is lower than the access to greenspace. Greenspace may be near, but it is not easy to use it, showing the weak human-nature relationship. The potential factors affecting the negative values of difference may include the lack of greenspace service facilities and infrastructure, and dense population sharing the greenspace.

3.3. A green city classification system (GCCS) based on the access-accessibility-difference relationships

According to the relationships among access, accessibility, and their differences, this study proposes a green city classification system (GCCS) (Table 4), which serves as a comprehensive tool for urban planning and development. GCCS provides a guide for cities' balancing natural environments with urban development, and improving greenspace access to residents. GCCS contains six types of cities from the perspective of greenspace access, including ideal green cities, resilient green cities, potential green cities, urban-nature balanced cities, underutilised green cities, and green-deprived cities. These categories can help understand the various aspects of greenspace access, including physical access to greenspace, the ease of reaching greenspace, and quality of service facilities, usability, and user experience. According to GCCS, urban planners, policymakers, and researchers can identify strengths and limitations of regional greenspace infrastructure. For instance, cities with high accessibility but low access (resilient green cities) may consider enhancing their greenspaces, while those with high access but low usability (underutilised green cities) might focus on improving the quality and service of their existing greenspaces. Cities in the green-deprived cities may need comprehensive strategies to increase both the access and usability of greenspaces. Therefore, stakeholders can use GCCS to make decisions to enhance greenspace access, improve healthy living, and achieve sustainable urban development.

3.4. Geospatial factors affecting the difference

This study employs the geographically optimal zones-based heterogeneity (GOZH), a machine learning geographical detector model, for examining geospatial factors and their geocomplexities that contribute to the spatial patterns of the difference between accessibility and access to greenspace. The GOZH is an improvement of the geographical detector model, where machine learning is used to derive the optimal spatial data discretisation. The geographical detector model was developed to measure spatial stratified heterogeneity by comparing variances within strata and between strata (Wang et al., 2010, 2016; Song et al., 2020a; Guo et al., 2020). It has been widely used in exploring factors in natural, built, and social environments (Luo et al., 2021; Song et al., 2020b; Zhang et al., 2023a). Recent studies have improved geographical detector models, such as the optimal parameters-based geographical detector (OPGD) (Song et al., 2020a), interactive detector for spatial associations (IDSA) (Song and Wu, 2021), generalised heterogeneity model (GHM) (Luo et al., 2023), GOZH (Luo et al., 2022), robust geographical detector (RGD) (Zhang et al., 2022), robust interaction detector (RID) (Zhang et al., 2024), locally explained stratified heterogeneity (LESH) (Li et al., 2023). The GOZH, due to its adaptable framework, is effective in analysing the factors influencing greenspace access and employs decision tree for spatial data discretisation (Cheng et al., 2023).

GOZH contains three major steps. First, a decision tree model is used to conduct the spatial data discretisation. This step involves a process of step-wise spatial discretisation of the response variable with spatial explanatory variables. Each variable is evaluated to identify optimal cut-off points, thus deriving the optimal spatial strata. A binary tree structure is subsequently established to represent the overall spatial discretisation (Luo et al., 2022). Second, geographical detector model is used to calculate the power of determinant (PD) value of individual geospatial variables. In geographical detector model, PD is calculated as (Wang et al., 2010):

$$q = 1 - \frac{\sum_{s=1}^{h} N_s \sigma_s^2}{N \sigma^2} \tag{6}$$

where q is the PD value of an individual geospatial variable, N_s and σ_s are the number and standard deviation of data within the strata $s(s = 1, \ldots, h)$, respectively, and N and σ are the number and standard deviation of all observations. The integration of the decision tree with the geographical detector model is used to derive the optimal spatial data discretisation. Accordingly, the PD in the GOZH is calculated as (Luo et al., 2022):

$$\Omega = 1 - \frac{\min\left(\sum_{s=1}^{h} \sum_{j=1}^{N_s} (y_{s,j} - \bar{c_s})\right)}{N \sigma^2} \tag{7}$$

where $y_{s,j}$ and $\bar{c_s}$ are the jth observation and mean value of the response variable in strata s, respectively. Finally, geographical interaction detector model is used to calculate the power of interaction determinant (PID) value of the spatial overlay of multiple variables. In this step, the decision tree model extracts the optimal spatial data discretisation based on multiple geospatial variables. The PID reveals the spatially combined impacts of these variables. The decision tree models are processed using the R package "rpart" (Therneau et al., 2015), and geographical detector and interaction detector models are conducted with the R package "GD" (Song et al., 2020a).

