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Exploring environmental equity and visitation disparities in *peri*-urban parks: A mobile phone data-driven analysis in Tokyo

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HIGHLIGHTS

- Conducts an assessment of inequity for Tokyo's *peri*-urban park.
- Leverages mobile-driven indicators for nuanced insights into park usage, complemented by Gaussian-based 2SFCA accessibility indicators for a more holistic view.
- Emphasizes the importance of actual visitation indicators in uncovering inequity in park accessibility.
- Identifies four distinct visitor groups, revealing visitor disparities in *peri*-urban park usage.

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ABSTRACT

Peri-urban parks play a crucial role in enhancing urban living conditions and promoting contact with nature. However, assessing environmental equity and visitor disparities in *peri*-urban parks requires a thorough understanding of visitation patterns, which has been lacking in previous research. To bridge the gap, this study utilizes mobile phone big data from over 40,000 visitors to *peri*-urban parks in Tokyo. We applied Local Moran's I, Lorenz Curve, Gini coefficient, and K-means clustering methods to scrutinize accessibility and disparities among residents of Tokyo's 23 special wards and within distinct visitor groups. The findings reveal significant insights: Firstly, mobile-based indicators expose disparities, underscoring the relevance of human activities in assessing *peri*-urban park accessibility, variations in these indicators highlight the need for a multi-dimensional approach. Secondly, Gini coefficient analysis of mobile-based and two-step floating catchment area (2SFCA) indicators suggest that extending the service radius beyond 10 km could mitigate environmental inequity. Furthermore, visitation disparities are more distinctly illustrated through mobile-derived visitor subgroups compared to age-demographic groups. These findings offer valuable insights for decision-makers in park planning policy, enabling the development of strategies that address accessibility inequity while establishing effective classifications for *peri*-urban park visitor groups.

1. Introduction

Recent research recognizes the crucial role of *peri*-urban parks in providing a wide range of environmental and health benefits (Wolch et al., 2014). Peri-urban parks, different from regional parks, are defined as expansive recreational open spaces on urban outskirts (Murray, 2021), offering unique benefits not typically seen in their urban counterparts. Their large size, diverse natural landscapes, and cultural heritage attributes (Zhang et al., 2021b) contribute to improved air quality, noise pollution mitigation, recreational opportunities, and enhanced biodiversity (Njoh, 2020). Moreover, these characteristics encourage urban and *peri*-urban residents to surmount temporal barriers, thereby promoting equity in accessing these spaces (Zhang et al., 2021a). Nevertheless, access to such green spaces tends to be inequitable across different regions and demographics globally, presenting a challenge that urban planners and policy makers must address (Rigolon, 2016; Wolch et al., 2014).

The advent of mobile phone big data and gravity-based accessibility models has broadened the scope of environmental equity research in urban parks (Lin et al., 2021; Ren et al., 2022; Wang et al., 2022; Xu

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et al., 2021). While distance thresholds and population indicators have been employed to gauge park accessibility (Chen et al., 2020b; Guo et al., 2019; Li et al, 2019), the role of human activities on environmental equity and visitation disparities within *peri*-urban parks remains insufficiently explored. Prior studies have predominantly assessed environmental inequity through demographic factors (Rossi et al., 2015), often neglecting actual park usage patterns. Moreover, recreational behavior significantly influences visitor propensity to travel to and dwell within *peri*-urban parks (Pickering & Rossi, 2016; Zhang et al., 2021b), thereby shaping usage patterns. Yet, research on visitor groups and potential disparities among them in *peri*-urban parks remains sparse.

This research aims to deepen our understanding of *peri*-urban park accessibility and visitation behaviors use a case study of Tokyo. The primary objective is to assess the implications of such behaviors on environmental equity and visitation disparities. We seek to uncover whether established methods, such as gravity-based models, fully capture the complexity of park accessibility, or if alternative methods derived from mobile usage data can offer additional insights. Additionally, our analysis will identify visitation disparities among distinct visitor groups and age demographics, potentially rooted in nuanced visitor behaviors. The ultimate goal of this research is to equip policymakers and urban planners with valuable insights for the enhanced development and management of *peri*-urban parks.

The paper is structured as follows: Section 2 provides an overview of previous research on *peri*-urban park accessibility and equity, focusing on the application of mobile phone data. Section 3 describes the data and empirical methods employed. Section 4 presents a case study in Tokyo. Section 5 discusses the implications of our findings for urban park policy making, while also acknowledging the limitations. Finally, section 6 summarizes the key contributions of the paper.

2. Literature review

2.1. Assessing peri-urban park accessibility

Unequal access to and exposure within urban green spaces are increasingly recognized as a critical issue, with profound impacts on public health and quality of life (Wolch et al., 2014; Wu et al., 2022a). While substantial research has addressed accessibility to *peri*-urban parks in medium-sized cities, including Nanjing, China, Ljubljana, Slovenia, and Edinburgh, Scotland (Zhang et al., 2021b; Žlender & Thompson, 2017), the specific patterns of use and accessibility in densely populated metropolis remain less understood. Recognizing the importance of these areas as crucial green spaces, particularly where urban parks may be scarce or overcrowded, is vital. It is essential to understand these dynamics, as the interplay between population density and park accessibility might differ between densely populated metros and medium-sized cities, potentially leading to varying implications for urban planning initiatives.

Gravity-based models, such as the two-step floating catchment area (2SFCA) model, have limitations in fully capturing the nuanced catchment areas of park visitors (Dai, 2011; Li et al., 2021; Wei, 2017). Consequently, recent research has shifted towards utilizing mobility metrics, where mobility pertains to the capacity to move (Levinson & King, 2020). Mobile phone data serves as a crucial source of these metrics, enabling the analysis of accessibility by capturing complex patterns of individuals' movements within their environment (Hu et al., 2020; Monz et al., 2019). The integration of these two models allows for a comprehensive analysis that capitalizes on the strengths of both methods. The 2SFCA provides a solid foundation of spatial accessibility, while mobile phone data add a layer of real-world behaviors and mobility patterns that may not be captured by gravity-based models alone (Lin et al., 2021; Ren and Guan, 2021; Xu et al., 2021; Zhang et al., 2022).

A comprehensive understanding of *peri*-urban park accessibility necessitates a comparison between gravity-based models and mobile phone-derived methods. However, such comparative studies are scarce, resulting in a limited understanding of human activity impact on *peri*-urban park access. Previous studies have primarily focused on urban parks, overlooking *peri*-urban parks at city fringes (Chen et al., 2018, Wu et al., 2022a). This oversight could potentially introduce sampling bias and neglect isolation studies for *peri*-urban parks (Zhang et al., 2011). This study aims to conduct a comprehensive analysis of both global and local accessibility patterns in *peri*-urban parks, thus addressing these research gaps.

