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# Uneven heat burden in the sunshine state: Spatial patterns and socio-economic disparities of heat-related illness in Florida

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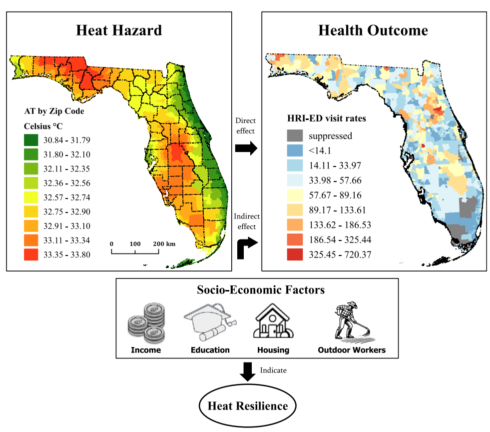
## HIGHLIGHTS

- Spatial analysis reveals an uneven distribution of heat-related illness emergency department (HRI-ED) visits in Florida.
- Compared to temperature, socio-economic factors shows a stronger association with HRI-ED visit rates.
- Vulnerable population groups bear a disproportionate health burden from extreme heat.
- Socio-economic and rural-urban disparities exist in HRI risk factors, calling for tailored heat resilience policies.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Climate change has increased the frequency and severity of extreme heat events globally, adversely affecting socio-economic conditions and public health. However, extreme heat has disparate effects on different population groups and the socio-economic determinants of its health effects are not well understood. In this study, we analyzed the spatial patterns of heat-related illness (HRI) visit rates at the zip-code level in Florida and applied statistical methods to examine the relationships between HRIs and environmental and socio-economic variables. Hierarchical regression analysis was used to evaluate the socio-economic effects on HRI visit rates under the same heat conditions. This is a two-step approach: we first included heat indicators in the baseline model and then added the socio-economic variables to assess their unique contributions in predicting HRI visits. Our findings indicate that temperature can only explain a small fraction of the variance in HRI cases ($R^2 = 0.04$, $p < 0.01$), while socio-economic variables show stronger associations ($R^2 = 0.42$, $p < 0.01$ in urban areas and $R^2 = 0.20$, $p < 0.01$ in rural areas). Notably, marginalized and disadvantaged populations (e.g., individuals in poverty, those employed in construction, and those with disabilities) are positively associated with HRIs ($p < 0.01$). These findings highlight the disproportionate impacts of heat-related health issues on disadvantaged groups, calling for climate justice policy interventions. Additionally, a comparative analysis between rural and urban areas revealed

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different determinants of HRIs. Our study enhances the understanding of the socio-economic determinants and disparities of HRIs in Florida, providing actionable insights for policymakers and health agencies to prioritize emergency services and heat resilience planning.

## 1. Introduction

Rising temperatures and climate variability lead to an increasing frequency of severe extreme heat waves worldwide (Margolis, 2021). In this context, heat-related illness (HRI) has become a growing public health concern (Schramm et al., 2021). Unlike acute natural hazards such as hurricanes and flooding, extreme heat is a slow-developing process, and its adverse effects are not always immediately obvious. However, extreme heat can exacerbate pre-existing health conditions (e. g., cardiovascular diseases, respiratory disorders, and diabetes), creating dangerous situations for vulnerable populations (Conlon et al., 2020). The death toll claimed by extreme heat is among the highest of all extreme weather events (NWS, 2023). According to the World Health Organization (2022), extreme heat has already caused over 166,000 fatalities from 1998 to 2017 and is estimated to cause approximately 38,000 additional deaths per year worldwide from 2030 to 2050. Given the high fatalities and latent effects on public health, extreme heat is often referred to as a “stealthy killer” (Arnott and Alvarez, 2022).

As the most vulnerable state to extreme heat in the U.S., Florida experiences warm weather year-round, with high temperatures during summers becoming the norm (Fig. 1). This increase in temperature contributes to a rise in HRIs across the state (Fig. 2). Climate Central (2019) projects that Florida will experience 130 hazardous heat days per year by 2050, more than any other state in the U.S. Understanding the health impacts of extreme heat enables early intervention for public health and promotes overall well-being (Bakhsh et al., 2018). Florida’s substantial elderly population, large number of immigrants, and low-income groups are likely to bear a disproportionate burden from extreme heat (Harduar Morano et al., 2016). In recent years, rapid urban development has intensified the urban heat island effect in Florida cities, while rural areas, still heavily reliant on agricultural industries, remain inherently vulnerable to heat. These diverse socio-economic conditions between rural and urban areas can result in varied health outcomes under extreme heat.

The relationship between human health and extreme weather conditions is a complex issue that involves health, social, and environmental dimensions (Clarke et al., 2022; Ebi et al., 2021; Hass et al., 2021; Robinson, 2021). Extensive research has established the fundamental links between extreme heat and public health outcomes (Dialesandro et al., 2021; Errett et al., 2023; Kovats and Hajat, 2008). However, the current literature presents several knowledge gaps that deserve further investigation. First, although studies have identified various risk factors for heat-related health outcomes (Faurie et al., 2022; Varghese et al., 2020), the spatial heterogeneity of these factors across different geographic and socio-economic contexts is not fully understood. More specifically, the interactions between heat exposure, resilience, and public health vary across different demographic groups (e.g., elderly residents, low-income households, and outdoor workers) and geographic settings (e.g., urban and rural areas), and these spatial and social disparities require further investigation. Second, the confounding effects of socio-economic conditions often obscure the causal links between heat and health. Systematic approaches are needed to disentangle the effects of the various factors and identify actionable levers to enhance heat resilience. Third, while different heat metrics have been proposed and applied in previous studies (Kodera et al., 2019; Perkins, 2015), there is no consensus on the optimal heat indicator for assessing heat-related health outcomes. The spatial variation in how different indicators—such as ambient temperature (AT), land surface temperature (LST), and heat events—relate to HRI has yet to be thoroughly investigated. Finally, the State of Florida is unique in its year-round warm temperatures, geographic disparities, high penetration of air-conditioning, and large vulnerable populations. A comprehensive investigation in Florida could provide valuable insights not only for the state but also for other regions with similar socio-environmental conditions.

This study attempts to address the above-mentioned issues by analyzing the spatial patterns of HRIs and the associations of HRIs with various heat indicators and socio-economic conditions in the State of Florida. The correlation between HRIs and common heat indicators (e. g., LST, AT, and heat events) is analyzed across geographic space to

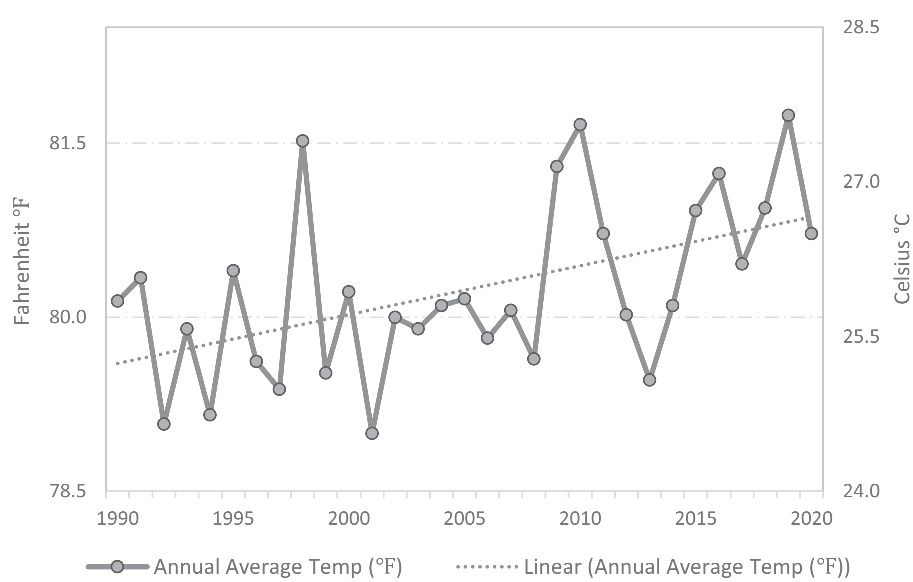


**Fig. 1.** Annual average summer temperature trend for Florida, 1990–2020 (NOAA, 2023). The solid gray line represents the annual average temperature (°F), with notable peaks around 1998, 2010, and 2019 reaching approximately 81.5 °F. The gray dashed line is the linear trend line of annual average temperatures, indicating a gradual increase in summer temperatures over the 30 years.

reveal the optimal heat indicator in various locations. Hierarchical regression analysis was applied to isolate the influence of socio-economic conditions on HRIs under various heat exposures. Additionally, we compared the associations between rural and urban areas to reveal geographic disparities in heat health impacts. Specifically, this study aims to address the following questions: (1) What is the spatial pattern of HRI rates in Florida, and are there significant spatial clusters of either high or low HRI visit rates? (2) Which temperature variable can best represent the impacts of extreme heat in Florida? (3) In addition to temperature, do socio-economic factors influence the occurrence of HRIs? Is there an uneven distribution of HRIs among different population groups and between rural and urban communities?

## 2. Related work

Extensive research has shown the adverse effects of extreme heat on human health (Ebi et al., 2021; Shindell et al., 2020; Weilnhammer et al., 2021). A comprehensive report by the Florida Department of Health (2015) documented the significant adverse health impacts of extreme heat exposure, including HRIs, cardiovascular diseases, mental and behavioral disorders, respiratory conditions, and endocrine and renal dysfunctions. The health impacts of extreme heat can be observed from a variety of outcomes, including hospital admissions (Karlsson and Ziebarth, 2018), emergency department (ED) visits (Sun et al., 2021), and mortality. Existing evidence indicates that heat can significantly increase the risk of mortality (Song et al., 2021). Zhao et al. (2024) show that between 1990 and 2019, about 1 % of deaths during the warm season were caused by heatwaves, accounting for 236 deaths per 10 million residents globally. This study also found that the risk of heat-related mortality varies geographically, and the highest mortality rate was in Southern and Eastern Europe. A study of 170 million German hospital admissions from 1999 to 2008 shows that extreme heat may cause a 12 % increase in mortality and a 6 % increase in hospital admissions (Karlsson and Ziebarth, 2018). Additionally, ED visits often serve as an early indicator of heat wave impacts, reflecting a broad spectrum of health issues caused by heat (Schramm et al., 2021). Sun et al. (2021) found that extreme heat was associated with a 7.8 % increase in excess ED visits for any cause and 66.3 % for HRI-related ED visits. Notably, this study also found that extreme heat causes an increase in ED visits for renal diseases and mental disorders.

Various heat indicators are used to measure the heat experienced by populations from multiple perspectives. AT typically measures the air temperature at 2 m above ground level. Faurie et al. (2022) found that a 1 °C increase in AT leads to an 18 % rise in HRI cases. LST primarily reflects the heat absorption and emission at the ground level and is commonly used to study urban heat island effects and their impact on residents' health (Hsu et al., 2021). Wang et al. (2021) revealed a strong correlation between LST and heat-related morbidity rates in Maricopa County, Arizona. The duration of heat is another important indicator, as prolonged heat may have stronger impacts on health than single hot days (Di Napoli et al., 2019). Anderson and Bell (2011) show that heat wave mortality risk increased by 0.38 % for every 1-day increase in heat wave duration. Additionally, the observation time and aggregation methods of temperature may also influence the relationship between heat and health outcomes. Xu et al. (2018) indicate that the mean temperature was slightly better than the maximum temperature in predicting heatwave impact on morbidity. Barnett et al. (2010) used Poisson regression to analyze the association between five temperature measures (e.g., maximum, minimum, mean, with/without humidity, and heat index) and mortality, revealing significant variations in the optimal temperature measure across age groups, seasons, and cities, with no single temperature indicator being superior to others in all conditions.

While high temperatures are a direct cause of heat illness, socio-economic conditions may influence the resilience of individuals and communities to extreme heat (Jung et al., 2021; Uejio et al., 2011; Wu et al., 2024). Published evidence shows that different communities and population groups exhibit varied health outcomes in extreme heat (Mitchell and Chakraborty, 2014). Particularly, minorities and disadvantaged population groups are often disproportionately affected by extreme heat (Fletcher et al., 2012; Hansen et al., 2013). Cultural isolation can further exacerbate these disparities, as individuals from certain racial and ethnic backgrounds may be less likely to access cooler public spaces or live in environments with adequate cooling infrastructure (Wilson, 2020). Kovach et al. (2015) found that rural areas with many outdoor workers and urban areas with high population density and low green space have higher HRI risk. Li et al. (2022) used spatial error/lag models and demonstrated that neighborhoods with a history of redlining experienced significantly higher rates of heat-related outpatient visits and hospital admissions. Other socio-economic conditions, such as education (Conlon et al., 2020), income (Fletcher et al., 2012), occupation (Kim et al., 2017; Stoecklin-Marois et al., 2013), age (Mac and McCauley, 2017), gender (Beckmann and Hiete, 2020), neighborhood safety (Royé, 2017; Uejio et al., 2011), and air conditioning usage, are also factors that influence heat resilience (O'Neill et al., 2005; Sera et al., 2020).

