



ORIGINAL PAPER

Open Access



Quantifying the recreational value of urban parks using smartphone mobility data

Guo Zipeng^{1*} , Yang Song¹, Hongmei Lu², Rui Zhu³, Yunpei Zhang¹, Hyewon Yoon¹ and Bo Zhang⁴

Abstract

Urban parks provide substantial environmental, social, and health benefits, yet their recreational economic value often remains unquantified due to limitations in traditional data collection methods. Although previous studies have estimated park recreational value, they rarely capture how this value varies across neighborhoods and seasons because fine-grained, time-sensitive data are typically unavailable. This study addresses this gap by applying large-scale smartphone mobility data and the Travel Cost Method (TCM) analysis to estimate the recreational use value of Dick Nichols District Park, which is one of the most visited District parks in Austin, Texas. Using consumer surplus as a monetary measure of recreational benefits, the analysis combines visitation rates, travel distances, and opportunity costs with neighborhood-level sociodemographic indicators to reveal spatial and temporal patterns in park use. Our results show that the Park's 2019 (Before COVID-19) annual recreational use value ranges from \$306,983.80 to \$307,067.72. Spatially, block groups in Austin's north-eastern quadrant exhibit higher recreational value, likely reflecting stronger connectivity and moderate travel distances. Our temporal analysis shows that June has the highest monthly recreational value. This study illustrates how large-scale mobility data can be integrated into recreational value assessment, offering greater visibility, scalability, and cost-effectiveness than traditional approaches. By leveraging these richer data streams, planners and policymakers can conduct more equitable, evidence-based park planning and resource allocation.

Keywords Urban park, Visitation, Mobility big data, Recreational value, Travel cost analysis

1 Introduction

Urban parks enhance the recreational and aesthetic quality of urban environments, offering substantial benefits to both ecosystems and society. Parks help improve air quality and mitigate urban heat, making cities cleaner and more comfortable (Armson et al., 2012). Green spaces with grass and tree cover significantly reduce local

temperatures, improving overall urban livability (Gago et al., 2013). In addition, parks provide important spaces for physical activity, contributing to the prevention of chronic conditions such as obesity and heart disease (Feyisa et al., 2014). They also function as social hubs that foster community interaction and strengthen social ties (Cranz & Boland, 2004).

Despite widespread recognition of these environmental and social benefits among researchers and public stakeholders, many cities still struggle with insufficient financial support for parks (Basiago, 1998; Eldridge et al., 2019). In our view, this challenge stems from the lack of quantitative evidence capable of giving decision-makers the confidence needed to justify increased investment in park systems. Currently, Park and Recreation Master Plans and City General Plans rely heavily on qualitative

*Correspondence:

Guo Zipeng
guo7501@tamu.edu

¹ Department of Landscape Architecture & Urban Planning, College of Architecture, Texas A&M University, 3137 TAMU, College Station, TX 77840, USA

² Institute for Environmental Studies, Vrije Universiteit Amsterdam, De Boelelaan 1111, Amsterdam 1081 HV, the Netherlands

³ Department of Landscape Architecture, College of Agricultural Sciences & Natural Resources, Texas Tech University, Lubbock, TX, USA

⁴ Department of Horticulture & Landscape Architecture, College of Agriculture, Oklahoma State University, Stillwater, OK 74078, USA

assessments to justify park development needs (Cohen et al., 2014). Although the existing literature provides broad qualitative agreement on the value of parks, the absence of rigorous quantitative evidence continues to hinder actionable policymaking.

Quantitative research has played a critical role in strengthening urban ecological management by generating empirical evidence that policymakers routinely rely on. For example, transportation departments rely on quantitative economic evaluations to justify strategic investment plans (Goetz et al., 2009; Maheshwari & Axhausen, 2021). Environmental agencies use monetized estimates of ecosystem services—such as flood mitigation and air purification—to inform land-use and green-infrastructure decisions (Gago et al., 2013; Qi et al., 2024). The park and recreation department applying comparable quantitative approaches to parks enables stakeholders and decision-makers to better understand the magnitude of the recreational and ecological benefits they generate. This clarity can strengthen the investment case for increased maintenance, improvements, and long-term development funding. When supported by rigorous economic evidence, parks could be recognized not merely as desirable amenities but as essential urban infrastructure (Mathy et al., 2002).

In fact, prior research has already attempted to quantify park-generated benefits through multiple approaches. Traditional methods—such as Economic Impact Studies, Cost–Benefit Analysis, and Visitor Spending Analysis—focus on direct financial outcomes like tourism revenue and local spending (Hosseinpour et al., 2022). More advanced valuation techniques, including the Contingent Valuation Method and the Travel Cost Method, estimate non-market benefits by analyzing visitor spending patterns and travel costs as indicators of willingness to pay (Blackwell, 2007). Although these approaches have been well developed, the quantitative assessment of urban parks remains challenging.

There are several challenges in the quantification of urban park economics, particularly in research subjects, data collection, and analytical approaches. Regarding research subjects, most studies tend to focus on well-known metropolitan urban parks and national parks (Li et al., 2021; Schägner et al., 2016), because data from these parks is easier to obtain compared to ordinary urban parks, such as district or neighborhood parks. However, this emphasis overlooks the economic value of everyday parks in medium-sized or large cities, where such parks are more closely connected to residents' quality of life (Van Leeuwen et al., 2006). Regarding data collection, this challenge is largely attributable to the difficulty of obtaining reliable data. Survey-based methods, including willingness-to-pay surveys, are expensive to

implement and are often affected by response bias, insufficient sample representativeness, and cultural misinterpretations (Harnik, 2009). These limitations reduce the precision, scalability, and policy relevance of traditional valuation methods. Consequently, there remains a need for more efficient and accurate approaches capable of capturing users' willingness-to-pay intentions. Regarding analysis, although some researchers have calculated the recreational value of parks, few studies have examined how this value changes over time, primarily due to data limitations. Yet previous research has shown that park use varies significantly across time (e.g., seasonally) (Song & Wei, 2024; Sun et al., 2024). Incorporating long-term temporal analysis can therefore help fill an important gap in park value research.

To address these challenges, we first selected district parks in large U.S. cities as our research subject. Second, we chose mobile phone data, which offers a practical and scalable alternative to traditional survey-based approaches. These datasets enable the examination of both spatial and daily temporal variations in park use across neighborhoods, providing insights that cannot be obtained from traditional data sources. Previous research has widely adopted similar methods for tracking public behaviors in response to environmental factors. Examples include studies examining daytime versus nighttime green-space use (Zhu et al., 2025), investigations of how disasters reshape travel patterns (Song et al., 2023), and analyses of equity in access to urban green spaces (Kim et al., 2025).

Research Questions

1. How can mobile phone mobility data be used to calculate the monetary recreational value of urban parks?
2. Do spatial and temporal patterns emerge in the monetary recreational value of urban parks, and what do these patterns reveal about differences in community access and usage across the city?

2 Methodology

2.1 Site selection

Austin, the capital of Texas, saw the metro area adding over 50,000 residents between 2022 and 2023. Over the past decade, Austin had the highest job growth rate (49.9%) among U.S. metro areas (Bureau, 2023). Projections suggest that the population of the Austin metropolitan area could reach 3.2 million by 2030, making it one of the fastest-growing large cities in the United States (*Austin, Texas Population 2024*, 2024). It was chosen as the focus city for our study due to its significant urban growth and increasing demand for recreational spaces (Pros Consulting, 2025). Austin offers a variety of

parks, ranging from metropolitan parks to neighborhood parks. The city has a growing population, but the racial-wealth divide in the city is high, and people with different socioeconomic statuses have different park visitation preferences (Lu & Song, 2024).