2.2. Environmental equity and visitation disparities in peri-urban parks

The focus of environmental equity is on how environmental benefits and burdens are distributed among populations (Deacon, 2020). The examination of environmental equity in *peri*-urban parks has gained significant attention in urban planning and sustainability research (Zhang et al., 2021a). The emergence of mobile phone data has provided new avenues for researching equity in urban parks (Jaung & Carrasco, 2020; Kupfer et al., 2021). Mobile phone data has been employed to assess accessibility for different sociodemographic groups (Guo et al., 2019; Xiao et al., 2019), and identify vulnerabilities to ecological issues (Zhang et al., 2022). Ren and Guan (2021) employed mobile phone data to evaluate the geographic and environmental inequity of urban parks in Shanghai, revealing significant associations between park use and factors such as park size and accessibility, as well as unequal park usage patterns among different socioeconomic groups and neighborhood types.

In the context of *peri*-urban parks, big data has been utilized to investigate equity and visitation disparities (Kim et al., 2023). Studies have shown disparities in green space accessibility between central and *peri*-urban areas, influenced by the spatial restructuring of cities (Chen et al., 2020b; Shores & West, 2010; Žlender & Thompson, 2017). Accessibility to *peri*-urban parks within urban agglomerations has also been examined, leading to the identification of underserved areas (Zhang et al., 2021a). These studies highlight the potential of big data in understanding equity in park access across different demographic groups and areas. While georeferenced data has been increasingly used in studying environmental equity and visitation disparities in *peri*-urban parks, there is a dearth of research specifically focusing on mobile phone-derived visitation behavior data. Nonetheless, studies conducted in other urban areas have demonstrated the potential of mobile phone data in identifying inequities in environmental exposure and mortality (Chen et al., 2022; Tian et al., 2021), underscoring the importance of considering *peri*-urban parks in the discourse of environmental equity within the realm of urban planning research.

Previous studies have examined the relationship between park systems and citywide demographic characteristics using geo-coded household data and census data in several countries, including the United States, Germany, and China (Rigolon et al., 2018; Wüstemann et al., 2017; Zhang et al., 2021a). Demographic factors, particularly age groups, have been commonly employed in *peri*-urban park studies (Pickering & Rossi, 2016; Rossi et al., 2015; Žlender & Thompson, 2017). Recently, the use of mobile phone data to identify park usage patterns through the clustering of visitor behavior has emerged as a novel approach (Rodríguez et al., 2018, Xu et al., 2021). However, specific studies on visitation disparities among *peri*-urban parks visitor subgroups are still scarce. This gap presents an opportunity to closely analyze park usage patterns, revealing variations and utilization beyond demographic factors.

3. Data and methods

3.1. Study area

This study focused on the 23 Special Wards of Tokyo, one of the world's most densely populated metropolitan areas with a population of over 9 million (United Nations, 2019). Spanning a total of 622 km2, the study area permits an intricate examination of the hurdles inherent in ensuring equitable access to *peri*-urban parks in densely populated urban landscapes. For park data collection, we adopted the QuickOSM plugin of the open-source Geographic Information System (GIS) software, QGIS. Parks were classified into six categories, each corresponding to an administrative park category, based on their estimated surface area: pocket parks (<0.03 ha), city block parks (0.05–1 ha), neighborhood parks (1–3 ha), district parks (3–10 ha), comprehensive parks (10–50 ha), and sports parks (15–75 ha) (Setagaya Ward Government, 2016).

Among the park categories identified, comprehensive parks in Tokyo are notable for their large size and variety of recreational offerings, including natural landscapes, sports facilities, walking trails, playgrounds, and picnic areas. After refining our selection to exclude purely man-made spaces such as temples and imperial palaces, and omitting parks located in central Tokyo (Liu et al., 2016), we find a strong resemblance between these parks and the defined concept of *peri*-urban parks (Murray, 2021; Zhang et al., 2021b). This improved alignment following adjustments underscores the potential applicability of Tokyo's approach to comprehensive parks in the development of *peri*-urban parks in other densely populated cities. Fig. 1 illustrates the geographical distribution of the 48 selected *peri*-urban parks in the study area.

3.2. Mobile phone data and population data

The mobile phone data used in this study was provided by ZENRIN DataCom Co., LTD. The dataset, Konzatsu-Tokei (R) Data, consists of anonymized movement data collected from mobile phones with users' consent through applications like "docomo map navi" service provided by NTT DOCOMO, INC. NTT DoCoMo processed the data collectively and statistically to protect the users' privacy. The comprehensive dataset spans the entirety of Japan for the year 2012. It includes a maximum of 288 data points per user within each 24-hour interval, encompassing user ID, datetime, and georeferenced data (latitude, longitude), without any specific identifying information about individuals.

This study utilized population data procured from WorldPop.org. The dataset employed offers granular details about population distribution, disaggregated by age and sex, within 100 m grid resolutions, specifically tailored for Tokyo. The data, derived from reliable sources such as national censuses and surveys, is processed via sophisticated geospatial techniques to yield a high-resolution population surface (WorldPop, 2018). Our research focuses on the age dynamics in *peri*-urban park visitation, informed by previous studies (Rossi et al., 2015), which highlighted age-effect in *peri*-urban park usage. Our study segmented age groups into five distinct categories: children (0–15 years), early working age (16–25 years), prime working age (26–55 years), mature working age (56–65 years), and the elderly (65 + years). This categorization aims to capture the nuanced visitation trends across different life stages, particularly noting the varying park needs of children and the elderly (Conedera et al., 2015).

3.3. Analytic methods

Fig. 2 presents the research framework for this study, encompassing data collection and pre-processing, extraction of accessibility metrics for environmental equity analysis, and comparing the visitation disparities in visitor groups and age-demographic groups.

3.3.1. Data pre-processing

Mobile data were cleaned and pre-processed for further analysis. To pinpoint park visitors, we first mapped the overlap between GPS coordinates and park boundary polygons, assuming any points within these boundaries to be potential visitors. We then defined a 'visitor' as any GPS point that remained within the park for over five minutes

