Access to urban parks: Comparing spatial accessibility measures using three GIS-based approaches

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A B S T R A C T

Urban parks are essential components of urban ecosystems, providing recreation and relaxation places to residents. Measuring the spatial accessibility to urban parks serves as an initial step in urban planning and developing urban development strategies to improve social and environmental justice. This study aims to evaluate measures of spatial accessibility to urban parks by comparing three geographic information systems (GIS)-based approaches, accounting for network complexity, transport modes, distance thresholds, and destination choices. Taking Ipswich City (Australia) and Enschede (the Netherlands) as two testbeds, we examine the spatial patterns of a total of 21 accessibility measures in the two cities and conduct a correlation and principal component analysis to unravel the interrelationship between these measures. The results suggest that among all measures under the three approaches, the selection of distance thresholds and transport modes matter more to accessibility measures than the destination choices. Furthermore, when distance threshold and transport mode are held constant, the network-based and entrance-based methods provide more realistic accessibility measures than other methods. We also discuss the generality of the entrance-based method we propose and suggest ways to choose the most appropriate accessibility measure for use in different contexts.

1. Introduction

Access to public green space or green infrastructure such as urban parks has been recognized to associate with people's physical activities (Cohen et al., 2007). Increasing access to urban parks holds the potential to alleviate the global decrease in physical activities and decelerate the worldwide increase in chronic diseases and obesity-related conditions (Booth, Roberts, & Laye, 2011; Durstine, Gordon, Wang, & Luo, 2013). Besides, living near urban parks has been considered to enhance the life quality of urban residents, contributing to a lower level of stress and fewer mental health problems (Barton & Pretty, 2010; Wood, Hooper, Foster, & Bull, 2017). Given the benefit of accessing urban parks, urban planners and policymakers need to ensure adequate access to urban parks by residents for better environmental and social justice and positive public health intervention.

Park access, by nature, is a multiple dimension concept (Zhang, Lu, & Holt, 2011). It can be conceptualised by the park's proximity to neighbourhoods where people reside, park size, or park attractiveness in terms of the type, quantity, and quality of amenities (Dony, Delmelle, & Delmelle, 2015). This further complicates the methods used to measure park access. A growing body of literature has emerged to measure urban park access by various spatial approaches, including measuring the closest distance to a nearby park, the density of parks, or the number of parks that can be accessed within a certain distance (Zhang et al., 2011). Most of these methods require a distance measure of sorts, which is a key element that affects the results (Talen & Anselin, 1998). While extensive literature on measuring park accessibility exist, most of them fall short on one (or more than one) of the three aspects: measuring proximity using Euclidean distance between residents' home and urban parks which can deviate substantially from their ground distance; using the centroid (the geographic centre) or the edge of a park to represent the destination choice; and overlooking the impact of transport modes and distance thresholds on accessibility measures (Halden, Mcguigan, Nisbet, & Mckinnon, 2000).

This study proposes a new method to measure park access by using distance measures from the road network and identifying park entrances

from where the park connecting with the road network. It aims to compare and evaluate the similarity, replaceability, and variability of park accessibility measures using three geographic information systems (GIS)-based approaches, accounting for network complexity, transport modes, distance thresholds, and destination choices. Taking Ipswich City in Queensland, Australia, as a testbed, we generate 21 accessibility measures using the three approaches. We then examine the spatial patterns of these 21 measures and conduct a correlation and principal component analysis (PCA) to unravel the interrelationship between these measures. We further test the entrance-based method in a European City—Enschede, The Netherlands, and discuss the generality of this method and suggest ways to choose the most appropriate measure for use in different contexts.

The rest of this paper is organised as follows. The following section provides the specification of accessibility measures using different approaches. Then, the study context, data, and methods used in this study are introduced. The results are presented next, consisting of the spatial distributions of 21 accessibility measures and the comparison of these measures resulted from correlation and principal component analysis. This is followed by a discussion of methodological generality that can be applied to other research contexts, with a concluding remark in the end.

2. Measuring accessibility

Spatial accessibility to amenities generally refers to the relative ease by which the locations of amenities can be reached as well as the quality, quantity, and type of activities offered by the amenities (Handy and Niemeier, 1997). In this study, spatial accessibility to urban parks is confined to the relative ease by which the location of urban parks can be reached by population from their homes (Zhang et al., 2011). Urban parks serve as a fundamental urban infrastructure and a vital component of an urban ecosystem (Chiesura, 2004). In particular, neighbourhood parks as spaces accessed by people in their daily lives are important for residents' physical and psychological soundness; it contributes to the social and ecological sustainability of cities (Nordh, Hartig, Hagerhall, & Fry, 2009). From a geographical perspective, urban park planning needs to consider the number and size of parks and the spatial distribution of park entrances, given that not every point along a park edge is accessible. The current scholarship has reported three types of approaches for measuring spatial accessibility of urban parks, all developed using GIS techniques (Zhang et al., 2011): 1) the statistical index approach, which measures the quantity, size, or density of parks in a defined geographic area; 2) the spatial proximity approach, which measures travel costs—travel time, distance, or monetary cost—spent to get to a park; and 3) the spatial interaction approach, commonly known as gravity models, which measures the force of attraction between residents' home locations and the park. The advantages and drawbacks of each approach are discussed below, leading to our objective to compare different park accessibility measures and evaluate the similarity, replaceability, and variability of the measures produced by different approaches.

2.1. Statistical index approach

The statistical index approach measures the number, total area, or density of parks within a specific geographic unit (Zhang et al., 2011), such as a census tract, postcode areas, suburb, and local neighbourhood; this geographic unit can also be defined as an area within a specified distance surrounding a residential location. Accordingly, many statistical indices have been produced, including the percentage area of urban parks over the total area and the per capita area of urban parks. These measures are commonly used in assessing equity in park access (e.g., Kaczynski, Potwarka, & Saelens, 2008; Talen, 1997); they are also widely applied in assessing the accessibility to public facilities by professional organizations and governments. The advantages of this approach include the convenience of data acquisition, simple calculation, easiness to explain and understand the result, and is suitable for

comparison across regions and over time.

However, a common drawback of this approach is the modifiable areal unit problem (MAUP). MAUP refers to the fact that geographic measures or relationships of interest could change because of different spatial scales of geographic units delineated in an analysis (Openshaw, 1984; Wong, 2004). Since the statistical index is calculated based on a specific geographic unit, it may introduce large biases between the city centre and rural regions. For instance, the size of a census tract (CT) used in the U.S. and the Statistical Area Level 2 (SA2) used in Australia are defined based on the number of population counts, leading to a smaller CT or SA2 in inner cities and a much larger size in the urban fringe. Accordingly, when spatial accessibility is measured by park density, the same size of urban parks located in inner-city areas and urban fringe would result in density measures, even though these parks may be accessed by a population of similar size. On the other hand, residents living in suburban or rural areas may drive to access local parks, while those living in inner cities may walk. Thus, it may be arbitrary to use one single transport mode to measure park accessibility. Instead, multiple transport modes would need to be taken into account. Furthermore, the assumption underpinning the statistical index approach that people would only visit parks within the spatial unit where they reside is also debatable (Zhang et al., 2011). Thus, the statistical index approach may oversimplify the complexity of people's actual decision to go to parks and introduce unrealistic measures to some degree.

2.2. Spatial proximity approach

The spatial proximity approach measures the minimum travel cost, time, or distances spent to access urban parks (e.g., the nearest distance from residential locations to parks), or the number of parks that can be accessed within a certain distance that residents bear to travel (Wang, 2012). Such travel distances can be measured based on the Euclidean distance between parks and residents' homes, convenient to generate in a GIS (Gutiérrez & García-Palomares, 2008). Compared to the easy computation of Euclidean distance, measuring distance based on the road network is commonly recognized as more accurate to capture the actual distance on the ground (Xiao, Wang, Li, & Tang, 2017; Zhou, Wang, & Li, 2019). Furthermore, the mode of transport is another consideration in measuring proximity to parks, for example, through public transport, driving, cycling, walking, or multiple transport modes (Xing, Liu, & Liu, 2018; Wang et al., 2020).

