Gravity-based models for evaluating urban park accessibility: Why does localized selection of attractiveness factors and travel modes matter?

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Abstract

Gravity-based models have been extensively utilized in urban studies for measuring geographic disparities in access to urban parks over the past several decades. However, despite methodological advancements incorporating various aspects of accessibility, there has been limited focus on the impact of variable selection (e.g., attractiveness factors) and transport modes on accessibility evaluations. This study investigates the differences in gravity-based models for assessing park accessibility based on varying assumptions about attractiveness factors and travel impedance. Semi-structured interviews with local residents were conducted to identify the reasons for park visits in Shanghai. Our bivariate correlation analyses reveal that factors such as park openness and access to public transport were crucial, in addition to conventional factors identified in the literature (i.e., park size and driving accessibility). This insight led to the development of localized accessibility measurements that incorporate park inclusiveness (i.e., entrance fees and opening hours) and multimodal travel options (based on multinomial logistic mode choice models). The results indicate that the refined model produces lower and more varied accessibility levels, which can better capture accessibility gaps across different geographic contexts. This accurate and practical identification of accessibility gaps can assist local planners and decision-makers in formulating effective policies and strategies to promote equitable access to urban public parks.

Keywords

Accessibility; Gravity model; Multimodal mode choice; Urban parks; Planning support systems

1. Introduction

Public parks are significant features of urban green infrastructure, which are closely associated with health and quality of life for residents by offering open green spaces that provide aesthetic, psychological, restorative, and recreational services (Kemperman and Timmermans, 2014; Weijs-Perrée et al., 2017). As accessing these services requires physical use of the parks, it is crucial to ensure equitable access to urban green spaces for high-demand populations, thereby promoting the sustainable development of cities. Achieving equitable access necessitates practical and accurate measurements of urban park accessibility (Liang et al., 2023).

Despite the common use of park accessibility in planning evaluations and policy analyses, it is not a universal measure. Instead, it is determined by residents' perceptions and travel habits, which are heavily influenced by local factors such as culture and economy (Dony et al., 2015; Liang and Zhang, 2018; Stessens et al., 2020). However, research on accessibility assessment using localized variables is limited, and few attempts have been made to compare the results of accessibility measurements using different variables (Xing et al., 2020). In addition, recent studies suggest that accessibility measurements may vary significantly depending on the mode of transportation chosen, emphasizing the need to consider mode choice in accessibility measurements for more practical results (Dony et al., 2015; Huang et al., 2022; Wang et al., 2022; Zhou et al., 2023).

This paper addresses these research gaps by demonstrating how the selection of locally-informed attractiveness factors and the consideration of multimodal travel modes can impact accessibility evaluation. We propose an improved gravity model that integrates attractiveness factors (i.e., park size, quality, and inclusiveness) derived from local interviews on park-visiting preferences, and a multinomial logistic model that considers multiple travel modes (i.e., motorized and non-motorized modes of transport) while accounting for residents' travel behavior. Our study contributes to the existing literature on accessibility in two ways. First, we enhance the variety of methods used to measure urban park attractiveness by considering the most influential factors through semi-structured interviews with local residents. Second, we incorporate a multimodal travel mode choice model, informed by previous studies on the local residents' travel behavior, into the gravity model. These improvements offer a more realistic representation of park accessibility and highlight the significance of incorporating local perspectives into gravity-based accessibility measurements.

The rest of the paper is organized as follows. Section 2 presents a review of the literature on park accessibility measurement and gravity model improvements. Section 3 describes the study area, data sources, and the three gravity models designed for making comparisons. Section 4 presents and compares the accessibility results derived from these models. Section 5 discusses the implications of the results and outlines the advantages and limitations of our proposed method.

2. Improving gravity-based accessibility models

2.1 Prevalent accessibility measurements

Urban studies primarily employ two types of accessibility measurements: place-based (or location-based) and people-based (or individual-based) (Macfarlane et al., 2021; Rad and Alimohammadi, 2022; Yang et al., 2023). Place-based measures assess the geographic proximity between service providers and users, typically quantifying the spatial distance between parks and residences in urban park accessibility studies (Liang et al., 2023; Wu et al., 2017). In contrast, people-based measures consider the individuals' activity schedules and service operating hours but often require a detailed observation dataset that may be unavailable in many developing countries (Rad and Alimohammadi, 2022). Therefore, place-based methods are more commonly employed by researchers.

Methodologically, place-based accessibility measurements can be categorized into four main approaches: (1) infrastructure-based, which focuses on street and transportation network features without considering activity locations; (2) distance-based, which examines the closet facilities or those within a predetermined distance; (3) gravity-based, which evaluates accessibility by considering the distance between opportunities and the origin, incorporating impedance functions; and (4) utility-based, which characterizes accessibility as a result of the destination-transportation alternative selections based on microeconomic random utility theory (Anjomshoaa et al., 2017; Vale, 2020; Vale et al., 2015).

Despite the convenience and flexibility of infrastructure-based and distance-based measures, their oversimplified and arbitrary definitions may limit comprehensive analysis (Macfarlane et al., 2021; Semenzato et al., 2023). Furthermore, utility-based specifications, often represented as a linear-in-parameters functions of destination attributes and travel costs with coefficients often estimated from surveys, may incorporate random components and are inherently difficult to interpret, explain, and compare independently (Vale et al., 2015). In comparison, the gravity method has gained popularity in accessibility studies due to its capacity to define individuals as having some level of access to all services (rather than imposing arbitrary cutoffs) (Guagliardo, 2004; Macfarlane et al., 2021) and its flexibility in including any service attribute deemed relevant by researchers (Macfarlane et al., 2021).

Hansen (1959) first introduced the gravity-based model to urban studies, testing the accessibility index by measuring service attributes and travel costs as follows:

$$A_i = \sum_{j=1}^{n} A_{ij} = \sum_{j=1}^{n} S_j f(c_{ij}); (1)$$

where A_i indicates the accessibility of population point i; A_{ij} refers to the accessibility from population point i to destination j; S_j equals the attractiveness factor for destination j; $f(c_{ij})$ refers to the impedance function of the generalized cost c_{ij} between point i point j; and n is the total number of destinations.

