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Smartphone locations reveal patterns of cooling center use as a heat mitigation strategy

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ABSTRACT

The increasing frequency and duration of extreme heat events prompts questions regarding mitigation proposals and evaluation of current strategies such as cooling centers. Cooling centers may be formally designated or informally used spaces such as indoor shopping centers that the public use as a refuge from heat. Smartphone location data show how a sample of the population moves during the day, what behavioral adjustments they apply in response to heat events, if cooling centers are being used, what factors correlate with use, and whether centers are serving vulnerable populations. We compared spatial patterns of smartphone locations in Los Angeles County between paired extreme heat days and control days (n = 12) in summer 2017. Cooling centers were used 1.1–1.7 times longer during heat events, depending on type, with formal cooling centers used longer. Informal centers, however, were used more (90% of visits). Distance to nearest public transit stop was inversely related to the number of center visits. Vulnerable communities, as measured by the Social Vulnerability Index (SoVI), used centers located in neighborhoods with higher vulnerability scores more. Use of smartphone data to assess activity space of individuals has substantial potential for evaluating mitigation strategies in the face of increasing extreme heat events.

1. Introduction

The frequency, intensity, and duration of extreme heat events have been increasing and this trend is projected to continue, triggering larger societal impacts, and increasing adverse health outcomes (Matthews et al., 2017; Tuholske et al., 2021). Even with the committed target of limiting global temperature increase to below 2 °C above pre-industrial levels, the frequency of extreme heat events is expected to increase, impacting more than 350 million people in megacities by midcentury and increasing cases of heat stress. Adaptation and mitigation strategies for communities are therefore essential, potentially reducing one-fourth of extreme heat mortalities (Jones et al., 2015; Kalkstein et al., 2022; Matthews et al., 2017). Extreme heat events are a hazard, constituting a leading weather-related cause of death in the United States (Howe et al., 2019), and their effects vary regionally depending on factors including acclimatization, air conditioning availability, socio-economic characteristics, and existing vulnerabilities. Mitigation strategies also vary from cooling centers and air conditioning management, to altering shifts in work schedules, neighbor check-ins, and behavioral controls (Turner et al., 2022; Vaidyanathan et al., 2019). Successful risk management requires an assessment of the efficacy and applicability of such mitigation strategies.

Cooling centers are one of the mitigation strategies often mentioned in the context of heat events (Turner et al., 2022), which are effective in providing a cool environment to reduce the adverse effects of extreme heat (Fraser et al., 2018; Widerynski et al., 2017). Accessible, indoor, air-conditioned spaces appear to be especially important for individuals without air conditioning at home, but very few studies have assessed the effectiveness of this strategy. A study of cooling center accessibility in New York City showed that a third of residents are within walking distance to centers and accounting for transit access, about 80% of population have access to centers, but rural heat-vulnerable areas had lower accessibility (Nayak et al., 2019). A network analysis of public cooling centers in Los Angeles County, California, and Maricopa County, Arizona, found that centers are clustered instead of an accessible distribution between vulnerable communities (Fraser et al., 2018). Another evaluation of cooling centers in Maricopa County through surveys at 53 facilities indicated that 78% of respondents visited the centers for the

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primary services of the facility rather than heat-refuge, a quarter of visitors used public transportation to reach the center, and most visitors learned about centers through word of mouth or by seeing the center (Berisha et al., 2017).

Certain socio-economic conditions have been associated with lack of access to resources and the susceptibility to suffer harm from hazardous events, including heat events (Cutter et al., 2003; Füssel, 2007; Harlan et al., 2013; Reid et al., 2009).Vulnerability of individuals to extreme heat events have been mostly studied in relation with hospitalizations and mortality counts, with a public health focus (Chuang & Gober, 2015; Reid et al., 2009; Uejio et al., 2011). The identified factors that have been associated with heat-related impacts include socio-economic disparities, occupational exposure, ethnicity, language barriers, nursing home residents, age, and living conditions (Hansen et al., 2013; Klenk et al., 2010; Reid et al., 2009). The Social Vulnerability Index (SoVI) is a place-based measure of an area's ability to prepare for, respond to, cope with, and recover from an environmental threat such as heat. It incorporates 27 indicators for the census tract level analysis and has been applied in study of several hazards and mitigation plans, where its multi-dimensional place-based construct provides the ability to trace the contributing factors to vulnerability at each location (Cutter et al., 2003; Cutter & Morath, 2013; Rufat et al., 2019). The accessibility of cooling centers in relation to existing vulnerabilities and an assessment of the centers' use has not previously been tested, and mobility data can provide insights on how accessible formal and informal centers are in different neighborhoods according to the underlying vulnerabilities.

Numerous studies have used mobile device data in the context of COVID-19 pandemic and mobility patterns (Badr et al., 2020; Grantz et al., 2020; Xiong, Hu, Yang, Luo, & Zhang, 2020). The application of GPS data, geotagged social media posts (like Twitter) and mobile phones in the context of hazards and disaster management has precedence as well, for example in relation to hurricane evacuations, environmental hazards like airborne pollutants, and wildfire evacuation (Gulliver & Briggs, 2005; Hatchett et al., 2021; Hong et al., 2021; Martin et al., 2017; Xing et al., 2021; Yabe et al., 2022; Yu et al., 2018). Such literature suggested a predictability in human movements after and during extreme events (Lu et al., 2012). Use of mobile phone data in heat risk and mitigation evaluations has room to grow. The very few current studies include, for example, Holec et al. (2021) who performed a heat risk assessment based on mobile phone data used as a measure of population density for Bratislava, Slovakia, or Yasumoto et al. (2019) who studied heat exposure based on mobility patterns in urban and suburban populations in Dhaka, Bangladesh.

