Socio-demographic Inequalities in the Impacts of Extreme Temperatures on Population Mobility

Abstract:

Extreme temperatures are occurring more frequently and intensely, leading to more significant impacts on a variety of populations in the world as climate change continues. Little research to date, however, has investigated the temporal, spatial, and social patterns in which human mobility responds to extreme temperatures from the perspective of regional heterogeneity. This study, taking the Greater Houston area in the United States as a testbed, conducted statistical and geospatial analyses to measure the unequal impacts of extreme temperatures on human mobility in cities. In particular, the changes in daily human mobility across dimensions (i.e., temperatures, spatial gradients, and social relationships) when experiencing extreme temperatures are examined. The results show that extreme heat inhibits people's willingness to make short trips, while cold weather promotes more frequent short trips. Besides, extreme temperatures impede the mobility of people near the city center while promoting movement to the suburbs. Furthermore, the areas with large numbers of disadvantaged social groups were more likely to be affected by extreme temperatures. The socio-demographic inequalities in the impacts of extreme temperatures quantified in this study could promote more scientific, targeted, and practical policy planning and implementation by local governments.

Keywords:

Extreme Weather; Human Mobility; Environmental Equity; Climate Change Adaptation; Regional Sustainability

1. Introduction

As climate change progresses, extreme events' frequency, intensity, and impact continue to increase. Over the past period, extreme temperatures have had devastating and deadly results worldwide, causing heatwaves, droughts, and wildfires (Klingelhöfer et al., 2023; van Hove et al., 2015; K. Zhang et al., 2015). In some regions, temperatures have soared to record-breaking levels, posing severe threats to human health, agriculture, and ecosystems(Clarke et al., 2022; Klingelhöfer et al., 2023). In the Houston region of the US, for example, five of the six hottest July months on record in Houston occurred after 2009, according to data from the National Weather Service 2022 survey. Heat waves have harmed the coastline, built environment, open water, and vegetation (K. Zhang et al., 2015). Houston is not an isolated case; extreme temperatures have threatened many cities around the globe in recent years. And the frequency, intensity, duration, and measured temperatures of these extreme events are increasing (Debbage & Shepherd, 2015; Klingelhöfer et al., 2023). Given that extreme temperatures have a wide range of potential societal impacts, quantifying the costs of these complex changes continues to be a significant barrier to an accurate assessment of the effects of climate change. Thus, local authorities and planning practitioners must come together to recognize cities' adaptation and resilience strategies to extreme temperatures.

Although many different aspects of cities may be experiencing the adverse effects of extreme temperatures, these effects are closely linked to human mobility in cities. They are ultimately reflected in human mobility and will persist. Human mobility in cities is the interaction between individuals and their physical environment (e.g., urban form, transport facilities, public resources). It is how individuals access various city resources and opportunities (X. Zhang & Li, 2022). It is worth noting that there have been many studies showing a strong correlation between urban human mobility and extreme temperatures. Due to their high degree of uncertainty, scale, irreversibility, and disruptiveness, extreme temperatures can cause significant disturbances to human mobility patterns (F. Zhang et al., 2019). For instance, Hatchett et al. (2021) found substantial reductions in mobility and varying increases in homebound populations when examining county-level population mobility responses in the US during extreme events, including wildfires and hurricanes. Similarly, F. Zhang et al. (2019) confirmed that extreme temperatures can disrupt the regular daily travel of urban residents by quantitatively assessing the trajectories of all taxis and buses in a major Chinese city during record-breaking rainstorms and snowstorm events. As temperatures become more extreme, people are forced to adapt and change their travel plans regarding their daily arrangements, resulting in large-scale mobility perturbation in the city.

In addition, the impact of extreme temperatures on human mobility is not limited to physical relocation. It can also have various consequences based on communities' economic and social aspects (Wambura & Wong, 2023). A few studies have proved that mobility perturbation caused by extreme climate varies between individuals, and this variation is related to individual demographic attributes, home location, and travel preferences (X. Zhang & Li, 2022). For example, poor or disabled people may face additional obstacles when trying to relocate due to limited financial resources, lack of access to transportation, or discrimination (Kosanic et al., 2022). Besides, groups that own vehicles may be more resilient to weather extremes than groups that rely on transit systems for travel. Younger people with a more extraordinary ability to travel and move around will adapt to weather extremes more readily than older people. (Wambura & Wong, 2023). Therefore, it is essential to understand and appreciate the inequality of extreme temperatures from the perspective of human mobility using quantitative measures (Lee et al., 2022).

The impact of climate change on human mobility is multifaceted and may have direct effects, such as reduced mobility. For example, W. Li et al. (2022) found that, by documenting the spatial and temporal differences in mobility caused by extreme temperature events such as tropical storms and winter freezes, extreme temperatures, regardless of spatial resolution, caused changes in human mobility behavior to show a downward trend. However, only some existing studies have examined what social-demographic and spatial patterns are associated with human mobility responses to extreme temperatures from the perspective of urban heterogeneity. As the physical distribution of cities is much more aggregated in the urban centers than in the suburbs, there is a spatial gradient, and human mobility is also spatiotemporally heterogeneous across different gradient circles (Chang et al., 2022; Liu et al., 2022). Besides, the impact of climate change on human mobility may also be indirectly linked to the frequency of mobility and the level of social development (Beine & Jeusette, 2021), and studies have often classified populations from different perspectives (e.g., age, gender, socioeconomic indicators, etc.) to reveal hidden patterns of mobility in other climatic regions fully.

Hence, this study aims to identify changes in daily human mobility in different dimensions (temperatures, spatial gradients, and social relationships) in the Greater Houston area in the U.S. during extreme temperatures by assessing the inequalities in the impacts of extreme temperatures on human mobility in cities. We integrate temperature indices with human mobility data, allowing for a more detailed spatial description of climate and mobility variables, which has been shown to help identify impacts in demographic data (Schwerdtle et al., 2019; Zander et al., 2019). Such integration is essential for assessing temperature extremes, as it allows for a more specific understanding of the impacts on different areas of the city, enhances the identification of causal effects between temperature change and population activity, and is suitable for addressing fine-grained climate sensitivity identification. The findings will enrich the existing body of knowledge, provide new insights into the impact of extreme temperatures on human mobility, and inform more scientific decision-making for city managers.

2. Materials and Methods

2.1 Study Area

Extreme heat is a significant factor in weather-related human deaths in the United States (Borden & Cutter, 2008). Excessive heat disproportionately affects urban inhabitants because the built environment keeps cities warmer than nearby rural areas (D. Li & Bou-Zeid, 2013). The most vulnerable populations in cities are disproportionately affected by extreme heat, including the elderly, small children, socially isolated people, disabled groups, and people with pre-existing medical issues (Medina et al., 2006; Semenza et al., 1996; Uejio et al., 2011).

One of the representative areas of extreme temperatures is Greater Houston, which has been described as "the most air-conditioned city in the world" (Marsha et al., 2018). According to anecdotal evidence, Houston's July-August months saw more dramatic temperature patterns than 40 years earlier (Carney et al., 2020). In July 2022, the National Weather Service recorded record high temperatures in Houston, 103 degrees, and warned people to stay indoors if possible. According to the data provided by the National Oceanic and Atmospheric Administration (NOAA) and preliminary findings on the temperature vector from the Houston station (Carney et al., 2020), the mean and variance of temperature maxima after 1981 appear to have changed significantly. Other researchers have noted an increase in higher temperature outliers since 1980, claiming that this rise in temperature extremes is caused by greenhouse gases produced by humans (Hansen et al., 2012; Meehl et al., 2016; Menne et al., 2012; Portmann et al., 2009).

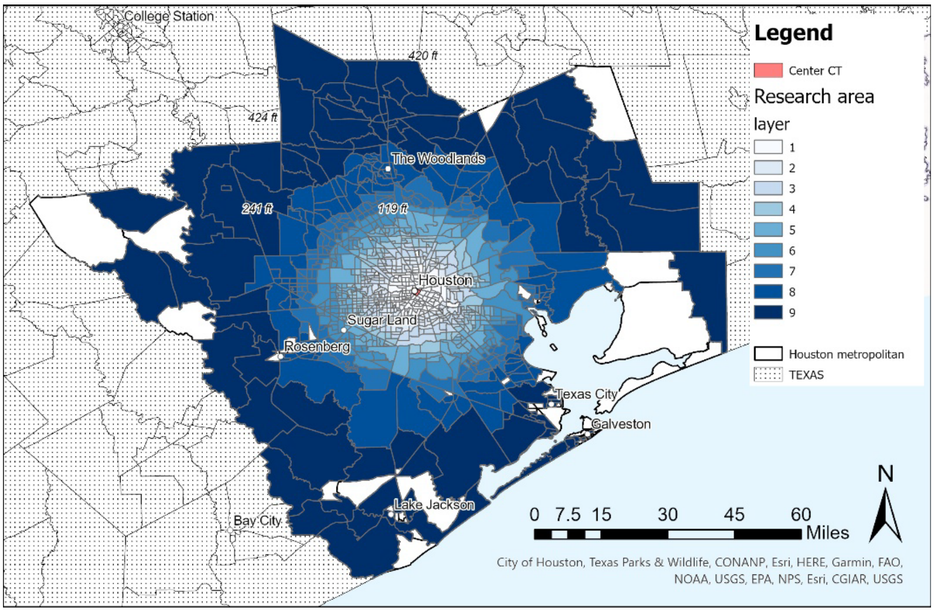

Fig. 1. Greater Houston, Texas, with counties and census tracts, 2019.

