Changes in Park Use During Extreme Heat Events in Los Angeles County

Team Members:

Alondra Gallegos, Bethany Woo, Danielle Sonobe, Jana Salomon, Jasmine Kim, Jeffrey Van, Renato Escobar, Samara Fruman

Practicum in Environmental Science
Institute of the Environment and Sustainability
University of California, Los Angeles

June 18, 2023

Clients:

Alison Frazzini, Andrea Vona, and Elizabeth Rhoades, Los Angeles County Chief Sustainability Office, County Department of Parks & Recreation, County of Los Angeles Department of Public Health

Advisors:

Dr. Travis Longcore and Dr. Sahar Derakhshan

Table of Contents

Executive Summary

Due to increasing effects of climate change, Los Angeles County will experience more frequent and intense extreme heat events, which cause negative health impacts such as heat stroke, organ damage, and death. Lower-income communities, Black and Hispanic populations, the elderly, children, pregnant women, and people with chronic health conditions are most vulnerable to extreme heat and heat-related illnesses (CDC, 2022; Bekkar et al., 2020). To inform the Los Angeles County Chief Sustainability Office, Department of Parks & Recreation, and Department of Public Health, we analyzed the geolocation of anonymized mobile phone data collected in the summer of 2017 using GIS intersections of mobile phone points, county parks, and census tracts. Specifically, we examined the influence of extreme heat, the day of the week, park amenities, and Social Vulnerability Index (SoVI) on park use and park user behavior.

We found park use to be higher on control days (average maximum temperature up to 87°F across the county) than on extreme heat days (average maximum temperature greater than 95°F across the county). This could be due to preferences for staying in air conditioned residential spaces or indoor cooling centers during extreme heat events (Derakshan et al., 2020). The difference in park use was more defined when comparing the number of park users on weekends versus weekdays, with park visitation increasing on weekends. When comparing total park visits on weekend vs weekdays, we found that park use on the weekend was higher than weekdays on both control and extreme heat days. The hours of the day with the greatest park use varied between weekends and weekdays. On weekends, park visitation peaked between 3:00-4:00 pm and declined throughout the evening. On the other hand, weekday park visitation increased during the evening, peaking around 6:00 pm. These patterns were consistent for both control and extreme heat days. This trend may be due to inelasticity of people's schedules on weekdays from time constraints like work and school. Together, these trends imply the status of weekend or weekday has a stronger effect on park use than extreme heat conditions.

Park amenities, specifically splash pads and pools, are thought to contribute to park use on extreme heat days due to their cooling abilities. However, we found that the presence of splash pads and pools at parks did not strongly correlate with increased park use during extreme heat. The amenities that had a positive correlation with park use during extreme heat days were the presence of restrooms and good and fair amenity quality. There was a negative correlation between park use and playgrounds, community centers, baseball fields, basketball courts, and tree canopy coverage on extreme heat days. When looking at agency level, we found city parks were used more frequently on weekdays, but experienced declines in visitation on weekends. State parks experience the inverse: heightened visitation on weekends and decline during weekdays. This inverted relationship is assumed to be due to time constraints and accessibility of city vs state parks. Residents experience greater time constraints during the weekdays and are more inclined to visit proximal city parks. On weekends, residents have more leisure time to travel further to visit federal, county, and state parks, including beaches, regardless of the temperature.

When looking at the SoVI (Social Vulnerability Index) score of both parks and park visitors, we found visitors who live in a neighborhood with a SoVI score of 1 (lowest vulnerability) visited parks more than visitors who live in neighborhoods with SoVI scores 2 and 3 (medium-highest vulnerability). Similarly, parks with a SoVI score of 1 are visited more than parks with SoVI scores of 2 and 3. These trends may imply parks are more accessible to users from lower vulnerability neighborhoods (i.e. closer proximity or more convenient access with personal vehicles or public transit). Park users were most likely to visit a park that matched their residence location SoVI score, likely due to proximity. According to these findings, heat mitigation should focus on bringing heat relief resources to more convenient and closer locations for residents. Urban city planners could strategize park placement to make parks more equitably accessible to citizens from different neighborhoods and socioeconomic status. Additionally, more funding could go towards city parks in denser areas of Los Angeles to improve the quality of their amenities.

Introduction

Los Angeles County is predicted to experience a significant increase in the frequency and intensity of extreme heat events as a result of climate change. These events, defined as periods of high heat with temperatures surpassing 90 degrees Fahrenheit for at least two to three consecutive days, pose a substantial threat to the region's population. In particular, certain areas within Los Angeles County are projected to endure three times the number of days with temperatures exceeding 95˚F (Hall, 2015). While the rise in extreme heat days is concerning, what exacerbates the issue further is the unequal distribution of heat throughout the county, giving rise to heat exposure inequities and their associated consequences.

Extreme heat has been linked to a wide array of both short-term and long-term health impacts. The immediate effects can range from heat exhaustion to more severe conditions such as heat stroke, tissue and organ damage, and even death. Over the long term, repeated exposure to extreme heat can lead to chronic health issues and exacerbate pre-existing conditions. Vulnerable populations, including lower-income individuals, socially marginalized communities, and Black and Hispanic populations, are particularly susceptible to the detrimental effects of extreme heat. These communities often face social vulnerabilities and have limited access to resources that provide protection and cooling during extreme heat events.

One potential solution to mitigate the adverse effects of extreme heat is the strategic utilization of parks. Parks managed by Los Angeles County have the potential to serve as valuable tools in reducing heat exposure for residents. These green spaces offer several natural features that help combat extreme heat. For instance, trees in parks cool the environment through evapotranspiration and provide shade, effectively reducing the surrounding temperatures. Additionally, water features such as pools and splash pads and shade amenities in parks contribute to the cooling effect by lowering the mean radiant temperature (a measure of individual comfort) and offering a refreshing experience.

During extreme heat events, these open spaces can provide a refuge for anyone seeking shelter from oppressive temperatures. Given the potential of parks in mitigating the impacts of extreme heat, it becomes crucial to understand behaviors in park usage and identify which types and locations of parks are visited more frequently than others—therefore understanding the role of parks during extreme heat days.

To evaluate park use patterns, we use locations of smartphones in Los Angeles County that have been made available to us through the Heat Resilient LA Project at UCLA. These data cover a two-month period during the summer of 2017, which is one of the warmest summers recorded in Los Angeles County. By analyzing the demographic characteristics associated with the origins of these smartphone signals at night, we can identify potential inequities in park use between socially vulnerable groups. This information should be valuable to the Department of Parks and Recreation, Chief Sustainability Office, and Department of Public Health in making informed decisions regarding resource allocation and funding for parks, as well as other public health strategies aimed at mitigating the effects of extreme heat.

The projected increase in extreme heat events in Los Angeles County due to climate change necessitates proactive measures to protect vulnerable populations from the associated risks from extreme heat exposure. Parks managed by LA County offer a promising solution by providing accessible green spaces with natural features that can mitigate the impacts of extreme heat. By leveraging spatial data from smartphones and analyzing demographic disparities in park usage, we can gain a comprehensive understanding of park use and inform targeted interventions to address heat exposure inequities. Ultimately, this knowledge will aid in the allocation of resources and implementation of effective strategies to safeguard public health in the face of rising temperature

Background

Climate Change

LA County Projections

Impacts of climate change are predicted to affect numerous regional variables including snowfall, precipitation levels, temperature, and extreme heat. Contributing to California's Fourth Climate Assessment, Alex Hall and other researchers from the University of California, Los Angeles conducted the most comprehensive study of climate change in the LA region during 2010–2015 using "hybrid downscaling" modeling methods. One of their key findings included average maximum temperature increasing by approximately 4–5˚F by the middle of the century and up to 5–8˚F by the end of the century under the representative concentration pathway 8.5 projection (RCP 8.5). Under this worst-case scenario, the research showed that the continuation of twenty-first-century emissions trends (or increased trends), coastal areas and central areas of Los Angeles county will experience an increase in extreme heat days (Sun et al., 2015). Divergence in scenarios by the end of the century demonstrates that different human policy approaches to tackling climate change can make drastic differences in projection outcomes and possibly mitigate future damages.

The Environmental Protection Agency (EPA) defines "extreme heat events" or "heat waves" as when a city's minimum temperature is above the 85th percentile of normal summer temperatures for two or more days in a row (EPA, 2022). Extreme heat events naturally occur from variation in local weather but will be greatly amplified by climate change. From 1895 to 2016, the annual average temperature in the US increased by 1.2–1.8ºF and is predicted to further increase by 2.5–2.9°F by 2050, based on different projections of greenhouse gas emissions (Vose et al., 2017). Extreme heat events are also expected to increase in frequency and intensity. Under the most extreme model, temperatures will be above 90°F for twenty to thirty more days each year and heat wave temperature maximums will rise by 11°F (Vose et al., 2017). If climate change continues at its current rate, hot spells in the Northern Hemisphere are projected to increase by 16 percent for each 1.8°F increase in global warming (Ebi et al., 2021).

Parallel trends have been observed at a smaller scale within Los Angeles County, California. Before 1956 there were no records of heat waves lasting six days, but these became a regular occurrence after the 1970s. Additionally, the county's average annual maximum temperature rose by 5.0°F in the last century, attributable to both the Urban Heat Island effect and changing climate (Tamrazian et al., 2008). By 2060, the coastal and central zones of Los Angeles County are forecasted to experience triple the number of days over 95°F (Los Angeles County Department of Public Health, 2017).

Urban Heat Island (UHI) Effect

With approximately 80% of the U.S. population living in urban areas, it is important to recognize the consequences of urban heat islands as a tangible example of anthropogenic climate change that impacts our daily lives. Urban Heat Islands (UHI's) are a temperature anomaly that form where there is an increase in air and surface temperature in urban areas compared to their surrounding rural neighborhoods; it is therefore understood that UHI's are primarily caused by urbanization (Mohajerani et. al., 2017).

Because of Los Angeles' interesting landscape, there is considerable complexity in how certain regions of the city experience the effects of urban heat. For specific zones in Los Angeles County, the urban heat island effect exacerbates extreme heat. The UHI in Los Angeles is caused not only by its land surface characteristics, but also by its topographical conditions such as proximity to the ocean and elevation. It was found that distance from the ocean was a main contributing factor to temperature variations in land surface and air temperatures (LaDochy et al., 2021). During the day, distance from the ocean had the greatest influence within 50 km of the coast, however, temperatures became independent of distance past that extent. Elevation also had a positive correlation with surface and air temperature due to the fact that inland areas are generally at higher elevations than coastal areas; elevations of at least 600m experienced cooling effects of increased altitude that would override the warming effects of distance from the ocean (LaDochy et al., 2021).

Health Effects from Extreme Heat Exposure

Both acute and chronic exposure to extreme heat has severe negative health impacts on people. On average, heat is responsible for over 9,000 hospitalizations and 700 deaths in the US each year according to the Centers for Disease Control & Prevention (CDC) (2022a). Heat is the primary weather-related cause of death in the United States, and the number of heat-related illnesses and hospitalizations is expected to increase due to higher temperatures in the coming decades (Riley, 2018). Other health afflictions include heat stroke, tissue/organ damage, heat exhaustion, dehydration, and complications from the interaction of heat with pre-existing health conditions. As climate change will only exacerbate the issue of extreme heat, it is paramount for governing officials of Los Angeles County to 1) understand the primary health risks for all people especially those with pre-existing health conditions, 2) identify and assist the most vulnerable communities, 3) study the long-term implications of extreme heat on public health, and 4) understand the public perception of heat-related health risks.

Primary Heat-Related Public Health Risks

The medical impacts of those suffering from extreme heat can cause minor impairments but in the most severe cases can also lead to death. Heat cramps take the form of painful muscle spasms but are minimal effects when one experiences extreme heat. The most common heat-related illness is heat exhaustion; when severely dehydrated individuals experience dizziness, fatigue, headache, nausea, vomiting and cramps (CDC, 2022b). Heat stroke, or the failure to thermoregulate, is nominated as the most serious health risk from heat waves by the CDC (2022). Heat stroke occurs when the body's internal temperature rises too rapidly for its natural defense mechanisms to mediate, resulting in mental confusion, seizures, loss of consciousness, and death if untreated. Heat stroke develops over multiple days and may severely affect the central nervous system and neurological health with similar side effects of heat exhaustion. Mortality is a direct consequence of increased body temperature making heat stroke a high priority concern and the cause of many hospitalizations within the city.The most obvious and devastating health impact is the death of a person. An investigation by the *Los Angeles Times* (2021) estimated extreme heat led to approximately 3900 deaths in California from 2010 to 2019. These deaths were often associated with heat stroke and complications from cardiovascular, respiratory, and cerebrovascular diseases.

The risk of death and/or any of the illnesses described above has a synergistic effect with air-pollution and pre-existing health conditions. During co-occurrences of extreme heat and high air pollution levels, the average person faced a 21% increased risk of death, while risk for people with cardiovascular disease increased 29.9% and respiratory diseases increased by 38% (Rahman et al., 2022). Thus, when attempting to mediate heat-related public health risks, it is essential to study how pre-existing health conditions interact with extreme heat.

Physiological Effects of Excessive Heat

Pre-existing health conditions such as cardiovascular, respiratory, cerebrovascular, kidney disease, and diabetes amplify mortality risk from extreme heat. Cardiovascular diseases such as heart attacks, coronary heart disease, chronic heart failure, and cardiomyopathy are becoming increasingly common. Cardiovascular illness is the primary cause of death during heat waves and the leading cause of death in LA County (Los Angeles County Department of Public Health, 2010). Researchers found that from 2008 to 2017 extreme heat was responsible for over 5900 additional deaths from cardiovascular disease in the US, with the cardiovascular death rate increasing by 0.12%with each consecutive day of extreme heat (Khatana et al., 2022).

The secondary cause of death during heat waves in the US is respiratory disease (Ebi et al., 2021). Respiratory conditions can include lung cancer, chronic obstructive pulmonary disease, pneumonia, cystic fibrosis, and asthma. Roughly 13% of LA County, or 1.3 million citizens, suffer from respiratory diseases and are at an increasingly higher risk of hospitalization and death as heat waves intensify (American Lung Association, 2022). Those with respiratory conditions are also more susceptible to negative synergistic effects of extreme heat and air pollution, both of which are worsening across the county.

Other common conditions that increase susceptibility to extreme heat include cerebrovascular disease, kidney disease, and diabetes. In the case of cerebrovascular disease, extreme heat may cause reduced blood flow to the brain, damaging the blood-brain barrier and potentially leading to death. Chronic or extreme dehydration can induce and exacerbate kidney disease such as kidney fibrosis and kidney failure (Ebi et al., 2021). Lastly, diabetics are more prone to dehydration and heat stroke, as diabetic complications reduce vasodilation and affect the sweat glands (CDC, 2022). Thus, efforts to mitigate heat waves should provide these groups with additional levels of protection.

Social Vulnerability Based on Demographics

Vulnerable Communities

As extreme temperature events grow in frequency and intensity with the cumulative effects of climate change, the concern for public health is at the forefront. Between 2010 and 2019, the hottest decade on record for the state of California, there were 599 deaths recorded that were related to heat exposure. However, the true death toll would account for thousands more people who died on extremely hot days than would have otherwise been average in a milder climate; an analysis estimated that extreme heat caused 3,900 deaths, six times greater than the original attribution (Philips et al., 2021). Often, it is low-income urban populations that are the most burdened by extreme heat. These communities include areas that have more hardscape and less urban tree cover and vegetation, which create a positive feedback loop of heating effects. Demographic groups that are vulnerable to heat include the elderly, children/infants, pregnant women, outdoor workers, low-income populations, the unhoused, and non-Hispanic, Black communities (Bekkar et al., 2020).

Race

Given the nature of private and governmental discriminatory practices (in both historical and contemporary home ownership) that restricts where minority populations live, Jesdale (2013) considers variables that could alter the association between racial segregation and land cover characteristics. In highly divided metropolitan areas, minority groups were often clustered in more densely populated neighborhoods near the central business district or the immediate area around the inner city. Jesdale found several socioeconomic disparities revealing that racial minority groups, renters, and households below the poverty line were more likely to live in areas marked as “heat risk related land cover (HRRLC)” than whites, homeowners, and households with higher income (Jesdale, 2013). There are also other risk factors associated with heat-related illness that have been caused by existing racial disparities. These include a higher likelihood of chronic disease, higher representation of physical and outdoor occupations, and unequal access to cooling centers or systems that increase susceptibility to heat.

Age

The elderly are more susceptible to extreme heat due to a diminished vasodilatation response and a greater probability of having pre-existing health conditions. Furthermore, medications prescribed to elderly people often reduce the natural bodily responses to heat stress, decreasing tolerance for extreme heat. For example, many prescriptions target acetylcholine, a neurotransmitter that has multiple functions including inducing sweating (Ebi et al., 2021). Additionally, elderly citizens have a “reduced behavioral capacity” to respond to heat stress, such as being confined to bed, living alone, and not being able to drive or walk to find shelter from extreme heat (Sarofim et al., 2016).

Similarly, children are often incapable of helping themselves thermoregulate due to their dependence on others. For toddlers, the primary cause of heat-related deaths is being unsupervised or forgotten in hot vehicles (Ebi et al., 2021). Additionally, children spend a greater portion of the day outside and have a higher body surface area to body mass ratio, lowering their sweating capacity (Sarofim et al., 2016).

Income Level

Low-income communities are disproportionately jeopardized by extreme heat. A study found that in 76% percent the poorest tract was significantly hotter than the richest neighborhoods (Benz & Burney, 2021). This disparity was attributed to greater building density and lower vegetation coverage in low-income areas. Within the low-income demographic group, the unhoused are the most endangered due to very sporadic and limited access to water, air-conditioning, and heat protection. This is a major concern for Los Angeles County, which has an unhoused population of 69,144 according to the annual count performed by the Los Angeles Homeless Services Authority (2022).

Social Vulnerability Index (SoVI)

Natural disasters and other catastrophic events have varying effects on different demographic groups. The Social Vulnerability Index (SoVI) quantifies a region's vulnerability to extreme events based on social indicators (such as race, age, income and other demographic characteristics) as well as "place inequities" (or characteristics within the built environment that increase susceptibility to extreme events) (Cutter et al., 2003). The SoVI model has applications in disaster management and preparation for hazards, in all levels of government (Spielman et al., 2020).

This study uses a social sensitivity index developed by the County of Los Angeles as part of its Social Vulnerability Assessment. LA County created a Climate Vulnerability Index (CVI) by developing graphical layers of the 5 most important climate hazards of the area: extreme heat, wildfire, inland flooding, coastal flooding, and drought (2021). On top of this layer was an added social sensitivity layer. This layer contains 29 indicators that are likely to make a person more susceptible to climate hazards. These include age, community and language, occupation, education, health, housing, income and wealth, race/ethnicity, access to information, and transportation. One issue with this index is that it is static and will not account for changes in vulnerability in the future. Social sensitivity is the same for a group across all hazards, not just one. A high climate vulnerability indicates that there is an overlap of high social sensitivity and high geographical exposure.

The CVI defines vulnerability as a combination of social sensitivity and exposure; however, this study looks only at the social sensitivity component, or defined in this report as "SoVI score". The social sensitivity values ranged from -9.97 to 7.8 on the LA County CVI and a SoVI third score is the SoVI score divided into tertiles that helps explain vulnerability levels in terms of high, medium, and low vulnerability. This score uses 1, 2, and 3 to indicate the lowest, medium, and highest vulnerability; these scores are split such that each SoVI third has the same number of census tracts. SoVI score of 1 represents low social vulnerability to climate hazards, SoVI score of 2 groups medium vulnerability, and SoVI score of 3 groups high vulnerability.

In their report, LA County recognizes that communities with low internet subscription rates, limited English speaking rates, and non citizens are less likely to respond to the census, which is their main source for quantitative data. To combat this, they collected qualitative data by having 6 listening sessions with 8–10 participants each who brought insight from lived experience or experience working with these communities. They asked how these groups experience, manage, and adapt to climate change.

Parks as a Heat Mitigation Strategy

Parks can have a cooling effect on surrounding communities, making them an attractive potential option to mitigating extreme heat. Gunawardena et al. (2017) examine the mechanics behind how vegetation and water bodies induce a cooling effect. Evaporation of water from both green space (trees, vegetation) and blue space (bodies of water) offers heat relief. Vegetation reduces surface and local air temperatures by limiting heat transfer into occupied spaces,storing solar energy, and releasing it back as evaporation. Shade from vegetation also helps lower temperatures by reflecting and absorbing solar energy. Other indirect effects of green space include pollution filtering (which reduces atmospheric scattering), altering wind flow, and reducing runoff. Blue space creates a cooling effect primarily through evaporation. In addition, surface mixing is due to wind shearing at water's surface, which creates turbulence and cooler temperatures. Gunawardena et al. note that parks with both green- and blue space can experience a synergistic effect when both these features are present. Additional research on urban environments operationalizes nature in terms of "green space" (e.g. forests, trees, vegetation cover) and thus under-represents the significance of "blue space" (beaches, rivers, lakes) in coastline communities (Völker & Kistemann, 2015). Although both spaces provide similar benefits to the environment, like their cooling effect and biodiversity, blue spaces can offer unique recreational activities and natural features that can potentially win the favor of those who live in close proximity. Quantitative approaches to understand the relation of coastal proximity to health by Wheeler et al. (2012) and White et al (2013) revealed that self-reported well-being increased with less distance to shore and was significantly more so amongst more socially vulnerable populations. Such evidence highlights the importance of contextualizing the area of analysis by its topographic features. This is especially true in counties like Los Angeles, that share a border with a massive water feature, the ocean. Categorizing beaches as urban parks in this analysis might have resulted in some of the insignificant findings or muddled the comparisons made.