The dynamic nature of mobility data is valuable in understanding the kinetic characteristics of heat exposure and people's activity space during the day. The use of mobile phone data and associated calculation of individual activity spaces avoids the known limitations of using administrative spatial units and the modifiable areal unit problem (MAUP), from either scale effect (variation in results from analysis at differing spatial resolution) or zoning effect (variation in results from regrouping of areas at a scale) (Kwan, 2009; Openshaw, 1984; Riva et al., 2009; Tobler, 1989). Another related problem has also been attributed to the uncertain geographic context problem (UGCoP) in terms of the spatial and temporal uncertainty in the areas and duration in which individuals are exposed to certain conditions (Kwan, 2012), which also calls the attention to modifiable temporal unit problem (MTUP) in aggregating or segmenting the data (Cheng & Adepeju, 2014). Exposure measures are often derived from areal units that are static and defined administratively (Kwan, 2009). However, the area-based analysis of exposure can lead to the known problem of ecological fallacy and making inferences about individuals based on the aggregated data. Therefore, a non-static representation of exposure to environmental conditions would be more favorable (Kwan, 2009). The application of mobility data provides more information on where people spend time and their activity space throughout the day and enables a "people-based understanding of exposure and context" (Kwan, 2009). Especially in the case of extreme heat, people are exposed to the outdoor conditions of many different neighborhood contexts besides their own residential area, and the time they spend outside, the paths they take during the day, and the places they visit are more indicative of exposure levels. In addition to outdoor space use behavior change, the use of cooling centers during extreme heat days, in comparison with paired control days with moderate temperatures, could be derived from the analysis of mobility data to gauge the efficacy of this mitigation method including its location.

We investigated the use of cooling centers during extreme heat events in Los Angeles County, California, US, which has been tackling the heat burden as a combination of extreme heat events within an urban heat island, while facing a changing pattern of seasonal higher temperatures as well (Broadbent et al., 2020; Hulley et al., 2020; Kalkstein et al., 2018; Taha et al., 2015). The excess heat-related mortality in Los Angeles is projected to increase from two to three times in one scenario to five to seven times under another scenario by the 2090s, even including a 20–25% buffer for acclimatization (Hayhoe et al., 2004). Therefore, understanding and evaluating currently available and adopted heat mitigation solutions in Los Angeles County is essential for effective planning and preparing for upcoming changes in it and other similarly situated megacities. The operation and management of cooling centers in the County is performed by the County Department of Public Health, County Chief Sustainability Office, and the County Office of Emergency Management (Chu et al., 2021). We consider cooling centers to include both formally designated locations like libraries, parks, and community centers provided by the County or other governmental agencies, and informal cooling centers such as commercial spaces, pools, and shopping centers that people could use for heat relief (Berisha et al., 2017; Fraser et al., 2018). We evaluate the use and accessibility of cooling centers in Los Angeles County during heat event days, comparing visits to the centers on hot days with paired control days with moderate temperatures (12 paired days from July and August of 2017), assess the social vulnerability of the surrounding neighborhood of cooling center locations and users' presumed residence location, and investigate the potential effects of distance from centers to users' residence and to closest transit stop on cooling center use.

2. Methodology and data

2.1. Mobility data

More than 24 million recorded locations of mobile device users in Los Angeles County for the months of July and August 2017 were acquired from Outlogic, a private location data provider that collects data on consenting users of third-party mobile phone applications with location information. The mobility data for six paired extreme heat days and control days were selected based on historical weather data (these paired control-hot days are: July 1st-July 8th, July 2nd-July 9th, July 26th-August 2nd, July 27th-August 3rd, August 23rd-August 30th, and August 24th-August 31st). The samples were selected from summer of 2017 because it had several record-breaking heat waves with highest fatality in the past decade (Tracking California, 2022) and is prior to COVID-19 pandemic, thus the mobility patterns are not arising from COVID-19 mitigation policies. Using Python for programming, a subset of daytime users from 12:00 p.m. to 4:00 p.m. was used to compare the behavioral patterns of cooling center use based on device locations that intersected with cooling center building footprints. The sample data were refined to remove records with horizontal accuracy of >25 m and eliminate points with recorded speeds of ≥3 miles per hour or more (to keep walking speeds or stationary conditions) (Bohannon & Williams Andrews, 2011; Peng et al., 2020; Rambhatla et al., 2022). The census tract associated with the nighttime resting location of each device was extracted by mapping consistent locations of mobile phone devices from 1:00 a.m. to 5:00 a.m. and intersecting with census tract polygons, using ArcGIS Pro 2.9 and Python programs. After removing duplicates and screening for speed and accuracy, the dataset included 143,241 unique users across Los Angeles County for the 12 days.

2.2. Cooling centers

Formal cooling centers are public facilities for heat relief, such as libraries and recreation centers, which are either provided by the County of Los Angeles and designated by its Department of Public Health or designated by one of the 88 cities in the county. Informal cooling centers were defined as commercial spaces or buildings that people could use for heat relief. We focused on shopping centers, pools, and recreation centers that had not been formally designated as cooling centers. The database for cooling centers in Los Angeles County was partially provided by the Los Angeles County Chief Sustainability Office for formal County centers, while we developed the layer of formal non-county centers and the informal centers, which are now available online as indicated in the data statement. Formal cooling centers were classified as parks, libraries, and senior and community centers operated by Los Angeles County, or non-county government agencies, while informal centers included pools, shopping centers, and recreation centers. The location of cooling centers was intersected with building footprint polygons (from Los Angeles Region Imagery Acquisition Consortium (LARIAC),2017 data) in ArcGIS Pro 2.9 to build a layer of cooling center buildings footprints. Cooling center occupancy was calculated based on the number of unique device locations (pings) in a center during a given hour and then standardized by cooling center area and total pings on the sample day. The ratio of pings in a center type to total pings was used to assess duration, and to present longer duration with a larger value, the duration indicator is equal to: 1 - (unique pings/total pings). The presumed residence location of cooling center users was extracted from the matched user identification code with the device resting location at night, which returned 29,430 unique cooling center users across Los Angeles County on the 12 study days (2,134 for formal centers and 27, 982 for informal centers, where 686 used both). As a test for the accessibility of centers, the coordinates of public transportation stops (bus, rail, and subway) in LA County (from Los Angeles County Metropolitan Transportation Authority, 2022) was compared with the cooling center locations in ArcGIS Pro 2.9 to measure the Euclidean distance between the centers and the nearest bus stop. The threshold used for defining walking distance is 0.25 miles (about 402 m) that is commonly used for studies in the U.S. (Yang & Diez-Roux, 2012). The distance between cooling centers and the resting location of nighttime mobile phone users was also calculated as a measure of the distance between users' potential residence to the centers, which is calculated using the geodetic distance.