Based on the basic accessibility measurement (Equation 1), Joseph and Bantock (1982) made a significant contribution to the gravity model by introducing a population demand adjustment factor that accounts for supply and demand factors, specifically by considering competition among potential service recipients and their respective demands, resulting a modified gravity model expressed as follows:

$$A_i = \frac{\sum_{j=1}^{n} S_j f(c_{ij})}{V_j}; \ V_j = \sum_{i=1}^{m} P_i f\left(c_{ij}\right); (2)$$

where V_j is the population demand adjustment factor; P_i indicates the population of the point i; and m denotes the total number of population points.

The modified fundamental equation for the gravity model (Equation 2) serves as a foundation for the following discussions on attractiveness factors, impedance functions, and their combinations for comparisons.

2.2 Measuring park attractiveness

Hansen (1959) originally proposed that urban park accessibility should be measured using the green space area factor as a single attraction coefficient. Subsequent studies have adopted this approach (Liu et al., 2021; Tian et al., 2021; Vîlcea and Șoșea, 2020; Wu et al., 2017). However, relying solely on area may not provide a comprehensive and accurate representation of resident demand on urban parks. Other characteristics of urban parks, such as scenery, facilities, and services, can also contribute to their attractiveness. Dony et al. (2015) evaluated the attractiveness of urban public parks based on their amenities, while Xing et al. (2020) considered various factors, including the number of playgrounds, sports fields, sports courts, walking/cycling paths, hiking trails, public swimming pools, supporting facilities, and nature-related variables (e.g., tree coverage).

Accessibility is also considered as a five-dimensional concept, encompassing approachability, acceptability, availability and accommodation, affordability, and appropriateness (Levesque et al., 2013; Usher, 2015). Therefore, assessing park attractiveness should involve multiple factors beyond size and quality (He et al., 2022; Sundevall and Jansson, 2020), emphasizing on factors related to inclusiveness, particularly those relevant to the local context (Liang and Zhang, 2018). For instance, previous studies have shown that park entry fees in developing countries act as a barrier for low-income groups, significantly impacting their park visits (Basu and Nagendra, 2021; Lal et al., 2017; Pinelo Silva, 2021). The availability of urban parks during nighttime is another major concern for park visitors (Shan, 2020), since park visits tend to peak in the afternoon and continue until midnight (Ullah et al., 2019; Zhang & Dong, 2016). Parks that close at night may fail to provide ecosystem services to low-income groups, who often have less recreational time during daytime on weekdays compared to their wealthier counterparts. Consequently, park inclusiveness, which can be assessed by examining affordability and availability, becomes a crucial determinant of park visits.

Against this backdrop, this study will measure how the incorporation of various park attractiveness factors (e.g., affordability and availability) influences the evaluation results of urban park accessibility.

2.3 Multimodal impedance function

The impedance function represents the cost of overcoming spatial separation between origin and destination points in a gravity model. The choice of impedance function and the variables included can significantly affect the results of accessibility measurements (Kwan, 1998; Tahmasbi and Haghshenas, 2019). Various forms of impedance functions exist, such as (inverse) power (Chang et al., 2019; Park et al., 2021; Xu et al., 2015), exponential (Grengs, 2015; Karner, 2018), and Gaussian (Liang et al., 2023; Xing et al., 2020), as well as combinations of these functions (Vale and Pereira, 2017; Xu et al., 2015). The inverse power function, defined in Equation 3, is one of the most common forms (Chang et al., 2019; Guagliardo, 2004; Tahmasbi and Haghshenas, 2019).

$f(c_{ij}) = c_{ij}^{-\gamma}$; (3)

where γ is the travel friction coefficient, and c_{ij} denotes the generalized cost.

The parameter γ is crucial in determining the rate at which attraction attenuates with distance (Kwan, 1998; Talen, 1998). Although the value of γ may vary based on research scope, target populations, and service types, previous research has shown that different values of the parameter and even varying impedance function forms may yield similar spatial patterns in terms of identifying locations with high and low accessibility levels (Vale and Pereira, 2017).

In an impedance function, generalized costs are commonly expressed in terms of travel distance

(Talen and Anselin, 1998; Wu et al., 2017; Yu et al., 2019), travel time (Chang et al., 2019; Liang and Zhang, 2018; Park et al., 2021), and monetary cost (Bills et al., 2022; El-Geneidy et al., 2016; Li et al., 2023). Among them, travel time is widely acknowledged as a more accurate measure of generalized cost in park accessibility studies, as it better aligns with people's perceptions (Chang et al., 2019; Park et al., 2021; Vale and Pereira, 2017). Existing literature typically assumes that all residents use their designated mode of transport to access parks, whether it be driving, walking, or public transport (Liang et al., 2023; Semenzato et al., 2023; Wang et al., 2020; Xing et al., 2020; Xu et al., 2015), with driving being a common mode of transport at the regional level (Dai, 2011; Gu et al., 2017; Kong et al., 2007). However, in dense urban areas, residents often use alternative modes of transport, including walking, cycling, and public transportation. To more accurately represent travel costs, it is necessary to develop an impedance function that considers multiple travel modes based on a mode choice model. The *logsum* mode choice model is the most commonly used model and can be expressed in Equation 4 (Khan et al., 2022; Limanond and Niemeier, 2003; Zhou et al., 2023) as:

$$P_{ijk} = \frac{e^{\beta_{ijk}\boldsymbol{X_{ijk}}}}{\sum_{r=1}^{R} e^{\beta_{ijr}\boldsymbol{X_{ijr}}}} \quad (4)$$

where P_{ijk} is the probability of choosing travel mode k from population point i to destination j; β_{ijk} is the coefficient vector of observed variables; $\boldsymbol{X}_{ijk}$ is a column vector of the observed attributes of mode k; and R is the total number of travel mode alternatives.

This study will measure and compare the effects of incorporating or excluding multiple travel modes in the impedance function of a gravity model, aiming to provide a more comprehensive understanding of park accessibility.