However, there are several major drawbacks to the spatial proximity approach. First, a key assumption underpinning this approach is that residents would always access the nearest park with the least travel cost to maximize convenience. The exclusive use of one nearest park by residents is not realistic, especially for people with different needs (e.g., to use certain facilities in parks, to explore some sceneries) or for weekend travellers who may access remote parks using multiple transport modes (Zhang et al., 2011). Thus, there is a need to consider multiple distance thresholds that residents would bear to travel to urban parks using different transport modes. Second, the destination choice in measuring the distance between residents' homes and urban parks is controversial. Most studies used the centroid (i.e., the geographic centre) of a park as the destination. However, simplifying a park polygon to a single point could introduce substantial bias to the accessibility measures, especially for large parks (Talen, 1997; Weiss et al., 2011). An alternative approach is to assume all points along the edge of a park as destinations; however, this is less likely in reality. On many occasions, a park may be partially surrounded by a creek or bridge or over a highway, or the edge may not be connected to a road; these park edges are not accessible and should not be treated as destinations. For ungated urban parks, the entrance/s to a park should be defined as locations (points) along the edge of the park connected to a road. As such, it would be more realistic to consider the collective effect of park entrances, distance thresholds, and transport modes when measuring access to urban parks, which we aim to achieve in this study.

2.3. Spatial interaction approach

The spatial interaction approach was initially developed based on Joseph and Bantock's (1982) traditional gravity model. This approach considers the force of attraction between the supply at destination and the demand at origin, assuming that such an attraction declines with a larger spatial separation (travel distance or time) between the origin and destination (OD) but increases with a greater demand at origin or with higher supply capacity and/or attractiveness at the destination (e.g., Wu, Smith, & Wang, 2021). The advantages of the spatial interaction approach are apparent: it avoids the MAUP associated with the aforementioned statistical index approach, given its measure of attraction between the OD points. Moreover, the spatial interaction approach generates more accurate localised population exposures to parks by considering the service capacity of parks and their attraction to the population (Kong, Yin, Nakagoshi, & Zong, 2010; Nicholls, 2001).

Nevertheless, challenges also exist in measuring the OD distance and quantifying the distance decay effect in the spatial interaction approach. First, OD distance measures can suffer from the same drawback as the spatial proximity approach, including selecting distance thresholds, transport modes, and destination choices. Second, the distance decay effect is subject to the magnitude of a parameter associated with distance, varying across local contexts (Kwan, 1998). A larger distance decay effect indicates that human behaviour is more sensitive to distance. Given the variety of geographic contexts (e.g., urban, suburban, and rural areas), the distance decay could be different among various destinations. However, the commonly applied practice uses one uniform distance decay parameter across the whole study area. Some studies optimised the gravity-based model to be a population- or cost-weighted distance model by considering the impact of the population or the travel cost on accessibility measures (Wang, 2012).

In summary, existing methods developed to measure park accessibility in the current literature have their advantages and drawbacks, including MAUP, the oversimplification of one point (the centroid) as park destination and single-mode access, and the arbitrary proposition of accessing only the nearest park by residents. Nevertheless, little is known about the relationship between accessibility measures produced by these approaches and the suitability in different geographical contexts. As such, our study aims to achieve three objectives: 1) to propose a new method that measures park access using a combined network- and entrance-based method; 2) to evaluate the similarity, replaceability, and variability of different measures produced by this and two other approaches, taking into account diverse destination choices, multiple transport modes, and different distance thresholds; and 3) to test the generality of our proposed method and how this method can generate more realistic measures of park access in a geographic context.

3. Case study context, data, and methods

3.1. Case study context

We first measured access to urban parks using three sets of approaches, including the new method we propose to the City of Ipswich in Australia, and then test the generality of our proposed new method by applying it to quantify park access in the City of Enschede in The Netherlands. Ipswich is located approximately 40 km southwest of the state capital city of Brisbane in Queensland and within the boundary of the Greater Brisbane metropolitan area. Its total land area is around 1090 km^2, with a total population of 228,544 in 2020 (Australian Bureau of Statistics, 2020). There are more than 500 different parks and natural reserves, with over 5000 ha of open space for recreational purposes (Fig. 1). The *Ipswich Planning Scheme* (City of Ipswich, 2020) advocates the future development of the city towards the major transit-oriented urban renewal with diverse land-use: major commercial and industrial areas permeated by urban parks to suit the recreational needs of a growing population and local communities (Ipswich City Council, 2019). Hence, Ipswich serves as an appropriate testbed to compare the different park accessibility measures in this study.

To demonstrate the generality of our proposed method, we conducted another case study in the City of Enschede, The Netherlands. As
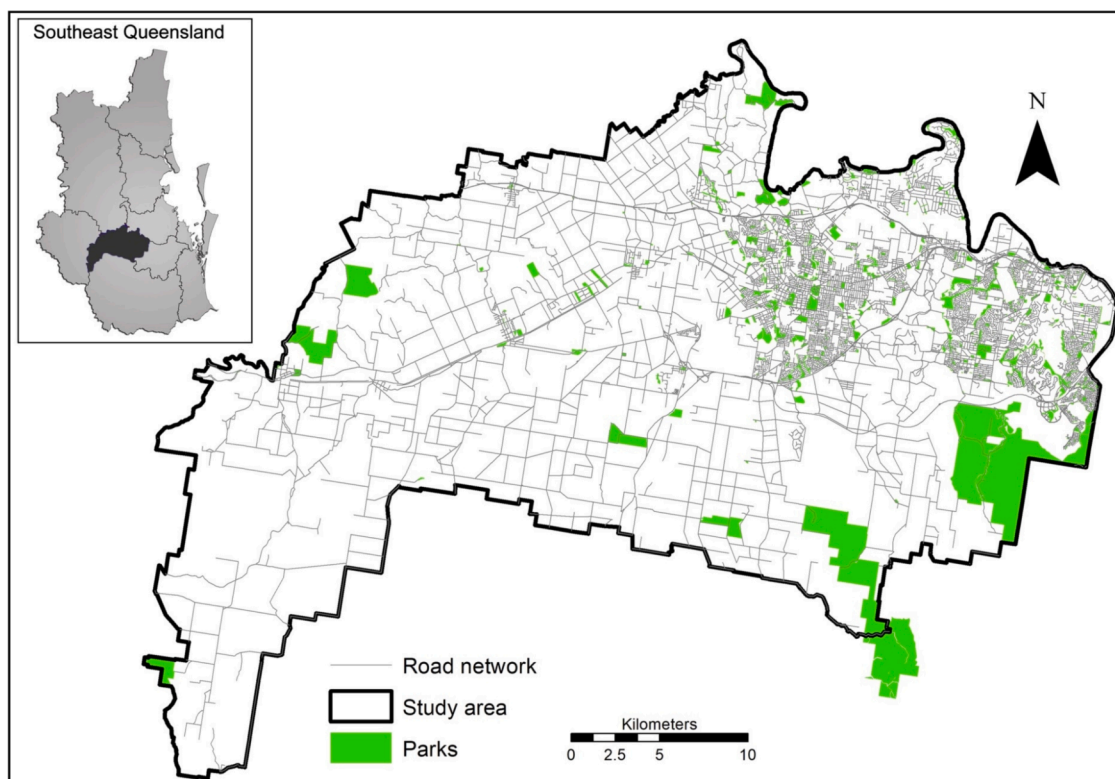

Fig. 1. The first study area in Ipswich, Queensland, Australia and its urban parks.

the largest city in the Twente region, Enschede is located in the Province of Overijssel in the east part of the Netherlands. As a green city, Enschede is surrounded by nature and urban parks, and its total municipal area is 142.72 km^2 with a total population of 158,986 in 2019 (Statistics Netherlands StatLine, 2020). To test our method, we defined the study area to the major urban area within the Broekheurne-Ring (the primary road network surrounding the city centre, Fig. 2). We also selected one major urban park—Volkspark—in the city centre as our park destination and explicitly measured the accessibility to this park. Compared to measuring accessibility to all parks, focusing on one park enabled us to zoom in to one particular park to differentiate accessibility measures based on park centroids, edges, and entrance points across various transport modes and distance thresholds.