Greater Houston has a humid subtropical temperature typical of the Southern United States and is rainy most of the year. Most of the year, the dominant winds are from the south and southeast, which bring heat and moisture from the surrounding Gulf of Mexico and the Galveston Bay region. The temperature impact assessment for Houston shows that hot and humid weather is typical within Greater Houston (Chakraborty et al., 2019). In addition to global warming and greenhouse gas emissions, this natural climatic condition also significantly contributes to frequent extreme temperature events, impacting people's daily travel and life.

Therefore, this study researched Greater Houston (see Fig. 1), officially known as Houston-The Woodlands-Sugar Land, which serves as the study's research region. The Greater Houston is in southeast Texas, spans roughly 26,061 square kilometers, and consists of nine counties and 1,098 census units. Following the Dallas-Fort Worth metroplex in terms of population, Greater Houston is the second-most populous region in Texas, with an estimated population of 6,997,384 as of the 2018 census and 7,122,240 by 2020 (Griego et al., 2020). In this study, we examine 1028 census tracts (CTs) in the Greater Houston area for two extreme temperatures (extreme high and extremely low temperatures) phases throughout 2019 and their gradients along with spatial and social attributes of the census tracts to gain a better understanding of the unequal impacts of extreme events on population mobility.

2.2 Data Collection

We collected three data sets, including human mobility data, meteorological data, and social data for the Greater Houston area in the entire 2019 period. All data is source-checked, desensitized, and cleaned.

Numerous academic fields have extensively researched human mobility, including geography, transportation, urban planning, physics, and computer sciences (Barbosa et al., 2018). It depicts patterns of how people move from place to place and is a predictor of socioeconomic circumstances and human behavior. Large-scale mobile phone data offers a previously unheard-of possibility for tracking human trajectories, which aids research on human mobility patterns. This opportunity has been made possible by the rapid growth of information and communication technologies (ICT) and GPS-embedded devices.

The human mobility data used in this study is a regularly updated multi-scale dynamic human mobility dataset for the United States, derived from millions of anonymous cell phone user visits to various locations provided by SafeGraph and demographic data from ACS. The visits to different places by millions of anonymous mobile phone users that can be tracked by SafeGraph consist of two types of visitor flows, namely daily census block group (CBG) visits to CBGs and weekly CBG visits to points of interest (POIs). Kang et al., 2020 spatially link local visitors to administrative areas at three different spatial scales. Visitors' origin-destination (O-D) flow is calculated to provide a multi-scale view of population movement and spatial interaction patterns between other places. As SafeGraph detected a sample of approximately 10% of the entire population in terms of the number of mobile phone users, Kang et al., 2020 further used the ACS demographic data and the mobile phone data sample to infer the population level of dynamic O-D flows. Their study also verified the representativeness of the data by showing the consistent flow patterns between mobile phone data and census data. Hence, our study adopted this dataset to represent population fluxes between census tracts in Greater Houston to quantify the impacts of extreme temperatures on human mobility.

The meteorological data are a population-weighted at the county level, a spatially explicit database of daily heat metrics, including daily minimum, maximum, and mean values of ambient temperature, dewpoint temperature, net effective temperature, heat index, humidex, wet-bulb globe temperature, and the Universal Thermal Climate Index for counties across the United States (Spangler et al., 2022). This dataset is initially derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 Land product (ERA5-Land), calculated and verified by Spangler et al., 2022, using the nearest-neighbor interpolation and Liljegren approach. Daily minimum ambient temperature and daily maximum ambient temperature were primarily used in this study to measure extremely high and extremely low temperatures. The relationship between 2019 monthly minimum and maximum daily ambient temperatures and population fluxes in the Greater Houston area is shown in Fig 2.

The social data is the CDC/ATSDR Social Vulnerability, created by the ATSDR's Geospatial Research, Analysis & Services Program (GRASP) to help emergency response planners and public health officials identify and map the communities most likely to need support before, during, and after an extreme event. A few factors, including poverty, lack of access to transportation, and crowded housing, may weaken a community's ability to prevent human suffering and financial loss in a disaster. These factors are social vulnerability (Ramesh et al., 2022). The CDC/ATSDR SVI uses U.S. Census data to determine the social exposure of each census tract based on 16 social factors, including poverty, race, disabled population, and crowded housing. As this data is only available for even years, we selected six social indicators: percentage of persons below poverty estimate, unemployment rate estimate, percentage of persons aged 65 and older estimate, percentage of households with no vehicle available estimate, percentage of single-parent households with children under 18 estimate and percentage of mobile homes estimate.

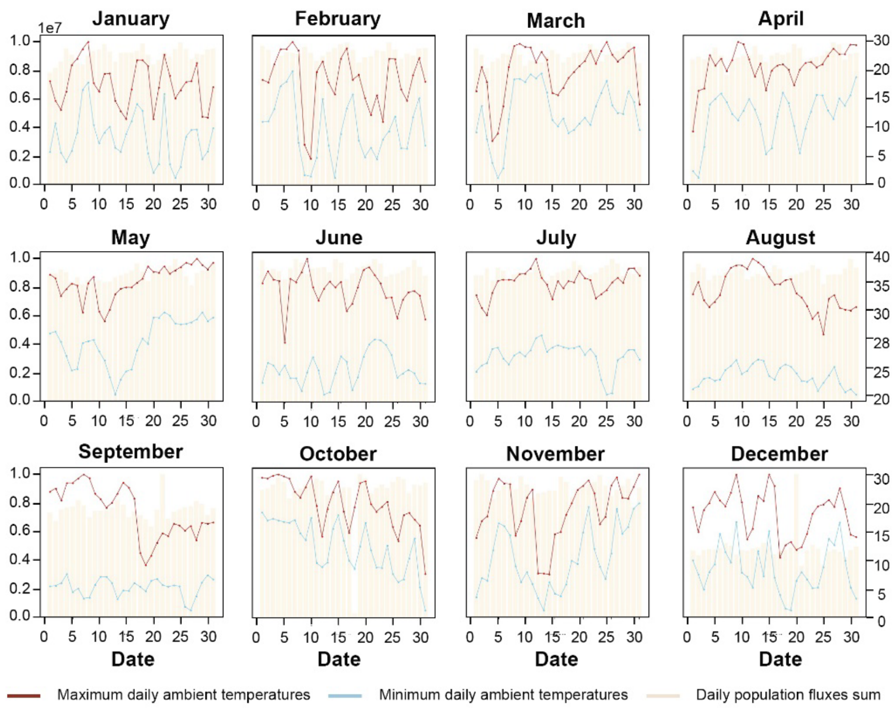

Fig. 2. The relationship between the monthly minimum and maximum daily ambient temperatures and population fluxes in the Greater Houston area, 2019.

2.3 Methods

This study examines the unequal impacts of extreme temperatures and human mobility. To do so, we conduct statistical experiments on demographic, economic, and spatial distance indicators correlating with extreme temperatures in the more excellent Houston, Texas, area to quantify the climate sensitivity of several population groups (see Fig. 3).

As a center, we take Houston City Hall (29°76' 01"N, 95°36' 94"W) in Downtown Greater Houston and divide the study area into several different circular areas by dividing concentric circles at equal distances outwards. The distance variable from the central location becomes the spatial gradient (Chang et al., 2022). In addition, we extend this idea of gradients to the division of population fluxes and socio-economic indicators; the detailed methods and formulas are described in detail later in this section. Therefore, this study investigates three dimensions, temperature impacts, spatial gradient, and social relationships, to analyze the effects of extreme temperatures on human mobility in cities. We quantify the impacts of extreme events utilizing statistical and spatial analyses of historical climate information.