Many studies have shown that urban parks help reduce the UHI effect (Cao et al., 2010; Cheng et al., 2015; Aram et al., 2019). However, not all parks have equal cooling effects, and some have none at all (Chen et al., 2021). It is important to know which amenities and parks are most effective at mitigating the UHI effect so that we can focus on improving cooling services provided by parks.

Several studies have quantified the cooling effect of parks, and vegetation within parks, on surrounding areas. Chen et al. (2022) quantified the urban cooling effect in 60 parks within the core of Wuhan, China, an area facing extreme heat and the urban heat island effect. They compared the satellite-measured land surface temperature of the park with the surrounding area to measure the intensity and area of the cooling effect. They found that most parks (54 of 60) can alleviate the urban heat island effect, with an average cooling intensity of 3.5 ± 0.2 °C. In a study of parks in Vancouver and Sacramento, Spronken-Smith and Oke (1998) found that the park cooling effect for each city was around 5°C and 7°C , respectively. In particular, they found that parks with trees saw a maximum cooling effect in the afternoon, suggesting that trees increase cooling through a combination of shade and evapotranspiration.

With heat waves becoming more common due to climate change, public parks help prevent the public from suffering under extreme heat. Specifically, pools and splash pads, trees and shaded areas, and marshes and ponds all have a contribution to serve as cooling amenities within parks. Pools or splash pads provide a means of cooling down in water bodies to escape hot temperatures. Trees in urban areas provide opportunities for respite on hot days including shade and protection from direct UV rays, reduced wastewater loads on treatment facilities, air pollution, and noise pollution (Jesdale, 2013).

Mobile Data Use in Research

Mobile phone data has been used by researchers to acquire relatively inexpensive, passively generated data to understand population distributions. By using mobility data to track human movement either over time or at an exact moment, researchers can better understand how people move to increase the effectiveness of urban planning and public transportation designs (Xu et al., 2015). Yin et al. (2021) combined heat hazard data with anonymized smartphone human mobility data to create a dynamic thermal exposure index, to determine heat exposed,areas within frequently visited locations and inform heat mitigation strategies. Hyper-localized spatio-temporal data collected from smart sensors, buses, or other local sources can be combined with hyper localized smartphone data to describe heat exposure more precisely than heat exposure studies that use satellite Land Surface Temperature (Jenerette et al., 2007, Liu and Zhang, 2011, Yuan and Bauer, 2007). The smart sensors allow researchers to understand microclimates within a city and determine which communities and areas are at a higher risk for heat hazards (Yin et al., 2021).

Researchers found that measuring the thermal environment as experienced by individuals more specifically describes heat exposure and shows differences in behaviors, attributes, preferences, and access to cooling sites within and between communities (Kuras et al., 2017). By measuring the environment on an individual basis, heat vulnerability can be described through suspected risk factors (e.g., urban form, poverty, social or linguistic isolation, housing quality) and capacity for resilience (e.g., adaptive behavior, heat-mitigating infrastructure) (Kuras et al., 2017).

Analyses of park visitation and temperature changes have shown a decrease in park visitation with an increase in temperature. Some studies have tracked visitation to America's national parks. Fisichelli et al. (2015) matched visitation data with mean air temperature data between 1979 and 2013, and used climate models (Coupled Model Intercomparison Project Phase 5), air temperature to forecast future visitation in climate change scenarios. They found a strong association between historical visitation and temperature; visitation rose with temperatures, before sharply decreasing at extreme temperatures (>77°F). They also found that visits to national parks are projected to increase due to increased warming. Another study by Hao et al. (2023) used a "big data" approach that used social media (particularly geocoded Twitter data) to measure park attendance in Hong Kong. This data provided a large sample size, given that Twitter is extremely popular in the region with 26% of Hong Kongers active on the network. They supplemented the study with on-site observations and a questionnaire to gauge thermal sensation. The on-site observations and Twitter data both showed a drop in park attendance with an increase in temperature; specifically, each 1°C increase corresponded with a 4% decrease in park attendance and a 1% decrease in tweets.

There is a limited amount of information on human mobility data from phones describing heat exposure and vulnerability. However, if personal heat exposure data were made available at a larger scale, it could be incorporated into epidemiological and geographical research, possibly allowing researchers to discover social and environmental determinants of risk and identify the most vulnerable populations. In one of few such studies, Derakshan et al. (2022) used smartphone data from LA County mobile devices to assess levels of cooling center usage and demographics of cooling center patrons. They obtained 24 million recorded locations for the months of July–August 2017 from a third-party provider, Outlogic. Using this data, the study deduced patterns of cooling center use based on device locations within cooling centers and compared patterns on extreme heat and non-extreme heat days. To determine cooling center user demographics, the study identified the location of cooling center users' devices from 1:00–5:00 AM and deduced demographic information associated with the locations of these devices. This methodology serves as a blueprint for future analyses of human behavior during extreme heat events. Other applications of personal mobility and exposure data currently inform other studies, such as heat modeling approaches (Kuras et al., 2017). By using mobile phone tracking data, we can better understand which people and communities are exposed to heat more frequently or severely, which will inform policy and targeting interventions.

Methods

Extreme Heat and Control Day Selection

To analyze the effects of extreme heat on park use, we established definitions for Extreme Heat (EH) and Control days. We pooled weather records during July to August 2017 across 18 weather stations throughout LA County using the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service website. Selected EH days had the most weather stations with average maximum temperatures at or above 95°F. More weather stations with temperatures above 95°F indicated widespread extreme heat throughout the county. This threshold was established by 1) the CDC and the State of California which suggest behavioral changes for extreme heat conditions starting at 95°F (CDC, 2016; State of California Division of Occupational Safety and Health), and 2) the precedent of previous research (Derakshan et al., 2022). Seven EH days, one for each day of the week, were selected to control for temporal variation in park use (Table 1). Each EH day was paired with a Control day that was 1) close in date, meaning ≤14 days, 2) the same day of the week, and 3) had an average maximum temperature close to that of the entire summer (87°F).

Extreme Heat			Control		
Date	**Day**	**Avg High Across Stations (F)**	**Date**	**Day**	**Avg High Across Stations (F)**
7/9/2017	Sunday	100.89	7/2/2017	Sunday	83.2
8/28/2017	Monday	106.14	8/21/2017	Monday	83
8/29/2017	Tuesday	104	8/15/2017	Tuesday	77.8
8/30/2017	Wednesday	103.27	8/23/2017	Wednesday	82.7
7/6/2017	Thursday	102.8	7/13/2017	Thursday	87.1
7/7/2017	Friday	102.6	7/14/2017	Friday	87.5
7/8/2017	Saturday	104.6	7/1/2017	Saturday	81.2

Table 1. Paired Extreme Heat and Control Days. List of the seven pairs of Extreme Heat and Control Days side-by-side, along with each day's date and average high temperature across LA County. The Extreme Heat Days fell into two groups of consecutive days: July 6 to July 9 and August 28 to August 29, 2017.

Extracting Smartphone Geolocation Data

Anonymized smartphone location data recorded across LA County between July to August 2017 was acquired from the Heat Resilient LA Project, which had obtained them from Outlogic (a private provider of smartphone location data). Outlogic collected spatial data from consenting third-party applications whose users agreed to location tracking in the applications' terms of agreement. During each "ping," the smartphone recorded its coordinates, speed, altitude, horizontal accuracy, etc., along with a date and timestamp. Based on the total number of pings, the dataset represents 1.02% to 17.17% of LA County's population in 2017 (Derakhshan et al., 2022). To protect user privacy, no individual locations were examined; only broad overall trends were analyzed.

We extracted two subsets of the smartphone location data: Daytime (12pm - 8pm) and Nighttime (12:30am - 5:30am). We intersected the Daytime subset with a county parks shapefile layer to analyze park amenities and user behavior. The Nighttime subset was intersected with a census tract layer to analyze park user demographics. Both subsets were filtered to exclude smartphone pings with a horizontal accuracy exceeding 25 m to increase the likelihood of the smartphone being inside the park and/or census tract.

Daytime Subset: Temporal & Park Amenities Comparisons

Extreme Heat	Total Unique Pings in Parks		Control
8/28 Monday	5412	5555	8/21 Monday
8/29 Tuesday	5686	6019	8/15 Tuesday
8/30 Wednesday	5661	6427	8/23 Wednesday
7/6 Thursday	6449	7375	7/13 Thursday
7/7 Friday	6238	6882	7/14 Friday
7/8 Saturday	6972	7450	7/1 Saturday
7/9 Sunday	6659	7115	7/2 Sunday

Table 2. Number of Smartphone Pings with Unique ID within Parks on Extreme Heat vs Control Days. This table shows the number of unique smartphones each day whose pings were recorded in parks across LA County. This was counted using an "advertiser ID" that is different for each smartphone device; this number equals the number of different individuals who visited parks. There is generally a chronological increase throughout the week in the number of park visitors.

We filtered the "Countywide Parks and Open Space (Public-Hosted)" shapefile layer from the LA City GeoHub website, then spatially joined it with the Daytime subset of each selected day to identify smartphone pings within park facilities. First, the park shapefile layer was filtered prior to the intersection via ArcGIS to exclude facilities without open access to the public, indoor recreation centers, and special use parks (i.e. equestrian parks, golf courses). The park shapefile layer included information on each park's characteristics/amenities such as park area, management agency, number of basketball courts, tennis courts, splash pads, pools, etc. We created a new variable and attributed parks with the SoVI score of its neighboring census tract. The Daytime subset was also filtered to exclude smartphone pings at speeds greater or equal to 5 m/s prior to the intersection. This filtering step excluded any pings in cars driving through or adjacent to parks, which could not truly represent park users. The filtered parks layer and Daytime subset were then spatially joined, resulting in intersections that only included smartphone pings in park areas (Table 2). These intersections were then analyzed to understand park user trends based on temperature, day of the week, hour of the day, and park amenities. We performed t-tests, generalized linear models, and data visualization using RStudio, Microsoft Excel, and JMP v.17.0.0.

Temporal Analysis

We compared the total number of park users per day between EH and Control days. For each day, we divided the number of unique advertiser IDs found within parks by the total number of pings within LA County overall, to estimate the proportion of LA County residents who visited parks that day. We repeated the same process hour by hour between 12 PM and 8 PM to compare differences in park visitation for different times of day.

Paired t-tests were performed between EH and Control days in each of the seven pairs to analyze significant differences across temperature conditions, by the day of the week, as well as each individual hour between EH and Control days. To standardize our data, we first divided the number of total unique advertiser IDs found within each individual park by the total number of unique advertiser IDs recorded for that day, to determine the proportion of LA County residents that visited a park. This value for each park was then divided by the park's area, and a paired t-test was performed using the resulting values. We also performed a kernel density analysis to show the changes in spatial distribution of park user density between paired EH and Control days in ArcGIS. Furthermore, changes in park visitation between EH and Control days were compared hour by hour.

Amenities Analysis

We created two generalized linear models of park attendance, one for EH and one for Control days, to identify significant amenities affecting park attendance under different temperatures. Park attendance was measured by counting the number of unique smartphones in each park per day. For each park, attendance was summed separately across all EH days and Control days before normalizing by the total number of park users and park area. Park attendance was the response variable; certain amenities were predictors or fixed effects. To narrow down what amenities to incorporate as fixed effects, a correlation matrix of park amenities and a response screening were generated in JMP v.17.0.0. For amenities that were highly correlated (>= 0.7) one of the two amenities was excluded; amenities from the response screening that were not significant (<= 0.05) were also excluded. A Poisson distribution was used for modeling because park attendance was derived from counting the number of unique smartphones recorded.

We analyzed splash pads and pools specifically, because these amenities are hypothesized to most effectively provide extreme heat relief (Lewis, 2005). Welch's two sample t-tests were performed to test for significant differences between the proportion of LA County residents who visited parks with and parks without splash pads and pools on EH vs Control days. The data were normalized by the number of users at parks with splash pads or pools, and also by the total number of park users during that day.

As prior studies have associated vulnerable neighborhoods with lower tree coverage (Nesbitt et. al., 2019; Wolch et. al, 2014; Zhou et. al., 2021), we wanted to further assess tree canopy as a park amenity. We acquired tree canopy raster layers from the U.S. Department of Agriculture Forest Service and transformed them into a shapefile layer to intersect with our parks of interest. However, there were limitations to this data source as it only covered "urban" areas of LA County, resulting in incomplete coverage of some parks. Out of the 2,305 parks analyzed, 311 fell outside the urban areas in the tree canopy layer, so a total of 1,994 parks were included in tree coverage comparisons. Some of the excluded parks were well visited, such as Griffith Park or the Los Angeles National Forest. This meant a number of user points were also not accounted for in quantifying visitation rates based on park tree coverage: the total users decreased by 7,086 for EH days and decreased by 5,563 on Control days. To compare park visitation rates between parks with varying tree coverage, we created a park ranking system of "Very Low", "Low", "Medium", and "High" tree coverage (Table 3). Only analyzing by tree percentage was found to be unreliable. A small park with high tree coverage could still have less trees than a medium park with low coverage. Therefore, with these rankings, we were able to analyze tree coverage percentage within each park ranking and normalize the data for acreage. We classified these variables by taking the quarter percentiles of parks covered by tree canopy. This created bins containing an equal number of parks within a range of tree acreage. The 25th percentile covered parks with up to 19.57% tree coverage, the 50th percentile up to 32.61%, and the 75th percentile up to 46.99%. To account for park size, the same quarter percentiles were calculated for total park acreage; the 25th percentile covered parks of up to 1.07 acres, the 50th percentile up to 4.41 acres and the 75th percentile up to 12.45 acres. This allowed us to analyze tree coverage according to park size, visitation rate, and vulnerability scores. Because beaches do not typically possess characteristics of "traditional parks", like tree canopy, but rank highly in attendance, we performed the same analysis excluding beaches to remove bias from "very low" tree canopy beaches. A total of 41 beaches were removed, leaving 1,953 analyzed for tree canopy.

Percentile	Park Size Rank (acres)		Tree Coverage Rank (percent)	
0.25	1.07217	Smallest	19.5736	Very low
0.5	4.41041	Small	32.6137	Low
0.75	12.4546	Medium	46.9874	Medium
1	>12.4546	Largest	>46.9874	High

Table 3. Rankings of percentiles for park size and tree coverage percentages. To account for the large variations in park size and tree coverage percentage, we created a ranking system based on the quarterly percentiles of each dataset.

The average percentage of park users serviced by different agency levels was analyzed at two levels: EH vs Control days and weekend vs weekdays. Using the existing classification in the county parks layer, the agency levels compared were city, county, federal, non profit, private, special district, and state.

Lastly, we generated two generalized linear models (GLMs) of park attendance, one for EH and one for Control days, using a correlation matrix and response screenings to identify amenities to include as fixed effects. Using the significant contributors from the response screening, we constructed a GLM with normalized park attendance as the response variable and the following fixed effects: park type, total "good" amenities, total "fair" amenities, tree canopy acreage, and the presence of restrooms, basketball courts, baseball fields, playgrounds, soccer fields, tennis fields, community centers, gyms, and multi-purpose fields. Park type had subcategories of node, pocket, neighborhood, community, community regional, regional, underdeveloped and special use (which was divided into botanic, equestrian, natural, staging area).

Nighttime Subset: Demographic Comparisons

The Nighttime subset of each day was spatially joined with an LA County census tract layer from LA City GeoHub's website. The census tract layer included the demographic breakdown of each census tract, including the percentage of children and elderly, percentage of households below the poverty line, rate of cardiovascular diseases, median income, and Social Vulnerability Index (SoVI score). Prior to this intersection, we compiled the Nighttime subset for all selected days and filtered only for advertiser IDs that matched a park user's advertiser ID in our Daytime subsets. We also filtered the smartphone pings to speeds between 0 and 1 m/s to exclude pings in moving cars. These steps ensured only stationary Nighttime locations of park users were included in the spatial joins. The Nighttime intersections were then analyzed to understand park user demographics based on parks' and park users' residence SoVI scores.

Demographic Analysis

Parks and park users were assigned a low, medium, or high vulnerability rank (SoVI score) based on their geographic location and associated data from the LA County Climate Vulnerability Assessment. Comparisons were then made between EH vs Control days and between weekends vs weekdays. Specifically, we calculated changes in abundance of park users with different SoVI scores and changes in visitation rates for parks of different SoVI scores. We also examined county-wide percentages of both parks and park users in each of the three SoVI score categories.

To supplement statistical analysis with qualitative data, group members also performed in-person surveys of six different parks, comparing parks in low vs high income areas, a variable factored into calculating overall SoVI scores. They made observations and took photographs of six parks and their amenities, comparing parks in low, medium, and high income levels.

Results

Temporal Analysis

For the paired t-tests conducted between each of the seven EH and Control day pairs, only Wednesday was found to be significantly different, with the EH day having significantly fewer park visits than the Control day (p = 0.000358) (Table 4). Thursday and Sunday were also marginally significant (p = 0.066) (Table 4).

Extreme Heat Day	Day of the Week	Control Day	P-value
7/6/2017	Thursday	7/13/2017	0.06603
7/7/2017	Friday	7/14/2017	0.1285
7/8/2017	Saturday	7/1/2017	0.396
7/9/2017	Sunday	7/2/2017	0.06602

8/28/2017	Monday	8/21/2017	0.7468
8/29/2017	Tuesday	8/15/2017	0.8399
8/30/2017	Wednesday	8/23/2017	0.0003588

Table 4. **Significance testing for temporal visits.** List of p-values generated from paired t-tests comparing park visits on each paired control and extreme heat day. None of the p-values were statistically significant at the $p<0.05$ level, with the exception of Wednesday.

We also created bar graphs to visualize the difference in the number of park visitors for each pair of days below.

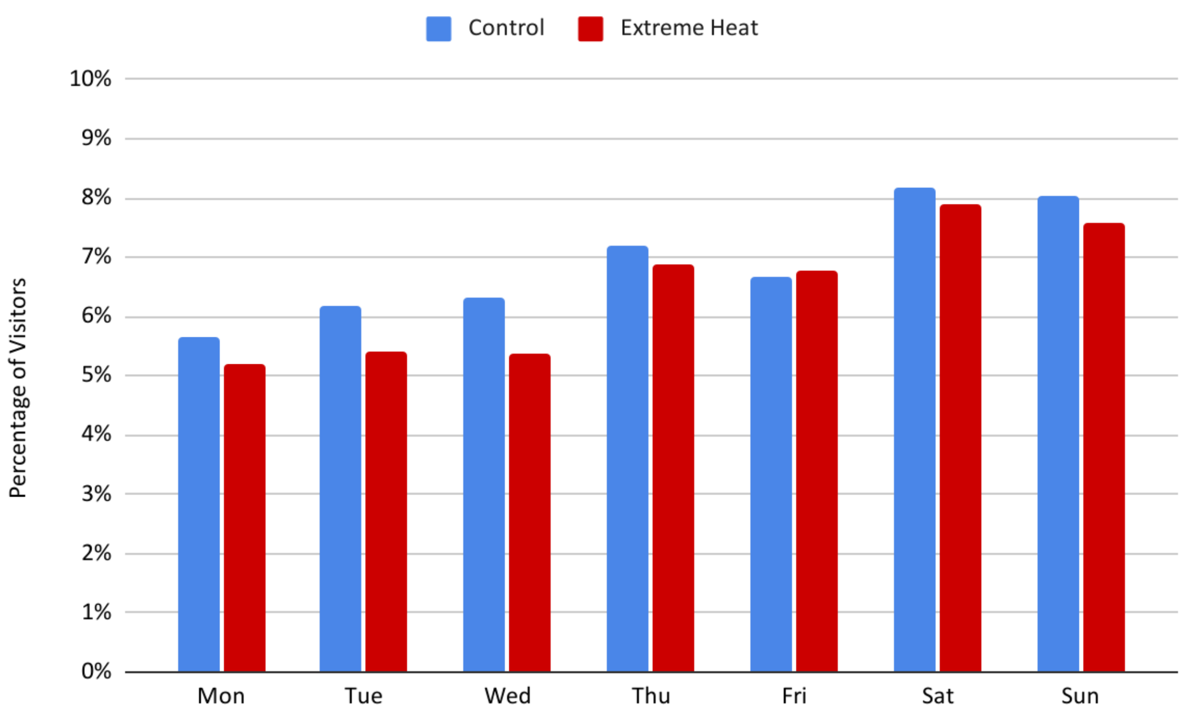


Figure 1. **Total Park Visitors as a Percentage of Total LA County Citizens Recorded per Day**. The number of unique park visitors a day is shown as a percentage of the total number of unique smartphones recorded in the county that day. The values are standardized by the total unique pings in parks and total unique pings in the county. On extreme heat days parks generally have less total visitors. On weekends parks tend to have higher visitation rates than weekdays, on both extreme heat and control days.