4. Results

4.1. Access and accessibility

Fig. 3 demonstrates the spatial distributions of standardised access (α) and standardised accessibility (β) to greenspace for residents at the block level, considering walking times ranging from 3 to 30 min. From the perspective of the whole study area, both access and accessibility show similar spatial patterns at multiple spatial scales. For short walking time of 3 and 5 min, the high values of access and accessibility are primarily located in areas adjacent to greenspaces. This indicates that residents in these areas with high values have the advantage of immediate greenspace access. However, as the spatial scale is expanded beyond 10 min, the high values of access and accessibility gradually form spatial clusters in specific regions. This suggests that there are spatial clustered areas where residents benefit from high access and accessibility, even at relatively long distances. The spatial clusters of high values at larger scales may be the regions with larger or more abundant greenspaces, or better connectivity and infrastructure that support access to greenspaces. In addition, spatial clusters of both extremely high and low values of access and accessibility increase with spatial scales, indicating the geographical inequality in greenspace access and accessibility in the study area. The distinct neighbourhood characteristics, demographic factors, or greenspace decisions may be related to the geographical inequality of greenspace access.

Table 4
Green city classification system (GCCS) considering the relationships among access, accessibility, and their difference.

Type of city	Access-accessibility relation			Description
	Access	Accessibility	Difference	
Ideal green cities	High	High	Positive	Accessibility exceeds physical access to greenspace. The greenspace supports a nature-oriented and healthy lifestyle.
Resilient green cities	Low	High	Positive	The positive difference indicates that the cities can provide a nature-friendly urban environment despite the constraints of physical access to greenspace.
Potential green cities	Low	Low	Positive	Although access and accessibility are low, the positive difference shows strong potential for improving the interaction with nature.
Urban-nature balanced cities	High	High	Negative	Both access and accessibility are high, but the negative difference suggests a high level of urban development, potentially affecting the current balance between urban development and natural environments.
Underutilised green cities	High	Low	Negative	The negative difference indicates that accessibility is limited despite the high physical access to greenspace. This phenomenon is potentially related to the high-density population in these cities.
Green-deprived cities	Low	Low	Negative	All aspects of greenspace access are constrained, including a negative difference, limited accessibility, and low physical access to greenspace. Access to greenspace is difficult due to a lack of greenspace and service infrastructure.

Table 5
Regions associated with each type of city.

Type of city	Region
Ideal green cities	Stirling, Fremantle (≤5 min), Canning (≤10 min)
Resilient green cities	Canning (>10 min)
Potential green cities	Belmont-Victoria Park, Melville, Bayswater-Bassendean, Fremantle (>5 min), Cottesloe-Claremont (≤5 min)
Urban-nature balanced cities	South Perth
Underutilised green cities	Perth City, Cottesloe-Claremont (>5 min)
Green-deprived cities	/

4.2. Difference between accessibility and access

Fig. 4 shows spatial distributions of the difference between greenspace accessibility and access at various walking distances. The δ maps demonstrate the following findings. First, within a 3-min walking distance, the difference is approximate to zero across the majority of the area, meaning that the physical greenspace access generally match the ease of residents' reaching greenspace within a small spatial scale in most areas. Next, when the spatial scale enlarges to 5–10 min of walking distance, zones of higher or lower difference between accessibility and access begin to form into small localised clusters. These small local clusters show that the available greenspace does not correspond with its accessibility, potentially due to the complexity of population distribution, urban design, transportation network, and physical barriers in the 5–10 min walking distance. Finally, when the walking distance is beyond 15 min, the difference between accessibility and access becomes more significant. The emergence of substantial spatial clusters with either significantly high or low values of the difference indicates that greenspace availability and the ease of residents' reaching them are no longer closely aligned with the increased spatial scale.