3. Study area, data, and method

3.1 Study area

This study uses Shanghai as a study case. In line with the local initiative to develop a “park city”, numerous parks have been constructed in Shanghai. According to data from the Shanghai Administration Department of Afforestation and City Appearance (https://sh.lhsr.cn/), the number of public parks increased from 161 in 2014 to 406 in 2021. However, despite this overall growth, disparities in the distribution of park services persist across the metropolitan region (Fan et al., 2017; Liang and Zhang, 2018; Ullah et al., 2019).

The zonal boundaries in our study align with the sub-district demarcations in Shanghai, namely *jiedao*, *xiang*, and *zhen*, totaling 233 zones. This alignment ensures compliance with planning regulations and facilitates comprehensive policy analysis. Each zone is represented by a transport centroid node, which signifies the location where people and economic activities tend to cluster. Due to the substantial variance in the sizes of central and suburban zones (refer to **Table S1** in **Supplementary Materials 1**), our methodology for centroid determination varies based on the urban context. In fully developed city centers, we use the geometric centroids as the representative nodes, while for partially developed areas, we use the locations of local governments as zonal centroids (Yang et al., 2019). Building on the research by Yang et al. (2019) and Yang (2020), we define six macro-zones in the city region: the inner ring, middle ring, outer ring, near suburbs, new towns, and far suburbs. The first three macro-zones constitute the city center, while the latter three are classified as suburbs. **Fig. 1** illustrates the zonal divisions in Shanghai and the distribution of urban parks.

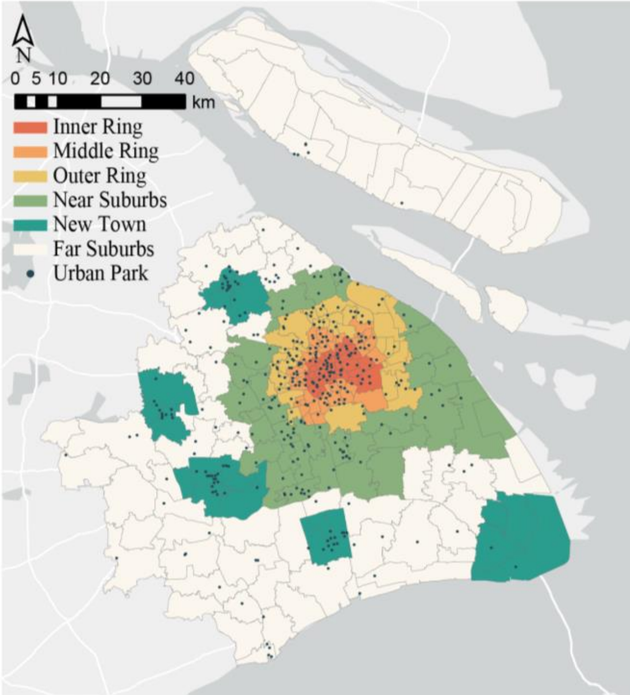

Fig. 1. Zonal divisions in Shanghai and the distribution of urban parks.

3.2 Data sources and processing

We evaluate local accessibility by employing data on park information, population, and travel time. Park data were sourced from the Shanghai Landscaping and City Appearance Administrative Bureau (http://lhsr.sh.gov.cn/), which provides comprehensive details on each park's location, size, star rating, and entrance fees. The five-star rating system (ranging from 1 to 5, with 5 representing the highest quality) has been widely accepted as a comprehensive means of evaluating park attractiveness in the local context. This system considers factors such as park classification, area, facilities, security, services, landscape, scenery, maintenance, and management (Liang et al., 2023; Liang and Zhang, 2021, 2018).

Population data at the sub-district level were obtained from the 2015 1% population sample survey, the latest year with zonal-level population data available. **Table S2** in **Supplementary Materials 1** presents the descriptive statistics for population data in each sub-district and the attributes of public parks.

We obtained travel time data between residences (represented by geometric centroids of sub-districts) and parks (represented by points of interest) using the Application Programming Interface (API) provided by Gaode Maps, one of China's largest map services companies.[1] While we acknowledge the limitation of utilizing centroids to represent relatively large sub-districts, it is currently the finest resolution available with population data in Shanghai, and we follow similar approaches employed by Ouyang et al. (2020) and Shen et al. (2017). The API used in this study provides actual travel time, distance, and cost, accounting for traffic conditions and flows of various modes of transportation, such as walking, cycling, driving, and public transport (including subways, buses, and ferries). We set the departure time from residences to parks at 3 p.m. for both a weekday (9 July 2023) and a weekend (10 July 2023). This choice is based on the observation that park visits in Shanghai typically peak between 3 p.m. and 5 p.m. (Ullah et al., 2019). We employ the mean of the travel times from both the weekday and the weekend to minimize the potential impact of fluctuations in traffic conditions, thus facilitating a more generalized representation. However, it should be noted that the use of two time periods may not fully capture temporal variations in accessibility, which is one of the limitations of this study.

3.3 Method

3.3.1 Semi-structured interviews

Evaluating the accessibility of urban parks necessitates an understanding of local residents'

[1] For a comprehensive, step-by-step guide regarding the collection of data related to travel distance, time, and costs, please refer to Supplementary Materials 2.

preferences regarding factors that contribute to park attractiveness. For this purpose, we conducted semi-structured interviews with randomly selected local residents during the week of 12–18 April 2021. Semi-structured interviews are qualitative research techniques that involve a flexible set of open-ended questions, allowing for a more conversational and exploratory approach to gathering information from participants (Bryman, 2006). This method is frequently employed in qualitative park accessibility research, as it enables researchers to gain in-depth insights into individuals' preferences and priorities for parks (Pearsall and Eller, 2020; Talal and Santelmann, 2021; Wright Wendel et al., 2012).

To ensure comprehensive representation of various sociodemographic backgrounds, we conducted interviews in neighborhoods adjacent to the top ten busiest subway stations as ranked by the Shanghai Municipal Transportation Commission. We recorded 100 valid interviews and used thematic analysis—a qualitative data analysis method that involves reviewing a set of data to identify patterns and themes in the meaning of the data—to extract and summarize the data (Matthews et al., 2015; Meerow and Keith, 2021). **Supplementary Material 3** summarizes the locations and the number of interviews held in each neighborhood and the representativeness of the interviewees, judging by their age and gender distributions. All interviews lasted over 30 minutes, with some extending to 45 minutes.