Accordingly, we want to select a district park as our study site, which is accessible to all groups, serving populations within a two-mile radius, and is suited to meet the needs of frequent, daily users (*Parkland Dedication | AustinTexas.Gov*, 2025). These parks provide ample space and a range of recreational facilities aimed at accommodating larger communities.

Regarding our selection process, we analyzed the annual visitation volume of the top ten district parks in the whole city of Austin in 2019 using visitation data from SafeGraph and Advan (Figure S1). Bartholomew District Park, which ranked first and is located near a university campus, was excluded due to complications arising from unusually high visitation rates and income variations associated with the student population.

As a result, we selected Dick Nichols District Park, which ranked second, as our study area. Located in southwest Austin, Texas, it spans 152 acres, making it one of the larger district parks in the city. The park serves the surrounding community by offering a variety of recreational facilities designed to accommodate a broad range of activities, including well-maintained trails for walking and biking, children's playgrounds, areas for field sports, and basketball and volleyball courts. Additionally, the park features a swimming pool and various water amenities, providing extensive opportunities for outdoor recreation (*Dick Nichols District Park & Neighborhood Pool*, 2022).

2.2 Data collection and data processing

This study utilizes SafeGraph/Advan smartphone mobility data, an affordable, high-precision dataset aggregated at the census block group level that captures high-frequency patterns of visitor movement. SafeGraph data provides anonymized location data for 19 million smartphone devices and six million Points of Interest (POI) listings across the U.S. (*SafeGraph: Places Accuracy*, 2023). The benefits of using SafeGraph as a dataset include its accuracy, frequent data updates, and user privacy protection (*Places Summary Statistics | SafeGraph Docs*, 2025). Advan Data analyzes mobile phone location information to derive daily foot traffic volume from home Block Groups (BG) to Points of Interest (POI), with our study area focusing on parks.

Our research focuses on weekly park visitation data from January 1, 2019, to December 31, 2019, to reveal

typical urban park visitation behaviors before the COVID-19 pandemic. To calculate park recreational value (consumer surplus), and analyzed the park's visitation rate and the travel costs for visitations from each block group. We utilized mobility and demographic data to describe visitation patterns and block group demographics about the neighborhoods where visitors reside, including income, travel distance, and population. These variables are crucial for accurately calculating consumer surplus.

Figure S2 illustrates the distribution of SafeGraph sampling percentages for each Block Group (BG) in Austin. On average, 5.67% of the total population of Austin, approximately 55,880 people, was sampled, with each observation representing a park visitation from the visitor's home BG to the park. Demographic data on visitors' home BGs were obtained from the 2019 American Community Survey (ACS) (Bureau, 2023). The studied variables include the total BG population and BG annual income.

After collecting and combining all the data mentioned above, we performed a thorough data cleaning to ensure data accuracy and reliability. First, we removed the top 5% of extremely high visitation observations, as these unusually large counts were likely driven by special events or other atypical park activities and could distort normal visitation patterns. Second, the demographic data, including income levels, were also carefully cleaned to avoid skewed results. Specifically, we excluded observations with hourly incomes below the federal minimum wage of \$7.25 (*Minimum Wage*, 2019), because these areas correspond to the University of Texas at Austin campus, where student-dominated BGs exhibit atypical income reporting and non-standard visitation patterns. Including these BGs would introduce distortions in the travel cost estimates. Third, observations with missing values, such as BG population and income data, were removed. Finally, we removed outliers or counterintuitive observations, such as visitations exceeding 12 h in a park.

2.3 Application of the travel cost method

The Travel Cost Method (TCM) analyzes consumer behavior in related markets; in this study, we focus on how far visitors travel and how frequently they visit, using the expenses incurred by visitors as a proxy for the park's recreational value (Halkos et al., 2020). It is particularly useful when direct market valuation is difficult to evaluate (Randall, 1994). The core assumption of TCM is that the time and money people spend visiting a site reflect their willingness to pay for its recreational services (Mayer & Woltering, 2018).

2.3.1 Travel costs and visitation rate estimation

Figure S3 illustrates the methodology of consumer surplus estimation, which is defined as the area (Green triangle) between the demand curve, the market price (Y-axis), and the quantity (X-axis). It quantifies the difference between the maximum amount consumers are willing to pay and the actual amount they pay, aggregated across the quantity consumed (Burns, 1973). For park visitation, the “market price” is not a direct purchase price but rather the costs incurred by users to visit the park, such as fuel and time expenses. The “quantity” is the number of park visits. As park visitation costs increase, the quantity of park visits typically decreases.

$$\text{Time opportunity cost} = \text{Round trip minutes walk} * \text{Opportunity cost per minute or Round trip minutes drive} * \text{Opportunity cost per minute} \quad (3)$$

The travel costs (Y-axis in Figure S3) of each park visitation include two parts, fuel costs and the time opportunity cost each visitor has to pay for a round-trip, as shown in Eq. 1.

$$\text{Travel Cost} = \text{Fuel cost} + \text{Time opportunity cost} \quad (1)$$

The fuel cost is calculated based on the distance between the park and the visitor's BG and the standard mileage rate (Eq. 2). For visitations within walking distance (<0.25 mile, detailed below), the fuel cost will be zero. The cost per mile of car use is provided by the Internal Revenue Service (IRS). The standard mileage rate for self-employed and business purposes is 40.7 cents per kilometer (Standard mileage rates | Internal Revenue Service, 2025).

$$\text{Fuel cost} = \text{Round trip travel distance} * \text{standard mileage rate} \quad (2)$$

The time opportunity cost is calculated based on the round-trip travel time from the home BG to a park and the average BG income (Eq. 3). To accurately assess visitors' travel time, we distinguish visitors' travel mode between car and walking and accordingly each mode's speeds. To compute travel distance, we used Euclidean (straight-line) distance between each BG centroid and the park location. Euclidean distance is commonly used in mobility and recreation-demand research when detailed street-network data are unavailable or when the objective is to estimate generalized travel effort rather than exact route paths.

In the U.S., over the past two decades, 400 m (0.25 miles or a 5-min walk) has been assumed to be the distance that the average American will walk rather than

drive, and this value has been used as the acceptable walking distance in previous studies (Speck, 2013). BGs with travel distances greater than 0.25 miles were classified as using cars (In this study, “car” refers specifically to private automobiles). We defined the average speeds as 72 km/h for cars and 5 km/h for walking, based on typical urban travel conditions (Brooks, 2023). Finally, we calculated the travel time for those who either walk or drive based on the distance between the park and their home BG. *The travel time calculation is based on a round trip.* The BG income data are from the U.S. Census. It involves determining the average annual income of each block group (BG) and converting it into an average income per minute.

In Eq. 4, *Round trip minutes (walk or drive)* is the total time spent traveling for the round trip between the BG and the park by walk or drive, measured in minutes.

Opportunity cost per minute accounts for the opportunity cost of the time spent traveling, and is based on the BG's average income.

As to the Visitation quantity (X-axis in Figure S3), we introduce the measure called visitation rate (Eq. 4) to minimize the impact of BG's population size. We divided the total number of real visitors from each block group by the total population of that block group (Eq. 5). This allows for a consistent comparison of visitation rates across different block groups, facilitating easier analysis and interpretation of the data in relation to population size.

$$\text{Visitation Rate} = \text{Real Visitor from BG} / \text{BG Population} \quad (4)$$

Real Visitor from BG is estimated from the metrics obtained from our mobility dataset. All block-group visitation metrics from SafeGraph/Advan are adjusted using their respective sampling rates to better reflect true visitation levels.