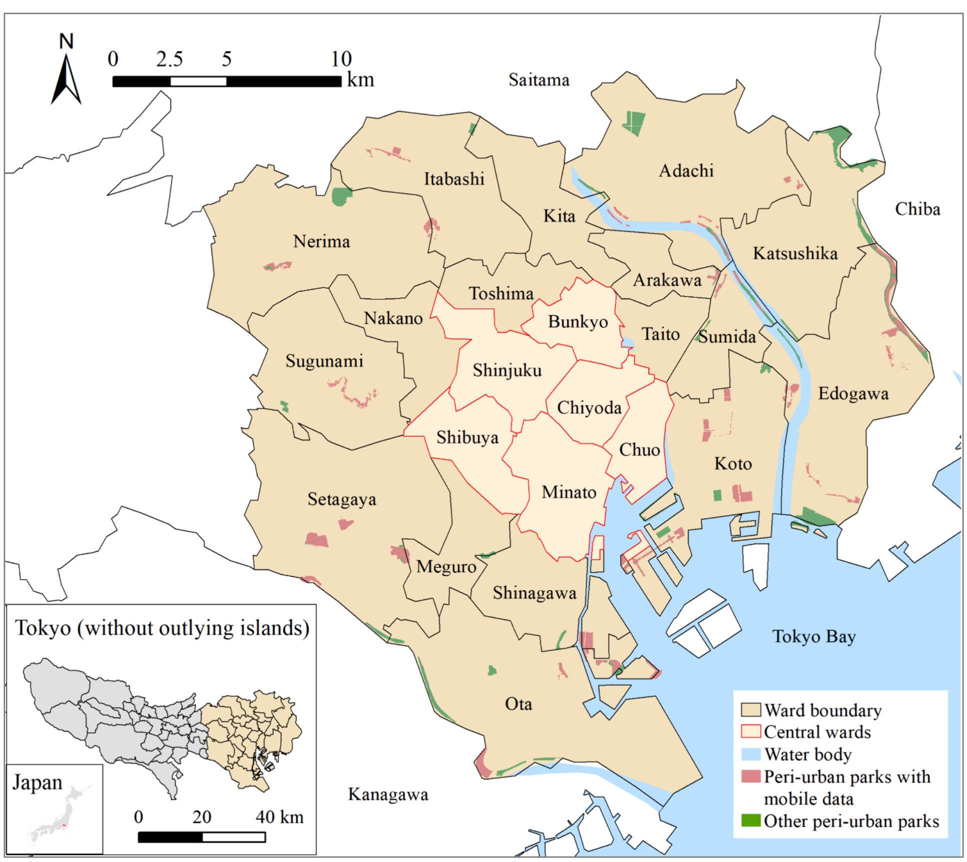

Fig. 1. Study area and the location of *peri*-urban parks.

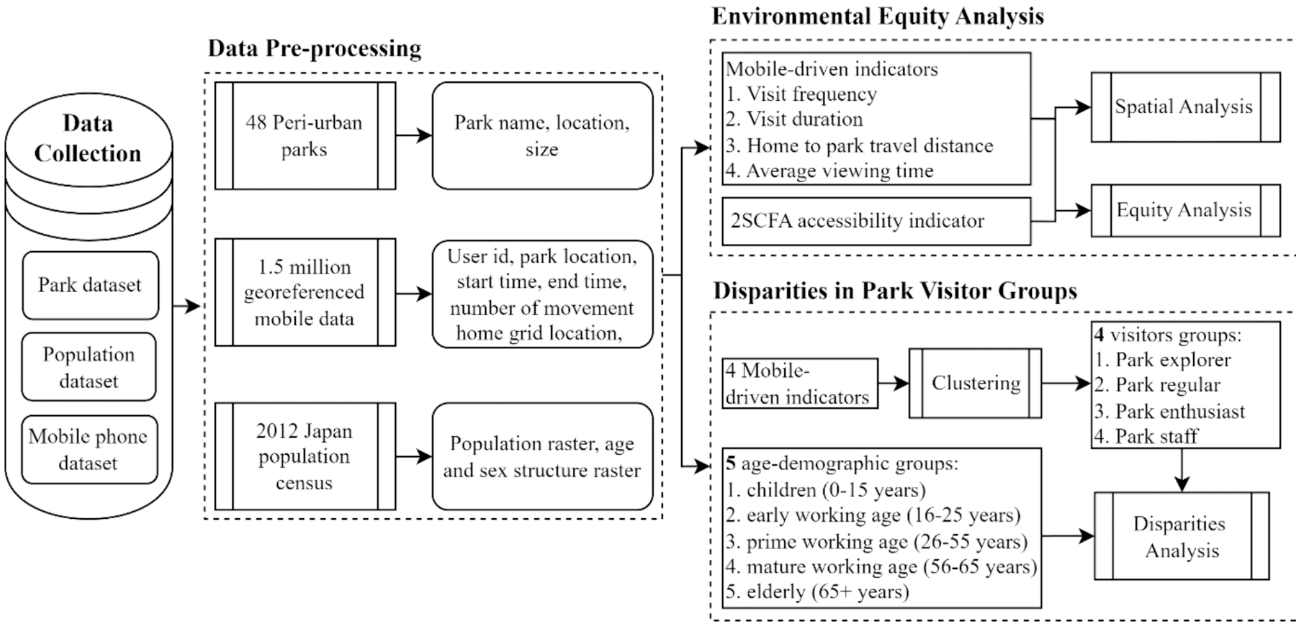

Fig. 2. Research framework.

(Akiyama et al., 2013). For identifying visitors' home locations, we traced their daily movements and filtered for residents within the 23 special wards of Tokyo. Adopting the principle that a visitor's mobile phone location, if consistently indicating overnight stays at a specific site throughout the year, likely represented their residence, we compiled these home locations into 2,620 fishnet areas, each measuring 500 m by 500 m (Chen et al., 2022). The criteria for detecting a residential location required a user to be at a consistent location from 8 pm to 7 am, for at least four days weekly, for more than half the year.

Table 1 presents a sample of the pre-processed mobile data, offering a glimpse into the data used in this study. The dataset, comprising over 1.5 million rows of records for the selected *peri*-urban parks, includes key fields such as user ID, date, start and end time, number of paths, along with park and estimated home grid location.

3.3.2. Accessibility metrics and spatial analysis

In this study, we operationalize environmental inequality as differential access to green spaces (Wu et al., 2022a; Žlender & Thompson, 2017). We evaluated accessibility equity through the application of various metrics and spatial analysis techniques. We utilized mobile phone data to measure four mobility and visitation metrics for each visitor: visit frequency, visit travel distance, visit duration, and average viewing time. These metrics could potentially serve as indicators of different accessibility levels (Guo et al., 2019; Xiao et al., 2019). In the context of our study, a high visit frequency, lengthy visit duration, and extended viewing time can suggest favorable accessibility, as individuals are more inclined to visit and spend time in locations that are readily reachable. However, greater travel distances to reach *peri*-urban parks may signal lower accessibility, attributable to the limited availability of green spaces and higher population density. These disparities in access are associated with environmental inequities (Chen et al., 2020b).

Visit frequency represents the annual count of individual users' visits to *peri*-urban parks, offering insights into park usage patterns. Visit travel distance, measured in meters, denotes the average distance travelled from home to park for each visit over a year, providing a gauge of distance tolerance. Visit duration, measured in hours, signifies the average time spent in the park per visit, reflecting engagement and satisfaction levels. Lastly, we calculate an approximate average viewing time by dividing the total duration of stay in the park by the number of movement paths per visit. This metric offers a measure of average engagement duration, reflecting the level of interest visitors show in specific park areas (Verdú-Vázquez et al., 2020). It serves as a potential indicator of the appeal or functionality of various park features or infrastructures. These four metrics were subsequently aggregated to a grid of 2,620 fishnet cells corresponding to home locations, generating a comprehensive view of mobile-driven accessibility indicators. The basic statistical breakdown of these aggregated metrics is presented in Table 2.