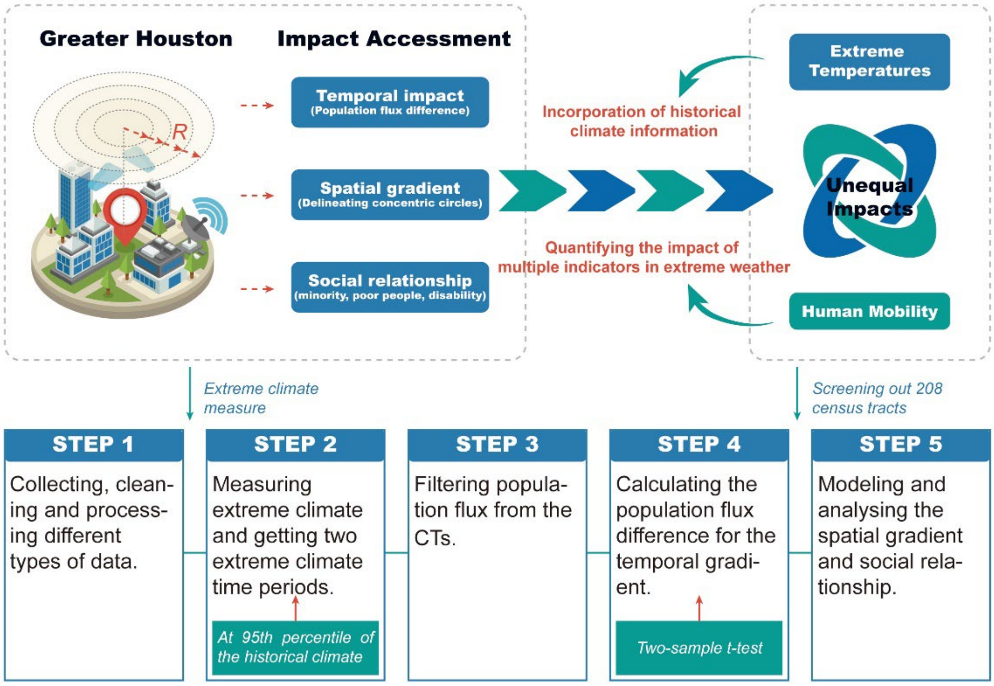

Fig. 3. The framework of this study.

Measuring extreme temperatures. The impacts of climate change vary across time scales and spatial and social characteristics. Quantifying the effects of these complex changes remains an essential barrier to thoroughly assessing the impacts of climate change, especially given that extreme temperatures have a wide range of potential societal impacts. Traditional meteorological statistics assume that the probability of different values of temperature at any location generally conforms to a Gaussian distribution, but extreme temperatures have non-Gaussian distribution characteristics, proven by many research (Qian et al., 2019; Sura, 2011), as we use a threshold approach to measure extreme high and low temperatures.

To do this, we calculate the number of days and temperatures above a range of critical thresholds to allow flexibility in identifying different channels of influence. The thresholds can be constants or a percentile (method) of the historical distribution of local daily rainfall. The latter allows us to implicitly interpret local adaptation to current climatic conditions (Kotz et al., 2022) so that multiple measures of the annual distribution of daily temperatures are necessary. Specifically, we calculate various estimates of the annual distribution of daily temperatures at the census tract (CT) level, including yearly and monthly total temperature values and measures of daily temperatures related to several critical thresholds. Then, we use the entire historical distribution to define percentile-based thresholds, essential for accurately assessing extremes. The vital thresholds are set at the 90th and 95th percentile of the cats' historical (2000-2020) daily temperature distribution. For a given year y and each threshold R_c, the number of days exceeding these values RD and the sum of the annual temperature values is calculated (equation (1)).

$$RD(R_c)_{x,y} = \sum_{d=1}^{D_y} R_{x,d} H\left(R_{x,d} - R_c\right) \tag{1}$$

where $R_{x,d}$ is the maximum or minimum temperature on census tracts x day d, D_y is the number of days in the given year, and H is the Heaviside step function. This step leads to different threshold measures of the annual distribution of daily temperature.

It has been verified that the temperature had not reached the extremes when the critical threshold was set to the 90th. Therefore, the critical threshold is set to the 95th, and only extreme high and low temperatures lasting three days or more are filtered out, excluding the effects of weekends or holidays. This setting results in two intense temperature periods, August 7 to August 13 in 2019 as the period of high maximum temperatures for five days, and March 4 to March 6 as extremely low minimum temperatures for three days. To control the accuracy of the experiment, the extreme temperatures that the study focused on did not occur with other extreme weather events. In addition, we set control weather groups for each of the two intense temperature periods (Table 1): the regular temperature periods selected for April, a month without extreme weather, and the regular temperature periods chosen for the month with extremely high temperatures. By setting up a control group and comparing the experimental group (extreme temperatures) with the control group to eliminate the influence of extraneous variables (e.g., daily tidal patterns, weekly long and short trips, etc.) on the experimental results, the credibility and accuracy of the results are enhanced.

Table. 1. The control weather groups for the two extreme temperature periods 2019.

	Testing periods	**Control periods**	
		Regular temperature period of the month without extreme weather	Regular temperature period of the month with extreme weather
Extreme heat (Tmax)	**08/07 - 08/13** (max 36.92℃, min 35.54℃)	**04/15 - 04/19** (max 24.40℃, min 21.60℃)	**08/19 - 08/23** (max 31.37℃, min 35.28℃)
Extreme cold (Tmin)	**03/04 - 03/06** (max 1.94℃, min -1.12℃)	**04/15 - 04/17** (max 20.23℃, min 9.83℃)	**03/11 - 03/13** (max 20.12℃, min 19.94℃)

Population flux measures. For the refined simulation evaluation of human mobility, the method based on the origin-destination (OD) matrix estimation, referred to as OD data, has become a standard microscopic transport simulation model. The OD data record the daily population flux between the two CTs. Notably, the population flux was calculated based on the human mobility data that collects the

GPS locations of mobile devices in real-time and reflects the movements of mobile devices from one place (origin) to another (destination). Here, we use CTs as the units of locations, and the number of mobile devices moved from one census tract to another census tract is defined as the population flux for the specific pair of ODs. It can reflect the varying intensity and proximity of human activities daily. Hence, the study is based on collecting high-resolution OD data sufficient to assess traffic changes between different census tracts at different periods (Chiu et al., 2007).

We calculated the population flux between any pair of census tracts within the research area. We filter the total population flux from each CT to the others for each weather group and define the population flux parameters for each weather group into the following six parameters:

- $EHpop$ represents the population flux in extreme heat temperature periods.
- $RHpop$ represents the population flux in the regular temperature period of the month with extreme heat weather.
- $RDpop$ represents the population flux in the regular temperature period of the month without extreme heat weather.
- $ELpop$ represents the population flux in extreme cold temperature periods.
- $RLpop$ represents the population flux in the regular temperature period of the month with extreme cold weather.
- $RDpop'$ represents the population flux in the regular temperature period of the month without extreme cold weather.

Since not all CTs in the Greater Houston area had population fluxes between each other during the selected climatic periods, to make the range of CTs studied consistent, we took the six climatic groups to be concurrent with each other, resulting in 1028 outer CTs.

Temporal impact measures. Based on the population flux parameters obtained from the six different temperature periods, we first performed the population flux difference calculation within each extreme temperature group to get four new population flux parameters (equation (2) - (5)).

$$popH = EHpop - RDpop \tag{2}$$

$$popR = RHpop - RDpop \tag{3}$$

$$popL = ELpop - RDpop' \tag{4}$$

$$popR' = RLpop - RDpop' \tag{5}$$

where the $popH$ represents the population flux difference between the extreme heat temperature periods and regular temperature periods of the month without extreme heat weather, the $popR$ represents the population flux difference between regular temperature period of the month with extreme heat weather and regular temperature periods of the month without extreme heat weather; the $popL$ represents the population flux difference of extreme cold temperature periods and regular temperature periods of month without extreme cold weather, and the $popR'$ represents the population flux difference of regular temperature periods of the month with extreme cold weather and regular temperature periods of the month without extreme cold weather.

Next, the Z-scores are used to clean the data extreme values of $popH$, $popR$, $popL$, and $popR'$. It helps us identify and manage outliers, which can significantly impact statistical analyses and modeling. Besides, by transforming variables into a common scale with a mean of 0 and a standard deviation of 1, Z-scores ensure that variables are measured consistently, allowing for meaningful comparisons.

Then, we perform a two-sample t-test on $popH$ & $popR$ and $popL$ & $popR'$. When two samples are selected independently of each other, the two-sample t-test (equation (6)) is often chosen to check whether the difference between the means of the two totals is equal to some predetermined value (FRALICK et al., 2017). This test can be used to check whether the two groups are different from each other. This difference between the data sets is tested by the p-value (Keselman et al., 2004), which is the probability (calculated under the assumption that the null hypothesis is true) that the test statistic will produce values at least as extreme as the t-score made for your sample (equation (7)).

$$T = \frac{X_1 - X_2}{\sqrt{\left(\frac{1}{n_0}\right) + \frac{1}{n_1}\frac{(n_0-1)S_0^2 + (n_1-1)S_1^2}{n_0+n_1-2}}} \tag{6}$$

where n_0 is the first sample size, n_1 is the second sample size; X_1 is the mean for the first sample, X_2 is the mean for the second sample; and S_0 is the standard deviation in the first sample, S_1 is the standard deviation in the second sample. When n_0 and n_1 are both large enough, the distribution of T can be safely approximated by standard normal distribution.

$$p - value = 2 * cdf_{t,d}(-|T|) \tag{7}$$

where cdf means the Cumulative Distribution Function.