4.3. Relationships among access, accessibility, and difference

Fig. 5 visualises the relationships among access (α), accessibility (β), and the difference between accessibility and access (δ) to greenspace for residents at the block level, considering varying walking times and regions within the study area. Using the Green City Classification System (GCCS), this study identifies different city types for the nine regions in Perth, Australia (Table 5).

In ideal and resilient green cities, such as Stirling, Fremantle (within 5 min walk), and Canning (more than 10 min walk), high accessibility values (β) that are higher than the access values (α) are identified. Despite physical access constraints in the resilient cities, these cities still maintain a positive accessibility experience, easy to reach greenspace, high usability, and good user experience.

In contrast, the potential green cities (Belmont-Victoria Park, Melville, Bayswater-Bassendean, Fremantle (beyond 5 min), and Cottesloe-Claremont (within 5 min)) have lower values for both access and accessibility. However, the positive difference (δ) indicates the potential for these cities to improve the interaction between residents with nature through various approaches, such as enhancing the quantity and quality of greenspaces, improving the accessibility to them, and implementing more service facilities and infrastructure.

The urban-nature balanced cities such as South Perth show high values of both access and accessibility. However, the negative difference (δ) indicates a high level of urban development that could potentially affect the balance with natural environments.

In the category of underutilised green cities, which include Perth City, Cottesloe-Claremont (beyond a 5-min walk), show high physical access but moderate and somewhat constrained accessibility. This phenomenon is potentially related to the high-density population in these cities. Fig. 5 shows that β values are negative but very close to zero, meaning that despite high-density population, the greenspace still can provide approximately moderate ease for residents to reach the greenspace.

Fig. 5 shows the absence of any green-deprived cities, meaning that there are no regions in the study area that experience constraints across all aspects of greenspace access.

4.4. Geospatial factors affecting the difference

Fig. 6 presents the Power of Determinant (PD) of individual geospatial variables with respect to the spatial pattern of the difference between accessibility and access (δ), considering varying walking time: 3 min, 5 min, 10 min, 15 min, 20 min, and 30 min. The results can be explained from the following aspects. First, within the 3- and 5-min walking distances, the distance to the nearest greenspace and its geocomplexity are the primary factors influencing δ. This suggests that at small spatial scales, the distance to greenspace and its local variability essential for the greenspace usability and user experience. Second, for walking time ranging from 10 to 20 min, the area of the nearest greenspace and its geocomplexity become the primary factors impacting δ. This means that, at these spatial scales, the size of the greenspace and its spatial variability contribute more to the greenspace usability and user experience than other variables. Third, at a 30-min walking distance, resident-related variables such as population density, dwelling density, and their geocomplexities have the highest contributions to δ. This indicates that the distribution and density of residents significantly affect the greenspace usability and user experience at