2.3.2 Evaluating consumer surplus

According to Figure S3, to estimate consumer surplus (the blue triangle), we first construct a demand curve (demand function) using estimated regression parameters for the BGs by predicting the visitation rate at different travel costs per trip. Specifically, we use an estimation where the visitation rate is the dependent variable, and the average travel cost from the block group to the park is the independent variable (the specific formula is Eq. 2). This approach helps us quantify how changes in travel

costs influence park visitation quantities, thereby enabling the calculation of consumer surplus.

$$\text{Visitation Rate} = \alpha + \beta * \text{Average Cost} + ER \quad (5)$$

All variables used in Eq. 5 are defined and explained in detail in Table S1.

The consumer surplus (Figure S3) is the aggregated difference between what visitors are willing to pay for park access and the actual fees they pay, reflecting the surplus recreational value that parks provide to users (Eq. 6). “Max price willing to pay” represents the y-intercept of the estimated travel cost demand curve (Figure S3).

Variable definitions for Eq. 6 are provided in Table S1.

The consumer surplus (CS) for each block group in 2019 is calculated by summing the daily consumer surplus values for each block group. The overall economic benefit of Dick Nichols District Park in 2019 is determined by aggregating the consumer surplus across all 215 block groups that recorded visits to the park.

3 Results

3.1 Visiting block group profile and travel cost

Figure 1 presents the spatial distributions of the 215 BGs that visited the Dick Nichols District Park in 2019 in

$$\text{Consumer Surplus} = 0.5 * (\text{Max price willing to pay} - \text{Real cost incurred}) * \text{Visitation Rate} \quad (6)$$

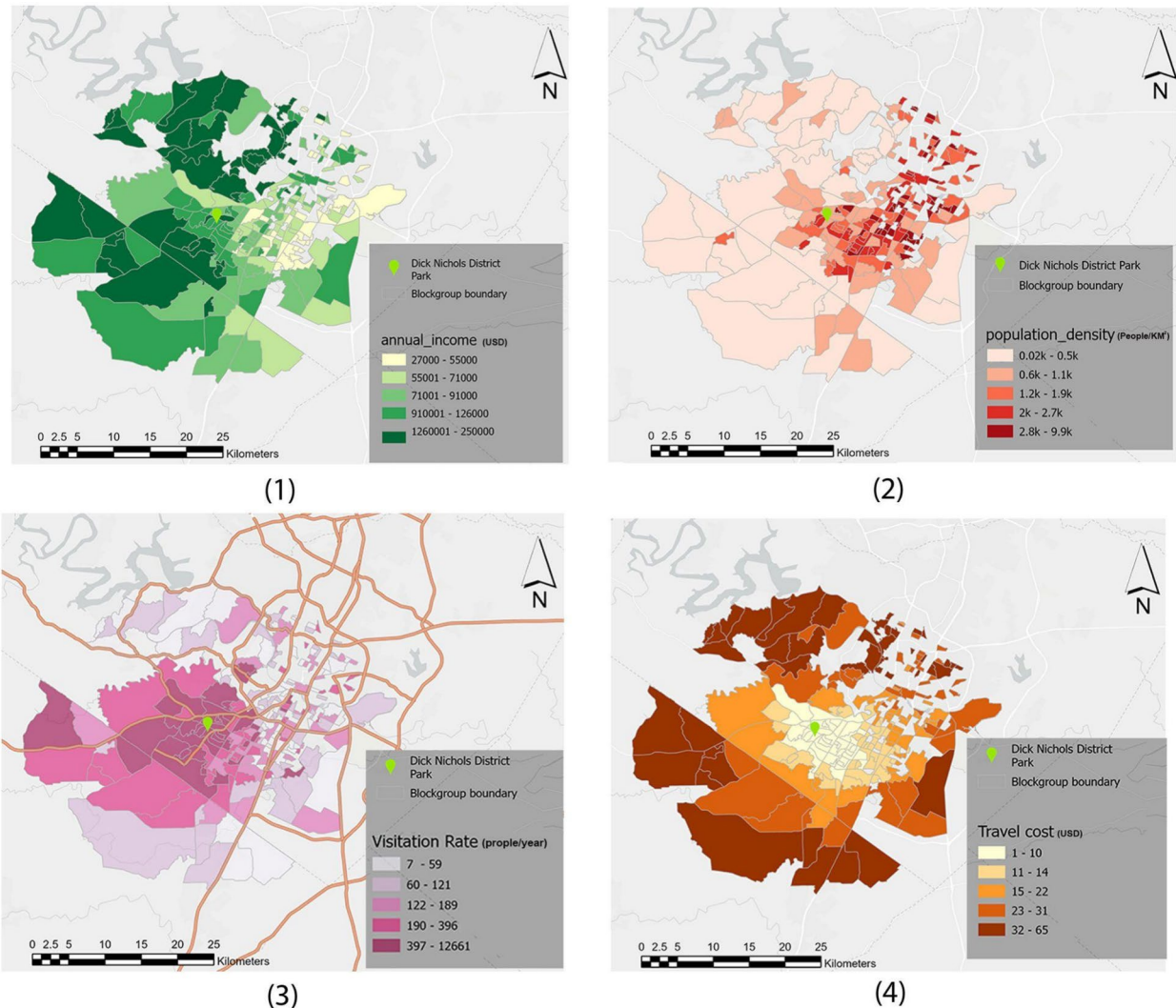


Fig. 1 Visualization of block group income, population density, visitation rate, and travel cost

Austin, Texas. As shown by Sub Fig. 1–1, the BG income data is divided into five different ranges, from \$27,000 to \$250,000. Lower-income areas are primarily in the city's eastern suburbs, while higher-income areas are in the west and northwest. Sub Fig. 1–2 depicts the population density, calculated by dividing the population of each BG by the area. The lower population density areas are

age. These variables help explain variation in travel costs beyond visitation alone. Specifically, higher income is associated with greater travel costs, while more densely populated and older communities tend to have lower travel costs, possibly reflecting proximity to the park or alternative travel behavior patterns.

The estimated travel cost function is expressed as follows:

$$\text{Total Travel Cost} = 10.7989 - 0.0594 \times \text{Visitors} + 0.0823 \times \text{Hourly Income} - 1.2766 \times \text{Population Density} - 0.0462 \times \text{Median Age} \quad (8)$$

mainly distributed in the southwest suburbs of Austin, with population densities ranging from 20 to 500 people per square kilometer. In contrast, the central and north-eastern areas of Austin have higher population densities ranging from 2,800 to 9,900 people per square kilometer. Sub Fig. 1–3 shows the total annual park visitation rate distribution, with BGs near the Dick Nichols District Park having the highest visitation rate. Conversely, neighborhoods farther from the park, especially in northeast and southwest Austin, attract fewer visitors. There are a few exceptions, including one BG residing at the far-left side of the study park, which still has a very high visitation rate, likely because of the proximity to Highway 290 (Chiang et al., 2023). Sub Fig. 1–4 shows the travel costs to the park, from a minimum of \$1.8 to a maximum of \$65. The lowest travel costs are in the areas closest to the park, ranging from \$1.8 to \$10. Higher travel costs, up to \$65, are incurred by visitors from the farthest areas, particularly the southwest and northwest suburbs.

