Landscape and Urban Planning 256 (2025) 105292

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Preferring Local over Non-Local Parks? Green Space Visit Patterns by Urban Residents in Desert Cities, Arizona

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HIGHLIGHTS

- Parks within walking distance may not automatically guarantee its frequent use by residents.
- Mobility data reveal urban residents' local vs. non-local park visit patterns.
- Some urban neighborhoods do not use nearby parks the most frequently.
- Park size non-linearly influences Hispanic residents' visits to local green spaces.

ARTICLE INFO

Keywords:
Urban green space
Green space equity
Green space use
SafeGraph data
Urban parks

ABSTRACT

This study investigates whether residents in urban neighborhoods use nearby green spaces more frequently than distant ones. Using mobile phone tracking data from 2019, we analyzed visitation patterns to green spaces within walking distance of residence (i.e., local parks) in the Phoenix-Mesa urbanized area, Arizona, USA. Key findings include: (1) about 40% of neighborhoods with available local parks did not prioritize local park use, (2) both accessibility measures and neighborhood social composition were significantly associated with frequent local park use by residents, and (3) the association between the percentage of Hispanic residents and local park use varied non-linearly based on access to local parks (proximity and average size). We conclude by discussing the implications of these findings for urban green space planning and equity considerations.

1. Introduction

Green space, defined as a vegetated form of open space (e.g., parks, urban forests, tree canopies, and riverbanks) (Taylor & Hochuil, 2017), is increasingly recognized for its diverse benefits to environmental sustainability, public health, and social well-being (Lovell & Taylor, 2013; Forest Research, 2010; European Environment Agency, 2020). Specifically, the presence of green spaces within walking distance not only improves social cohesion and a sense of place but also yields health benefits (European Environment Agency, 2022; Mao et al., 2020; Pfeiffer et al., 2020; Vierikko et al., 2020). Giles-Corti and colleagues (2005) found that individuals living within walking distance of parks are three times more likely to achieve the recommended daily exercise levels than those who do not live near parks. Some scholars have concluded that proximity to parks and the use of those parks is positively correlated with increased cardiovascular health and physical activity levels (Brown et al., 2014; Cohen et al., 2009).

However, researchers have found evidence of inequalities in the distribution or accessibility of green space across different neighborhoods. For example, green spaces are often unevenly distributed by race, ethnicity, income, and education in the U.S. (Nesbitt et al., 2019; Rigolon, 2016). Likewise, in Norwegian cities, immigrants and ethnic minorities have unequal access to high-quality green and blue spaces (European Environment Agency, 2020). Ensuring that all residents have access to green spaces is fundamental to achieving equity because it guarantees that every social group has fair opportunities to experience the physical and mental health benefits that these spaces provide (Pitas et al., 2019). Yet, equitable access does not guarantee that all residents will experience the health benefits through frequent use of nearby green spaces.

Discussions of green space equity in U.S. communities have frequently highlighted unmet needs for green space access, but they often fail to consider how residents actually engage with and use these environments (Kim et al., 2023; Pitas et al., 2019). The assumption that

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https://doi.org/10.1016/j.landurbplan.2024.105292
Received 18 July 2024; Received in revised form 13 December 2024; Accepted 28 December 2024
Available online 3 January 2025

making green areas accessible will automatically promote their use warrants closer examination, especially given that the likelihood of engagement with green spaces depends significantly on the specific preferences and needs of potential user groups (Ahn et al., 2020; Bratman et al., 2019; Wolff et al., 2022). The potential misalignment between the accessibility of green spaces and the frequent use of local green spaces presents a significant policy issue.

To better understand how urban residents use green spaces within walking distance (i.e., local green spaces), we examine the following research questions:

1. To what extent do residents in urban neighborhoods choose green spaces within walking distance (i.e., local green spaces) as their primary destination?
2. Which factors drive urban residents to use their local green spaces as their primary destination over those beyond walking distance (i.e., non-local green spaces)?

We address the first question by empirically analyzing the behavior of neighborhood residents regarding green space use in the Phoenix-Mesa urbanized area of Arizona. The study area includes desert cities that experience hot and dry weather throughout the year. We use cell-phone tracking data to analyze visit patterns to green spaces. We then use the results of this analysis to answer the second research question.

2. Literature review

2.1. Green space visits using cell phone data

Recent research on green space use has benefited from the availability of detailed human mobility data, made possible by the widespread adoption of cell phones and global positioning system (GPS) technology. Advanced data vendors (e.g., Google, Dewey, and SafeGraph, where SafeGraph data are now housed) provide GPS tracking data on individuals' travel to points of interest (Becker et al., 2013; Kang et al., 2020; Chang et al., 2022). These data have been used to generate insights into how people interact with urban environments, including green spaces, in cities worldwide, particularly during the COVID-19 pandemic (Ding et al., 2022; Jay et al., 2022; Li et al., 2023; Yang et al., 2021; Zhao et al., 2023).

These studies have reported shifts in visitation patterns before, during, and after the pandemic (Ding et al., 2022; Zhao et al., 2023). Many studies have found that park and neighborhood characteristics are correlated with green space use during this period. Some studies address these trends through an equity lens (Kim et al., 2023; Lu & Song, 2024; Jay et al., 2022; Zhao et al., 2023). For example, research showed that visits to green spaces were higher in neighborhoods with more children or seniors before the pandemic (Kim et al., 2023). Other studies found a more pronounced rebound in green space visits during the pandemic in park service areas with wealthier, predominantly White residents (Jay et al., 2022). Note that given the unique social environment of the pandemic period, we have carefully referenced the temporal context of prior studies in our review.

This study does not focus on green space visits related to COVID-19. However, it is worth noting that the surge in research on green space visitation using cell phone data is primarily attributed to the fact that data vendors like SafeGraph and Google offered mobility data free of charge during the pandemic. The unique availability of extensive mobility data during the pandemic allowed researchers to study park visitation citywide, but these studies do not necessarily reflect residents' use behavior in *choosing their local green spaces over all available ones*, regardless of whether the community is in the middle of a pandemic or not. Previous studies have focused on the general use of parks by counting the number of visits (frequency) to green spaces over a given time period (e.g., Kim et al., 2023; Song et al., 2022). Yet, they did not examine whether residents visited local green spaces more frequently than distant ones. The goal of our research is to address this gap.

2.2. What drives the frequent use of local green spaces?

2.2.1. Accessible local green spaces

Accessible green spaces are often defined as publicly available green areas free from physical or psychological barriers (Biernacka & Kronenberg, 2019). Here we use the term "green space access" to refer to the availability of publicly accessible green spaces in urban neighborhoods. In recent green space equity literature, the distance to public green spaces, their size, and their overall number in a neighborhood commonly serve as key indicators for accessibility (Kim et al., 2023; Nelson et al., 2024; Rigolon, 2016). These accessibility measures highlight how governments and communities distribute green spaces throughout neighborhoods.

Local green spaces are often preferred destinations for urban residents because their proximity allows residents to experience health benefits more easily than distant green spaces (Mears et al., 2020). The closer these local green spaces are to one's residence, the more frequently people may use them over other alternatives. Yet, empirical evidence on the relationship between proximity and usage is mixed. While some studies have identified a significant correlation – finding that shorter distances lead to more frequent visits – others have not observed this pattern (Schipperijn et al., 2010a; Giles-Corti et al., 2005; Kim et al., 2023; Zuniga-Teran et al., 2019). For example, individuals living within 300 m of their nearest green space were over three times more likely to visit a green space at least a few times a week than those living 300 m to 1 km away (Schipperijn et al., 2010a). Conversely, other studies have found that residents were willing to travel further than the widely cited proximity standards of 300–500 m for walking and that frequently used parks were not always the nearest ones (Phillips et al., 2023; Schindler et al., 2022; Schipperijn et al. (2010)). Recent research offers more nuanced findings, yet distance remains a critical factor for frequent green space users, unlike for occasional users (Xu et al., 2024).