The semi-structured interviews are centered around the following questions, with room for follow-up questions and probes: (1) How often do you visit urban public parks? (2) What do you like or dislike about parks in general? (3) To what extent does the entrance fee impact your decision to visit urban public parks? If it does, why and what price would you consider to be excessively high? (4)

Do you consider whether a park is open at night before visiting? If so, what are the reasons behind your decision? (5) If you were asked to allocate points to describe the relative importance of the entrance fee and opening hours in attracting you to an urban public park, how many points would you give (with 8 points awarded for an emphasis on entrance fee, and -8 points awarded for an emphasis on opening hours? What are your rationales for assigning the points?

Our findings revealed the following five attributes of parks that visitors found most appealing, listed in order of frequency of mention: (high quality) environmental aesthetics (mentioned 82 times), (sufficient) sports space (mentioned 72 times), social environment (mentioned 68 times), (short) travel distance (mentioned 60 times), and supporting facilities (mentioned 48 times). By contrast, the five factors that most commonly deterred people from visiting parks, listed in order of frequency of mention, were: (long) travel distance (mentioned 66 times), (short) opening hours (mentioned 59 times), crowds (mentioned 48 times), entrance fees (mentioned 40 times), and lack of sports spaces (mentioned 34 times). These findings validate that the quality and size of a park, which were the focus of previous research, are key factors in influencing the attractiveness of urban public parks. Moreover, our findings highlight that affordability (termed as entrance fees) and availability (termed as opening hours), are also crucial factors in determining park attractiveness in Shanghai. Thus, we propose the inclusiveness index to measure affordability and availability, given their mutual significance in promoting inclusivity and addressing the needs of marginalized populations who may not have the financial means or leisure time of more affluent groups (Ezbakhe et al., 2019; Lal et al., 2017; Shan, 2020). The introduction of the inclusiveness index echoes discussions about the impacts of affordability and availability on urban park attractiveness (see Section 2.1).

Our interviews revealed that 78% of respondents considered entrance fees when deciding whether to visit parks, with 54% stating that an entrance fee of over 20 Chinese yuan/RMB[2] would discourage them from visiting. Furthermore, 72% of interviewees reported that they would consider a park's opening hours. Therefore, we developed a method to measure inclusiveness (Table 1), with maximum values assigned to each factor based on its relative importance according to the interviews (with a mean value of 1.54 for the relative importance of entrance fee over opening hours). As an example, Gongqing Forest Park charges 15 Chinese yuan/RMB for an entrance ticket and is closed from 5 p.m. to 8 a.m.; hence, its inclusiveness score was 3 based on our methodology.

Table 1. Measurements of inclusiveness of Shanghai parks based on semi-structured interviews.

Factor	Description	Value
Entrance fee (EF)	free	3
	≤20 yuan	2
	> 20 yuan	1
Opening period (OP)	open at night	2
	close at night	1

3.3.2 Park accessibility measurement

This study aims to refine the gravity model by incorporating locally-informed attractiveness factors and considering multiple travel modes when assessing park accessibility. To evaluate the effectiveness of these improvements, three models are proposed for comparison. Model 1 (Equation 5) is based on previous literature and considers only park size and quality as attractiveness factors. Model 2 (Equation 6) incorporates context-specific attractiveness factors derived from on-site interviews in Shanghai, accounting for size, quality, and inclusiveness simultaneously (see Section 3.3.1). Both Model 1 and Model 2 use driving time as a proxy for travel impedance.

[2] 1 RMB ≈ 0.14 USD

Building on Model 2, we examine the impact of transport mode on accessibility measurements by proposing Model 3 (Equation 7), which encompass multiple travel modes, including walking, cycling, public transport (e.g., buses, subways, and ferries), and driving. Model 3 integrates the multinomial logistic mode choice model to determine the share of each travel mode (Baradaran and Ramjerdi, 2011; Guagliardo, 2004; Luo and Qi, 2009) and calculate the weighted travel time to each park for accessibility measurements.

Model 1: $A_i = \sum_{j=1}^{n} \frac{S_j * Q_j}{T_{ij}^{\gamma} * V_j}$; $V_j = \sum_{i=1}^{m} \frac{P_i}{DT_{ij}^{\gamma}}$ (5)

Model 2: $A_i = \sum_{j=1}^{n} \frac{S_j * Q_j * I_j}{T_{ij}^{\gamma} * V_j}$; $V_j = \sum_{i=1}^{m} \frac{P_i}{DT_{ij}^{\gamma}}$ (6)

Model 3: $A_i = \sum_{j=1}^{n} \frac{S_j * Q_j * I_j}{\sum_{k=1}^{4} (P_{ijk} * T_{ijk}) * V_j}$; $V_j = \sum_{i=1}^{m} \frac{P_i}{\sum_{k=1}^{4} (P_{ijk} * T_{ijk})}$; $P_{ijk} = \frac{e^{\beta_T * T_{ijk} + \beta_C * C_{ijk}}}{\sum_{r=1}^{4} e^{\beta_T * T_{ijr} + \beta_C * C_{ijk}}}$ (7)

where S_j refers to the acreage of park j; Q_j denotes the quality index of park j, measured using a park's star-rating in this study; I_j represents the inclusiveness of park j; T_{ij} measures the travel time from i to j; P_{ijk} is the probability of using mode k when traveling from i to j; β_T refers to the coefficient of travel time from i to j; T_{ijk} is the travel time of using mode k; β_C signifies the coefficient of travel cost from i to j; and C_{ijk} is the travel cost associated with using mode k.