3.2 Consumer surplus and park's economic value

Table S2 outlines the main characteristics of the block group (BG) that visited Dick Nichols District Park, which are utilized to calculate the Demand Curve and the Consumer Surplus (CS) of the park throughout the year. Table S3 presents the results of the OLS regression model estimating total travel cost. The intercept is \$10.80, representing the baseline travel cost when all explanatory variables are held constant. The coefficient for daily visitation is -0.0594 , indicating a statistically significant inverse relationship between visitation and travel cost. This implies that a \$0.059 decrease in travel cost is associated with the addition of one more visitor from a block group. In other words, as the cost of travel decreases, visitation increases, reflecting the principle of price sensitivity in recreational demand, where lower costs encourage higher participation, a pattern also reported in earlier studies (Parsons, 2003).

The regression model also includes additional covariates to account for socioeconomic and demographic confounders: hourly income, population density, and median

age. Figure 2 visualizes the estimated recreational value of park access for two example block groups. The shaded regions represent the recreational value, also referred to as consumer surplus, for each group. For example, Block Group 1, the observed behavior closely matches the modeled demand, and the area beneath the demand curve and above the observed cost (green shaded region) reflects a substantial consumer surplus, representing the economic benefit derived from park access. In Block Group 2, the observed visitation rate exceeds the predicted level at the given cost, suggesting a deviation from the estimated demand. In this case, the observed point is projected back onto the demand curve (yellow marker) to estimate a consistent surplus area (yellow shaded region).

3.3 Spatial mapping and temporal analysis

Sub Fig. 3–1 presents the spatial distribution of consumer surplus (CS) across block groups (BGs). Block groups located in the northeastern quadrant exhibit higher CS values, likely due to a combination of strong urban connectivity and closer park proximity. In contrast, negative consumer surplus values are observed in portions of the western and northwestern fringe areas. Supporting this interpretation, additional spatial layers (Sub Fig. 3–2 and 3–3) show that block groups with higher population density and greater reliance on driving alone tend to have higher consumer surplus, underscoring the importance of both mobility and demographic context in determining the recreational value of urban parks. (Further supporting this spatial analysis, Figures S4, S5, and S6 illustrate the distribution of other factors, including average travel cost, household income, and property values.)

As shown in Fig. 4, block groups with positive consumer surplus values are primarily located east of the park, where transportation networks are denser, and population concentrations are higher. In contrast, block groups with negative consumer surplus values are mostly situated west of the study park, and these areas tend to be more spatially dispersed and substantially less dense, averaging 0.6 (1,000 people/sq km) compared to 2.14 in positive-surplus areas. Indicating that more urbanized neighborhoods tend to generate higher consumer

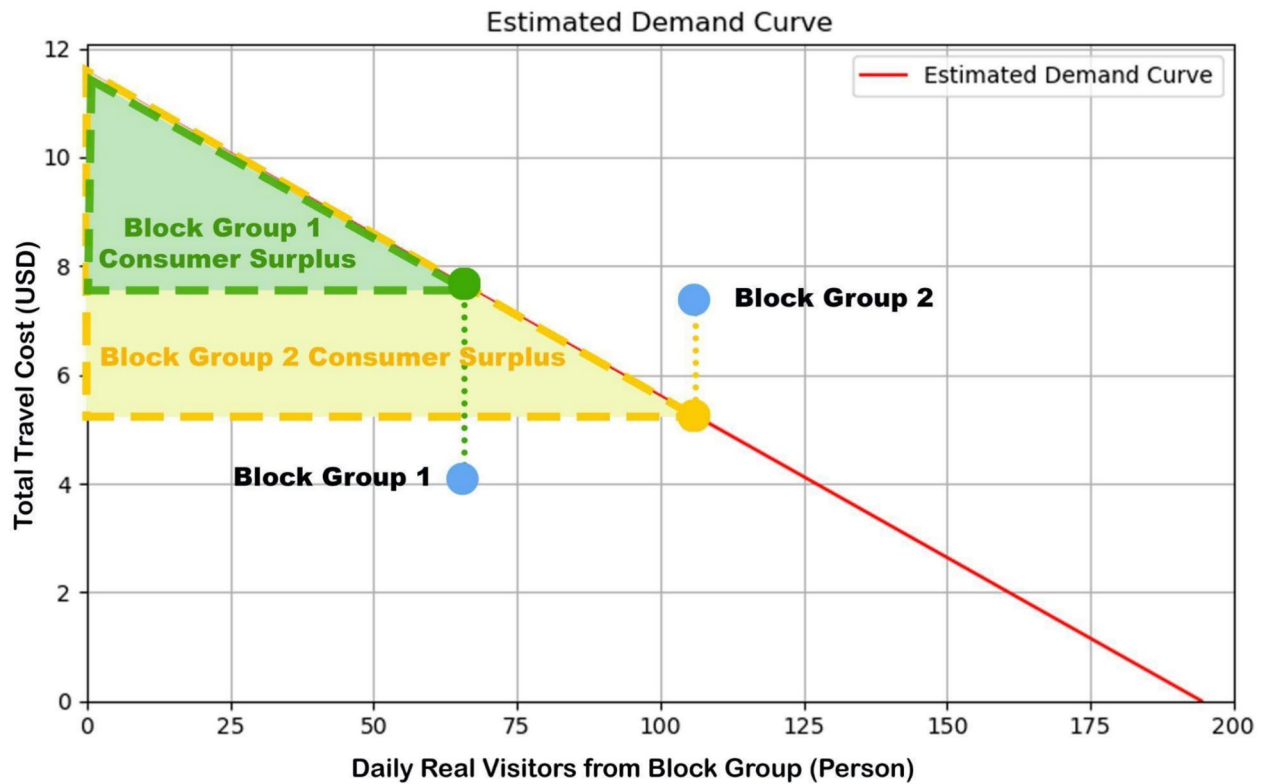


Fig. 2 Travel cost method demand curve by block group

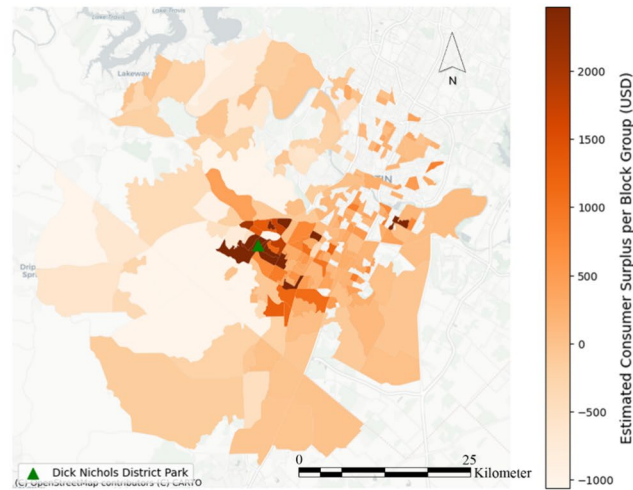
surplus. Regarding travel distance (dist Euclidean km), negative consumer surplus areas have a longer average distance to the park compared to positive consumer surplus areas. Other variables show less pronounced differences and can also be reviewed in Table S4.

To estimate the total consumer surplus while incorporating uncertainty in both income and travel speed, we employed a Monte Carlo simulation approach with 1,000 iterations. In each simulation, hourly income values for all 215 census block groups were randomly drawn from a normal distribution with a mean of \$52.13 and a standard error of 0.16, based on U.S. Census data. This probabilistic modeling accounts for variability in wage rates across the study area. In addition, we introduced individual-level variation in travel speeds by simulating car speeds with a mean of 72 km/h and walking speeds with a mean of 5 km/h, reflecting typical ranges reported in urban transportation literature. A travel cost coefficient of -0.68 was applied to model the sensitivity of visitation rates to travel costs. After aggregating the simulation outputs, the results yielded an average total consumer surplus of \$307,024.45, with a standard deviation of 21.72. As shown in Figure S7, the 95% confidence interval for total consumer surplus ranged from \$306,983.80 to \$307,067.72, indicating a high degree of stability in the

estimates despite the stochastic variation in input variables. The final simulation produced a total consumer surplus of \$306,975.96.

