Article

Behavior-encoded models reveal differentiated access to public cooling environment by race and income

Check for updates

Chao Li [1], Xing Su [1,2] ✉, Chao Fan [3] ✉ & Haoying Han[1,4]

Extreme heat events caused by continuous anthropogenic climate change have been increasing. Establishing public cooling environments (PCEs) is imperative for protecting public health and enhancing productivity. Yet, disparities in access to PCEs based on race, travel behavior, and income status can undermine their role in helping communities cope with extreme heat. This study investigates the varied access to three types of PCEs across 40 U.S. counties. Our findings reveal that White people enjoy greater access to PCEs than other groups, especially to tree-covered green spaces (TCGSs), outperforming Black people approximately three times. Driving can disproportionately narrow the racial/ethnic inequality gap compared to walking. Non-expense-required public environments (NERPEs) and expense-required public environments (ERPEs) are less accessible to high-income groups. Our research underscores the ongoing challenges in achieving environmental justice through equitable PCE access and stresses the importance of further studies and policy actions to eliminate disparities.

Extreme heat diminishes work productivity and economic performance, and increases morbidity and mortality[1–4]. Studies have shown that in the United States, extreme heat is responsible for over 1300 deaths annually[5,6], with non-Hispanic Black Americans experiencing higher mortality rates[2]. The issue of extreme heat is exacerbated by anthropogenic climate change, predicting a future where it becomes more ubiquitous and intense[7–10].

Despite the immediate need to address these heat-related issues, climate change policies have predominantly focused on long-term solutions, such as inducing new, low-carbon energy technologies and transforming energy production patterns. These strategies face decades-long challenges across technical, economic, and social barriers[11,12]. On the other hand, short-term and direct options in climate adaptation, such as cooling environments, including indoor and outdoor cooling environments, serve as an effective infrastructure to reduce the impacts of extreme heat[13]. Recent studies have shown that spending even a few hours in a cool environment effectively reduces the risk of heat exposure, and are less likely to suffer from heat-related mortality[14–17]. Given this, there is a growing acknowledgment of the importance of access to cooling environments against extreme heat such as indoor cooling, housing quality, energy accessibility/affordability, thermal safety and school/workplace thermal comfort.

As society faces the need of providing cooling environments, the deployment of cooling centers operated by public health departments and their partners, like libraries, schools, and community and religious centers, is increasing[18–20]. However, these centers are not yet widespread[20–22], and studies indicated that low-risk individuals use cooling centers more frequently than high-risk individuals[23]. Similarly, the disparate access across population groups is prevalent in existing research related to other public open space (POS), especially among different racial/ethnic groups and income groups[24–31]. For instance, restricted access to healthcare facilities significantly contributes to higher cancer mortality rates among Black people[32,33].

Here, we define public cooling environments (PCEs) as a POS that provides cooling environments, including those previously identified as cooling centers, and we thoroughly explore the spatial distribution of PCEs and the differentiated accessibility to different groups. Specifically, based on different entry thresholds, PCEs can be divided into tree-covered green space (TCGS), non-expense-required public environment (NERPE), and expense-required public environment (ERPE). TCGS has no entry threshold and offers a productive cooling environment. Several studies have shown that a green space exposed to sunlight is not effective in lowering the ambient temperature[34–36], while TCGS can be 4–7 °C cooler than the

[1]College of Civil Engineering and Architecture, Zhejiang University, Hangzhou, Zhejiang 310058, China. [2]Center for Balance Architecture, Zhejiang University, Hangzhou, Zhejiang 310058, China. [3]College of Engineering, Computing, and Applied Sciences, Clemson University, Clemson, SC 29631, USA. [4]Innovation and Design, City University of Macau, Macau, China. ✉e-mail: xsu@zju.edu.cn; cfan@clemson.edu

1
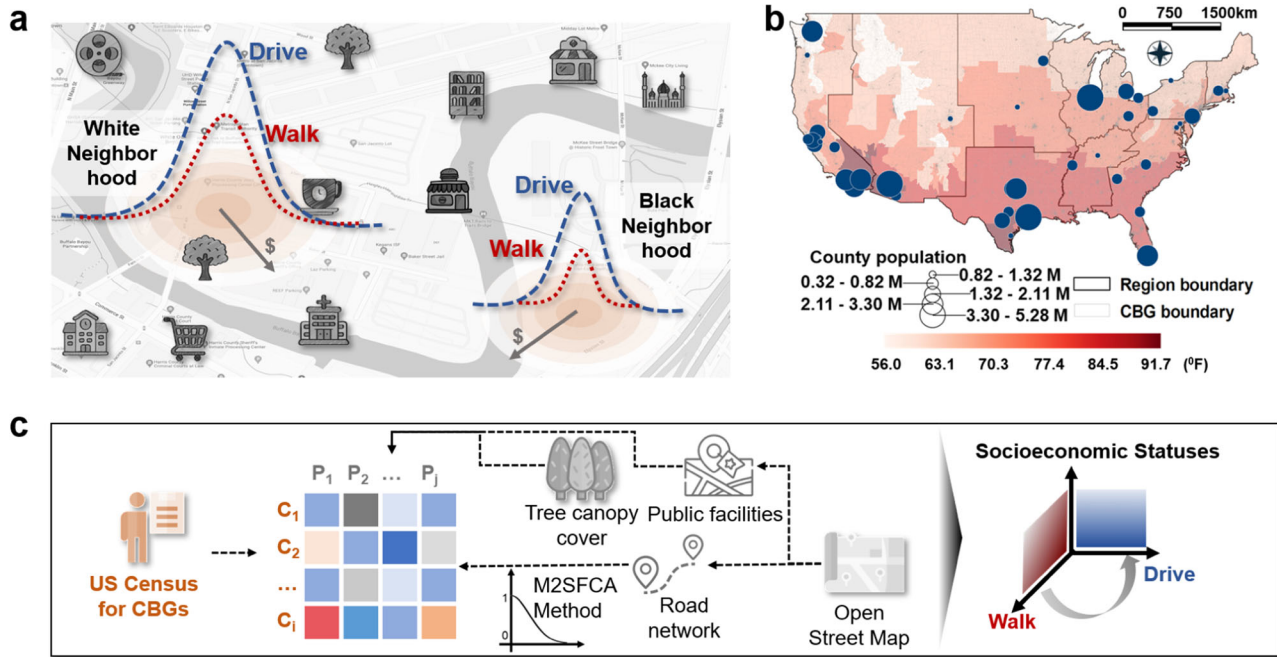
Fig. 1 | Schematic overview of the study. a The results are to be developed in this study. Icons represent the three categories of PCE, the map represents the spatial distribution of icons, and the results to be developed focus on the inequality of PCE accessibility between races/ethnicities from two behavioral patterns, i.e., driving and walking, we then encoded behavior patterns by vehicle ownership and compare the results, and finally examine the inequality within race/ethnicity based on income. b The distribution of the 40 Counties we selected. We chose at least two counties in each type of region division and air temperature division, and these counties overall comprise 44,539 CBGs and a total population of 65,031,016. The base map for region division uses the United States Census Bureau (USCB) definition of nine divisions, which are widely used for census data collection and analysis. The base map of the air temperature division uses the climate division map from National Oceanic and Atmospheric Administration (NOAA), and the temperature data is the average air temperature of June-August between 2014–2023. c The sources of study data and the processes of assessing. PCE data was extracted from tree canopy cover data and public facilities data from OpenStreetMap, CBG-level socio-economic data was extracted from the decennial census of the United States, and the CBG-level PCE accessibility distribution was calculated by matrix operations and the M2SFCA method.

exposed surroundings[35,37,38] with 30w/m^2 more radiant energy reduction[39]. NERPE has a low entry threshold and requires no cost to stay, such as places of worship, libraries and malls, and so on. ERPE, where the entry requires some expenses, is more accepted by the group with better financial status. ERPE includes restaurants, cafes and cinemas, and so on.