Park attendance primarily decreases on EH days, with the exception of Friday (Figure 1). Regardless of temperature conditions, more individuals visit parks as we move chronologically through the week. Park attendance is lower starting on Monday, and increases throughout the week, peaking during the weekend. The highest park attendance on both EH and Control days occurs on Saturday and the lowest on Monday. These trends indicate that the day of the week exerts greater influence on trends in park usage compared to EH conditions.

Saturday, July 1 to Saturday, July 8

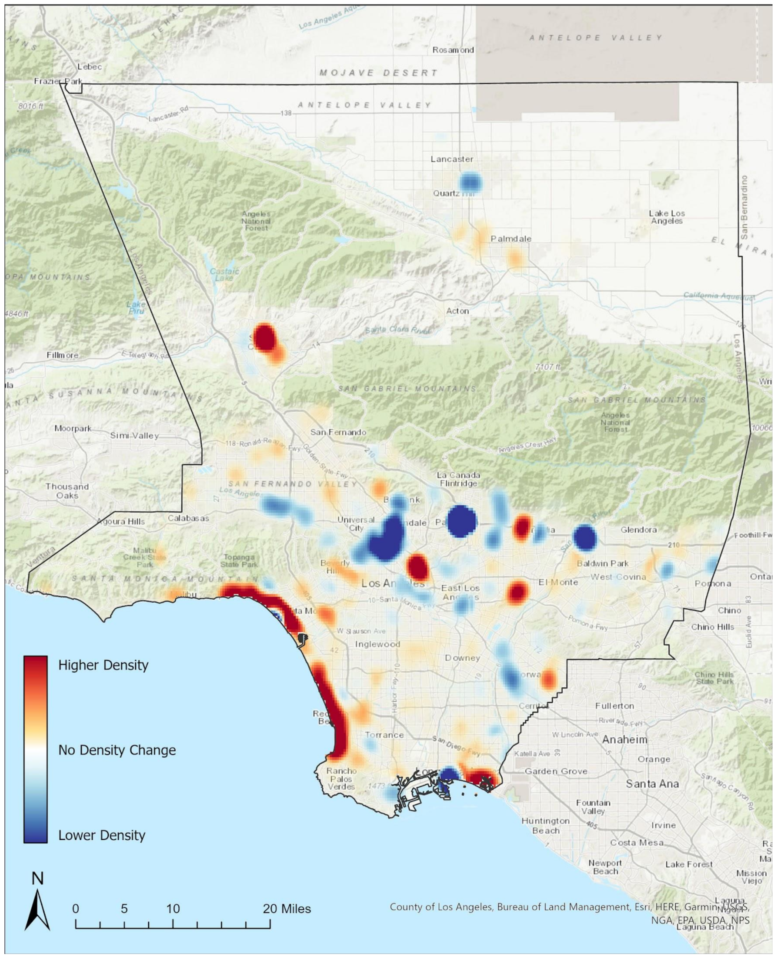


Figure 2. Kernel Density Changes of Park Attendance on Extreme Heat and Control Saturdays. Shows changes in park visitor density, with red indicating greater concentration and blue indicating lower concentration on the EH Saturday compared to the Control Saturday. The most noticeable change is a significant increase in park user density along the coastline from Malibu to Long Beach. There are large decreases in central LA County on the EH day.

The kernel density analysis (which displays changes in park user density between paired EH and Control days) supplements these observations by providing a qualitative visualization of how park usage shifts throughout the week. Throughout the week, there was not a consistent spatial pattern to park user density fluctuations, but one defined outlier was Saturday (Figure 2). On the EH Saturday compared to the Control Saturday, there is a notably larger number of park visitors clustered along the coastline, indicating beach attendance skyrockets during extreme heat on the weekends.

			Hour							
	Extreme	Control	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM	7:00 PM
Friday	7/7	7/14	0.297	0.293	0.284	0.291	0.278	0.282	0.261	0.277
Saturday	7/8	7/1	0.292	0.290	0.274	0.274	0.269	0.254	0.258	0.244
Sunday	7/9	7/2	0.286	0.287	0.265	0.272	0.254	0.250	0.264	0.229
Monday	8/28	8/21	0.275	0.264	0.227	0.251	0.248	0.219	0.244	0.266
Tuesday	8/29	8/15	0.274	0.208	0.268	0.212	0.247	0.234	0.264	0.260
Wednesday	8/30	8/23	0.228	0.271	0.211	0.247	0.220	0.232	0.183	0.270
Thursday	7/6	7/13	0.246	0.267	0.245	0.239	0.254	0.190	0.269	0.289

Table 5. Significance testing for temporal visits (hourly). List of p-values generated from paired t-tests comparing park visits on each hour within each paired control and extreme heat day. None of the p-values were statistically significant at the p<0.05 level.

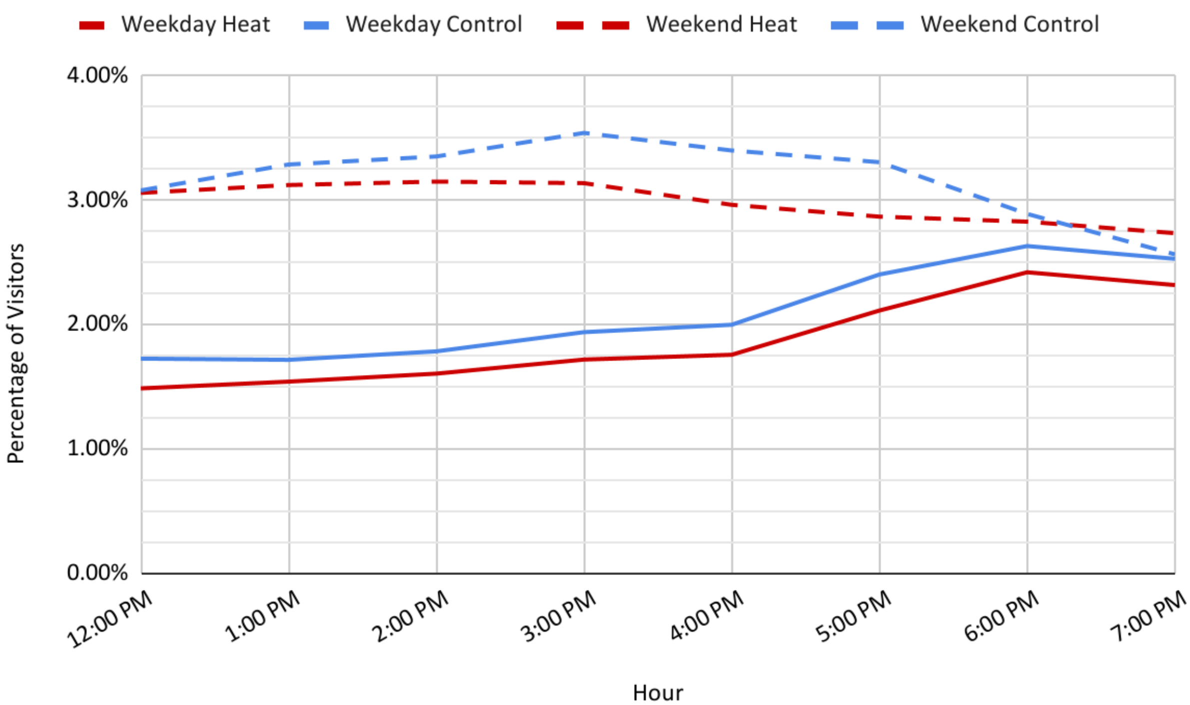


Figure 3. **Hourly Park Visits as a Percentage of All Total Park Visitors and Total Individuals in the County.** The data are normalized by the total number of park visitors and the total number of individuals recorded that day.

Taking analysis another level further, we examined the change in park visitors per hour between 12–8 pm. When comparing the percentage of individuals at parks by hour (normalized by dividing the total number of individuals at parks by individuals in the county on that day), we see two trends emerge: weekday and weekend hourly use. For EH and Control weekdays, hourly visitation increased as the day progressed, peaking around 6 pm. The inverse pattern occurs on EH and Control weekends. Hourly visitation started and remained generally high during the afternoon, before declining throughout the late afternoon and evening, starting around 4 pm. For both weekdays and weekends, the EH and Control days followed the same pattern, suggesting that day of the week, over temperature, had the stronger influence on hourly visitation rates. Additionally, paired t-test were performed by hour between the EH and Control day pairs that found there were no statistically significant differences between hourly attendance (Table 5).

These trends reinforce the previous finding that on EH days park attendance drops. The average hourly attendance of Control weekends and weekdays (Figure 3; dotted and solid blue lines) are higher than the average of the EH weekends and weekdays (dotted and solid red lines). The only exception occurs on Saturday, where hourly attendance on the EH day exceeds the Control Day after 6 pm. The percentage of park visitors on the Control Saturday declines until it is lower than the hot day percentage, which stays constant around 3%. Similarly, although Control Day attendance still remains higher, attendance on the Control Sunday dips and gets close to the EH day percentage, which also stays relatively constant around 3 percent.

Amenities Analysis

From the GLM, park type (all subcategories except special use botanic and natural) and the quality of park amenities ("good" and "fair") significantly influenced park attendance. Significant amenities also included the presence of restrooms, basketball courts, baseball fields, playgrounds, and community centers. Being an underdeveloped park or special use equestrian park type most negatively impacted park attendance. The presence of basketball courts, baseball fields, community centers, had small, but significant, negative effects. Interestingly, tree canopy acreage also had a small, but significant, negative relationship with park attendance. On the other hand, being a node park (small open area that connects spaces and breaks up urban landscapes) had a strong positive association with park attendance. Restrooms, total "good" amenities, and total "fair" amenities, all had small, but significant, positive effects on park attendance as well.

Similarly for Control days, we used the significant contributors from the response screening to generate a GLM of park attendance. included park type, agency level, and the presence of basketball courts and multi-purpose fields. Normalized park attendance was the response variable and park type, tree canopy acreage, and the presence of restrooms and basketball courts were the fixed effects. From the GLM results, all subcategories of park type (listed above) except special use staging area were found to be significant. Tree canopy acreage and the presence of restrooms and basketball courts were all significant as well. Being a special use park (specifically the sanctuary, natural, and equestrian subcategories) had the strongest negative significant impact on park attendance, followed closely by being a regional park. Tree canopy acreage and the presence of basketball courts had significant, but very small negative correlations with park attendance. On the other hand, being a node park type, followed by a pocket park type, had the strongest positive effects on park attendance. The presence of restrooms also had a small but positive significant effect.

Day of the Week	Extreme Heat Day	Control Day	P-value (POOLS)	P-value (SPPAD)

Thursday	07/06	07/13	0.804	0.4529
Friday	07/07	07/14	0.6919	0.1831
Saturday	07/08	07/01	0.4995	0.4101
Sunday	07/09	07/02	0.1639	0.1816
Monday	08/28	08/21	0.1484	0.4511
Tuesday	08/29	08/15	0.9091	0.4289
Wednesday	08/30	08/23	0.2243	0.03744

Table 6. T-test Results between Parks With and Without Pools and Splash Pads. For the majority of the t-tests there was no statistically significant difference found between parks with pools, and parks with splash pads on EH vs Control days. The only exception was the t-test for attendance on the Wednesday EH vs Control day for parks with splash pads ($p = 0.03744$).

To assess visitation to parks with cooling amenities, locations of splash pads and pools are shown throughout LA County (Appendix X). Statistical t-tests found no significant differences in visitation of parks on EH and Control days for parks with and without pools for all seven compared pairs (Table 6). Similar results were found for comparisons of parks with and without splash pads.The sole exception was Wednesday, which saw a significant difference in park visitation between parks with and without splash pads ($p = 0.03744$).

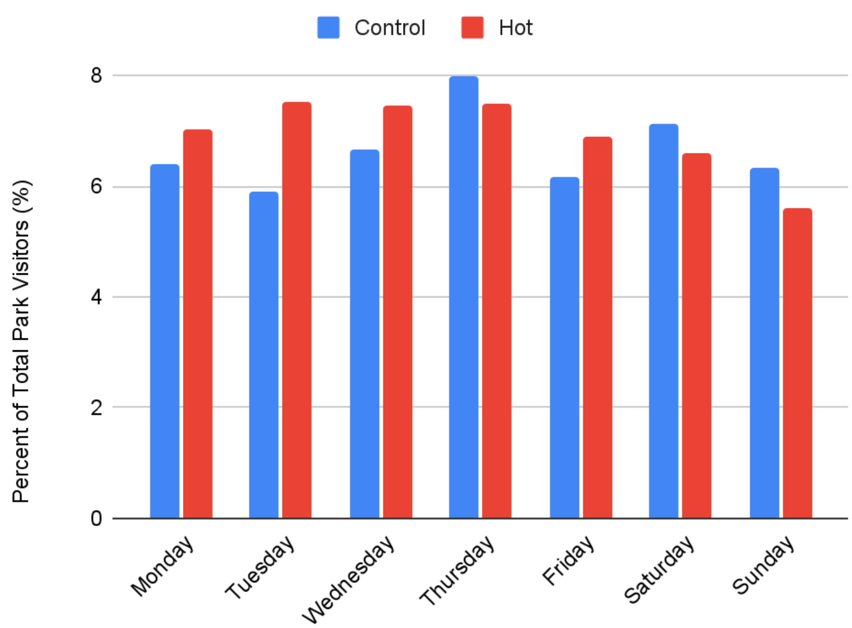


Figure 4. Percentage of Park Visitors that Attended Parks with Splash Pads on EH and Control Days. Shows the percentage of park visitors that visited parks with splash pads on EH and Control days for all seven paired days. Parks with splash pads had a higher percentage of park visitors on EH days than Control days for Monday, Tuesday, Wednesday, and Friday. For the rest of the days, parks with splash pads serviced a greater percentage of park visitors on the Control day.

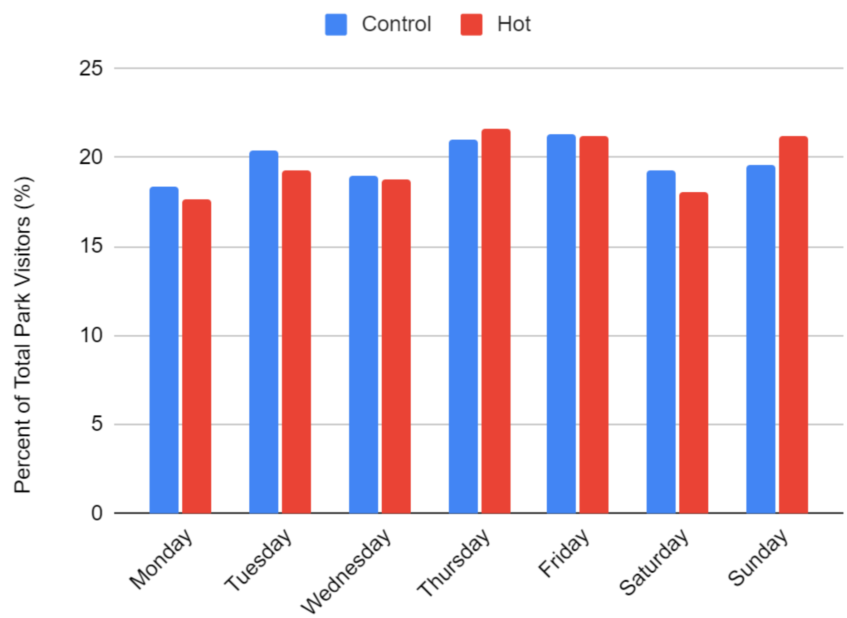


Figure 5. Percentage of Park Visitors that Attended Parks with Pools on EH and Control Days. Shows the percentage of park visitors that visited parks with pools on EH and Control days for all seven paired days. Parks with pools had a higher percentage of park visitors on EH days than Control days for Thursday, Friday, and Sunday. For the rest of the days, parks with pools serviced a greater percentage of park visitors on the Control day.

Parks with splash pads served a higher percentage of park visitors on EH days than Control days for four days of the week: Monday, Tuesday, Wednesday, and Friday. For the rest of the days, parks with splash pads serviced a greater percentage of park visitors on the Control day (Figure 4). Surprisingly, parks with splash pads serviced a greater percentage of park visitors earlier in the week–the percentage of park visitors attending parks with splash pads was lower on the weekends. This could be attributed to the observation made in the kernel density map where it appears that a significant amount of park users move from inner city parks to coastline beaches on the weekend. Parks with pools had a higher percentage of park visitors on EH days than Control days for Thursday, Friday, and Sunday. For the other days of the week, parks with pools serviced a greater percentage of park visitors on Control days. The largest difference for visits to parks with pools between EH and Control days occurred on Sunday (Figure 5). Neither amenity demonstrated a clear, consistent pattern between EH and Control day temperature conditions nor temporal trends between weekdays and weekends.

Figure 6. Tree Canopy Coverage in Urban Parks Throughout LA County. Out of the total 2,305 parks in the county that were analyzed, only 1,994 parks fell within the urban area boundaries set by the data source. Parks designated in natural areas such as the Santa Monica Mountains and the LA National Forest are not included.

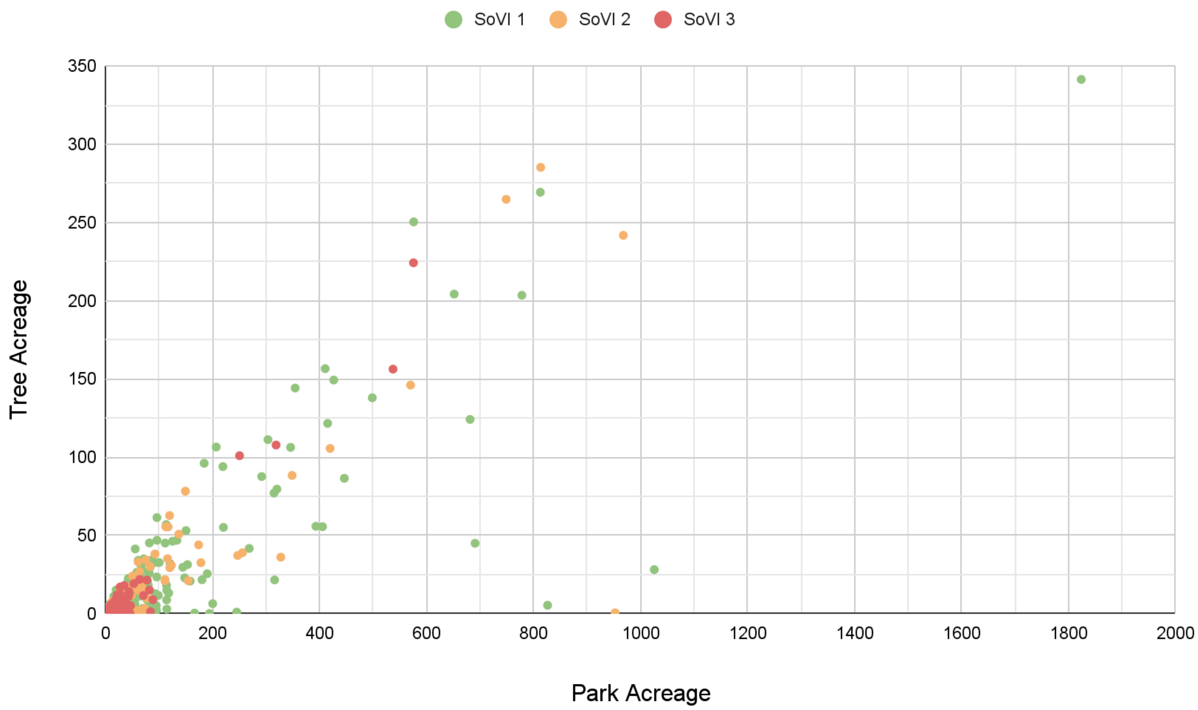


Figure 7. Tree Canopy Coverage in Relation to Park Size and Social Vulnerability of Surroundings.

Tree canopy as a park amenity was visualized (Figure 6). Across all the parks with tree canopy data, the parks had on average 35.35% of tree canopy coverage by area and an average of 5.72 acres of tree canopy coverage. The scatter plot shows a clear positive correlation between park size and tree canopy (Figure 7). As expected, smaller parks tend to have smaller tree coverage and vice versa. The points are color coded by SoVI score. Parks near low vulnerability census tracts are more likely to be larger in size with greater tree coverage, while highly vulnerable areas tend to have smaller parks and lower tree coverage. Based on the GLM results and additional analyses, we observe parks with higher tree canopy have fewer visitors or are less crowded. Parks with lower canopy courage are associated with vulnerable neighborhoods, so these patterns may be a function of proximity and not choice.