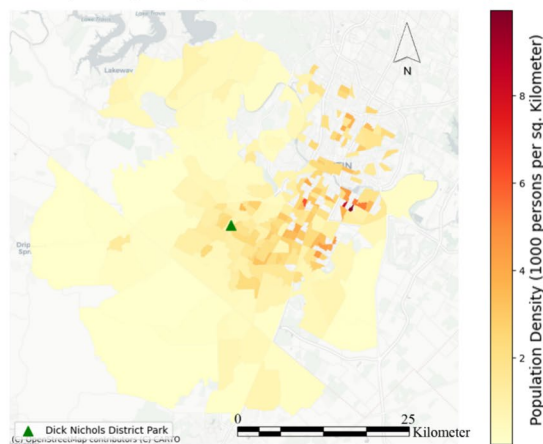
To evaluate the robustness of the travel cost model (Table S5), a leave-one-zone-out sensitivity analysis was conducted by sequentially excluding each zone and re-estimating the model. Zones were ordered from nearest (Zone 1) to farthest (Zone 5) from the park. Across all specifications, the coefficient for travel cost remained consistently negative and statistically significant ($p < 0.001$), confirming the expected inverse relationship between travel cost and visitation. While the magnitude of the travel cost coefficient varied slightly depending on the excluded zone (ranging from -0.04 to -0.26), the overall direction and significance of the results did not change. This suggests that no single zone disproportionately influenced the model outcomes. Moreover, the variation in coefficient magnitude reflects differences in travel behavior, with more distant zones exhibiting higher cost sensitivity. These findings collectively demonstrate that the model is robust to potential spatial biases and provide confidence in the stability of the estimated travel cost effect.

Estimated Consumer Surplus per Block Group (USD) Across Block Groups in Austin, TX



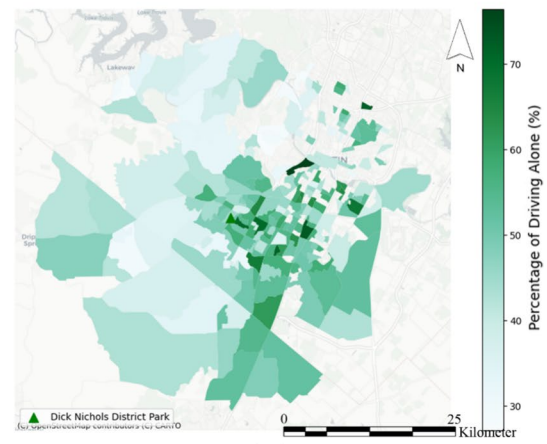
(1)

Population Density (1000 persons per sq. Kilometer) Across Block Groups in Austin, TX



(2)

Percentage of Driving Alone (%) Across Block Groups in Austin, TX



(3)

Fig. 3 Spatial analysis of consumer surplus for each block group visiting Dick Nichols District Park

Figure 5 presents the monthly distribution of Dick Nichols District Park's economic value in 2019, based on the mean total consumer surplus calculated using a Monte Carlo simulation. The estimates are derived by aggregating consumer surplus from 215 visiting block groups, categorized into five zones according to their distance from the park. The 215 block groups are divided into five zones as follows: Zone 1 (<2 km), Zone 2 (2–5 km), Zone 3 (5.1–9 km), Zone 4 (9.1–16 km), and Zone 5 (>16 km). The economic value of Dick Nichols District Park, as measured by total monthly consumer surplus, exhibited substantial seasonal variation throughout 2019. As shown in the left panel of Fig. 5, the park's economic value peaked in June, reaching over \$100,000, which represents the highest monthly total observed

during the year. In contrast, the lowest value occurred in January, with consumer surplus falling below \$400. The distribution of consumer surplus across block groups (right panel of Fig. 5) further illustrates that June not only had the highest aggregate value but also exhibited the greatest variation across neighborhoods, suggesting concentrated usage by high-value visitors.

4 Discussion

4.1 Overall economic value for park recreation

This study provides an empirical valuation of Dick Nichols District Park and addresses a notable gap in the literature regarding the economic benefits of individual district-level parks in the City of Austin, Texas. Existing research has primarily concentrated on large metropolitan or