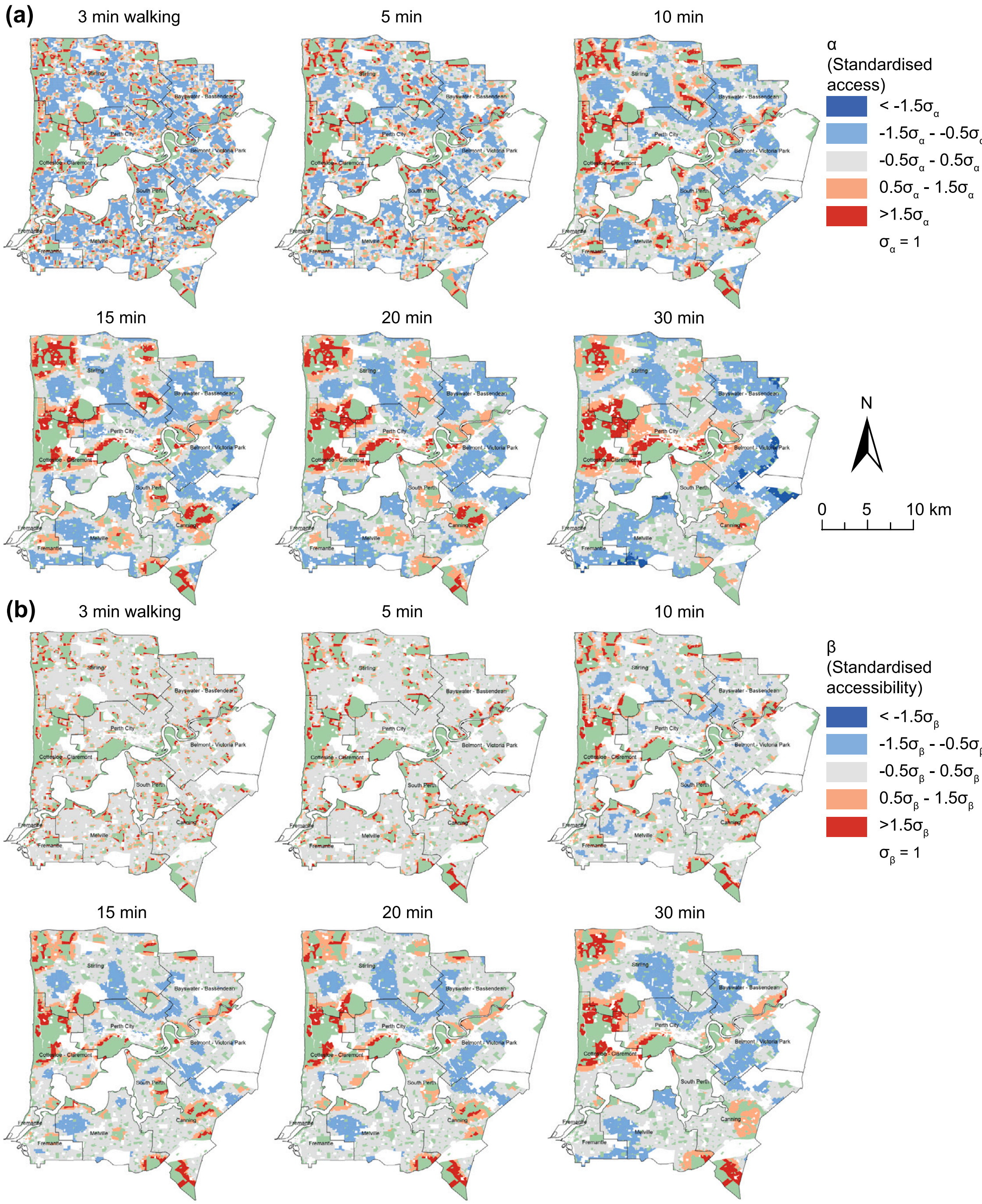

Fig. 3. Spatial distributions of standardised access (α) (a) and standardised accessibility (β) (b) to greenspace for residents at the block level, considering walking times of 3 min, 5 min, 10 min, 15 min, 20 min, and 30 min.

larger spatial scales. Fourth, for both resident- and greenspace-related variables, their geocomplexities' effects on δ are comparably significant even higher than the variables themselves, which is particularly evident in the 5-, 10-, 15-, and 30-min scenarios, meaning that local variability of both greenspace and resident distributions essentially affect the access to greenspace. Finally, regional differences have a significant impact on δ, with their influence gradually increasing with the spatial scale. At the 3-min scale, the effect of region is low, but at the 30-min scale, the variable of region becomes the leading factor. In summary, distance to greenspace contributes most to δ at small scales, area of the near greenspace is the primary explanatory variable of δ at medium scales, and geographical characteristics and socio-economic factors at the regional level become increasingly critical at large spatial scales.

Table 6 shows the Power of Interaction Determinant (PID) values at various walking times. The PID, represented as the Q value, quantifies the contribution of the spatial interaction among residential, morphological, and greenspace variables to the δ. On the one hand, for the 3-min scale, the PID is 0.262, suggesting a moderate contribution of the interaction among geospatial variables to δ. With the increase in walking times to 5, 10, 15, and 20 min, the PID values show slight fluctuations but generally remain in the moderate range, from 0.197 to 0.272, demonstrating the relatively consistent contributions of