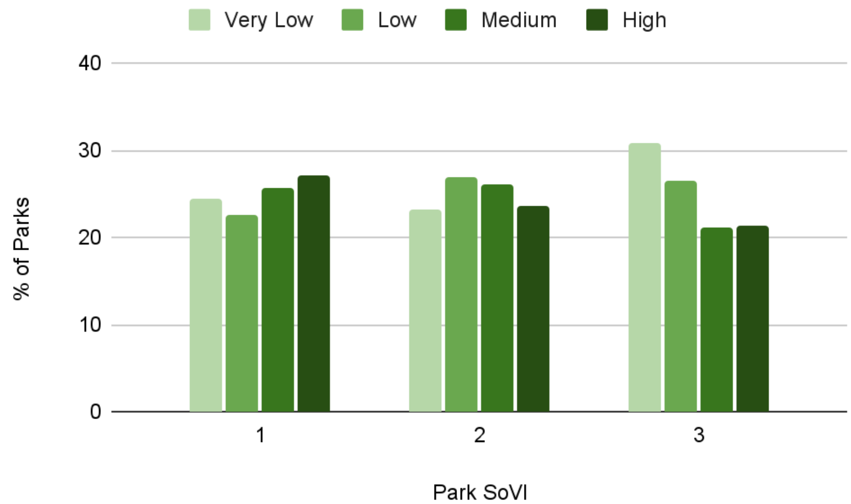


Figure 8. **Tree Coverage Rankings by Park SoVI Score.**

SoVI score 3 parks, or highly vulnerable parks, had greater percentages of low and very low tree coverage and the least amount of high and medium coverage of all parks. SoVI score 2 parks, or moderately vulnerable parks, had more medium and low coverage (Figure 8). The majority of SoVI score 1 parks, or the least vulnerable parks, had either high or medium tree coverage (Figure 8). For the analysis of tree cover, beaches were removed from consideration. Beaches often do not have many trees, and including them greatly skewed the distribution of SoVI Score 1 parks (Appendix D9). With beaches included, the distribution became bimodal, with most of the parks having either high or very low tree canopy.

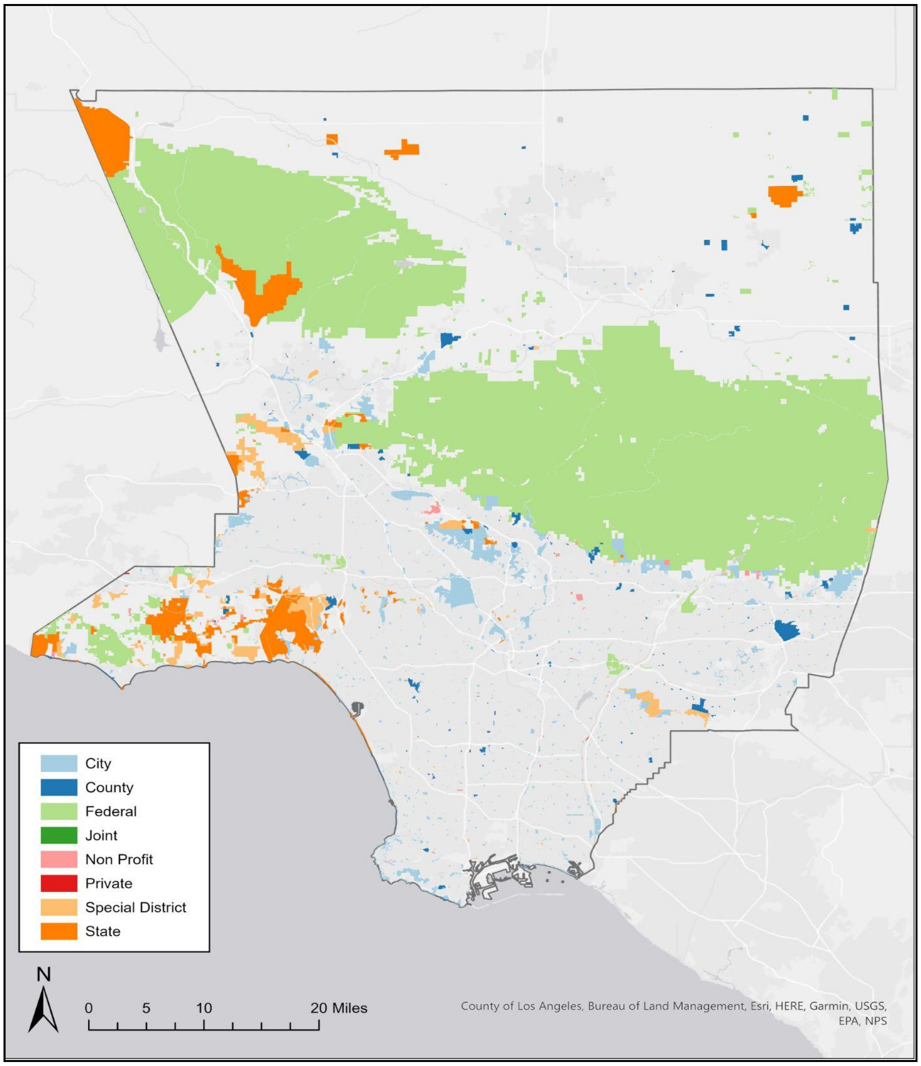


Figure 9. Parks Color-coded by Managing Agency.

The map above depicts the parks according to their agency level (Figure 9). Smaller parks within neighborhoods are often city or county parks. The larger parks that lie farther from urban areas are federal or state. Beaches are typically state or county.

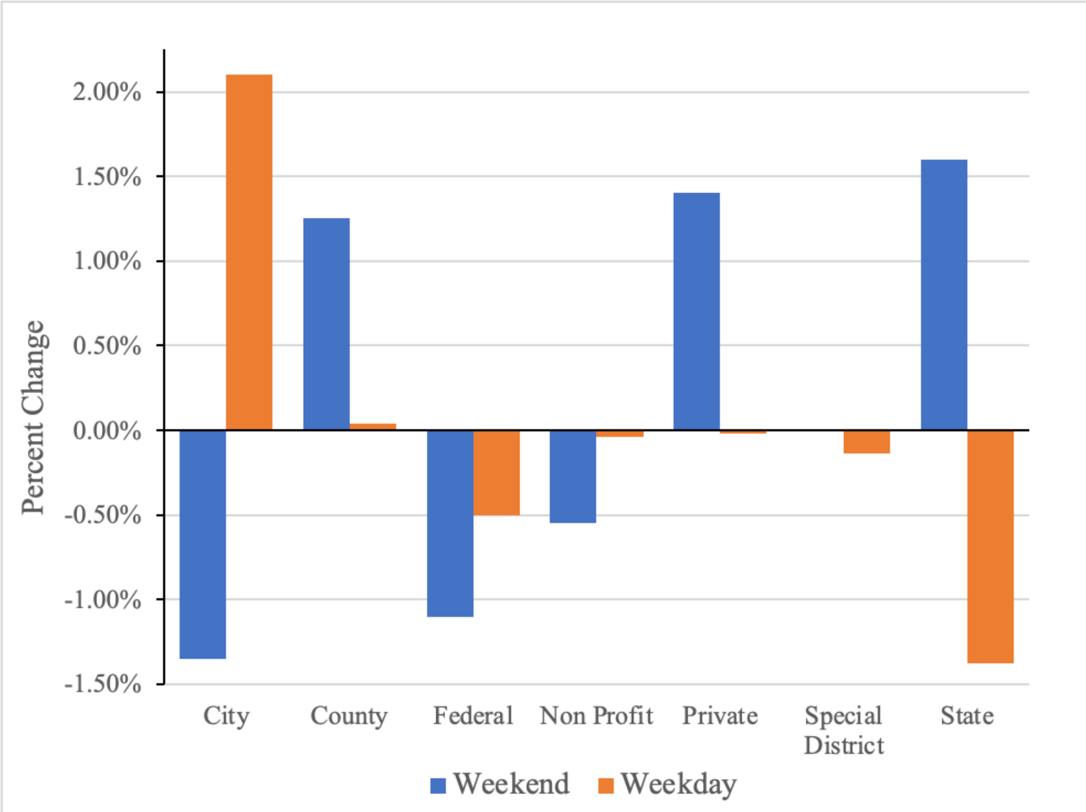


Figure 10. Difference in the Average Percent of Park Users from Control to EH Days by Agency Level. The percentage of park users that visited parks of different agency level was calculated for each day, then the average was taken across all EH and across all Control days. These two averages were then subtracted from one another to find the difference between EH and Control days. City and state parks experience opposite trends: city park service decreases on EH weekends and increases on EH weekdays, while state park service increases on EH weekends and decreases on EH weekdays.

Changes in park attendance by park agency level (divided into city, county, federal, non profit, private, special district, and state) were also further explored. We made comparisons between changes in average percent of park users served between EH and Control days, and between weekends and weekdays. City parks served 1.35% less park users on EH days during the weekend, but 2.10% more users on EH days during weekdays. State parks experienced the opposite trend; state parks served 1.60% more park visitors during EH weekends and 1.38% fewer park visitors on EH weekdays. As city and state parks experience opposite trends, we hypothesize these changes are due to time constraints and proximity - during EH weekdays citizens are potentially more restricted by work/school and so thus visit more proximal city parks. During EH weekends, citizens have more time to travel further to the large state parks (including beaches), thus city park attendance decreases while state park attendance increases. County parks service a greater percentage of park users on EH days than Control days on both weekends and weekdays. Meanwhile, federal and non profit parks both experience decreases in percentage of park users served on EH days, regardless if it is a weekend or weekday.

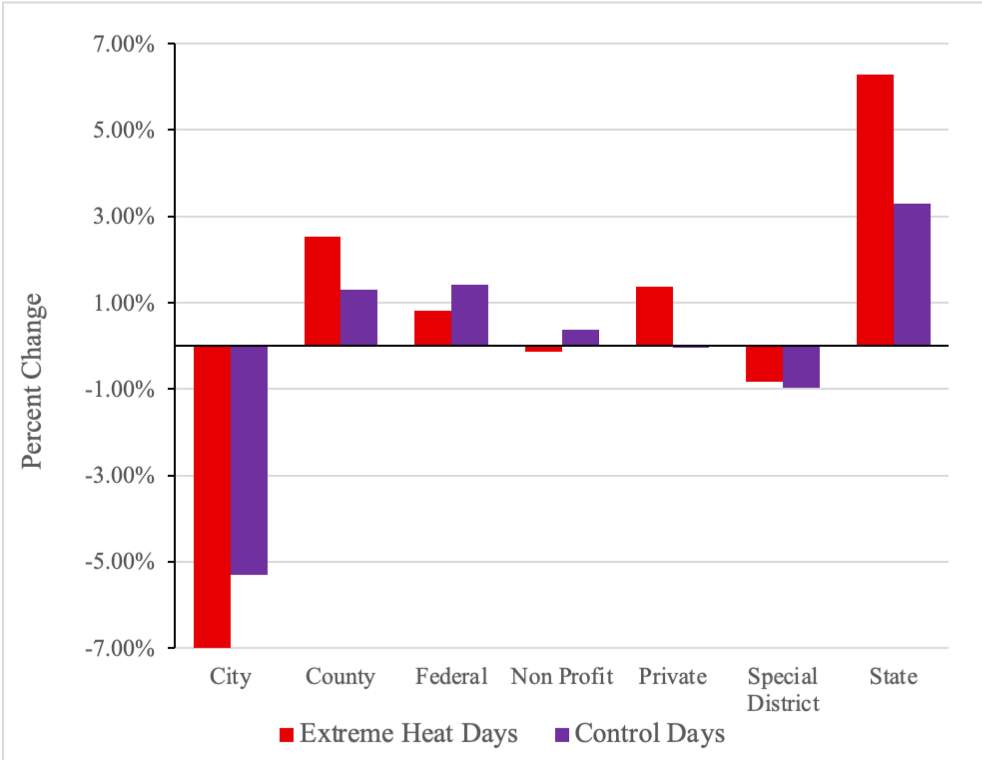


Figure 11. Changes in Average Percentage of Park Users Serviced from Weekday to Weekend. The percentage of park users that visited parks of different agency levels was calculated for each day, then the average was taken across weekends and across weekdays. These two averages were then subtracted from one another to find the change between weekends and weekdays. City and state parks experience opposite trends: city park service decreases on EH weekends and increases on EH weekdays, while state park service increases on EH weekends and decreases on EH weekdays.

Comparisons between weekend and weekdays depicted similar trends. At city parks, the percentage of park visitors served dropped during the weekend regardless of temperature conditions (decreased by 8.75% on EH days and 5.30% on Control days). Again, state parks experienced the opposite trend, with the percentage of park visitors serviced increasing on weekends, regardless of temperature (increased by 6.28% on EH and 3.30% on Control days). For county and federal parks, percent of park users also increased on the weekends regardless of temperature conditions. Meanwhile, special district parks decreased in visitors served on weekends for both EH and Control days. The inverted trends seen between city and state parks in Figure 11 corroborate the trends observed in Figure 10.

Demographic Analysis

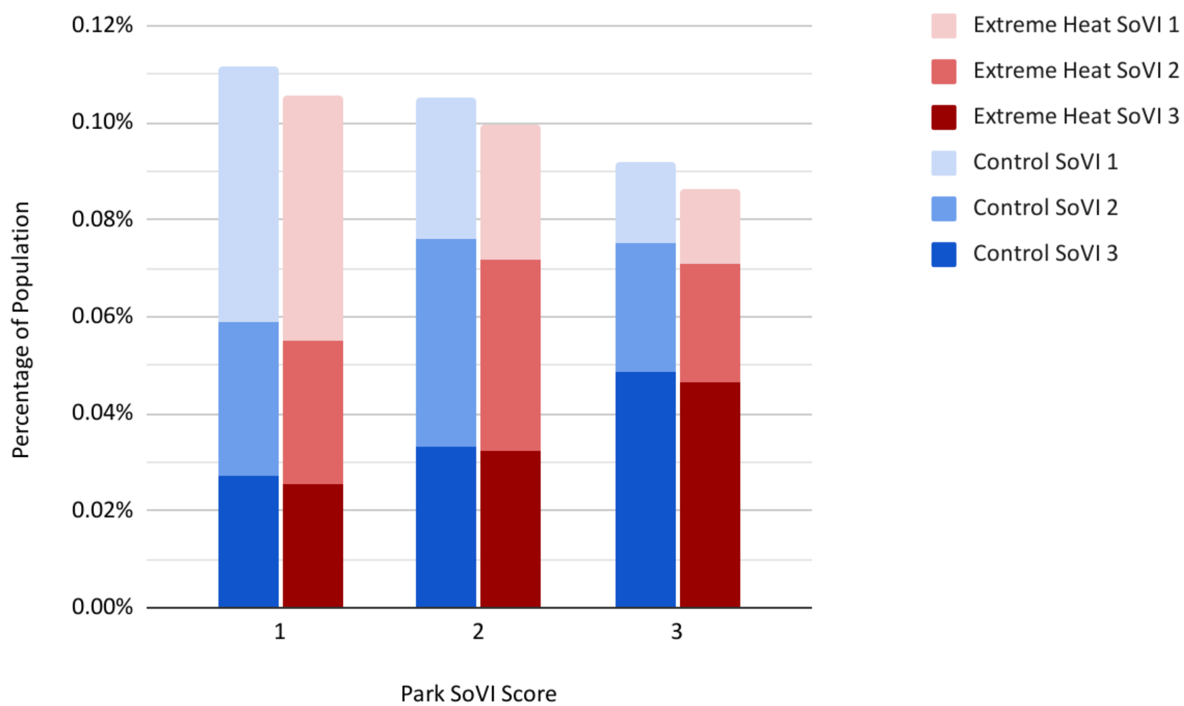


Figure 12. Percentage of Park Visitors By Visitor SoVI Score at Parks of Different SoVI Scores. Shows the average percentage of park visitors in each of the three SoVI scores by park SoVI scores across all EH and Control days. Values are normalized by SoVI group populations and park acreage.

Finally, patterns of park visitation were quantified by the SoVI score of the park visitor as determined by nighttime resting location and of the location of the park itself (Figure 12). Generally, parks in areas with SoVI scores of 1 (Low Vulnerability) were visited the most, while SoVI score 3 parks (High vulnerability) were least visited. Additionally, park visitors tended to go to parks that matched their SoVI score, and were less likely to attend a park with a greater difference in SoVI score. Parks with SoVI score 1 saw the greatest percentage of visitors with SoVI 1 scores, parks with SoVI scores 2 had fewer, and parks with SoVI scores 3 had even less visitors from SoVI score 1 neighborhoods. This trend holds true for park visitors of SoVI score 3, but in the opposite direction. Parks with SoVI score 3 have the most SoVI 3 score visitors, SoVI score 2 parks have less, and SoVI 1 parks service even less SoVI score 3 visitors. Regardless of park and park visitor SoVI score, these results further corroborate our previous conclusions that parks are used less during extreme heat.

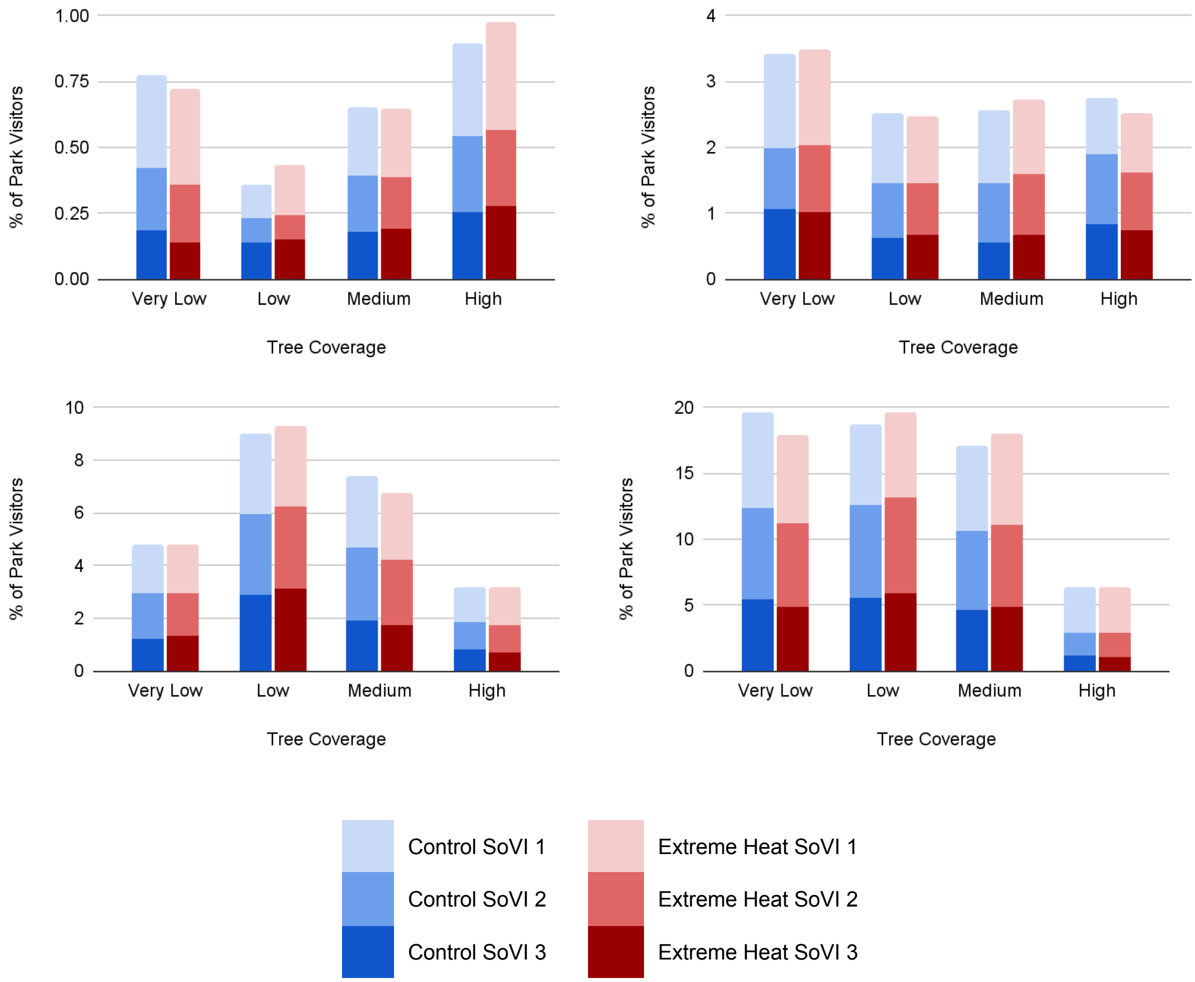


Figure 13. SoVI Percentage of Park Visitors in Different Sized Parks by Tree Canopy Percentage. Parks are divided into four size categories: smallest (top left), small (top right), medium (bottom left), and largest (bottom right). Then they are further divided by their tree canopy percentage (tree canopy acres/park acres).

