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Sensitivity and vulnerability to summer heat extremes in major cities of the United States

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Abstract

Many cities are experiencing increases in extreme heat because of global temperature rise combined with the urban heat island effect. The heterogeneity of urban morphology also leads to fine-scale variability in potential for heat exposure. Yet, how this rise in temperature and local variability together impacts urban residents differently at exposure-relevant scales is still not clear. Here we map the Universal Thermal Climate Index, a more complete indicator of human heat stress at an unprecedentedly fine spatial resolution (1 m), for 14 major cities in the United States using urban microclimate modeling. We examined the different heat exposure levels across different socioeconomic and racial/ethnic groups in these cities, finding that income level is most consistently associated with heat stress. We further conducted scenario simulations for a hypothetical 1 °C increase of air temperature in all cities. Results show that a 1 °C increase would have a substantial impact on human heat stress, with impacts that differ across cities. The results of this study can help us better evaluate the impact of extreme heat on urban residents at decision-relevant scales.

1. Introduction

Rising temperatures due to global warming would expose more people to less preferable climate conditions and have huge human costs (Lenton *et al* 2023). Every year, many people, especially elderly people, are hospitalized or even die because of increasingly frequent heat waves as well as chronic heat exposure. The urban heat island effect has been shown to exacerbate the mortality increase within cities (Gabriel and Endlicher 2011, Iungman *et al* 2023).

On a local scale, not all neighborhoods and communities are equally impacted by extreme heat (Reid *et al* 2009, Chakraborty *et al* 2019, Hsu *et al* 2021). Fine level quantitative information about where and which populations are vulnerable to heat is important to identify the most vulnerable neighborhoods and populations in order to minimize the negative impacts of heat stress on urban residents (Reid *et al* 2012, Gronlund 2014).

The land surface temperature (LST) derived from remotely sensed thermal imageries is the most widely used metric to indicate the heat distribution at large scale because it is readily obtained at reasonably high resolution (<100 m) over large geographic areas. Hoffman *et al* (2020) used LST to study the impacts of historical housing policy on the current heat exposure across 108 US urban areas. Hsu *et al* (2021) studied environmental inequities across the United States using LST and found in most cities, people of color live in neighborhoods of higher heat intensity than non-Hispanic whites.

While the LST derived from satellite imagery provides an efficient way to quantify the spatial distribution of heat intensity across neighborhoods, LST cannot fully indicate human outdoor heat stress level, since it is not air temperature and does not consider several other factors that impact human heat stress level such as radiation, wind, and humidity (Budd 2008, Lindberg *et al* 2008, Lindberg *et al* 2016, Li 2021, Park *et al* 2014, Di Napoli *et al* 2018, Lau *et al* 2015, Chakraborty *et al* 2022). In addition, the satellite-view LST indicates the surface temperature of all satellite-visible surfaces, including building roofs and treetops, which are not the places where human activities take place (Li *et al* 2023).

In contrast to remote sensing-based LST, urban microclimate modeling has the capability to map hyperlocal urban heat exposure from a more human-centric perspective. However, the microclimate modeling using high resolution urban geometrical constraints is time-consuming, which is the major obstacle for large scale analyses. In 2021, Li and Wang (2021) proposed a GPU-accelerated algorithm to make the process much more efficient, which dramatically increases the applicability of the method for mapping the large-scale urban heat exposure. Here, we adopt the GPU-accelerated algorithm to calculate and map a more human-centric heat stress indicator, the Universal Thermal Climate Index (UTCI). The UTCI considers the human body's energy balance, accounting for air temperature, shade, wind speed, and humidity (Blazejczyk *et al* 2012, Bröde *et al* 2012, Jendritzky *et al* 2012). Moreover, the method considers fine-scale urban variability that modulates radiation exposure, and thus overall human heat loading. In order to investigate the sensitivity of ambient heat stress to higher air temperature in those cities, this study further simulated and mapped the UTCI for a hypothetical scenario of a local 1 °C air temperature increase. Finally, we used these fine-resolution UTCI estimates to examine heat exposure across different socioeconomic and racial/ethnic groups in these cities.