2.3. Social Vulnerability Index (SoVI)

The vulnerability scores used here follow the methodology for Social Vulnerability Index (SoVI) (Cutter et al., 2003), and were computed for the census tracts in Los Angeles County using the raw data from ACS 5-year estimates for 2017 (to match the year of mobility data). The SoVI factors explain 72.4% of the variation in input data (Components details are provided in Table 1). The 27 indicators of SoVI (Cutter & Morath, 2013) are calculated from the raw ACS data, then normalized by z-scores, and components of a Principal Component Analysis (PCA) with Varimax rotation, and then are integrated with assigned cardinality based on vulnerability contribution of factors to produce the SoVI scores. The layer of SoVI scores was intersected with the cooling center polygons to extract the vulnerability scores for the center's location. Additionally, the resting location during night (1:00 a.m. to 5:00 a.m.) for mobile phone users who had visited the cooling centers was extracted to identify the vulnerability of users' residence and compare with the cooling centers they visited, as another measure of accessibility.

Table 1
Components and summary results of Social Vulnerability Index (SoVI) 2017 for Los Angeles County[a].

Factor	Description	% Variance Explained	Dominant Variables
1	Poverty, Ethnicity (Hispanic), and Education	26.119%	% Hispanic % With Less than 12th Grade Education % Female Headed Households Linguistic Isolation % Employed in Service Occupation Per Capita Income (*Negative loading in PCA*) % Households Earning over $200,000 annually (*Negative loading in PCA*) Median Housing Value (*Negative loading in PCA*) Median Gross Rent (*Negative loading in PCA*) % Civilian Unemployment
2	No automobile access, and Renters	11.021%	% Housing Units with No Car % Renters % Poverty % Children Living in Married Couple Families (*Negative loading in PCA*)
3	Dependence and Age (Elderly)	8.981%	% Households Receiving Social Security Benefits % Population under 5 years or 65 and over Median age
4	Female, and Race (African American)	6.183%	% Female Participation in Labor Force % Female % African American
5	Race (Asian)	5.803%	% Asian
6	Nursing home residents	5.175%	Nursing Home Residents Per Capita
7	Mobile home residents	4.354%	% Employment in Extractive Industries % Mobile Homes % Unoccupied Housing Units
8	Race (Native American)	4.165%	% Native American

[a] Variables with lower than 0.5 coefficient threshold in the PCA's rotated component matrix are not included in the summary table of components (i.e., the variable for people per housing unit).

2.4. Statistical analysis

The paired days of extreme heat day and control days were compared with tests of significance in difference of means, using SPSS Statistics 28 software (*t*-test and ANOVA) and correlations. The distance decay model is also tested with different regression curve fitting models in SPSS and the Power Model had the highest R-Square and closer fit. The JMP Pro 16 statistical software was used for data exploration, visualization, and analysis.

3. Results

The mobile phone users sample included more than 176,000 unique devices (from more than 24 million recorded location points), which refinements for accuracy reduced to 143,241 unique devices across Los Angeles County with the presumed residence census tract of each device user. Of this sample, 20.5% used cooling centers (either formal or informal) on the control or heat days, with 1.5% using formal centers and 19.5% using informal centers. In comparison with residents who did not use cooling centers, center visitors were from neighborhoods with lower income, higher age average, more mobile home residents, and higher percent of Hispanic and Asian residents (significant difference (*p*

< 0.001) shown in an independent samples T-test for equality of means). Visits to formal centers were mainly to libraries and formal cooling centers (48% to county or non-county centers, 51.7% to libraries, 1.7% to parks, where 1.4% have visited more than one type) and visits to informal centers were nearly all to shopping centers (98%), with 1.8% to recreation centers, 0.5% to pools, and 0.3% having visited more than one type. From the subset of formal cooling center users (2,134 unique devices), 54% visited cooling centers on the control day and 63% visited on heat event day; while for the subset of informal cooling center users (27,982 unique devices), 58% visited the centers on the control day, and 75% visited on heat day (686 unique devices have visited both formal and informal centers). Therefore, the number of cooling center visits on heat days increased, with the percent increase being about two times higher for informal centers.

For all center types, the visit duration ratio was longer on heat days versus control days with a significant difference ($p < 0.001$) in an independent samples T-test for equality of means, indicating that visitors will stay longer in centers on hot days, especially for formal county centers and parks, and informal recreation centers (Table 2).

Detailed results are described in the following sections with respect to vulnerability of cooling center locations, vulnerability of cooling center visitors' residence location, and comparison results between control and heat event days.

3.1. Neighborhood vulnerability of cooling center locations

Formal cooling centers are located mostly in more socially vulnerable areas, while informal cooling centers are uniformly distributed between all vulnerability levels. However, vulnerable groups with no access to automobiles and renters are less covered by county libraries and parks. For both county and non-county (i.e., city) libraries, there seems to be a lack of access for Hispanic populations and lower-income households, but city-run libraries are more accessible to households without cars in comparison to county ones. Parks, either run by the county or cities, cover low-income neighborhoods, but are missing for households without a car, renters, and Asian communities. For the informal cooling centers, while the distribution of the total vulnerability score follows a normal distribution across centers, shopping centers are less available in Hispanic, low-income neighborhoods, and households without a car, also pools are less accessible for elderly population, Asian and Native American communities (Fig. 1).