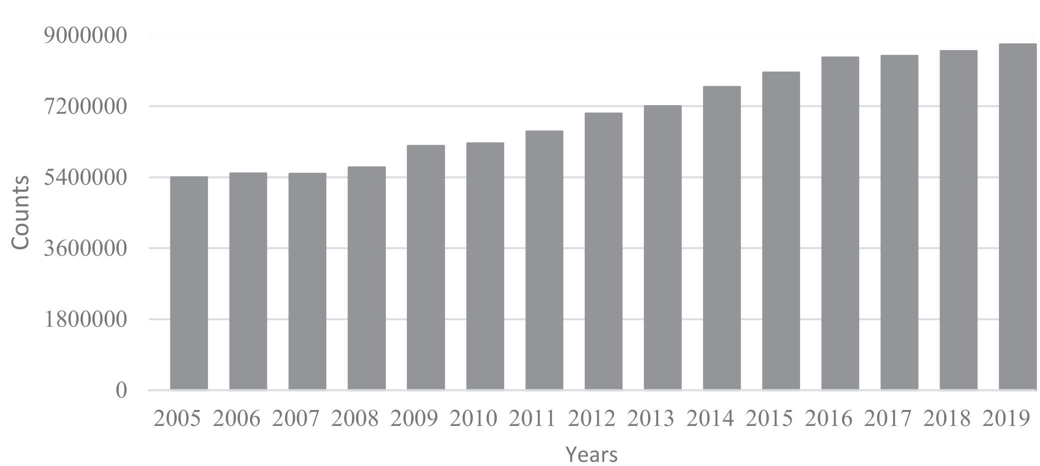


**Fig. 2.** Trends in heat-related emergency department (HRI-ED) visits in Florida, 2005–2019 (Florida Department of Health, 2023). The figure shows a steady increase in HRI-ED visits in Florida, with counts rising from approximately 5.4 million in 2005 to 8.8 million in 2019, representing a nearly 63 % increase over the 15-year period.

## 3. Study area and data

### 3.1. Study area

Due to its unique geographic location, Florida has been historically vulnerable to climate change and extreme heat events (NOAA, 2023). Moreover, Florida has consistently been characterized by high humidity levels, which limit a person's ability to perform evaporative cooling, thus exacerbating the HRI risk (NOAA, 2016). Florida's unique demographic characteristics increase its vulnerability to extreme heat. Florida ranked 2nd in the ratio of elderly adults (Statista Research Department, 2023) and has 620,000 people aged 65 and older, or under 5 years old, living below the poverty line—far above the average among the lower 48 states (Climate Central, 2015). These population groups are particularly vulnerable to extreme heat due to relatively lower physical capacity, limited access to resources, pre-existing health conditions, and restricted access to healthcare (Abrahamson et al., 2009; Nitschke et al., 2013). Additionally, Florida has the third-largest Hispanic and Latino population, as well as a sizable African American and Asian population (U.S. Census Bureau, 2020). It is noteworthy that Florida has one of the largest immigrant populations in the U.S. and is renowned as a preferred retirement destination (American Immigration Council, 2015). Furthermore, Florida's economy heavily relies on agriculture, tourism, and construction—sectors where workers are particularly vulnerable to illnesses from prolonged exposure to high temperatures (Moyce et al., 2016; Naseem, 2021). Due to its specific geographic and socio-economic conditions, Florida faces unique challenges in combating the adverse impacts of extreme heat.

### 3.2. Data

In this study, three types of data are collected for the analyses. First, we use HRI-ED visit rates at the zip-code level to represent the health outcomes of extreme heat. The zip-code level is the finest spatial resolution available for HRI data in Florida. Additionally, socio-economic and demographic variables at the zip-code level are widely available from Census and American Community Survey (ACS) data, allowing us to study the association between HRI and socio-economic conditions. Unlike heat fatalities, which only represent extreme outcomes of heat hazards, HRI-ED visits include a more extensive array of health outcomes, including heat exhaustion, dehydration, respiratory ailments, and cardiovascular complications, and thus can be considered a more comprehensive measure of health outcomes of extreme heat. HRI-ED visit cases were defined based on International Classification of Diseases 9th revision Clinical Modification (ICD-9-CM) codes: 992.0–992.9, E900.0, E900.1, and E900.9. Cases were classified if at least one of the HRI codes was found in the primary diagnosis field or in one of the secondary diagnosis fields (Florida Department of Health, 2023). The HRI-ED visit rate data at the zip-code level (from May to September) in 2019 was obtained from the Florida Agency for Health Care Administration (https://www.floridatracking.com/healthtracking). The data have been age-adjusted to ensure equitable comparisons among groups with varying age distributions (CDC, 2022). The HRI-ED visit rates are the total number of HRI-ED visits per 100,000 population. In total, 984 out of 992 zip codes that have HRI-ED data were used in our analyses. Geographic and socio-economic disparities between rural and urban areas significantly influence HRI (Choi et al., 2021). Rural communities face multiple challenges, particularly structural barriers such as limited access to cooling centers, inadequate emergency services, and underdeveloped public health infrastructure (Zeng et al., 2022). In contrast, urban populations encounter distinct challenges, including heightened temperatures from the heat island effect and different patterns of occupational exposure (Spector et al., 2019), leading to varying HRI patterns across these settings. Rural and urban zip codes were defined using the U.S. Census Bureau's urban definition (U.S. Census Bureau, 2023), which requires at least 2000 housing units or a minimum population of 5000. Zip codes with their centroids within the Census-defined urban boundaries were defined as urban zip codes, while those outside were classified as rural. In total, 554 zip codes were classified as urban and 430 as rural.

Second, we included four temperature indicators as proxies to represent the heat hazard, including LST, AT, number of heat days (NHD), and the number of heat events (NHE). As a common indicator of heat hazard, LST measures the heat absorbed and emitted by the surface (Johnson et al., 2011). In this study, we used LST images derived from Landsat 8 satellites. A total of 153 images at a 30 m resolution were collected from Google Earth Engine to calculate the average LST from May 1 to September 30, 2019 (Malakar et al., 2018). Open-source codes developed by Ermida et al. (2020) were applied to mask cloud and shadow-affected pixels in the Landsat images. Then, the average LST was calculated from the cloud-free images.

AT, which measures the temperature of the surrounding air, is widely used in heat-related studies as it directly affects human thermal comfort and physiological responses (Avashia et al., 2021). The AT at 2 m height was obtained from NASA's Daymet Version 4 dataset (Thornton et al., 2022), which provides gridded estimates of daily AT at a spatial resolution of 1 km. In this study, 153 images of AT from May 1 to September 30 were used to calculate average AT.

NHD is the sum of days that exceed a given heat threshold, while NHE captures sequences of consecutive heat days, emphasizing the cumulative effects of sustained heat conditions (Kim et al., 2017). Both NHD and NHE were determined using the maximum heat index data acquired from the Centers for Disease Control and Prevention (CDC). This index is calculated from both temperature and humidity (NOAA, 2022), offering a comprehensive perspective on extreme heat experienced by humans (Perkins, 2015; Steadman, 1984). In this study, an extreme heat day is defined as a day when the maximum heat index in a specific census tract exceeds the 90th percentile, a relative threshold calculated from the historical heat index for May to September between 1991 and 2019. The 90th percentile threshold is commonly used in defining extreme heat events (Keellings and Waylen, 2014). Following this standard, a heat event is defined as three or more consecutive extreme heat days. Thus, NHD is the total number of heat days, while NHE is the total number of heat events during the period from May 1 to September 30, 2019. The heat index is calculated using Forcing File A of Phase 2 of the North American Land Data Assimilation System (NLDAS-2), and the gridded raw data are then aggregated to the U.S. county or census tract level (LDAS, 2024). In this study, we used areal interpolation to resample NHD and NHE from census tracts to zip codes. Areal interpolation calculates a weighted average of values from census tracts, where the weights correspond to the proportion of census tracts that overlap specific zip codes (Netrdová et al., 2020).

Finally, we selected 21 variables to represent the socio-economic and demographic conditions of communities. The selection of these variables was based on a comprehensive literature review on socio-economic indicators of heat resilience (Harlan et al., 2006; Johnson and Wilson, 2009; Reid et al., 2009). Median household income and the ratio of the population in poverty represent economic capital, which affects individuals' ability to afford air conditioning (Ortiz et al., 2022), access healthcare services (Wu et al., 2024), cooling centers (Gao et al., 2022), and healthy work environments (Xiang et al., 2015). Housing density can differentiate rural and urban environments, which exhibit different built environments, availability of green spaces (Yu et al., 2024), and prevalent occupations (Pramanik et al., 2022; Uejio et al., 2011). The ratio of population without a high school diploma represents educational attainment (Cheng and Sha, 2024). Higher education levels are often associated with better knowledge and awareness of health risks in extreme heat. Compared to renters, homeowners have greater control of their homes and are thus more willing to invest in heat mitigation (Klinenberg, 2002). People working in agriculture, construction, transportation, and material moving are more likely to be exposed to outdoor heat environments (Sabrin et al., 2021). People without a vehicle have higher exposure to extreme heat in transportation (Gu et al., 2024). Additionally, we included age, racial, and ethnic variables to investigate potential disparities in the health impacts of extreme heat across different population groups. Populations with limited English proficiency often include new immigrants who may face challenges in accessing information about heat risks (Song et al., 2021). These socio-economic variables were obtained at the zip-code level from various American Community Survey (ACS) 5-Year Estimates (https://data.census.gov/) from 2019 by the U.S. Census Bureau.

## 4. Analysis

### *4.1. Data processing*

The abovementioned variables at different spatial resolutions were aggregated or interpolated to the zip-code level. The LST was aggregated to zip-codes in two steps: (1) computing the mean LST raster from daily LST rasters for the period between May 1 and September 30; (2) aggregating the mean LST raster in zip-codes using the zonal statistics. The same procedure was applied to calculate the average AT in zip codes. Areal interpolation was used to convert NHD and NHE from census tracts to zip codes (Matisziw et al., 2008). The entire analytical workflow of this study is illustrated in Fig. 3.

### *4.2. Exploratory data analysis*

We applied both global and local Moran's *I* to examine the spatial patterns of HRI-ED visit rates in Florida. As a common indicator of spatial autocorrelation, Moran's *I* measures the degree to which similar or dissimilar values are clustered in space. The Moran's *I* statistic offers a numerical representation of spatial autocorrelation ranging from −1 to 1 (Griffith, 1987). When calculating Moran's *I*, we utilized the "queen" contiguity rule to define neighborhoods in the weight matrix. Global Moran's *I* provides an overall measure of spatial autocorrelation for the entire dataset, indicating the general trend in the study area. In contrast, local Moran's *I* represents spatial autocorrelation in the neighborhoods of individual spatial units, helping identify local clusters of high and low spatial autocorrelation.

### *4.3. Association analysis*

We conducted four types of statistical analyses to examine the relations between HRI-ED visits and environmental and socio-economic variables. First, we analyzed the correlation between HRI-ED visit rates and the four temperature variables, including LST, AT, NHD, and NHE. Logarithmic transformation was applied to the raw data to address the non-normality and skewness problems of the variables (Zhang et al., 2008). We used Spearman's correlation coefficient to compare the correlations between the heat indicators and HRI-ED visit rates. Correlation strengths were interpreted using the following thresholds (Evans, 1996): $|\rho| < 0.20$ (very weak), $0.20 \leq |\rho| < 0.40$ (weak), $0.40 \leq |\rho| < 0.60$ (moderate), $0.60 \leq |\rho| < 0.80$ (strong), and $|\rho| \geq 0.80$ (very strong). The most correlated heat indicator was selected to represent extreme heat in the following analysis.

Second, we performed Geographically Weighted Pearson Correlation (GWPC) analysis to investigate the spatial variation of the correlations between HRI-ED visit rates and the four heat indicators. Unlike Spearman's correlation, which describes the correlation for the entire study area, the GWPC reveals local variability and identifies hotspots of the correlations (Kalogirou, 2014). Building upon these correlation analyses, the heat indicators most correlated with HRI-ED visits in different areas were highlighted. In addition, we calculated the corresponding local *t*-test statistics to assess the significance of the correlations at each location (Kalogirou, 2012).