Urban residents' use of local green spaces also depends on both the number and size of these spaces. A greater quantity of local green spaces can provide residents with more diverse options, a factor associated with increased visitation in the Phoenix metro area (Kim et al., 2023). Similarly, larger green spaces typically offer a broader range of physical activities and amenities (Petrunoff et al., 2022). In Helsinki, a higher supply of green spaces—both in terms of proximity and size—correlated with more frequent use by urban residents (Neuvonen et al., 2007). Although our study does not directly measure attractiveness or quality, previous research has used park size as a proxy for perceived quality, suggesting that larger parks may draw more visitors (Cutts et al., 2009). Meanwhile, small green spaces have become increasingly valuable in densely populated cities, fulfilling residents' daily desire for outdoor experiences (Peschardt et al., 2012). Overall, the literature suggests that residents generally regard more numerous or larger local green spaces as conducive settings for a variety of leisure activities, thereby increasing the likelihood of frequent visits. Based on this review, we hypothesize that residents in neighborhoods with greater access to local green spaces (through proximity, number, and size) are more likely to use them as their primary destination.

2.2.2. Varying local green space usage by different social groups

The use of local green spaces can reflect the needs of different groups of urban residents. For example, residents with mobility limitations—whether related to age, ability, or lack of personal resources—and those without private yards are especially likely to depend on and frequently visit nearby green spaces (Payne et al., 2005; Pitas et al., 2019). Also, having children or a dog has been associated with greater use of local parks in both European and U.S. cities (Schipperijn et al. (2010); Garrido-Cumbrera et al., 2020; Bloemsma et al., 2018; Derose et al., 2018). In Cleveland, older adults aged 50 and above who lived within walking distance of a park used it significantly more often than individuals living farther away (Payne et al., 2005). Research in the Phoenix area found that green space use increased in neighborhoods with higher percentages of children and seniors over 65 (Kim et al., 2023). Taken together, these findings suggest that residents facing mobility challenges or resource constraints may prefer local green spaces and are, therefore, more likely to visit them regularly. Our second hypothesis is that residents in neighborhoods with higher percentage of children or seniors are more likely to use local green spaces as their primary destination.

The choice to visit local green spaces can be driven not only by residents' lack of resources to travel to distant areas but also by cultural values. In the U.S., studies have found that people of Hispanic ethnicity tend to visit local parks more frequently but are less likely to visit national parks than White individuals (Floyd, 1999; Lu et al., 2023; Pitas et al., 2019). Since family interaction is a central cultural value in many Hispanic communities, the motivation for visiting local parks may be rooted in spending time with family and children rather than pursuing activities such as sightseeing, fishing, or hunting, which are more common in national parks (Floyd, 1999). Further evidence from the Phoenix metropolitan area shows that Hispanic residents often visit green spaces to socialize with others in their community, particularly within close personal networks, such as friendships (Floyd et al., 1993). These findings suggest that Hispanic communities may prefer nearby green spaces for social gatherings. Therefore, we hypothesize that residents in neighborhoods with a higher percentage of Hispanic residents are more likely to use local green spaces as their primary destination.

After testing these three hypotheses, we examine how green space accessibility (proximity, number, and size) interacts with neighborhood demographic characteristics (proportions of children, seniors, and Hispanic residents). Given the limited findings in the literature, we do not propose a specific hypothesis for this interaction.

3. Data and methods

3.1. Phoenix-Mesa urbanized area in Arizona

The Phoenix-Mesa urbanized area is located in the state of Arizona, U.S. The U.S. Census Bureau (2010) defines urbanized regions as having a population of 50,000 or more. The study area encompasses multiple desert cities over 1,110.5 square miles (2,876.2 square kilometers) and has a population exceeding 4 million (Census Reporter, 2022). The median age of the population is 38.2 years old, with 22 percent of residents under 18, 61 percent between 19 and 64, and 17 percent over 65 (U.S. Census Bureau, 2019). The population is composed of approximately 30 percent Hispanic and 70 percent non-Hispanic residents. Among the non-Hispanic population, 54 percent identify as White, 5 percent as Black, 1 percent as Native American, 5 percent as Asian, 4