The study also employed Gaussian-based 2SFCA accessibility indicators for its ability to effectively model spatial interactions between *peri*-urban park supply and population demand, while incorporating distance decay effects. This methodology aligns seamlessly with the

Table 1
Sample of the pre-processed mobile phone records.

User ID	Date	Path count	Start time	End time	Park coordinates	Home grid ID
304,550	5/2	3	9.090	10.758	(139.752, 35.591)	25
108,502	5/2	3	8.876	10.129	(139.752, 35.591)	82
564,348	5/22	3	1.068	1.650	(139.752, 35.591)	413
415,835	7/22	2	18.848	18.933	(139.752, 35.591)	306
1,013,963	7/22	8	11.970	18.554	(139.752, 35.591)	81
1,198,867	7/28	3	15.001	15.256	(139.871, 35.653)	138
838,422	7/28	2	11.871	13.540	(139.871, 35.653)	286

Table 2
Descriptive statistical analysis of aggregated mobile-driven metrics.

	Count in Grid	Frequency	Travel Distance	Duration	Viewing Time
mean	9.643	16.823	8.180	1.775	0.671
std	8.065	43.651	4.038	1.700	0.717
min	1.000	1.000	0.163	0.084	0.042
25 %	4.000	3.000	5.066	0.921	0.322
50 %	8.000	5.286	8.242	1.329	0.476
75 %	12.000	11.333	11.064	1.928	0.716
max	88.000	664.000	26.450	15.185	6.640

research's goal of comprehensively assessing park usage and visitor behaviors. For a more detailed explanations of Gaussian-based 2SFCA accessibility indicators, see Appendix A in the supplementary material. For illustrative purposes, grid cells are color-coded to represent different levels of visitation, as indicated by data-driven mobility metrics, and potential accessibility, as measured by 2SFCA metrics. Lower metrics are shown in green and higher values in red, categorized into eight groups using the natural break (Jenks) method.

We also conducted a spatial autocorrelation analysis, utilizing Global Moran's I and Anselin Local Moran's I (LISA), to examine spatial patterns and identify areas of high or low park accessibility and potential environmental inequity (Chen et al., 2020b; Hu et al., 2020). These methods help us understand the spatial structure and dynamics of data to detect areas of concentration and identify spatial trends. For a detailed discussion of these spatial correlation methods, please see Appendix B in the supplementary material. We used the LISA to categorize areas into five groups based on their clustering attributes. Dark red areas (High-High Cluster) denote high-accessibility zones surrounded by other high-accessibility areas. Dark blue regions (Low-Low Cluster) represent low-accessibility zones encircled by other low-accessibility areas. Light red areas (High-Low Outlier) depict high-accessibility zones surrounded by low-accessibility areas, and light blue blocks (Low-High Outlier) illustrate low-accessibility zones surrounded by high-accessibility areas.

3.3.3. Visitor group clustering, environment equity, and visitation disparities analysis

The K-means method, an unsupervised clustering technique, was employed to segment *peri*-urban park visitors into clusters based on the four visitation indicators derived from mobile phone data. This approach, chosen for its simplicity and effectiveness in deciphering complex visitor behavior patterns, was complemented by the use of the Silhouette score to ascertain the optimal number of clusters, thereby enhancing cluster quality and distinctness (Marques et al., 2010; Sinaga and Yang, 2020). Further details on the K-means method and the Silhouette score are expounded in Appendix C.

To evaluate the environment equity and visitation disparities, we employed the Lorenz curve and Gini coefficient. The Lorenz curve, a cumulative distribution function, represents the proportion of the total park accessibility (y-axis) that corresponds to a given percentage of the population (x-axis), ranked by ascending park accessibility. It provides a visual illustration of the distribution of park accessibility across different segments of the population. The Gini coefficient, a numerical measure ranging from 0 to 1 (Guo et al., 2019, Wang et al., 2023), quantifies the degree of inequality in park accessibility. It is computed as the ratio of the area between the Lorenz curve and the line of perfect equality to the total area under the line of perfect inequality. A Gini coefficient of 0 implies perfect equality, where all grid cells have equal park accessibility, whereas a coefficient of 1 suggests perfect inequality, with one grid cell possessing all the park accessibility while others have none. For a detailed explanation of the inequity and disparities assessment methods, please refer to Appendix D in the supplementary material.

4. Results

4.1. Accessibility analysis of peri-urban parks

Fig. 3 illustrates the results of the *peri*-urban park visitation and accessibility analysis in Tokyo. By analyzing mobile data, we identified several outskirts of the study area, specifically within the Edogawa, Suginami, and Itabashi wards, as key points of interest. These regions exhibited substantial appeal, as indicated by high visit frequencies, extended stay durations, and longer viewing times. High visit frequency, extended duration, and longer viewing times suggest good accessibility, as these factors often correlate with ease of reaching a location. In the central wards of Tokyo, such as Shinjuku, Minato, and Toshima, the data indicated a higher average trip length. This implies that residents in these zones underwent longer commutes to reach *peri*-urban parks, reflecting lower accessibility due to scarce green spaces and dense population.

In contrast, the 2SFCA index showed that as the distance threshold value increased, the number of areas with higher accessibility to *peri*-urban parks also increased. For example, at a limited threshold distance of 5 km, wards like Shinjuku, Shibuya, and Toshima demonstrated limited accessibility, while Katsushika and a portion of Adachi showed high accessibility. Beyond a distance threshold of 10 km, *peri*-urban park services covered the entire study area. Wards adjacent to the Arakawa River and Edo River, such as Edogawa, Koto, and Katsushika, exhibited higher accessibility. As the distance threshold further increased, the areas with higher accessibility shifted towards the center of the study area, including Chiyoda, Taito, and Chuo. Conversely, residents in the central and western parts of the 23 special wards of Tokyo, such as Nakano, had less access to *peri*-urban parks. However, wards connected to Tokyo Bay, such as Shinagawa and Ota, consistently showed higher accessibility.

4.2. Spatial correlation analysis of peri-urban parks

The spatial correlation analysis of *peri*-urban parks, using the mobile-driven and 2SFCA accessibility indicators, demonstrated a clustered pattern throughout the study area. The Global Moran's I index, ranging from 0.327 to 1.000, indicated spatial autocorrelation in the accessibility metrics, The corresponding Z-scores, ranging from 26.208 to 71.271 with p-values less than 0.001, confirmed that the clustered patterns were not due to chance. Please refer to Table Appendix E for details. The 2SFCA indicators exhibited higher Moran's I indices overall, above 0.9, suggesting a stronger spatial autocorrelation or a more pronounced clustering effect, compared to the mobile-driven metrics. Meanwhile, the mobile-driven indicators, particularly trip length and visit frequency, demonstrated a notable degree of clustering, reflected in a Moran's I index around 0.5.