3.2. Data

Data used in our two study areas are from multiple sources. For the first study area, Ipswich, Australia, the spatial distribution of urban parks was extracted from the Digital Cadastral Database via the Open Data Portal of Queensland Government (2020). The digital boundary data at the Statistical Area Level 1 (SA1) and the population data at SA1 were obtained from the 2016 Census of Population and Housing via the online TableBuilder, Australian Bureau of Statistical (Australian Bureau of Statistics, 2016). The road network data were sourced from the Department of Transport and Main Roads, Queensland Government (2020) and used to calculate the network distance between residential locations and urban parks in GIS. We selected six road types to measure the driving distance: 'frees ways/motor ways', 'highways', 'secondary ways', 'local connector roads', 'street/local roads only for property access', and 'notified private or restricted roads'. We excluded 'frees ways/ motor ways' and 'highways' to calculate walking distance but added 'bikeway/walkway' and 'tracks'.

For the second study area, Enschede, The Netherlands, the digital boundary data at the 5-digit zip code (PC5) level were obtained from Statistics Netherlands StatLine (2020). The spatial data of urban parks and road network data were extracted from the OpenStreetMap (2020). Road networks were constructed based on the 'drivable' and 'walkable' roads, with drivable roads including 'primary', 'secondary', 'tertiary', 'trunk', 'residential' roads and 'motorway', and walkable roads consisting of 'cycleway', 'path', 'pedestrian', 'track' in addition to the drivable roads but excluding 'motorway'. s.

3.3. Methods

Four elements matter most to the measure of OD distances: road network, transport modes, distance thresholds, and destination choices. We constructed two road network datasets for each study area in GIS, one for driving and one for walking. Using the three approaches—the statistical index, spatial proximity, and spatial interaction approaches—we generated 21 types of park accessibility measures (3 measures by the statistical index approach, 12 measures by the spatial proximity approach, and 6 measures by the spatial interaction approach) in the first study area, Ipswich, Australia, based on different definitions of destination choices and distance thresholds, which we discuss below. We further analyse and compare the relationships and spatial patterns of these 21 measures using thematic mapping, a correlation analysis, and principal component analysis. To demonstrate the improvement of our method based on park entrances and its generality in different geographic contexts, we further generated 12 measures of park accessibility using this method and other spatial proximity measures in the second study area, Enschede, the Netherlands.

3.3.1. Defining destination choices

The most common method used in the literature to define the destination of an urban park is either the centroid of the park or the closest edge point to the park. However, in the Australian context, urban parks are likely to be surrounded by creeks or separated by highways
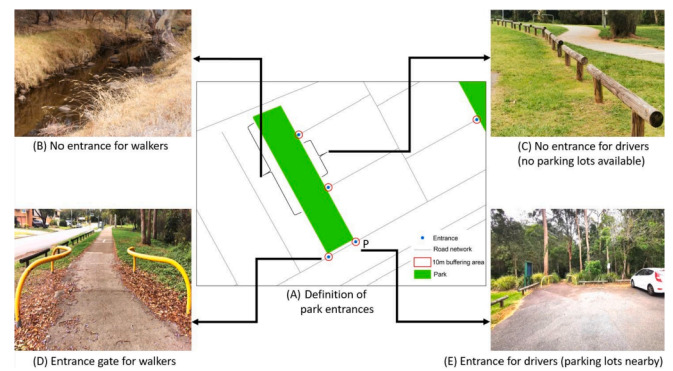

Fig. 3. Definition of park entrances (photo by the author).
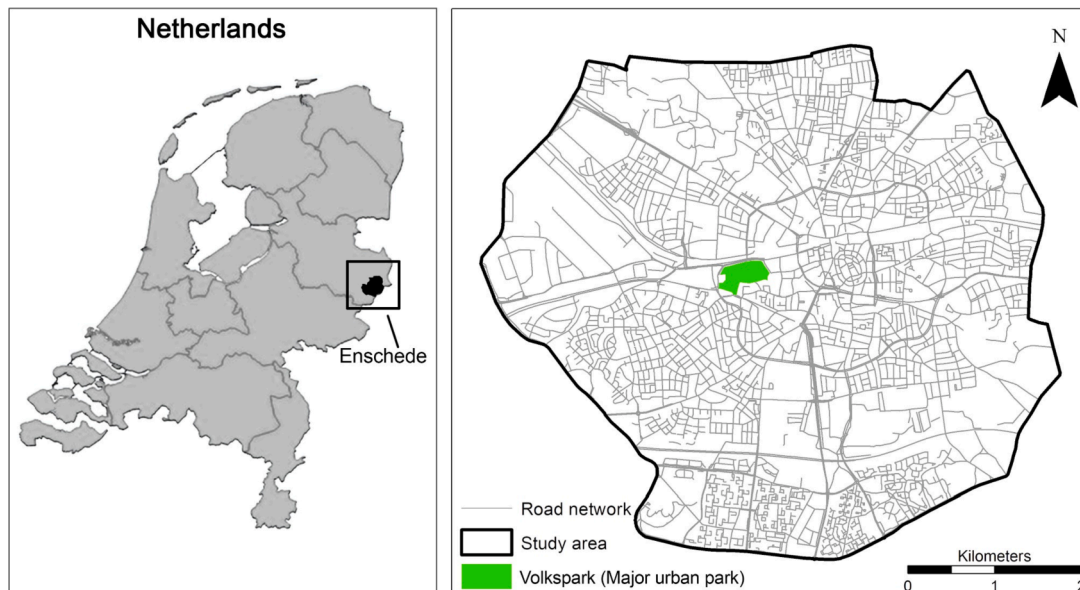

Fig. 2. The second study area in Enschede, The Netherlands, and the selected park in the city.

(Fig. 3B) and cannot be accessed through all points along its edge. Thus, we propose a new type of destination choice, namely, the park entrance, which is defined as the intersections of the road network with the park within a small buffer distance to the park boundary. In reality, such intersections are usually designed as entrance gates for walkers (Fig. 3D) or configured by parking lots for drivers (Fig. 3E). The buffer distance is necessary to extend the road network to connect with the parks in GIS so network analysis can proceed. To operationalise this concept, we assign this buffer distance as 20 m for our first study area, given the relatively wider roads and large space between a road and the adjacent park. If a road runs parallel to a park, the vertex of the park polygon within a 20 m-distance to the nearest road will be snapped to the road. Therefore, the park entrances can be identified (Fig. 3A). To compare our approach with other methods, we also defined park destinations as either the centroid of a park or the closest edge point of a park to a residential location (represented by the centroid of a residential area) for later use.

3.3.2. Defining distance thresholds by transport mode

Four distance thresholds were tested in the Ipswich study area: 500 m and 1 km for walking and 3 km and 5 km for driving. These distance thresholds were used based on the following considerations. The World Health Organization (2013) recommends that cities provide a minimum of 9 m^2 of green area per inhabitant, assuming that green areas are designed so that residents live within an 8–10 min walk of open space. Given that walking speeds between 0.9 and 1.5 m/s are considered as normal for children, and the average walking speed of adults sits at the upper range of the normal range for children (Chen, Kuo, & Andriacchi, 1997), an 8–10 min walk implies a distance between around 500 and 1000 m. For driving, we assumed that people would be most likely to bear 5 min driving to access to a park. As the driving speed ranges from 40 and 60 km/h locally, a 5-min drive implies a distance between 3 km and 5 km. The distance thresholds defined in the Enschede study area were slightly different—500 m and 1 km for walking and 1 km and 2 km for driving—given the fact that the major urban area of Enschede (5.7 km from north to south and 6.3 km from west to east) is much smaller than Ipswich.

Fig. 4 illustrates the three park accessibility measures based on different distance thresholds and destination choices. The demand area of an SA1 (pink areas) is a polygon defined by the *Service Area* function in *Network Analyst* in ArcMap based on the road network. Specifically, A demand area (network service area) is a region that encompasses all accessible streets within a specified impedance. For instance, the 5-min service area for a point on a network includes all the streets that can be reached within five minutes from that point. Herein, the demand area of

an SA1 encompasses all streets that can be reached by residents within the travel distance between their home and a park (e.g., 1 km walking distance vs. 3 km driving distance). In the areas with low road density, the demand area of an SA1 would be seen as a polygon with a buffer distance along the central line of a road; while in the areas with high road density, the demand area of an SA1 would be seen as a regular polygon merged from multiple polygons with a buffer distance along the central line of a road. In Fig. 4A, the demand area within a 1 km walking distance covers zero park centroid, two park edge points, and four park entrances; while the demand area within a 3 km driving distance (Fig. 4B) covers zero park centroid, four park edge points, and two park entrances.