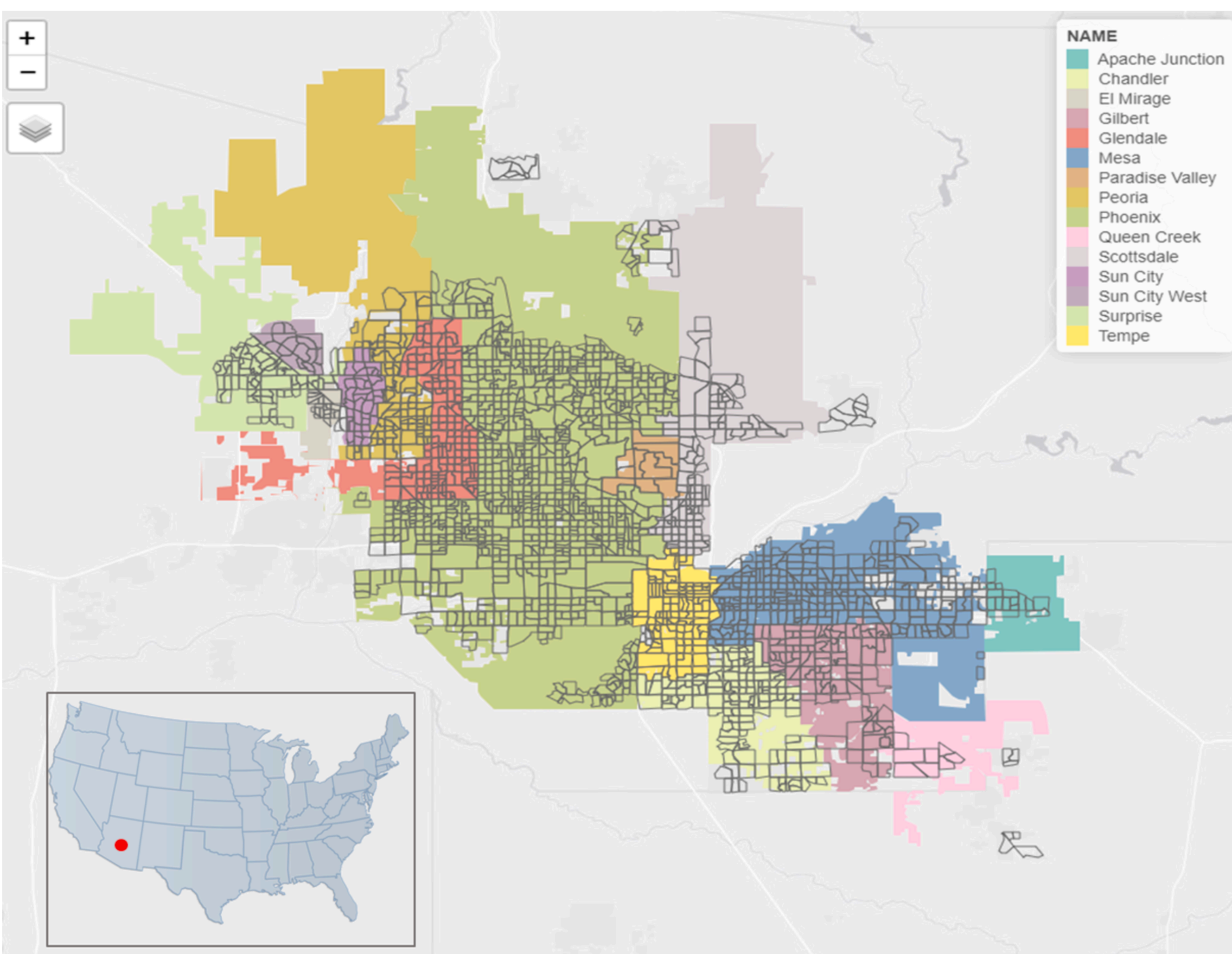


Fig. 1. Cities and Census Block Groups (CBGs) in the Phoenix-Mesa Urbanized Area. *Note*: The colored areas represent the boundaries of each city. Gray cells represent census block groups located within the boundaries of an urbanized area. The map's city boundaries may include CBGs in areas without gray cells, but these CBGs do not meet the criteria for an urbanized area defined by the U.S. Census.

percent as two or more races, and around 1 percent as another category (Census Reporter, 2022). Because the U.S. Census classifies ethnicity and race as separate variables, figures representing race alone differ from those provided here. See Fig. 1 for cities included in the urbanized area.

The area experiences a hot and sunny climate year-round, with summer temperatures often exceeding 100°F (37.8 °C) (National Weather Service, 2020). Given that green spaces are scarce yet crucial for mitigating heat waves, research on green space equity has examined how these environmental resources are distributed among neighborhoods in the area (Kim et al., 2023; Cutts et al., 2009; Nelson et al., 2024). Although no clear disparities in green space access have been identified for specific racial or ethnic groups in the Phoenix metropolitan area (Kim et al., 2023; Nesbitt et al., 2019), Hispanic communities tend to have fewer trees and less tree connectivity (Nelson et al., 2021; Stuhlmacher & Kim, 2024).

3.2. Data

In this study, urban neighborhoods (our unit of analysis) are defined using Census Block Groups (CBGs), the smallest geographical unit for which the U.S. Census Bureau publishes sample data. We utilize three data sources: (1) SafeGraph, a private data vendor, tracks the flow of visitors between Points of Interest (POIs) and their residential locations, providing anonymous mobile phone location data (Squire, 2019). A visit is valid when a device remains in the POI area for more than 4 min, and the data can include walking through a park that takes more than 4 min. SafeGraph offers weekly visit data at the CBG level (not at the individual level) and includes residential location identifiers (i.e., CBG identifiers) based on the origin of devices that visited park POIs, determined by common nighttime locations; (2) Because the SafeGraph Weekly Visit Patterns dataset includes only those parks identified through cell phone visits, we also use the Trust for Public Land (TPL) ParkServe data to identify parks available in CBGs. The TPL dataset encompasses publicly owned open spaces, school parks with joint-use agreements with local governments, and privately owned parks managed for full public use (Trust for Public Land, 2022); (3) We linked the CBG identifiers in the SafeGraph data with U.S. Census data to obtain demographic information on CBGs (U.S. Census, 2019). We use “CBGs” when referring to neighborhoods and “residents in a CBG” or “residents in a neighborhood” when discussing the behavior of residents in CBGs using local parks.

This study integrates the datasets to: (1) assess local park availability within Census Block Groups (CBGs), (2) identify parks that residents in each CBG use as primary destinations, and (3) analyze factors associated with local park use patterns. The data processing steps are listed below:

1) Use of U.S. Census boundary of CBGs in the Phoenix-Mesa urbanized area as a base map (2102 CBGs)
2) Use of an overlay of the TPL’s park data to identify all parks available in the area (958 parks)
3) Measurement of the distance to the nearest boundary of a TPL park from the centroid of each CBG (i.e., Euclidean distance)
4) Analysis of whether each CBG has parks within the 1 km (*km*) radius of the centroid of each CBG to identify “local” parks
5) Measurement of the numbers and sizes of local parks in CBGs
6) Integration of the TPL data with SafeGraph’s data (702 parks; 73 percent of TPL parks) by linking park unique IDs in both datasets to calculate total visit counts to parks and identify the most visited park by residents in each CBG
7) Differentiation of CBGs into three groups based on how residents in a CBG used parks
8) Test of whether the measures of accessibility and social groups can predict the probability of using a local park the most frequently

As noted in step 6), approximately 27 percent of TPL parks were not observed in the SafeGraph dataset. The issue of missing park POIs in the SafeGraph dataset has been documented in previous studies (e.g., Liang et al., 2022). Several factors contribute to this, including poor signal coverage in park areas, SafeGraph’s focus on business-related POIs, and privacy policies that restrict the provision of visit data when fewer than four devices are detected from a CBG (Miyasaka et al., 2018; Muñoz et al., 2019). Our additional analysis found that smaller parks are more likely to be missing from the SafeGraph dataset (see Appendix A). These missing POIs are of less concern for this study, as smaller parks generally attract fewer visitors and are, therefore, less likely to be identified as the most visited park by neighborhood residents (see Appendix B).

3.3. Measures

3.3.1. Dependent variable

We identified the most frequently visited park by residents in each census block group (CBG) within the area (referred to as the most used park). To achieve this, we created a matrix of all parks and CBGs in the study area, indicating whether residents from each CBG visited those parks between January 1 and December 31, 2019. Since the SafeGraph data includes the number of devices traveling between CBGs and park POIs, we converted the device counts into visit counts using SafeGraph’s normalization procedure (Ouyang, 2020). Specifically, the device count from CBG i to park j during week t is divided by the total number of devices detected in CBG i during week t and then multiplied by the population of CBG i. This result is further multiplied by the visit-to-visitor ratio at park j during week t, calculated as total visits divided by unique visitors to account for repeat visits. Finally, we calculated the annual normalized visit count from CBG i to park j by summing the weekly visit counts for all weeks in 2019.

$$VisitCounts_{ijt} = \frac{DeviceCount_{ijt}}{TotalDevicesDetected_{it}} xPopulation_{i} x \frac{Visit_{jt}}{Visitor_{jt}}$$

Using the annual normalized visit counts between each CBG and the parks visited by its residents, we computed the percentage of visit counts for all parks visited by residents in each CBG. We then identified the park with the highest percentage of visit counts for each CBG (see Appendix C for an illustration of this process). Therefore, each CBG was assigned its most frequently visited park (i.e., the most frequently used park).

Separately, we identified local parks for each CBG by measuring the distance between the CBG’s centroid and the nearest point of the TPL park boundary within a 1 *km* radius. This method follows previous research on the study area (Kim et al., 2023; Nesbitt et al., 2019). The most frequently visited park by residents in each CBG may be within the 1 *km* buffer (i.e., local) or beyond (i.e., non-local). Our definition of “local” encompasses the boundaries of most CBGs in the study area (see Appendix D).

Fig. 2 illustrates three different groups based on whether the most frequently visited park by residents in each CBG is local or non-local. Group 1 includes CBGs, where residents often use one of the local parks. Group 2 contains CBGs with local parks, but residents most frequently use a non-local park. Group 3 includes CBGs without local parks, which were excluded from the logit analysis. Therefore, the dependent variable is whether a CBG belongs to Group 1 (assigned a value of 1) or Group 2 (assigned a value of 0).