2. Methods

2.1. Data preparation

This study selected 14 major cities across the United States in different climate zones. The climate zone data was collected from U.S. Department of Energy Building America Program based on the climate designations used by the International Energy Conservation Code. Figure 1 shows the locations of those selected cities. The datasets used in this study include building footprint maps, Light Detection and Ranging (LiDAR) data, National Agriculture Imagery Program (NAIP) imageries, and meteorological data. The building footprint map was collected from Microsoft building footprint database. The most recent high-resolution LiDAR datasets from United States Geological Survey were used to generate digital surface models (DSMs) for all selected cities. The building footprint maps and the generated DSMs were combined to generate building height models. The NAIP imageries with a spatial resolution around 1 m were used to generate the tree canopy cover maps using the thresholding method on the normalized difference vegetation index for each city. The tree canopy cover maps were then refined based on the generated DSM by removing those pixels lower than 2 m. The generated tree canopy maps were then overlayed on the DSMs to generate the tree canopy height model for each city.

The meteorological data of 2017 was collected from the National Renewable Energy Laboratory (https://nsrdb.nrel.gov/). The meteorological data include the air temperature, global horizontal radiation, direct radiation, diffuse radiation, wind speed, and relative humidity. See Appendix for more details about datasets.

2.2. UTCI mapping

This study quantifies heat stress using the UTCI, measured in °C, which has been used widely to indicate human heat stress levels (Young *et al* 2021). UTCI values higher than 32 °C is generally considered strong heat stress levels (figure 2(c)). The mean radiation temperature (T_{mrt}) is the most important input parameter for calculating the UTCI. The T_{mrt} is the net shortwave and longwave radiation that the human body is exposed to in an environment. The T_{mrt} is the most significant meteorological input parameter for the human energy balance, especially during clear and calm summer days (Mayer and Höppe 1987). Based on the Stefan–Boltzmann law, T_{mrt} (in °C) can be calculated as,

$$T_{\mathrm{mrt}} = \sqrt[4]{R/_{\varepsilon_p \sigma}} - 273.15 \quad (1)$$

where ε_p is the emissivity of the human body (standard value 0.97), σ is the Stefan–Boltzmann constant, and R denotes total radiation exposure as the sum of short and long wave radiation from above, below, and the four cardinal directions. The R can be calculated as,

$$R = \xi_k \sum_{1}^{6} K_i F_i + \varepsilon_p \sum_{1}^{6} L_i F_i \quad (2)$$

where K_i is the shortwave radiation component from 6 directions (north, south, west, east, top and bottom), L_i is the longwave radiation, F_i is the angular factor between a person and the surrounding environment, ξ_k is the absorption coefficient for shortwave radiation (standard value 0.7). This study adopted the previously developed GPU-accelerated SOlar and LongWave Environmental Irradiance Geometry