We adopted the modified two-step floating catchment area (M2SFCA) method[40], a behavior-encoded approach, to measure PCE accessibility. We first computed the shortest travel time from a PCE-demanded location (e.g., a census block group) to a PCE-supplied location (e.g., a mall), considering travel patterns, speeds, and road networks. We then evaluated PCE accessibility of the PCE-demanded location using factors such as time buffer, demand capacities, and supply capacities. The detailed computation process is shown in the method section.

Our study focused on 40 U.S. counties severely affected by extreme heat, located in diverse geographical regions (Fig. 1b). We assessed PCE accessibility by analyzing travel behaviors for walking and driving, factoring in different travel speeds and road networks[41–43] (Fig. 1a). A probability matrix, which comprised the minimum travel time from each census block group (CBG) to the PCE, the M2SFCA method was calibrated to determine the accessibility of the residents living in a CBG (Fig. 1c). The results revealed significant racial/ethnic disparities in accessing PCEs in counties. Effective estimation of people's accessibility does not only require capturing where they live but also the actual travel behaviors of the people living in these neighborhoods. Hence, our model encoded the travel behaviors and capacity, derived from vehicle ownership, in computing the PCE accessibility for people in each CBG. Vehicle ownership is, to a great extent, driven by household income. To dig into the inequity of access, we further investigated whether there is differentiated PCE accessibility within race/ethnic groups based on income.

Results

Differentiated access by race and ethnicity

Experiments began in each county, taking Harris County in Texas as an example. This county is among the most populous and hottest in the U.S. For ease of exposition, we presented a comparative analysis between White and Black people, highlighting behavioral patterns in walking and driving scenarios (refer to Figs. 2 and 3). In Fig.2a, White people show an increase in walking accessibility from the county's center to its outskirts, with lower access in the center and southeast, and higher in the north. In contrast, Black people have generally lower accessibility in the south, improving towards the north. In terms of walking access to NERPE, White people face lower accessibility in the north and northwest, but better access in the center and southeast. Black people, however, experience generally lower accessibility, with some central areas showing better access. White people's access to ERPE is high, improving from the outskirts to the center, with notable access in the northwest and southeast. Black people see lower access in the north and south but better in the center, also improving from the outskirts to the center, especially in the southeast. We also provided the detailed PCE accessibility distribution of overrepresented CBGs in the walking scenario for Hispanic or Latino, American Indian, and Asian groups in Supplementary Fig. 1A.

Figure 2b reveals that across all PCE categories, White people have higher maximum probability density values for PCE access than Black people. Specifically, White people's maximum density (0.50) for accessing TCGS is less than Black people's (0.61), but their access to PCE (0.42) and average accessibility (0.50) are higher than those of Black people (0.29 and 0.47, respectively). For NERPE and ERPE, White people also show higher maximum densities and mean accessibility values than Black people. The detailed probability density curves of PCE accessibility distribution in the
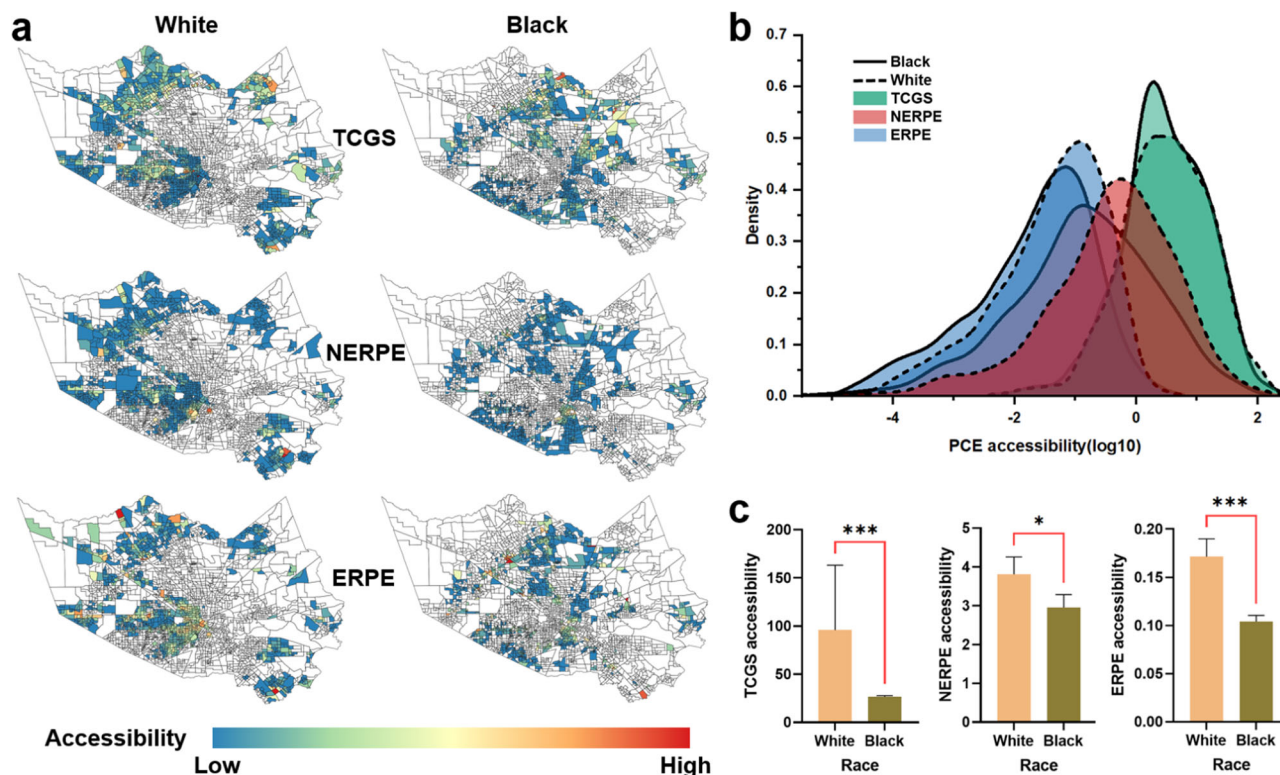
Fig. 2 | Differentiated access to PCE for White and Black people in the walking scenario. We first investigated the differentiated access between the two races to the three categories of PCE taking Harris County as an example, **a** Visualization of the distribution of PCE accessibility for the overrepresented CBGs of White and Black people. We used White people fraction of the CBG population to compute the average White population fraction (aWf) across all CBGs (approximately 42%). Similarly, we computed the average Black population fraction (aBf) (approximately 17%). PCE accessibility in CBGs with a White fraction of greater than aWf (left), and in CBGs with a Black population fraction of greater than aBf (right). **b** Probability density curves for the two races for the three categories of PCE accessibility, a kernel smoothed density curve was adopted because the data do not obey a Gaussian distribution, in order to put the probability density curves of the three PCEs together, we took the PCE accessibility as a logarithm with a base of ten. We then examined the overall potential inequities of the selected counties. **c** Overall PCE accessibility in overrepresented CBGs. There are 22026 overrepresented CBGs for White people and 11628 overrepresented CBGs for Black people, the height of the bar chart represents the mean PCE accessibility of the selected CBGs, the error bars show the 95% confidence interval of the statistical data, and the error bars are equivalent throughout the figure. The statistical data do not obey a normal distribution, so the Mann-Whitney U test in the nonparametric t-test was used to test whether the difference between the two groups of data was significant, * denotes the degree of significance, i.e., the P value, ***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, ns means $P \geq 0.05$.