3.2. Cooling center users' residence vulnerability

According to the resting location of mobile phone users during nighttime who have visited cooling centers during the day, the potential residence of our sample indicates that the plurality of cooling center users reside in medium vulnerability neighborhoods (47%), with a slightly higher representation of lower vulnerability areas with 29% residents (24% living in high vulnerability census tracts). These results are similar to the distribution of census tract population across Los Angeles County with 48% in medium, 29.5% in low, and 22.5% in high vulnerability groups. There are only 36 census tracts without a resident from our sample of cooling center users (from 2326 populated census tracts in Los Angeles County, with population), which are mostly in low vulnerability areas with higher-income populations (10 of the tracts are in high vulnerability category due to higher number of nursing home residents). Also, about 1.3% of cooling center users (i.e., 380 unique devices), do not reside in Los Angeles County and their nighttime location is outside the county. The average of social vulnerability factor values for the presumed residence location of cooling center users show that users are coming from neighborhoods which have a slightly higher percentage of elderly, Asian, and Hispanic population, but lower percentage of nursing home and mobile home residents.

3.3. Cooling center use: heat event vs. control days

Comparing unique user locations in cooling centers on hot days versus control days shows that 41% of the visits are only on heat event days, and 39% are only on control days, while 20% have visited in both. The number of visits on heat day and control day are highly correlated (Spearman's rho of 0.87, $p < 0.001$). All center types have a higher number of unique visitors on heat event days than control days (Fig. 2); however, the difference in total center visits is not statistically significant for either formal centers ($p = 0.204$), or informal ones ($p = 0.592$) in an independent samples T-test for equality of means. The Levene's test for equality of variances also does not show a significant difference, and the independent samples' effect sizes with either Cohen's d or Hedges correction, does not show a substantial difference either (i.e., d < 0.2).

Most of the visited cooling centers are not in the same census tract of our sample's residence location (95.6%), which is also seen in the pattern of number of centers' visitors that is not correlated with the population of the center's location tract but is moderately and significantly correlated with the population of visitors' residence tract (Spearman's rho of 0.41 for control day and 0.32 for heat day, $p < 0.001$). The vulnerability scores of cooling center users on control days and heat days are moderately correlated (Spearman's rho of 0.35, $p < 0.001$) based on their residence neighborhoods. The vulnerability score of the cooling center location has a significantly moderate correlation with vulnerability of visitors' residence location for formal centers (Spearman's rho of 0.31 for control day and 0.28 for heat day, $p < 0.001$), but the association is not significant for informal centers. The use of centers across the sample of users who reside in higher vulnerability areas, varies, where elderly and age dependent populations, or Asian communities, use formal County centers more in medium to high vulnerability areas during heat days, while lower-income, or households without a car would use formal non-county centers more in low

Table 2
Cooling centers in Los Angeles County and visits per heat day and control day.

Center Type		Number of Centers	Total Area (acres)	People per acre		Visit Duration Ratio (1 - unique IDs/total visits)	
				Control day (Std. Err.)	Heat day (Std. Err.)	Control day (Std. Err.)	Heat day (Std. Err.)
Formal	County Centers	57	22.68	9.94 (1.28)	12.94 (1.71)	0.33 (0.021)	0.51 (0.013)
	County Libraries	38	18.97	9.45 (1.64)	6.16 (1.82)	0.33 (0.028)	0.38 (0.032)
	County Parks	8	2.74	4.75 (1.49)	3.97 (2.56)	0.25 (0.148)	0.43 (0.175)
	Non-County Centers	316	118.10	14.66 (0.91)	15.53 (1.50)	0.33 (0.003)	0.41 (0.005)
	Non-County Libraries	209	82.49	13.30 (1.31)	12.70 (0.91)	0.34 (0.006)	0.37 (0.004)
	Non-County Parks	45	13.29	11.98 (1.63)	11.74 (1.69)	0.31 (0.031)	0.38 (0.018)
Informal	Shopping Centers	324	1,692.45	9.04 (0.39)	9.32 (0.30)	0.44 (0.006)	0.49 (0.001)
	Recreation Centers	202	77.63	11.66 (1.05)	11.51 (0.54)	0.28 (0.011)	0.40 (0.005)
	Pools	84	25.40	13.23 (1.35)	13.46 (1.46)	0.29 (0.015)	0.37 (0.014)
All Centers		1,283	2,053.75	10.89 (1.23)	10.82 (1.39)	0.41 (0.003)	0.47 (0.001)