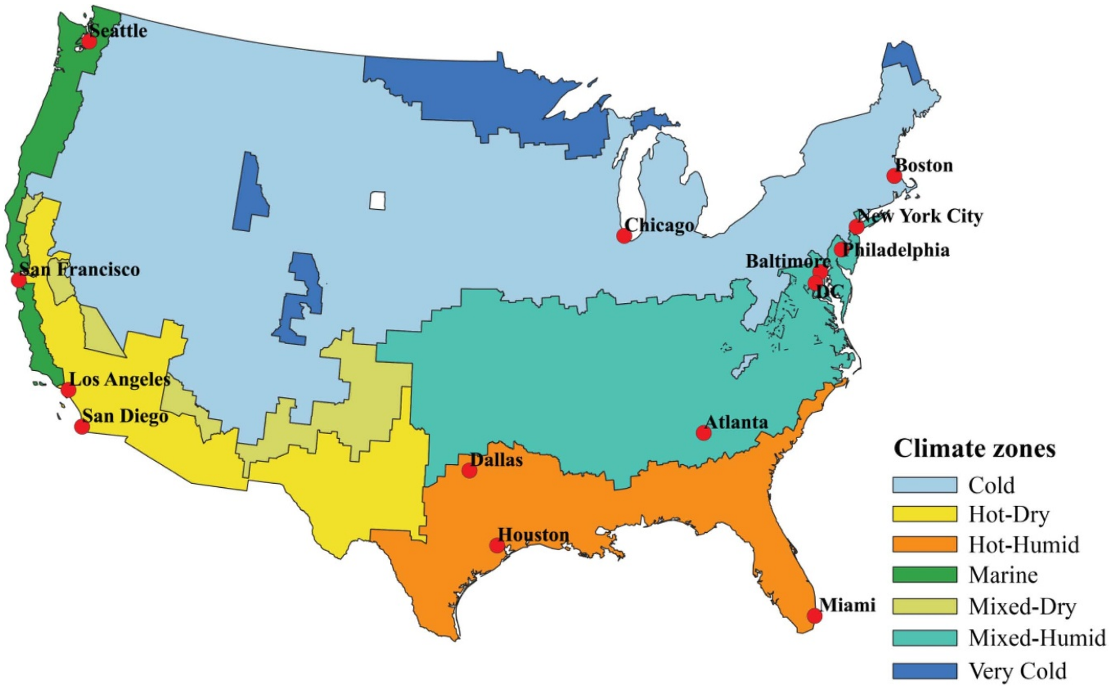


Figure 1. The locations of the selected 14 major US cities in different climate zones.

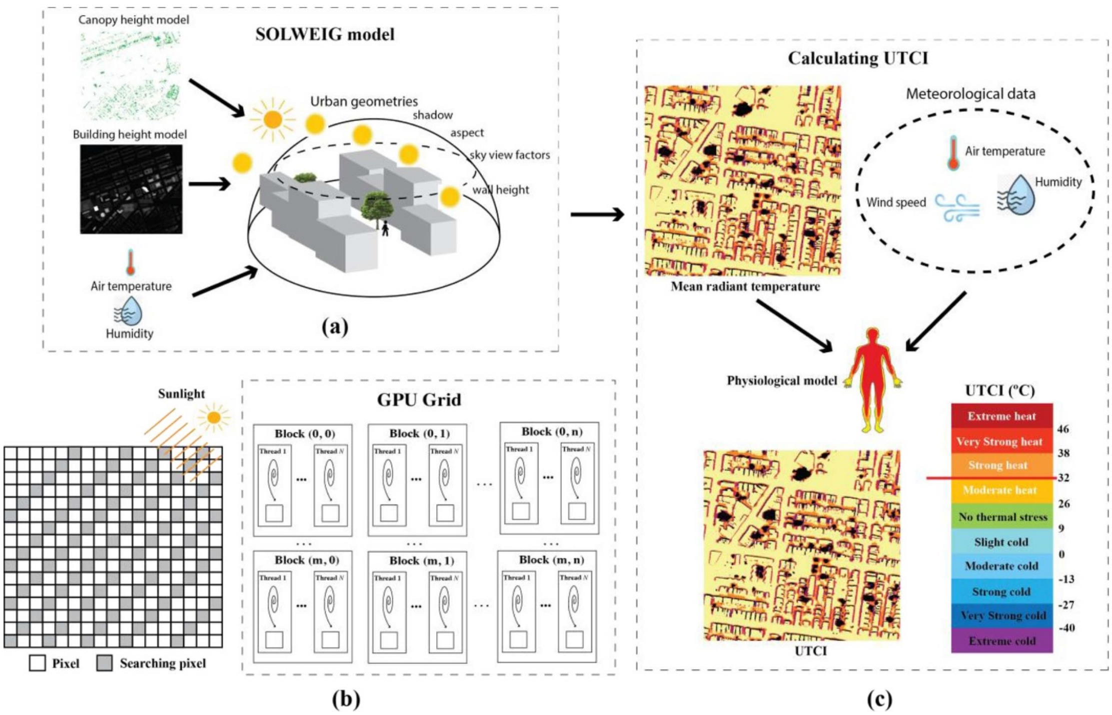


Figure 2. The calculation of the UTCI and the T_{mrt} using the SOLWEIG model based on tree canopy height model, building height model, and meteorological data using the GPU-accelerated algorithm, (a) the SOLWEIG model for computing the mean radiant temperature, (b) the GPU-accelerated algorithm, (c) the human physiological model for UTCI calculation and scale of UTCI.

model (SOLWEIG) model (Li and Wang 2021) to calculate the T_{mrt} based on the input urban 3D model and the meteorological data (figure 2). Based on the estimated T_{mrt}, this study adopted the UTCI approximation algorithm in Fortran (Bröde *et al* 2012), and rewrote a GPU-based script to calculate and map the UTCI in all selected cities, considering wind speed, humidity, and air temperature.