3.3.3. Measuring park accessibility

We used the spatial proximity, statistical index, and spatial interaction approach to generate 21 measures (Table 1). In the statistical index approach, we had two simple measures: *park percentage* as the percentage of the total size of all parks in an SA1 over the total area of that SA1 and *park per capita* as the areal size of parks in an SA1 per capita. In the spatial proximity approach, we had 13 measures. The first one, the *closest distance*, measures the road network distance between an SA1 centroid (as the population centre of an SA1) and the closest urban park using the *Closest Route* function in *Network Analysis* in ArcMap. The other 12 measures were based on the number of access points within the demand area of an SA1. The definition of the demand area of an SA1 was calculated by the *Service Area* function in *Network Analysis,* which was subject to the selection of destination choices (park centroids, edges, and entrances) and distance thresholds by transport mode (500 m/1 km walking distance vs. 3 km/5 km driving distance). In the spatial interaction approach, we applied the gravity model as below to calculate the total park accessibility (A_i) of an SA1 (i) to all nearby parks within the demand area of that SA1 (Wang, 2012):

$$A_i = \sum_{j=1}^{n} S_j \times P_i \Big/ d_{ij}^2 \tag{1}$$

where S_j is the size of the urban park (j) in square meters to represent the supply capability of that park; P_i is the number of population in an SA1 (i) to represent the demand of that SA1; d_{ij} is the road network-based distance between the centroid of an SA1 (i) and the access points (park centroids, edges, or entrances) of an urban park (j). The number of parks accessed by the population living in an SA1 is subject to selecting distance thresholds. In the gravity model, the population as the numerator is much larger than the distance as the denominator, generating measures with subtle differences across a walking distance of 500
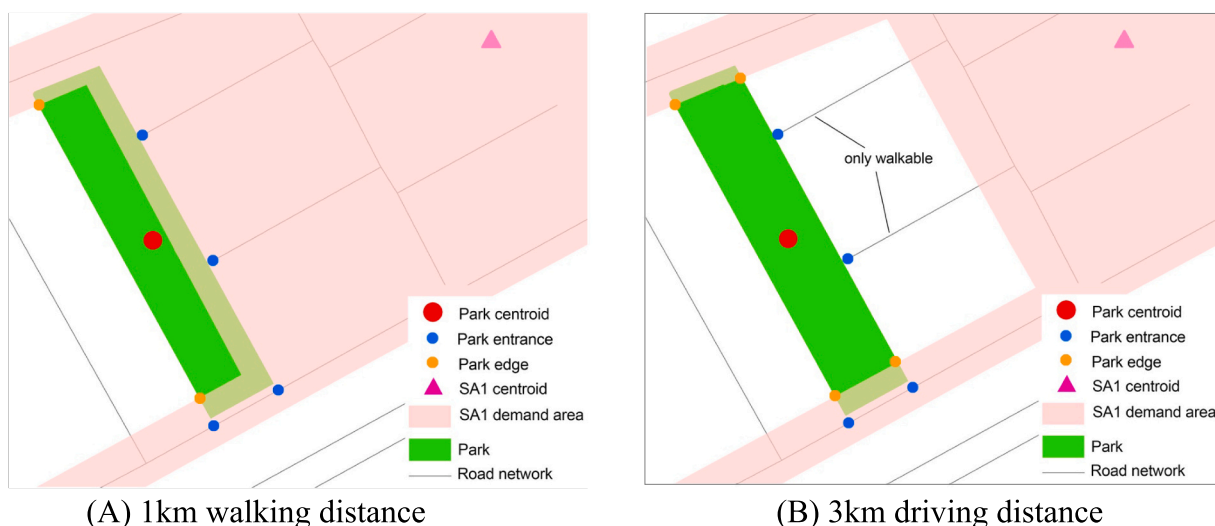

(A) 1km walking distance

(B) 3km driving distance

Fig. 4. An illustration of three different measures of accessibility based on different distance thresholds and destination choices.

Table 1
Specification of 21 accessibility measures using three different approaches.

Approaches	Definition of measures	Distance thresholds by transport mode	Destination choices	Name of measures
Statistical index	Park percentage: the percentage of parks in an SA1 over the total area of that SA1	N/A	N/A	SI_Park percentage
	Park per capita: the areal size of parks in an SA1 per capita	N/A	N/A	SI_Park per capita
Spatial proximity	Non-cumulative: the distance of an SA1 centroid to the closest park	The closest distance	Edge	SP_Closest distance
	Cumulative: the number of all access points within a demand area of an SA1	Walking distance 500 m	Centroid	SP_W0.5_cen
			Edge	SP_W0.5_edge
			Entrance	SP_W0.5_entran
		Walking distance 1 km	Centroid	SP_W1_cen
			Edge	SP_W1_edge
			Entrance	SP_W1 _entran
		Driving distance 3 km	Centroid	SP_D3_cen
			Edge	SP_D3_edge
			Entrance	SP_D3_entran
		Driving distance 5 km	Centroid	SP_D5_cen
			Edge	SP_D5_edge
			Entrance	SP_D5_entran
Spatial interaction	Gravity model: the attraction between the population of an SA1 (demand) and the size of a park (supply) over the distance between that SA1 and that park	Driving distance 5 km	Centroid	Grav_D5_cen
			Edge	Grav_D5_edge
			Entrance	Grav_D5_ entran
		Walking distance 1 km	Centroid	Grav_W1_cen
			Edge	Grav_W1_edge
			Entrance	Grav_W1_ entran

m and 1 km (or driving distance of 3 km and 5 km). Thus, we only selected the driving distance of 5 km and the walking distance of 1 km as the thresholds used in this formula.

3.3.4. Comparing accessibility measures

We map the spatial distribution of the 21 accessibility measures and compare these measures using correlation analysis and principal component analysis to evaluate the suitability, replaceability, and variability of these measures. We commence with mapping the spatial patterns of the 21 accessibility measures in ArcMap at the SA1 level. Then, we conduct a Pearson correlation analysis (Benesty, Chen, Huang, & Cohen, 2009) to reveal the relationships between the 21 accessibility measures with coefficients showing the magnitude of each bivariate correlation. In order to further identify the variability among the correlated accessibility measures, a principal component analysis (PCA) is then conducted to generalise the underlying structure of the 21 measures and quantify the extent (reflected by variable loadings) to which each measure is related with an extracted principal component (e. g., distance thresholds or destination choices) (Bryant & Yarnold, 1995). Based on the variable loadings, we summarise the effect of measuring approaches, transport modes, distance thresholds, and destination choices on park accessibility measures.

3.3.5. Testing the generality of the park-entrance-based method

To further test the usefulness of the park-entrance-based method proposed in this study and its re-applicability in different geographic contexts, we conducted two additional sets of analyses: 1) to map out the suburbs in the first study area, Ipswich, Australia, with high accessibility (top 20% of accessibility measures classified by quintile) identified solely by an entrance-based measure and collectively by three measures of destination choices (park centroids, edges, and entrances) based on one distance threshold; and 2) to apply the same spatial proximity approach used in the Ipswich case study to the Enschede study area, and generated 12 measures of park accessibility to test the potential of our method that can be applied to various study areas.

4. Results

4.1. Spatial patterns of accessibility measures

Fig. 5 shows that the spatial patterns of the accessibility measures in

the first study area, Ipswich, Australia, produced by the spatial proximity and spatial interaction approach are similar but substantially distinctive to those produced by statistical index measures. In statistical index measures, high accessibility (red spots) produced by *park* per capita appears in the southwest part of the study area away from the city centre. The high values of accessibility in the southwest may be explained by the smaller number of people living in the remote suburbs in the southwest compared to the larger number of people living in or around the city centre. Besides, the spatial units (SA1) on the urban fringe in the southwest are much larger than those in or around the city centre, resulting in a large area of high accessibility appearing in the southwest in Fig. 5 [2].