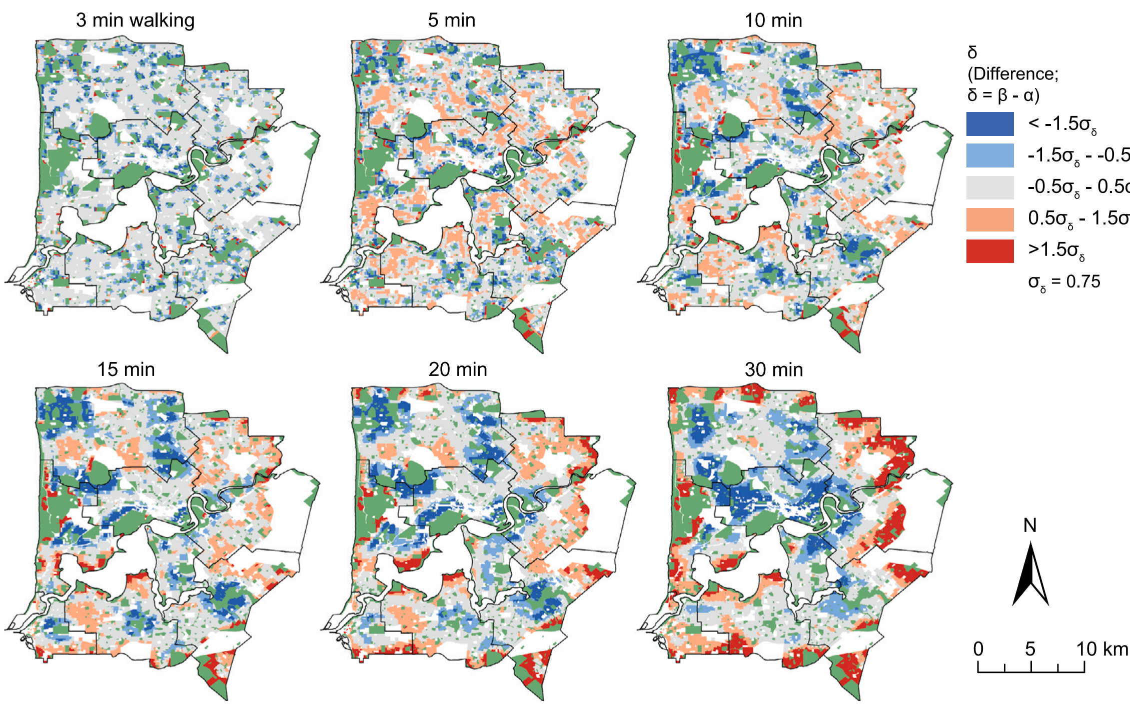

Fig. 4. Spatial distributions of the difference between accessibility and access (δ; $\delta = \beta - \alpha$) to greenspace for residents at the block level, considering walking times of 3 min, 5 min, 10 min, 15 min, 20 min, and 30 min.