3.3.2. Independent variables

We used three measures to assess local green space accessibility for each neighborhood. First, we measured the *proximity* of each CBG to the nearest park by calculating the Euclidean distance between the centroid of the CBG and the closest boundary of a park in the TPL dataset. Second, we calculated *the number* and *average size* of local parks for each CBG. The average size was determined by dividing the total acreage of local parks by the number of parks. Additionally, we considered three demographic characteristics that may indicate stronger motivation for local green space use: *the percentage of children (under 18), seniors (over*

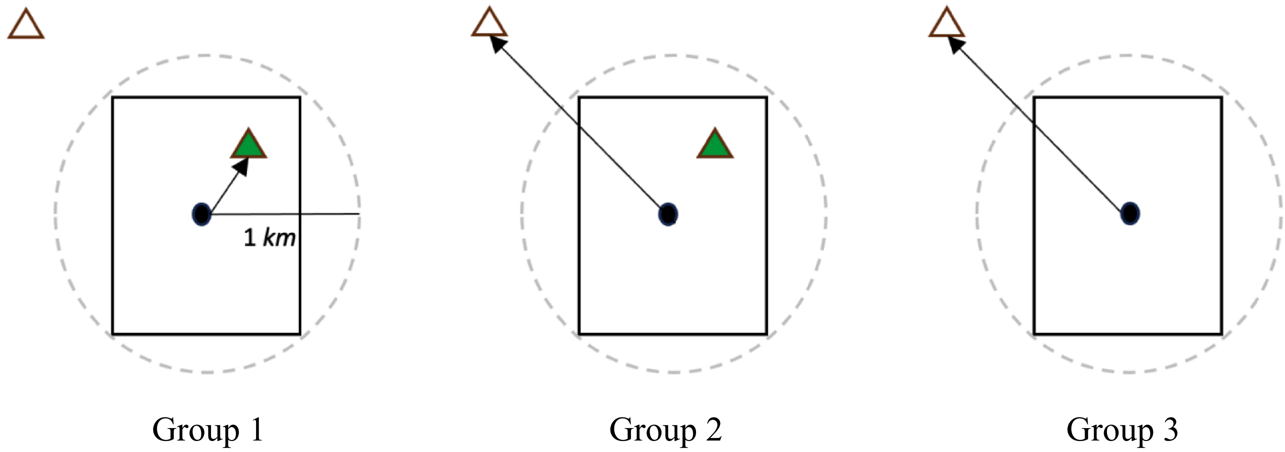


Fig. 2. Illustration of Groups Based on Different Uses of Local Parks. *Note*: Squares represent CBGs, dashed circles represent the CBG's 1 *km* buffer zone (walking distance), triangles represent parks (green triangles = local, white triangles = non-local), and arrows represent the most visited parks by residents in each CBG. Group 1 includes a line that shows a radius of 1 *km* from the center to represent walking distance.

65), and *Hispanic residents* in each neighborhood. Hispanics refers to the percentage of residents of any race who identify as Hispanic in the U.S. Census survey.

3.4. Logit model

We used a logit model to test whether green space use predictors are associated with the probability of using a local park the most frequently over non-local parks. The generic regression model is represented as follows:

$$\eta(\boldsymbol{x}) = G(\boldsymbol{x\beta})$$

where $\eta(\boldsymbol{x})$ shows that the predictions of a CBG's residents' choice of a local park as their most frequently used one are contingent on values of the independent variables in a vector, $\boldsymbol{x}$ (i.e., distance to the nearest park from CBG's centroid, number of local parks, average size of local parks, percent children under age 18, percent seniors over age 65, and percent Hispanic residents), and $\boldsymbol{\beta}$ is a vector of regression coefficients. In the binary logit that we are using, $\boldsymbol{x\beta}$ is in terms of log-odds of the dependent variable, which can transform the predictions into the metric of predicted probabilities with $\eta = \Pr(y = 1) = \frac{\exp(\boldsymbol{x\beta})}{1+\exp(\boldsymbol{x\beta})}$.

We also reported Average Marginal Effects (AME) derived from logit coefficients to provide an intuitive interpretation. AME represents the average change in the probabilities of the outcome variable for a one-unit change in the predictor variable, averaging over all observations. We presented the statistically significant interaction effects using AME charts because the coefficient of the product term in the binary logit model does not necessarily provide accurate information about the significance, magnitude, or even the direction of the underlying interaction effect on the predictions (see Mustillo et al., 2018; Mize, 2019).

4. Results

4.1. Descriptive statistics

In the Phoenix-Mesa urbanized area in Arizona, the average distance from the centroid of each census block group (CBG) to the nearest park was 638 m, ranging from 0 m (when the centroid is within the park boundary) to a maximum of 4.7 km. On average, CBGs had about two local parks, and the median size of these parks was 11.1 acres (4.5 ha). As mentioned in section 3.1, on average, 30 percent of CBG residents were Hispanic, 22 percent were children under 18, and 17 percent were seniors over 65. See Table 1 for descriptive statistics of the independent variables.

Table 1
Independent Variables.

	Mean	Std. Dev.	Min.	Median	Max.
Accessibility					
Distance to the nearest park, *meters*	638.4	594.7	0	477.3	4733.4
Number of local parks	2.3	2.3	0	2.0	21.0
Average size of local parks, *acreage*	162.9	857.4	0	11.1	17349.0
Social Groups					
% Children under 18	0.22	0.11	0	0.23	0.54
% Seniors over 65	0.17	0.19	0	0.11	0.97
% Hispanic residents	0.30	0.25	0	0.22	1.00

Number of CBGs (neighborhoods) in the study area = 2102.

4.2. Identifying the most frequently used parks

Within the Phoenix-Mesa urbanized area, there were 2,102 census block groups (CBGs). Of these, 82 percent (1,721 CBGs) had at least one local park, while 18 percent (381 CBGs) did not have a local park at all. Among the 1,721 CBGs with local parks, residents in 1,051 CBGs (Group 1) most frequently used local parks, whereas residents in 670 CBGs (Group 2) primarily visited non-local parks. Although these CBGs had access to local parks, in approximately 40 % of them, residents did not use local parks as their primary destination. In Group 3, a majority of CBGs (i.e., 373 of 381 CBGs) did not have local parks within the 1 *km* buffer, and only eight CBGs had parks located within or at the border of their CBG boundaries (see Appendix E). Residents of the large eight CBGs may have a long distance to a park even if the park is located within their CBG (see Appendix F). Fig. 3 shows the location of CBGs in each group within the Phoenix-Mesa urbanized area.

4.3. Predicting local parks as primary destination

Table 2 indicates that measures of green space accessibility help predict whether residents use local parks as their primary destination. As the distance to the nearest park increased, the probability that residents in a CBG would use a local park diminished, all else being equal. In other words, the farther the nearest park is from the CBG centroid, the less likely its residents are to choose a local park as their most frequently visited option. Conversely, having more local parks or larger average park sizes within a CBG increased the probability that residents would visit a local park most frequently.