In spatial proximity measures, similar spatial patterns are observed across different measures: higher accessibility in and around the northeast city centre and lower accessibility in remote areas in the southwest. The *closest distance* captures more SA1 with high accessibility in the northeast than other measures, possibly due to the denser distribution of urban parks in and around the city centre where people can easily access parks within short distances. The spatial patterns of cumulative spatial proximity measures (Fig. 5 [4–15]) are consistent across different transport modes (driving and walking) and distance thresholds. The increase of distance thresholds (from 500 m to 1 km for walking and from 3 km to 5 km for driving) enlarges the areas of high accessibility. A further comparison of three destination choices within one transport mode and one distance threshold (e.g., Fig. 5 [10−12]) reveals that entrance-based measures capture more SA1 with high accessibility in the east compared to centroid- and edge-based measures. It is possibly due to the dense coverage of the road network in the east.

Finally, spatial interaction measures based on the gravity model (Fig. 5 [15–21]) tend to generate more pronounced accessorily patterns challenging to generalise. In general, areas with high accessibility captured by spatial interaction measures are located northeast with denser coverage of road networks. However, the variations of park accessibility across spatial units in the northeast are sharp compared to the gradually changing patterns by the spatial proximity approach (Fig. 5 [4–15]). It is possible because gravity-based measures are primarily dominated by the population and the parks' size as the gravity model numerator. A further comparison of three destination choices within one transport mode and distance threshold shows that entrance-based measures capture more SA1 with high accessibility in the east compared to centroid- and edge-based measures. It is consistent with the
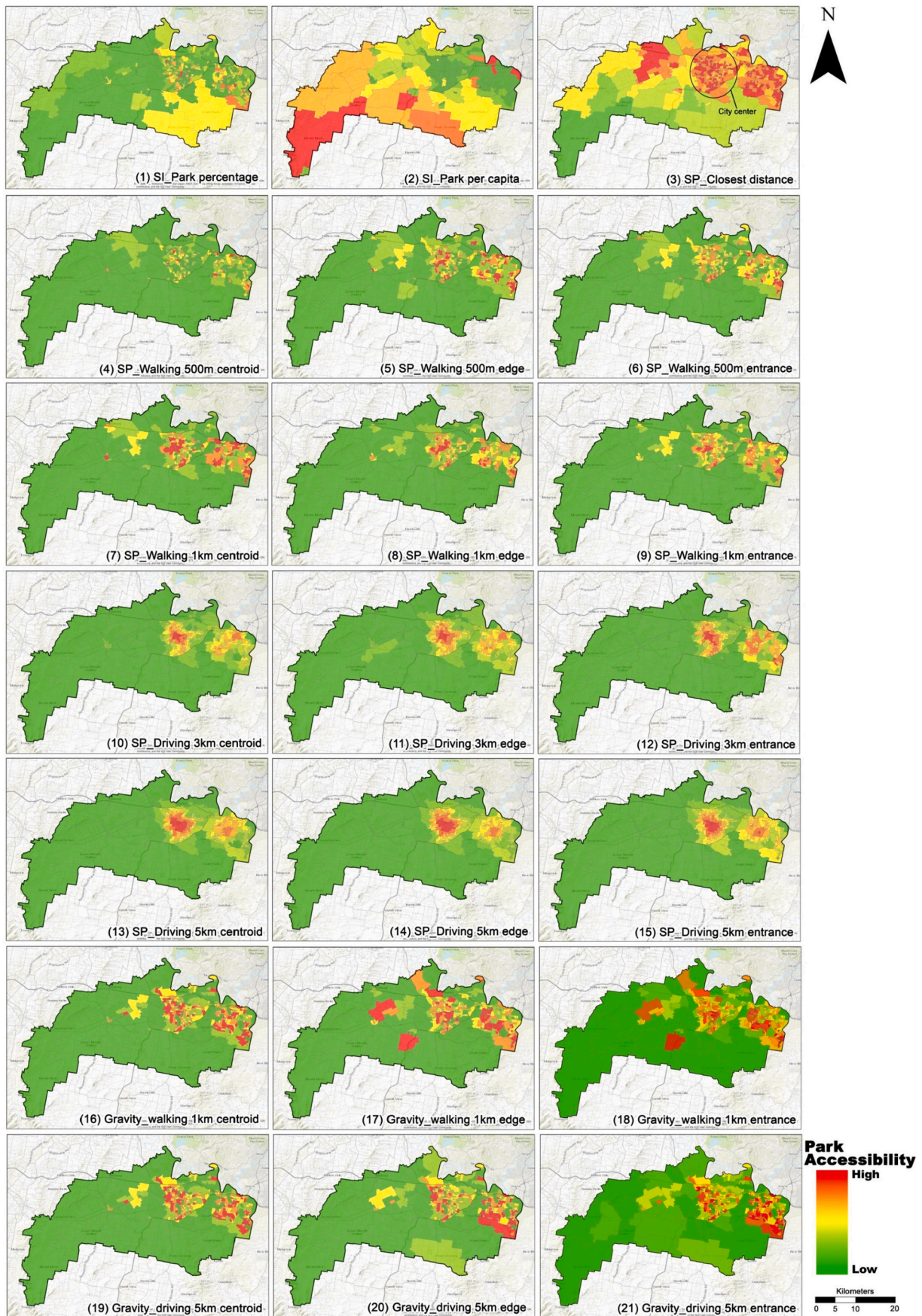
Fig. 5. Spatial patterns of 21 park accessibility measures in Ipswich, Australia.

spatial proximity measures.

4.2. Correlation of accessibility measures

To evaluate the similarity and replaceability of the 21 accessibility measures, the relationships between these measures are examined by the Pearson correlation coefficients shown in Table 2, and bold values indicate significance at the level of 99% ($p < 0.01$). The table shows that all spatial proximity measures are pairwisely correlated, though the magnitude of correlation varies. A further comparison of destination choices within one transport mode and distance threshold reveals that entrance-based measures are more correlated with edge-based measures than the centroid-based ones. Furthermore, the selection of distance thresholds matters the accessibility measures. Especially, *park percentage* keeps positively correlated with spatial proximity measures based on a walking distance but not a driving distance. It means that the consistency among different statistical proximity measures is subject to the selection of distance thresholds. Compared to a driving distance, a walking distance around an SA1 covers local neighbourhoods. Within a short travel distance threshold, residents may tend to access to the nearest parks. In that way, walking-based spatial proximity measures are consistent with the measure of *park percentage*. Both *park* per capita and *closest distance* are negatively correlated with all spatial proximity measures. It might be explained by the difference of algorithms applied in the measure of *park* per capita and *closest distance*. All spatial proximity measures based on driving and walking distances are based on the number of access points to a park: the larger value means the better accessibility, while the smaller value of *park* per capita and *closest distance* means the better accessibility.

The relationship between spatial interaction measures and other measures is relatively challenging to generalise given that spatial interaction measures consider the number of populations as demand and the size of parks as supply in the gravity model. Three spatial interaction measures based on the driving mode and the 5 km distance threshold (*gravity driving 5 km*) are correlated with each other across different destination choices, but none of them are correlated with measures of *gravity walking 1 km*. For the three measures of *gravity walking 1 km* based on different destination choices, the entrance-based measure is highly correlated with the edge-based one, but none of both is correlated with the centroid-based measures. Thus, spatial interaction measures involve multiple parameters, among which the selection of destination choices might not play a key role in differentiating the results.

4.3. Principal component analysis of accessibility measures

The PCA helps identify the variability of correlated accessibility measures and quantifies the extent to which each measure is related to an extracted principal component (PC) (Table 3). Five PCs are extracted from the 21 measures, and an orthogonal varimax rotation is performed to make these factors more interpretable (Bryant & Yarnold, 1995). These five PCs include spatial-proximity-driving-based component (PC1), spatial-proximity-walking-based component (PC2), spatial-interaction-driving-based component (PC3), spatial-interaction-walking-based component (PC4), and statistical-index-based component (PC5), together explaining 81.59% of the total variance. The large communalities for most measures (except *closest distance* and *park* per capita with communalities less than 0.6) indicate that a large amount of their variance has been extracted. The PCA produces a relatively clean structure where variable loadings on the five PCs reveal four observations about measuring approaches, transport modes, distance thresholds, and destination choices affecting accessibility measures.