The *logsum* model can incorporate various variables, such as sociodemographic factors and specific variables related to different transportation modes (Huang et al., 2022; Macfarlane et al., 2021). However, due to data availability limitations, this study only considers travel time and travel cost. As utility-based parameter calibration is unfeasible with the available data, we follow Wang et al. (2022) in adopting β_T and β_C values of -0.0413 and to -0.0765, respectively, in the context of

Shanghai. Travel time is measured in minutes, while the travel cost for driving is expressed as the corresponding taxi fare. Public transport cost is determined in accordance with the prevailing policy in Shanghai, which sets the fare at 2 RMB for trips within 6 kilometers and increases by 1 RMB for every additional 10 kilometers of travel distance (Shanghai Municipal Development & Reform Commission, 2022). Cycling and walking travel costs are considered as 0. In addition, in the absence of empirical investigation, we adopt a value of γ of 1 following studies by Park et al. (2021), Semenzato et al. (2023), Yang et al. (2023), Yao et al. (2013), and Zhu et al. (2018). Future research may perform sensitivity analyses to validate the chosen values.

3.3.3 Comparisons of different models

To standardize the accessibility results for comparison purposes, we employed the linear form of the global value function (Equation 8) to normalize the raw data into a scale ranging from 0 to 1 (Dony et al., 2015; Yang et al., 2023).

$$NA_i = \frac{A_i - A_{min}}{A_{max} - A_{min}} \quad (8)$$

where NA_i is the normalized accessibility of zone i, while A_{max} and A_{min} denote the maximum and minimum values, respectively, of accessibility observed across all zones within the study area.

We then employed a t-test to investigate the disparities across macro-zones. Furthermore, the spatial and statistical variances of the normalized accessibility results were compared across the different models. We also included spatial statistics for local indicators of spatial autocorrelation (LISA) to further identify the spatial clustering of accessibility distribution (Anselin, 1995). The LISA values were derived based on local Moran's I using inverse Euclidean distance.

4. Results

4.1 Model comparison at the macro-zonal level

Table 2 presents the normalized accessibility values derived from the three distinct models. A comparative analysis between Model 1 and Model 2 demonstrates the influence of integrating the inclusiveness factor into the gravity model. While both models generally yield similar outcomes, Model 2 exhibits higher accessibility within the macro zones located in city centers. In addition, Model 2 demonstrates a slightly larger accessibility variance at the city scale (0.22) compared to Model 1 (0.21).

Further comparisons between Model 2 and Model 3 highlight the effects of incorporating the multimodal choice model into the gravity model. Overall, Model 3 produces lower accessibility values compared to Model 2. However, it yields higher accessibility within the inner ring and larger disparities between the city center and suburbs. Notably, Model 3 reveals a greater variance (0.25) in accessibility levels when compared to Model 2.

Table 2. Descriptive statistics of normalized accessibility.

Model	Zonal category	#Obs	Mean (95% CI)	Std.Dev	Min	Max
Model 1						
	Center	**106**	**0.78 (0.77,0.79)**	**0.07**	**0.61**	**1.00**
	Inner Ring	37	0.78 (0.77,0.80)	0.05	0.69	0.89
	Middle Ring	37	0.80 (0.78,0.82)	0.06	0.64	0.90
	Outer Ring	32	0.76 (0.73,0.79)	0.09	0.61	1.00
	Suburbs	**126**	**0.47 (0.44,0.51)**	**0.19**	**0.00**	**0.88**
	Near suburbs	33	0.66 (0.62,0.69)	0.11	0.44	0.88
	New Town	24	0.54 (0.49,0.59)	0.13	0.27	0.76
	Far Suburbs	70	0.37 (0.33,0.41)	0.17	0.00	0.71

	Overall	**233**	**0.62 (0.59,0.64)**	**0.21**	**0.00**	**1.00**
Model 2						
	Center	**106**	**0.80 (0.79,0.81)**	**0.07**	**0.61**	**1.00**
	Inner Ring	37	0.81 (0.79,0.82)	0.05	0.71	0.92
	Middle Ring	37	0.82 (0.80,0.84)	0.06	0.64	0.93
	Outer Ring	32	0.77 (0.74,0.80)	0.09	0.61	1.00
	Suburbs	**126**	**0.47 (0.44,0.51)**	**0.19**	**0.00**	**0.90**
	Near suburbs	33	0.66 (0.62,0.70)	0.11	0.43	0.90
	New Town	24	0.53 (0.48,0.59)	0.13	0.27	0.76
	Far Suburbs	70	0.37 (0.33,0.40)	0.17	0.00	0.71
	Overall	**233**	**0.62 (0.59,0.65)**	**0.22**	**0.00**	**1.00**
Model 3						
	Center	**106**	**0.79 (0.77,0.81)**	**0.10**	**0.50**	**1.00**
	Inner Ring	37	0.88 (0.85,0.90)	0.07	0.74	1.00
	Middle Ring	37	0.80 (0.78,0.82)	0.07	0.78	0.82
	Outer Ring	32	0.69 (0.66,0.72)	0.08	0.50	0.82
	Suburbs	**126**	**0.40 (0.37,0.43)**	**0.18**	**0.00**	**0.88**
	Near suburbs	33	0.58 (0.54,0.63)	0.12	0.32	0.88
	New Town	24	0.45 (0.41,0.49)	0.10	0.25	0.65
	Far Suburbs	70	0.30 (0.26,0.34)	0.16	0.00	0.73
	Overall	**233**	**0.58 (0.55,0.61)**	**0.25**	**0.00**	**1.00**

Although the findings of all three models exhibit consistent patterns, indicating a decrease in accessibility from city centers to suburbs, a more detailed analysis at the macro-zonal level reveals nuanced disparities among the models (**Fig. 2**).

When compared to Model 1, both Model 2 and Model 3 reveal larger disparities among the macro zones. Model 3 consistently exhibits the largest accessibility variances among the macro zones, except for the difference between the new town and far suburbs. Substantial disparities are also highlighted by Model 3 between the macro zones in the city center and those in the suburbs.

For accessibility level with the city center (i.e., the inner ring, middle ring, and outer ring), Model 1 does not identify statistically significant differences in park accessibility between zones. In contrast, Model 2 reveals significant disparities between the middle ring and outer ring zones, while still indicating insignificant differences between the inner ring and middle ring, as well as the inner ring and outer ring. Model 3, on the other hand, reveals statistically significant disparities between each pair of macro zones within the urban center, due to the co-determinants of park inclusiveness and multimodal transport accessibility.