Table 2 further demonstrates that a higher percentage of children

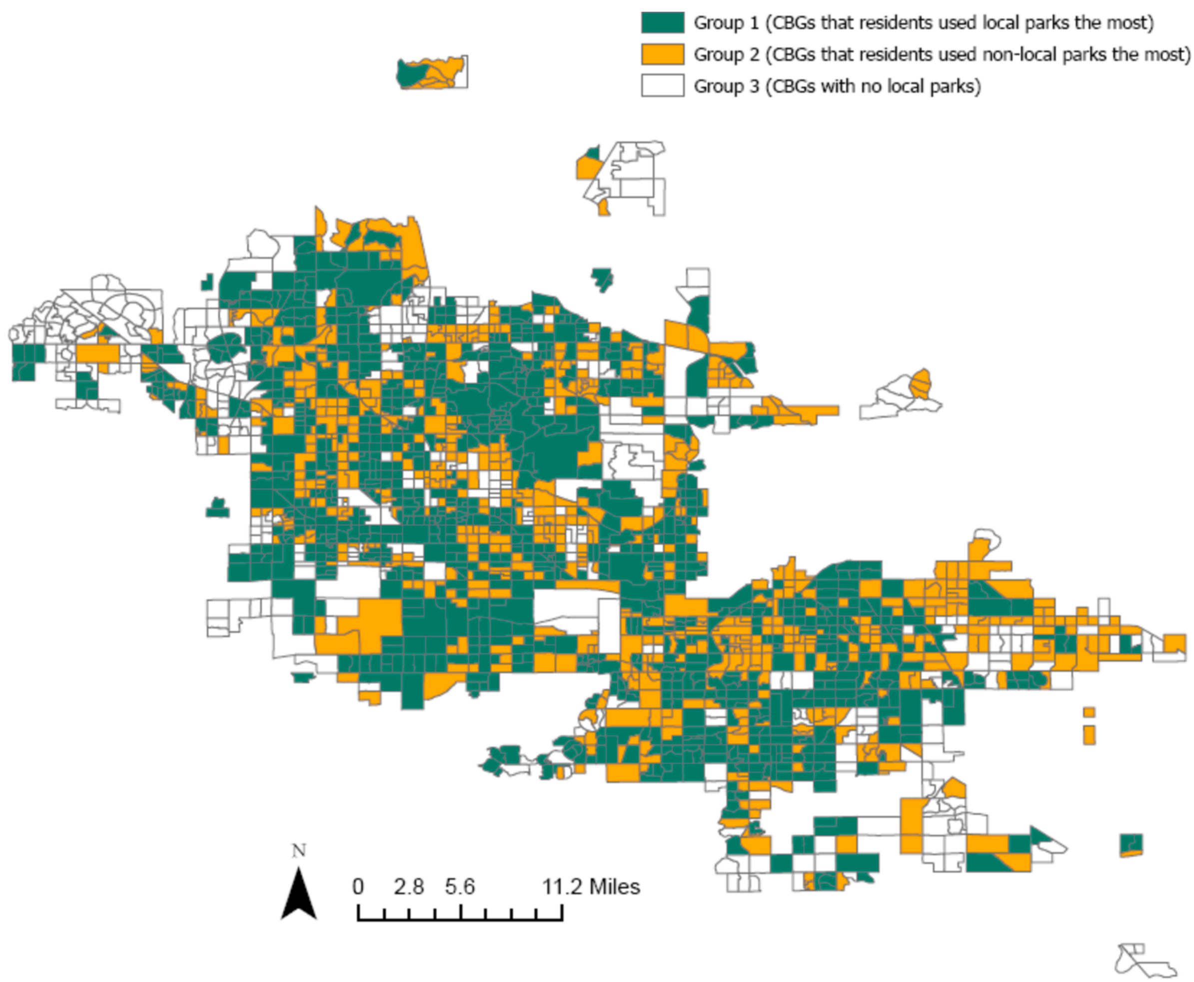


Fig. 3. Local Park Use Groups in the Phoenix-Mesa Urbanized Area.

Table 2
Logit Regression Results and Average Marginal Effects (AME).

	Logit Coef.	S.E.	Stat. Sig.	AME
Distance to the nearest park[a]	−0.499	0.063	***	−0.001
Number of local parks	0.087	0.027	**	0.018
Average size of local parks[a]	0.297	0.035	***	0.004
% Children under 18	1.789	0.677	**	0.372
% Senior over 65	0.214	0.452		0.044
% Hispanic residents	0.486	0.248	*	0.101
Constant	1.535	0.452	***	
N	1721			
Log-likelihood	−1030.4			
AIC	2074.9			
McFadden R^2	0.104			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
a. log transformed.
Note.
a. Dependent variable: One is assigned to a CBG if its residents choose a local park as their most used, while zero is assigned if residents choose a non-local park as their most used.
b. CBGs without a local park (381 CBGs) were excluded from the analysis.

under 18 in a CBG was significantly associated with the probability that residents in a CBG would use a local park. In contrast, the percentage of seniors over 65 did not display a statistically significant result. Additionally, a higher percentage of residents identifying as Hispanic in a CBG was significantly associated with the probability of local park use.

4.4. Interaction between accessibility measures and the percentage of Hispanic residents

Table 3 presents the logit regression results with interaction terms between accessibility and social groups. Only the interaction between the two accessibility measures (proximity to the nearest park and the average size of local parks) and the percentage of Hispanic residents was statistically significant. We present the statistically significant interaction effects in Fig. 4.

In Fig. 4(a), the association between a neighborhood's Hispanic resident proportion and the probability of residents using local parks as their primary destination depends on the distance to the nearest park. If the distance between a CBG's center and its nearest park was shorter than 796 m, an increase in the percentage of Hispanic residents increased the probability of the most frequent use of a local park (positive AMEs in the y-axis). If the distance exceeded 796 m, an increase in the percentage of Hispanic residents decreased the probability of the most frequent use of a local park (negative AMEs).

Fig. 4(b) shows a significant non-linear interaction between the percentage of Hispanic residents and the average size of local parks. In neighborhoods where the average size of local parks was larger than 7.8 acres (3.6 ha), the probability of residents using local parks as their primary destination increased with a higher percentage of Hispanic residents. However, in neighborhoods with smaller average park sizes than 7.8 acres, a higher percentage of Hispanic residents decreased the probability. This pattern demonstrates that the association between the percentage of Hispanic residents and local park use depends on park size.

Table 3
Logit Regression Results with Interactions between Accessibility and Social Groups.

	(1) % Hispanic Residents		(2) % Under 18		(3) % Over 65	
	Logit Coef. (S.E.)	Stat. Sig.	Logit Coef. (S.E.)	Stat. Sig.	Logit Coef. (S.E.)	Stat. Sig.
Distance to the nearest park[a]	−0.227 (0.092)	*	−0.353 (0.135)	**	−0.560 (0.096)	***
Number of local parks	0.123 (0.048)	**	0.135 (0.075)		0.073 (0.039)	
Average size of local parks[a]	0.167 (0.054)	**	0.274 (0.083)	***	0.309 (0.054)	***
% Children under 18	1.785 (0.678)	**	6.096 (4.084)		1.798 (0.679)	**
% Senior over 65	0.144 (0.449)		0.180 (0.455)		−2.543 (3.518)	
% Hispanic residents	5.851 (2.065)	**	0.481 (0.248)		0.479 (0.248)	
Distance to the nearest park[a] X % Hispanic residents	−1.086 (0.316)	***				
Number of local parks X % Hispanic residents	−0.121 (0.123)					
Average size of local parks[a] X % Hispanic residents	0.454 (0.149)	**				
Distance to the nearest park[a] X % Children under 18			−0.700 (0.595)			
Number of local parks X % Children under 18			−0.200 (0.290)			
Average size of local parks[a] X % Children under 18			0.107 (0.348)			
Distance to the nearest park[a] X % Senior over 65					0.448 (0.507)	
Number of local parks X % Senior over 65					0.112 (0.227)	
Average size of local parks[a] X % Senior over 65					−0.073 (0.286)	
Constant	0.259 (0.641)		0.634 (0.939)		1.905 (0.660)	**
N	1721		1721		1721	
Log-likelihood	−1019.221		−1029.597		−1029.979	
AIC	2058.443		2079.194		2079.957	
McFadden R^2	0.114		0.105		0.105	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
a. log transformed.