Third, we applied hierarchical regression analyses to analyze the relations between socio-economic variables (independent variables) and HRI-ED visits (dependent variable). Hierarchical regression is often used to control for confounding factors (Hood et al., 2016). In this study, we hypothesized that HRI is influenced by both extreme heat and socio-economic conditions. Thus, we applied the hierarchical regression analyses to isolate the contribution of the socio-economic variables to the HRI-ED visits while controlling for heat intensity (control variables).

Finally, we conducted multivariate regression analyses between all the variables (heat indicators and socio-economic variables) and HRI-ED visits. The multivariate regression analysis examined the overall variability of HRI-ED visits that can be explained by the selected variables. The goodness-of-fit of the model implied the predictive power of the selected variables for HRIs. Variance Inflation Factors (VIF) were calculated for the independent variables to examine their collinearity. All variables and their descriptive statistics used in the statistical analyses are summarized in Tables S1 and S2 in the Supplementary Information (SI).

## 5. Results

### *5.1. Exploratory data analysis*

The four heat indicators (LST, AT, NHD, and NHE) show different spatial distributions. As illustrated in Figs. 4(A & B), LST exhibits a clear urban heat island effect, with higher values observed in urban areas, such as Miami, Tampa, Clearwater, Sarasota, Orlando, Tallahassee, and Jacksonville. In contrast, lower LST is evident in vegetated areas. Compared to LST, AT shows a different spatial distribution (Figs. 4(C & D)), with high values primarily distributed in inland areas. The AT in coastal areas, particularly along the east coast, is generally lower. As illustrated in Figs. 4(E & F), northwest and southeast Florida

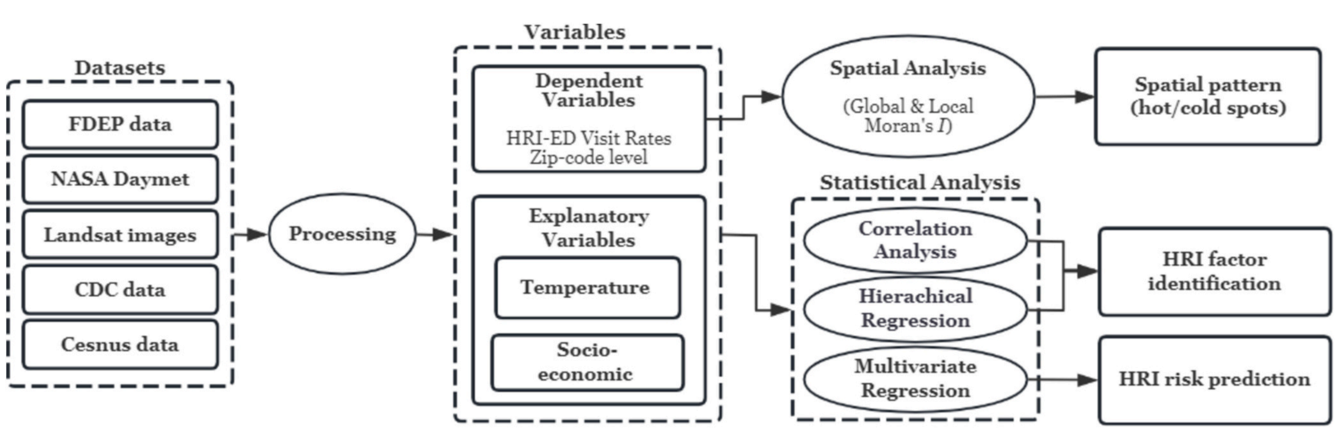


**Fig. 3.** The analytical workflow of the study.

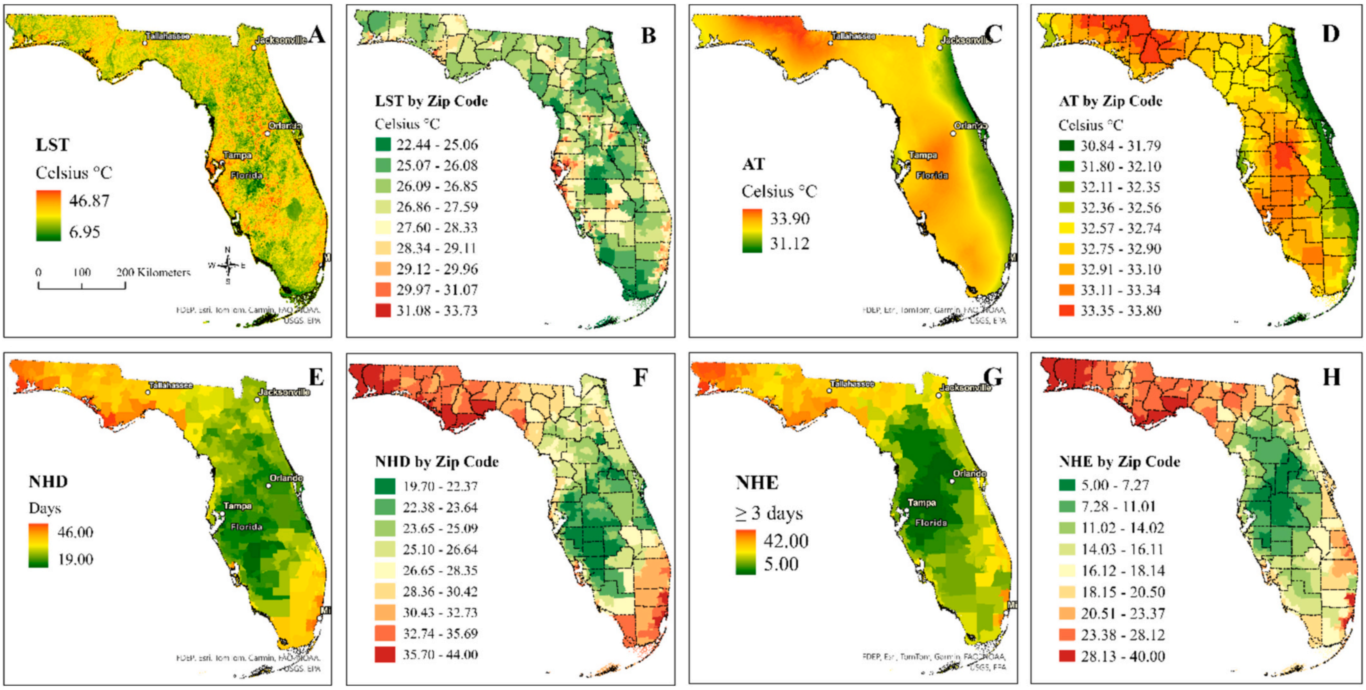


**Fig. 4.** Spatial distribution of the heat indicators. (A) LST in 30-m resolution raster; (B) LST aggregated in zip-codes; (C) AT in 1-km resolution raster; (D) AT aggregated in zip-codes; (E) original NHD in census tracts; (F) NHD interpolated in zip-codes; (G) original NHE in census tracts, and (H) NHE interpolated in zip-codes.

experienced high NHD during the summer of 2019, while central Florida generally had fewer NHD. As illustrated in Figs. 4(G & H), the spatial pattern of NHE is quite similar to that of NHD.

The HRI-ED visit rates in Florida show significant spatial heterogeneity (Fig. 5A). High HRI-ED visit rates are primarily concentrated in the central and northeastern parts of the state, including the corridor between Tampa and Orlando (Lakeland urban area), Jacksonville and its surrounding areas, as well as some suburban and rural counties in the northern region. In contrast, low HRI-ED visit rates are mainly found in the southern urban regions, such as Miami, Fort Lauderdale, and West Palm Beach. Overall, urban areas tend to have lower HRI-ED visit rates, while rural and peri-urban areas generally exhibit higher rates.

The global Moran's $I$ of 0.22 ($p < 0.001$) demonstrates statistically significant spatial autocorrelation in HRI-ED visit rates in Florida. The Local Moran's $I$ reveals High-High clusters (hotspots) of HRI-ED visit rates in north and northeast Florida, which are areas with high HRI-ED visit rates surrounded by neighborhoods with similarly high rates. As shown in Fig. 5B, several hotspots of HRI-ED visit rates are detected in central Florida, including the areas between Tampa and Orlando and surrounding Gainesville. Another hotspot is in the panhandle region of northwest Florida, including the counties of Santa Rosa, Jackson, and Gulf. These areas are distinguished by high poverty rates and diminished

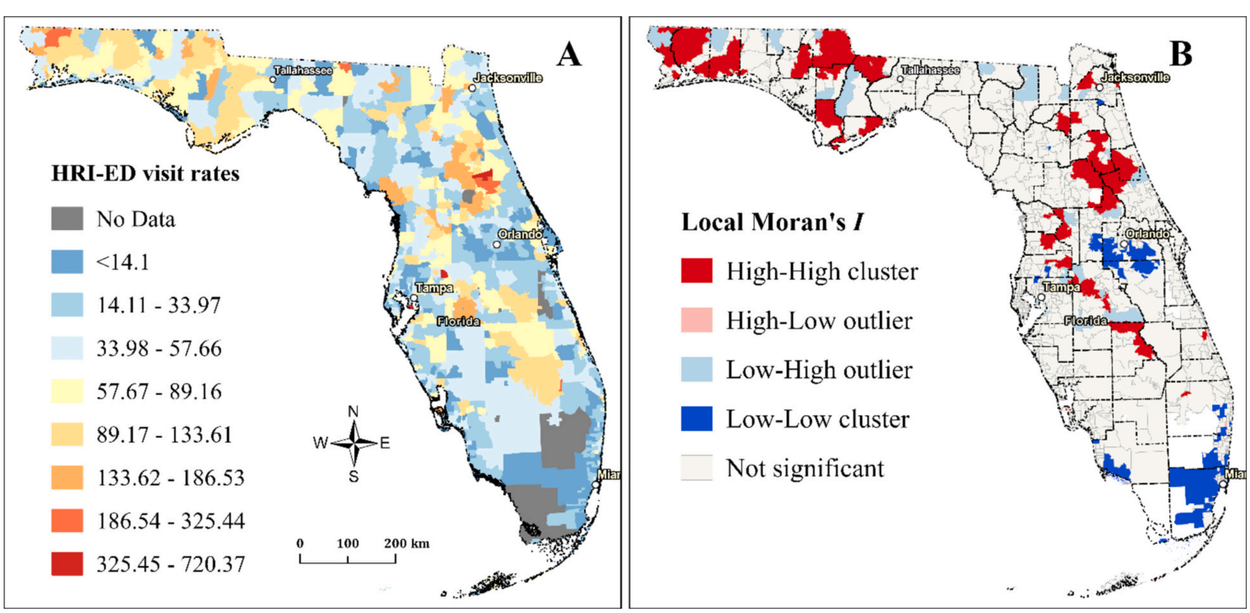


**Fig. 5.** Spatial distribution of HRI-ED visit rates. (A) Age-adjusted rate of HRI-ED visits (visits per 100,000 population) in the summer of 2019 (May to Sept.) in zip-codes in Florida, and (B) Anselin Local Moran's $I$ analysis for HRI-ED visit rates.

median household incomes compared to the state average.

Conversely, the Low-Low clusters (coldspots), where low HRI areas are surrounded by similarly low HRIs neighborhoods, are primarily found around Orlando, Miami, and Naples, which are large metropolitan areas that have relatively high population density and personal income. Furthermore, High-Low and Low-High clusters are scattered in several locations throughout Florida, which implies negative spatial autocorrelation where HRI-ED visit rates are surrounded by dissimilar values (Fig. 5B).

### 5.2. Association analysis

#### 5.2.1. Relation between heat and HRI-ED visit rates

Fig. 6 shows that HRI-ED visit rates are significantly correlated ($p < 0.001$) with the four temperature variables in different directions. As expected, HRI-ED visit rates are positively correlated with AT, indicating that high air temperatures above the ground may increase the risk of HRIs. However, HRI-ED visit rates are negatively correlated with LST and NHD, implying that higher LST and NHD are associated with fewer HRIs. The correlation between HRI-ED visits and NHE is not statistically significant. These counterintuitive results suggest that the relation between HRI and the heat variables may be influenced by other factors. The significant correlation between HRI and AT indicates that AT may be a better measure of heat intensity in humans than the other three variables. Considering the correlation analysis and the existing literature (Good, 2016), we selected AT to represent heat hazard in the hierarchical regression analyses (Section 5.2.3).