Spatial gradient and socio-economic relationship measures. Spatial gradient has been used in several fields, such as biology (Moseley et al., 2009), fluid dynamics (Sakamoto et al., 2010), and earth sciences (Fan et al., 2020), and has been defined differently by different disciplines. In this study, we define a spatial gradient as a central subdivision of the urban spatial structure, where each subdivision has dynamically changed urban spatial components, including population concentration, commercial distribution, and industrial layout, because it is at a different gradient (i.e., radius from the city center). These components can be modeled as a gradient model to simulate their density profile, determined by a combination of urban attributes (e.g., land rent, population, and people's environmental preferences) and external attributes (e.g., social factors and environmental influences).

We refer to the gradient model of cities proposed by Chang et al., 2022, which divides the spatial structure of cities into equidistant gradient radio and establishes mathematical relationships and statistical models for the complex drivers (population density, social factors) behind each level of urban structure. Chang et al., 2022 concluded that in urban centers, where the population is much higher than in the urban fringe and rural areas, the best place for regression of population density is the distance from the city center to the rural areas. Hence, the distance to the city center can imply the level of urbanization, which reflects the population density and various elements such as urban facilities and landscape. In urban planning research, distance from the city center is typical and accepted as a proxy for quantifying urbanization (Chang et al., 2022; Mcintyre et al., 2000; Ortiz-Báez et al., 2021).

This study calculated the distances from each CT to the central CT based on the specific extent of the Greater Houston area. It divided them into nine radius layers based on the distance, and the CTs corresponding to each layer are shown in Figure 1. The data were then linearly fitted using the spatial gradient distances as the horizontal axis and the population flux difference as the vertical axis. Based on such data analysis, it is possible to understand that CTs with different spatial gradients exhibit distinct activity differences in extreme weather.

Similarly, social gradients are often defined as the different probability of mobility for professional socio-economic classes versus middle or lower socio-economic classes. Most studies have found that spatial mobility may be greater among those with higher socio-economic status due to superior migration resources and potentially more significant migration incentives (Catney & Simpson, 2010). Social gradients can more richly explain the different responses of social groups in the face of the same extreme temperatures due to their differential conditions, and this paper considers the relationship between mobility and socio-economic classes to understand better whether there is a more significant negative impact of extreme temperatures on disadvantaged and vulnerable populations.

The study integrated the OD data based on the original CTs, calculated the mean of the population fluxes, and then connected it to the sociability indicator data for each CT. Each social indicator is divided into corresponding intervals according to its value. The logarithm of the population flux difference was taken, with the social gradient as the horizontal axis and the logarithm of the population flux difference as the vertical axis, and the data were linearly fitted.

3 Results

In this case study, changes in human mobility in the Greater Houston area during extreme heat and extreme cold events are assessed using the four population flux parameters described in the method section, namely $popH$, $popL$, $popR$ and $popR'$. The results are interpreted from three perspectives, including comparisons between the two extreme temperatures, the spatial variation of population fluxes, and the social interpretations of population fluxes under extreme weather.

3.1 The inhibition of extreme temperatures

Statistical analyses of the four population flux parameters are shown in Fig 4, in which the more significant difference between $popH$ & $popR$ or between $popL$ & $popR'$, the more significant the impact of extreme weather on daily population flux. Intuitively, the overall population flux of the extreme weather group significantly differs from the non-extreme weather group, indicating that climate has a significant impact on population activity. Moreover, the average population flux of the extreme weather group is lower than that of the non-extreme weather group, suggesting an increase in travel disparity due to the weather. Lastly, the mean difference value for the highly high-temperature group is negative, while the mean difference value for the extremely low-temperature group is positive. This may be because, in the hot southern regions of the United States, the inhibitory effect of extremely high temperatures is significantly more potent than that of extremely low temperatures.

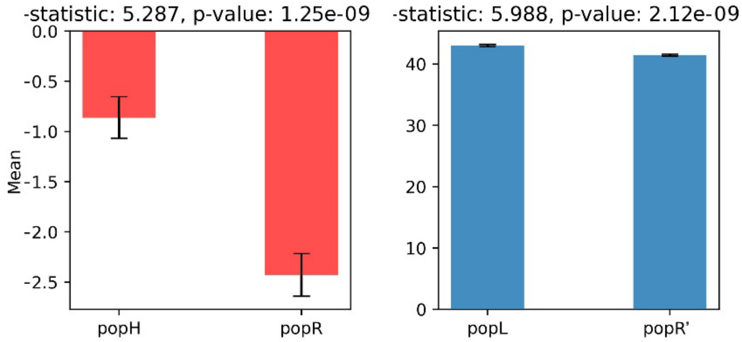

Fig. 4. The result of a two-sample t-test on $popH$ & $popR$ (left), and $popL$ & $popR'$ (right). Note, that the *p-value* < *0.001* indicates that the difference between the two data sets is significant.

While in the results of the two-sample t-test, the *p-value* of $popL$ & $popR'$ is 2.12e-09 and the *p-value* of $popH$ & $popR$ is 1.25e-09. Since the smaller *p-value* in the t-test proves that the difference between the two arrays is quite significant, which may show that extreme weather significantly impacts daily travel activities, even prominent people must undertake commuting activities during the working day; a few will change their travel plans due to the bad weather, so there is quite a difference in the overall daily big data. Besides, it can also indicate that the difference is more significant in the extremely hot weather group than in the extreme cold weather group, i.e., extreme heat can substantially affect population movement.

3.2 The unequal impacts of the spatial gradient

The simple t-test partially explains the effect of extreme weather on daily travel. Still, it cannot clarify whether this effect inhibits or promotes travel and whether the impact on travel distances differs. Therefore, we conducted a more detailed data analysis on the interflow of CTs within the nine distance layers, and the results are shown in Figure 5.

The relationship between the different gradients and the population flux is established starting from the central census tracts and dividing the gradient towards the periphery (Fig 5). First and foremost, it can be observed that within each distance layer, the shortest distance travel can be regarded as a representation of short-distance movement across CTs. In the extremely high-temperature group (Fig 5a), the intra-layer travel volume reaches its lowest point compared to long-distance travel. Conversely, in the extreme low-temperature group (Fig 5b), the intra-band travel volume reaches its highest point. This indicates that in Houston, hot weather affects people's willingness to engage in short-distance travel, whereas cold weather promotes more frequent short-distance travel.

We can consider the population flux to nearby layers as short-distance travel and the population flux to outer layers as long-distance travel. In Fig 5a, for CTs near the city center (layers 1-5), extremely high temperatures inhibit short-distance daily travel ($popH < popR$) but do not have an inhibitory effect on long-distance travel ($popR < popH$). On the contrary, for CTs far from the city center (layers 5-9), hot weather inhibits long-distance travel but does not inhibit short-distance travel. Similar travel patterns and analytical conclusions can also be applied to the extremely low-temperature group (Fig 5b). This can be summarized as extreme temperatures inhibit population flux to the vicinity of the city center while promoting population flux towards the suburbs.