5. Discussion

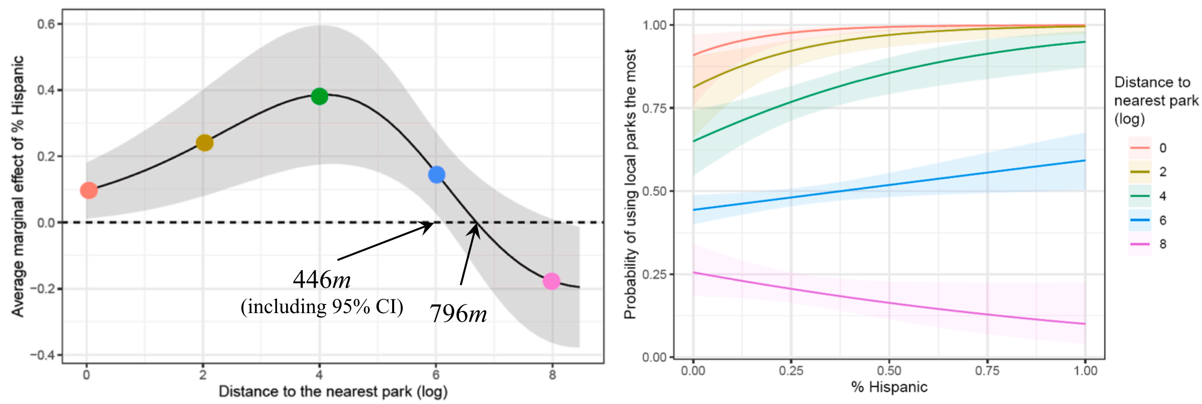
The health benefits of green spaces are most fully realized when residents frequently visit publicly accessible areas that are located close to their residences (World Health Organization, 2016). In the Phoenix-Mesa urbanized area, approximately 18 percent of neighborhoods lack access to a park within 1 *km* of a CBG's center (Group 3 in Fig. 3). Residents without local parks must travel longer distances to access green spaces, which can be costly. This issue is especially pressing in a region with consistently high summer temperatures and low humidity, where parks can provide critical shade and mitigate the intensity of heat waves (Song et al., 2024). A study in Alice Springs, Australia—where the climate is similar to Phoenix—found that the absence of nearby green spaces exposed people to significant heat stress, and the most substantial cooling effects occurred in such climates when green spaces were present (Brown et al., 2015). These findings underscore the importance of policy measures that can enhance green space equity and use in urban environments with extreme heat. We recommend that local government officials and planners in the southwestern desert region of the U.S. continue to prioritize equitable, convenient access to green spaces for all neighborhoods.

Our findings also show that in 40 percent of neighborhoods with access to local parks, residents do not choose it as their primary destination. This does not suggest that residents avoid local parks entirely but rather that they often prefer traveling farther to non-local parks. While the benefits of green spaces within walking distance have been well documented (e.g., European Environmental Agency, 2022), our results suggest that simply ensuring access does not guarantee frequent use of green space. While accessibility is a necessary condition for maximizing the benefits that green spaces can offer, it is not sufficient in itself. To better realize the potential benefits of neighborhood green spaces, local planners and governments must examine how residents actually engage with these spaces.

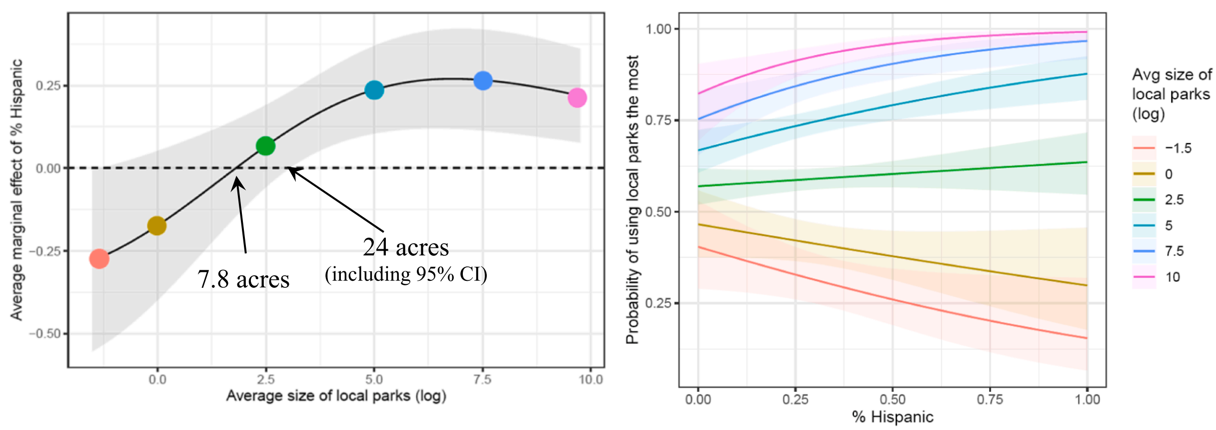
Newly available cell phone tracking data can provide novel insights into green space usage patterns that can be difficult to capture through traditional data collection methods, such as surveys or on-site interviews. However, these emerging data sources may still fall short of explaining the underlying motivations for choosing one green space over another. For example, research suggests that certain preferences – such as a desire for a particular natural setting – can compel residents to visit more distant green spaces (Phillips et al., 2022; Schindler et al., 2022). Similarly, if local green spaces do not meet residents' needs or quality expectations, they may remain underutilized by neighborhood residents (Carter & Horwitz, 2014; Gold, 1972). Future research should focus on identifying the attributes of those non-local parks that regularly attract visitors. This information could help planners enhance local parks and increase their usage.

Previous studies in the Phoenix area have not identified significant differences in access to local parks based on Hispanic ethnicity (Kim et al., 2023; Nesbitt et al., 2019). However, our findings, as shown in Table 2, highlight differences in how frequently local parks are used by residents, particularly in neighborhoods with a higher percentage of Hispanic residents. Additionally, we observed a non-linear interaction between proximity to the nearest park or average park size and the percentage of Hispanic residents (Fig. 4). While previous studies have suggested that Hispanic communities may prefer closer parks (Floyd, 1999; Lu et al., 2023; Pitas et al., 2019), this non-linear interaction with park size is a novel finding. Since the higher percentage of Hispanic residents in a neighborhood predicts the frequent visit of local parks by residents, we recommend that city planners engage these communities in participatory processes to improve green space accessibility in such neighborhoods. Such efforts are especially important given that these neighborhoods often face challenges related to park quality, limited park size, fewer trees, and reduced tree connectivity (Cutts et al., 2009; Lara-Valencia & Garcia-Perez, 2018; Nelson et al., 2021; Stuhlmacher & Kim, 2024).