The GWPC analysis reveals the spatial variation in the correlations between HRI-ED visit rates and the heat indicators (Fig. 7). HRI-ED visit rates and LST are positively correlated along the coast but negatively correlated in inland areas and the Panhandle of northwest Florida. HRI-ED visit rates and AT are positively correlated around Naples, Cape Coral, and Ocala, while negatively correlated around Gainesville. Notably, in the Panhandle, HRI-ED is negatively correlated with LST but positively correlated with AT. In the areas surrounding Miami, HRI-ED is positively correlated with LST but negatively correlated with AT. This disparity suggests that, relative to AT, LST could play a more dominant role in influencing HRI within these areas. Both NHD and NHE exhibit a positive correlation with HRI-ED in the northwest and central regions, as well as along the southeast coast. However, a negative correlation is evident in several major cities, such as Jacksonville, Orlando, and Miami, where higher NHD and NHE are associated with lower HRI-ED visits. The varying relations between the heat indicators and HRI-ED visit rates suggest that localized metrics should be used to measure extreme heat in different regions. Detailed maps illustrating the significance level ($p < 0.01$) of the GWPC are provided in Fig. S1 in the SI.

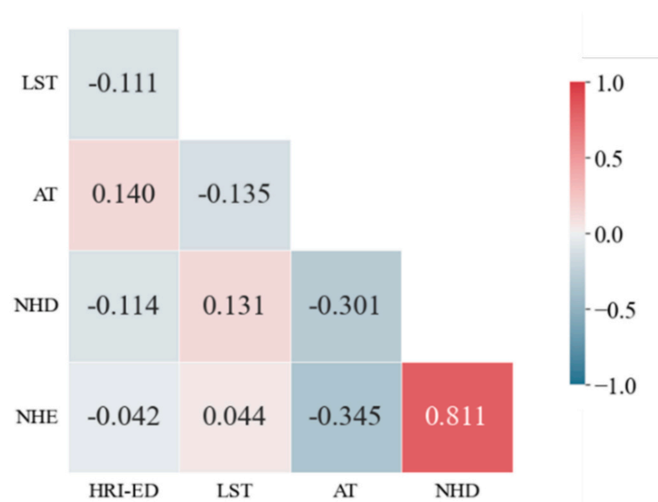


**Fig. 6.** Correlation coefficients between HRI-ED visit rates and four temperature variables.

To compare the correlations between HRI and the heat indicators, we created a map (Fig. 8) to highlight the heat indicator with the highest absolute GWPC correlation coefficient in each zip code. This map reveals the heat indicators that exhibit the strongest correlation with HRI in different areas. Specifically, LST is most correlated with HRI in the Florida Panhandle, as well as in areas surrounding Sarasota, Lakeland, and those near Port St. Lucie and Miami. AT displays a pronounced correlation spanning from the northeastern region, covering Gainesville, Lake City, and St. Augustine Beach, to the central region around Ocala and further south to areas near Lake Okeechobee and West Palm Beach. The strongest correlation for NHD is observed in the southwestern areas around Cape Coral and Naples, as well as the central areas around Tampa Bay, Palm Bay, and the Three Lakes Wildlife Management Area. Finally, NHE emerges as the dominant heat indicator in the vicinity of major cities such as Jacksonville, Orlando, and Tampa, as well as in the central part of the Gulf Coast.

#### 5.2.2. Hierarchical regression analysis

The hierarchical regression analysis was used to investigate the influence of the socio-economic variables on HRI-ED visit rates by setting AT representing heat intensity as the control variable. In the analysis results (Table 1), the baseline value indicates the amount of variance explained by the control variable alone. The incremental $R^2$ value denotes the additional variance explained by other explanatory variables after controlling for the heat indicator. The low baseline $R^2$ indicates that AT only explains a limited variance of HRI-ED visit rates. The higher incremental $R^2$ implies that, compared to AT, socio-economic variables are more influential factors for HRI-ED visit rates. The VIF values for all socio-economic variables were found to be <1.2, indicating no significant multicollinearity between AT and the socio-economic variables (see Table S3 in SI). As shown in Table 1, the percentages of population living in poverty (POV), unemployed individuals (UNEMP), individuals without a high school diploma (EDU), individuals employed in construction (CONSTR) and agricultural occupations (AGR), percentage of children (> 5 years old) (CHILD), individuals with disabilities (DISABLE), and the Black population (Black) are positively correlated with HRIs in both rural and urban areas ($p < 0.01$ for all, except rural Black population: $p < 0.05$). These results imply that, under the same heat intensity, the aforementioned variables have a strong positive effect on HRI-ED visits. Conversely, the median household income (INC), the percentages of White individuals (WHITE), and housing density (HDEN) demonstrated a negative effect on HRI-ED visit rates in both urban and rural areas ($p$-values: INC $< 0.01$; WHITE: urban $< 0.01$, rural $< 0.05$; HDEN: urban $< 0.01$, rural $< 0.05$). Notably, several other variables show urban-rural disparities. For example, the percentages of Asian (ASIAN) and Hispanic/Latino population (HISP) are negatively correlated ($p < 0.01$) with HRI-ED visit rates in urban areas. However, this relation is insignificant in rural areas. The access to electricity displays a significant negative relation ($p < 0.01$) with HRI-ED visit rates only in rural areas. In urban areas, limited English proficiency (ENGLISH) is negatively correlated, while lack of a vehicle (NOCAR) is positively correlated with HRI-ED visit rates ($p < 0.01$).

#### 5.2.3. Multivariate regression analysis

The Ordinary Least Squares (OLS) regression models show that AT and the socio-economic variables can predict 42.2 % and 20.0 % of the variance in HRI-ED visit rates in urban and rural areas respectively. However, the significance of the Lagrange Multiplier (LM) test and Moran's $I$ indicates the presence of spatial dependence in the residuals of the OLS model. The increase in $R^2$ in the spatial lag model (from 0.422 to 0.456 in urban areas, and 0.200 to 0.250 in rural areas) demonstrates an improvement in goodness-of-fit compared to the OLS models (Table 2). The decrease in AIC also indicates that the spatial lag models provide a better fit to the data than the OLS model. Therefore, we adopted the

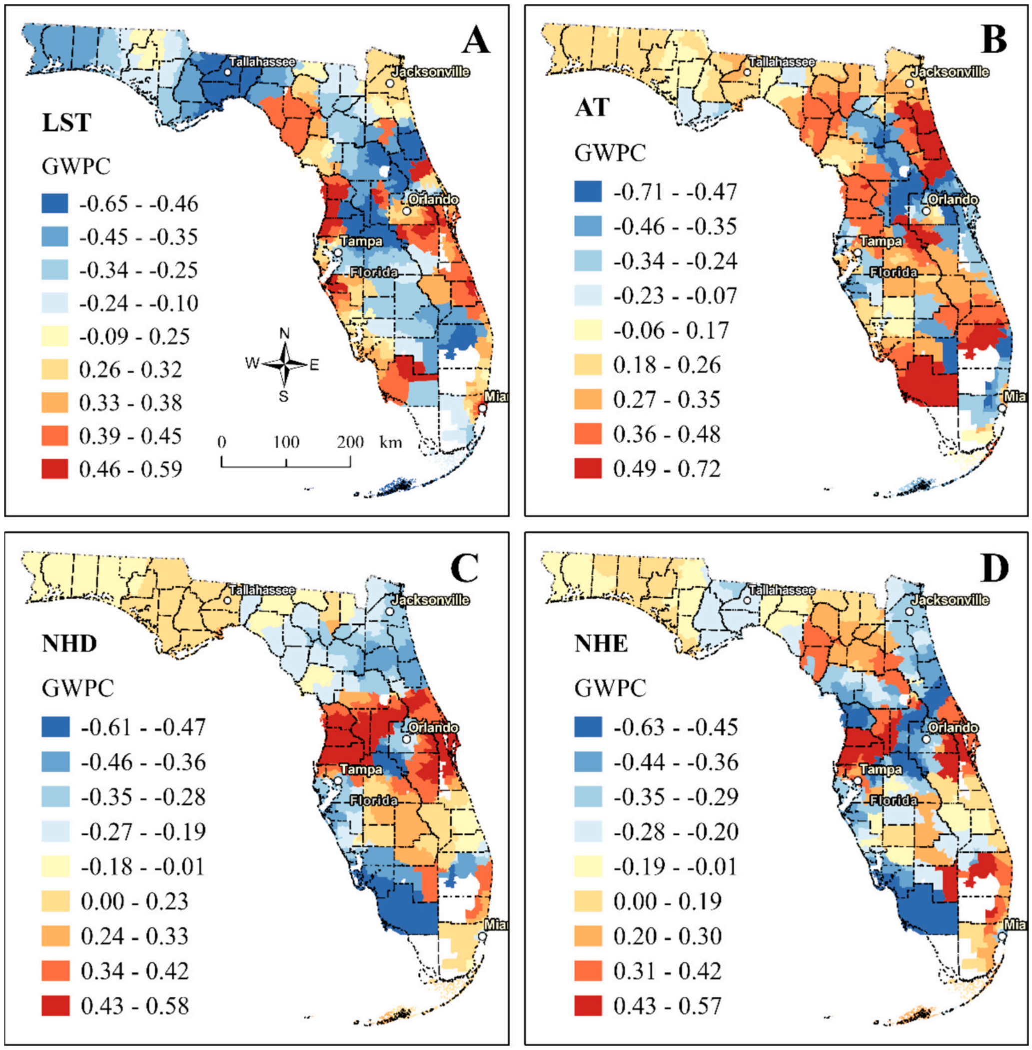


**Fig. 7.** Spatial distribution of four temperature indicators using GWPC. (A) LST, (B) AT, (C) NHD, and (D) NHE.

spatial lag model to quantify the relations in the dataset. It is worth noting that both the OLS and spatial lag models exhibit a higher $R^2$ in urban zip-codes than in rural zip-codes, implying that the selected variables are more effective in predicting HRIs in an urban setting.

Fig. 9 illustrates the regression coefficients and their significance levels for the spatial lag model in both rural and urban areas. The specific regression coefficients are detailed in Table S4 of the SI. Unemployment (UNEMP), the disabled population (DISABLE), and people without a high school diploma (EDU) have a positive effect ($p < 0.05$) on HRI-ED visit rates in both urban and rural areas. Meanwhile, agricultural (AGR) and construction workers (CONSTR), children (<5 years old) (CHILD), and the Black population (BLACK) are positively associated ($p < 0.05$) with HRI-ED visits only in urban zip-codes, while these relations are insignificant in rural areas. The percentage of the Hispanic population (HISP) is negatively associated ($p < 0.05$) with HRIs in urban areas, but the relation is not significant in rural areas. The median household income (INC) negatively influences ($p < 0.05$) HRI-ED visits only in rural zip codes.

## 6. Discussion

This paper provides a comprehensive assessment of the spatial patterns and contributing factors of HRIs at the zip-code level in Florida. The spatial autocorrelation analysis reveals significant clustering patterns in the HRI-ED visit rates throughout Florida. The hotspots (High-High clusters) of HRI were predominantly located in rural counties, while the coldspots (Low-Low clusters) were concentrated in urban areas. This finding is consistent with prior research showing that HRI is more prevalent in rural areas (Fechter-Leggett et al., 2016). Several factors might explain the observed pattern. For example, occupations and lifestyles in rural areas might increase outdoor exposure (Lippmann et al., 2013), while urban areas benefit more from the widespread use of air conditioning in homes and public facilities (Scott and Timothy, 2003). Rural residents may have limited access to or knowledge of HRI risks and prevention measures (Braveman et al., 2011). Their willingness or ability to commute long distances to access cooling centers or participate in community-led HRI prevention initiatives is also constrained in rural areas (O'Neill et al., 2009). Moreover, a study in North Carolina found that rural areas experience higher rates of HRI (Kovach et al., 2015).