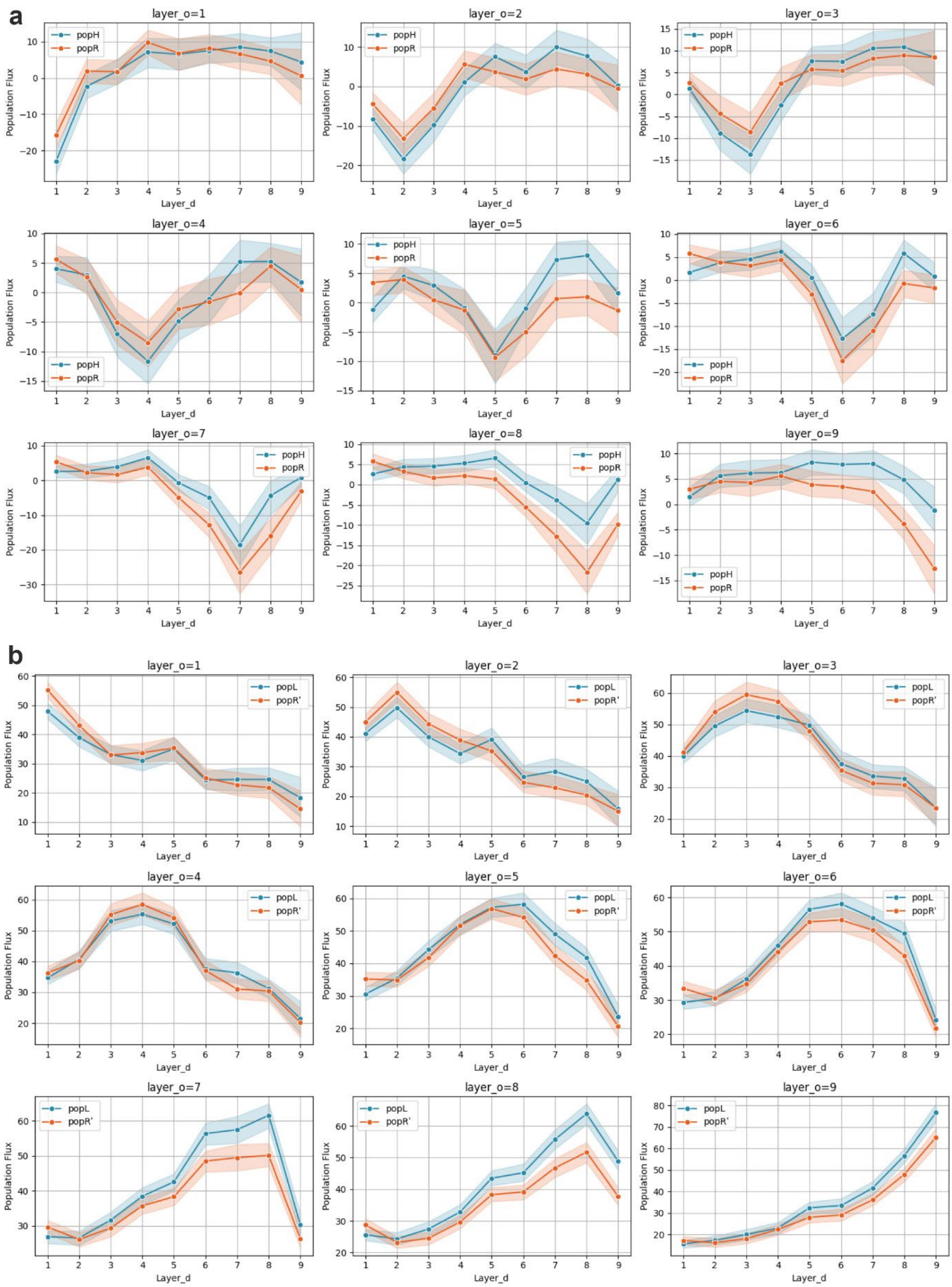

Fig. 5. Four population flux parameters with spatial gradient. (a) the relationships between $popH$ & $popR$ and distances and (b) the relationships between $popL$ & $popR'$.

This result may be because people's travel plans could change under different weather conditions. Travel to the city center is often for meeting daily life needs, such as shopping, which are relatively flexible and adjustable. Therefore, such trips tend to be reduced during extreme weather conditions. Conversely, traveling to the suburbs is often for planned leisure trips or visiting relatives and friends, and these long-distance travel activities are less likely to be canceled due to changes in temperature (especially during holiday periods coinciding with selected periods of extreme temperatures). Moreover, in the case of Houston, the southern region of the United States, the severe hot weather encourages people to avoid the city center, which is prone to the heat island effect, and instead head to the more open, comfortable, and green suburbs.

3.3 The unequal impacts of the social relationship

In the sociological assessment, six essential social indicators were analyzed, specifically: the proportion of inhabitants living in poverty, the unemployment rate, the demographic ratio of seniors aged 65 years and above, the proportion of Single-parent households with children under 18, the fraction of the populace without vehicles, and the mobile homes. We take the average of the pops corresponding to each socio-economic stratum to fit a line to obtain the relationship between populations and socio-economic attributes. The analysis was represented through graphical illustrations (Figure 6, Figure 7, Figure 8). These indicators provide valuable insights into the complex relationship between population mobility and extreme weather conditions.

In examining the relationship between "population mobility" and the poverty ratio under extremely cold conditions, we find a significant negative correlation between "popL" and "poverty," suggesting that population mobility in areas with higher poverty rates declines considerably during the cold months. Intriguingly, this relationship does not persist in hotter months, as the correlation between "popH" and poverty levels is not significant, suggesting that factors other than temperature may drive changes in population dynamics during periods of extreme heat. In exploring the link between population movements and the unemployment proportion, we find that the R-squared values for popH and popL hover between 0.2 and 0.4. This shows a moderate relationship between the unemployment rate and extreme weather-induced population fluctuations.

A notable positive correlation exists between population mobility and the proportion of residents aged 65 and over during extreme hot and cold weather conditions. Under these extreme temperature conditions, older adults may be more inclined to relocate, possibly in search of a more comfortable living environment or to escape the health risks associated with severe temperatures. Conversely, this relationship is not apparent under normal weather conditions, suggesting the unique impact of extreme temperatures on this population.

Our analysis reveals a compelling correlation between extreme weather-induced population fluctuations (popH and popL) and the incidence of single-parent families with children under 18. The strong negative correlation suggests that the number of single-parent households with children traveling during extreme weather is significantly reduced, and it is noteworthy that the R-squared value associated with this relationship is significant.

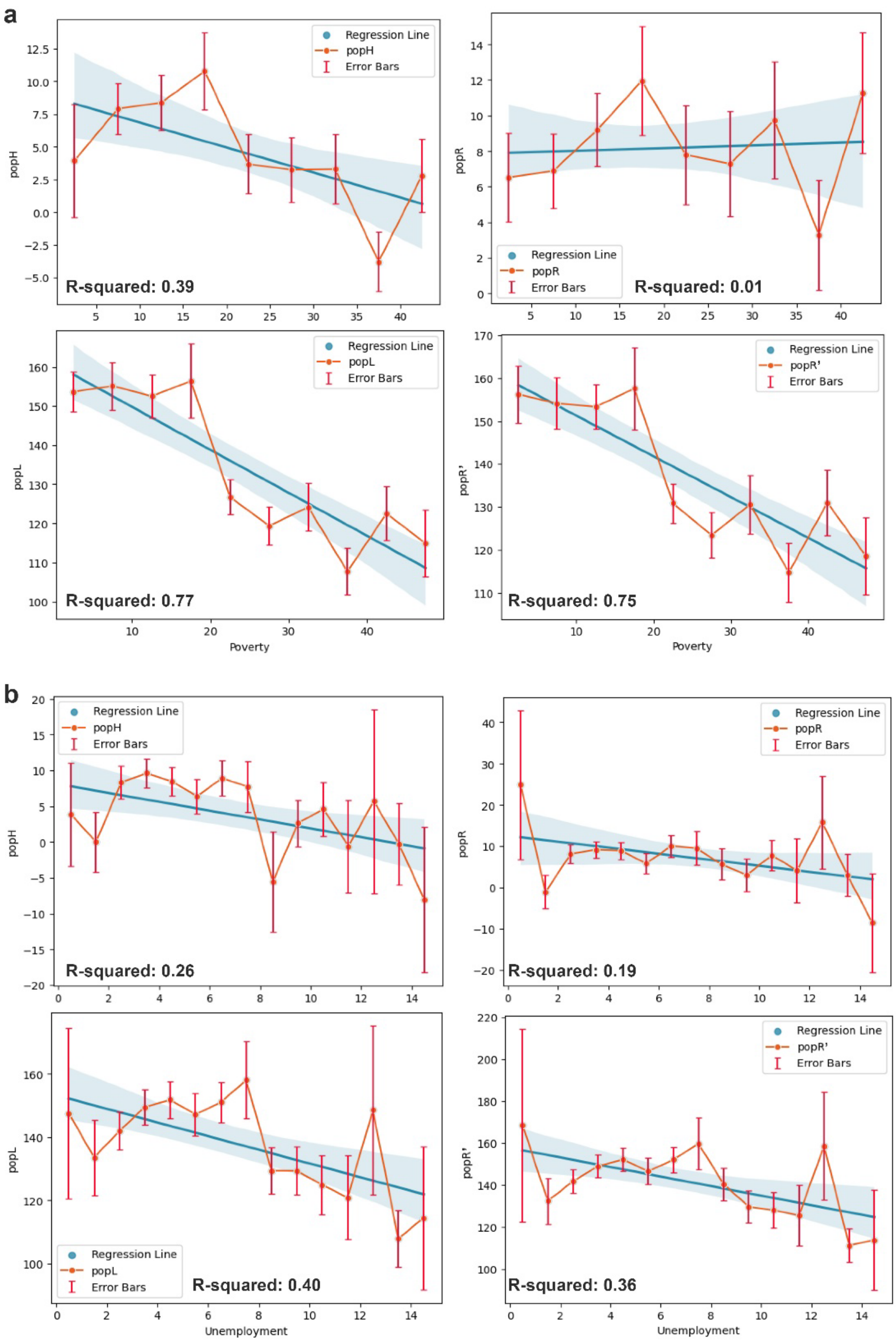

Fig. 6. Statistical analysis of the population flux parameters with social gradients. (a) the linear relationship between population flux and the percentage of persons below the poverty estimate, and (b) the linear relationship between population flux and the unemployment rate estimate.