Comparing only tree canopy, the smallest parks with the highest tree coverage were the most populated. For small parks visitation was roughly consistent across all levels of tree coverage. For the medium and largest-sized parks, however, visitation was highest at parks with low and very low tree canopy. There is no significant preference for parks with greater tree coverage however there is a correlation between sum of park visits and park acreage. Generally, as park size increased, the total number of visitors increased; the largest parks had close to thirty times more visitors than the smallest parks. Across all park sizes and tree coverages, most park visitors tend to be of the SoVI score 1 (from Low Vulnerability neighborhoods) (Figure 13).

Park Name	Income Level	Amenities
Atlantic Avenue Park	Low	Splash pad
Apollo Community Regional Park	Low	Lake
Belvedere Community Regional Park	Low	Splash pad, Lake
Whittier Narrows Recreation Center	Low	Lake
Castaic Lake State Recreation Area	High	Lake
Castaic Regional Sports Complex	High	Splash pad

Table 7. Attributes of Parks Surveyed In-Person. Income levels and notable amenities offered at the six parks observed and photographed in person.

From our qualitative survey of six parks from varying income levels (Table 7), the main difference between low and high income parks seemed to be access to indoor activity centers and playground structures. At the Castaic Parks, there were aquatic workout classes being held, along with buildings for basketball courts and senior activities like line dancing. The Castaic Parks also had more intricate, engaging, and newer playground structures. There was a stark contrast in playground materials; the Belvedere Park playground was older, metal, and used wood chips on the ground, while the Castaic Park playgrounds were made of plastic (potentially to reduce heating), and used a rubbery material on the ground. Both Atlantic Avenue and Belvedere Parks (low income areas) had pools (Table 7), but these amenities were closed or covered and inaccessible.

Discussion

Our results consistently affirm that parks are not widely used by people on extreme heat days as a heat mitigation strategy. Despite their cooling abilities, they are used less during extreme heat days than on their paired control day. Other factors appear to have stronger effects on park use than heat, including the time of day or week, park agency level, park amenities, and social vulnerability of people and parks. These patterns should be taken into account by LA County departments to ensure heat safety among LA residents during increasingly hotter summer months.

Clear trends emerged from analyzing park visits throughout the week and the hours of the day, which can be attributed to the behavioral inelasticity of LA County residents (Derakshan et al., unpublished analysis). Time constraints such as school and work hours limit park attendance during the morning and early afternoon. This is clear from the lower visitor percentages on the weekdays compared to the weekend. Average end times for school and work are 3 pm and 5 pm respectively, and correspondingly, the hourly graph shows the largest increase in park attendance between 4 and 5 pm with peak attendance at 6 pm on weekdays. In contrast, on the weekend, when people usually have days off, park attendance is higher and more evenly distributed throughout the day. To better align with park visitors' schedules, park events during the week should be promoted later in the afternoon or early evening to avoid extreme heat and accommodate as many visitors as possible.

In order for the county to support their residents during extreme heat events, parks could be improved by following the visitation patterns that are seen regardless of heat. The findings from the hourly graph imply that investments in nighttime activities starting at 6 pm during the week and afternoon beach activities over the weekend are the most promising strategies to help the community during extreme heat events. The Los Angeles County Parks and Recreation Department created the Parks After Dark Program, which hosts safe, and fun activities for the public on hot nights. They could extend the program throughout the week to target heavily populated and highly vulnerable neighborhoods, thus increasing the accessibility of cooling activities and amenities to parks that can service those most vulnerable to heat.

With more leisure time on weekends, people also have the ability to travel further, contributing to additional differences between weekend and weekday trends in park attendance. Figure 11 depicts high attendance at federal, state, and county parks on weekends. As shown in Figure 9, federal and state parks are further away from densely populated areas of LA County, in contrast to city parks, which are closer to these neighborhoods and visited more frequently on weekdays. The accessibility of city parks with regards to distance and time make them more convenient for park visitors, whereas federal, state, and county parks become more accessible on weekends. These patterns are seen regardless of heat, indicating that day of the week has greater influence over park usage than weather conditions.

In addition, beaches are a weekend hotspot of park visitation during extreme heat. While some are categorized as city parks, the majority of beaches are county and state beaches managed by Beaches and Harbors. Since beaches accumulate large crowds on extreme heat days, it can be useful to examine who has access to them, along with parks spread out throughout the county. According to the Parks and Recreation Needs Assessment from 2022, "Only about 100,000 Los Angeles County residents (1% of the population) live within walking distance of an ocean beach access point. The majority of ocean beach access points (71%) are not served by public transit." Management of both beaches and parks should support fair transit accessibility to all their locations to provide open spaces during times of need, especially extreme heat events. The California Coastal Act was made to address issues involving shoreline public access and decreased visitor costs, but similarly, the city and county can make their own efforts to increase beach accessibility.

The patterns found in our amenities analyses also appear to be minimally influenced by heat. No significant differences were found statistically or visually between parks with pools and splash pads on extreme heat versus control days. The design choice to build more pools at parks is a fiscal challenge that our results show is not cost-effective because of the lack of increased visitation. The Los Angeles Pool Replacement and Management Program established as a special task force to enhance pool operating budgets has consolidated data on existing pools in the city. Funding to buy chlorine has increased approximately 43% from the early 90s compared to the early 2000s while the cost of chlorine itself has increased 100% during that same time comparison. On top of the costs of inflation for necessary maintenance chemicals, leakage is another issue that can add an extra $230,000 per year (Mukri, Dept. of Parks & Recreation, 2004). The cost of operation and maintenance for pools are not financially feasible especially in low income areas combined with environmental hazards such as drought. Millions of dollars to build new facilities or upkeep existing ones will come out of taxpayer dollars when there is no positive significant correlation that water amenity use increases on extreme heat days. Though pools can bring communities together through close interaction and fun recreational activities, further research should be conducted on their cost-benefit analysis to ensure investments are suitable with future climate predictions and community impacts. Resources may be better allocated towards other community improvements such cooling center infrastructure or increased accessibility to existing locations and beaches.

The GLMs showed that the park amenities with significant effects on park attendance were not those that are typically associated positively with heat. It seems reasonable for sports fields to have negative impacts on heat day attendance as they are not cooling activities, but given the significance of trees and their shade in mitigating heat, it was expected that tree canopy would have a positive effect on park attendance. There are a few possible explanations. First and most importantly, the tree canopy geodatabase that was provided did not cover the entire area of LA County. It strictly mapped out only urban tree canopy, which meant that less developed areas with significant tree coverage, such as the Angeles National Forest and the Santa Monica Mountains, were not included in the calculation and thus affected the results. As a result, there is greater representation of people going to parks with less tree coverage. Our results also suggest that tree coverage may not have much of an effect on park visitation, a finding which is reflected in literature. When assessing whether greater levels of tree cover or vegetation led to increased park visitation, researchers found results where both features had limited influence on higher attendance (Shanahan et al., 2015). In fact, their findings suggest that urban residents may actually prefer to visit parks with low tree cover. They attribute this to many possibilities, including people's stated preference for open landscapes, or a perception that areas with more vegetation are less safe.

The parks that were excluded from the tree canopy layer were further away from urban areas and less accessible in terms of distance. As mentioned above, on weekdays, people tend to go to parks that are closer because they do not have the time to travel farther away. Multiple studies, as well as our own findings, support the fact that there are less trees in parks near highly vulnerable neighborhoods. Wolch et al. (2014) states that green space is differentially distributed within the city's urban landscape due to mutually reinforcing conditions of "park design, history of land development, evolving ideas about leisure and recreation, and histories of class and ethno-racial inequality and state oppression." More vulnerable communities often occupy urban centers where green space is scarce or poorly maintained, while affluent communities in the urban periphery have access to well maintained and abundant green space. Furthermore, the parks that were excluded from the tree canopy database were mostly high vulnerability (SoVI score 1) parks. Figure 7 indicates a positive correlation between tree canopy and park acreage and depicts a greater range of park and tree canopy acreage for less vulnerable parks than for more vulnerable parks. As a result, people visiting nearby parks are more likely going to a SoVI score 3 park with less tree coverage, leading to the results found in the GLM.

Analyzing which amenities draw more visitors to parks can be vital to helping communities access green spaces and provide relief from heat. In 2021, LA County Regional Park and Open Space District (RPOSD) announced $33 million would be provided by funding opportunities to assist LA County parks. These funds are accrued through Measure A, an annual parcel tax, to help support beaches, open spaces, parks and natural water resources within the county. A portion of these efforts include improving park amenities and increasing accessibility to local parks or building new ones all together (LA County Parks and Recreation). Supporting research also shows, "a mapping of park-bond funding allocations by location reveals that funding patterns often exacerbate rather than ameliorate existing inequalities in park and open-space resource distributions" (Wolch 2013). In older neighborhoods, there is a lack of large spaces available for repurposing, thus leaving many residents marginalized. SoVI score 1 parks were also likely to be of higher quality based on their overall ranking within the census tract they were located within. These parks within a higher scored group are not ranked this way without reason; they shared overall better quality amenities compared to SoVI score 3 parks. Park equity is an underlying issue that influences park usage, and has the potential to only grow into a larger problem as economic gaps widen in the future. Taking extreme heat into consideration should be a factor into deciding what amenities to build, but officials should also be advised to look at other social determinants for community development and planning.

Addressing park amenities can be helpful in the solution to alleviate heat, however though parks have been proven to have a cooling effect, these numbers pale in comparison to the power and consistency of air conditioning (A/C). While parks and their cooling abilities fluctuate by size, green space, tree cover, wind speed, humidity, and many other factors, A/C is able to provide strong, consistent cooling that meets people's needs more reliably. A/C is an obvious resource to cool down, however the problem many county residents can face is the lack of access to buildings equipped with it. Older homes may not have units built in, or disadvantaged areas may lack fully functioning systems or any at all. Low income communities may also be less likely to afford adding A/C units. During heat waves, too many people simultaneously running their systems can cause outages and leave many without any way to cool down quickly. The increased use of A/C can also be associated with its own environmental problems. According to Southern California's Association of Government's (SCAG) Extreme Heat and Public Health Report, running A/C constantly can create a positive feedback loop by contributing to the UHI and sending more heat back into the atmosphere. (Nurazzaman 2015). Adding more A/C to individual homes may not be a reasonable solution, but our findings also show that parks themselves are not used as a means to safety from extreme heat either. In a similar study analyzing smartphone data and the use of cooling centers by last year's practicum group, they found an increase in the duration of cooling center use especially near public transit stops (Derakhshan et al 2022). Providing cooling spaces within parks can be a solution to increase park attendance while also keeping visitors cool.

Demographic analysis coupled with the temporal and park amenity patterns can help show the full picture explaining how parks are used during extreme heat. Since we observed a greater number of park visitors who had scores reflecting lower vulnerability, we have to examine park equity and accessibility. Figure 12 shows that people from SoVI score 1 used parks more than the other 2 categories, while people with a SoVI score of 3 used parks the least. Furthermore, people tend to visit parks that share their same SoVI score, likely due to proximity. Because a park's SoVI score was assigned by joining nearby tracts rather than given an official score, this indicates people prefer parks that are located in close proximity to them. Given that our amenity analyses found little difference in park usage between extreme heat and control days, we can infer accessibility is a bigger influencing factor in determining which parks users choose to go to compared to park amenities. In low income areas, residents may lack the resources to travel towards nicer parks or even access public transit stops to take them there. This can lead to more time spent outside in the sun while walking to and from public transportation. This does not allow for easy access to parks and cooling centers on extreme heat days.

Bias/Error

Anonymized location data from personal devices can serve as a powerful metric for spatial and temporal analysis. However, there are many considerations to be made about the biases and assumptions it imposes. An individual's behavior is unpredictable and difficult to quantify solely based on their device's GPS location. The conclusions made in this report are limited to a sample of LA County residents that may not fully represent the county's population. The data sourced from Outlogic was made up of a convenient sample of smartphone data that was collected from users with smartphones who agreed to share their location data through a downloaded application. This basis removes county residents who may not have smartphones due to economic disparities, have location services disabled out of safety concerns, or do not use the specified applications. The use of a device also varies depending on the type of activity, such as exercising, or if the assumption that people visit parks to connect with nature is true, visitors may not use their device at all (Filazzola et. al. 2022). Cellular network coverage could also vary due to geographic barriers and infrequent placement of cell towers in rural green spaces.

The range of horizontal accuracy embedded in the data introduces error to our analysis. Coordinates located at the edges of parks may, in reality, not be in the park at all. Vice versa, there may be points that were recorded to be outside a park while the phone itself was inside. The same concerns apply to our demographic data. Pings that were recorded within one census tract may have actually been in another nearby tract. It was also assumed that the user would be at home during the nighttime hours of 12:30 am to 5:30 am, but this may not always be the case. Potential nighttime trips could have placed points in a different census tract, resulting in assigning the wrong SoVI score to an individual. The errors introduced by short trips were corrected by assigning the individual the SoVI score of the census tract that they were found in the most. Because they would be home most of the time, they were likely recorded in the correct census tract more than any other location. Additionally, having a large number of data points minimized the effect of these errors. By having thousands of points to map out park visitation trends, small variations and errors would become negligible. The same concept was used for speed. Filtering for pings that were recorded at speeds of less than 5 m/s during the day was meant to remove people driving near or within parks. However, even people within cars could be moving at low speeds and still be accounted for in our analysis. At night, filtering for pings at speeds of less than 1 m/s ensured that most of the pings were stationary and not traveling, but this does not guarantee their nighttime location reflected their true residential area.

Additionally, some manual errors may have accounted for extra location points that should have otherwise been excluded. When creating the parks shapefile, equestrian parks were one of the special use parks that were to be filtered out, but a few managed to bypass the filtering and appear as significant factors in our GLM analysis.

Another factor that heavily influenced our results is the chosen days of the week we decided to examine. By choosing 14 days out of the entire summer following our specifications, we could have overgeneralized trends that neglected special events or circumstances explaining location patterns. LA has many events that take place during the week and weekend, which can cause large fluctuations in population movement. We hoped to overcome this assumption by using large data but there is still a possibility that some events were too significant causing over assumptions in people's behavior during extreme heat or control days.

Conclusion

Based on our comprehensive analysis, it becomes evident that the use of parks during extreme heat days is influenced by various social factors that extend beyond the mere presence of extreme heat. Therefore, we propose specific recommendations for optimizing park usage during extreme heat events. During weekdays, when local parks observe higher usage, it is advisable to focus efforts on promoting these smaller parks as refuges from extreme heat. This can be achieved by extending their opening hours into the evening, allowing individuals to seek respite from the heat after work. On weekends, the emphasis should be on facilitating transportation options to larger regional parks and beaches, making them easily accessible to a wider population. Furthermore, identifying and removing any existing barriers to coastal and regional park access will be instrumental in ensuring equitable use during extreme heat events.

To further enhance our understanding of the factors influencing park usage during extreme heat days, we recommend incorporating qualitative research methods in future studies. Conducting interviews or focus groups with community members and park visitors would enable us to delve deeper into their motivations, perceptions, and barriers when deciding whether to visit parks on such days. By gaining insights from these perspectives, we can refine our strategies, tailor interventions, and ensure that planning for extreme heat waves aligns with the needs and preferences of the community.

In conclusion, our research provides valuable insights into park use patterns during extreme heat events and highlights the significance of social factors beyond extreme heat alone. By implementing our recommendations, including promoting local parks during weekdays, facilitating transportation to regional parks on weekends, and prioritizing park access for vulnerable communities, we can enhance the utilization of parks as effective measures to cope with extreme heat. Furthermore, integrating qualitative research methods into future studies will contribute to a more comprehensive understanding of the complexities surrounding park usage, ultimately aiding the county in planning for extreme heat waves and raising awareness about park access—all in hopes of creating equity in park access and use.

References

American Lung Association. (2022). *California: Los Angeles*. American Lung Association | State of the Air. https://www.lung.org/research/sota/city-rankings/states/california/los-angeles

Aram, F., Solgi, E., Higueras García, E., Mosavi, A., & R. Várkonyi-Kóczy, A. (2019). The cooling effect of large-scale urban parks on surrounding area thermal comfort. *Energies*, 12(20), 3904.

Bekkar B, Pacheco S, Basu R, DeNicola N. (2020). Association of Air Pollution and Heat Exposure With Preterm Birth, Low Birth Weight, and Stillbirth in the US: A Systematic Review. *JAMA Network Open*. 3(6):e208243. doi:10.1001/jamanetworkopen.2020.8243

Benz, S.A. and Burney, J.A. (2021). Widespread Race and Class Disparities in Surface Urban Heat Extremes Across the United States. *Earth's Future,* 9(7). https://doi.org/10.1029/2021EF002016

Cao, X., Onishi, A., Chen, J., & Imura, H. (2010). Quantifying the cool island intensity of urban parks using ASTER and IKONOS data. *Landscape and Urban Planning*, 96(4), 224–231.

Centers for Disease Control and Prevention. (2022, August 25). Protecting vulnerable groups from extreme heat. Centers for Disease Control and Prevention. https://www.cdc.gov/disasters/extremeheat/specificgroups.html

Centers for Disease Control and Prevention. (2016, October). Extreme heat events. https://www.cdc.gov/climateandhealth/pubs/ClimateChangeandExtremeHeatEvents.pdf

Cheng, X., Wei, B., Chen, G., Li, J., & Song, C. (2015). Influence of park size and its surrounding urban landscape patterns on the park cooling effect. *Journal of Urban Planning and Development*, 141(3), A4014002.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, 84(2), 242–261.

Derakhshan, S., Bautista, T. N., Bouwman, M., Huang, L., Lee, L., Tarczynski, J., Wahagheghe, I., Zeng, X., & Longcore, T. (2023). Smartphone locations reveal patterns of cooling center use as a heat mitigation strategy. *Applied Geography*, 150, 102821.

Ebi, K. L., Capon, A., Berry, P., Broderick, C., de Dear, R., Havenith, G., Honda, Y., Kovats, R. S., Ma, W., Malik, A., Morris, N. B., Nybo, L., Seneviratne, S. I., Vanos, J. and Jay, O. (2021). Hot weather and heat extremes: health risks. *Lancet,* 398(10301), 698–708. https://doi.org/10.1016/S0140-6736(21)01208-3

Environmental Protection Agency. (2022). *Climate Change Indicators: Heat Waves*. EPA: United States Environmental Protection Agency. https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves

Filazzola A, Xie G, Barrett K, Dunn A, Johnson MTJ, et al. (2022) Using smartphone-GPS data to quantify human activity in green spaces. *PLOS Computational Biology* 18(12): e1010725. https://doi.org/10.1371/journal.pcbi.1010725

Gunawardena, K. R., Wells, M. J., & Kershaw, T. (2017). Utilising green and bluespace to mitigate urban heat island intensity. *Science of the Total Environment*, *584*, 1040–1055.

Jenerette, G. D., Harlan, S. L., Buyantuev, A., Stefanov, W. L., Declet-Barreto, J., Ruddell, B. L., Myint, S. W., Kaplan, S., & Li, X. (2015, October 19). Micro-scale urban surface temperatures are related to land-cover features and residential heat related health impacts in Phoenix, AZ USA. *Landscape Ecology*, *31,* 745-760.

Jesdale, B. M., Morello-Frosch, R., & Cushing, L. (2013). The racial/ethnic distribution of heat risk-related land cover in relation to residential segregation. *Environmental Health Perspectives*, *121*(7), 811–817. https://doi.org/10.1289/ehp.1205919

Khatana, S. A., Werner, R. M. and Groeneveld, P. W. (2022). Association of extreme heat and cardiovascular mortality in the United States: A county-level longitudinal analysis from 2008 to 2017. *Circulation, 146*(3), 249–261. https://doi.org/10.1161/circulationaha.122.060746

Kuras, E. R., Calkins , M. M., & Richardson, M. B. (2017, August 1). Opportunities and challenges for personal heat exposure research. National Institute of Environmental Health Sciences. https://ehp.niehs.nih.gov/doi/full/10.1289/EHP556

LaDochy, Steve. (2021). Los Angeles' Urban Heat Island Continues to Grow: Urbanization, Land Use Change Influences. *Journal of Urban and Environmental ENgineering, 152*(2), 103-116. https://doi.org/10.4090/juee.2021.v15n2.103116

Liu, L., & Zhang, Y. (2011). Urban heat island analysis using the Landsat TM data and Aster Data: A case study in Hong Kong. *Remote Sensing*, *3*(7), 1535–1552.

Los Angeles County Climate Vulnerability Assessment. (2021, October). https://ceo.lacounty.gov/wp-content/uploads/2021/10/LA-County-Climate-Vulnerability-Assessment-1.pdf

Los Angeles County Department of Parks and Recreation. 2022. “EXECUTIVE SUMMARY.” Parks Needs Assessment. https://lacountyparkneeds.org/wp-content/uploads/2023/03/PNA-Plus-ExecSum-ENG_Dec2022.pdf.