The hotspots detected in central and northwest Florida show a significant presence of labor-intensive outdoor occupations, particularly in the agricultural industry (Harduar Morano et al., 2016). These areas are distinguished by high poverty rates, low household incomes, and lower education levels compared to the state average. Additionally, research has revealed a notable Hispanic/Latino population residing in the Panhandle region, with a majority engaged in service or construction/extraction occupations (Bonauto et al., 2007). This unique demographic composition may contribute to the hotspot of HRIs in northwest Florida. Conversely, the two coldspots (Low-Low clusters) identified in Orlando

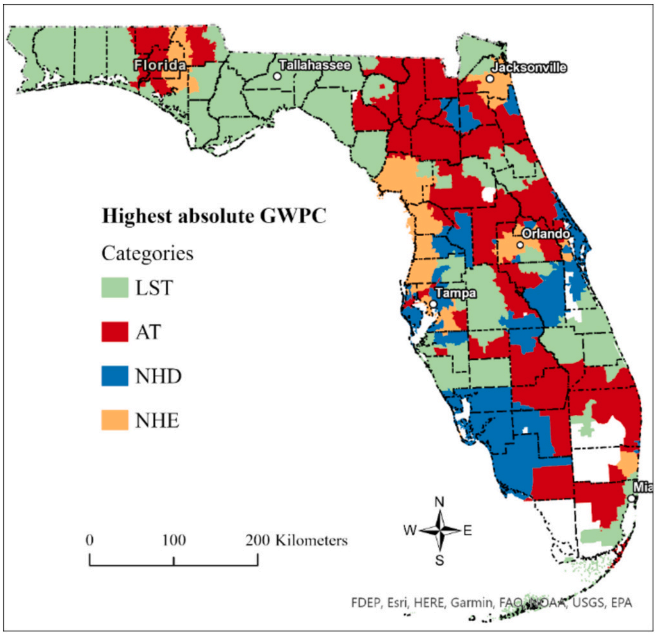


**Fig. 8.** Heat indicators with the highest absolute correlation coefficient in each zip code.

and Miami can be attributed to the greater availability of cooling facilities in indoor environments (Hondula et al., 2015), higher education and income levels, and abundant green spaces and shaded areas (Flocks et al., 2011; Hwang et al., 2017). The regression analysis indicates that the Hispanic population is negatively correlated with HRI-ED visit rates. However, the underlying factors behind this correlation remain unclear. Published evidence suggests that the unique social and spatial characteristics, including high population density and vibrant public and retail spaces, may mitigate the HRI risk in Hispanic communities (Klinenberg, 2002). These characteristics can enhance social cohesion and the sharing of resources and information to cope with heat impacts, which in turn foster communal resilience against HRIs (Harduar Morano et al., 2016). Black population show a positive correlation with HRI-ED visit rates in both hierarchical and multivariate regression analyses. This result reveals the disproportionate health burden of extreme heat in Black communities. Higher levels of poverty in Black communities can limit access to healthcare and cooling resources, thereby increasing their vulnerability to HRIs (O'Neill et al., 2005). Similar patterns have been documented in numerous studies (Khatana et al., 2022; Madrigano et al., 2018; Uejio et al., 2011).

When comparing the four heat indicators (LST, AT, NHD, and NHE), only AT is positively correlated with HRIs, despite accounting for only a small portion of the variance. Instead, the socio-economic variables show stronger relations with HRIs. This finding implies that, compared to the intensity of heat hazards, socio-economic disparities are more important factors in differentiating HRI occurrences. These findings align with previous research, which indicates the crucial role of socio-economic resources in heat adaptation and vulnerability (Barreca et al., 2016; Diboulo et al., 2012; Lindeboom et al., 2012). The negative correlation between LST and HRI suggests that LST may not be the optimal measure of heat intensity for human health. This result confirms previous studies, which show that LST does not always reflect the temperature individuals experience (Chakraborty et al., 2022). Instead, the stronger relation ($p < 0.05$) suggests that AT may be a better indicator of heat impacts on human health, as it represents the air temperature people are exposed to (Good, 2016). NHD and NHE can be influenced by the temperature thresholds used to define heat days (Hajat et al., 2006). Studies have identified "morbidity displacement," where heat-related morbidity spikes during or after a heatwave but is followed by a period of below-average illness rates (Anderson and Bell, 2011). In southern regions, prolonged higher temperatures allow individuals to

**Table 2**
Model diagnostics for OLS and spatial lag regression in urban and rural areas.

| Measurement | OLS | | Spatial Lag | |
|---|---|---|---|---|
| | Urban | Rural | Urban | Rural |
| Adjusted/Pseudo $R^2$ | 0.422 | 0.200 | 0.456 | 0.250 |
| Moran's $I$ of Residuals | 0.081** | 0.061** | 0.021** | 0.003** |
| Akaike Information Criterion (AIC) | 1351.87 | 1401.96 | 1344.1 | 1402.31 |
| Lagrange Multiplier (SARMA) | 9.826** | 3.283 | Likelihood Ratio Test | |
| Lagrange Multiplier (lag) | 9.450* | 3.382* | 9.773** | 3.425 |
| Lagrange Multiplier (error) | 6.041* | 2.650 | | |

* $p < 0.05$.
** $p < 0.01$.

**Table 1**
Hierarchical regression of HRI-ED visit rates and socio-economic variables with AT as the control variable.

| | AT (control variable) | | | | |
|---|---|---|---|---|---|
| | Urban zip code | | | Rural zip code | |
| Category | Variable | Coef. | (Baseline $R^2$, Incremental $R^2$) | Coef. | (Baseline $R^2$, Incremental $R^2$) |
| Socio-economic conditions | POV | 0.371** | (0.004, 0.100) | 0.312** | (0.002, 0.074) |
| | INC | −0.428** | (0.005, 0.174) | −0.377** | (0.003, 0.070) |
| | UNEMP | 0.273** | (0.003, 0.111) | 0.224** | (0.001, 0.178) |
| | EDU | 0.185** | (0.004, 0.056) | 0.278** | (0.002, 0.077) |
| | AGR | 0.162** | (0.004, 0.033) | 0.171** | (0.002, 0.005) |
| | CONSTR | 0.237** | (0.004, 0.080) | 0.245** | (0.002, 0.097) |
| Vulnerable population | OLD | 0.028 | (0.004, 0.006) | 0.018 | (0.002, 0.001) |
| | CHILD | 0.186** | (0.004, 0.102) | 0.076** | (0.002, 0.040) |
| | FEMALE | −0.021 | (0.004, 0.017) | −0.072 | (0.002, 0.016) |
| | DISABLE | 0.461** | (0.004, 0.187) | 0.369** | (0.002, 0.139) |
| Demographic conditions | WHITE | −0.202** | (0.004, 0.042) | −0.097* | (0.002, 0.013) |
| | ASIAN | −0.131** | (0.004, 0.005) | −0.154 | (0.002, 0.001) |
| | HISP | −0.296** | (0.004, 0.037) | −0.090 | (0.002, 0.001) |
| | BLACK | 0.277** | (0.004, 0.095) | 0.117* | (0.002, 0.030) |
| | ENGLISH | −0.250** | (0.004, 0.018) | −0.096 | (0.002, 0.000) |
| Housing and transportation | NOCAR | 0.148** | (0.005, 0.035) | 0.110 | (0.002, 0.015) |
| | ELECT | 0.122 | (0.004, 0.000) | −0.175** | (0.002, 0.004) |
| | HDEN | −0.201** | (0.003, 0.000) | −0.193* | (0.001, 0.009) |
| | OWNER | −0.107 | (0.003, 0.040) | −0.142 | (0.001, 0.028) |

* $p < 0.05$.
** $p < 0.01$.

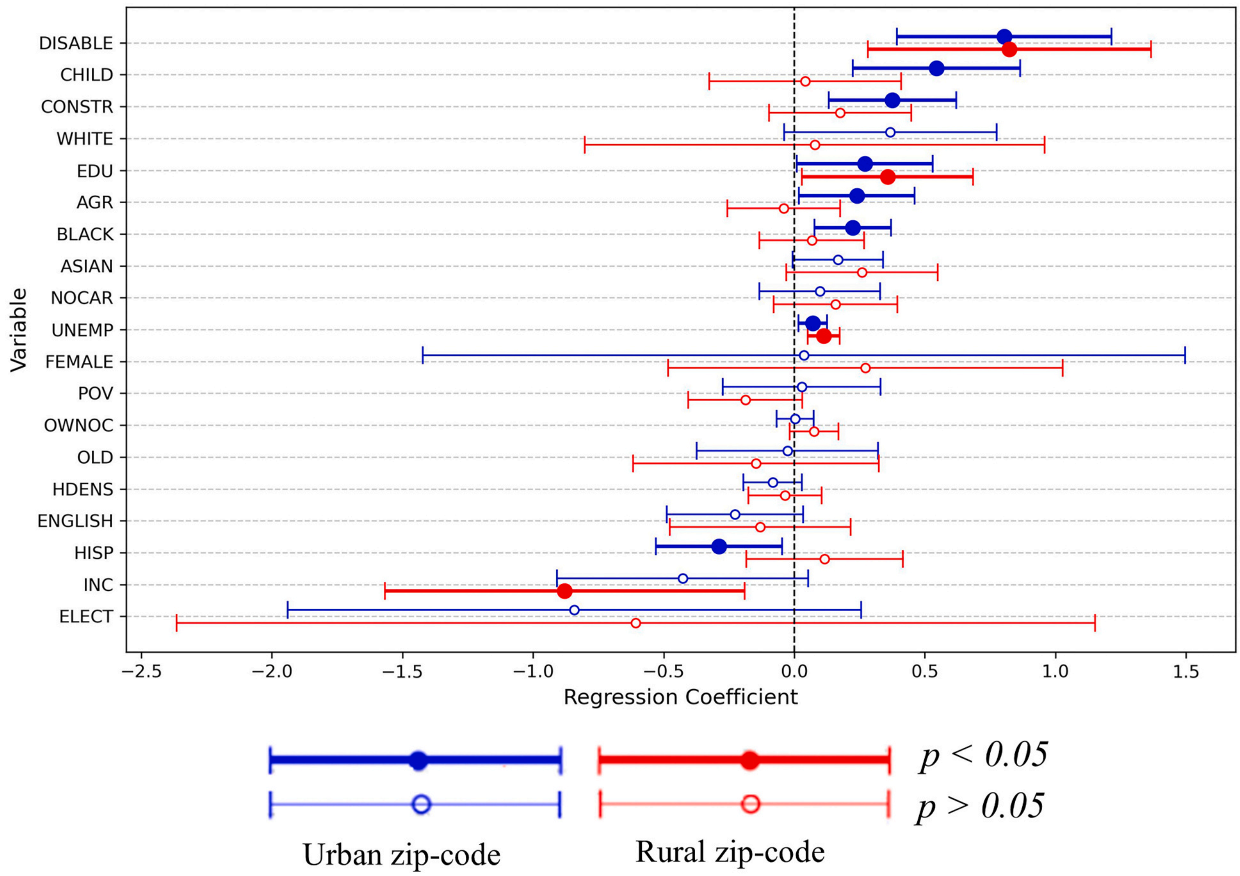


**Fig. 9.** The regression coefficients of the spatial lag models between HRI rates and socio-economic variables in both rural and urban areas.

acclimate, reducing the incidence of HRIs (Bouchama and Knochel, 2002). Another potential issue to consider is the accuracy of common temperature measures in capturing the actual intensity of heat experienced by individuals. Research highlights the need for alternative measures of heat hazards, such as the wet-bulb globe temperature, which incorporates humidity and solar radiation (Heo et al., 2019), or the Universal Thermal Climate Index (UTCI), which accounts for air temperature, wind speed, humidity, and radiation (Bröde et al., 2012). Moreover, future research at different spatial scales (Bai et al., 2024) could help to better understand how these heat-health relationships and various temperature measures interact with socio-economic factors in shaping heat vulnerability.

The regression analysis shows that urban and rural areas differ in several factors for HRI-ED visits (Fig. 9). In urban areas, agricultural and construction workers, children, and the Black population are positively associated with HRIs, while these associations are not significant in rural areas. The higher risk for agricultural and construction workers is consistent with the study by Zeng et al. (2022), which indicates that the urban heat island effect increases heat exposure for outdoor workers (Moda et al., 2019). The higher HRI risk for children in urban areas is partly due to spending more time in indoor, air-conditioned environments. When they engage in outdoor physical activities, their risk of HRI increases significantly (Falk, 1998; Gilchrist et al., 2011). In contrast, the lifestyle and living environment in rural areas may foster children's resilience to extreme heat. Additionally, the Black population, historically affected by residential segregation and socioeconomic inequalities, often resides in older neighborhoods that lack cooling resources, which increases their health risks (Hoffman et al., 2020). In rural areas, heat-related risks are predominantly associated with income levels. Low-income households often lack the financial means to purchase cooling equipment or cover the high electricity bills required to operate them (Conor and Jeff, 2013). Furthermore, rural areas tend to suffer from inadequate infrastructure and medical resources, making it difficult for these families to access timely healthcare and support during heat waves. Urban and rural populations, however, also share common risk factors, including unemployment, low educational attainment, and disabilities. Unemployment and low educational attainment are often associated with lower income (Majeed and Baumann, 2023), which limits their access to cooling equipment, increasing their exposure to health risks during heat waves. People with disabilities face heightened health risks in hot weather due to limited mobility, dependence on care, and impaired physiological regulation, and this is particularly pronounced in rural areas where medical services are less accessible and emergency response systems are weaker (Junod et al., 2023). A significant positive association between heat risk and disability status was also found in Los Angeles (Mitchell and Chakraborty, 2014). Taken together, this indicates a higher incidence of HRIs in economically disadvantaged and racially segregated zip code areas. The relation between socio-economic conditions and heightened HRI risks further highlights the interwoven nature of social, economic, and environmental systems. The high incidence of HRI is most commonly detected in rural and inland areas, where the socially vulnerable neighborhoods and labor-intensive industries are concentrated. This pattern demonstrates a deep-seated issue of environmental justice, wherein the most vulnerable segments of society are the hardest hit by the heat hazards. Overall, these findings align with prior research on socio-economic disparities and emphasize the critical role of economic status, race, and ethnicity in explaining HRI inequality patterns, thereby raising urgent concerns about climate justice and socio-economic disparities (Bonauto et al., 2007; Lehnert et al., 2020).