Fig. 4 showcases the spatial clusters and outliers of *peri*-urban parks, as identified through the mobile-driven and 2SFCA accessibility indicators using LISA. Mobile-driven indicators highlighted high-accessibility clusters predominantly in Edogawa, Suginami, and Toshima, concentrating around the larger *peri*-urban parks. In contrast, the visit frequency indicator pinpointed a significant low-accessibility cluster within the central region of Tokyo's 23 special wards, extending into Meguro, southern Setagaya, and northern Ota. This was further reinforced by the trip length indicator, which exhibited a unique pattern with most low-low clusters in the eastern part of the 23 special wards and high-high clusters centrally, particularly in Nerima. Other mobile-driven indicators, such as visit duration and average viewing time, identified smaller low-accessibility clusters, mainly concentrated near Tokyo Bay and northern Adachi.

Meanwhile, the 2SFCA accessibility indicators showed that the highest park accessibility rates were in the eastern part of the 23 special wards. As the service radius expanded, the central wards, including Chiyoda, Minato, and Bunkyo, transitioned from low to high accessibility clusters. Most low–high outlier areas were pinpointed in northern Adachi and southern Ota, while high-low outlier areas were distributed largely in eastern Setagaya, Shibuya, and Nakano City.

4.3. Environmental inequity of peri-urban parks

We examined environmental inequity in *peri*-urban parks by assessing accessibility distribution using Lorenz curves and calculating the Gini coefficients. The results, shown in Fig. 5 and Table Appendix F, indicate the level of inequity in park accessibility. The analysis revealed that the Gaussian-based 2SFCA accessibility Gini coefficient decreased from 0.438 to 0.146 as the service radius expanded from 5 km to 20 km. This trend suggests an increasingly equitable distribution of accessibility to *peri*-urban parks with a larger service radius. However, the Gini

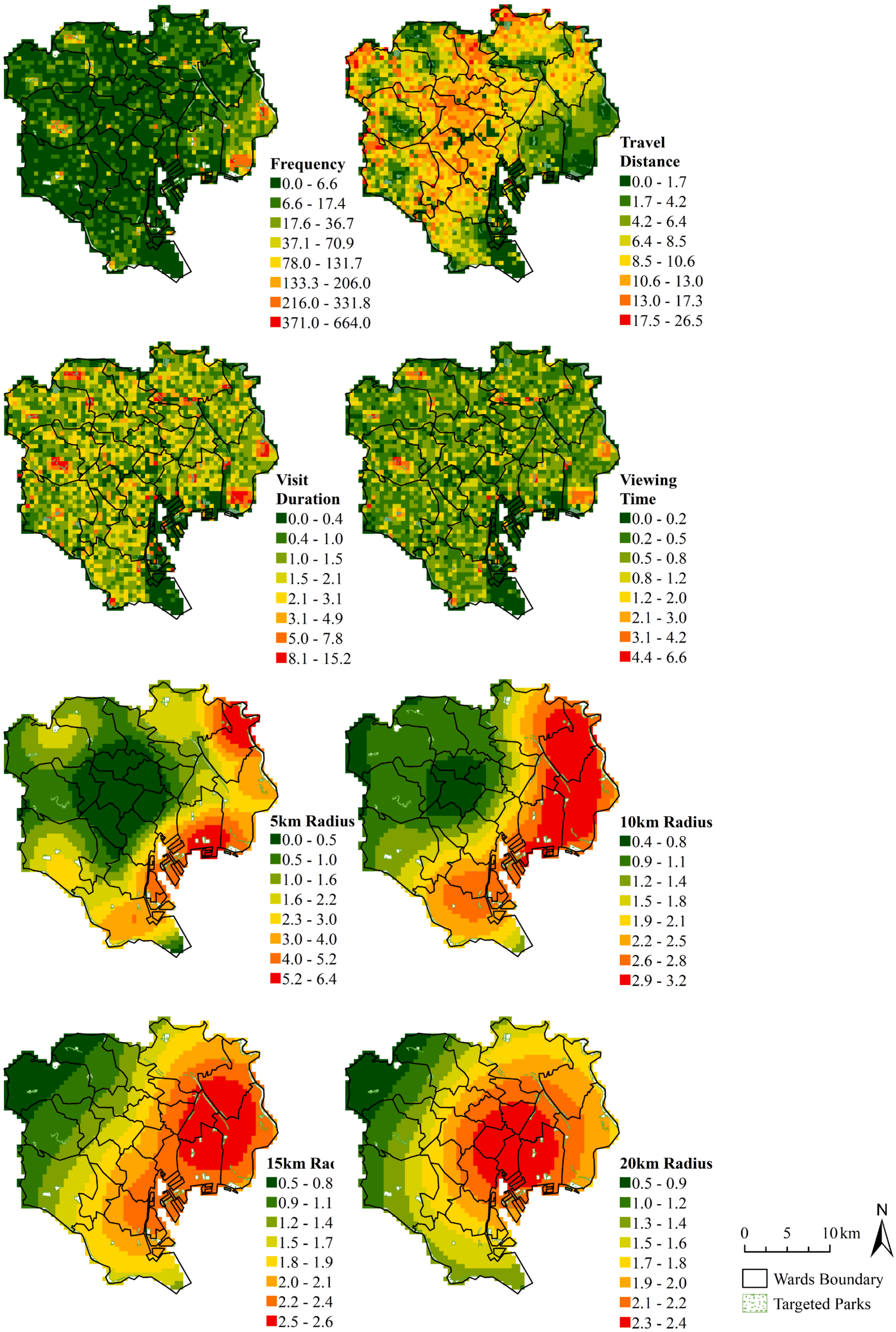

Fig. 3. Comparison of mobile-driven indicators and 2SFCA accessibility indicators.