walking scenario of overrepresented CBGs for five race/ethnic groups are shown in Supplementary Fig. 1B.

Summarizing results from the 40 counties, we observed a consistent advantage in PCE accessibility for White people over other races/ethnicities (Supplementary Fig. 3). Figure 2c illustrates the comparative analysis for White and Black people, the overall means of PCE accessibility for White people are 95.81 for TCGS, 3.81 for NERPE, and 0.17 for ERPE. For Black people, they are 26.64, 2.95, and 0.10, for TCGS, NERPE and ERPE, respectively. In general, White people have 259.7% (TCGS), 64.6% (NERPE), and 28.8% (ERPE) more accessibility than Black people. This significant disparity in accessibility by race is widespread and statistically significant in counties experiencing extreme heat, exacerbating the local populations' vulnerability to extreme heat effects.

In the driving scenario, we adhered to a similar research approach. Figure 3a, compared to Fig. 2a, exhibits more CBGs with PCE accessibility and more clustering effects. Specifically, for driving access to TCGS, White people have greater accessibility in the northeast, but less in the central and southeast areas, whereas Black people experience higher accessibility in the north-central region, diminishing southward. Regarding NERPE driving access, White people find better accessibility in the central and southeast, indicating a clustering effect, and less in the northeast and west, while Black people see higher accessibility centrally, tapering off in all directions. For ERPE driving access, White people enjoy greater accessibility in the central and western regions, but not in the northeast, with Black people also showing higher central accessibility, decreasing outward. The detailed PCE

accessibility distribution of overrepresented CBGs in the driving scenario for Hispanic or Latino, American Indian, and Asian people are demonstrated in Supplementary Fig. 2A.

Figure 3b, compared to Fig. 2b, exhibits overall smaller differences in PCE accessibility probability density, yet with more irregular distribution curves featuring additional peaks, suggesting a more precise division of the PCE-access population by driving. The detailed probability density curves of PCE accessibility distribution in the driving scenario of overrepresented CBGs for five race/ethnic groups are illustrated in Supplementary Fig. 2B.

Figure 3c, compared to Fig. 2c, reflects less inequality in PCE accessibility. Specifically, the average PCE accessibility for White people were 139.08 (TCGS), 4.15 (NERPE), and 0.18 (ERPE), compared to 110.54 (TCGS), 4.62 (NERPE), and 0.16 (ERPE) for Black people. Thus, White people's accessibility is 25.8% and 8.6% higher than that of Black people for TCGS and ERPE, respectively, but 10.3% lower for NERPE.

We also calculated the overall population-weighted PCE accessibility for each racial/ethnic group (Supplementary Fig. 4). For walking, White people experienced 8.5%, 21.1%, and 75.5% more population-weighted accessibility than Black people for TCGS, NERPE, and ERPE accessibility, respectively. For driving, White people had 5.7% and 11.3% more population-weighted accessibility than Black people for TCGS and ERPE accessibility, respectively, but 10.2% less accessibility for NERPE.

These findings indicate that White people generally benefit from greater accessibility than Black people in TCGS and ERPE, particularly when walking. However, accessibility disparities between walking and
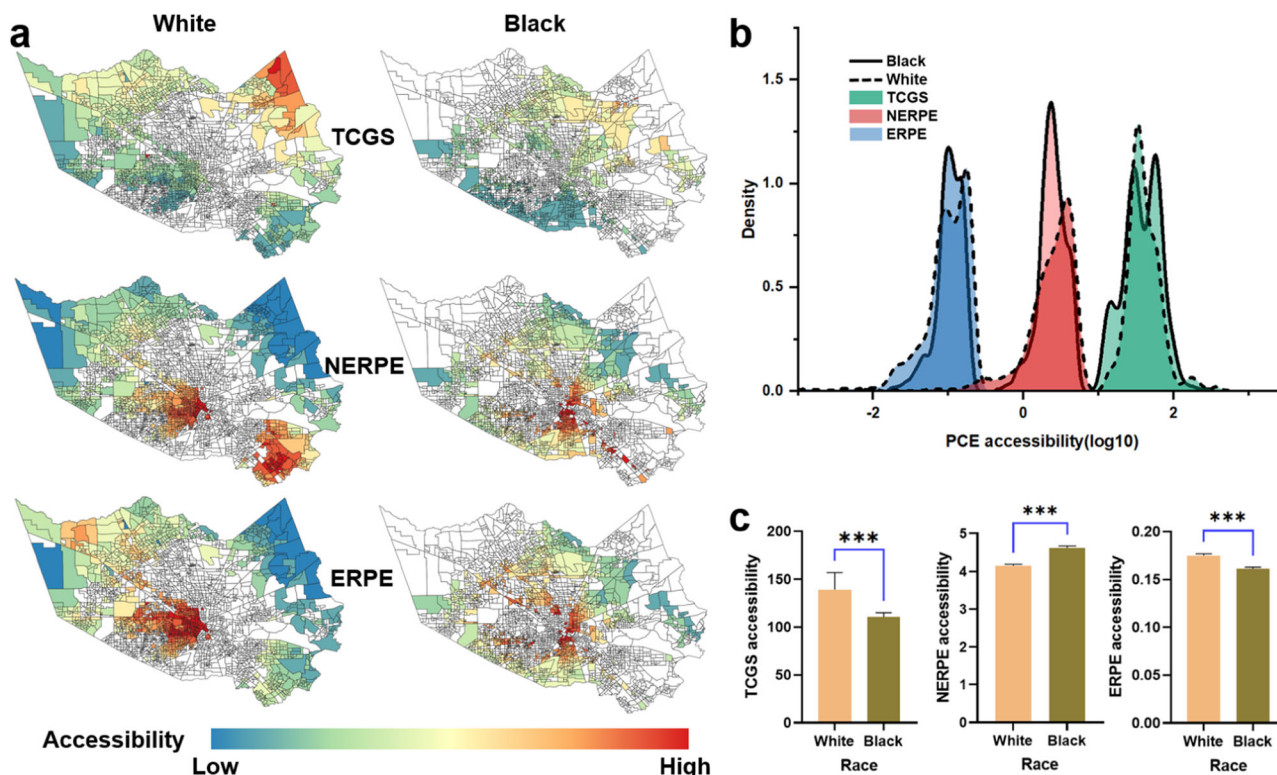
Fig. 3 | Differentiated access to PCE for White and Black people in the driving scenario. The selection method of overrepresented CBGs, the calculation method of accessibility and probability density, and the visualization method of the three graphs are similar as Fig.2. **a** Visualization of the distribution of PCE accessibility for the overrepresented CBGs of White and Black people. **b** Probability density curves for the two races for the three categories of PCE accessibility. **c** Overall PCE accessibility in overrepresented CBGs. The error bars show the 95% confidence interval of the statistical data, and the error bars are equivalent throughout the figure. The Mann–Whitney *U* test in the nonparametric t-test was used to test whether the difference between the two groups of data was significant, * denotes the degree of significance, i.e., the *P* value, ***P < 0.001, **P < 0.01, *P < 0.05, ns means P ≥ 0.05.