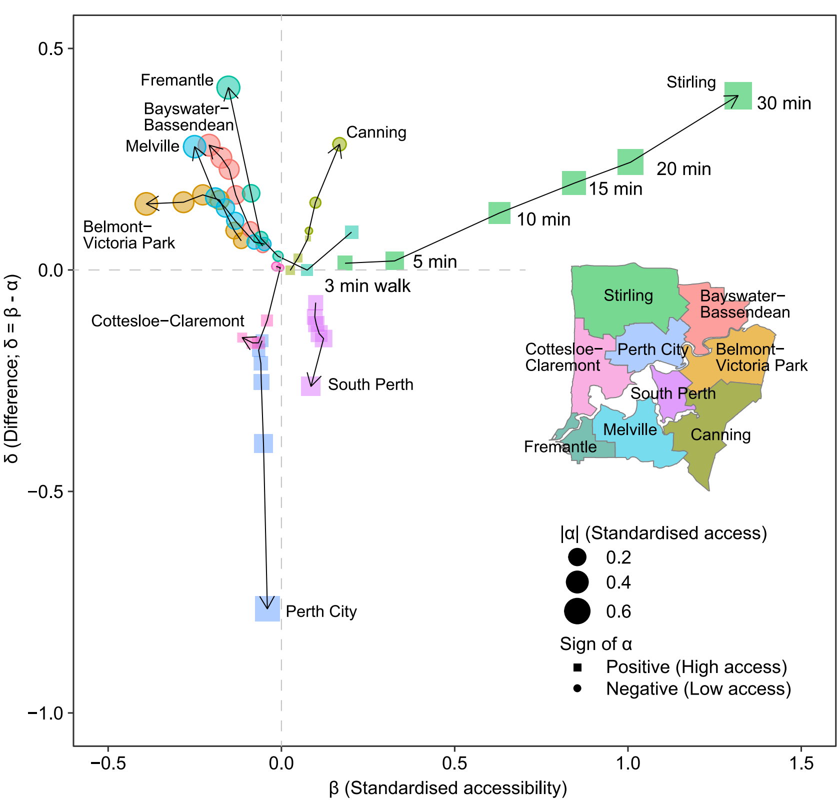

Fig. 5. Relationships among access (α), accessibility (β), and the difference between standardised accessibility and access (δ) to greenspace for residents at the block level, and in varying walking times and regions within the study area. The square indicates access is higher than accessibility, and the circle indicates access is lower than accessibility. The sizes of the square and circle are the absolute values of standardised access.

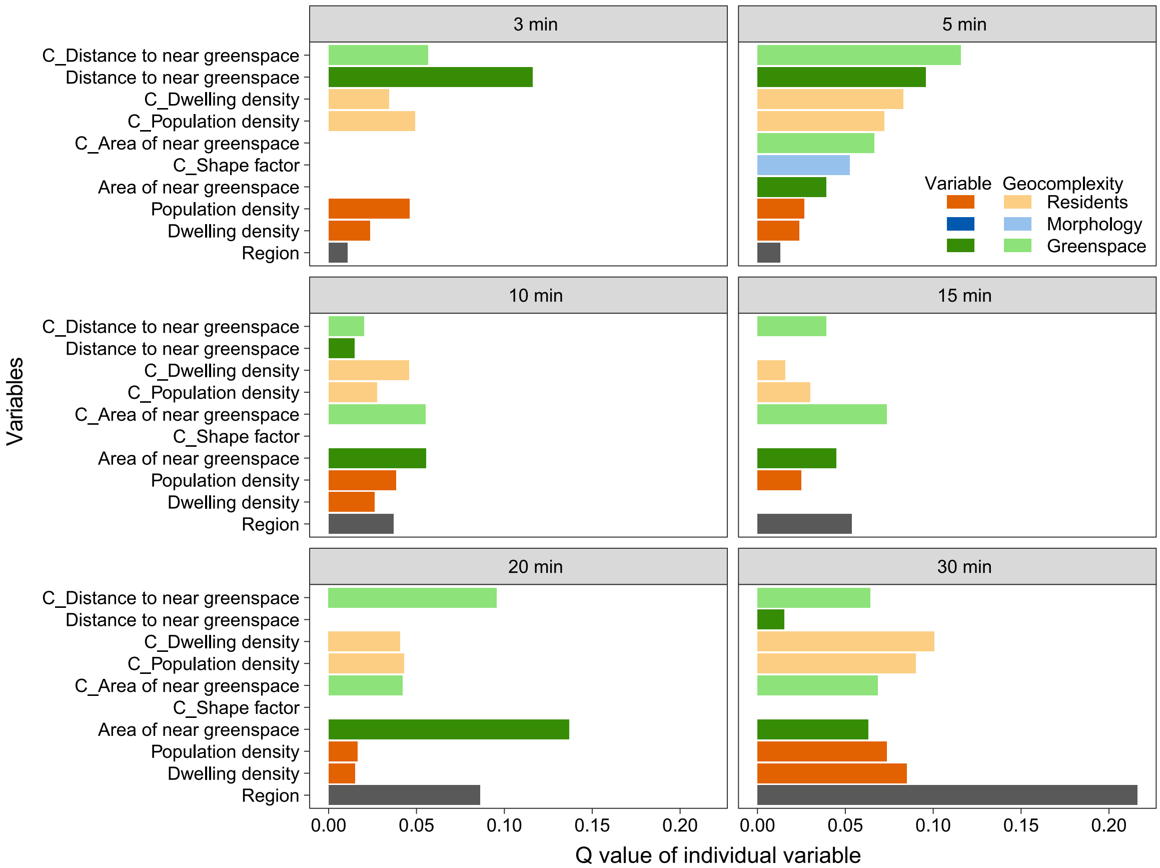

Fig. 6. Values of the Power of Determinant (PD) of individual geospatial variables related to the difference between accessibility and access, considering walking times of 3 min, 5 min, 10 min, 15 min, 20 min, and 30 min. 'C' in the name of a variable means the geocomplexity of the variable.