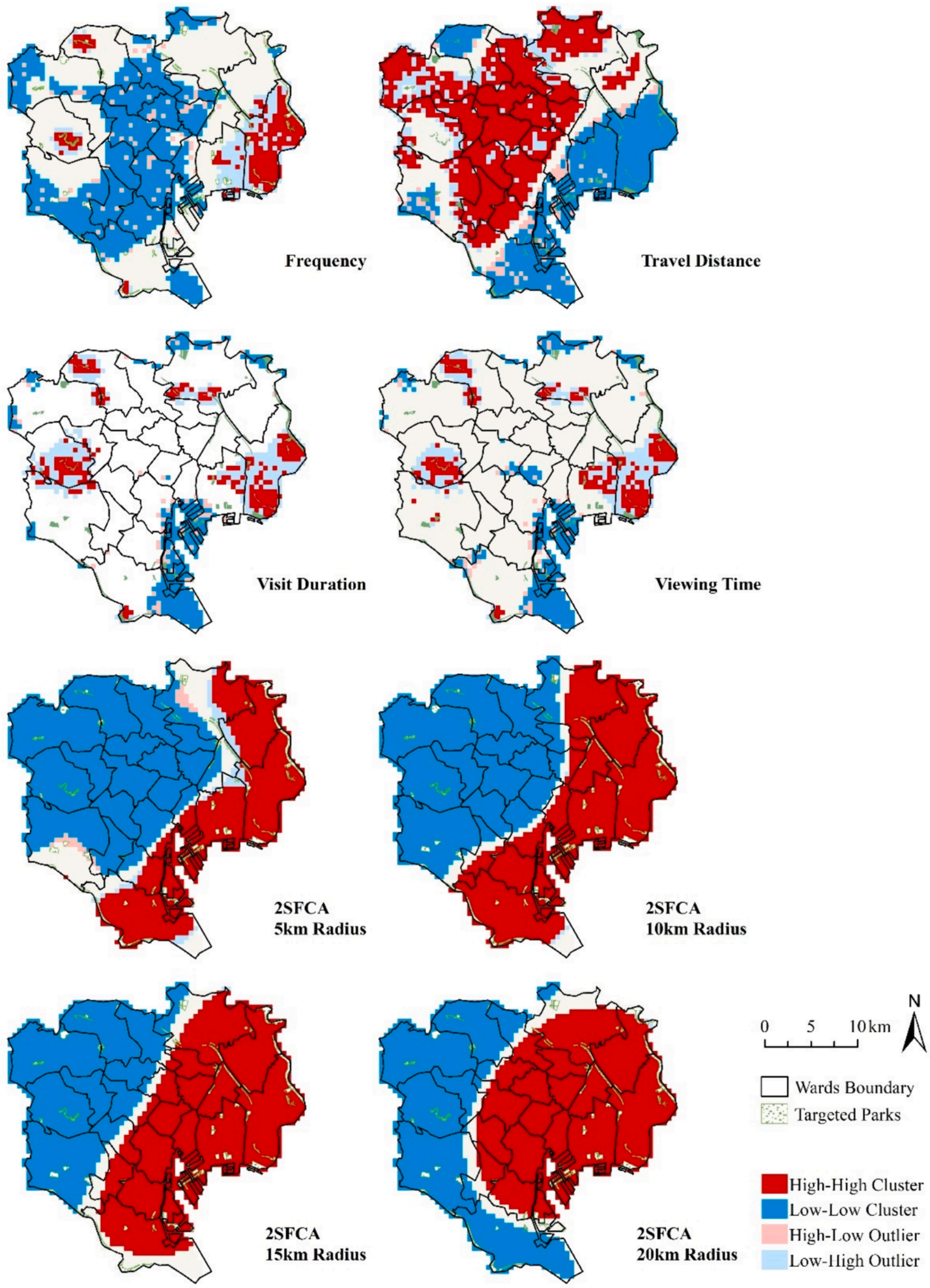

Fig. 4. Spatial cluster and outlier with mobile-driven and 2SFCA accessibility indicators.

coefficients of the four mobile-driven indicators exceeded that of the 2SFCA accessibility indicator for a service radius of 10 km or more, signifying considerable inequality in human activity concerning park visitation.

Among the mobile-driven indicators, travel trip distance to *peri*-urban parks had the lowest Gini coefficient (0.278), suggesting a relatively even distribution of trip lengths among visitors. Visit duration and viewing time showed moderate variations, with Gini coefficients of 0.396 and 0.425 respectively, indicating differing engagement levels with the parks. In contrast, the Gini coefficient for park visit frequency was much higher (0.707), highlighting a significant disparity in visit frequency, with some individuals visiting more frequently than others.

4.4. Visitation disparities in visitor groups and age-demographic groups

Upon analyzing a sample of park visitor mobile phone data, we identified four distinct *peri*-urban park visitor groups. The most representative Silhouette score was 0.883 when k = 4, with each cluster scoring above 0.5, suggesting clear visitor group segregation. The characteristics of each group, outlined in Table Appendix G, are as follows: (1) Park explorers: Infrequent visitors averaging nine visits annually, traveling approximately 7 km, and spending around 1.7 h per visit. (2) Park regulars: Frequent visitors making about 200 visits per year, staying for extended periods (seven hours per visit), and residing approximately 2 km from the park. (3) Park enthusiasts: Highly frequent visitors with over 500 visits per year, staying for over seven hours per visit, and living less than 1.2 km from the park. (4) Park staff: Extremely

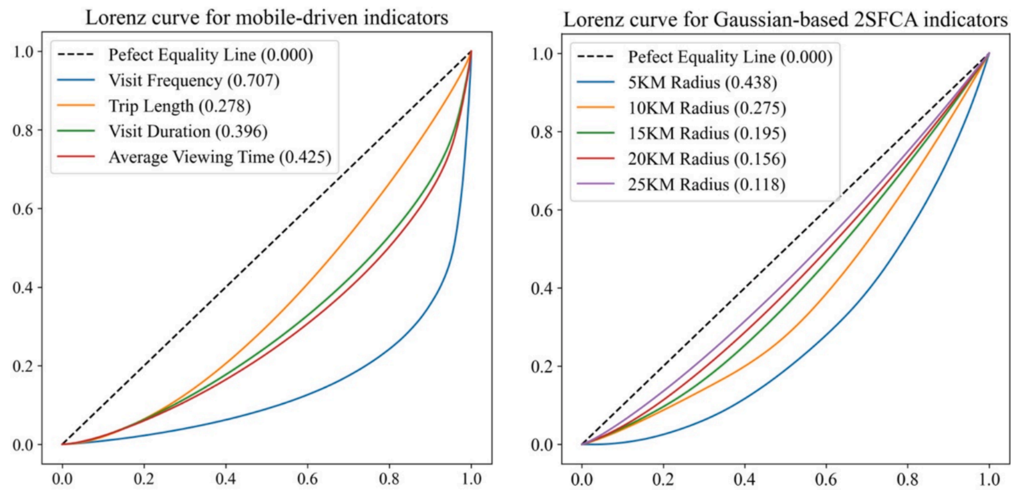

Fig. 5. Lorenz curve for mobile-driven and 2SFCA *peri*-urban park accessibility indicators.

frequent visitors due to work-related purposes, with over 2,000 visits annually and shorter stay times of about two hours, likely residing very close to the park.