There are several limitations to acknowledge. First, our definition of "local parks" relies on a uniform 1 *km* buffer from each CBG centroid, potentially overlooking differences in travel distances for residents in the center of the CBG versus those living on the periphery of the CBG. Addressing this spatial variability remains an important goal for future research. Second, the SafeGraph dataset excludes individuals without cell phones (approximately 3 percent of the U.S. population, according to the Pew Research Center, 2024) and those who do not carry their phones during park visits. Third, while the number of recorded visits



(a) The Percentage of Hispanic Residents and CBG's Proximity to the Nearest Park



(b) Between the Percentage of Hispanic Residents and the Average Size of Local Parks

Fig. 4. Non-linear Interaction Effects *Note*: An AME on the Y-axis greater than 0.00 means that the relationship between Hispanics and the variable on the X-axis is positive for the dependent variable, whereas an AME less than 0.00 means that the relationship is negative for the dependent variable. The gray bands in (a) and (b) represent the 95% confidence intervals of the AME corresponding to the values on the X-axis. The figure on the right shows the relationship between the percentage of Hispanics and the dependent variable for (a) proximity or (b) average size. The color of each line in the right plot represents the color of each point in the left plot when zoomed in. The values in the logarithm can be exponentiated to calculate actual meters or acres.

indicates usage, it may not fully capture variations in the intensity of park use, such as time spent jogging, hiking, or sitting. Nonetheless, any form of usage begins with an initial visit, making our measure a meaningful, if partial, indicator. Finally, while our findings are context-specific to this particular region, our research approach may inform investigations of green space access and use in other settings.

6. Conclusion

In the study areas, where high temperatures place significant stress on urban residents, our findings underscore a persistent need for equitable and accessible green spaces. Even when local parks are available, many neighborhoods do not rely on them as their primary green spaces, indicating that simply providing local parks does not guarantee frequent use. Additionally, our results show that for Hispanic residents, frequent visits to local parks depend not only on their proximity but also on their size. To align green space provision in line with residents' revealed preferences, local governments and urban planners must consider the interplay between accessibility and the demographic characteristics that shape green space use. Newly available datasets, such as those derived from cellphone-based human mobility tracking, can provide valuable insights into these relationships.

CRediT authorship contribution statement

Jieun Kim: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Youngjae Won:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Yushim Kim:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Elizabeth Corley:** Writing – review & editing, Writing – original draft, Supervision.

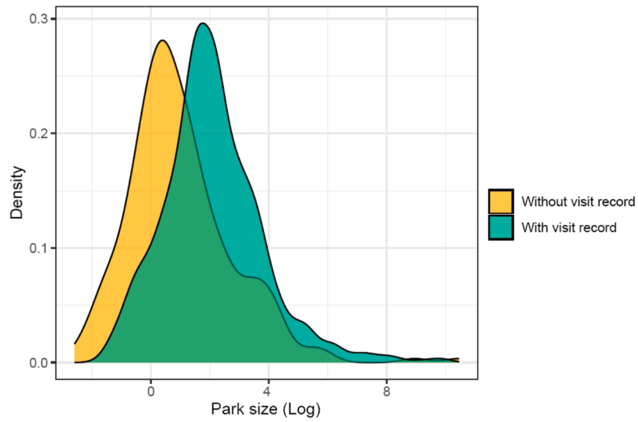
Funding

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (Ministry of Science and ICT) (No. 2018R1A5A7059549).

Declaration of Competing Interest

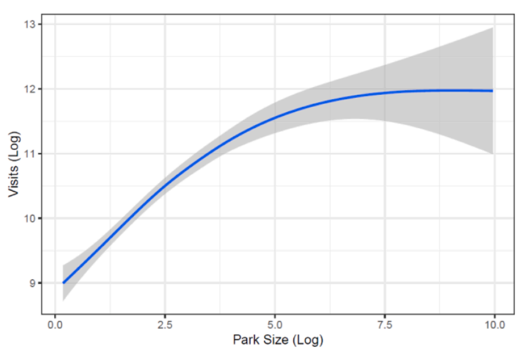
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Distribution of park size with or without visit records

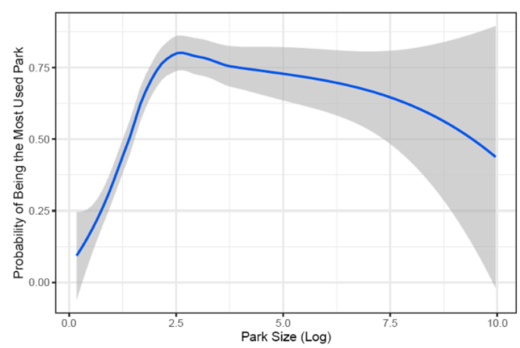


Note: Welch Two Sample *t*-test showed a significant difference in mean log-transformed size between parks with visit records—702 parks in both SafeGraph and TPL (mean = 2.10 acre) and parks without visit records—256 parks only in TPL (mean = 1.01 acre) ($t(430.08) = -8.43, p < 0.001$). The mean size of parks without visit records is significantly smaller than that of parks with visit records.

Appendix B. Park size and probability of being used the most by residents in CBGs



(a) Visit counts by park size (702 parks)



(b) Probability of being CBG's most used park by park size (702 parks)

Note: (a) The number of visits represents the log-transformed total number of visits to 702 parks in 2102 CBGs in the Phoenix-Mesa urbanized area 2019. The relationship between park size and the number of visits was estimated using a generalized additive model with integrated smoothing estimation. (b) The figure shows that the smaller the park, the less likely it is to be the most visited in a CBG using SafeGraph's 702 parks.

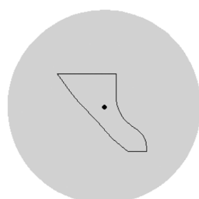
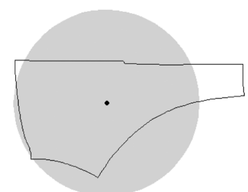
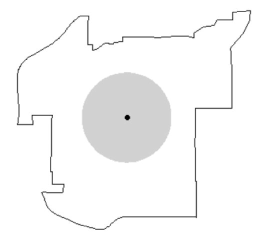
Appendix C. Illustration of identifying the most used park for each CBG

Table A	Park 1	Park 2	Park 3	Park 4	Park 5	sum
CBG 1	10	0	8	8	15	41
CBG 2	5	3	4	11	10	33
CBG 3	20	5	0	15	0	40
CBG 4	15	10	0	0	6	31
CBG 5	1	3	25	7	0	36