Los Angeles County Department of Public Health. (2010). *Protect Your Heart*. Los Angeles County Department of Public Health. http://publichealth.lacounty.gov/docs/heartdisease.pdf

Los Angeles County Department of Public Health. (2017). *Extreme Heat and Climate Change*. Los Angeles County Department of Public Health - Environmental Health. http://publichealth.lacounty.gov/eh/climatechange/ExtremeHeatNClimateChange.htm

Los Angeles County Parks & Recreation. (2021). “RPOSD Unveils $33 Million in Innovative Park Funding Opportunities and $1 Million for Technical Assistance Program – Parks & Recreation.” LA County Parks. https://parks.lacounty.gov/news-rposd-021621/.

Los Angeles Homeless Services Authority (LAHSA). (2022, September 8). *LAHSA releases 2022 Greater Los Angeles Homeless Count Results.* Los Angeles Homeless Services Authority (LAHSA).

Los Angeles Times. (2021). *Heat waves are far deadlier than we think. How California neglects this climate threat*. Los Angeles Times. https://www.latimes.com/projects/california-extreme-heat-deaths-show-climate-change-risks/#nt=0000016d-d0cb-d12e-a7fd-d5dfb2650002-liH0promoSmall-7030col2

Mukri, J.K. (2004). "The State of City Swimming Pools in Los Angeles." LA County Department of Parks and Recreation. https://www.laparks.org/sites/default/files/aquatic/pdf/poolSummary.pdf

Mohajerani, A., Bakaric, J., Jeffrey-Bailey, T., (2017). The urban heat island effect, its causes, and mitigation, with reference to the thermal properties of asphalt concrete, *Journal of Environmental Management*, *197,* 522–538. https://doi.org/10.1016/j.jenvman.2017.03.095.

National Weather Service. n.d. “Climate.” Climate. Accessed June 12, 2023. https://www.weather.gov/wrh/climate?wfo=lox.

Nesbitt, L., Meitner, M. J., Girling, C., Sheppard, S. R., & Lu, Y. (2019). Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 US cities. *Landscape and Urban Planning*, *181*, 51–79.

Phillips, A. M., Barboza, T., Vives, R., & Greene, S. (2021, October 7). Heat waves are far deadlier than we think. How California neglects this climate threat. Los Angeles Times. https://www.latimes.com/projects/california-extreme-heat-deaths-show-climate-change-risks/

Rahman, M. M., McConnell, R., Schlaerth, H., Ko, J., Silva, S., Lurmann, F. W., Palinkas, L., Johnston, J., Hurlburt, M., Yin, H., Ban-Weiss, G. and Garcia, E. (2022). The effects of coexposure to extremes of heat and particulate air pollution on mortality in California: Implications for climate change. *American Journal of Respiratory and Critical Care Medicine, 206*(9), 1117–1127. https://doi.org/10.1164/rccm.202204-0657oc

Riley, K., Wilhalme, H., Delp, L., & Eisenman, D. (2018). Mortality and Morbidity during Extreme Heat Events and Prevalence of Outdoor Work: An Analysis of Community-Level Data from Los Angeles County, California. *International Journal of Environmental Research and Public Health*, *15*(4), 580. http://doi.org/10.3390/ijerph15040580

Sarofim, M.C., Saha, S., Hawkins, M.D., Mills, D.M., Hess, J., Horton, R., Kinney, P., Schwartz, J. and Juliana, A. (2016). Temperature-Related Death and Illness. In *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment* (pp. 43-68). U.S. Global Change Research Program.

Shanahan, D.F., Lin, B.B., Gaston, K.J. *et al.* (2015). What is the role of trees and remnant vegetation in attracting people to urban parks?. *Landscape Ecology 30,* 153–165. https://doi.org/10.1007/s10980-014-0113-0

Southern California Association of Governments. 2020. “Extreme Heat & Public Health Report.” Southern California Association of Governments. https://scag.ca.gov/sites/main/files/file-attachments/extremeheatpublichealthreportfinal_09302020.pdf?1634674354.

State of California Department of Industrial Relations. n.d. “Heat Illness Prevention | High Heat Procedures.” California Department of Industrial Relations. https://www.dir.ca.gov/dosh/etools/08-006/EWP_highHeat.htm.

State of California Division of Occupational Safety and Health (n.d.). High heat procedures elements of your written program and Effective Work Practices. Heat Illness Prevention | High Heat Procedures. https://www.dir.ca.gov/dosh/etools/08-006/EWP_highHeat.htm

Sun, F., Hall, A., Schwartz, M., Walton, D. B., & Berg, N. (2015). Twenty-First-Century Snowfall and Snowpack Changes over the Southern California Mountains. *Journal of Climate*, *29*(1), 91–110. https://doi.org/10.1175/jcli-d-15-0199.1

Sun, F., Walton, D. B., & Hall, A. (2015). A Hybrid Dynamical–Statistical Downscaling Technique. Part II: End-of-Century Warming Projections Predict a New Climate State in the Los Angeles Region. *Journal of Climate*, *28*(12), 4618–4636. https://doi.org/10.1175/jcli-d-14-00197.1

Tamrazian, A., LaDochy, S., Willis, J. and Patzert, W.C. (2008). Heat Waves in Southern California: Are They Becoming More Frequent and Longer Lasting?. *Association of Pacific Coast Geographers, 70,* 59–69. https://doi.org/10.1353/pcg.0.0001

Völker, S. & Kistemann, T. (2015). Developing the urban blue: Comparative health responses to blue and green urban open spaces in Germany, *Health & Place*, *35*, 196–205, https://doi.org/10.1016/j.healthplace.2014.10.015.

Wheeler, B. W., *et al.* (2012). Does living by the coast improve health and wellbeing?. *Health & Place, 18*(5), 1198–1201.

White, M. P., *et al.* (2013). Coastal proximity and health: A fixed effects analysis of longitudinal panel data. *Health & Place, 23*, 97–103.

Wolch, J., Wilson, J., & Fehrenbach, J. (2013). Parks and Park Funding in Los Angeles: An Equity-Mapping Analysis. *Urban Geography*, *26*, 4–35. 10.2747/0272-3638.26.1.

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning*, *125,* 234–244.

Vose, R.S., Easterling, D.R., Kunkel, K.E., LeGrande, A.N. and Wehner, M.F. (2017). Temperature changes in the United States. In D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (Eds.), *Climate Science Special Report: Fourth National Climate Assessment*, *1*, 185–206. U.S. Global Change Research Program.

Xu, Y., Shaw, S. L., Zhao, Z., Yin, L., Fang, Z., & Li, Q. (2015). Understanding aggregate human mobility patterns using passive mobile phone location data: A home-based approach. *Transportation*, *42*, 625–646.

Yin, Y., Grundstein, A., & Mishra , D. R. (2021). DTEX: A dynamic urban thermal exposure index based on human mobility patterns. *Environment International* 155, 106573.

Yuan, F., & Bauer, M. E. (2006). Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in landsat imagery. *Remote Sensing of Environment*, *106*(3), 375–386.

Appendices

Appendix A: Python and R Code

A1: Python Code

Practicum Code

IMPORT PACKAGES

In [ ]:
```
import pandas as pd
from datetime import datetime, date, time
import geopandas as gpd
```

READ CSV

In [ ]:
```
#
# CHANGE FOR EACH DAY
#

day = pd.read_csv('FILE_NAME.csv')
day['LocalTime'] = pd.to_datetime(day['LocalTime'])

# Create separate Date and Time columns
# Didn't end up using these for filtering like I thought, but useful on Excel
day['Date'] = day['LocalTime'].dt.date
day['Time'] = day['LocalTime'].dt.time

# Shows number of rows in the dataframe
# Just for me to keep track of how much data is being lost at each step
day.shape[0]
```

In [ ]:
```
#
# CHANGE FOR EACH DAY
#

day_add = pd.read_csv('FILE_NAME.csv')
day_add['LocalTime'] = pd.to_datetime(day_add['LocalTime'])
day_add['Date'] = day_add['LocalTime'].dt.date
day_add['Time'] = day_add['LocalTime'].dt.time
day_add.shape[0]
```

FILTER

We filtered by horizontal accuracy first because we wanted every single point to be within a certain level of accuracy, whether it's night or day. Speed was last because we wanted to filter day and night by different speeds.

HORIZONTAL ACCURACY

```
In [ ]: day = day[(day['horizontal_accuracy'] >= 0) & (day['horizontal_accuracy'] <= 2
        5)]
        day.shape[0]
```

```
In [ ]: day_add = day_add[(day_add['horizontal_accuracy'] >= 0) & (day_add['horizontal
        _accuracy'] <= 25)]
        day_add.shape[0]
```

DATE & TIME

Date

```
In [ ]: #
        # CHANGE FOR EACH DAY
        #

        day = day[(day['LocalTime'].dt.strftime('%Y-%m-%d') == 'yyyy-mm-dd')]
        day.shape[0]
```

```
In [ ]: #
        # CHANGE FOR EACH DAY
        #

        day_add = day_add[(day_add['LocalTime'].dt.strftime('%Y-%m-%d') == 'yyyy-mm-d
        d')]
        day_add.shape[0]
```

```
In [ ]: # Merged the separate day files here. Files were too big before, makes filteri
        ng after easier
        day = pd.concat([day,day_add])
        day.shape[0]
```

12-8 PM

```
In [ ]: daytime = day.loc[(day['LocalTime'].dt.time >= time(12)) & (day['LocalTime'].d
        t.time <= time(20))]
        daytime.shape[0]
```

SPEED

In [ ]:
```
daytime = daytime[(daytime['speed'] >= 0) & (daytime['speed'] <= 5)]
daytime.shape[0]
```

In [ ]:
```
#
# CHANGE FOR EACH DAY
#

# Create CSV file
daytime.to_csv('FILE_NAME.csv', index = False)
```

PARKS

In [ ]:
```
# Read the parks shapefile and change the CRS
parks = gpd.read_file('PARK_SHAPEFILE_NAME.shp')
parks = parks.to_crs(epsg = 4326)
```

In [ ]:
```
#
# CHANGE FOR EACH DAY
#

# Read the file with people
daytime = pd.read_csv('FILE_NAME.csv')

# Create a geodataframe out of it so that we can perform geopandas functions
geoday = gpd.GeoDataFrame(daytime, geometry = gpd.points_from_xy(daytime.longi
tude, daytime.latitude))

# Make sure the CRS is the same as the parks
geoday.crs = 'epsg:4326'

# Spatial join: only returns the points that were found in the polygons with t
he attributes of the polygons
parkpeople_spatialjoin = geoday.sjoin(parks)
parkpeople_spatialjoin.shape[0]
```

In [ ]:
```
#
# CHANGE FOR EACH DAY
#

# Create CSV file
parkpeople_spatialjoin.to_csv('FILE_NAME.csv', index = False)
```

DEMOGRAPHICS

Refiltering and Creating Master Night File

This is only for the days I was in charge of (Aug. 21-30). The full master file was created in R.

In [ ]:
```
# Create empty dataframe to concatenate everything to
master = pd.DataFrame()

# Set up file name for code to read at each loop
file = 'DailyData/HztalAcc_08{:02d}.csv'

# Set up dates
dates = [21, 23, 28, 29, 30]

for d in dates:
    # To keep track of file names
    print(file.format(d))

    # Read CSV of the day
    day = pd.read_csv(file.format(d))

    # To keep track of how many rows there originally were
    print(day.shape[0])

    # Same as when CSVs were read in the beginning
    day['LocalTime'] = pd.to_datetime(day['LocalTime'])
    day['Date'] = day['LocalTime'].dt.date
    day['TimeStamp'] = day['LocalTime'].dt.time

    # Drop unnecessary columns
    day = day.drop(['...1', 'X'], axis = 1)

    # Filter for times 12:30am - 5:30am
    night = day.loc[(day['LocalTime'].dt.time >= time(0,30,0)) & (day['LocalTi
me'].dt.time <= time(5,30,0))]

    # Filter for speeds 0-1 m/s (excluded 1)
    night = night[(night['speed'] >= 0) & (night['speed'] < 1)]

    # Add filtered day to master dataframe
    master = pd.concat([master, night], copy = False)

    # To keep track of how many rows were lost
    print(night.shape[0])

# To make sure everything was added properly
print(master.shape[0])
```

In [ ]:
```
master.to_csv('JasminesNightFiles.csv', index = False)
```

Getting Demographics

In [ ]:
```
# Read master night file
night = pd.read_csv('allnighttimes.csv')

# Read tract shapefile
tracts = gpd.read_file('Social Vulnerability Index File/Los_Angeles_County_CVA
_Social_Vulnerability_Index.shp')
tracts = tracts.to_crs(epsg = 4326)

# Set up for the for loop
file = 'PeopleinParks/{}{:02d}_parkpeople.csv'
month = [7,8]

for m in month:                     # Loops through months
    if m == 7:                      # Start with July
        day = [1,2,6,7,8,9,13,14] # The days we chose for July
        for d in day:               # Loops through these days

            # Make sure it's reading the right file
            print(file.format('july',d) + ':')

            # Read day file
            parkpeople = pd.read_csv(file.format('july',d))

            # Drop duplicates in parks since we don't need them
            parkpeople = parkpeople.drop_duplicates(subset = ['advertiser_i
d'])

            # Keep only the nighttime individuals that were in parks during th
e day
            night_parkpeople = night.loc[night['advertiser_id'].isin(parkpeopl
e['advertiser_id'])]

            # Only keep the first 3 columns of the night file (advertiser_id,
lat, long)
            night_parkpeople = night_parkpeople.iloc[:,[0,1,2]]

            # Makes a geodataframe and sets the CRS so that we can perform the
proper function
            geonight = gpd.GeoDataFrame(night_parkpeople, geometry = gpd.point
s_from_xy(night_parkpeople.longitude, night_parkpeople.latitude))
            geonight.crs = 'epsg:4326'

            # Spatial join
            sjoined = geonight.sjoin(tracts)

            # Get counts of how many times an individual appears in a specific
census tract
            sjoined['Count'] = sjoined.groupby(['advertiser_id','Census_Tra'])
['Census_Tra'].transform('count')

            # Sort so that highest counts come first
            sjoined = sjoined.sort_values(['advertiser_id', 'Count'], ascendin
g = [True, False])

            # Drop duplicates, only keeping the first appearance of an ID, whi
```

```
ch is the highest count
            sjoined = sjoined.drop_duplicates(subset = ['advertiser_id'], keep
= 'first')

            # Drop unnecessary columns
            sjoined = sjoined.drop(columns = ['latitude','longitude','geometr
y','index_right'])

            # Merge the files with people and the parks they visited with thei
r tract demographics
            people_park_demographics = parkpeople.merge(sjoined, how = 'left',
on = ['advertiser_id'], suffixes = ('', '_SoVI'))

            # The rest of these print() lines are just to see the percentage o
f people we were able to get demographics for
            print(sjoined.shape[0])
            print(parkpeople.shape[0])
            print(sjoined.shape[0]/parkpeople.shape[0]*100)

            # Make CSV
            people_park_demographics.to_csv('ParkDemographics/{:02d}{:02d}.cs
v'.format(m,d), index = False)

            # Double check that nobody was lost in the original people and par
ks file
            print(people_park_demographics.shape[0])
            print()

    # Same as above, but for August
    if m == 8:
        day = [15, 21, 23, 28, 29, 30]
        for d in day:
            print(file.format('aug',d) + ':')
            parkpeople = pd.read_csv(file.format('aug',d))
            parkpeople = parkpeople.drop_duplicates(subset = ['advertiser_i
d'])
            night_parkpeople = night.loc[night['advertiser_id'].isin(parkpeopl
e['advertiser_id'])]
            night_parkpeople = night_parkpeople.iloc[:,[0,1,2]]
            geonight = gpd.GeoDataFrame(night_parkpeople, geometry = gpd.point
s_from_xy(night_parkpeople.longitude, night_parkpeople.latitude))
            geonight.crs = 'epsg:4326'
            sjoined = geonight.sjoin(tracts)
            sjoined['Count'] = sjoined.groupby(['advertiser_id','Census_Tra'])
['Census_Tra'].transform('count')
            sjoined = sjoined.sort_values(['advertiser_id', 'Count'], ascendin
g = [True, False])
            sjoined = sjoined.drop_duplicates(subset = ['advertiser_id'], keep
= 'first')
            sjoined = sjoined.drop(columns = ['latitude','longitude','geometr
y','index_right'])
            people_park_demographics = parkpeople.merge(sjoined, how = 'left',
on = ['advertiser_id'], suffixes = ('', '_SoVI'))
            print(sjoined.shape[0])
            print(parkpeople.shape[0])
            print(sjoined.shape[0]/parkpeople.shape[0]*100)
```

```
            people_park_demographics.to_csv('ParkDemographics/{:02d}{:02d}.cs
v'.format(m,d), index = False)
            print(people_park_demographics.shape[0])
            print()
```

A2: R Code

ENV180_CompiledRCode_ParksHea t

Bethany Woo

5/3/2023

Compiled Code for ENV180 Practicum Project: LA County Parks & Extreme Heat

Team Members: Alondra Gallegos, Bethany Woo, Danielle Sonobe, Jana Salomon, Jasmine Kim, Jeffrey Van, Renato Escobar, Samara Fruman

Advisors: Dr. Travis Longcore and Dr. Sahar Derakhshan

Clients: LA County Sustainability Office, LA County Dept. of Public Health, and LA County Dept. of Parks & Recreation

Processing Steps: 1) Rearranging mobile points by date, 2) Filtering by horizontal accuracy, 3) Subsetting into Day and Night times per day, and filtering subsets by speed, 4) Spatial join between mobile points and park layer **not included in this file**, 5) Appending all Night time points into a Master Night file for demographic data, 6) Spatial join between Night time locations and census tracts **not included in this file**

1) Rearranging mobile points by date

```
library(readr)
```

```
library(tidyverse)
## ── Attaching packages ───────────────────────────────────────
tidyverse 1.3.2 ──
## ✔ ggplot2 3.4.0     ✔ dplyr   1.1.0
## ✔ tibble  3.1.8     ✔ stringr 1.4.0
## ✔ tidyr   1.2.0     ✔ forcats 1.0.0
## ✔ purrr   1.0.1
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
library(dplyr)
#import data (each day's files only ran until 5 pm of that date, so to
find observations in the time frame of 12-8 pm, append 5-8 pm
observations from the following date's file)
JULY_01 <- read_csv("MOBILEDATA/JULY_01.csv",
     col_types = cols(latitude = col_number(),
         longitude = col_number(), altitude = col_number(),
         horizontal_accuracy = col_number(),
         vertical_accuracy = col_number(),
         speed = col_number()))
#split the LocalTime column into two columns: Date and Timestamp, at
the space, adds these as 2 new columns to the dataset
JULY_01[c('Date', 'TimeStamp')]<-str_split_fixed(JULY_01$LocalTime, '
', 2)
#subsets the dataset to keep only rows with in which the Date Column
is 07/02/2017
JULY_01<-subset(JULY_01,Date=="2017-07-01")

#import the next day data to get the mobile points after 5 pm
JULY_02 <- read_csv("MOBILEDATA/JULY_02.csv",
     col_types = cols(latitude = col_number(),
         longitude = col_number(), altitude = col_number(),
         horizontal_accuracy = col_number(),
         vertical_accuracy = col_number(),
         speed = col_number()))
#split the LocalTime column into two columns: Date and Timestamp, at
the space, adds these as 2 new columns to the dataset
JULY_02[c('Date', 'TimeStamp')]<-str_split_fixed(JULY_02$LocalTime, '
', 2)
#subsets the dataset to keep only rows with in which the Date Column
is 07/02/2017
JULY_01_pt2<-subset(JULY_02,Date=="2017-07-01")
#rm(list="JULY_02")

#combine the two datasets together
alltimes_JULY_01<-bind_rows(JULY_01,JULY_01_pt2)
#write.csv(alltimes_DATE, file='~/pathway/alltimes_DATE.csv',
```

```
row.names=FALSE)
#rm(list="JULY_01")
```

2) Filtering by horizontal accuracy

```
#subsets the dataset to keep only rows where horizontal accuracy is
>=0 and <= 25 m
alltimes_JULY_01
<-subset(alltimes_JULY_01,alltimes_JULY_01$horizontal_accuracy>=0 &
alltimes_JULY_01$horizontal_accuracy<=25)
```

3) Subsetting into Day and Night times per day and filtering by speed

```
#subset into day and night times using timestamp column
library(lubridate)
##
## Attaching package: 'lubridate'
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
library(dplyr)
library(tidyverse)

#creates nighttime subset, keeps mobile points collected between
12:30-5:30 am
nighttime_0701<-subset(alltimes_JULY_01, alltimes_JULY_01$TimeStamp
>="00:30:00" & alltimes_JULY_01$TimeStamp <="05:30:00")

#creates daytime subset, keeps mobile points collected between 12-8 pm
daytime_0701<-subset(alltimes_JULY_01, alltimes_JULY_01$TimeStamp
>="12:00:00" & alltimes_JULY_01$TimeStamp<="20:00:00")

#filters by speed, Day = 0 <= speed <= 5 m/s, Night = 0 <= speed < 1
m/s)
nighttime_0701<-subset(nighttime_0701,nighttime_0701$speed>=0 &
nighttime_0701$speed<1)
daytime_0701<-subset(daytime_0701,daytime_0701$speed>=0 &
daytime_0701$speed<=5)
```