As depicted in Fig. 6 and Table Appendix H, Lorenz curves and Gini coefficients reveal the disparities across various visitor groups for each indicator. The visit frequency indicator for all park visitors displayed a high Gini coefficient of 0.707, which significantly dropped when segmented into groups, with regulars, enthusiasts, and staff showing Gini coefficients between 0.124 and 0.164, suggesting a more equitable frequency distribution within these groups. For the trip length indicator, park explorers had a relatively low Gini coefficient (0.276), indicating a more evenly distributed trip length, whereas park regulars and enthusiasts showed higher Gini coefficients (0.554 and 0.603 respectively), suggesting more trip length variation. The visit duration indicator revealed a high Gini coefficient for park regulars (0.425), indicating less evenly distributed visit durations. Additionally, the average viewing time indicator suggested minimal disparities among the staff and enthusiasts. Despite the strong correlation between viewing time and visit duration across all visitor groups, as shown by the Pearson correlation in Appendix I, a pronounced disparity in the average viewing time

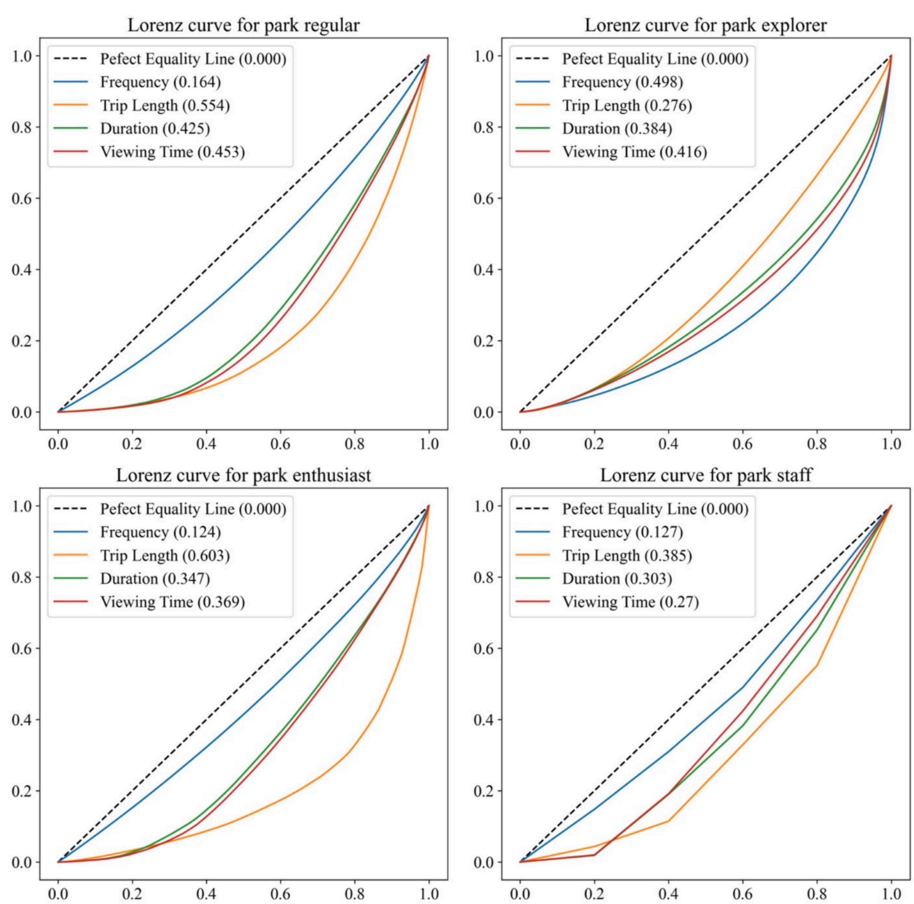

Fig. 6. Lorenz curve for each *peri*-urban park visitor group.

distribution is revealed by the Gini coefficient. Furthermore, the Pearson correlation validates the disparities analysis, indicating that park visitation can indirectly reflect accessibility, but the influence varies among different visitor groups.

We analyzed *peri*-urban park accessibility not only based on visitor groups but also on age demographic groups. However, the analysis revealed negligible variations in the Gini index (0.232) and Lorenz curve across all age groups' 2SFCA accessibility indicators, suggesting that age alone might not be a significant determinant of *peri*-urban park accessibility or visitation disparities within the study area. For a more detailed perspective, refer to Tables Appendix J and Figure Appendix K. This outcome can be attributed to the limited scope of the study area, the low resolution of the population dataset, and the relatively homogeneous distribution of the population across age groups. Consequently, we conclude that employing visitor group clusters, derived from mobile data, provides a more effective method for examining the visitation disparities of *peri*-urban parks in Tokyo.

5. Discussion

5.1. Evaluating peri-urban park environmental equity through visitation behavior

Environmental equity, conceptualized as differential access to green spaces in this study, aligns with existing literature (Wu et al., 2022a; Zhang et al., 2021b; Žlender & Thompson, 2017). This study delves into *peri*-urban park usage in Tokyo, a city characterized by its high population density, sophisticated urban infrastructure, and dedicated green space preservation amidst rapid urban development. While Tokyo's unique attributes provide a rich context for this study, they also resonate with the challenges of other densely populated metropolis globally, enhancing the relevance of our findings. Nevertheless, the distinct sociocultural fabric, rigorous urban planning policies (Setagaya Ward Government, 2016), and environmental initiatives of Tokyo call for a careful interpretation of these findings in other urban contexts. By integrating mobile-driven and 2SFCA accessibility indicators, this study sheds light on the complex patterns of park usage in Tokyo (Chen et al., 2020a; Ren and Guan, 2021; Rossi et al., 2015; Zhang et al., 2021b), offering valuable insights into environmental equity within highly urbanized areas.

The advantage of using both mobile-driven and 2SFCA indicators is that it enables a more holistic evaluation of park accessibility and equity, effectively pinpointing immediate areas for improvement (Lin et al., 2021; Ren and Guan, 2021; Xu et al., 2021; Zhang et al., 2022). Mobile-driven indicators such as visit frequency can enhance an evaluation of park accessibility and the quality of park experience (Guan et al., 2020; Kupfer et al., 2021; Monz et al., 2019), while visit duration and viewing time can inform about the quality of park usage. Conversely, 2SFCA indicators encompass population density and proximity to parks, offering a comprehensive view of park accessibility, consistent with earlier research (Li, et al., 2016, Li, et al., 2021). More specifically in this study, mobile-driven indicators identify specific underutilized sections within wards, while 2SFCA indicators, corroborating broader trends of the whole study area. For example, the study underscores prioritizing efforts to ensure serve areas located beyond a 10 km radius from *peri*-urban parks, and the urgent need to improve park accessibility in central wards of Tokyo, such as Shinjuku and Chiyoda. These areas exhibit a lower visit frequency to *peri*-urban green spaces, longer travel distances, and reduced viewing time align with 'low-low' clusters identified by 2SFCA indicators, suggesting high population density and limited park distribution.

Our findings offer actionable insights and recommendations for decision-makers and stakeholders, with the potential to significantly enhance urban planning strategies and park development policies. Urban planners could strategize on transforming existing city center green spaces and tourist spots into enticing destinations for residents. By introducing features such as glamping areas or activity fields, longer engagement with green spaces could be encouraged. This could include the development of cycling paths or pedestrian-friendly routes leading to these parks, fostering active travel and reducing carbon footprints (Tian et al., 2021).