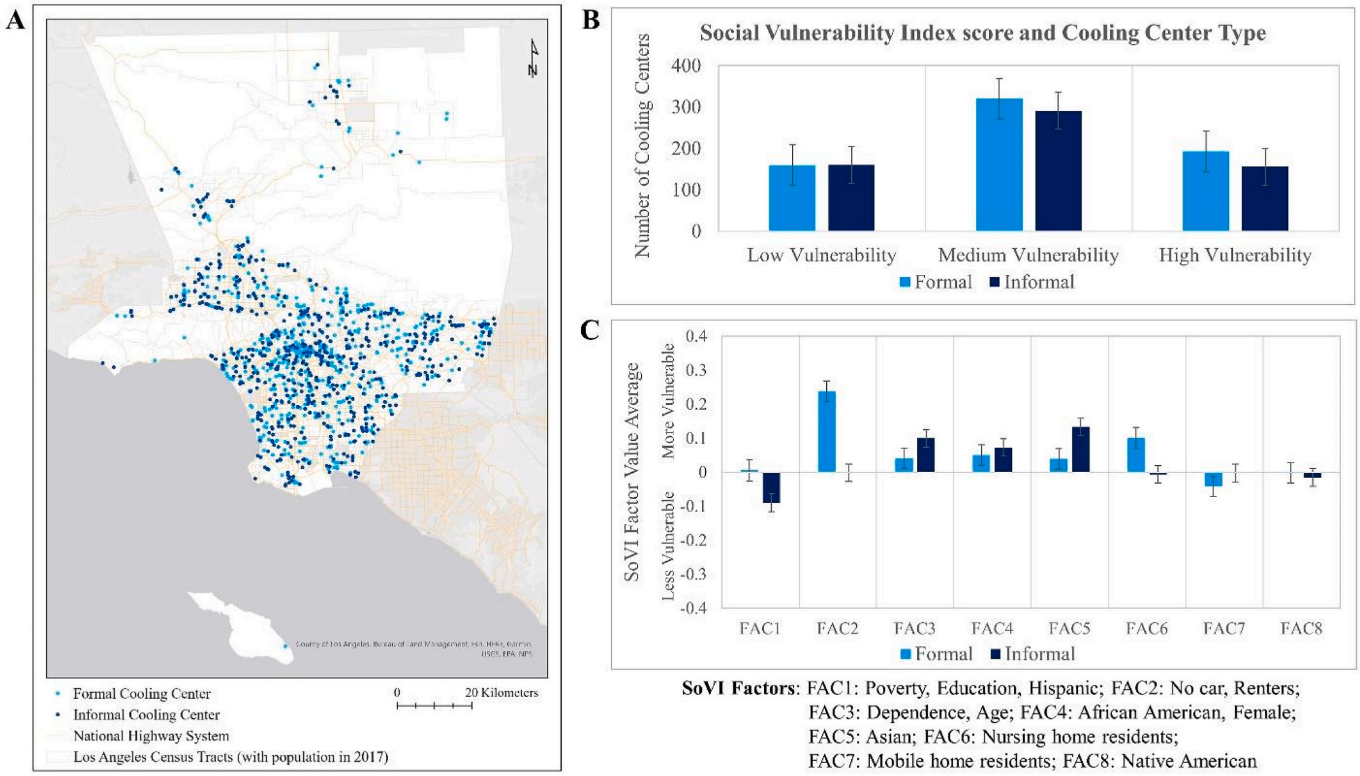

Fig. 1. Cooling center types (A) distribution across Los Angeles County, with (B) Social Vulnerability Index (SoVI) scores of the center's locations, and (C) decomposed components of SoVI of the center's location. Uncertainty by standard error of data variability is shown.

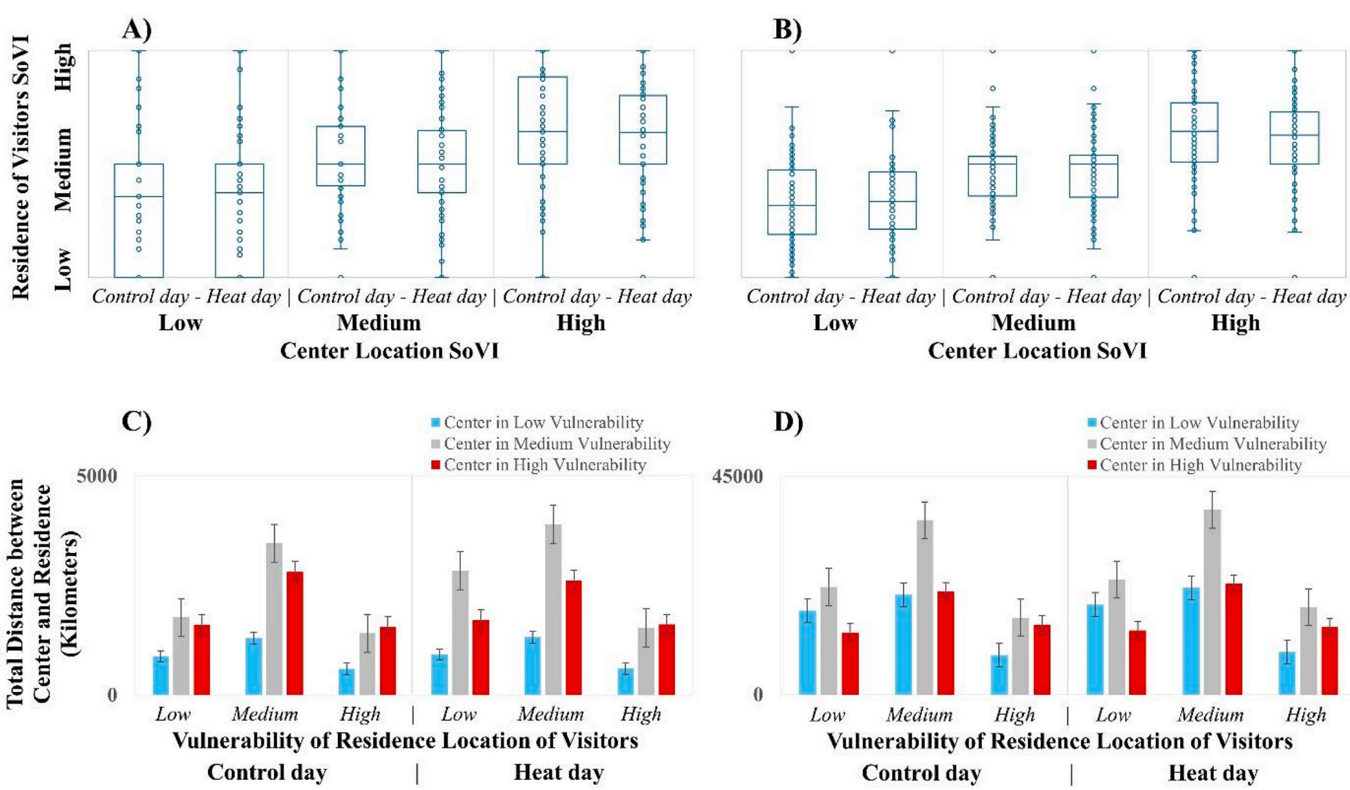

Fig. 2. Visits to (A) formal and (B) informal cooling centers by vulnerability scores of both visitors' residence and location of cooling centers (Quintile and Medians are marked); Total distance from visitors' residence to (C) formal and (D) informal cooling centers by vulnerability scores of both visitors' residence and location of cooling centers (Standard errors marked).

vulnerability areas on hot days. The visitors of centers located in low vulnerability areas are coming from higher vulnerability residents significantly more on hot days ($p = 0.029$), but visitors of centers in other vulnerability levels do not show a statistically significant difference.