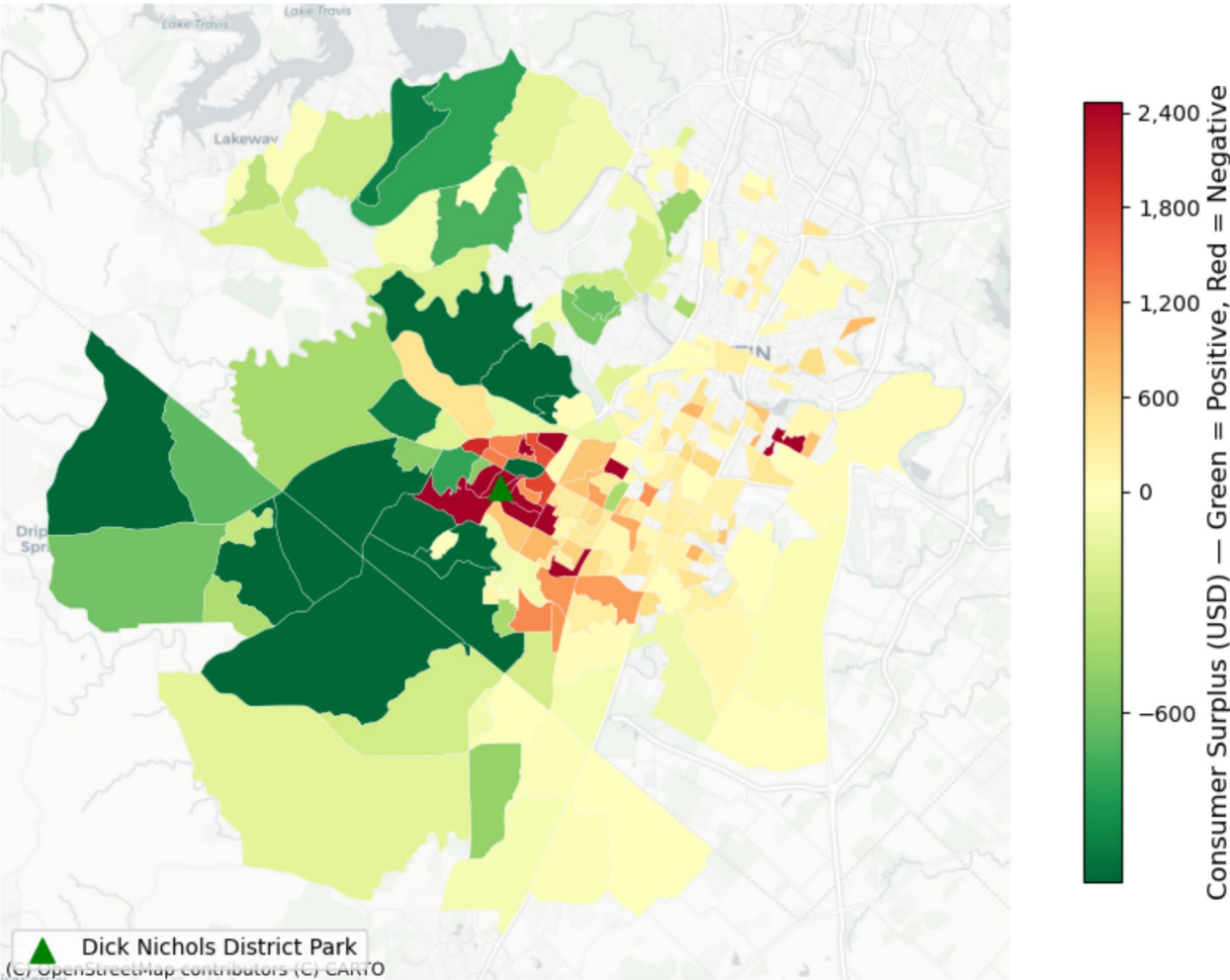


Fig. 4 Positive and negative consumer surplus with Dick Nichols District Park

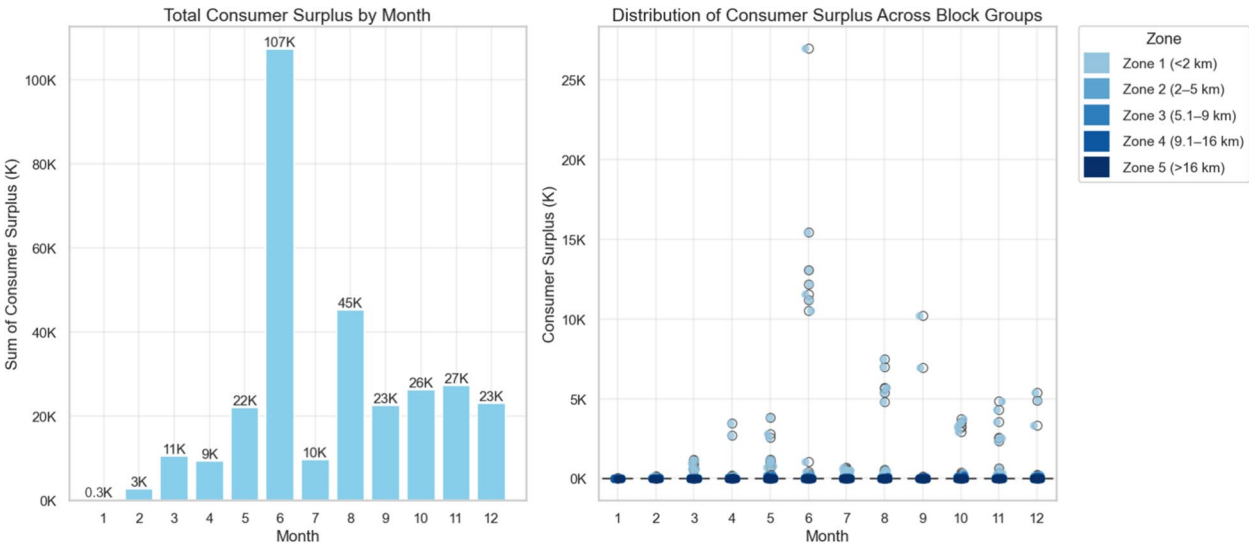


Fig. 5 Dick Nichols District Park's monthly economic benefit analysis

nationally recognized parks. For instance, the Trust for Public Land reported that Balboa Park, a major tourism destination in San Diego, attracted nearly 20 percent of all city visitors in 2007 and generated approximately 40 million dollars in local economic activity (Harnik, 2009). Similarly, a 2022 Trust for Public Land report estimated that New York City's park system as a whole generates billions in annual economic value, including \$17.9 billion in tourism spending and roughly \$680 million from local resident expenditures (Clinton et al., 2022). These studies highlight the substantial economic contribution of large, complex urban park systems across factors such as health benefits, environmental services, and hedonic property value effects; however, recreational value is not their primary focus. For smaller, neighborhood-serving parks, very few studies have the capacity to examine recreational value in detail for a specific park individually, leaving a notable gap in the literature.

Our analysis found that Dick Nichols District Park provides an estimated annual recreational value ranging from \$306,983.80 to \$307,067.72. This is lower than the estimate from the existing research. However, Dick Nichols District Park functions primarily as a neighborhood-serving urban park with modest visitation levels rather than a regionally significant destination. Moreover, the temporal scope of our data is restricted to weekday activity, yielding a conservative estimate relative to studies that evaluate full-year visitation patterns. It is also important to note that TCM provides a direct and unbiased measure of visitor satisfaction, allowing researchers to isolate and quantify the nonmarket recreational use value of a park, reflected through visitors' own travel, time, and costs (Ward & Beal, 2000).

To further contextualize this value, we compared it to revenue figures from other local amenities. For example, a typical McDonald's generates approximately 2.7 to 2.9 million dollars annually, with an estimated 30 percent profit margin that translates to roughly 900,000 dollars in surplus value (Laliberte, 2020). Based on this comparison, the park's recreational value represents roughly one-third of that surplus. Similarly, a local gym may generate \$1.5 to \$3 million annually, with about a 10% profit margin, yielding approximately \$300,000 in surplus value—comparable to the park's estimated annual recreational value (Gupta, 2023). This comparison provides a tangible benchmark for interpreting the park's recreational value within the context of other local amenities. By situating the park's consumer surplus alongside private-sector revenue models, the analysis offers a practical reference point for city decision-makers considering park investment relative to other community services. Our future research will expand this approach across larger spatial and temporal scales to further clarify the role of park investment in urban economic planning.

4.2 Spatial and temporal fluctuation

This research contributes a novel spatiotemporal analysis of the recreational economic value of urban parks. As illustrated in Sub Fig. 3–1, we observed that the park's recreational value varied across different block groups. Residents located closer to a park typically derive greater consumer surplus from its use. The findings align with the conclusions presented in the previous works, which suggest that an increase in travel distance leads to a reduction in consumer surplus (Hughes et al., 2008).

When the park values were compared with income distributions in Sub Fig. 1–1, significant spatial correlations between income and recreational values were not found. Previous studies have demonstrated a significant relationship between park accessibility and community wealth (Park, 2017). However, accessibility does not imply perceived benefits recreationally.

Another key finding we have is the revelation that not every block group will receive positive CS. Although consumer surplus is theoretically expected to be non-negative, previous Travel Cost Method studies have also reported negative estimates, often arising from functional-form choices, extreme travel behaviors (Bateman et al., 1996; Heagney et al., 2019). Therefore, the negative values identified in this study are not anomalous but rather reflect patterns documented in earlier TCM applications. In our study, some BGs also exhibit negative CS, especially in less dense areas. This suggests that residents in more sparsely populated suburban or semi-rural areas do travel to the Dick Nichols District park, but competing nearby parks or natural areas may offer experiences that better capture their satisfaction and attention, resulting in less frequent use of Dick Nichols District Park and contributing to the observed negative consumer surplus values. These findings require further validation, as the differences in economic value between our study and others can be influenced by various factors, including park size, location, amenities, surrounding population density, and differences in valuation methodologies. Future studies that use regression analysis to control for all relevant variables across all parks in the city will be necessary to gain a clearer understanding of these disparities.