Table 6
Values of the power of interaction determinant (PID) for residential, morphological, and greenspace variables related to the difference between accessibility and access.

Walking time (min)	Q value
3	0.262 ($p < 0.01$)
5	0.235 ($p < 0.01$)
10	0.197 ($p < 0.01$)
15	0.272 ($p < 0.01$)
20	0.250 ($p < 0.01$)
30	0.426 ($p < 0.01$)

geospatial variables to δ across these spatial scales. On the other hand, as the spatial scale is expanded to 30-min walk, the PID shows a critical increase to 0.426, indicating a significantly higher contributions of the interaction among the geospatial variables to δ. The higher PID suggests that the interaction among residential, morphological, greenspace, and region variables has a greater influence on the greenspace usability and user experience at larger spatial scales.

Fig. 7 shows the relationships between δ and the area of the nearest greenspace at varying spatial scales. The data points are plotted using quantile values of both variables, and their fitted curves show a characteristic 'V' shape at all spatial scales. This pattern reveals an essential trend: smaller areas of nearby greenspace correspond to positive δ values, meaning better balance between accessibility and access. In addition, Fig. 7 also shows that larger areas of greenspace can generate positive δ values. However, there are relatively fewer large-area greenspaces. Therefore, an increased number of smaller greenspaces could contribute more effectively to maintaining a positive balance between accessibility and access, and better greenspace usability and user experience.

5. Discussion

This study developed a Spatial Delta Model (SDM) to quantify the difference between accessibility and access (δ) to greenspace at various spatial scales to understand the greenspace usability and user experience. The study also proposed a green city classification system (GCCS) to evaluate the characteristics of greenspace access for cities considering the relationships among access, accessibility, and their difference. Through the geospatial analysis, the study has the following primary findings. First, SDM-based δ analysis is effective in measuring the urban greenspace usability and user experience, which is an essential further analysis of greenspace access in addition to access and accessibility that measure the available greenspace and the ease to reach greenspaces, respectively. Second, according to GCCS, cities can be classified into six categories based on the relationships among access, accessibility, and δ. Each category of cities show different conditions and needs to greenspace access, which provide quantitative evidence and practical suggestions to improve the regional greenspace access from the perspective of access-accessibility-difference relationships. Employing nature-driven principles in the development of 'regenerative living cities' can contribute to the mitigation and adaptation of global climate change, enhance urban biodiversity, and improve community well-being (Pedersen Zari et al., 2022). The evidence and suggestions demonstrate that GCCS is an innovative and effective tool for urban planning and decision-making in the greenspace service facilities and infrastructure development and sustainable urban development. Finally, this study identifies residential, spatial morphological, and greenspace related geospatial variables, and their geocomplexity variables, for explaining the varied spatial patterns of δ. Results show that the distance to greenspace contributes most to δ at small scales, area of the near greenspace is the primary explanatory variable of δ at medium