driving are evident in NERPE. The smaller accessible area for walking more mirrors the unequal spatial distribution of the original PCE[44], highlighting a significant bias in PCE spatial distribution favoring White people.

Differentiated access by travel behaviors

Figure 4 illustrates the significant impact of behavioral patterns on the access to the three categories of PCE across the selected counties. The analysis reveals that in these counties, access metrics such as the maximum, upper quartile, median, lower quartile, and minimum of the accessibility of the three categories of PCEs were consistently higher for driving than walking scenarios (Fig. 4a–c).

Results also suggest that PCE accessibility via driving is significantly ($P < 0.001$) and positively (Slope>0) correlated with PCE accessibility via walking. Notably, Fig. 4d demonstrates that an increase in TCGS accessibility by walking (log10) by one-unit results in a 0.743 unit increase in TCGS accessibility by driving (log10), signifying a 0.553 unit increase in driving accessibility for every unit increase in walking accessibility. Similarly, Fig. 4e highlights that a one-unit increase in NERPE accessibility by walking translates to a 0.709 unit increase by driving. Despite a relatively low R-square value of 0.356, it indicates a significant positive correlation. Figure 4f reveals that for ERPE accessibility, a one-unit increase by walking leads to a 1.078 unit increase by driving, showcasing the highest regression accuracy with an R-squared value of 0.810.

Despite the general trend of driving significantly enhancing PCE accessibility in most counties, some exceptions were noted where walking proved more advantageous, such as Fresno County in California and Worcester County in Massachusetts for TCGS, Lancaster County in Nebraska, and Monroe County in New York for NERPE, Bexar County in Texas and Fresno County in California for ERPE. There are still some counties where walking is a better option to access PCE compared to driving,

such as Orange County in California for TCGS, Alameda County in California for NERPE, and Tarrant County in Texas for ERPE (Fig. 4d–f).

By incorporating vehicle ownership data to calculate behavior-weighted PCE accessibility (Supplementary Fig. 5), we observed a reduction in racial/ethnic disparities in PCE access. Specifically, White people exhibited a 3.6% and 19.4% higher mean PCE accessibility and a 3.3% and 26.5% higher population-weighted accessibility than Black people for TCGS and ERPE, respectively, with no significant difference for NERPE.

Combining the results, we found that the effects of driving on mitigating the racial/ethnic disparities in PCE accessibility varies among the three PCE categories. Driving reduces the race/ethnicity-based disparities in TCGS accessibility more that for ERPE and NERPE. Taking Black and White people as an example, the disparity reduction in TCGS, ERPE and NERPE was 233.9%, 56%, and 39.1%, respectively.

Differentiated access by income within racial/ethnic groups

Table 1 reveals that White and Asian people's income levels were significantly and positively correlated with TCGS accessibility, whereas the income levels of the other three groups showed no significant correlation. In the case of NERPE accessibility, all races/ethnicities' income levels were significantly and negatively correlated, with American Indian groups experiencing the largest NERPE accessibility gap and Asian groups the smallest NERPE accessibility gap for the same income gap. For ERPE accessibility, the incomes of all races/ethnicities, except Black people, were significantly negatively correlated. Black people's income showed no significant correlation with ERPE accessibility. Moreover, American Indian people faced the largest ERPE accessibility gap, while White people had the smallest for the same income gap.

To delve deeper into the PCE accessibility trends across different races/ethnicities, we performed statistical analyses for five racial/ethnic groups
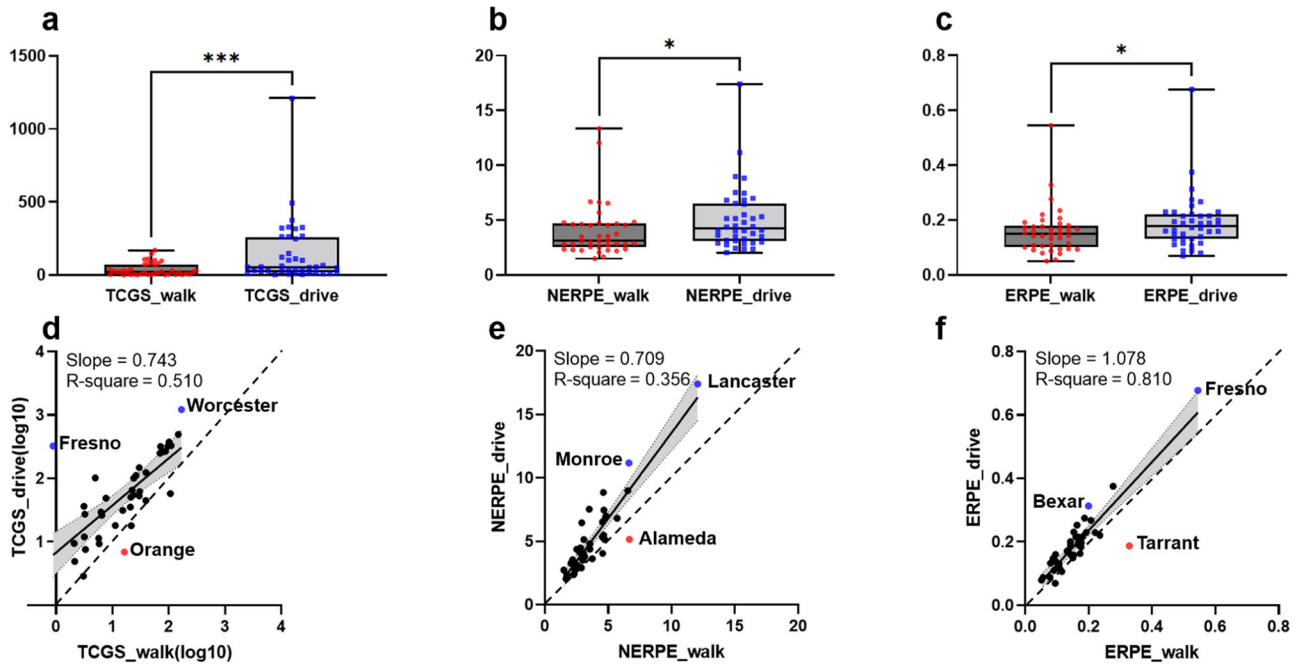
Fig. 4 | Comparative analysis of PCE accessibility for two behavioral patterns. We first took a statistical analysis and plotted mean PCE accessibility in 40 counties by categories of PCE, include (**a**) TCGS, (**b**) NERPE, (**c**) ERPE. The distribution of the mean PCE accessibility in 40 counties were plotted using a box plot, with the five horizontal lines from top to bottom indicating the maximum, upper quartile, median, lower quartile, and minimum of the data, respectively, the method of significance test and the meaning of * are consistent with Figs. 2 and 3. We also adopted a simple linear regression analysis and plotted the regression results in 40 counties by categories of PCE, include (**d**) TCGS, (**e**) NERPE, (**f**) ERPE, the accessibility gaps between accessing PCE by walking and driving is large, and to make the regression plots clearer and more readable, we have taken a logarithm with a base of 10 for all the data used in (**d**). The distribution of the mean PCE accessibility in 40 counties were plotted using a scatter plot, the solid black line indicates the fitted straight line, the gray area indicates the 95% confidence interval, and the dashed black line indicates the marginal of equal PCE accessibility in both models, with greater PCE accessibility for driving above this line indicates and greater PCE accessibility for walking below this line.