To reduce the health risks associated with extreme heat in Florida, policymakers can implement targeted measures to enhance the resilience of communities to high temperatures. In Florida's diverse communities, unemployed individuals and those with low education levels often face financial barriers that limit their ability to protect themselves during extreme heat events. Florida can leverage its unique resources to implement cooling solutions for these population groups. For instance, cities could mitigate urban heat island effects by expanding green spaces along streets and in residential areas to create natural shade corridors (Pereira et al., 2024). Additionally, public libraries, which already function as hurricane shelters, could be upgraded to serve as dual-purpose extreme weather shelters (Derakhshan et al., 2023). In rural areas, setting up multi-language emergency hotlines could help people who are immigrants and people with disabilities receive timely assistance during extreme heat (Matthies et al., 2008). Heat protection measures are particularly important for Florida's outdoor workers in tourism (with theme parks being a prime example) and agriculture (e.g., citrus harvesters). Tourist facilities should expand cooling areas and provide shade for both visitors and staff, while agricultural operations require portable shade and adjusted work schedules during periods of extreme heat (Ebi et al., 2021). For children, schools should be equipped with sufficient cooling systems, and educational programs should be implemented to teach families how to protect themselves during extreme heat events (Bernstein et al., 2022). Low-income rural households often struggle to cover air conditioning costs during extreme heat. Meanwhile, a tiered subsidy system, tailored to household income and heat vulnerability, could help ensure the most at-risk households receive adequate support (Austin et al., 2024).

Our study acknowledges several limitations that should be addressed in future research. First, the multivariate regression model explains 45.6 % of the variance in HRIs in urban areas and only 25.0 % in rural areas, indicating that the selected variables do not capture all factors influencing HRIs, particularly in rural settings. Future studies should incorporate a broader range of variables to identify other determinants of HRIs. Second, although our linear regression models quantified the contributions of various factors, they are limited in handling non-linear and complex relationships. Once the primary drivers of HRIs are identified, future research should explore the use of machine learning algorithms to enhance predictive accuracy, which could then be applied to regions beyond Florida. Third, the HRI-ED visit data may not capture all HRI instances. Individuals with mild symptoms or those facing healthcare access barriers might not seek emergency care. Instead, they may opt for alternative non-emergency care options, such as community clinics or self-treatment, which can lead to potential underreporting (Harduar Morano et al., 2016). Nevertheless, these groups could represent crucial target populations for future health policies and interventions. Missing milder HRI cases potentially underestimates the true burden of HRIs within the population and limits the applicability and generalizability of the findings in informing broader public health interventions. Furthermore, other conditions exacerbated by heat exposure might not be classified as HRIs, further contributing to underestimation (Hajat and Kosatky, 2010). Moreover, some ED visits could involve non-Florida residents, such as tourists or out-of-state workers, whose socio-economic conditions are not reflected in the ACS data. Future research could benefit from integrating additional data sources, such as community health surveys or questionnaires, to improve data accuracy (He et al., 2021). Finally, our study used the HRI-ED visit data in 2019, the latest pre-pandemic year, to avoid potential distortion of COVID-19 on ED visits. Lockdown measures, work-from-home arrangements, and concerns about visiting health facilities during the pandemic likely deterred individuals from seeking care for HRIs. Therefore, including data from post-COVID years would further strengthen the robustness of the analysis.

## 7. Conclusions

Our zip-code level analysis of HRI-ED visits in Florida revealed that socio-economic conditions are more strongly associated with HRI incidences than temperature alone. Vulnerable population groups (e.g., unemployed, lower educational attainment, and with disabilities) are strongly correlated with HRI cases. The results highlight the need to prioritize actions that mitigate the unequal consequences of extreme heat events on marginalized communities. The multivariate regression models demonstrate that the selected socio-economic and environmental variables can predict a significant proportion of the HRI variance, indicating the potential transferability of these models for predicting HRI risk in other regions or under hypothetical climate scenarios. Additionally, our analysis of rural versus urban disparities offers insights into tailored strategies that could enhance heat resilience across different community settings.


## CRediT authorship contribution statement

**Cong Ma:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yi Qiang:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Kai Zhang:** Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper


## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.177985.

## Data availability

Data will be made available on request.

## References


Abrahamson, V., Wolf, J., Lorenzoni, I., Fenn, B., Kovats, S., Wilkinson, P., Adger, W.N., Raine, R., 2009. Perceptions of heatwave risks to health: interview-based study of older people in London and Norwich, UK. J. Public Health 31 (1), 119–126. https://doi.org/10.1093/pubmed/fdn102.

American Immigration Council, 2015. Immigrants in Florida. https://www.americanimmigrationcouncil.org/research/immigrants-florida.

Anderson, G.B., Bell, M.L. [Michelle L.], 2011. Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. Communities. Environ. Health Perspect. 119 (2), 210–218. https://doi.org/10.1289/ehp.1002313.

Arnott, J., Alvarez, G., 2022. Heat waves are silent killers. Yale Climate Connections. https://yaleclimateconnections.org/2022/10/battling-heat-waves-the-silent-killer/.

Austin, A., Shastry, V., Krasniqi, Q., Hernández, D., 2024. Utilities' Low-Income Discount Programs Help Address Energy Insecurity, But Some US States Lag Behind. Columbia University. https://www.energypolicy.columbia.edu/utilities-low-income-discount-programs-help-address-energy-insecurity-but-some-us-states-lag-behind/.

Avashia, V., Garg, A., Dholakia, H., 2021. Understanding temperature related health risk in context of urban land use changes. Landsc. Urban Plan. 212, 104107. https://doi.org/10.1016/j.landurbplan.2021.104107.

Bai, X., Yu, Z., Wang, B., Zhang, Y. [Yanting], Zhou, S., Sha, X., Li, S., Yao, X., Geng, X., 2024. Quantifying threshold and scale response of urban air and surface temperature to surrounding landscapes under extreme heat. Build. Environ. 247, 111029. https://doi.org/10.1016/j.buildenv.2023.111029.

Bakhsh, K., Rauf, S., Zulfiqar, F., 2018. Adaptation Strategies for Minimizing Heat Wave Induced Morbidity and Its Determinants. 2210-6707, 41, pp. 95–103. https://doi.org/10.1016/j.scs.2018.05.021.

Barnett, A.G., Tong, S., Clements, A.C.A., 2010. What measure of temperature is the best predictor of mortality? Environ. Res. 110 (6), 604–611. https://doi.org/10.1016/j.envres.2010.05.006.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., Shapiro, J.S., 2016. Adapting to climate change: the remarkable decline in the US temperature-mortality relationship over the twentieth century. J. Polit. Econ. 124 (1), 105–159.

Beckmann, S.K., Hiete, M., 2020. Predictors associated with health-related heat risk perception of urban citizens in Germany. Int. J. Environ. Res. Public Health 17 (3), 874. https://doi.org/10.3390/ijerph17030874.

Bernstein, A.S., Sun, S., Weinberger, K.R., Spangler, K.R., Sheffield, P.E., Wellenius, G.A., 2022. Warm season and emergency department visits to U.S. Children's hospitals. Environ. Health Perspect. 130 (1), 17001. https://doi.org/10.1289/EHP8083.

Bonauto, D., Anderson, R., Rauser, E., Burke, B., 2007. Occupational heat illness in Washington State, 1995-2005. Am. J. Ind. Med. 50 (12), 940–950. https://doi.org/10.1002/ajim.20517.

Bouchama, A., Knochel, J.P., 2002. Heat stroke. N. Engl. J. Med. 346 (25), 1978–1988. https://doi.org/10.1056/NEJMra011089.

Braveman, P., Egerter, S., Williams, D.R., 2011. The social determinants of health: coming of age. Annu. Rev. Public Health 32(Volume 32, 2011), 381–398. https://doi.org/10.1146/annurev-publhealth-031210-101218.

Bröde, P., Fiala, D., Błażejczyk, K., Holmér, I., Jendritzky, G., Kampmann, B., Tinz, B., Havenith, G., 2012. Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). Int. J. Biometeorol. 56 (3), 481–494. https://doi.org/10.1007/s00484-011-0454-1.

CDC, 2022. Age adjustment - health, United States. https://www.cdc.gov/nchs/hus/sources-definitions/age-adjustment.htm.

Climate Central, 2019. Florida's climate threats - states at risk. https://www.climatecentral.org/.

Chakraborty, T., Venter, Z.S., Qian, Y., Lee, X., 2022. Lower urban humidity moderates outdoor heat stress. AGU Adv. 3(5), Article e2022AV000729, e2022AV000729. https://doi.org/10.1029/2022AV000729.

Cheng, Q., Sha, S., 2024. Revealing the injustice and factors that affect the resilience responses of residents in the full period of heat waves. Sustain. Cities Soc. 107, 105467. https://doi.org/10.1016/j.scs.2024.105467.

Choi, H.M., Chen, C., Son, J.-Y., Bell, M.L., 2021. Temperature-mortality relationship in North Carolina, USA: regional and urban-rural differences. Sci. Total Environ. 787, 147672. https://doi.org/10.1016/j.scitotenv.2021.147672.

Clarke, B., Otto, F., Stuart-Smith, R., Harrington, L., 2022. Extreme weather impacts of climate change: an attribution perspective. Environ. Res. Clim. 1 (1), 12001. https://doi.org/10.1088/2752-5295/ac6e7d.

Climate Central, 2015. America's preparedness report card 2015. http://assets.statesatrisk.org/summaries/Florida_report.pdf.

Conlon, K.C., Mallen, E., Gronlund, C.J., Berrocal, V.J., Larsen, L., O'Neill, M.S., 2020. Mapping human vulnerability to extreme heat: a critical assessment of heat vulnerability indices created using principal components analysis. Environ. Health Perspect. 128 (9), 97001. https://doi.org/10.1289/EHP4030.

Conor, H., Jeff, P., 2013. "Because you got to have heat": the networked assemblage of energy poverty in Eastern North Carolina. In: The New Geographies of Energy. Routledge, pp. 248–260. https://doi.org/10.4324/9780203722299-24.

Derakhshan, S., Bautista, T.N., Bouwman, M., Huang, L., Lee, L., Tarczynski, J., Wahagheghe, I., Zeng, X., Longcore, T., 2023. Smartphone Locations Reveal Patterns of Cooling Center Use as a Heat Mitigation Strategy. 0143-6228, 150, 102821. https://doi.org/10.1016/j.apgeog.2022.102821.

Di Napoli, C., Pappenberger, F., Cloke, H.L., 2019. Verification of heat stress thresholds for a health-based heat-wave definition. J. Appl. Meteorol. Climatol. 58 (6), 1177–1194. https://doi.org/10.1175/JAMC-D-18-0246.1.

Dialesandro, J., Brazil, N., Wheeler, S., Abunnasr, Y., 2021. Dimensions of thermal inequity: neighborhood social demographics and urban heat in the Southwestern U. S. Int. J. Environ. Res. Public Health 18 (3), 941. https://doi.org/10.3390/ijerph18030941.

Diboulo, E., Sié, A., Rocklöv, J., 2012. Weather and mortality: a 10 year retrospective analysis of the Nouna Health and Demographic Surveillance System, Burkina Faso. Glob. Health Action 5, 6–13. https://doi.org/10.3402/gha.v5i0.19078.

Ebi, K.L., Vanos, J., Baldwin, J.W., Bell, J.E., Errett, N.A., 2021. Extreme weather and climate change: Population health and health system implications. In: Annual Review of Public Health, 42(Volume 42, 2021), pp. 293–315. https://doi.org/10.1146/annurev-publhealth-012420-105026.

Ermida, S.L., Soares, P., Mantas, V., Göttsche, F.M., Trigo, I.F., 2020. Google earth engine open-source code for land surface temperature estimation from the Landsat Series. Remote Sens. 12 (9), 1471. https://doi.org/10.3390/rs12091471.