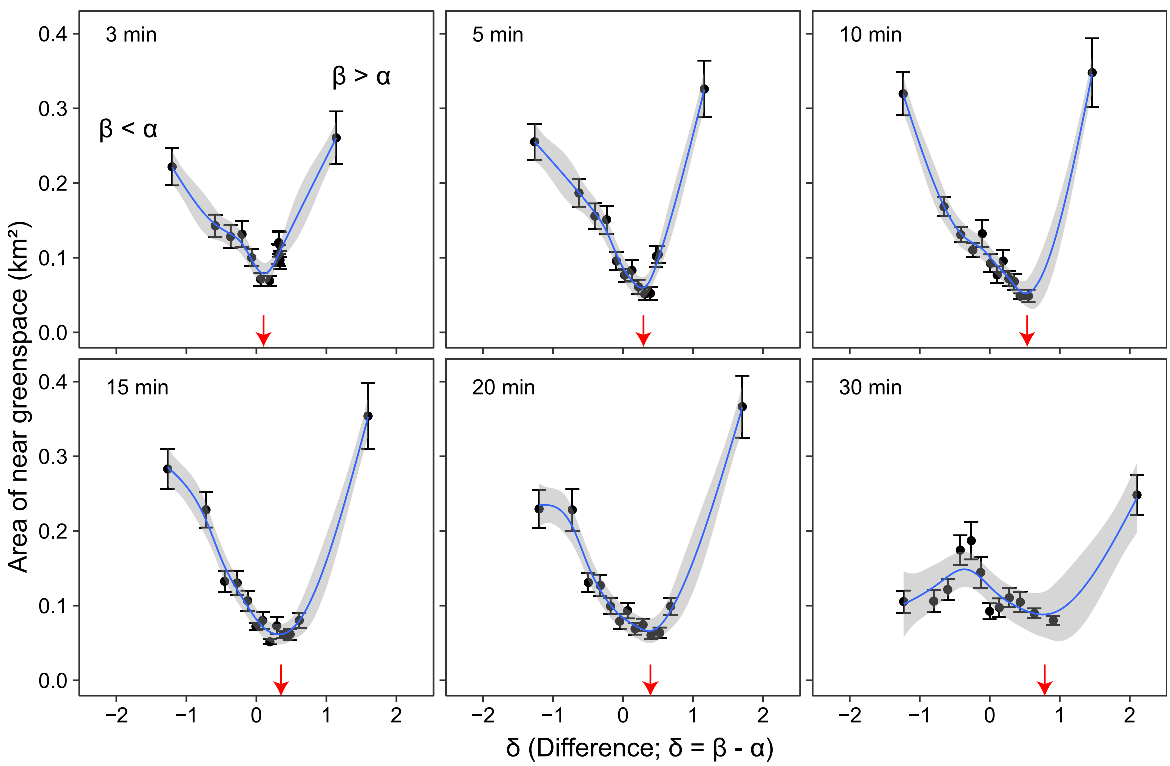

Fig. 7. Relationships between the difference of accessibility and access and the area of near greenspace at different spatial scales.

scales, and geographical characteristics and socio-economic factors at the regional level become increasingly critical at large spatial scales.

There are still limitations in the study and future research recommends in the following aspects. First, the scope of this study is to assess access, accessibility, and their difference from the perspective of physical greenspace access. In future studies, it is recommended to consider related social, cultural, and psychological factors that may affect greenspace usability and benefits. In addition, if the data of greenspace quality and attractiveness are available in future studies, it is recommended to examine the impacts of these factors on δ.

6. Conclusions

This study employed geospatial methods to understand and quantify the difference between accessibility and access to urban greenspace, a largely unexplored topic until now. A Spatial Delta Model (SDM) was developed and applied to data from Perth, Australia, enabling the identification of variations in greenspace usability and user experience across different spatial scales. The study's findings suggest that the SDM can effectively demonstrate the difference between greenspace accessibility and access, making the proposed Green City Classification System (GCCS) a valuable tool for urban planning and green city management. The spatial machine learning analysis revealed that a variety of greenspace-related, residential, and morphological variables, along with their geocomplexities, are significantly associated with the greenspace usability and user experience quantified through the difference between accessibility and access. The developed geospatial methods and analyses have broad impacts on both academic research and practical urban management, informing decision-making for the development of sustainable, healthy, and resilient cities.

CRediT authorship contribution statement

Gang Lin: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Yongze Song:** Conceptualization, Methodology, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Dong Xu:** Formal analysis, Writing – original draft, Writing – review & editing. **Mohammad Shahidul Hasan Swapan:** Supervision, Writing – review & editing. **Peng Wu:** Supervision, Writing – review & editing. **Weitao Hou:** Data curation, Writing – review & editing. **Zhuoyao Xiao:** Data curation, 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.

Data availability

Data will be made available on request.

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