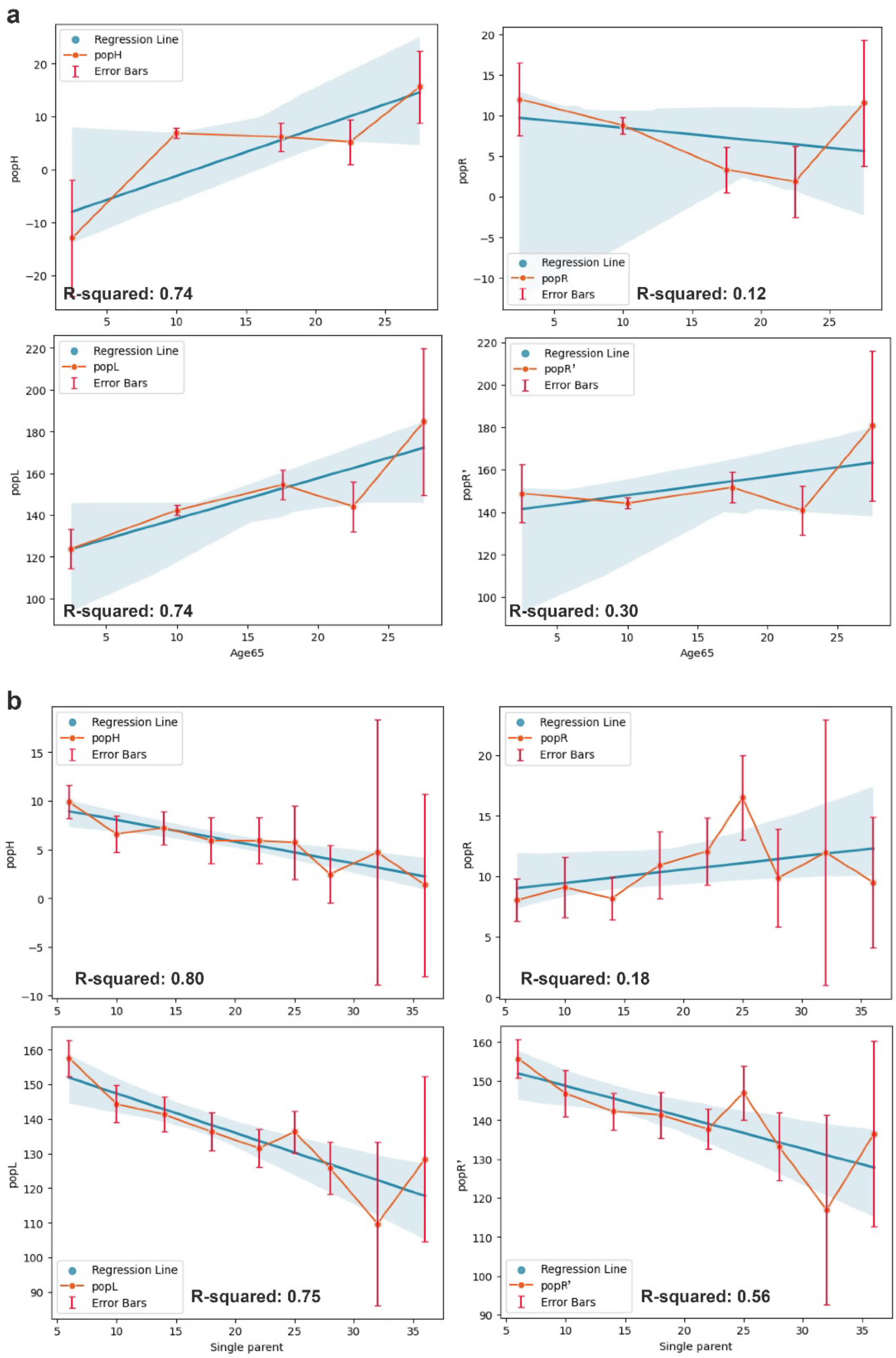

Fig. 7. Statistical analysis of the population flux parameters with social gradients. (a) the linear relationship between population flux and the percentage of persons aged 65 and older estimate, (b) the linear relationship between population flux and the rate of single-parent households with children under 18.

Remarkably, the indices popH and popL demonstrate an exceptionally strong association with the lack of access to vehicles ($R^2 \approx 0.97$). This correlation is particularly pronounced during colder months. This finding underscores the impact of extreme weather conditions on mobility, as individuals with limited vehicle access may face challenges in coping with temperature extremes.

The correlation between 'mobile homes' and population movement shows high R-squared (R^2) values, especially during the cooler months. There is a robust positive correlation between the variables. We observed a significant increase in mobile homes during extreme cold and heat. This finding reflects the importance of considering mobile home communities in emergency response and urban planning efforts to ensure the safety and well-being of residents during extreme weather events, especially during harsh climatic conditions.

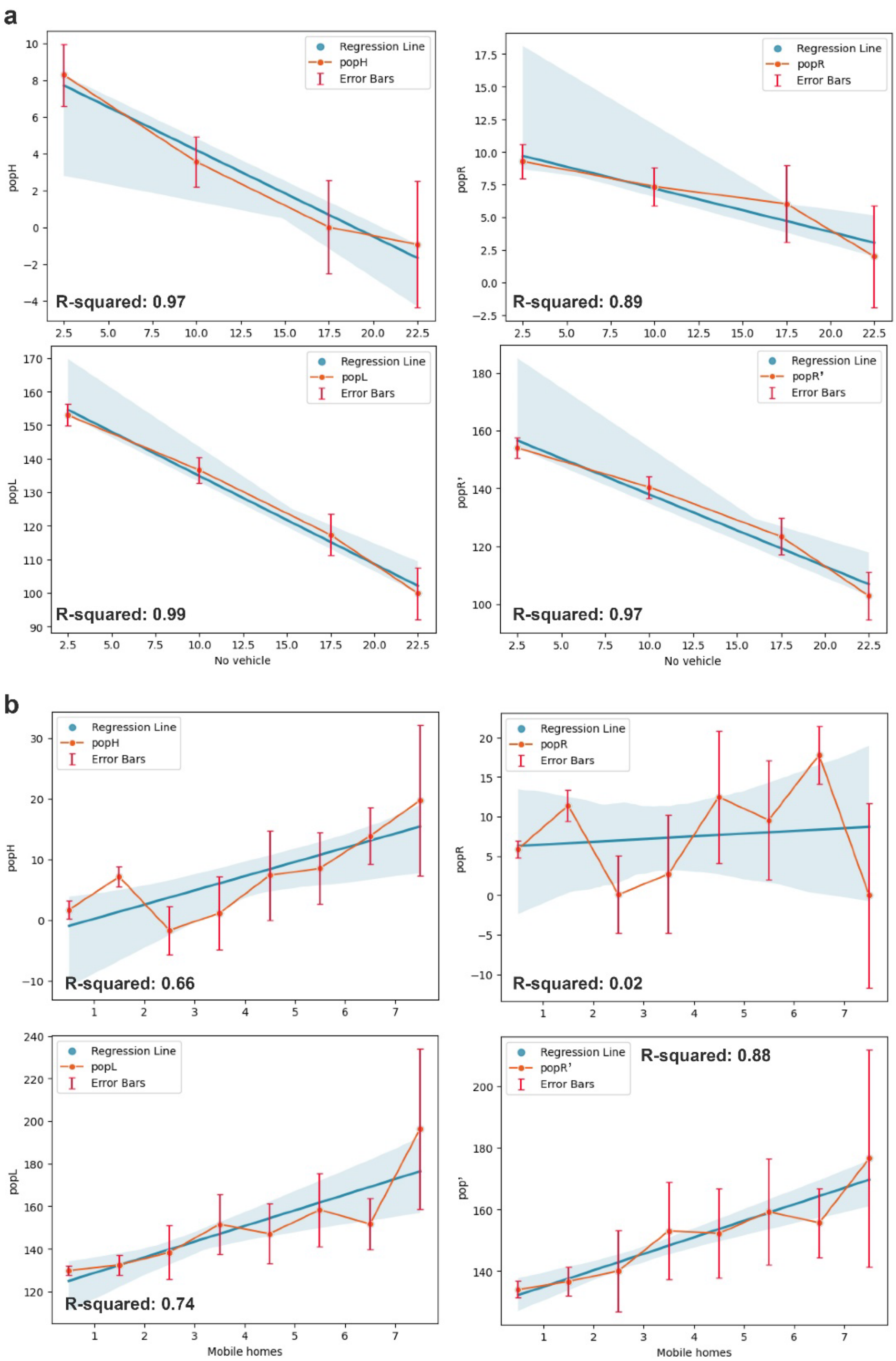

Fig. 8. Statistical logarithm population flux parameters analysis with social gradients. (a) the linear relationship between population flux and the percentage of households with no vehicle available estimate, (b) the linear relationship between population flux and the rate of Mobile homes.

4 Discussion

4.1 The unequal impacts of extreme temperature

The quantification of extreme climate on mobility is challenging because of its complex interactions with many interconnected systems (Roy et al., 2019). We selected the Greater Houston area, where extreme weather is frequent, across US regions to identify changes in mobility due to extreme events, using generalizable statistical models and spatial analysis. The results and findings in this study have significant implications for understanding the impacts of extreme temperatures on populations to inform adaptation strategies in coping with future climate extreme events.