Errett, N.A., Hartwell, C., Randazza, J.M., Nori-Sarma, A., Weinberger, K.R., Spangler, K.R., Sun, Y., Adams, Q.H., Wellenius, G.A., Hess, J.J., 2023. Survey of extreme heat public health preparedness plans and response activities in the most populous jurisdictions in the United States. BMC Public Health 23 (1), 811. https://doi.org/10.1186/s12889-023-15757-x.

Evans, J.D., 1996. Straightforward statistics for the behavioral sciences. J. Am. Stat. Assoc. 91 (436), 1750. https://doi.org/10.2307/2291607.

Falk, B., 1998. Effects of thermal stress during rest and exercise in the paediatric population. Sports Med. 25 (4), 221–240. https://doi.org/10.2165/00007256-199825040-00002.

Faurie, C., Varghese, B.M., Liu, J., Bi, P., 2022. Association between high temperature and heatwaves with heat-related illnesses: a systematic review and meta-analysis. Sci. Total Environ. 852, 158332. https://doi.org/10.1016/j.scitotenv.2022.158332.

Fechter-Leggett, E.D., Vaidyanathan, A., Choudhary, E., 2016. Heat stress illness emergency department visits in national environmental public health tracking states, 2005–2010. J. Community Health 41 (1), 57–69. https://doi.org/10.1007/s10900-015-0064-7.

Fletcher, B.A., Lin, S., Fitzgerald, E.F., Hwang, S.A., 2012. Association of summer temperatures with hospital admissions for renal diseases in New York State: a case-crossover study. Am. J. Epidemiol. 175 (9), 907–916. https://doi.org/10.1093/aje/kwr417.

Flocks, J., Escobedo, F., Wade, J., Varela, S., Wald, C., 2011. Environmental justice implications of urban tree cover in Miami-Dade County, Florida. Environ. Just. 4 (2), 125–134. https://doi.org/10.1089/env.2010.0018.

Florida Department of Health, 2015. Health Effects of Summer Heat in Florida. Public Health Research Unit, Division of Community Health Promotion.

Florida Department of Health, 2023. Emergency department visits. https://www.flhealthcharts.gov/ChartsDashboards/rdPage.aspx?rdReport=NonVitalInd.Dataviewer&cid=9834.

Gao, Z., Zaitchik, B.F., Hou, Y., Chen, W., 2022. Toward park design optimization to mitigate the urban heat island: assessment of the cooling effect in five U.S. cities. Sustain. Cities Soc. 81, 103870. https://doi.org/10.1016/j.scs.2022.103870.

Gilchrist, J., Haileyesus, T., Murphy, M.W., Yard, E.E., 2011. Nonfatal sports and recreation heat illness treated in hospital emergency departments–United States, 2001–2009. MMWR Morb. Mortal Wkly. Rep. 60 (29), 977–980.

Good, E.J., 2016. An in situ-based analysis of the relationship between land surface "skin" and screen-level air temperatures. J. Geophys. Res. Atmos. 121 (15), 8801–8819. https://doi.org/10.1002/2016JD025318.

Griffith, D.A., 1987. Spatial Autocorrelation: A Primer Resource Publications in Geography. Association of American Geographers.

Gu, X., Chen, P., Fan, C., 2024. Socio-demographic inequalities in the impacts of extreme temperatures on population mobility. J. Transp. Geogr. 114, 103755. https://doi.org/10.1016/j.jtrangeo.2023.103755.

Hajat, S., Kosatky, T., 2010. Heat-related mortality: a review and exploration of heterogeneity. J. Epidemiol. Community Health 64 (9), 753–760. https://doi.org/10.1136/jech.2009.087999.

Hajat, S., Armstrong, B., Baccini, M., Biggeri, A., Bisanti, L., Russo, A., Paldy, A., Menne, B., Kosatsky, T., 2006. Impact of high temperatures on mortality: is there an added heat wave effect? Epidemiology 17 (6), 632–638. https://doi.org/10.1097/01.ede.0000239688.70829.63.

Hansen, A., Bi, L., Saniotis, A., Nitschke, M., 2013. Vulnerability to extreme heat and climate change: is ethnicity a factor? Glob. Health Action 6, 21364. https://doi.org/10.3402/gha.v6i0.21364.

Harduar Morano, L., Watkins, S., Kintziger, K., 2016. A comprehensive evaluation of the burden of heat-related illness and death within the Florida population. Int. J. Environ. Res. Public Health 13 (6), 551. https://doi.org/10.3390/ijerph13060551.

Harlan, S.L., Brazel, A.J., Prashad, L., 2006. Neighborhood microclimates and vulnerability to heat stress. Soc. Sci. Med. 63 (11) (2874-2863).

Hass, A.L., Runkle, J.D., Sugg, M.M., 2021. The driving influences of human perception to extreme heat: a scoping review. Environ. Res. 197, 111173. https://doi.org/10.1016/j.envres.2021.111173.

He, B.J., Zhao, D., Xiong, K., Qi, J., Ulpiani, G., Pignatta, G., Prasad, D., Jones, P., 2021. A framework for addressing urban heat challenges and associated adaptive behavior by the public and the issue of willingness to pay for heat resilient infrastructure in Chongqing, China. Sustain. Cities Soc. 75, 103361. https://doi.org/10.1016/j.scs.2021.103361.

Heo, S., Bell, M.L., Lee, J.T., 2019. Comparison of health risks by heat wave definition: applicability of wet-bulb globe temperature for heat wave criteria. Environ. Res. 168, 158–170. https://doi.org/10.1016/j.envres.2018.09.032.

Hoffman, J.S., Shandas, V., Pendleton, N., 2020. The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas. Climate 8 (1), 12. https://doi.org/10.3390/cli8010012.

Hondula, D.M., Balling, R.C., Vanos, J.K., Georgescu, M., 2015. Rising temperatures, human health, and the role of adaptation. Curr. Clim. Chang. Rep. 1 (3), 144–154. https://doi.org/10.1007/s40641-015-0016-4.

Hood, C.M., Gennuso, K.P., Swain, G.R., Catlin, B.B., 2016. County health rankings: relationships between determinant factors and health outcomes. Am. J. Prev. Med. 50 (2), 129–135. https://doi.org/10.1016/j.amepre.2015.08.024.

Hsu, A., Sheriff, G., Chakraborty, T., Manya, D., 2021. Disproportionate exposure to urban heat island intensity across major US cities. Nat. Commun. 12 (1), 2721. https://doi.org/10.1038/s41467-021-22799-5.

Hwang, W.H., Wiseman, P.E., Thomas, V.A., 2017. Enhancing the energy conservation benefits of shade trees in dense residential developments using an alternative tree placement strategy. Landsc. Urban Plan. 158, 62–74. https://doi.org/10.1016/j.landurbplan.2016.09.022.

Johnson, D.P., Wilson, J.S., 2009. The socio-spatial dynamics of extreme urban heat events: the case of heat-related deaths in Philadelphia. Appl. Geogr. 29 (3), 419–434. https://doi.org/10.1016/j.apgeog.2008.11.004.

Johnson, D.P., Lulla, V., Stanforth, A., Webber, J., 2011. Remote sensing of heat-related health risks: the trend toward coupling socioeconomic and remotely sensed data. Geogr. Compass 5 (10), 767–780. https://doi.org/10.1111/j.1749-8198.2011.00442.x.

Jung, J., Uejio, C.K., Adeyeye, T.E., Kintziger, K.W., Duclos, C., Reid, K., Jordan, M., Spector, J.T., Insaf, T.Z., 2021. Using social security number to identify sub-populations vulnerable to the health impacts from extreme heat in Florida, U.S. Environ. Res. 202, 111738. https://doi.org/10.1016/j.envres.2021.111738.

Junod, A., Russell, N., Scally, C., 2023. Climate Planning Has Left Out Disabled People in Rural Areas. Here's How to Fix That. https://www.urban.org/urban-wire/climate-planning-has-left-out-disabled-people-rural-areas-heres-how-fix.

Kalogirou, S., 2012. Testing local versions of correlation coefficients. Jahrb. Reg. 32 (1), 45–61. https://doi.org/10.1007/s10037-011-0061-y.

Kalogirou, S., 2014. A Spatially Varying Relationship between the Proportion of Foreign Citizens and Income at Local Authorities in Greece. Aristotle University of Thessaloniki, Thessaloniki. http://geolib.geo.auth.gr/digeo/index.php/pgc/article/view/10525.

Karlsson, M., Ziebarth, N.R., 2018. Population health effects and health-related costs of extreme temperatures: comprehensive evidence from Germany. J. Environ. Econ. Manag. 91, 93–117. https://doi.org/10.1016/j.jeem.2018.06.004.

Keellings, D., Waylen, P., 2014. Increased risk of heat waves in Florida: characterizing changes in bivariate heat wave risk using extreme value analysis. Appl. Geogr. 46, 90–97. https://doi.org/10.1016/j.apgeog.2013.11.008.

Khatana, S.A.M., Werner, R.M., Groeneveld, P.W., 2022. Association of extreme heat with all-cause mortality in the contiguous US, 2008-2017. JAMA Netw. Open 5 (5), e2212957. https://doi.org/10.1001/jamanetworkopen.2022.12957.

Kim, D.W., Deo, R.C., Lee, J.-S., 2017. Mapping heatwave vulnerability in Korea. Nat. Hazards 89 (1), 35–55. https://doi.org/10.1007/s11069-017-2951-y.

Klinenberg, E., 2002. Heat Wave: A Social Autopsy of Disaster in Chicago, Second edition. University of Chicago Press.

Kodera, S., Nishimura, T., Rashed, E.A., Hasegawa, K., Takeuchi, I., Egawa, R., Hirata, A., 2019. Estimation of heat-related morbidity from weather data: A computational study in three prefectures of Japan over 2013-2018. Environ. Int. 130, 104907. https://doi.org/10.1016/j.envint.2019.104907.

Kovach, M.M., Konrad, C.E., Fuhrmann, C.M., 2015. Area-level risk factors for heat-related illness in rural and urban locations across North Carolina, USA. Appl. Geogr. 60, 175–183. https://doi.org/10.1016/j.apgeog.2015.03.012.

Kovats, R.S., Hajat, S., 2008. Heat stress and public health: a critical review. Annu. Rev. Public Health 29(Volume 29, 2008), 41–55. https://doi.org/10.1146/annurev.publhealth.29.020907.090843.

LDAS, 2024. NLDAS-2 Forcing Dataset Information. https://ldas.gsfc.nasa.gov/nldas/v2/forcing.

Lehnert, E.A., Wilt, G., Flanagan, B., Hallisey, E., 2020. Spatial exploration of the CDC's Social Vulnerability Index and Heat-related Health Outcomes in Georgia, 2212-4209, 46, 101517. https://doi.org/10.1016/j.ijdrr.2020.101517.

Li, D., Newman, G.D., Wilson, B., Zhang, Y., [Yue], & Brown, R. D., 2022. Modeling the relationships between historical redlining, urban heat, and heat-related emergency department visits: an examination of 11 Texas cities. Environ. Plan. B: Urban Analyt. City Sci. 49 (3), 933–952. https://doi.org/10.1177/23998083211039854.

Lindeboom, A.N., Begum, D., Kim, S.P., 2012. The association of weather and mortality in Bangladesh from 1983-2009. Glob. Health Action 5, 53–60. https://doi.org/10.3402/gha.v5i0.19121.

Lippmann, S.J., Fuhrmann, C.M., Waller, A.E., Richardson, D.B., 2013. Ambient temperature and emergency department visits for heat-related illness in North Carolina, 2007-2008. Environ. Res. 124, 35–42. https://doi.org/10.1016/j.envres.2013.03.009.

Mac, V.V.T., McCauley, L.A., 2017. Farmworker vulnerability to heat hazards: a conceptual framework. J. Nurs. Scholarsh. 49 (6), 617–624. https://doi.org/10.1111/jnu.12327.

Madrigano, J., Lane, K., Petrovic, N., Ahmed, M., Blum, M., Matte, T., 2018. Awareness, risk perception, and protective behaviors for extreme heat and climate change in New York City. Int. J. Environ. Res. Public Health 15 (7), 1433. https://doi.org/10.3390/ijerph15071433.

Majeed, H., Baumann, S., 2023. Understanding the association between county-level unemployment and health stratified by education and income in the southwestern United States. Sci. Rep. 13 (1), 21988. https://www.nature.com/articles/s41598-023-49088-z.