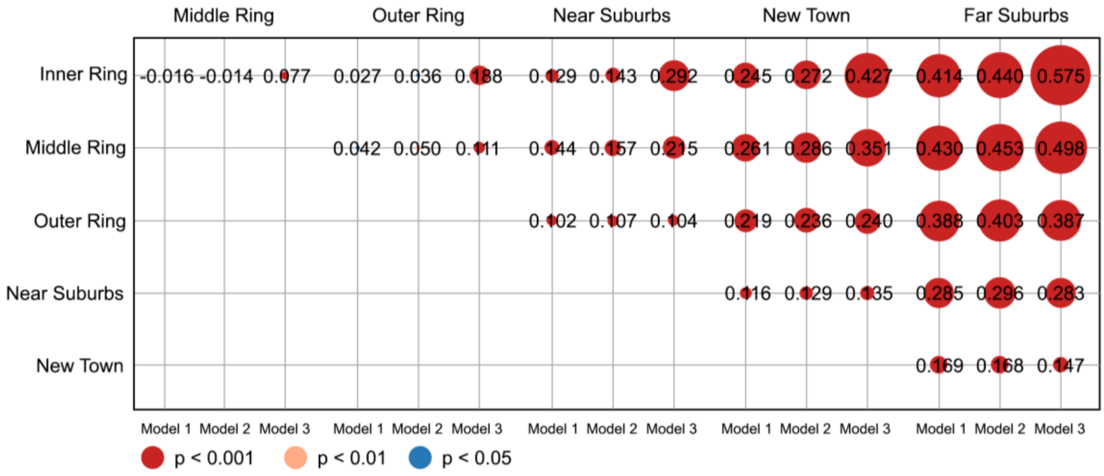

Fig. 2 Zonal differences of park accessibility.

4.2 Model comparison at the subdistrict level

Fig. 3 displays the normalized accessibility values and LISA statistics for sub-districts. The accessibility value maps derived from the three models exhibit similar spatial distribution patterns; high-high clusters are predominantly concentrated in the urban core, while low-low clusters are dispersed towards the city's outer periphery with similar coverage.

Nevertheless, the comparisons drawn between Models 1 to 3 suggest that the assumption of homogeneity regarding park inclusiveness and travel mode can lead to the overestimation of park accessibility, particularly in the inner ring area, near suburbs and new towns. Compared to Model 1 and Model 2, Model 3 display a more pronounced concentration of high-high clusters towards the city center, with central zones generally displaying higher accessibility values. In addition, Model 3 captures more localized accessibility differences, with additional low-high clusters identified in near suburbs and high-low clusters emerging in and around new towns.

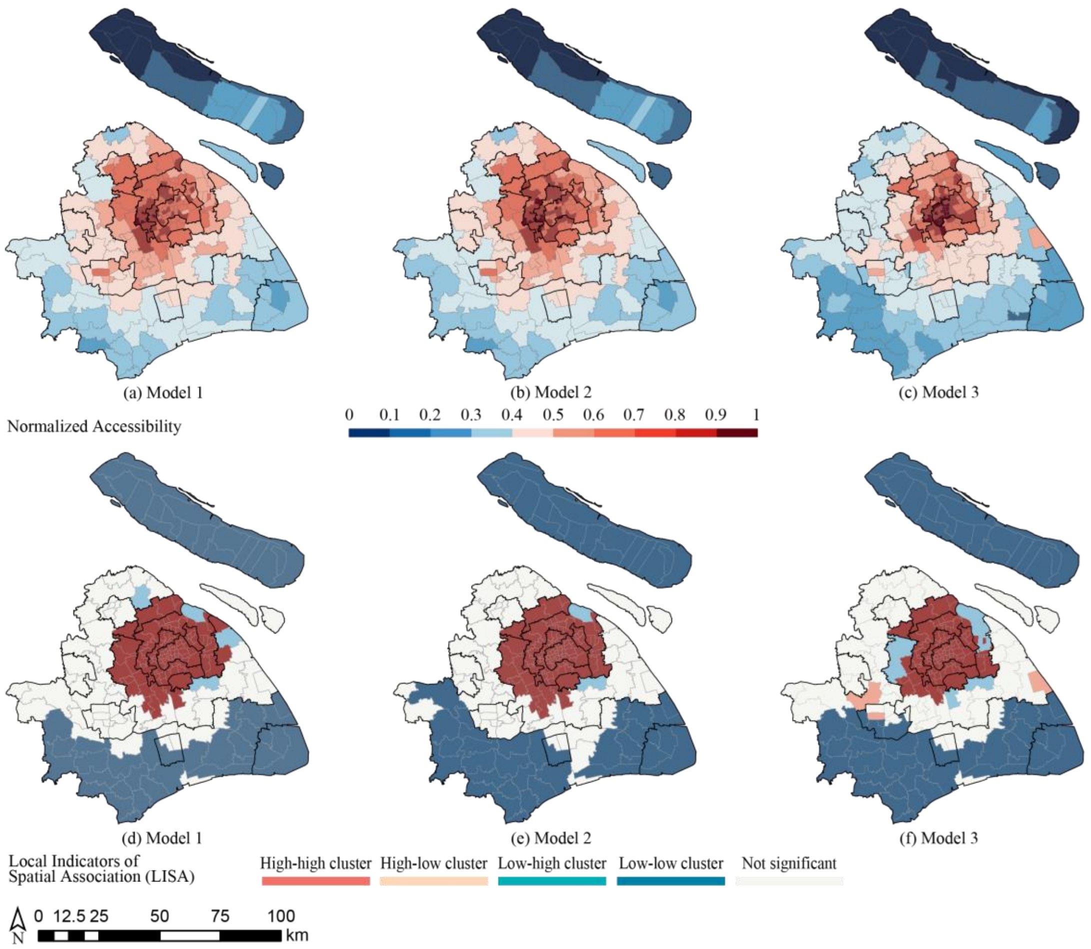

Fig. 3 Spatial distribution of normalized accessibility values and LISA statistics across three models

The bivariate correlation analysis further corroborates the LISA-related findings (**Fig. 4**). The zonal-level accessibility values share similar patterns between Model 1 and Model 2, while the incorporation of park inclusiveness (Model 2) yields higher park accessibility levels for zones in the city center. The consideration of multi-mode transport (Model 3) enlarges the accessibility gaps not only across but also within subdistricts. While the overall results derived from Model 2 and Model 3 exhibit a strong correlation (r = 0.94), a closer examination of the results in the inner ring (r = 0.55) and middle ring (r = 0.59) reveals considerable variance.