First, we found that extreme temperatures dampen population movement to the vicinity of city centers while promoting activity to the suburbs. In addition, hot weather affects people's willingness to make short trips, while cold weather promotes more frequent short trips. Fear of natural hazards such as heat stroke, heat stroke, and severe cold can affect people's willingness to travel (Berry et al., 2010). Extreme heat tends to last longer, and the personal hazards of heat exposure are greater, making people more selective in avoiding going out on days of extreme heat (Thorsson et al., 2004) or moving away from the center of the heat island to the cooler countryside. Therefore, to cope with the problem of heat and high temperatures in summer, the Government can enhance the infrastructure development of the suburbs and provide better transportation, education, medical, and shopping services. This will attract more people to choose to live and work in the suburbs and promote their economic development. At the same time, the Government should consider improving the city center's attractiveness, for example, by improving the city center's green spaces, landscaping, cultural facilities, and business environment. On the contrary, in winter, the government can encourage and support Houston to organize various winter activities in the cold season, such as skiing, ice sculpture exhibitions, and Christmas markets. This will increase the vibrancy of the city's tourism industry and drive economic development.

Secondly, closer to the city center, such temperature extremes have a more pronounced dampening effect on human mobility, while in contrast, areas far from the city center do not suffer a significant dampening impact. On the one hand, this is because city centers are densely populated and have high daily travel flows, so the overall suppressive effect follows and is more pronounced; on the other hand, the more pronounced impact of extreme weather may rely on short trips, mainly by walking and cycling (Böcker et al., 2019; Winters et al., 2011), and not so much on private cars and rail transport, so the suppressive effect on short distance mobility is stronger. This means that the disincentive effect is stronger. As a result, the relevant agencies in the city center should anticipate this population loss and plan for traffic diversion when extreme weather strikes.

Finally, based on the analyses of the unequal impacts of extreme temperatures for six socio-economic characteristics: poverty, unemployment, aging people, single-parent housing, no vehicle, and mobile homes population. The study found that climate extremes inhibit the mobility of the poor, the unemployed, and single-parent families while conversely facilitating the mobility of the elderly and mobile home lovers. This is a conclusion in line with everyday perceptions that disadvantaged social groups have fewer travel options and less free money. For example, many poor people cannot access private cars and must travel on foot or by public transport. Hence, such limited travel approaches may make people vulnerable to extreme temperatures. Consequently, in urban areas with a high concentration of people from disadvantaged social groups, the government should monitor their mobility and home situation to provide them with the transport or material assistance they need to get around in time for extreme temperatures. At the same time, the government should consider the people who tend to move around in extreme weather and do a better job of protecting and improving public transportation.

4.2 Limitations and perspectives

This study proposes a method for calculating the impact of extreme weather on population mobility in a gradient and validating the proposed indicator's validity. The study examines daily population fluxes at different distance circles from city centers under extreme temperatures. It assesses whether changes are influenced by socio-economic indicators, advancing the existing knowledge on human mobility during extreme temperatures in various ways. The study's findings are important for a more refined understanding of the impact of extreme temperatures on human behavior in different regions, and it contributes to the knowledge of the higher-order impacts of disruptive climate events on human societies and national economies. It can also help facilitate differentiated policy and management across different census tracts in the Greater Houston area, such as resilience in climate-vulnerable areas and improved accessibility to emergency services (Yin et al., 2017), to mitigate the adverse impacts of extreme weather.

However, there are limitations to using population flux data in this study; all trips in this dataset are aggregated to represent population mobility in the Greater Houston area relatively as a whole, but we do not break it down into trips by public transit, private vehicle, etc. These more detailed comparative trip analyses are directions that could be pursued in subsequent studies. In addition, we only analyzed two extreme temperature periods in 2019 for the Greater Houston area, and related research methods could be extended to other years or urban areas for cross-sectional comparative analyses to enhance the generalizability of the findings. In addition, the study aims to examine the unequal impacts of temperatures on human mobility among population groups, which can be quantified through simple statistical analysis. Further studies could develop a regression model, such as GWR or machine learning, that considers multiple factors to reveal the relationship between mobility and various factors.

5 Conclusion

This study identifies changes in daily human mobility across different dimensions, temperatures, spatial gradients, and social relationships during extreme temperatures. The main findings are as follows：

1) Extreme heat inhibits people's willingness to make short trips, while cold weather promotes more frequent short trips.

2) Extreme temperatures inhibit the mobility of people near the city center while promoting movement to the suburbs.

3) The areas with large numbers of disadvantaged social groups were more likely to be affected by extreme temperatures while conversely promoting the mobility of the elderly and mobile homes.

These findings are important for assessing temperature extremes because they allow for a more thorough analysis of how temperature affects different parts of the city, make it simpler to determine the causal links between temperature change and population activity, and are appropriate for identifying fine-grained climate sensitivity. The findings will also contribute to the corpus of existing information, provide new insights into how severe temperatures affect human movement, and help city managers make more logical decisions.

Reference

Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., Menezes, R., Ramasco, J. J., Simini, F., & Tomasini, M. (2018). Human mobility: Models and applications. *Physics Reports*, *734*, 1–74. https://doi.org/10.1016/j.physrep.2018.01.001

Beine, M., & Jeusette, L. (2021). A meta-analysis of the literature on climate change and migration. *Journal of Demographic Economics*, *87*(3), 293–344. https://doi.org/10.1017/dem.2019.22

Berry, H. L., Bowen, K., & Kjellstrom, T. (2010). Climate change and mental health: A causal pathways framework. *International Journal of Public Health*, *55*(2), 123–132. https://doi.org/10.1007/s00038-009-0112-0

Böcker, L., Priya Uteng, T., Liu, C., & Dijst, M. (2019). Weather and daily mobility in international perspective: A cross-comparison of Dutch, Norwegian and Swedish city regions. *Transportation Research Part D: Transport and Environment*, *77*, 491–505. https://doi.org/10.1016/j.trd.2019.07.012

Borden, K. A., & Cutter, S. L. (2008). Spatial patterns of natural hazards mortality in the United States. *International Journal of Health Geographics*, *7*(1), 64. https://doi.org/10.1186/1476-072X-7-64

Carney, M., Azencott, R., & Nicol, M. (2020). Nonstationarity of summer temperature extremes in Texas. *International Journal of Climatology*, *40*(1), 620–640. https://doi.org/10.1002/joc.6212

Catney, G., & Simpson, L. (2010). Settlement area migration in England and Wales: Assessing evidence for a social gradient. *Transactions of the Institute of British Geographers*, *35*(4), 571–584. https://doi.org/10.1111/j.1475-5661.2010.00400.x

Chakraborty, J., Collins, T. W., & Grineski, S. E. (2019). Exploring the Environmental Justice Implications of Hurricane Harvey Flooding in Greater Houston, Texas. *American Journal of Public Health*, *109*(2), 244–250. https://doi.org/10.2105/AJPH.2018.304846

Chang, J., Yang, G., Liu, S., Jin, H., Wu, Z., Xu, R., Min, Y., Zheng, K., Xu, B., Luo, W., Mao, F., Ge, Y., & Cheong, K. H. (2022). A Gradient Model for the Spatial Patterns of Cities. *Advanced Theory and Simulations*, *5*(3), 2100486. https://doi.org/10.1002/adts.202100486

Chiu, Y.-C., Zhou, X., & Hernandez, J. (2007). Evaluating Urban Downtown One-Way to Two-Way Street Conversion Using Multiple Resolution Simulation and Assignment Approach. *Journal of Urban Planning and Development*, *133*(4), 222–232. https://doi.org/10.1061/(ASCE)0733-9488(2007)133:4(222)

Clarke, B., Otto, F., Stuart-Smith, R., & Harrington, L. (2022). Extreme weather impacts of climate change: An attribution perspective. *Environmental Research: Climate*, *1*(1), 012001. https://doi.org/10.1088/2752-5295/ac6e7d

Debbage, N., & Shepherd, J. M. (2015). The urban heat island effect and city contiguity. *Computers, Environment and Urban Systems*, *54*, 181–194. https://doi.org/10.1016/j.compenvurbsys.2015.08.002

Fan, L., Gao, J., Du, X., & Wu, Z. (2020). Spatial gradient distributions of thermal shock-induced damage to granite. *Journal of Rock Mechanics and Geotechnical Engineering*, *12*(5), 917–926. https://doi.org/10.1016/j.jrmge.2020.05.004

FRALICK, D., ZHENG, J. Z., Wang, B., TU, X. M., & FENG, C. (2017). The Differences and Similarities Between Two-Sample T-Test and Paired T-Test. *Shanghai Archives of Psychiatry*, *29*(3), 184–188. https://doi.org/10.11919/j.issn.1002-0829.217070

Griego, A. L., Flores, A. B., Collins, T. W., & Grineski, S. E. (2020). Social vulnerability, disaster assistance, and recovery: A population-based study of Hurricane Harvey in Greater Houston, Texas. *International Journal of Disaster Risk Reduction*, *51*, 101766. https://doi.org/10.1016/j.ijdrr.2020.101766

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. *Proceedings of the National Academy of Sciences*, *109*(37). https://doi.org/10.1073/pnas.1205276109