Moreover, the study documents temporal variation in the park's recreational economy at the census block group level, offering a clear view of how the public perceives the benefits of parks throughout the year. In our case, January exhibits the lowest recreational value, whereas June reaches the annual peak. This pattern is likely influenced by temperature, as previous research has highlighted interactions between temperature fluctuations, seasonality, and park visitation (Song & Wei, 2024). Information can help urban park managers

allocate resources more effectively and plan seasonal programming for the urban park. Future studies could incorporate more advanced analyses by integrating other temporal data, such as weather patterns, traffic development, and crime rates. Sophisticated modeling approaches, such as time series analysis and machine learning predictions, could offer more granular insights into how park performance may vary over time.

4.3 Application of mobility data in evaluating the park's recreational economic value

A central contribution of this study is its use of SafeGraph smartphone mobility data, which provides affordable and high-precision access to park behaviors. Although a few prior studies have used mobility data to quantify or monetize park use, very few have examined longitudinal patterns or the fine-grained spatial heterogeneity of recreational economic benefits (Jaung & Carrasco, 2020; Monz et al., 2019). Unlike previously used datasets, the SafeGraph dataset, which includes repeated observations of visits from individual census block groups (CBGs) across an entire year, enables a clear assessment of how recreational value varies both spatially (across CBGs) and temporally (month to month). However, this study is still constrained by the absence of detailed park-level characteristics due to data limitations. Future research could expand this approach by incorporating additional emerging data sources, such as weather records, park facility inventories, and crime data, to improve the accuracy, scalability, and depth of analyses related to urban park characteristics.

5 Conclusion

Using Dick Nichols District Park in Austin, Texas, as a case study, this research demonstrates how high-resolution mobility data can strengthen quantitative evaluations of urban parks. By tracking recreational economic value over time, the study addresses a key gap in the literature, as earlier work rarely examined longitudinal variation in park use or recreational value. Although the findings provide important insights, several limitations should be noted. This study examines only one district-level park, which may limit the generalizability of the results to other park types or urban settings. Additionally, influential factors such as transportation infrastructure quality, weather conditions, and specific park amenities were not explicitly modeled and merit further investigation. Expanding future analyses to multiple parks and integrating additional data sources could deepen understanding of recreational economic benefits and improve the robustness of urban park valuation frameworks.

Taken together, this research illustrates the potential of mobility-based, spatiotemporal valuation to inform equitable park planning and resource allocation. By identifying where and when recreational economic benefits are highest or lowest, planners and policymakers can better prioritize investments, enhance accessibility, and tailor park programming to community needs. This approach underscores the importance of incorporating novel data sources into urban ecological management and reinforces the role of parks as essential components of sustainable and equitable urban systems.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1007/s43762-026-00257-6>.

Supplementary Material 1.

Acknowledgements

The authors thank SafeGraph Inc. (www.safegraph.com) and Advan for providing access to Texas POI data.

Authors' contributions

G.Z., S.Y. and Z.B. conceived the study, developed the methodology, processed the mobility data, conducted the analyses, interpreted the results, and wrote the manuscript. L.H. and Z.R. contributed to manuscript review and revisions. Y.H. and Z.Y. assisted with figure preparation and graphical editing. All authors read and approved the final manuscript. Y.H. and G.Z. finish the revision section for final manuscript submission.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

The smartphone mobility data used in this study were obtained from SafeGraph/Advan and are subject to licensing restrictions. Due to data use agreements, the raw datasets cannot be publicly shared. Aggregated results and derived variables used for analysis are available from the corresponding author upon reasonable request.

Declarations

Competing interests

The author declares that there are no known competing financial or personal interests that could have influenced the work reported in this paper.

Received: 12 December 2025 Revised: 15 March 2026 Accepted: 23 March 2026

Published online: 01 April 2026

References

- Armson, D., Stringer, P., & Ennos, A. R. (2012). The effect of tree shade and grass on surface and globe temperatures in an urban area. *Urban Forestry & Urban Greening*, 11(3), 245–255. <https://doi.org/10.1016/j.ufug.2012.05.002>
- Austin, Texas Population 2024. (2024). Retrieved July 29, 2024, from <https://worldpopulationreview.com/us-cities/austin-tx-population>
- Basiago, A. D. (1998). Economic, social, and environmental sustainability in development theory and urban planning practice. *Environmentalist*, 19(2), 145–161. <https://doi.org/10.1023/A:1006697118620>