based on income deciles. This involved categorizing individual counties by racial income deciles, then calculating both the population-weighted PCE accessibility and the average population-weighted PCE accessibility for 40 counties within each decile. The findings mirror the linear regression outcomes, revealing a general trend where PCE accessibility for the five racial/ethnic groups tends to decrease and then increase with rising income (Supplementary Fig. 6), indicating that the highest income groups often have moderate PCE accessibility.

Discussion

The frequency and severity of extreme heat pose a significant threat to people globally. PCE plays a crucial role in reducing heat exposure and improving living comfort. However, the disparity in PCE access among people of varying demographics remains poorly understood due to inconsistent distribution. Addressing this critical issue, we utilized behavior-encoded models to investigate the distribution and accessibility discrepancies of PCEs among various groups.

The analysis reveals a widespread disparity in PCE access among racial/ethnic groups, with White people having the highest accessibility and the largest advantages in TCGS accessibility. The results of the raw PCE accessibility and the behavior-weighted PCE accessibility show a strong correlation between behavioral patterns and PCE accessibility, with a disproportionate reduction of driving on racial/ethnic disparities in the accessibility of different categories of PCE. The linear regression results indicate a near absence of income-based PCE access disparities within the selected racial/ethnic groups, suggesting that higher-income people, due to their greater ease of access to cooling solutions like air conditioning[45], are less affected by the associated costs[46,47], thus likely to maintain a cooler home environment.

This research points out the stark differences in PCE accessibility reduction among racial/ethnic groups due to driving, particularly noticeable in TCGS. This discrepancy may stem from the broader distribution of TCGS in suburban areas, as opposed to ERPE and NERPE, which are more urban-centric. Driving allows for covering larger distances in suburbs compared to urban settings. Vehicle ownership rates also play a role, with White people having higher ownership rates. For example, in the U.S. in 2019, 18% of Black households were without a vehicle, yet only 6% of White households. It exacerbates the accessibility gap for people of color who rely more on walking or public transport[48].

Our study highlights the persistent advantage of White people on access to PCE across the United States. The main contributions are twofold. First, our findings can inform national policy and emerging state and local environmental justice laws to identify unequal PCE access to racial/ethnic groups and develop heat-reduction plans for vulnerable racial/ethnic groups. Deriving policies specifically to targeted areas is helpful to address racial/ethnic inequities in PCE accessibility, which also makes the approach transferrable to other cities in the county. Second, an uneven distribution of PCE at a very fine spatial scale, CBG levels, is observed. Such detailed insights for individual CBGs could inform the planning and design of PCEs

Table 1 | Regression results for the relationship between PCE accessibility and income within racial/ethnic groups

Race/ethnicity	TCGS		NERPE		ERPE	
	Slope	P > |t|	Slope	P > |t|	Slope	P > |t|
Hispanic or Latino	−0.0025	0.897	−0.0563	0.000***	−0.0495	0.000***
White	0.0751	0.000***	−0.0684	0.000***	−0.0280	0.000***
Black	−0.0155	0.443	−0.0505	0.000***	−0.0098	0.100
American Indian	0.0313	0.719	−0.0842	0.000***	−0.0673	0.000***
Asian	0.1071	0.000***	−0.0439	0.000***	−0.0332	0.000***

*P < 0.05, **P < 0.01, ***P < 0.001.

in cities to improve the infrastructure for reducing public heat exposure. PCE planning policies could be tailored to local conditions can be adopted. Our study supports the longstanding request from environmental justice areas and local organizations for location-specific solutions that center CBGs with less PCE distributed and more accessibility disparities.

A limitation of this study is that we used air temperature data without considering the effect of air humidity. Researchers have indicated that urban heat islands may differ when considering humidity[49,50], potentially affecting our county selection. Additionally, no public datasets capture varying behaviors in accessing PCE at the CBG level. While census data detail commuting methods like driving, public transport, and walking at the CBG level, it wasn't used to infer PCE access. This decision was based on two reasons. First, accessing PCE differs significantly from commuting, often involving leisure activities post-work that are not captured by commuting data. Secondly, commuting to work is only a subset of people's PCE-related activities, primarily concentrated among people aged 20–60, while PCE encompasses people of all age groups. The reliability of road network data from OpenStreetMap, particularly for pedestrian paths, also poses a limitation. Despite its widespread academic use[51–53] and validations confirming its over 90% reliability for U.S. roads[54], accurately mapping all pedestrian routes remains challenging. People often take shortcuts through parking lots, parks, and trails, not always reflected in the data, introducing some uncertainty to our findings. In addition, our findings clearly demonstrate that driving reduces the accessibility gap to PCE compared to walking. The accessibility gap revealed by modes that represent a moderate economic burden theoretically would be smaller than those brought by walking but greater than those brought by driving. Therefore, we selected only driving (highest economic burden) and walking (lowest economic burden) as the modes of transportation, while excluding public transportation and cycling, which have relatively lower economic burdens. We also acknowledge that such considerations may negatively impact the comprehensiveness and generalizability of the results.

The primary purpose of this study is to examine inequalities in PCE accessibility based on race/ethnicity, behavioral patterns and income within racial/ethnic groups, so we did not consider the differences in lifestyle and inherent features of different people. We suggest a more refined analysis for a specific group of heat-exposed vulnerable people, such as the over-65s[55], pregnant women, and the homeless, and after considering the above multiple scenarios and effect simulations, so that the conclusions drawn can characterize the distribution of more vulnerable groups.

Methods
County selection
This study spotlights PCE inequality of access based on race/ethnicity, income, and travel behavior in the United States. As urban areas concentrate large populations and are often site of socio-spatial inequity[56,57], urban PCE accessibility inequalities are urgent and need to be uncovered. Therefore, our counties were selected from metropolitan counties, which refers to counties located in metropolitan statistical areas (MSAs), according to the 2013 NCHS Urban-Rural Classification Scheme for Counties (the most recent version to date) from Centers for Disease Control and Prevention (CDC)[58].