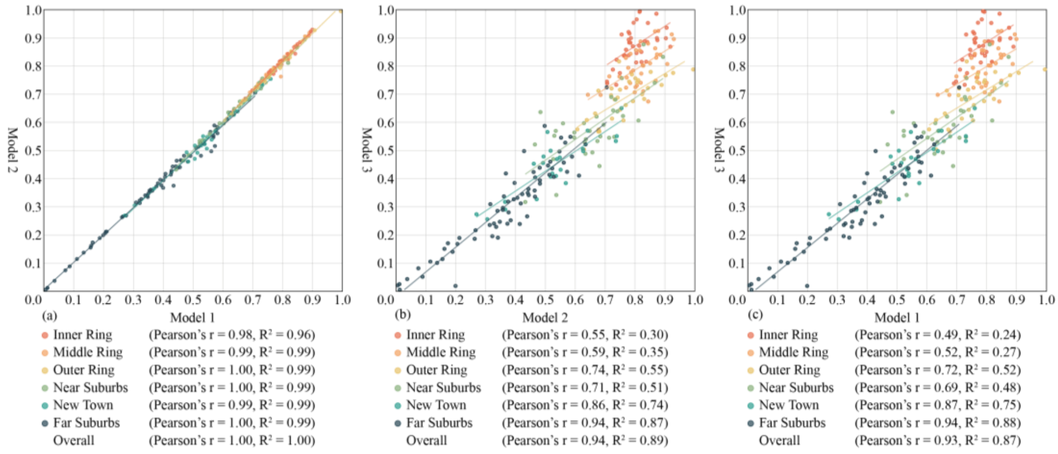

Fig. 4 Bivariate correlation of accessibility obtained from three models.

The accessibility results obtained from the different models exhibit nuanced variations, necessitating further investigation and comparison. **Fig. 5a** highlights a noticeable disparity in accessibility between Model 1 and Model 2. The inclusion of the inclusiveness index leads to a slight increase in accessibility for subdistricts in Shanghai, while this increase is not consistent across all subdistricts. Specifically, the majority of subdistricts in the inner ring and middle ring, with only one outlier, experience higher accessibility in Model 2 compared to Model 1; the longer operation hours and higher quality of parks in the city center are well represented in Model 2. Conversely, new towns and far suburbs witness a decrease in park accessibility in Model 2, reflecting a larger variance in park inclusiveness between the city center and suburbs.

The incorporation of the multimodal transport choices into the gravity model also has notable effects on the accessibility results **(Fig. 5b)**. Compared to Model 2, subdistricts in the inner ring demonstrate significantly higher accessibility in Model 3 due to the well-connected public transport systems therein. However, with the distance to the city core, Model 3 displays a sharper decrease in accessibility levels. Notably, new towns are found to have the most significant drop in park accessibility levels in Model 3, attributing to the underestimation of travel frictions based on car-only mode in Model 2.

Incorporating both the inclusiveness factor and the multimodal choice model leads to more nuanced changes in the measurement of accessibility. Although the accessibility derived from Model 3 and Model 1 generally exhibits a strong correlation (r = 0.93), the correlation between accessibility results of subdistricts in the inner ring (r = 0.49), middle ring (r = 0.52), and near suburbs (r = 0.69) is lower compared to those located in other macro-zones (see **Fig. 4c**). **Fig. 5c** illustrates the changes in accessibility when comparing Model 3 to Model 1. The accessibility evaluation results tend to be similar between Model 1 and Model 3 in the middle ring area due to the off-set effects of attractiveness enhancement by incorporating park inclusiveness and travel friction growth by adding multi-mode transport options. The overall results indicate larger disparities in park accessibility between subdistricts in the city center and suburbs.