Distribution of cooling center visits on heat days versus control days, in comparison with walkability to centers from the resting location of visitors (i.e., potential residence) varies between different cooling center types (Fig. 3-B); however, for all centers, the percent of visits within walking distance decreases on heat days in comparison with control days. This change in pattern of center visits may suggest that individuals would not choose to walk during periods of extreme heat and walkability is not an impetus for accessibility of cooling centers as heat deters people from outside spaces. Additionally, the distance between cooling centers and nearest public transportation is tested as another measure of accessibility (Fig. 3-A, 3-C), which shows a clear trend of distance decay as number of visits decreases with increase in the distance to the nearest transportation stop, for both control and heat days. The relationship between social vulnerability score of the cooling center's location and the distance to the nearest public transportation is not statistically significant. However, the trends suggest that visits are less frequent on heat days for centers farther from public transportation stops, which is more observable for centers in moderate vulnerability, suggesting that middle income individuals are more reliant on public transportation access.

Regardless of the social vulnerability score of the presumed residence of a mobile device user, the total distance between visitors' residence to a cooling center is higher on heat event days versus control days, and the maximum distance is increased for both formal and informal centers (Fig. 4), indicating that people are willing to travel longer distances to get to a center across all vulnerability groups. This difference in distance on a hot day is not, however, statistically significant for formal centers ($p = 0.540$) or informal centers ($p = 0.625$), in a *t*-test for difference of means. The total distance traveled to centers is highly correlated for heat days and control days (Spearman's rho of 0.81, $p < 0.001$), showing a similar pattern across centers, where the distance decay model for both follows the same power function as well (Fig. 4, Table 3). Visits to formal centers are more localized as the percent visits is higher for those living closer to the centers with a slight increase on heat days, which is also indicated by the fitted distance decay inverse power functions (Fig. 4 - C and D). The difference between distance decay models for formal and informal centers follows previously identified patterns of travel distance by trip purpose (Yang & Diez-Roux, 2012), which in the case of informal cooling this trend is seen for shopping centers regardless of day temperatures (i.e., control day or heat event). The distance from centers to nearest public transportation did not have a significant association with the distance between visitors' residence and the centers.

Considering the underlying vulnerabilities, the informal cooling center users traveled relatively longer distances to centers located in medium or low vulnerability tracts on hot days. The total distance between residence locations of visitors to informal cooling centers is about 10 times higher than the distance to formal centers, which is mainly due to the distance to shopping centers. Total distance from visitors' residence to shopping centers does not change much from control day to hot days. The social vulnerability score of visitors' residence has a weak negative significant correlation with the distance between visitors' residence and the visited cooling center for formal centers (Spearman's rho of −0.14 for control day and −0.17 for heat day, $p < 0.001$), but the relationship is not significant for informal centers, suggesting that vulnerability level of visitors is inversely related to the distance to the formal centers (i.e., longer distance to formal centers is an impediment in access for higher vulnerable populations). The residents of lower vulnerability areas would travel a longer distance on hot days to go to pools (informal center) that are in low to medium vulnerability neighborhoods, but more vulnerable residents only travel longer to the pools in high vulnerability tracts, which might be related to the working