Specifically, our county selection layer is a hybrid layer consisting of nine divisions delineated by the United States Census Bureau (USCB) and 344 climate regions delineated by the National Oceanic and Atmospheric Administration (NOAA). We mapped the average summer June-August air temperature data for all counties between 2014–2023 onto the layer. We segmented the air temperature into five equal intervals, i.e., from 56.0–91.7 °F, each interval 7.1 °F. Finally, we ensured that no fewer than two Metropolitan counties were taken from each part of the intersection of the 9 major regions from the USCB and the 5 regions of air temperature.

Overall, we selected 40 representative counties from different demographic, geographic, and air temperature regions, and the Supplementary Table 1 shows the full list of the 40 counties selected for this study.

Accessibility assessment
This study employed a special form of a gravity-based model, a modified two-step floating catchment area (M2SFCA) method, to measure PCE accessibility at the CBG level of 40 U.S. counties, respectively. Compared with the traditional accessibility calculation method (based on cumulative opportunity[59,60], gravity[61,62], and 2SFCA[63–65]), the M2SFCA method can better consider the demand and supply of the realities to be used to describe the overall "efficiency" of spatial accessibility[51]. Specifically, we used the total population to represent the demand capacity of each CBG; for TCGS, we used the tree canopy cover area of each CBG to represent its supply capacity, for ERPE and NERPE, we used the floor area to represent its supply capacity. PCE accessibilities were calculated in two steps based on Eqs. (1, 3):

Step 1: For every CBG i, we find PCE j whose centroid is within half an hour's distance buffer (by walking or driving) from the centroid of CBG i and calculate the PCE supply-to-demand ratio S_{ij} within the buffer from the centroid of CBG i:

$$S_{ij} = \frac{c_j * w_{ij}}{\sum_{i \in p_i} w_{ij} * p_i} \tag{1}$$

where S_{ij} is the supply-to-demand ratio for PCE j to CBG i, c_j is the supply capacity of the PCE j; p_i represents the demand situation of the CBG i; w_{ij} represents the weight between the CBG i and the PCE j. In this study, w_{ij} is calculated by the Gaussian function, shown as follows:

$$w_{ij} = e^{\left(-\frac{(d_{ij}-\mu)^2}{2\sigma^2}\right)} \tag{2}$$

where d_{ij} is the shortest travel time between the CBG i and the PCE j, which is calculated by Origin-Destination Matrix (O.D. Matrix) using the QNEAT3 library for QGIS 3.8. We consider travel modes involving walking and driving, the vehicle speed is set according to the American road speed limit standard, and the walking speed is set at 5 km/h, we also deleted travel time pairs which values are more than 30 min; μ is the expectation value of Gaussian distribution and set to 0 here, that means, the accessibility gradually decreases from the first minute; σ^2 is the variance, which is obtained according to the desired distance decay effect, In this paper, the weight of catchment boundary set at 30 min is reduced to 0.2, and σ^2 is calculated as 125.

Step 2: For each CBG i, search all CBGs with PCE whose centroids are within half an hour's distance buffer (by walking or driving) from the centroid of CBG i and weighted sum up the supply-to-demand ratios for PCE j to CBG i calculated from step 1, S_{ij}, at these CBGs:

$$A_i = \sum_{j \in c_j} S_{ij} * w_{ij} \tag{3}$$

where A_i is the PCE accessibility for CBG i.

Differentiated access investigation
Initially, we applied statistical analysis to explore the variance in PCE access across different racial/ethnic groups. We identified CBGs in which the race/ethnicity is overrepresented for each group (Hispanic or Latino, non-Hispanic White, Black, American Indian, Asian) for our analysis. For instance, in the case of non-Hispanic Whites, we calculated the proportion of White people (dividing the population of White people by the total CBG population) across CBGs in 40 U.S. counties. We then established a threshold using the average proportion (approximately 42%) and included only those CBGs where the White people exceeded this threshold for further analysis. This process allowed us to calculate the average PCE accessibility for CBGs with an overrepresentation of each racial/ethnic group. The same methodology was applied to determine the margins for other racial/ethnic groups.

In order to validate the robustness of the racial PCE accessibility inequality results, we computed the above statistical methods alongside the population-weighted PCE accessibility for the 5 racial/ethnic groups, respectively. Specifically, the calculation was conducted based on Eq. (4).

$$A_g = \frac{\sum_{i \in p_{icounted}} p_g * A_i}{\sum_{i \in p_{icounted}} p_g} \quad (4)$$

where A_g is the population-weight PCE accessibility for the specific race/ethnicity g; p_g is the population for the specific race/ethnicity g of counted CBGs; A_i is the PCE accessibility for CBG i.

Moreover, we also took into account how behavioral patterns affect PCE accessibility. Using Census data on vehicle availability, we treated the population with More than or equal to one vehicle as accessing PCE by driving and computed the proportion of such people in each CBG's overall population. For the population without a vehicle, we treated PCE as accessible by walking and computed the proportion in a manner similar to that described above. Then, the behavior-weighted PCE accessibility was calculated based on Eq. (5).

$$A_{bw} = \sum_{i \in p_i} A_{iwalk} * f_{iwalk} + A_{idrive} * f_{idrive} \quad (5)$$

where A_{bw} is the behavior-weighted PCE accessibility for selected counties; A_{iwalk} is the PCE accessibility of CBG i by means of walking; f_{iwalk} is the proportion of the population in CBG i by means of walking; A_{idrive} is the PCE accessibility of CBG i by means of driving; f_{iwalk} is the proportion of the population in CBG i by means of driving. We conducted statistical analysis using the same post-processing as the PCE accessibility obtained by the previous two travel modes after computing the behavior-weighted PCE accessibility.

Finally, we conducted a simple linear regression model based on ordinary least squares (OLS) to examine income-based disparities in PCE accessibility within each race/ethnicity. Specifically, the horizontal coordinate is the income within a specific race/ethnicity and the vertical coordinate is the value of PCE accessibility, and the above data are taken as logarithms with a base of 10 to reduce the effect of extreme values.

To validate and demonstrate detailed intra-racial income-based PCE accessibility inequality results, we also conducted a statistical method for five race/ethnic groups based on income deciles. Specifically, the horizontal coordinate is the income decile within a specific race/ethnicity and the vertical coordinate is the value of PCE accessibility, and the PCE accessibility data are taken as logarithms with a base of 10.

All of the above data analyses were done utilizing python 3.9 with libraries such as pandas, numpy, matplotlib, sklearn, and statsmodels, except as noted above of O.D. Matrix.