Moreover, the active engagement of policymakers and planners with local communities in the planning process is pivotal, reflecting the UN's Sustainable Development Goal (SDG) 11, which emphasizes sustainable cities and communities (Guan et al., 2023). Such engagement is critical in shaping green spaces that cater to the needs and preferences of the residents. In this context, the development of targeted outreach programs can be instrumental. These programs could incorporate technology, such as Chatbots, to actively solicit public feedback and boost resident interest in *peri*-urban parks. Furthermore, the implementation of mobile apps or online platforms can be a game-changer in improving park accessibility. By providing real-time information on park facilities, events, and transportation options, these digital tools can make *peri*-urban park visitation more convenient and appealing.

Further, the introduction of dedicated bus routes from city centers to *peri*-urban parks could incentivize residents to visit these parks by reducing both travel costs and time. This strategy targets the improvement of accessibility for city center dwellers, likely increasing their willingness to visit *peri*-urban green spaces. These inclusive strategies can promote physical activity, alleviate stress, and improve overall well-being, thereby addressing environmental inequities and enhancing the quality of urban life (Njoh, 2020; Wu et al., 2022b).

5.2. Visitation disparities assessment with mobile phone data

Building upon previous studies (Pickering & Rossi, 2016; Žlender & Thompson, 2017), the use of mobile data to form visitor group clusters offers an innovative method that counteracts limitations found in demographic-based studies. Demographic approaches often hinge on self-reporting, extensive surveys, or geospatially processed population data, each of which can introduce biases and inaccuracies due to recall issues, respondent interpretation, or loss of granular *peri*-urban park usage details (Guo et al., 2019; Li et al, 2019). Mobile data, particularly in forming visitor group clusters, offers distinct advantages: it provides real-time, objective park visitation data, thereby reducing recall biases and subjective errors. It uncovers sophisticated patterns in park usage, validating prior research (Kupfer et al., 2021; Monz et al., 2019; Xiao et al., 2019). Given the ubiquity of mobile phones across various demographics, mobile data offers a comprehensive, representative sample of the population (Jaung & Carrasco, 2020; Zhang et al., 2021a), effectively mitigating biases from over- or under-representation of certain demographic groups, and enhancing the validity of findings.

The absence of considerable variation in *peri*-urban park accessibility across diverse age groups prompts a nuanced examination. Equal accessibility does not guarantee uniform park usage or experience, as needs and preferences differ across age groups (Guo et al., 2019; Pickering & Rossi, 2016). For instance, younger and older visitors may be attracted to different activities, such as hiking or bird-watching, respectively. Therefore, it is vital that park amenities reflect these diverse interests to encourage usage. Uniform accessibility also presents opportunities for targeted programming and outreach, such as educational initiatives for children or guided walking groups for older visitors. Research emphasizing the importance of walkable green spaces for the health of seniors (Takano et al., 2002) and the mental well-being benefits of urban green spaces for older adults (Lu et al., 2022) further supports the need for inclusive urban park policies. These studies from Tokyo provide a foundation for developing park policies that, while mindful of local nuances, can offer insights applicable in other urban contexts, promoting parks as versatile, health-supportive environments for all age groups.

Utilizing mobile data to categorize visitor clusters illuminates the behavior and needs of diverse park visitor groups. This allows the development of specific management strategies for *peri*-urban parks, as supported by earlier studies (Guo et al., 2019; Jaung & Carrasco, 2020; Rodríguez et al., 2018; Xu et al., 2021; Zhang et al., 2021b). Visitor groups such as Regulars and Explorers, who may prioritize safety, benefit from guided tours, enabling a confident exploration of the park. Regular safety checks on paths, facilities, and equipment could be initiated to ensure optimal conditions. Additionally, the provision of guided tours, highlighting the unique flora, fauna, and history of the *peri*-urban ecosystem, could enrich their park experience. Park Enthusiasts, often willing to travel greater distances for a more profound park engagement, may appreciate secluded, peaceful spaces. The establishment of dedicated quiet zones, positioned away from high-traffic areas such as picnic spots or play areas, could facilitate an immersive, tranquil park experience. These zones could be located in less frequented park areas, promoting visitor dispersion while ensuring the preservation of these tranquil spaces. Despite being frequently overlooked in earlier research (Pickering & Rossi, 2016; Rossi et al., 2015; Zhang et al., 2021b; Žlender & Thompson, 2017), Park Staff, a crucial component of park operations, can significantly benefit from practical enhancements. Specifically, establishing well-equipped, conveniently located workspaces, and secure, easily accessible storage facilities for equipment can boost operational efficiency. Strategically placed rest areas, offering respite during breaks, further enhance staff well-being. Regular, comprehensive training sessions covering topics from managing urban-wildlife interactions to emergency response can elevate staff competency.

5.3. Limitations and future work

Despite its valuable contributions, this study has a few limitations and opportunities for further research. The park classification, based solely on estimated surface area, could be enhanced by incorporating more nuanced criteria such as amenity diversity or user demographics, providing a richer *peri*-urban park analysis (Ibes, 2015). Additionally, the use of mobile phone data may introduce biases. Certain demographics, such as the elderly or very young, who might be underrepresented due to less frequently mobile phones use, potentially skewing results. Supplementing mobile phone data with additional datasets, such as surveys, socioeconomic indicators (income, education level, poverty rates, employment status, and transportation mode) could further refine the investigation into visitor group dynamics. Another limitation involves the aggregation of year-long data without considering possible temporal variations in park activities. Future work could incorporate a temporal analysis to better understand park usage dynamics and identify peak and off-peak visitation periods. In addition, the study's reliance on a fixed distance threshold for analyzing accessibility indicators may not accurately reflect actual travel time or methods utilized by park visitors. Future research could explore actual travel time calculations based on transportation networks and other factors.

6. Conclusion

In conclusion, this study has demonstrated the value of mobile phone data in examining both environmental equity and visitation disparities in *peri*-urban parks. By analyzing anonymous mobile phone records from over 40,000 park visitors in Tokyo's 23 special wards, the study has provided valuable insights into park accessibility patterns and visitor behaviors. The findings emphasize the importance of incorporating mobile-driven indicators and understanding human activities when evaluating *peri*-urban park accessibility and equity among different visitor groups, as demonstrated through various analyses.

The results highlight the need for multi-dimensional approaches in *peri*-urban park accessibility research, as different indicators reveal significant variations in park access patterns. Expanding the service area beyond a 10 km radius can enhance environmental equity as revealed by the Gini coefficient analysis. Furthermore, the park visitor groups provide a more comprehensive reflection of disparities in visitation behavior compared to age demographic groups. Policymakers and urban planners can leverage these insights to develop effective policies and strategies aimed at promoting environmental sustainability in *peri*-urban park planning and management efforts. By incorporating mobile phone data into gravity models, policymakers can make informed decisions and take proactive steps to create more inclusive and accessible *peri*-urban parks for all members of the community.

CRediT authorship contribution statement

ChengHe Guan: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yichun Zhou:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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