4) Spatial join between mobile points and park layer **not included in this file**

5) Appending all Night time points into a Master Night file for demographic data

```
library(readr)
nighttime_0702 <-
read_csv("MOBILEDATA/Step5-NightTimeLocations/nighttime_0702.csv")
## Rows: 887125 Columns: 12
## — Column specification
────────────────────────────────────────────────────────
## Delimiter: ","
## chr  (2): advertiser_id, publisher_id
## dbl  (7): latitude, longitude, altitude, horizontal_accuracy,
vertical_accur...
## dttm (1): LocalTime
## date (1): Date
## time (1): TimeStamp
##
## i Use `spec()` to retrieve the full column specification for this
data.
## i Specify the column types or set `show_col_types = FALSE` to quiet
this message.
nighttime_0706 <-
read_csv("MOBILEDATA/Step5-NightTimeLocations/nighttime_0706.csv")
## Rows: 915227 Columns: 12
## — Column specification
────────────────────────────────────────────────────────
## Delimiter: ","
## chr  (2): advertiser_id, publisher_id
## dbl  (7): latitude, longitude, altitude, horizontal_accuracy,
vertical_accur...
## dttm (1): LocalTime
## date (1): Date
## time (1): TimeStamp
##
## i Use `spec()` to retrieve the full column specification for this
data.
## i Specify the column types or set `show_col_types = FALSE` to quiet
this message.
#and so forth...
#make sure all the columns match in the order and column title before
joining
nighttime_0701<-nighttime_0701[,-1]
allnighttimes<-rbind(nighttime_0701, nighttime_0702, nighttime_0706)
#and so forth...
#write.csv(allnighttimes,file='pathway/allnighttimes.csv',row.names=FA
LSE)
```

6) Spatial join between Night time locations and census tracts **not included in this file**

Appendix B: Methodology Figures

B1: Table of paired extreme heat and control days

Extreme Heat			Control		
Date	**Day**	**Avg High Across Stations (F)**	**Date**	**Day**	**Avg High Across Stations (F)**
7/9/2017	Sunday	100.89	7/2/2017	Sunday	83.2
8/28/2017	Monday	106.14	8/21/2017	Monday	83
8/29/2017	Tuesday	104	8/15/2017	Tuesday	77.8
8/30/2017	Wednesday	103.27	8/23/2017	Wednesday	82.7
7/6/2017	Thursday	102.8	7/13/2017	Thursday	87.1
7/7/2017	Friday	102.6	7/14/2017	Friday	87.5
7/8/2017	Saturday	104.6	7/1/2017	Saturday	81.2

B2: Table of number of smartphone pings unique within parks on extreme heat vs control days

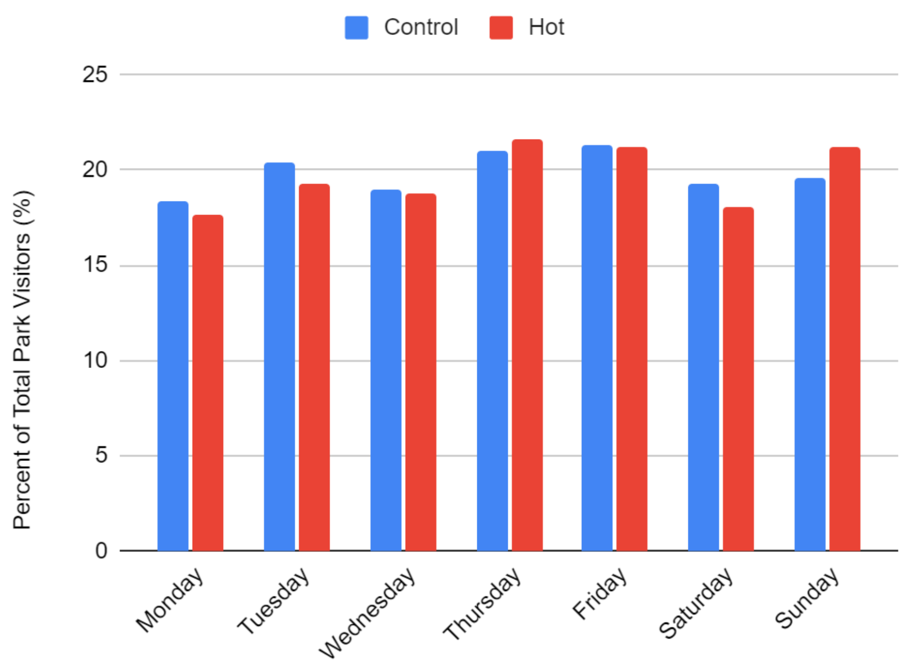
Extreme Heat	Total Pings with Unique Pings in Parks		Control
8/28 Monday	5412	5555	8/21 Monday
8/29 Tuesday	5686	6019	8/15 Tuesday
8/30 Wednesday	5661	6427	8/23 Wednesday
7/6 Thursday	6449	7375	7/13 Thursday
7/7 Friday	6238	6882	7/14 Friday
7/8 Saturday	6972	7450	7/1 Saturday
7/9 Sunday	6659	7115	7/2 Sunday

Appendix C: Temporal Figures

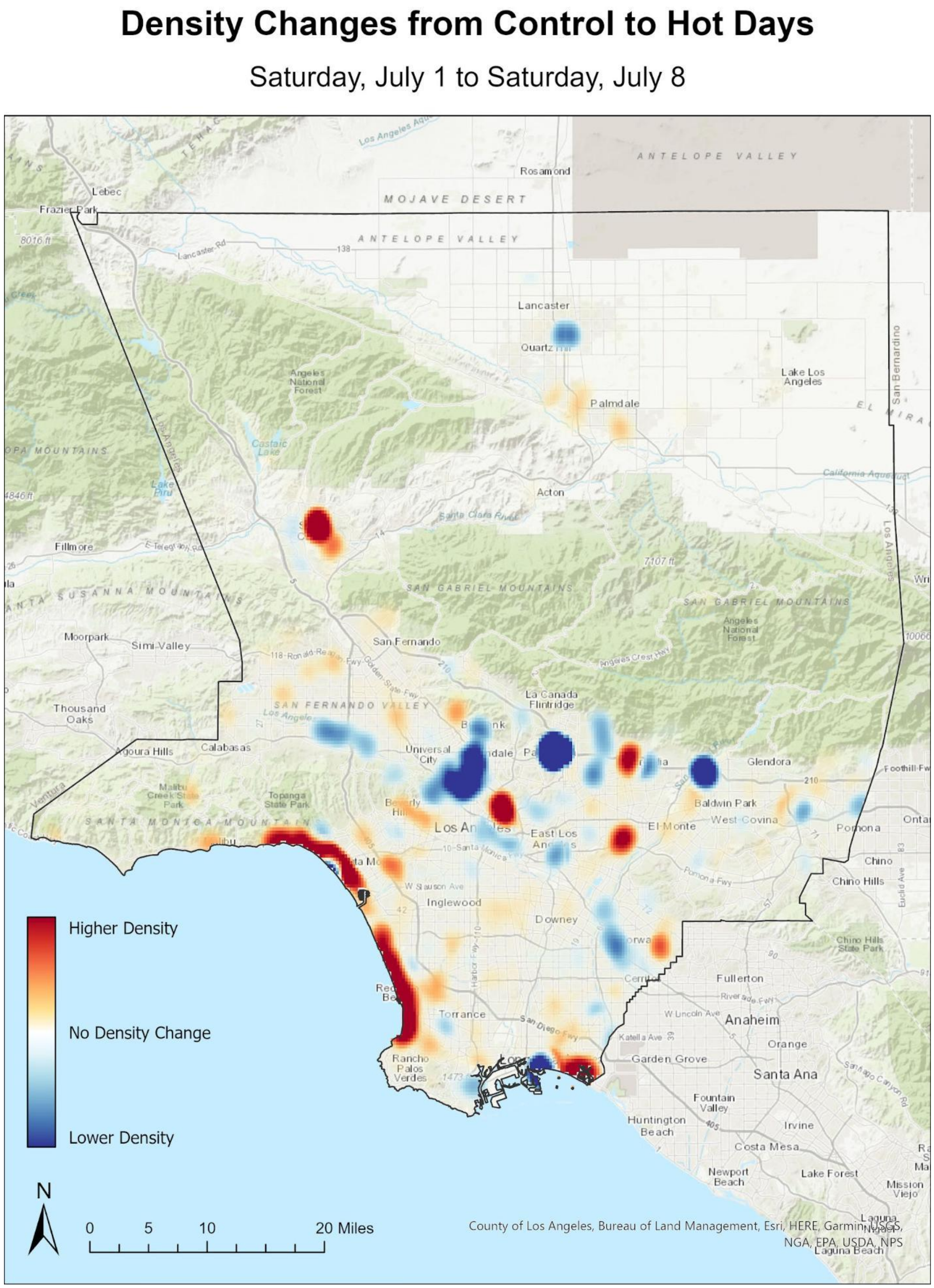
C1: Table of significance testing for temporal visits

Extreme Heat Day	Day of the Week	Control Day	P-value
7/6/2017	Thursday	7/13/2017	0.06603
7/7/2017	Friday	7/14/2017	0.1285
7/8/2017	Saturday	7/1/2017	0.396
7/9/2017	Sunday	7/2/2017	0.06602
8/28/2017	Monday	8/21/2017	0.7468
8/29/2017	Tuesday	8/15/2017	0.8399
8/30/2017	Wednesday	8/23/2017	0.0003588

C2: Figure of total park visitors as a percentage of total LA County citizens recorded per day



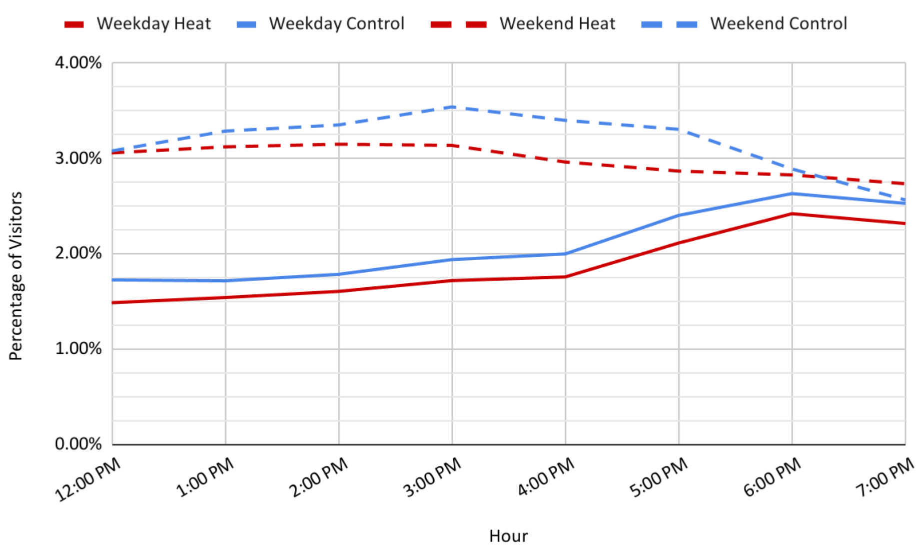
C3: Map of kernel density from control to hot days



C4: Table of significance testing for temporal visits

			Hour							
	Extreme	Control	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM	7:00 PM
Friday	7/7	7/14	0.297	0.293	0.284	0.291	0.278	0.282	0.261	0.277
Saturday	7/8	7/1	0.292	0.290	0.274	0.274	0.269	0.254	0.258	0.244
Sunday	7/9	7/2	0.286	0.287	0.265	0.272	0.254	0.250	0.264	0.229
Monday	8/28	8/21	0.275	0.264	0.227	0.251	0.248	0.219	0.244	0.266
Tuesday	8/29	8/15	0.274	0.208	0.268	0.212	0.247	0.234	0.264	0.260
Wednesday	8/30	8/23	0.228	0.271	0.211	0.247	0.220	0.232	0.183	0.270
Thursday	7/6	7/13	0.246	0.267	0.245	0.239	0.254	0.190	0.269	0.289

C5: Figure of hourly park visits as a percentage of all total park visitors and total individuals in the county



Appendix D: Amenities Figures

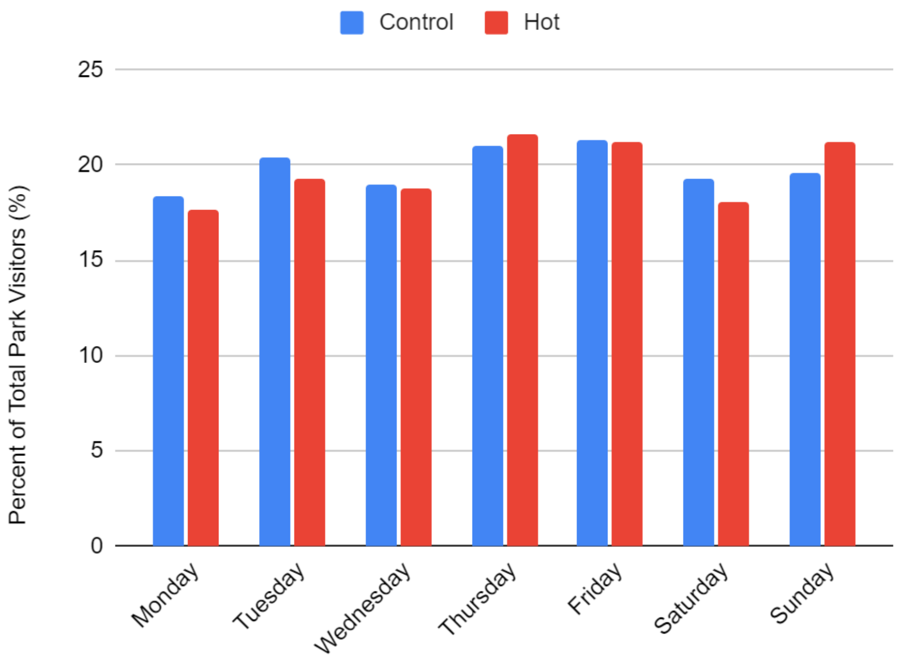
D1: Table of rankings of percentiles for park size and tree coverage percentages

Percentile	Park Size Rank (acres)		Tree Coverage Rank (percent)	
0.25	1.07217	Smallest	19.5736	Very low
0.5	4.41041	Small	32.6137	Low
0.75	12.4546	Medium	46.9874	Medium
1	>12.4546	Largest	>46.9874	High

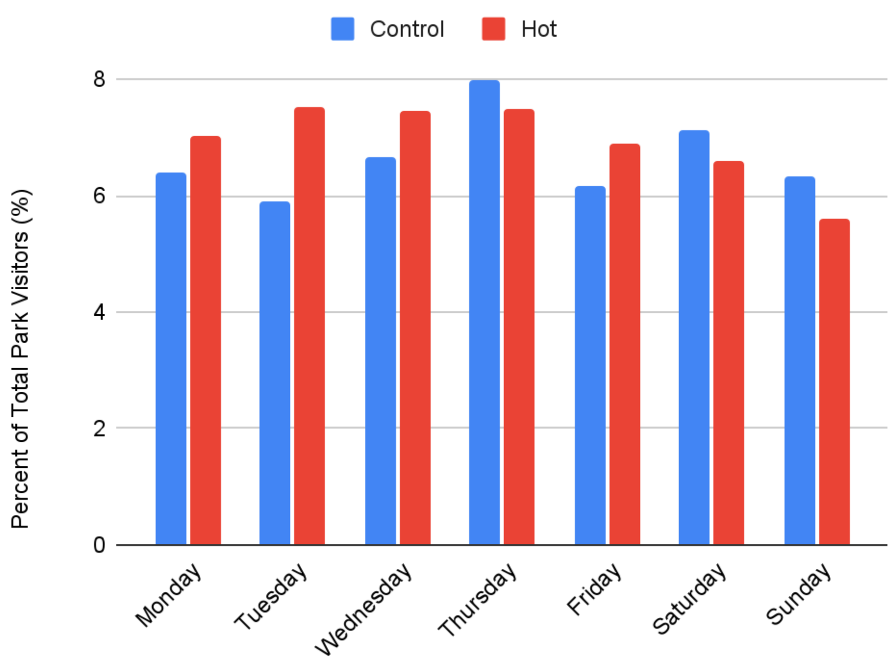
D2: Table of t-test results between parks with and without pools and splash pads

Day of the Week	Extreme Heat Day	Control Day	P-value (POOLS)	P-value (SPPAD)
Thursday	07/06	07/13	0.804	0.4529
Friday	07/07	07/14	0.6919	0.1831
Saturday	07/08	07/01	0.4995	0.4101
Sunday	07/09	07/02	0.1639	0.1816
Monday	08/28	08/21	0.1484	0.4511
Tuesday	08/29	08/15	0.9091	0.4289
Wednesday	08/30	08/23	0.2243	0.03744

D3: Figure of percentage of park visitors that attended parks with pools on extreme heat and control days

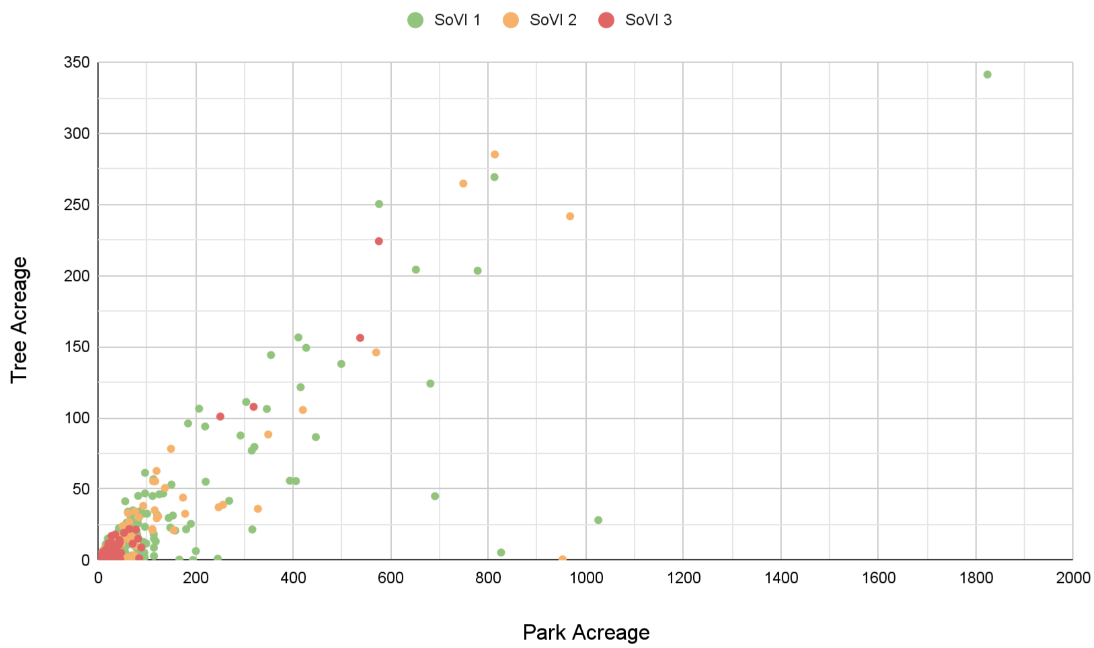


D4: Figure of percentage of park visitors that attended parks with splash pads on extreme heat and control days