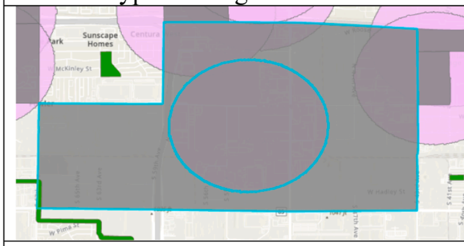
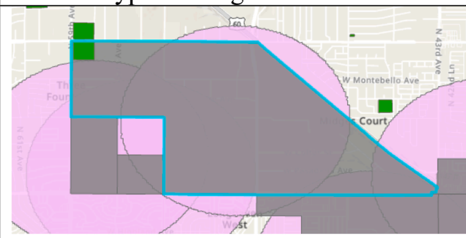
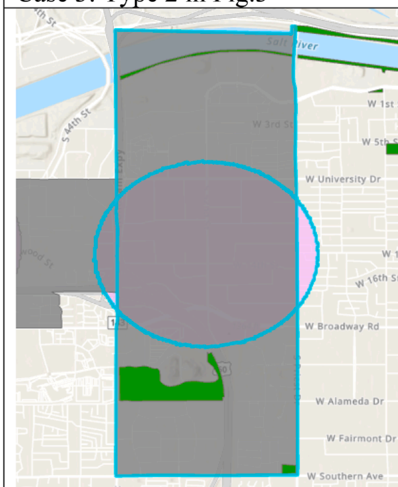
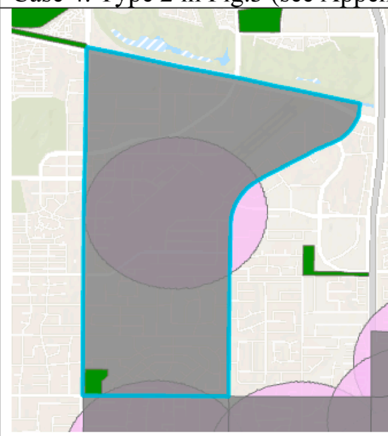
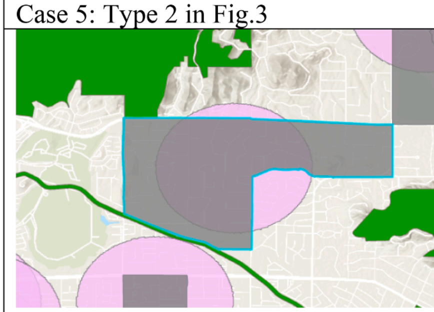
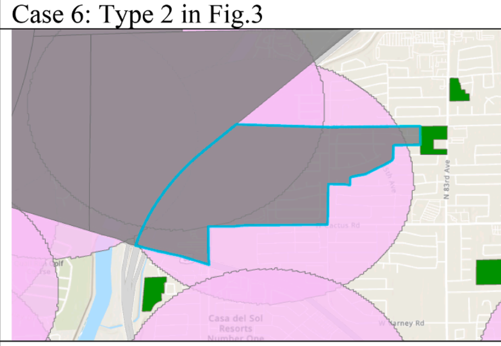
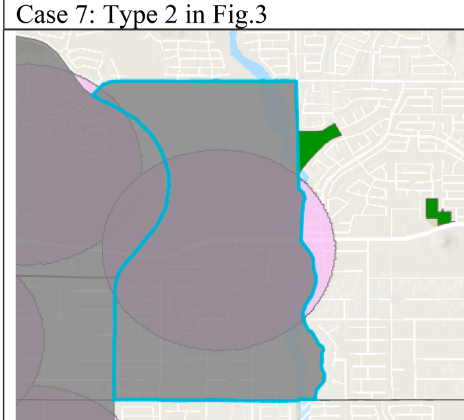
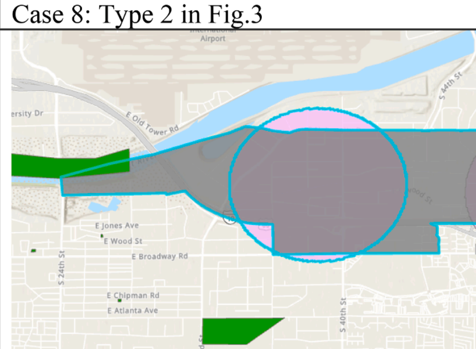
Table B	Park 1	Park 2	Park 3	Park 4	Park 5	sum
CBG 1	24 %	0 %	20 %	20 %	**37 %**	100 %
CBG 2	15 %	9 %	12 %	**33 %**	30 %	100 %
CBG 3	**50 %**	13 %	0 %	38 %	0 %	100 %
CBG 4	**48 %**	32 %	0 %	0 %	19 %	100 %
CBG 5	3 %	8 %	**69 %**	19 %	0 %	100 %

Note: The normalized visit counts for the CBG and park pairs in Table A are hypothetical: we calculated the total number of visits to each park that each CBG visited (0 indicates no visits). In Table B, we calculated the percentage of visits to each park visited by residents in each CBG. For example, of CBG 1′s total visits, 24 % were to Park 1, 20 % were to Park 3, 20 % were to Park 4, and 37 % were to Park 5 (the top-ranked park). Therefore, the most visited park for CBG 1 is Park 5. Park 2 was not the most visited in any of the CBGs. Park 1 is the most visited of the two CBGs (CBG 3 and CBG 4). Whether or not each park is within the definition of walking distance determines a local park. For example, Park 1 could be a local park in CBG 3 but a non-local park in CBG 4.

Appendix D. Spatial relationship between CBG boundaries and the 1 *km* buffers

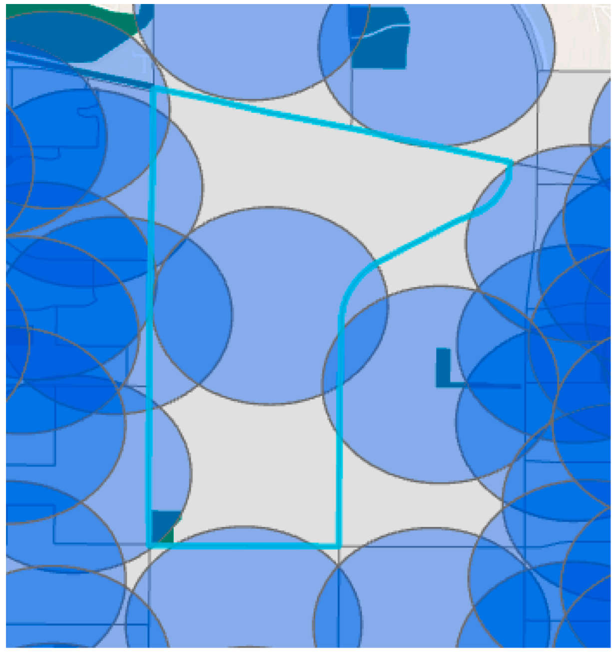
	Type 1	Type 2	Type 3
Description	CBG boundary completely encloses a 1 *km* buffer (gray circle)	CBG boundary and the 1 *km* buffer largely overlap without completely enclosing each other	1 *km* buffer completely enclosing the CBG boundary
Example			
Of 2102 CBGs (100 %)	1710 (81.4 %)	386 (18.4 %)	6 (0.2 %)

Appendix E. CBGs that their boundaries are not completely covered by the 1 *km* buffer but have a park within the boundary of the CBGs

Case 1: Type 3 in Fig.3	Case 2: Type 2 in Fig.3
	
Case 3: Type 2 in Fig.3	Case 4: Type 2 in Fig.3 (see Appendix E)
	
Case 5: Type 2 in Fig.3	Case 6: Type 2 in Fig.3
	
Case 7: Type 2 in Fig.3	Case 8: Type 2 in Fig.3
	

Note: The gray area with a blue border represents the CBG. A 1 *km* buffer around the center point of the CBG is shown as a pink circle. The green squares or lines are parks from the TPL dataset.

Appendix F. Coverage of parks in the eight CBGs in Appendix D



Note: For example, in CBG ID 40132168161, the park at the bottom right corner of the CBG is captured as a local park of the adjacent CBG (blue circle).

CBG ID	Number of parks within the boundaries of CBGs but outside their 1 *km* buffers	Are these parks covered by the 1 *km* buffers of adjacent CBGs' walking distance?
40,133,197,041	4	Yes
40,131,051,033	2	Yes
40,130,715,171	1	Yes
40,136,109,003	1	Yes
40,132,168,161	2	Yes
40,131,152,003	1	Yes
40,131,125,121	1	Yes
40,130,931,044	1	Yes

Data availability

Data will be made available on request.

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