First, the effect of the three GIS-based approaches on accessibility measures can be reflected by comparing the loadings across five PCs. All spatial interactive measures (except *gravity walking 1 km centroid*) with high loadings (over 0.984) are extracted as PC3 and PC4; while the spatial proximity measures of *driving 5 km and 3 km* with high loadings

Table 2
Pearson correlation analysis.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	SI_Park percentage	1																				
2	SI_Park per capita	−0.056	1																			
3	SP_Closest distance	−0.173	0.277	1																		
4	SP_D5_centroid	0.083	−0.199	−0.433	1																	
5	SP_D5_edge	0.091	−0.207	−0.446	0.994	1																
6	SP_D5_entrance	0.108	−0.216	−0.468	0.868	0.963	1															
7	SP_D3_centroid	0.093	−0.229	−0.463	0.880	0.876	0.879	1														
8	SP_D3_edge	0.093	−0.242	−0.476	0.922	0.922	0.910	0.975	1													
9	SP_D3_entrance	0.117	−0.253	−0.485	0.818	0.814	0.888	0.826	0.917	1												
10	SP_W1_centroid	0.119	−0.175	−0.367	0.366	0.356	0.424	0.537	0.504	0.572	1											
11	SP_W1_edge	0.179	−0.206	−0.418	0.438	0.433	0.485	0.584	0.565	0.622	0.908	1										
12	SP_W1_entrance	0.182	−0.189	−0.371	0.325	0.316	0.428	0.474	0.457	0.612	0.861	0.864	1									
13	SP_W0.5_centroid	0.186	−0.120	−0.315	0.161	0.153	0.215	0.280	0.260	0.318	0.655	0.580	0.582	1								
14	SP_W0.5_edge	0.316	−0.146	−0.378	0.257	0.256	0.315	0.383	0.365	0.421	0.681	0.728	0.678	0.733	1							
15	SP_W0.5_entrance	0.257	−0.138	−0.338	0.178	0.171	0.272	0.300	0.284	0.418	0.678	0.647	0.788	0.774	0.791	1						
16	Grav_D5_centroid	0.184	−0.054	−0.110	0.072	0.067	0.116	0.117	0.110	0.190	0.082	0.132	0.137	0.142	0.203	0.189	1					
17	Grav_D5_edge	0.207	−0.065	−0.128	0.055	0.053	0.109	0.104	0.098	0.186	0.083	0.138	0.147	0.150	0.220	0.206	0.986	1				
18	Grav_D5_entrance	0.209	−0.063	−0.125	0.052	0.050	0.106	0.101	0.095	0.183	0.082	0.137	0.146	0.149	0.219	0.205	0.986	0.992	1			
19	Grav_W1_centroid	0.327	−0.089	−0.191	0.094	0.095	0.138	0.180	0.164	0.220	0.294	0.279	0.296	0.320	0.287	0.321	0.252	0.256	0.258	1		
20	Grav_W1_edge	0.054	−0.028	−0.058	−0.073	−0.083	−0.004	−0.020	−0.029	0.061	0.195	0.220	0.221	0.219	0.211	0.239	0.014	0.035	0.036	0.057	1	
21	Grav_W1_entrance	0.054	−0.028	−0.058	−0.073	−0.083	−0.004	−0.020	−0.029	0.061	0.195	0.220	0.221	0.219	0.211	0.239	0.014	0.035	0.036	0.056	0.991	1

Note: Bold: $p < 0.01$.

Table 3
Variable loadings of 21 accessibility measures.

Accessibility measures	Variable loadings[*]					Communalities
	PC[1]	PC2	PC3	PC4	PC5	
SP_D5km centroid	**0.965**	0.083	0.004	−0.052	0.049	0.944
SP_D5km edge	**0.965**	0.075	0	−0.061	0.064	0.945
SP_D5km entrance	**0.952**	0.161	0.048	0.006	0.069	0.938
SP_D3km edge	**0.945**	0.235	0.034	−0.033	0.056	0.953
SP_D3km centroid	**0.916**	0.271	0.041	−0.031	0.047	0.918
SP_D3km entrance	**0.867**	0.352	0.117	0.039	0.063	0.895
SP_Closest distance	−0.463	−0.274	−0.029	−0.035	−0.343	0.41
SP_W1km edge	0.081	**0.864**	0.109	0.096	0.193	0.811
SP_W1km centroid	0.323	**0.863**	−0.012	0.066	0.014	0.853
SP_W1km entrance	0.291	**0.855**	0.051	0.097	0.063	0.831
SP_W500m edge	0.16	**0.817**	0.118	0.077	0.232	0.766
SP_W500m entrance	0.4	**0.812**	0.038	0.105	0.059	0.836
SP_W500m centroid	0.05	**0.807**	0.06	0.08	0.177	0.696
Grav_D5km edge	0.044	0.087	**0.987**	0.013	0.11	0.995
Grav_D5km entrance	0.04	0.086	**0.987**	0.014	0.112	0.995
Grav_D5km centroid	0.057	0.077	**0.985**	−0.006	0.085	0.987
Grav_W1km edge	−0.042	0.165	0.008	**0.984**	0.025	0.998
Grav_W1km entrance	−0.042	0.165	0.008	**0.984**	0.025	0.998
SI_Park percentage	0.013	0.096	0.107	0.019	**0.82**	0.693
Grav_W1km centroid	0.039	0.266	0.187	−0.022	0.63	0.506
SI_Park per capita	−0.253	−0.073	0.011	−0.045	−0.309	0.167
Total	5.925	4.727	3.018	1.998	1.466	17.134
% of Variance	28.216	22.509	14.371	9.516	6.982	81.594

[*] PC = principal components. Bold: variables have significant contributions to an extracted PC (loadings larger than 0.8). PC1: Spatial-proximity-driving-based component; PC2: Spatial-proximity-walking-based component; PC3: Spatial-interaction-driving-based component; PC4: Spatial-interaction-walking-based component; PC5: Statistical-index-based component.

(over 0.867) are extracted as PC1, and *walking 500 m, and 1 km* with high loadings (over 0.807) are extracted as PC2. Only one statistical index measure with the loading of 0.82 is extracted as PC5. The variability of loadings across these five PCs is more evident than those within one PC, indicating that selecting measuring approaches matters more to accessibility measures than selecting transport modes, distance thresholds, and destination choices.

Second, the effect of transport modes on accessibility measures can be reflected by the variability of loadings on PC1 and PC2. Specifically, the loadings of driving-based measures with long distances (3 km and 5 km) on PC 1 (0.867 to 0.965) are all higher than the loadings of walking-based measures with short distances (500 m and 1 km) on PC2 (0.807 to 0.864). It indicates that the selection of transport modes plays an important role in differentiating accessibility measures within the same measuring approach.

Third, the effect of distance thresholds on accessibility measures can be revealed by the variability of loadings within PC1 or PC2. Within the spatial proximity driving-based measures extracted as PC1, the loadings of longer distances (5 km) are all larger than those of shorter distances (3 km). Similarly, within the spatial proximity walking-based measures extracted as PC2, the loadings of longer distances (1 km) are all larger than those of shorter distances (0.5 km). It means that within the same measuring approach and transport mode, the selection of distance thresholds matters more to accessibility measures than destination choices.

Fourth, the effect of destination choices on accessibility measures can be reflected by comparing loadings within PC1, PC2, or PC3. Specifically, destination choices affect accessibility measures within the same transport mode and the same distance threshold. For example, in the spatial proximity measures of *driving 5 km,* the centroid-based measure has a heavier loading than the edge- and entrance-based one; but it is not the case for the spatial proximity measure of *walking 1 km.* It means that the selection of destination choices matters to accessibility measures variously across different approaches. The discussion of the effect of destination choices on accessibility measures needs to have a prerequisite based on the same selection of measuring approaches, transport modes, and distance thresholds.

4.4. Testing the park-entrance-based measure of accessibility in Enschede, the Netherlands

For the spatial proximity measures in Ipswich, Australia (Fig. 6 [1–4]), the areas with high accessibility collectively identified by three destination choices are concentrated mainly in the city centre. It means that accessibility measures in the city centre with a high density of road network and urban parks have no substantial differences across the three types of destination choices. However, entrance-based measures identify more suburbs in the east of the study area (further east to the city centre) where the density of road network and urban parks is lower, but the size of urban parks is larger than that in the city centre. The same case for spatial interaction measures (Fig. 6 [5–6]) shows that suburbs with high park accessibility in the east of the study area are captured by entrance-based measures but not by other measures. With this regard, we may suggest that among accessibility measures within one particular distance threshold, the entrance-based method provides more realistic accessibility measures, and it is mainly applicable to areas close to large urban parks connected by road networks.