Reporting summary
Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
All data aggregated or analyzed in the current study are available from the corresponding author on reasonable request. In this study, all the data utilized was obtained from public datasets. There are four main sources of datasets: First, datasets from the United States Census Bureau, including 1) geodatabases of 2020 TIGER/Line shapefiles for US Geographical boundaries at CBG level (https://www.census.gov/geographies/mapping-files/2020/geo), which were used to determine the exact location and boundaries of CBG in 40 US Counties, 2) Demographic information dataset from the decennial census for 2020 (https://data.census.gov), containing CBG-level population, racial/ethnic percentage, income and vehicle availability information, which were used to preliminary linear regression and statistical analysis; second, the air temperature data of contiguous U.S. from the National Oceanic and Atmospheric Administration (NOAA), which contains air temperature data of 344 climate

divisions since 1895 (https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance), and we collected the average summer June-August air temperature data between 2014–2023; third, the Multi-Resolution Land Characteristics (MRLC) Consortium U.S. Forest Service (USFS) Enterprise Data Warehouse CONUSS TCC 2016 NLCD dataset (https://www.mrlc.gov/), which contains 30 m*30 m accuracy tree canopy cover data, we used these data to represent TCGS supplement and aggerated them at the CBG-level in our study area; fourth, datasets from OpenStreetMap (https://www.openstreetmap.org), which is widely used for academic purposes[51], including 1) public facilities dataset, which contains NERPE and ERPE information, including location and area, 2) road networks dataset, which contains road networks both in the walking and driving scenarios, they were all used to calculate the shortest travel time and accessibility between each pair of CBG and PCE.

Code availability
Codes to replicate all analyses in the paper are available at https://github.com/CLi-hub1/Behavior-encoded-Models-reveal-inequity.

References
1. He, C. et al. The inequality labor loss risk from future urban warming and adaptation strategies. *Nat. Commun.* **13**, 3847 (2022).
2. Vaidyanathan, A. & Malilay, J. Heat-Related Deaths — United States, 2004–2018. *MMWR Morb. Mortal Wkly Rep.* **69**, 729–734 (2020).
3. Somanathan, E., Somanathan, R., Sudarshan, A. & Tewari, M. The impact of temperature on productivity and labor supply: evidence from indian manufacturing. *J. Polit. Econ.* **129**, 1797–1827 (2021).
4. Rocklöv, J. & Forsberg, B. The effect of temperature on mortality in Stockholm 1998–2003: a study of lag structures and heatwave effects. *Scand. J. Public Health* **36**, 516–523 (2008).
5. Kalkstein, L. S., Greene, S., Mills, D. M. & Samenow, J. An evaluation of the progress in reducing heat-related human mortality in major U.S. cities. *Nat. Hazards* **56**, 113–129 (2011).
6. Vanos, J. K., Kalkstein, L. S. & Sanford, T. J. Detecting synoptic warming trends across the US Midwest and implications to human health and heat-related mortality. *Int. J. Climatol.* **35**, 85–96 (2015).
7. Easterling, D. R. et al. Climate extremes: observations, modeling, and impacts. *Science* **289**, 2068–2074 (2000).
8. Lopez, H. et al. Early emergence of anthropogenically forced heat waves in the western United States and Great Lakes. *Nat. Clim. Change* **8**, 414–420 (2018).
9. Meehl, G. A. & Tebaldi, C. More intense, more frequent, and longer lasting heat waves in the 21st Century. *Science* **305**, 994–997 (2004).
10. Coumou, D. & Robinson, A. Historic and future increase in the global land area affected by monthly heat extremes. *Environ. Res. Lett.* **8**, 034018 (2013).
11. Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C. & Vandenbergh, M. P. Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proc. Natl. Acad. Sci.* **106**, 18452–18456 (2009).
12. Przychodzen, W. & Przychodzen, J. Determinants of renewable energy production in transition economies: A panel data approach. *Energy* **191**, 116583 (2020).
13. Jay, O. et al. Reducing the health effects of hot weather and heat extremes: from personal cooling strategies to green cities. *Lancet* **398**, 709–724 (2021).
14. Bouchama, A. et al. Prognostic factors in heat wave–related deaths: a meta-analysis. *Arch. Intern. Med.* **167**, 2170–2176 (2007).
15. Luber, G. & McGeehin, M. Climate change and extreme heat events. *Am. J. Prev. Med.* **35**, 429–35 (2008).
16. Semenza, J. C. et al. Heat-related deaths during the July 1995 heat wave in Chicago. *N. Engl. J. Med.* **335**, 84–90 (1996).

17. Vandentorren, S. et al. August 2003 heat wave in France: risk factors for death of elderly people living at home. *Eur. J. Public Health* **16**, 583–91 (2006).

18. Berisha, V. et al. Assessing adaptation strategies for extreme heat: a public health evaluation of cooling centers in Maricopa County, Arizona. *Weather Clim. Soc.* **9**, 71–80 (2017).

19. White-Newsome, J. L. et al. Strategies to reduce the harmful effects of extreme heat events: a four-city study. *Int. J. Env. Res. Public Health* **11**, 1960–88 (2014).

20. Nayak, S. G. et al. Surveying local health departments and county emergency management offices on cooling centers as a heat adaptation resource in New York State. *J. Commun. Health* **42**, 43–50 (2017).

21. Alberini, A., Gans, W. & Alhassan, M. Individual and public-program adaptation: coping with heat waves in five cities in Canada. *Int. J. Env. Res. Public Health* **8**, 4679–701 (2011).

22. Cusack, L., van Loon, A., Kralik, D., Arbon, P. & Gilbert, S. Extreme weather-related health needs of people who are homeless. *Aust. J. Prim. Health* **19**, 250–5 (2013).

23. Kovats, R. S. & Kristie, L. E. Heatwaves and public health in Europe. *Eur. J. Public Health* **16**, 592–599 (2006).

24. Ghorbanzadeh, M., Kim, K., Erman Ozguven, E. & Horner, M. W. Spatial accessibility assessment of COVID-19 patients to healthcare facilities: A case study of Florida. *Travel Behav. Soc.* **24**, 95–101 (2021).

25. Kim, K. & Kwon, K. Time-varying spatial accessibility of primary healthcare services based on spatiotemporal variations in demand, supply, and traffic conditions: A case study of Seoul, South Korea. *J. Transp. Health* **27**, 101531 (2022).

26. Liu, D., Kwan, M.-P. & Kan, Z. Analysis of urban green space accessibility and distribution inequity in the City of Chicago. *Urban For. Urban Green.* **59**, 127029 (2021).

27. Luqman, M. & Khan, S. U. Geospatial application to assess the accessibility to the health facilities in Egypt. *Egypt. J. Remote Sens. Space Sci.* **24**, 699–705 (2021).

28. Poklewski-Koziełł, D., Dudzic-Gyurkovich, K. & Duarte, C. M. Investigating urban form, and walkability measures in the new developments. The case study of Garnizon in Gdansk. *Land Use Policy* **125**, 106471 (2023).

29. Zhou, S., Chen, F. & Xu, Z. Evaluating the accessibility of urban parks and waterfronts through online map services: A case study of Shaoxing, China. *Urban For. Urban Green.* **77**, 127731 (2022).

30. Wang, S., Yung, E. H. K. & Sun, Y. Effects of open space accessibility and quality on older adults' visit: Planning towards equal right to the city. *Cities* **125**, 103611 (2022).