- Bateman, I. J., Garrod, G. D., Brainard, J. S., & Lovett, A. A. (1996). Measurement Issues in the Travel Cost Method: A Geographical Information Systems Approach. *Journal of Agricultural Economics*, 47(1–4), 191–205. <https://doi.org/10.1111/j.1477-9552.1996.tb00684.x>
- Blackwell, B. (2007). The Value of a Recreational Beach Visit: An Application to Mooloolaba Beach and Comparisons With Other Outdoor Recreation Sites*. *Economic Analysis and Policy*, 37, 77–98. [https://doi.org/10.1016/S0313-5926\(07\)50005-6](https://doi.org/10.1016/S0313-5926(07)50005-6)
- Brooks, A. (2023). *Average Walking Speed By Sex and Age (And How to Improve It)*. RunToTheFinish. <https://www.runtothefinish.com/average-walking-speed/>
- Bureau, U. C. (2023). *American Community Survey 5-Year Data (2009–2022)*. Census. Gov. <https://www.census.gov/data/developers/data-sets/acs-5year.html>
- Burns, M. E. (1973). A note on the concept and measure of consumer's surplus. *American Economic Review*, 63(3), 335–344. <https://www.jstor.org/stable/1914365>
- Chiang, Y.-C., Weng, P.-Y., Li, D., & Ho, L.-C. (2023). Quantity and quality: Role of vegetation in park visitation and physical activity. *Landscape and Ecological Engineering*, 19(3), 337–350. <https://doi.org/10.1007/s11355-023-00558-6>
- Clinton, J., Hwang, L., & Egan, J. (2022). Economic Benefits of Parks in New York City. *Trust for Public Land*. <https://www.tpl.org/economic-benefits-nyc>
- Cohen, P., Potchter, O., & Schnell, I. (2014). A methodological approach to the environmental quantitative assessment of urban parks. *Applied Geography*, 48, 87–101. <https://doi.org/10.1016/j.apgeog.2014.01.006>
- Cranz, G., & Boland, M. (2004). Defining the Sustainable Park: A Fifth Model for Urban Parks. *Landscape Journal*, 23(2), 102–120. <https://doi.org/10.3368/lj.23.2.102>
- Dick Nichols District Park & Neighborhood Pool. (2022). Austin Parks Foundation. <https://austinparks.org/park/dick-nichols-district-park/>
- Eldridge, M., Burrowes, K., & Spauster, P. (2019). *Investing in Equitable Urban Park Systems: Emerging Funding Strategies and Tools*. Urban Institute. <https://www.urban.org/research/publication/investing-equitable-urban-park-systems>
- Feyisa, G. L., Dons, K., & Mellby, H. (2014). Efficiency of parks in mitigating urban heat island effect: An example from Addis Ababa. *Landscape and Urban Planning*, 123, 87–95. <https://doi.org/10.1016/j.landurbplan.2013.12.008>
- Gago, E. J., Roldan, J., Pacheco-Torres, R., & Ordóñez, J. (2013). The city and urban heat islands: A review of strategies to mitigate adverse effects. *Renewable and Sustainable Energy Reviews*, 25, 749–758. <https://doi.org/10.1016/j.rser.2013.05.057>
- Goetz, A. R., Vowles, T. M., & Tierney, S. (2009). Bridging the Qualitative–Quantitative divide in transport geography*. *The Professional Geographer*, 61(3), 323–335. <https://doi.org/10.1080/00330120902931960>
- Gupta, A. (2023). Gym Profit Margins, Cost, Revenue Explained 2024. *DrFranchises*. <https://drfranchises.com/gym-profitability-margins/>
- Halkos, G., Leonti, A., & Sardanou, E. (2020). Assessing the preservation of parks and natural protected areas: A review of contingent valuation studies. *Sustainability*, 12(11), Article 11. <https://doi.org/10.3390/su12114784>
- Harnik, P. (2009). *Measuring the economic value of a city park system*. Trust for Public Land.
- Heagney, E. C., Rose, J. M., Ardeshtari, A., & Kovac, M. (2019). The economic value of tourism and recreation across a large protected area network. *Land Use Policy*, 88, Article 104084. <https://doi.org/10.1016/j.landusepol.2019.104084>
- Hosseinpour, N., Kazemi, F., & Mahdizadeh, H. (2022). A cost-benefit analysis of applying urban agriculture in sustainable park design. *Land Use Policy*, 112, Article 105834. <https://doi.org/10.1016/j.landusepol.2021.105834>
- Hughes, H., Wieland, R., & Horowitz, J. (2008). *Estimating the Recreational Consumer Surplus at Maryland's State-owned Forests*.
- Internal Revenue Service. (2025). Standard mileage rates. <https://www.irs.gov/tax-professionals/standard-mileage-rates>
- Jaung, W., & Carrasco, L. R. (2020). Travel cost analysis of an urban protected area and parks in Singapore: A mobile phone data application. *Journal of Environmental Management*, 261, Article 110238. <https://doi.org/10.1016/j.jenvman.2020.110238>
- Kim, Y., Kim, J., Won, Y., Nelson, J., & Stuhlmacher, M. (2025). Connecting park access and use data for equitable environmental planning. *Environment and Planning B: Urban Analytics and City Science*, 23998083251366735. <https://doi.org/10.1177/23998083251366735>
- Li, F., Yao, N., Liu, D., Liu, W., Sun, Y., Cheng, W., Li, X., Wang, X., & Zhao, Y. (2021). Explore the recreational service of large urban parks and its influential factors in city clusters – Experiments from 11 cities in the Beijing-Tianjin-Hebei region. *Journal of Cleaner Production*, 314, Article 128261. <https://doi.org/10.1016/j.jclepro.2021.128261>
- Lu, H., & Song, Y. (2024). Informing inclusive park planning: Neighborhood park visitation modeling based on smartphone big data in Austin, Texas. *Land Use Policy*, 144, Article 107234. <https://doi.org/10.1016/j.landusepol.2024.107234>
- Maheshwari, T., & Axhausen, K. W. (2021). How will the technological shift in transportation impact cities? A review of quantitative studies on the impacts of new transportation technologies. *Sustainability*, 13(6), Article 3013. <https://doi.org/10.3390/su13063013>
- Mathy, R. M., Schillace, M., Coleman, S. M., & Berquist, B. E. (2002). Methodological rigor with Internet samples: New ways to reach underrepresented populations. *Cyberpsychology & Behavior*, 5(3), 253–266. <https://doi.org/10.1089/109493102760147259>
- Mayer, M., & Woltering, M. (2018). Assessing and valuing the recreational ecosystem services of Germany's national parks using travel cost models. *Ecosystem Services*, 31, 371–386. <https://doi.org/10.1016/j.ecoser.2017.12.009>
- Minimum Wage. (2019). DOL. Retrieved July 29, 2024, from <https://www.dol.gov/general/topic/wages/minimumwage>
- Monz, C., Mitrovich, M., D'Antonio, A., & Sisneros-Kidd, A. (2019). Using mobile device data to estimate visitation in parks and protected areas: An example from the Nature Reserve of Orange County, California. *Journal of Park and Recreation Administration*, 37(4), Article 4. <https://doi.org/10.18666/JPra-2019-9899>
- Park, K. (2017). Psychological park accessibility: A systematic literature review of perceptual components affecting park use. *Landscape Research*, 42(5), 508–520. <https://doi.org/10.1080/01426397.2016.1267127>
- Parkland Dedication | AustinTexas.gov. (2025). Retrieved October 19, 2024, from <https://www.austintexas.gov/PLD>, <https://www.austintexas.gov/PLD>
- Parsons, G. R. (2003). The Travel Cost Model. In P. A. Champ, K. J. Boyle, & T. C. Brown (Eds.), *A Primer on Nonmarket Valuation* (pp. 269–329). Springer Netherlands. https://doi.org/10.1007/978-94-007-0826-6_9
- Places Summary Statistics | SafeGraph Docs. (2025). SafeGraph. Retrieved September 17, 2023, from <https://docs.safegraph.com/docs/places-summary-statistics>
- Pros Consulting. (2025). *Significant urban growth and increased demand for recreational spaces*. https://www.austintexas.gov/sites/default/files/files/Parks/longrangeplan/Community_Profile_and_Recreation_Trend_PROS_FINAL_1_31_20.pdf
- Qi, W., Liu, Y., Ma, C., Xu, H., Lian, J., Xu, K., & Yao, Y. (2024). A combined qualitative–quantitative method for adaptive configuration of urban flood mitigation measure. *Urban Climate*, 56, Article 102004. <https://doi.org/10.1016/j.uclim.2024.102004>
- Randall, A. (1994). A difficulty with the travel cost method. *Land Economics*, 70(1), 88–96. <https://doi.org/10.2307/3146443>
- SafeGraph: Places Accuracy. (2023). SafeGraph. <https://docs.safegraph.com/docs/neighborhood-patterns>
- Schägnier, J. P., Brander, L., Maes, J., Paracchini, M. L., & Hartje, V. (2016). Mapping recreational visits and values of European National Parks by combining statistical modelling and unit value transfer. *Journal for Nature Conservation*, 31, 71–84. <https://doi.org/10.1016/j.jnc.2016.03.001>
- Song, Y., & Wei, Q. (2024). Impact of apparent temperatures on park visitation behavior: A comprehensive analysis using large-scale mobility data. *Science of the Total Environment*, 940, Article 173388. <https://doi.org/10.1016/j.scitotenv.2024.173388>
- Song, Y., Lee, S., Park, A. H., & Lee, C. (2023). COVID-19 impacts on non-work travel patterns: A place-based investigation using smartphone mobility data. *Environment and Planning B: Urban Analytics and City Science*, 50(3), 642–659. <https://doi.org/10.1177/23998083221124930>
- Speck, J. (2013). *Walkable City: How Downtown Can Save America*. Macmillan.
- Sun, P., Liu, P., & Song, Y. (2024). Seasonal variations in urban park characteristics and visitation patterns in Atlanta: A big data study using smartphone user

- mobility. *Urban Forestry & Urban Greening*, 91, Article Article 128166. <https://doi.org/10.1016/j.ufug.2023.128166>
- Van Leeuwen, E. S., Vreeker, R., & Rodenburg, C. A. (2006). A framework for quality of life assessment of urban green areas in Europe: An application to District Park Reudnitz Leipzig. *International Journal of Environmental Technology and Management*, 6(1–2), 111–122. <https://doi.org/10.1504/IJETM.2006.008256>
- Ward, F. A., & Beal, D. (2000). *Valuing Nature with Travel Cost Models*. <https://www.elgaronline.com/monobook/9781840640786.xml>
- Zhu, R., Song, Y., & Newman, G. (2025). Exploring the relationship between day-time and nighttime mobility and park visitation: A case study of Austin, TX. *Environment and Planning B: Urban Analytics and City Science*, 52(9), 2084–2098. <https://doi.org/10.1177/23998083251325909>

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.