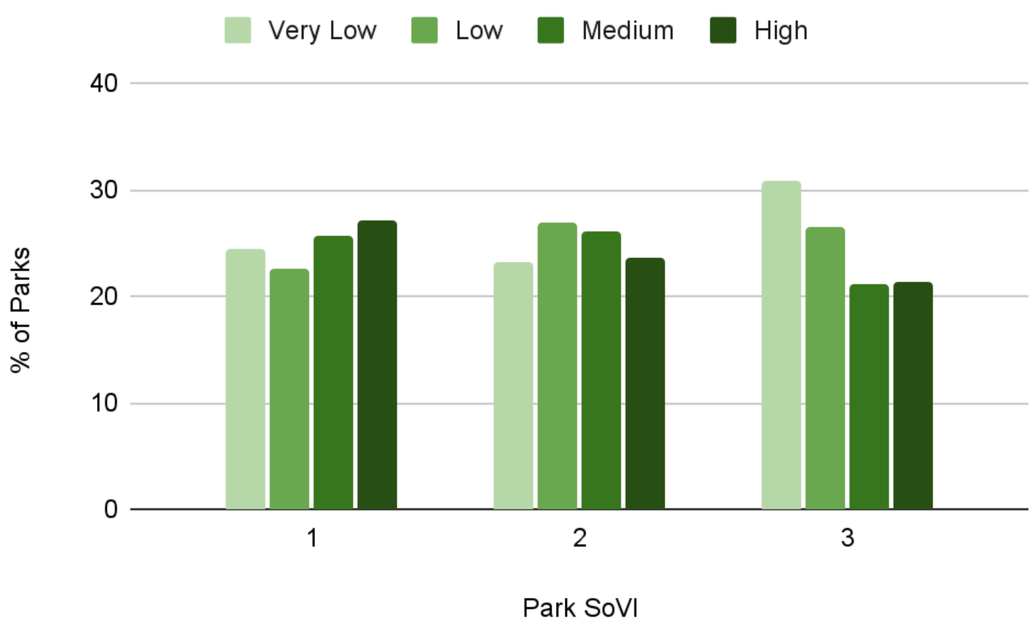


D5: Map of tree canopy coverage throughout LA County

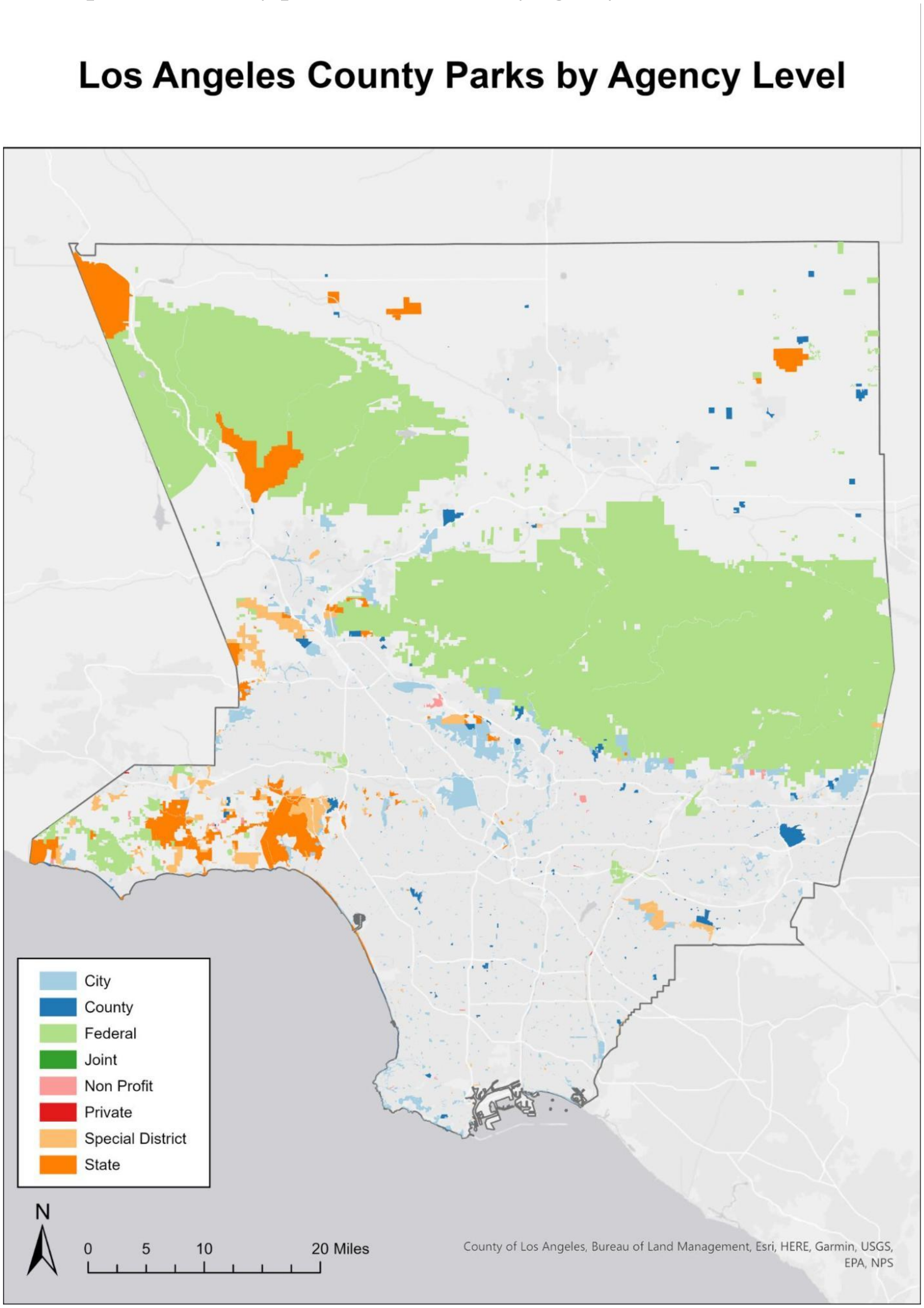
D6: Figure of tree canopy in relation to park size



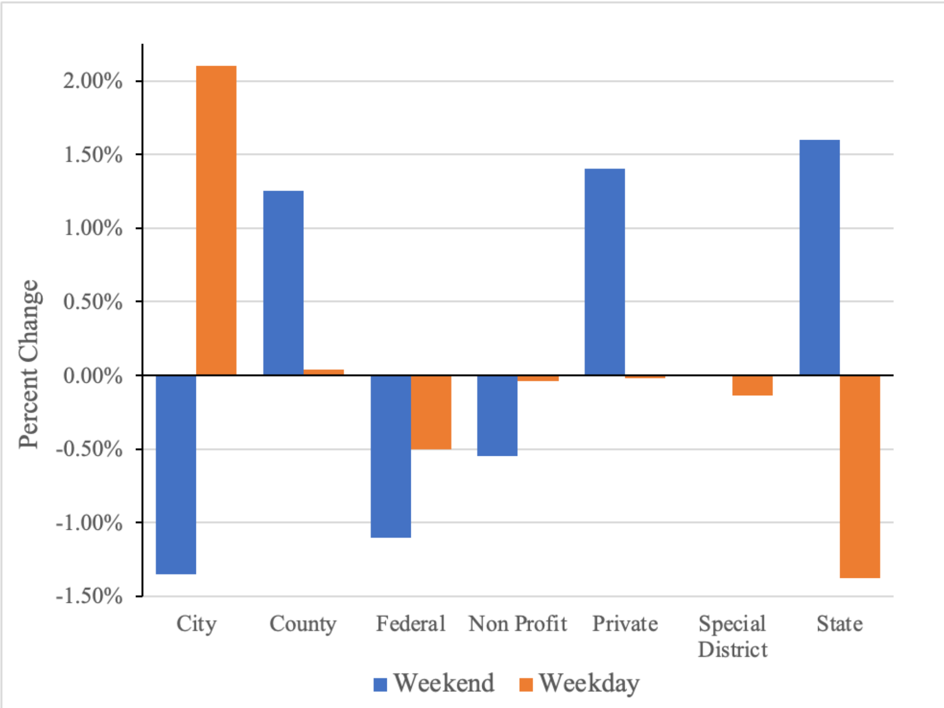
D7: Figure of tree coverage rankings by park SoVI, beaches included



D8: Map of LA County parks color-coded by agency level



D9: Figure of change in average percent of park users serviced between extreme heat and control days by agency level



D10: Figure of changes in average percentage of park users serviced between weekend and weekdays

D11: Figure of Control Day GLM output in RStudio, showing the amenities included as fixed effects and their coefficient and p-value

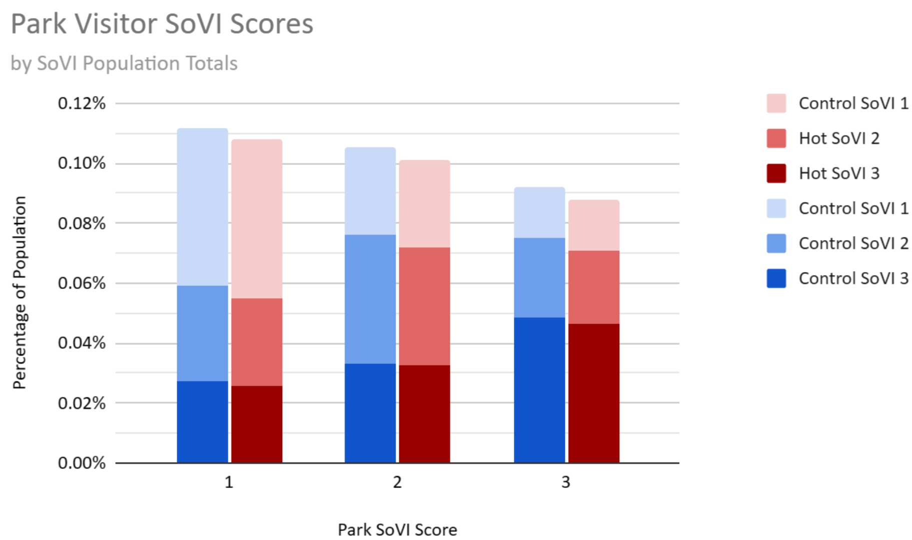
```
Call:
glm(formula = Normalized_Multiplied ~ COGP_TYP + BSKTB + RSTRM +
    tree_acre, family = poisson(link = "log"), data = parkamenities_NEHmodel)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-10.562   -5.364   -2.803    0.818   52.301

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                       3.133495   0.016489 190.041  < 2e-16 ***
COGP_TYPCommunity Regional Park  -0.116467   0.022958  -5.073 3.91e-07 ***
COGP_TYPNeighborhood Park         0.097401   0.017267   5.641 1.69e-08 ***
COGP_TYPNot Analyzed              0.693803   0.019258  36.026  < 2e-16 ***
COGP_TYPPark Node                 1.094649   0.023836  45.923  < 2e-16 ***
COGP_TYPPocket Park               0.359355   0.018136  19.815  < 2e-16 ***
COGP_TYPRegional Park            -1.463012   0.063722 -22.959  < 2e-16 ***
COGP_TYPSpecial Use               0.573667   0.043852  13.082  < 2e-16 ***
COGP_TYPSpecial Use - Botanic    -0.681556   0.175875  -3.875 0.000107 ***
COGP_TYPSpecial Use - EQ Park    -1.917652   0.494954  -3.874 0.000107 ***
COGP_TYPSpecial Use - Natural    -2.121926   0.360183  -5.891 3.83e-09 ***
COGP_TYPSpecial Use - Sanctuary  -4.555836   1.508799  -3.020 0.002532 **
COGP_TYPSpecial Use - Staging Area  0.034178   0.085210   0.401 0.688347
COGP_TYPUndeveloped              -4.570245   2.106436  -2.170 0.030033 *
BSKTB                            -0.186068   0.007357 -25.290  < 2e-16 ***
RSTRM                             0.228860   0.005343  42.833  < 2e-16 ***
tree_acre                        -0.029185   0.001034 -28.221  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

D12: Figure of Extreme Heat Day GLM output in RStudio, showing the amenities included as fixed effects and their coefficient and p-value

```
Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                       2.565596   0.029990  85.548  < 2e-16 ***
COGP_TYPCommunity Regional Park  -0.305512   0.040842  -7.480 7.42e-14 ***
COGP_TYPNeighborhood Park         0.098256   0.028314   3.470  0.00052 ***
COGP_TYPNot Analyzed              1.218730   0.031556  38.622  < 2e-16 ***
COGP_TYPPark Node                 1.892327   0.035141  53.849  < 2e-16 ***
COGP_TYPPocket Park               0.759706   0.030031  25.297  < 2e-16 ***
COGP_TYPRegional Park            -1.066039   0.136376  -7.817 5.41e-15 ***
COGP_TYPSpecial Use               1.294706   0.050063  25.861  < 2e-16 ***
COGP_TYPSpecial Use - Botanic    -0.422400   0.319459  -1.322  0.18609
COGP_TYPSpecial Use - EQ Park    -2.790804   1.251915  -2.229  0.02580 *
COGP_TYPSpecial Use - Natural    -0.436562   0.261728  -1.668  0.09532 .
COGP_TYPSpecial Use - Staging Area  0.772675   0.113571   6.803 1.02e-11 ***
COGP_TYPUndeveloped              -2.337025   1.069094  -2.186  0.02882 *
BSKTB                            -0.174395   0.012816 -13.608  < 2e-16 ***
TOTAL_GOOD                        0.043691   0.003680  11.873  < 2e-16 ***
TOTAL_FAIR                        0.042243   0.004660   9.065  < 2e-16 ***
RSTRM                             0.193346   0.011067  17.471  < 2e-16 ***
BASEB                            -0.144452   0.010868 -13.292  < 2e-16 ***
PLGND                            -0.227349   0.013447 -16.907  < 2e-16 ***
SOCCR                             0.008438   0.015110   0.558  0.57654
TENIS                             0.011454   0.006055   1.892  0.05852 .
COMCT                            -0.043704   0.015167  -2.881  0.00396 **
GYM                              -0.047643   0.028970  -1.645  0.10006
MPFLD                            -0.019936   0.015152  -1.316  0.18826
AGNCY_LEVCounty                  -0.343413   0.026233 -13.091  < 2e-16 ***
AGNCY_LEVFederal                 -1.315149   0.093415 -14.079  < 2e-16 ***
AGNCY_LEVNon Profit               0.011066   0.049940   0.222  0.82464
AGNCY_LEVPrivate                 -0.286356   0.063987  -4.475 7.63e-06 ***
AGNCY_LEVSpecial District        -0.667371   0.035202 -18.958  < 2e-16 ***
AGNCY_LEVState                   -0.666184   0.057916 -11.503  < 2e-16 ***
tree_acre                        -0.057524   0.002440 -23.575  < 2e-16 ***
---
```

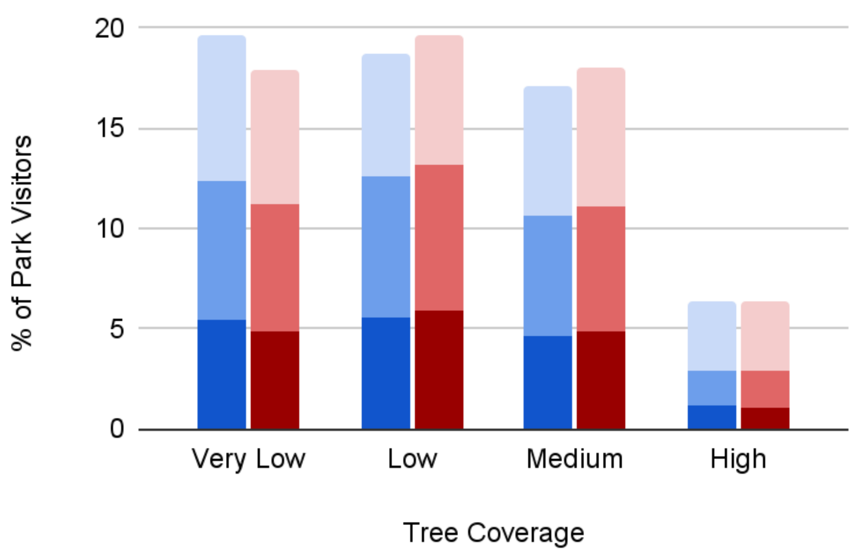
Appendix E: Demographic Figures

E1: Figure of percentage of park visitors by visitor SoVI score at parks of different SoVI scores

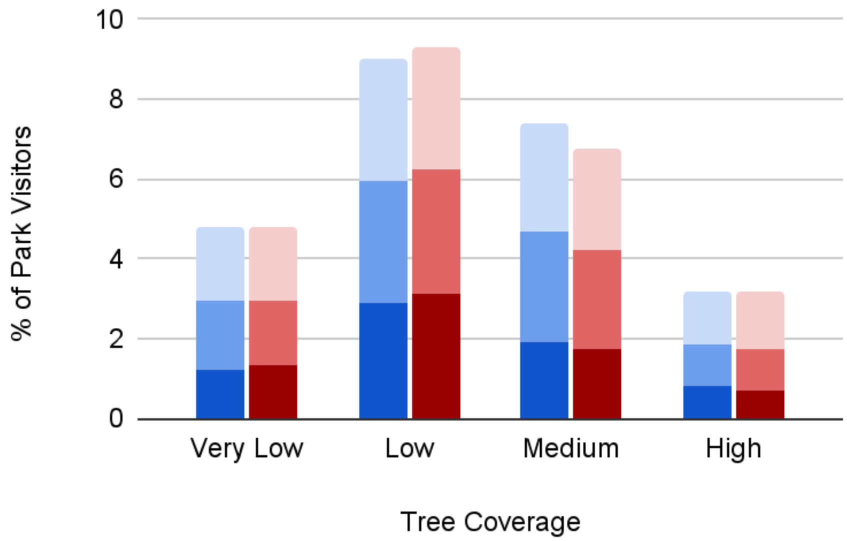


E2: Figures of SoVI percentage of park visitors in different sized parks by tree canopy percentage (beaches not included)

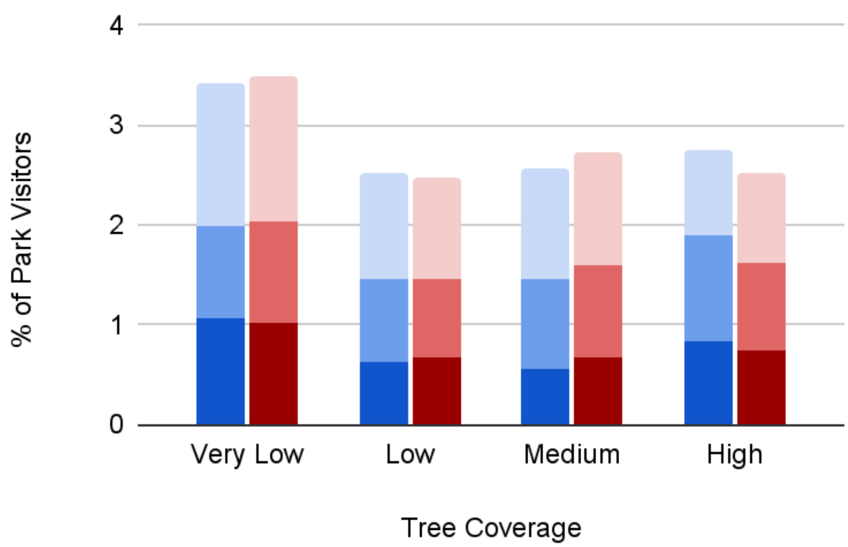
1. Largest parks



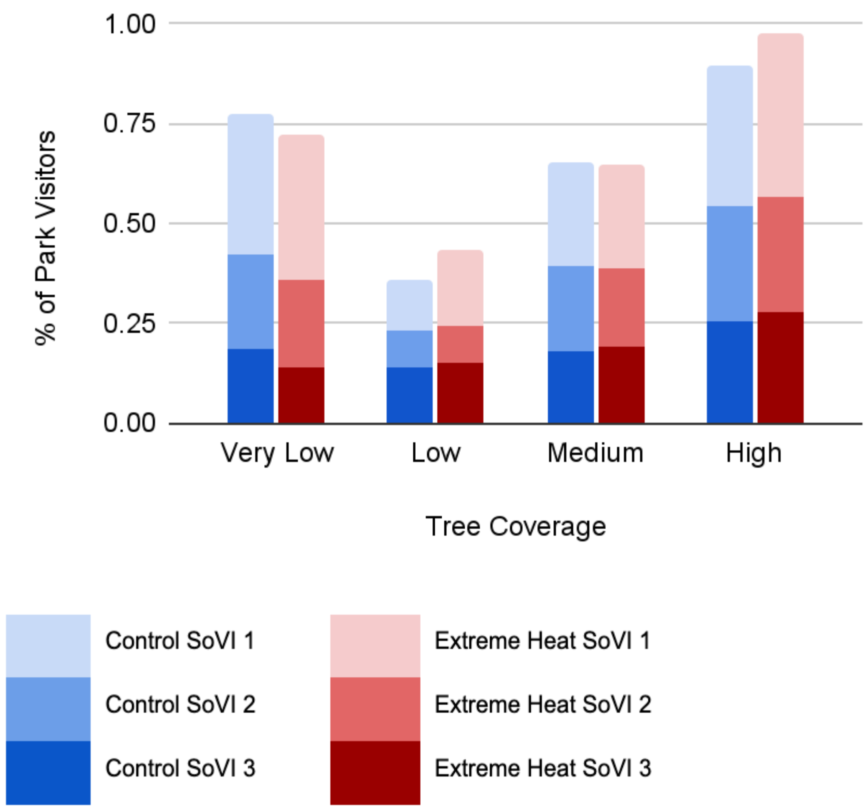
2. Medium parks



3. Small parks



4. Smallest parks



E3: Table of attributes surveyed in-person

Park Name	Income Level	Amenities
Atlantic Avenue Park	Low	Splash pad
Apollo Community Regional Park	Low	Lake
Belvedere Community Regional Park	Low	Splash pad, Lake
Whittier Narrows Recreation Center	Low	Lake
Castaic Lake State Recreation Area	High	Lake
Castaic Regional Sports Complex	High	Splash pad