Hatchett, B. J., Benmarhnia, T., Guirguis, K., VanderMolen, K., Gershunov, A., Kerwin, H., Khlystov, A., Lambrecht, K. M., & Samburova, V. (2021). Mobility data to aid assessment of human responses to extreme environmental conditions. *The Lancet Planetary Health*, *5*(10), e665–e667. https://doi.org/10.1016/S2542-5196(21)00261-8
Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020). Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic. *Scientific Data*, *7*(1), 390. https://doi.org/10.1038/s41597-020-00734-5
Keselman, H. J., Othman, A. R., Wilcox, R. R., & Fradette, K. (2004). The New and Improved Two-Sample t Test. *Psychological Science*, *15*(1), 47–51. https://doi.org/10.1111/j.0963-7214.2004.01501008.x
Klingelhöfer, D., Braun, M., Brüggmann, D., & Groneberg, D. A. (2023). Heatwaves: Does global research reflect the growing threat in the light of climate change? *Globalization and Health*, *19*(1), 56. https://doi.org/10.1186/s12992-023-00955-4
Kosanic, A., Petzold, J., Martín-López, B., & Razanajatovo, M. (2022). An inclusive future: Disabled populations in the context of climate and environmental change. *Current Opinion in Environmental Sustainability*, *55*, 101159. https://doi.org/10.1016/j.cosust.2022.101159
Kotz, M., Levermann, A., & Wenz, L. (2022). The effect of rainfall changes on economic production. *Nature*, *601*(7892), 223–227. https://doi.org/10.1038/s41586-021-04283-8
Lee, C.-C., Rajput, A. A., Hsu, C.-W., Fan, C., Yuan, F., Dong, S., Esmalian, A., Farahmand, H., Patrascu, F. I., Liu, C.-F., Li, B., Ma, J., & Mostafavi, A. (2022). Quantitative measures for integrating resilience into transportation planning practice: Study in Texas. *Transportation Research Part D: Transport and Environment*, *113*, 103496. https://doi.org/10.1016/j.trd.2022.103496
Li, D., & Bou-Zeid, E. (2013). Synergistic Interactions between Urban Heat Islands and Heat Waves: The Impact in Cities Is Larger than the Sum of Its Parts. *Journal of Applied Meteorology and Climatology*, *52*(9), 2051–2064. https://doi.org/10.1175/JAMC-D-13-02.1
Li, W., Wang, Q., Liu, Y., Small, M. L., & Gao, J. (2022). A spatiotemporal decay model of human mobility when facing large-scale crises. *Proceedings of the National Academy of Sciences*, *119*(33), e2203042119. https://doi.org/10.1073/pnas.2203042119
Liu, C., Fan, C., & Mostafavi, A. (2022). *Graph Attention Networks Unveil Determinants of Intra- and Inter-city Health Disparity* (arXiv:2210.10142). arXiv. https://doi.org/10.48550/arXiv.2210.10142
Marsha, A., Sain, S. R., Heaton, M. J., Monaghan, A. J., & Wilhelmi, O. V. (2018). Influences of climatic and population changes on heat-related mortality in Houston, Texas, USA. *Climatic Change*, *146*(3), 471–485. https://doi.org/10.1007/s10584-016-1775-1
Medina, -Ramón Mercedes, Zanobetti, A., Cavanagh, D. P., & Schwartz, J. (2006). Extreme Temperatures and Mortality: Assessing Effect Modification by Personal Characteristics and Specific Cause of Death in a Multi-City Case-Only Analysis. *Environmental Health Perspectives*, *114*(9), 1331–1336. https://doi.org/10.1289/ehp.9074
Meehl, G. A., Tebaldi, C., & Adams-Smith, D. (2016). US daily temperature records past, present, and future. *Proceedings of the National Academy of Sciences*, *113*(49), 13977–13982. https://doi.org/10.1073/pnas.1606117113
Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An Overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology*, *29*(7), 897–910. https://doi.org/10.1175/JTECH-D-11-00103.1
Moseley, J. B., Mayeux, A., Paoletti, A., & Nurse, P. (2009). A spatial gradient coordinates cell size and mitotic entry in fission yeast. *Nature*, *459*(7248), Article 7248. https://doi.org/10.1038/nature08074
Portmann, R. W., Solomon, S., & Hegerl, G. C. (2009). Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proceedings of the National Academy of Sciences*, *106*(18), 7324–7329. https://doi.org/10.1073/pnas.0808533106

Qian, C., Zhang, X., & Li, Z. (2019). Linear trends in temperature extremes in China, with an emphasis on non-Gaussian and serially dependent characteristics. *Climate Dynamics*, *53*(1), 533–550. https://doi.org/10.1007/s00382-018-4600-x

Ramesh, B., Jagger, M. A., Zaitchik, B., Kolivras, K. N., Swarup, S., Deanes, L., Hallisey, E., Sharpe, J. D., & Gohlke, J. M. (2022). Flooding and emergency department visits: Effect modification by the CDC/ATSDR Social Vulnerability Index. *International Journal of Disaster Risk Reduction*, *76*, 102986. https://doi.org/10.1016/j.ijdrr.2022.102986

Roy, K. C., Cebrian, M., & Hasan, S. (2019). Quantifying human mobility resilience to extreme events using geo-located social media data. *EPJ Data Science*, *8*(1), 18. https://doi.org/10.1140/epjds/s13688-019-0196-6

Sakamoto, N., Saito, N., Han, X., Ohashi, T., & Sato, M. (2010). Effect of spatial gradient in fluid shear stress on morphological changes in endothelial cells in response to flow. *Biochemical and Biophysical Research Communications*, *395*(2), 264–269. https://doi.org/10.1016/j.bbrc.2010.04.002

Schwerdtle, P. N., Bowen, K., McMichael, C., & Sauerborn, R. (2019). Human mobility and health in a warming world. *Journal of Travel Medicine*, *26*(1). https://doi.org/10.1093/jtm/tay160

Semenza, J. C., Rubin, C. H., Falter, K. H., Selanikio, J. D., Flanders, W. D., Howe, H. L., & Wilhelm, J. L. (1996). Heat-Related Deaths during the July 1995 Heat Wave in Chicago. *New England Journal of Medicine*, *335*(2), 84–90. https://doi.org/10.1056/NEJM199607113350203

Spangler, K. R., Liang, S., & Wellenius, G. A. (2022). Wet-Bulb Globe Temperature, Universal Thermal Climate Index, and Other Heat Metrics for US Counties, 2000–2020. *Scientific Data*, *9*(1), 326. https://doi.org/10.1038/s41597-022-01405-3

Sura, P. (2011). A general perspective of extreme events in weather and climate. *Atmospheric Research*, *101*(1), 1–21. https://doi.org/10.1016/j.atmosres.2011.01.012

Thorsson, S., Lindqvist, M., & Lindqvist, S. (2004). Thermal bioclimatic conditions and patterns of behaviour in an urban park in Göteborg, Sweden. *International Journal of Biometeorology*, *48*(3), 149–156. https://doi.org/10.1007/s00484-003-0189-8

Uejio, C. K., Wilhelmi, O. V., Golden, J. S., Mills, D. M., Gulino, S. P., & Samenow, J. P. (2011). Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health & Place*, *17*(2), 498–507. https://doi.org/10.1016/j.healthplace.2010.12.005

van Hove, L. W. A., Jacobs, C. M. J., Heusinkveld, B. G., Elbers, J. A., van Driel, B. L., & Holtslag, A. A. M. (2015). Temporal and spatial variability of urban heat island and thermal comfort within the Rotterdam agglomeration. *Building and Environment*, *83*, 91–103. https://doi.org/10.1016/j.buildenv.2014.08.029

Wambura, V., & Wong, S. D. (2023, October 18). *Strengthening Public Transit Equity in Evacuation Planning through a Community-Centered Approach*. ERA. https://doi.org/10.7939/r3-9cdb-r238

Winters, M., Davidson, G., Kao, D., & Teschke, K. (2011). Motivators and deterrents of bicycling: Comparing influences on decisions to ride. *Transportation*, *38*(1), 153–168. https://doi.org/10.1007/s11116-010-9284-y

Yin, J., Yu, D., Lin, N., & Wilby, R. L. (2017). Evaluating the cascading impacts of sea level rise and coastal flooding on emergency response spatial accessibility in Lower Manhattan, New York City. *Journal of Hydrology*, *555*, 648–658. https://doi.org/10.1016/j.jhydrol.2017.10.067

Zander, K. K., Richerzhagen, C., & Garnett, S. T. (2019). Human mobility intentions in response to heat in urban South East Asia. *Global Environmental Change*, *56*, 18–28. https://doi.org/10.1016/j.gloenvcha.2019.03.004

Zhang, F., Li, Z., Li, N., & Fang, D. (2019). Assessment of urban human mobility perturbation under extreme weather events: A case study in Nanjing, China. *Sustainable Cities and Society*, *50*, 101671. https://doi.org/10.1016/j.scs.2019.101671

Zhang, K., Chen, T.-H., & Begley, C. E. (2015). Impact of the 2011 heat wave on mortality and emergency department visits in Houston, Texas. *Environmental Health*, *14*(1), 11. https://doi.org/10.1186/1476-069X-14-11

Zhang, X., & Li, N. (2022). Characterizing individual mobility perturbations in cities during extreme weather events. *International Journal of Disaster Risk Reduction*, *72*, 102849. https://doi.org/10.1016/j.ijdrr.2022.102849