Additionally, we compare 12 park accessibility measures based on park centroids, edges, and entrances in Enschede, The Netherlands. For the measures based on the park centroid of Volkspark (Fig. 7 [1,4,7,10]), they can only identify a few PC5 areas that can access the park across different distance thresholds since the unrealistic extraction of an area-based park to be a single centroid would neglect the effect of park areas on the accessibility measures which might bring substantial bias, particularly for large urban parks. For the measures based on park edges (Fig. 7 [2,5,8,11]), the number of PC5 areas that can access Volkspark increases along with the increase of distance thresholds. However, there is no variation of parking accessibility among such PC5 areas since the edge-based measure depends on whether the edge of the park (one single point on the edge of one park) can be approached by a certain travel distance. For the entrance-based measures (Fig. 7 [3,6,9,12]), we can observe more variations of parking accessibility based on one distance threshold and one transport mode compared to edge-based measures (e. g., Fig. 7 [6] vs. Fig. 7 [5] based on walking 1 km distance, or Fig. 7 [12] vs. Fig. 7 [11] based on 2 km driving distance). As park entrances are defined distinctively across the drivable and walkable road networks, it
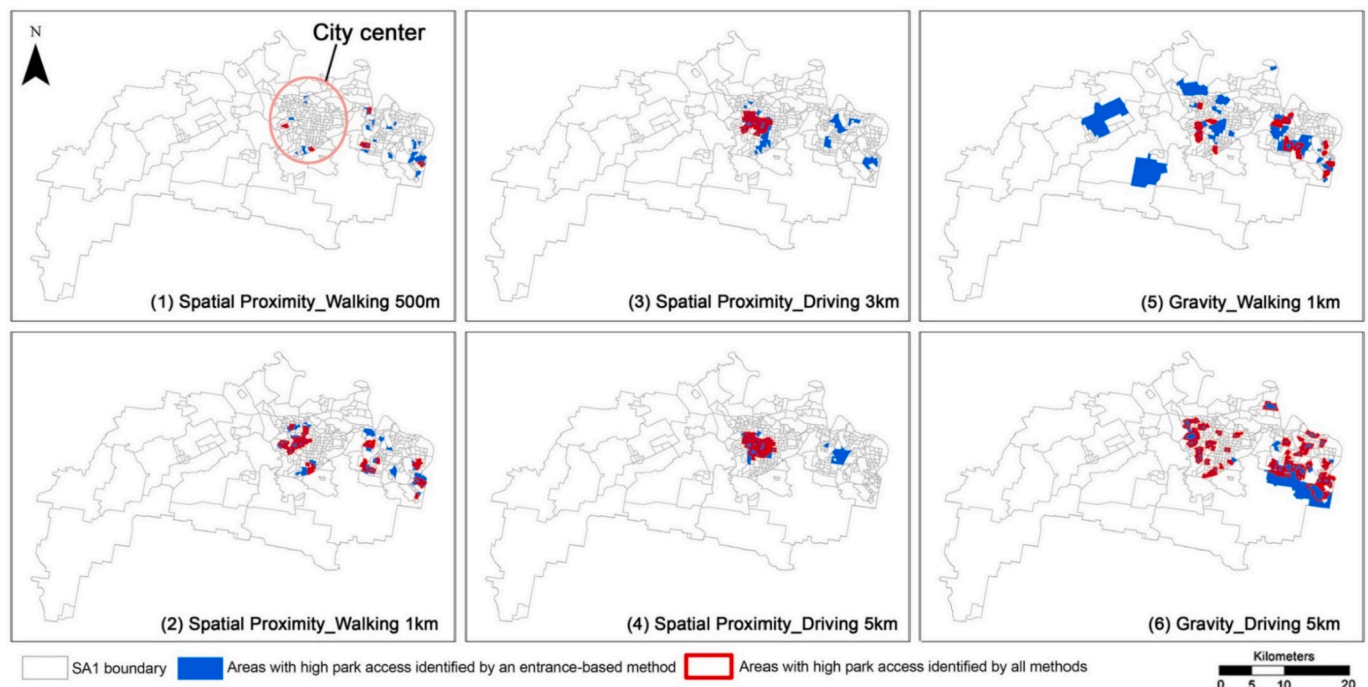
Fig. 6. Comparison of the areas with high park accessibility identified by an entrance-based method and other methods in Ipswich, Australia.

will generate different numbers of entrances around one park, capturing that drivers and walkers enter parks at different entrances. Parks with different roads connectivity will also be accessed variously. In sum, the validation of the park-entrance-based method in Enschede, The Netherlands, provides additional evidence regarding the applicability of our method in various geographic contexts with different spatial units and complexity of road networks.

5. Discussions

5.1. Choose an appropriate approach to measure park accessibility

Through examining the spatial pattern, correlation, and factor loadings of the 21 accessibility measures, we suggest that the statistical index, spatial proximity, and spatial interaction approaches generate distinctive types of accessibility measures that might be suitable in different contexts. Similar to the findings by Zhang et al. (2011), we observe that the statistical index approach provides simple statistical measures (e.g., *park per capita* or *park percentage*) but might not fully describe the realistic access to park without the consideration of how and where people could travel and enter urban parks. However, the statistical index approach is easy for computation and may be better applied to uniformed spatial units if park and population data are available.

Instead, the spatial proximity approach allows assessing spatial variations in accessibility independent of arbitrarily defined administrative boundaries. The spatial proximity approach in our study accounts for network complexity, transport modes, distance thresholds, and destination choices. Road networks enable the more accurate assessment of an OD distance by considering road levels, travel speed, transport modes, turning restrictions (e.g., one-way lane), and traffic disruptions (Chen, Yang, Kongsomsaksakul, & Lee, 2007). Defining the service area of a park based on the flexible selection of a distance threshold rather than a specific spatial unit enables one to consider that individuals often travel across the boundaries of their residential neighbourhoods to access parks. Moreover, compared to the literature that treated the edge points of an urban park or the centroid of a park as destinations (e.g., Gutiérrez & García-Palomares, 2008; Weiss et al.,

2011), the defined park entrances used in our study more realistically capture the location of where people can access to parks, and thus have great potentials to provide a more realistic measure of park access. However, we find that the selection of distance thresholds and transport modes matters more to the accessibility measures than destination choices. In general, the spatial proximity approach based on network distances and park entrances is less sensitive to the administrative boundaries and thus suitable for regions various in the size of parks and spatial units, although the pre-condition is that such regions need to be explicitly connected by road network.

Last but not least, the spatial interaction approach provides a distinctive type of accessibility measures compared to the other two approaches, given that this method considers population size as the demand and the size of parks as the supply in the gravity model. Our study defines OD distances in the gravity model as defined in the spatial proximity approach, subject to network complexity, transport modes, distance thresholds, and destination choices. Different from the measures of accessibility to other facilities (e.g., Charreire et al., 2010; Dony et al., 2015; Neutens, 2015), the park accessibility measures generated by the spatial interaction approach may be biased and affected by the number of population and the size of parks because of the assumption that an urban park has a maximum service capability for a certain amount of population. However, when the service capability of parks is not the primary concern, the spatial interaction approach may overestimate or underestimate accessibility measures if the population and the size of parks substantially vary across the whole study area. Thus, the spatial interaction approach may be better applied to parks with specific functionalities or with the provision of specific facilities where the service capability needs to be considered.