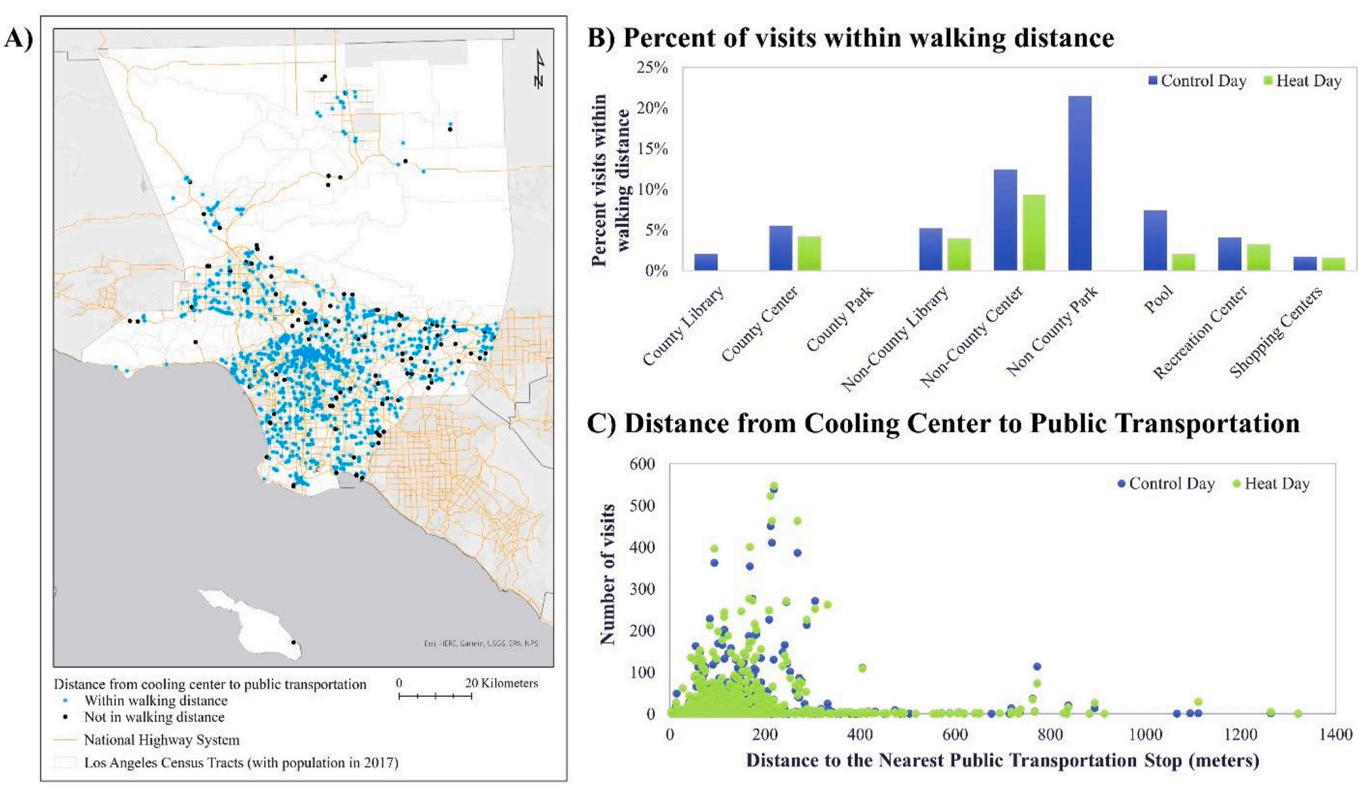

Fig. 3. (A) Distribution of cooling centers by walking distance to the nearest public transportation stop; (B) Percent of cooling center visits within walking distance by center type, for control day and heat day; and (C) Number of visits to cooling centers by the distance to nearest public transportation stop, for control day and heat day.

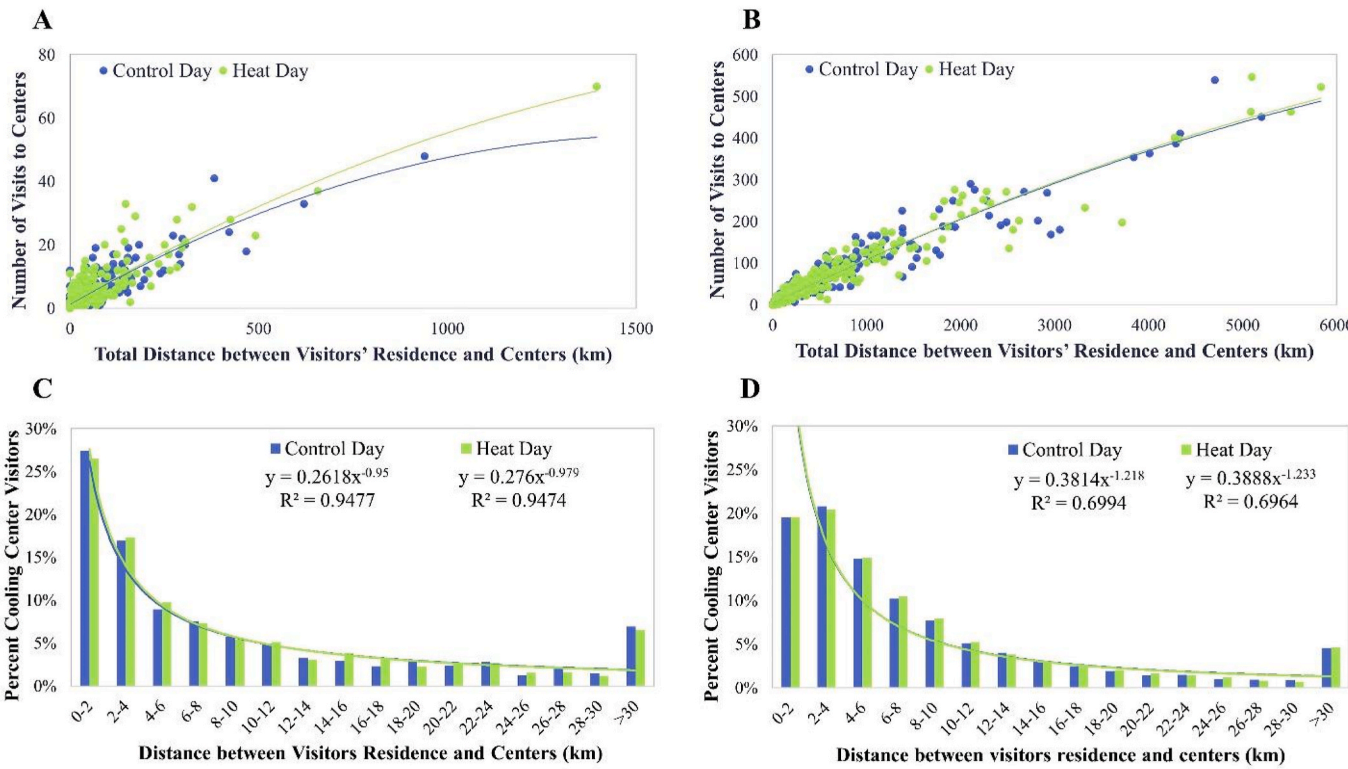

Fig. 4. Number of visits to cooling centers by cumulative distance between all visitors' residences and each cooling center visited, on control day and heat day, (A) for Formal Centers, and (B) for Informal Centers. Percent of cooling center visitors by the distance between each visitors' residence and the visited center, on control day and heat day, with fitted distance decay power model, (C) for Formal Centers, and (D) for Informal Centers.

Table 3
Distance decay inverse Power Model for number of visits to cooling centers by distance between visitors' residence and the visited center.