31. Caragliu, A. & Del, Bo, C. F. Smart cities and the urban digital divide. *Npj Urban Sustain.* **3**, 43 (2023).

32. Dai, D. Black residential segregation, disparities in spatial access to health care facilities, and late-stage breast cancer diagnosis in metropolitan Detroit. *Health Place* **16**, 1038–1052 (2010).

33. Russell, E., Kramer, M. R., Cooper, H. L. F., Thompson, W. W. & Arriola, K. R. J. Residential racial composition, spatial access to care, and breast cancer mortality among women in Georgia. *J. Urban Health* **88**, 1117–1129 (2011).

34. Chang, C.-R., Li, M.-H. & Chang, S.-D. A preliminary study on the local cool-island intensity of Taipei city parks. *Landsc. Urban Plan.* **80**, 386–395 (2007).

35. Chow, W. T. L., Pope, R. L., Martin, C. A. & Brazel, A. J. Observing and modeling the nocturnal park cool island of an arid city: horizontal and vertical impacts. *Theor. Appl. Climatol.* **103**, 197–211 (2011).

36. Zhang, Y., Murray, A. T. & Turner, B. L. Optimizing green space locations to reduce daytime and nighttime urban heat island effects in Phoenix, Arizona. *Landsc. Urban Plan.* **165**, 162–171 (2017).

37. Spronken-Smith, R. A. & Oke, T. R. The thermal regime of urban parks in two cities with different summer climates. *Int. J. Remote Sens.* **19**, 2085–2104 (1998).

38. Wong, N. H. & Yu, C. Study of green areas and urban heat island in a tropical city. *Habitat Int.* **29**, 547–558 (2005).

39. Vanos, J. K. et al. Human energy budget modeling in urban parks in toronto and applications to emergency heat stress preparedness. *J. Appl. Meteorol. Climatol.* **51**, 1639–1653 (2012).

40. Delamater, P. L. Spatial accessibility in suboptimally configured health care systems: A modified two-step floating catchment area (M2SFCA) metric. *Health Place* **24**, 30–43 (2013).

41. Dejen, A., Soni, S. & Semaw, F. Spatial accessibility analysis of healthcare service centers in Gamo Gofa Zone, Ethiopia through Geospatial technique. *Remote Sens. Appl. Soc. Environ.* **13**, 466–473 (2019).

42. Ochoa, C. et al. Vulnerability to snakebite envenoming and access to healthcare in the Terai region of Nepal: A geospatial analysis. *Lancet Reg. Health - Southeast Asia* **9**, 100103 (2023).

43. Kotavaara, O. et al. Geographical accessibility to primary health care in Finland – Grid-based multimodal assessment. *Appl. Geogr.* **136**, 102583 (2021).

44. Litman, T. Evaluating accessibility for transportation planning. Victoria Transport Policy Institute; Victoria, Canada (2008). http://www.vtpi. org/access.pdf.

45. Davis, L., Gertler, P., Jarvis, S. & Wolfram, C. Air conditioning and global inequality. *Glob. Environ. Change* **69**, 102299 (2021).

46. Pavanello, F. et al. Air-conditioning and the adaptation cooling deficit in emerging economies. *Nat. Commun.* **12**, 6460 (2021).

47. Furszyfer Del Rio, D. D., Sovacool, B. K., Griffiths, S., Foley, A. M. & Furszyfer Del Rio, J. A cross-country analysis of sustainability, transport and energy poverty. *Npj Urban Sustain.* **3**, 41 (2023).

48. Roberts, J. D., Mandic, S., Fryer, C. S., Brachman, M. L. & Ray, R. Between privilege and oppression: an intersectional analysis of active transportation experiences among Washington D.C. Area Youth. *Int. J. Environ. Res. Public. Health* **16**, 1313 (2019).

49. Chakraborty, T., Venter, Z. S., Qian, Y. & Lee, X. Lower urban humidity moderates outdoor heat stress. *AGU Adv.* **3**, e2022AV000729 (2022).

50. Chakraborty, T. C., Newman, A. J., Qian, Y., Hsu, A. & Sheriff, G. Residential segregation and outdoor urban moist heat stress disparities in the United States. *One Earth* **6**, 738–750 (2023).

51. Xue, J. et al. Quantifying the spatial homogeneity of urban road networks via graph neural networks. *Nat. Mach. Intell.* **4**, 246–257 (2022).

52. Kirkley, A., Barbosa, H., Barthelemy, M. & Ghoshal, G. From the betweenness centrality in street networks to structural invariants in random planar graphs. *Nat. Commun.* **9**, 2501 (2018).

53. Higgs, C. et al. Policy relevant health related liveability indicator datasets for addresses in Australia's 21 largest cities. *Sci. Data* **10**, 113 (2023).

54. Barrington-Leigh, C. & Millard-Ball, A. The world's user-generated road map is more than 80% complete. *PLoS One* **12**, e0180698 (2017).

55. Chen, M. et al. Rising vulnerability of compound risk inequality to ageing and extreme heatwave exposure in global cities. *Npj Urban Sustain.* **3**, 38 (2023).

56. Caggiano, H., Kocakuşak, D., Kumar, P. & Tier, M. O. U.S. cities' integration and evaluation of equity considerations into climate action plans. *Npj Urban Sustain.* **3**, 50 (2023).

57. Lenzi, C. & Perucca, G. Economic inequalities and discontent in European cities. *Npj Urban Sustain.* **3**, 26 (2023).

58. Ingram, D. D. & Franco, S. J. 2013 NCHS Urban-Rural Classification Scheme for Counties. *Vital Health Stat. 2,* 1–73 (2014).

59. Widener, M. J. Comparing measures of accessibility to urban supermarkets for transit and auto users. *Prof. Geogr.* **69**, 362–371 (2017).

60. El-Geneidy, A. et al. The cost of equity: Assessing transit accessibility and social disparity using total travel cost. *Transp. Res. Part Policy Pract.* **91**, 302–316 (2016).

61. Liu, D. & Kwan, M.-P. Measuring spatial mismatch and job access inequity based on transit-based job accessibility for poor job seekers. *Travel Behav. Soc.* **19**, 184–193 (2020).

62. Wu, C., Ye, X., Du, Q. & Luo, P. Spatial effects of accessibility to parks on housing prices in Shenzhen, China. *Habitat Int.* **63**, 45–54 (2017).

63. Luo, W. & Wang, F. Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region. *Environ. Plan. B Plan. Des.* **30**, 865–884 (2003).

64. Luo, W. & Qi, Y. An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. *Health Place* **15**, 1100–1107 (2009).

65. Ye, C., Hu, L. & Li, M. Urban green space accessibility changes in a high-density city: A case study of Macau from 2010 to 2015. *J. Transp. Geogr.* **66**, 106–115 (2018).

Author contributions
C.F., X.S. and H.H. designed the research; C.L., X.S., C.F. and H.H performed the research; C.L. collected and analyzed data; C.L., C.F. and X.S. wrote the paper.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary information The online version contains

supplementary material available at https://doi.org/10.1038/s42949-024-00157-w.

Correspondence and requests for materials should be addressed to Xing Su or Chao Fan.

Reprints and permissions information is available at http://www.nature.com/reprints

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