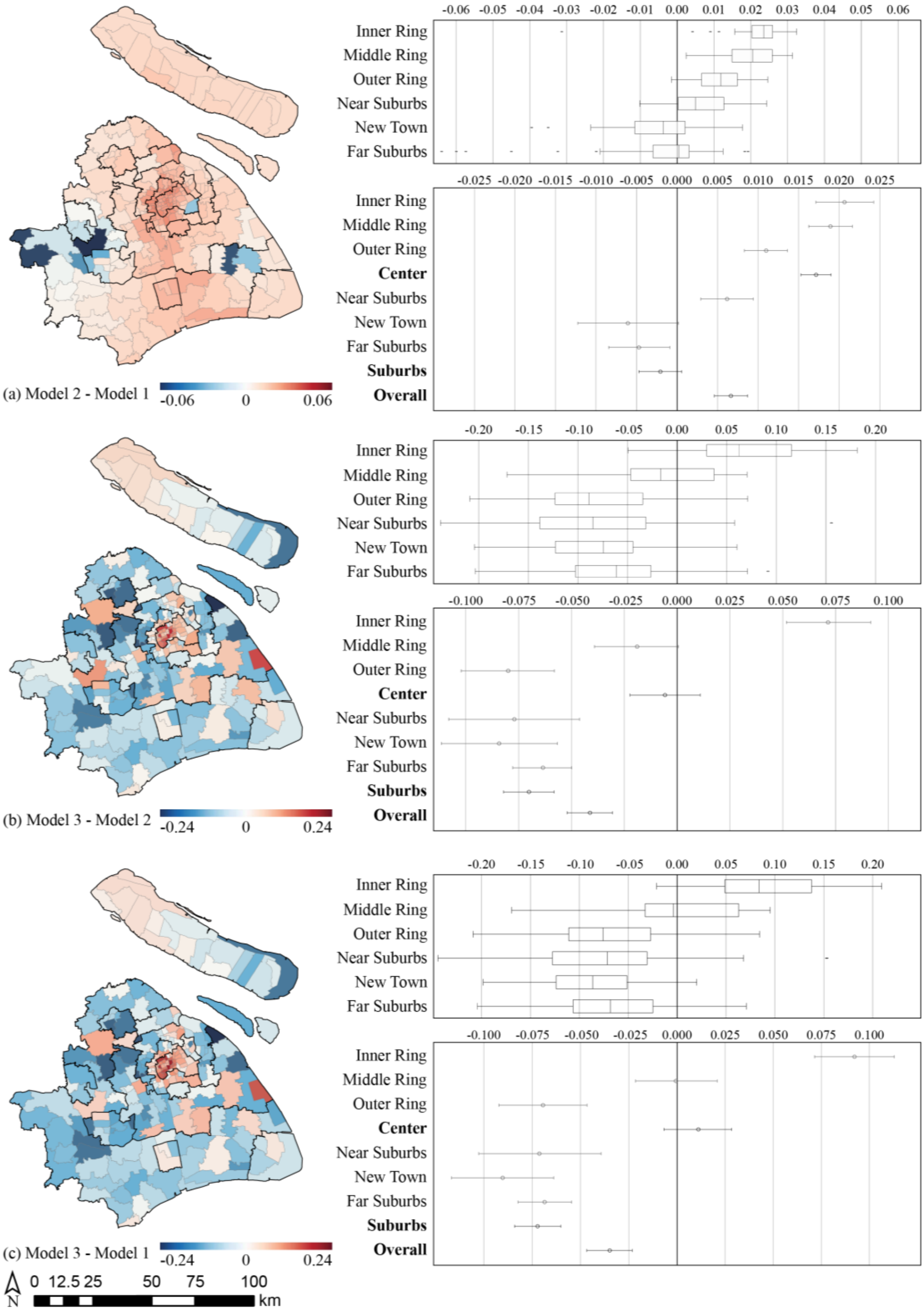

Fig. 5 Accessibility value change across three models, and distribution and mean of the change by macro-zone.

5. Discussion and Conclusions

This study emphasizes the importance of incorporating context-specific attractiveness factors and localized transport modal choices into a gravity model for evaluating park accessibility. By using localized attractiveness factors (e.g., size, quality, and inclusiveness) and travel modes (i.e., multimodal choice) based on local residents' perceptions and travel habits, the improved model can better address potential biases in park accessibility evaluations.

We introduced an inclusiveness index that considers park entrance fees and opening hours, weighted according to the results of the semi-structured interviews conducted in Shanghai, into the calculation of the attractiveness coefficient. Our findings show that a detailed representation of park attractiveness from a local perspective reveals larger accessibility gaps between central and suburban areas, with suburban areas generally performing worse in park inclusiveness (e.g., having more expensive entrance fees). This discrepancy could be attributed to the lower levels of public funding that suburban parks receive compared to parks in central locations, causing them to depend more heavily on entrance fees to cover maintenance costs (Wolch et al., 2014). Moreover, land use dynamics in suburban areas might favor residential or commercial development over public spaces, leading to a diminished allocation of resources for parks (Jackson, 1985).

Regarding travel modes, our results suggest that focusing solely on motorized travel time may produce imprecise results across a city region, particularly one with well-connected and affordable public transport systems. The consideration of multiple transport modes reveals more pronounced differences in accessibility levels. In the case of Shanghai, the improved model better captures the unevenness in park accessibility caused by available modal choices, particularly in the inner ring area and new towns.

In summary, the improved gravity model produces lower and more variable accessibility levels than the conventional model, revealing a greater accessibility gap between the city center and suburbs, as well as within these areas themselves. Accurately assessing accessibility levels and variations is crucial for urban planning, particularly for ensuring a spatially equitable distribution of public park services. The empirical evidence from this study can inform policy-making in park planning and maintenance in several ways. First, a comprehensive understanding of park attractiveness factors and transport modal choices is vital for ensuring accurate accessibility measurements in planning. Isolated considerations of these factors can lead to biased evaluation results, limiting the effectiveness of the planning interventions. Second, localized planning interventions should be designed and implemented to improve park accessibility. For Shanghai, this may involve reducing park entrance fees in suburban areas, adjusting night-closure management policies in new towns' parks, and improving transit connections between the center and suburbs to bridge accessibility gaps.

While this study provides a more accurate representation of park accessibility by incorporating locally-informed, accessibility-related factors, several limitations should be acknowledged, along with suggestions for future research. First, the limited availability of data constrains the study's ability to conduct more comprehensive sensitivity tests. For instance, other factors such as park safety, service facilities, and the built environment can impact park attractiveness (Liu et al., 2021; Rigolon and Németh, 2018), while heterogeneity also exists in people's park visit and travel preferences. Future research could compare the weights of universally-adopted and local-context-informed attractiveness factors, as well as calibrate multimodal travel choice models based on travel surveys with socio-economic information (Huang et al., 2022; Wang et al., 2022). The optimal spatial units for analysis can be also explored when datasets across different spatial scales become available. Due to data availability, our study relied on subdistrict level data, which is the most detailed jurisdictional dataset we had access to. As a result, we were unable to control the size of the zones in this study. Future research seeking to delve deeper into these issues would benefit from the use of higher-resolution data, which would allow for a more precise understanding of the dynamics within each zone. Second, we selected afternoons on two days as the time periods for measuring travel time, which may not fully capture the temporal variations in accessibility. Future studies could validate the results using different time periods to analyze the temporal dynamics of accessibility more accurately. Third, although the semi-structured interviews facilitated an in-depth understanding of local residents' park visit preferences, the sample size of 100 respondents is relatively small. Future research could consider expanding the sample size and utilizing big data (e.g., location-based movement trajectories) to enhance the analysis. Comparative studies are also encouraged to explore the extent to which the localized selection of attractiveness factors and travel modes matter in cities with various socio-economic contexts. The comparison will allow for both generalizable and context-specific planning implications for improving park accessibility.

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