Percent of visits to cooling center = a (Distance between residence and cooling center) ^{b}						
	Parameter	Estimate	T-test probability	Coefficient Standard Error	Adjusted R-Square	ANOVA probability
Heat day						
Formal center	a	0.27	<0.005	0.097	0.947	<0.001
	b	−0.98	<0.001	0.112		
Informal center	a	0.39	0.028	0.184	0.696	<0.001
	b	−1.23	<0.001	0.154		
Control day						
Formal center	a	0.26	<0.005	0.094	0.948	<0.001
	b	−0.95	<0.001	0.115		
Informal center	a	0.38	0.023	0.174	0.699	<0.001
	b	−1.22	<0.001	0.148		

location of individuals. These variations are not significant, and the only significant difference is in the vulnerability level of cooling center visitors (based on their residence) on hot days ($p = 0.032$), showing that residents of highly vulnerable neighborhoods would visit cooling centers more on hot days.

4. Discussion

We found that about one fifth of the sample population in Los Angeles County have used formal or informal cooling centers. Nearly 90% of the cooling center visitors used informal centers and the majority of these were shopping centers. Therefore, publicly available cooled spaces, like commercial spaces, are visited more frequently, which is an available adaptation solution for heat refuge. Devising and providing effective incentives for owners and managers of air-conditioned commercial spaces to allow their use by vulnerable residents during extreme heat events regardless of whether those visitors are paying customers would be an adaptation policy that provides cooling without the delays of long-term construction or tree-planting.

4.1. Neighborhood vulnerability and cooling center visits

The overlaying of mobile phone users' location with the underlying vulnerability of neighborhoods, complements the anonymous data of mobile phone users by providing a range for the sample's vulnerability measures based on their presumed residence community characteristics and the location of cooling centers. There is some level of uncertainty in whether our sample falls within the range of vulnerability scores measured for their residing neighborhoods, but it provides a general overview of the distribution of resources in relation to communities' attributes, and whether centers are disproportionately distributed across different populations. The results indicated that higher vulnerability populations use cooling centers more, which was previously suggested by surveys or census data in Los Angeles County, California and

Maricopa County, Arizona (Berisha et al., 2017; Fraser et al., 2018). The use of formal centers is more localized than informal centers, and visitors tend to go to formal centers that are closer to their residences; however, the walkable location of centers did not prove to promote higher visits on heat days, and cooled transportation to centers might be more favorable than walking in heat. The additional test of evaluating the distance to transportation stops showed that the vulnerable groups would visit centers less by an increase in the distance to the nearest transportation stop. These findings can all guide the siting and establishment of new centers by local jurisdictions.

4.2. Cooling center use efficacy as a heat mitigation strategy

The novel application of mobile phone data for gauging the use of cooling centers during heat event days, proved to provide some insight into this less-studied mitigation strategy that is informative for both future mitigation plans, and other applications of the method for assessment of similar strategies. Even though there are some considerations regarding the sampling bias and representation, as mobile phone users appear to slightly represent the higher income, younger populations, and white neighborhoods more, the size of sample data partially accommodates this aspect. We acknowledge that implementation of this method in other regions may show variations in use of different types of cooling centers, since our results could be specific to the unique characteristics of Los Angeles County. The sample size is, however, large and provides empirical evidence to support policy decisions that are now urgent. Insights from Los Angeles are likely to be relevant with other large cities in similar climatic and cultural conditions and certainly to the semi-arid and arid southwest of the United States.

4.3. Uncertainties and considerations for future studies

While we consider the distance between cooling centers and residence location, some of the visitors might have visited cooling centers that are closer to their work location -depending on availability of air conditioning systems at the workplace-, which could be extracted in future studies and compare if the work location of individuals is a defining factor in their use of cooling centers. Additionally, we did not account for variations in individuals' activity space and hypermobility (i.e., highly mobile individuals who take frequent trips, over great distances), which could be included in future studies to distinguish between individuals traveling behavior and how much it might adapt to temperature changes. Use of APIs to calculate network distances and travel times could provide a refined view of distance traveled to centers or to transportations stops in future studies. Finally, from our sample of Los Angeles County residents, about 79.5% did not use the centers, who in comparison with the visitors of cooling center, are living in neighborhoods with relatively higher income, higher percentage of renters, lower number of mobile homes, younger population, and higher percentage of individuals without a car. However, there is no geographical pattern across the County associated with residents who visited or did not visit the cooling centers, and the distance to the centers or distance to nearest transportation stop is not related to the decision to visit the centers. Future studies can further illuminate the reasons behind the choice to visit cooling centers.

5. Conclusion

The study of a sample population from mobile phone users in Los Angeles County showed that about 20% of the population use cooling centers, while the majority of visitors use publicly available cooled spaces like shopping centers. Therefore, one available adaptation solution is to provide incentives and accommodations for accessibility of cooled commercial spaces and allow their use by vulnerable residents during extreme heat events. The findings suggest that cooling center visitors stay longer in the centers during heat events, thus confirming their adoption and use as a heat refuge. Additionally, higher vulnerability populations use cooling centers more, which aligns with accessibility goals and confirms previous surveys or census data in Los Angeles County, California and Maricopa County, Arizona. Finally, cooling center visitors are more likely to travel longer distances to informal centers, but the visitors of formal centers are more local, suggesting that formal centers are serving their neighborhoods. These results may arise from the particular environment and characteristics of Los Angeles County, and studies from other regions can further illuminate the efficacy of cooling centers as a heat mitigation strategy.

Data statement

All data, shapefiles, and code are available through https://la-heatwaves-gisucla.hub.arcgis.com.

Author contributions

Sahar Derakhshan: Conceptualization, Methodology, Software, Validation, Formal Analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Trisha N. Bautista:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Mari Bouwman:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Liana Huang:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Lily Lee:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Jo Tarczynski:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Ian Wahagheghe:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Xinyi Zeng:** Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft. **Travis Longcore:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project Administration, Funding Acquisition.

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