Malakar, N.K., Hulley, G., Hook, S.J., Laraby, K., Cook, M., Schott, J.R., 2018. An operational land surface temperature product for Landsat thermal data: methodology and validation. IEEE Trans. Geosci. Remote Sens. 56 (10), 5717–5735. https://doi.org/10.1109/tgrs.2018.2824828.

Margolis, H.G., 2021. Heat waves and rising temperatures: human health impacts and the determinants of vulnerability. Clim. Chang. Glob. Publ. Health 123–161. https://doi.org/10.1007/978-3-030-54746-2_7.

Matisziw, T.C., Grubesic, T.H., Wei, H., 2008. Downscaling spatial structure for the analysis of epidemiological data. Comput. Environ. Urban. Syst. 32 (1), 81–93. https://doi.org/10.1016/j.compenvurbsys.2007.06.002.

Matthies, F., Bickler, G., Marín, N.C., Hales, S., 2008. Heat-health action plans: guidance. https://books.google.com/books?hl=zh-CN&lr=&id=iMZbfQn_4akC&oi=fnd&pg=PA1&dq=disabled+extreme+heat+HOTLINES&ots=s2eS0nlHuj&sig=BJs7HNyDecZQjFE-i4Iv8GfHAzg.

Mitchell, B.C., Chakraborty, J., 2014. Urban heat and climate justice: a landscape of thermal inequity in Pinellas County, Florida. Geogr. Rev. 104 (4), 459–480. https://doi.org/10.1111/j.1931-0846.2014.12039.x.

Moda, H.M., Filho, W.L., Minhas, A., 2019. Impacts of climate change on outdoor workers and their safety: some research priorities. Int. J. Environ. Res. Public Health 16 (18), 3458. https://doi.org/10.3390/ijerph16183458.

Moyce, S., Joseph, J., Tancredi, D., Mitchell, D., Schenker, M., 2016. Cumulative incidence of acute kidney injury in California's agricultural workers. J. Occup. Environ. Med. 58 (4), 391–397. https://doi.org/10.1097/JOM.0000000000000668.

Naseem, M., 2021. In Florida, worsening heat puts more people at risk. https://publicintegrity.org/environment/hidden-epidemics/florida-heat-illness-health-risks-farmworkers-elderly/.

Netrdová, P., Nosek, V., Hurbánek, P., 2020. Using areal interpolation to deal with differing regional structures in international research. Int. J. Geo-Inform. 9 (2), 126. https://doi.org/10.3390/ijgi9020126.

Nitschke, M., Hansen, A., Bi, P., Pisaniello, D., Newbury, J., Kitson, A., Tucker, G., Avery, J., Dal Grande, E., 2013. Risk factors, health effects and behavior in older people during extreme heat: a survey in South Australia. Int. J. Environ. Res. Public Health 10 (12), 6721–6733. https://doi.org/10.3390/ijerph10126721.

NOAA, 2016. How does the ocean affect climate and weather on land?: Ocean Exploration Facts: NOAA Ocean Exploration. https://oceanexplorer.noaa.gov/facts/climate.html.

NOAA, 2022. The heat index equation. https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml.

NOAA, 2023. Climate at a glance. https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/.

NWS, 2023. Weather Related Fatality and Injury Statistics. National Weather Service. https://www.weather.gov/hazstat/.

O'Neill, M.S., Zanobetti, A., Schwartz, J., 2005. Disparities by race in heat-related mortality in four US cities: the role of air conditioning prevalence. J. Urban Health 82 (2), 191–197. https://doi.org/10.1093/jurban/jti043.

O'Neill, M.S., Carter, R., Kish, J.K., Gronlund, C.J., White-Newsome, J.L., Manarolla, X., Zanobetti, A., Schwartz, J.D., 2009. Preventing heat-related morbidity and mortality: new approaches in a changing climate. Maturitas 64 (2), 98–103. https://doi.org/10.1016/j.maturitas.2009.08.005.

Ortiz, L., Gamarro, H., Gonzalez, J.E., McPhearson, T., 2022. Energy burden and air conditioning adoption in New York City under a warming climate. Sustain. Cities Soc. 76, 103465. https://doi.org/10.1016/j.scs.2021.103465.

Pereira, C., Flores-Colen, I., Mendes, M.P., 2024. Guidelines to reduce the effects of urban heat in a changing climate: green infrastructures and design measures. Sustain. Dev. 32 (1), 57–83. https://doi.org/10.1002/sd.2646.

Perkins, S.E., 2015. A review on the scientific understanding of heatwaves—their measurement, driving mechanisms, and changes at the global scale. Atmos. Res. 164-165, 242–267. https://doi.org/10.1016/j.atmosres.2015.05.014.

Pramanik, S., Punia, M., Yu, H., Chakraborty, S., 2022. Is dense or sprawl growth more prone to heat-related health risks? Spatial regression-based study in Delhi, India. Sustain. Cities Soc. 81, 103808. https://doi.org/10.1016/j.scs.2022.103808.

Reid, C.E., O'Neill, M.S., Gronlund, C.J., Brines, S.J., Brown, D.G., Diez-Roux, A.V., Schwartz, J., 2009. Mapping community determinants of heat vulnerability. Environ. Health Perspect. 117 (11), 1730–1736. https://doi.org/10.1289/ehp.0900683.

Robinson, W.A., 2021. Climate change and extreme weather: A review focusing on the continental United States. J. Air Waste Manage. Assoc. 71 (10), 1186–1209. https://doi.org/10.1080/10962247.2021.1942319.

Royé, D., 2017. The effects of hot nights on mortality in Barcelona, Spain. Int. J. Biometeorol. 61 (12), 2127–2140. https://doi.org/10.1007/s00484-017-1416-z.

Sabrin, S., Zech, W.C., Nazari, R., Karimi, M., 2021. Understanding occupational heat exposure in the United States and proposing a quantifying stress index. Int. Arch. Occup. Environ. Health 94 (8), 1983–2000. https://doi.org/10.1007/s00420-021-01711-0.

Schramm, P.J., Vaidyanathan, A., Radhakrishnan, L., Gates, A., Hartnett, K., Breysse, P., 2021. Heat-related emergency department visits during the northwestern heat wave—United States, June 2021. Morb. Mortal. Wkly Rep. 70 (29), 1021. https://www.ncbi.nlm.nih.gov/pmc/articles/pmc8297695/.

Scott, C., Timothy, J., 2003. Heat, mortality, and level of urbanization: measuring vulnerability across Ohio, USA. Clim. Res. 24 (3), 255–265. https://doi.org/10.3354/cr024255.

Sera, F., Hashizume, M., Honda, Y., Lavigne, E., Schwartz, J., Zanobetti, A., Tobias, A., Iñiguez, C., 2020. Air conditioning and heat-related mortality: a multi-country longitudinal study. Epidemiology 31 (6), 779–787. https://doi.org/10.1097/EDE.0000000000001241.

Shindell, D., Zhang, Y., Scott, M., Ru, M., Stark, K., Ebi, K.L., 2020. The effects of heat exposure on human mortality throughout the United States. GeoHealth 4 (4), e2019GH000234. https://doi.org/10.1029/2019GH000234.

Song, J., Yu, H., Lu, Y., 2021. Spatial-scale dependent risk factors of heat-related mortality: a multiscale geographically weighted regression analysis. Sustain. Cities Soc. 74, 103159. https://doi.org/10.1016/j.scs.2021.103159.

Spector, J.T., Masuda, Y.J., Wolff, N.H., Calkins, M., Seixas, N., 2019. Heat exposure and occupational injuries: review of the literature and implications. Curr. Environ. Health Rep. 6 (4), 286–296. https://doi.org/10.1007/s40572-019-00250-8.

Statista Research Department, 2023. Population of adults aged 65 and older in the United States in 2021, by state. https://www.statista.com/statistics/736211/senior-population-of-the-us-by-state/.

Steadman, R.G., 1984. A universal scale of apparent temperature. J. Clim. Appl. Meteorol. 23 (12), 1674–1687. https://doi.org/10.1175/1520-0450(1984)023<1674:AUSOAT>2.0.CO;2.

Stoecklin-Marois, M., Hennessy-Burt, T., Mitchell, D., Schenker, M., 2013. Heat-related illness knowledge and practices among California hired farm workers in The MICASA Study. Ind. Health 51 (1), 47–55. https://doi.org/10.2486/indhealth.2012-0128.

Sun, S., Weinberger, K.R., Nori-Sarma, A., Spangler, K.R., Sun, Y., Dominici, F., Wellenius, G.A., 2021. Ambient heat and risks of emergency department visits among adults in the United States: time stratified case crossover study. BMJ 375, e065653. https://doi.org/10.1136/bmj-2021-065653.

Thornton, M.M., Shrestha, R., Wei, Y., Thornton, P.E., Kao, S., Wilson, B.E., 2022. Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 4. https://doi.org/10.3334/ORNLDAAC/2129.

U.S. Census Bureau, 2020. FLORIDA: 2020 Census. U.S, Census Bureau. https://www.census.gov/library/stories/state-by-state/florida-population-change-between-census-decade.html.

U.S. Census Bureau, 2023. Urban and Rural. https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html.

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.

Varghese, B.M., Hansen, A.L., Williams, S., Bi, P., Hanson-Easey, S., Barnett, A.G., Heyworth, J.S., Sim, M.R., Rowett, S., Nitschke, M., Di Corleto, R., Pisaniello, D.L., 2020. Determinants of heat-related injuries in Australian workplaces: perceptions of

health and safety professionals. Sci. Total Environ. 718, 137138. https://doi.org/10.1016/j.scitotenv.2020.137138.
Wang, C., Solís, P., Villa, L., Khare, N., Wentz, E.A., Gettel, A., 2021. Spatial modeling and analysis of heat-related morbidity in Maricopa County, Arizona. J. Urban Health 98 (3), 344–361. https://doi.org/10.1007/s11524-021-00520-7.
Weilnhammer, V., Schmid, J., Mittermeier, I., Schreiber, F., Jiang, L., Pastuhovic, V., Herr, C., Heinze, S., 2021. Extreme weather events in europe and their health consequences - a systematic review. Int. J. Hyg. Environ. Health 233, 113688. https://doi.org/10.1016/j.ijheh.2021.113688.
Wilson, B., 2020. Urban heat management and the legacy of redlining. J. Am. Plan. Assoc. 86 (4), 443–457. https://doi.org/10.1080/01944363.2020.1759127.
World Health Organization, 2022. Heatwaves. World Health Organization. https://www.who.int/health-topics/heatwaves#tab=tab_1.
Wu, H., Xu, Y., Zhang, M., Su, L., Wang, Y., Zhu, S., 2024. Spatially explicit assessment of the heat-related health risk in the Yangtze River Delta, China, using multisource remote sensing and socioeconomic data. Sustain. Cities Soc. 104, 105300. https://doi.org/10.1016/j.scs.2024.105300.
Xiang, J., Hansen, A., Pisaniello, D., Bi, P., 2015. Extreme heat and occupational heat illnesses in South Australia, 2001-2010. Occup. Environ. Med. 72 (8), 580–586. https://doi.org/10.1136/oemed-2014-102706.
Xu, Z., Cheng, J., Hu, W., Tong, S., 2018. Heatwave and health events: a systematic evaluation of different temperature indicators, heatwave intensities and durations. Sci. Total Environ. 630, 679–689. https://doi.org/10.1016/j.scitotenv.2018.02.268.
Yu, Z., Chen, J., Chen, J., Zhan, W., Wang, C., Ma, W., Yao, X., Zhou, S., Zhu, K., Sun, R., 2024. Enhanced observations from an optimized soil-canopy-photosynthesis and energy flux model revealed evapotranspiration-shading cooling dynamics of urban vegetation during extreme heat. Remote Sens. Environ. 305, 114098. https://doi.org/10.1016/j.rse.2024.114098.
Zeng, P., Sun, F., Liu, Y., Chen, C., Tian, T., Dong, Q., Che, Y., 2022. Significant social inequalities exist between hot and cold extremes along urban-rural gradients. Sustain. Cities Soc. 82, 103899. https://doi.org/10.1016/j.scs.2022.103899.
Zhang, C., Fay, D., McGrath, D., Grennan, E., Carton, O.T., 2008. Statistical analyses of geochemical variables in soils of Ireland. Geoderma 146 (1–2), 378–390. https://doi.org/10.1016/j.geoderma.2008.06.013.
Zhao, Q., Li, S., Ye, T., Wu, Y., Gasparrini, A., Tong, S., Urban, A., Vicedo-Cabrera, A.M., Tobias, A., 2024. Global, regional, and national burden of heatwave-related mortality from 1990 to 2019: A three-stage modelling study. PLOS Medicine 21 (5), e1004364. https://doi.org/10.1371/journal.pmed.1004364.