5.2. More realistic accessibility measures based on road network and park entrances

Defining the destination choice plays a primary role in calculating the distance between a resident's home and a park which further affects park accessibility measures. While Euclidean distances are computationally efficient (Gutiérrez & García-Palomares, 2008), road network distances allow us to capture the *actual* distance people travel along
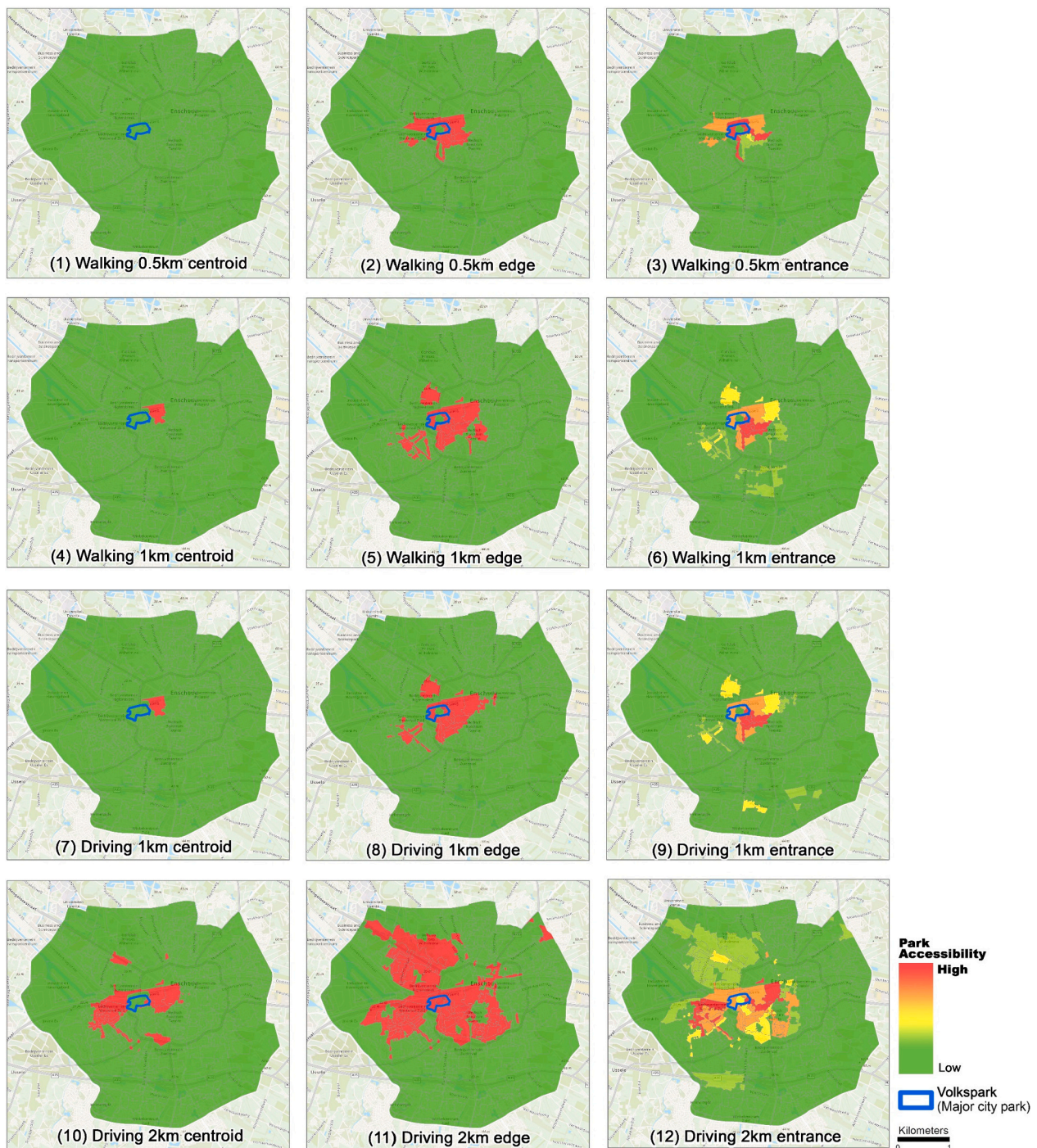
Fig. 7. Spatial patterns of 12 park accessibility measures based on park centroids, edges, and entrances in Enschede, The Netherlands.

roads and consider different transport modes in accessibility measures based on the drivable or walkable roads. In this context, park entrances are defined as specific points on the edge of urban parks within a certain buffering distance to the road network's nearest interactions. Using such pre-defined park entrances as the destination choice has great potentials to provide more realistic accessibility measures given the fact that people essentially access urban parks through entrances rather than a random point on the park edge or a park centroid.

Through the application of the entrance-based method in two study areas in Australia and The Netherlands, the generality and applicability of this method are validated, which can be further employed in other geographic contexts with different spatial units and data availability or

to measure accessibility to other types of area-based facilities (e.g., recreational parks and industrial parks). The definition of park entrances is relatively straightforward using any GIS-based software (e.g., ArcGIS or QGIS), which is available to different stakeholders, including urban planners, government agencies, policymakers, and researchers. The procedure for defining park entrances using our approach is straightforward, suitable for users with limited GIS knowledge. Such a procedure can be refined or simplified, subject to the complexity and accuracy of data. For example, road network data with more accurate road classifications would provide measures across different transport modes (e.g., public transport, private car, ferry, or walk). Fine-scale spatial units provided by the cadastral data (e.g., at the level of land parcels, lots, or

street blocks) would provide more accurate measures of origins to a park compared to a simplified centroid of a coarse spatial unit. In summary, our proposed method has great potential to improve accessibility measures more broadly across multidisciplinary studies.

6. Conclusion

The continuous refinement of park accessibility measures and the increased availability of precise datasets have contributed substantially and will continue contributing to accessibility literature. Our study proposes a combined network- and entrance-based method for more realistic park accessibility measures and suggests the suitability of accessibility measures in different contexts by comparing 21 park accessibility measures using three GIS-based approaches and validating our proposed method across two study areas in Australia and the Netherlands. These three approaches take into account network complexity, transport modes, distance thresholds, and destination choices. By comparing the measuring results, we suggest that statistical index, spatial proximity, and spatial interaction approaches generate distinctive accessibility measures that might be suitable in different contexts. Despite such measuring variations, the selection of distance thresholds and transport modes matters more to accessibility measures than destination choices. However, among the accessibility measures within one particular distance threshold based on one transport mode, the combined network- and entrance-based method has a great potential to provide a more realistic measure. It is mainly applicable to areas close to large urban parks connected by road networks.

This study makes several contributions to the broad literature concerning park accessibility. First, it provides different ways for more realistic accessibility measures by comparing the importance of factors involved in the measuring process. The selection of such factors (e.g., destination choices and distance thresholds) for measuring optimization can be decided by and suitable in different research contexts and purposes (e.g., Santos, Almeida, Martins, Gonçalves, & Martins, 2019; Tahmasbi & Haghshenas, 2019; Tomasiello, Giannotti, & Feitosa, 2020). Second, the methodological framework used in this study is applicable to other study areas with different geographic contexts and data availability. It is particularly beneficial to developing or undeveloped countries with less spatial data (e.g., Kaplan, Burg, & Omer, 2020; Wigley et al., 2020). For example, the accessibility of an area without available network data may be measured via the statistical index approach. Third, the measuring optimization by accounting destination choices, distance thresholds, transport modes can be employed to measure the accessibility to other types of facilities and utilities (e.g., healthcare, public transport, sport, and recreational centres) or more general destinations (e.g., central business districts and employment centres). Our measurements can be extended to diverse disciplines to deepen the understanding of human behaviours, mobility patterns, and urban systems.

This study has some limitations that can be improved in future studies. First, the distance used to define the service area remains subject to debate because of the complexity of the relationship between environment and behaviour. The choice of the service area size is based on the assumption concerning the geographic zone that the urban park environment would influence an individual's physical activity and travel behaviour. It is essential to underline that future survey is needed to question individuals about the distance they would bear to travel to access an urban park (Zhang et al., 2011). Second, the transport modes in our study only include driving and walking but do not deal with public transport or mixed travel modes. As families with low income may not own a car or even have access to public transportation, future studies can be extended to more sophisticated GIS modelling incorporating different types of transport available (e.g., public transport, ridesharing), the accessibility of different groups of the population to urban parks (Wang & Mu, 2018), and the role of road network structure (Wang et al, 2020). Third, it should be noted that access is a complex notion and a broad concept in five dimensions (Penchansky & Thomas, 1981),

including accessibility, availability, affordability, acceptability, and accommodation. We only consider the first dimension, corresponding to the spatial accessibility based on the geographic distribution of urban parks. However, the other dimensions reflecting the cultural, social, and economic factors are not considered. Future study can be extended to more dimensions related to park access, including availability (service capability), affordability (cost), accommodation (types of urban parks), and acceptability (personal attitude and perception to urban parks), which a social survey might collect to provide complementary information for characterising urban parks. In other words, the methodology in future research would have to combine GIS potentials and survey approaches to describe the multidimensional accessibility of urban parks.

Declaration of Competing Interest

All authors declare no competing interests.

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