2.3. Sensitivity and vulnerability analysis to the extreme heat

The UTCI was calculated and mapped for the hottest month in each city. Based on the meteorological data, in San Francisco the hottest month is September; in Seattle, Los Angeles, and San Diego the hottest month is August; and in the other cities the hottest month is July based on the air temperature in the meteorological input data. The UTCI was calculated at hourly level from 8 am to 5 pm every day in the hottest month for each city in 2017. In order to examine the sensitivity of heat stress level to higher air temperatures, this study also modeled and mapped the spatial distributions of the UTCI for a hypothetical 1 °C warming scenario in all cities. The generated hourly level UTCI maps were averaged to indicate the general pattern of the UTCI values distribution for both the present day and for the 1 °C warming scenario.

Finally, the spatial UTCI data was compared with socioeconomic and demographic statuses of residents in different cities. To represent the socioeconomic and demographic statuses, we selected variables of per capita income, proportion of non-Hispanic whites, proportion of African Americans, proportion of Hispanic, proportion of Asian Americans, proportion of people older than 65, proportion of people younger than 18, proportion of people with bachelor or higher degrees, and proportion of people without high-school degrees based on previous studies (Landry and Chakraborty 2009, Hsu *et al* 2021, Li 2021). All the socio-economic variables were collected from the 2015–2019 American Community Survey 5 year data. To make the hourly averaged pixel level heat maps comparable to the census data in each city, we aggregated the pixel level UTCI maps to census tract level by calculating the mean value of pixels in each census tract for each city and those building roof pixels were masked out before the aggregation.

The ordinary least square regression models (OLS) were applied to investigate the associations between the social variables and UTCI values. In order to examine the heat stress level for residents of different racial/ethnic groups, only income and the non-white population groups were selected as features of the OLS regression models. The global Moran's *I* statistics were used to examine the spatial autocorrelation in the residuals of the OLS regression models. The spatial lag regression (SAR_{lag}) models were then applied when the residuals had significant spatial dependence in the OLS models for different cities (Anselin *et al* 2009).

3. Results

3.1. Spatial distributions of UTCI

Figure 3 shows the spatial distributions of the daytime hourly averaged UTCI with the spatial resolution of 1 m in different cities in the hottest month of the year 2017. Within each city, the UTCI values vary significantly across space due to different urban forms, since the shade provided by tree canopies and buildings is the most important factor affecting the UTCI. Generally, for most cities, the denser urban areas have higher UTCI values, while the less dense areas have relatively lower UTCI values, which are attributed to the tree canopy cover. The most densely urban areas (usually the downtown area) have relatively lower UTCI values because of the shade by high-rise buildings.

Different cities have different levels of outdoor heat exposure level in the hottest month. Generally, in the cities of Boston, Chicago, Seattle, San Francisco, Philadelphia, New York City, San Diego, the heat stress levels are moderate based on the present-day simulation results, since the entire cities have the UTCI values lower than 32 °C, which is the threshold of strong heat stress. The cities of Washington, D.C., Baltimore, Dallas, Atlanta, Los Angeles, Houston, and Miami have some areas currently exposed to strong heat stress (monthly average UTCI values larger than 32 °C). Please note that this is the hourly averaged UTCI values from 8 am to 5 pm every day in the hottest month, which smooths the peak UTCI values in one day. For Atlanta, Dallas, and Houston, the entire cities are exposed to strong heat stress.

Figure 4 shows the spatial distribution of the aggregated UTCI values at the census tract level using the mean values of pixels in each census tract by masking out the building roof pixels since the building roofs are generally not frequented by people.

3.2. Sensitivity analysis of heat stress level to a 1 °C air temperature increase

Figure 5 shows the histograms of the UTCI values based on the current meteorological parameters input and for the hypothetical 1 °C warming scenario in different cities at the pixel level. All cities have skewed distributions of UTCI to the high values, except for Atlanta. With 1 °C air temperature increase, the histograms shift toward higher heat stress level for all cities. The shapes of the histograms of the UTCI in different cities also show that different cities may have different susceptibility levels to the potential extreme heat events. For cities with histograms more skewed to higher UTCI values, larger proportion of pixels in those cities have higher UTCI values, which means that larger areas will be exposed to higher heat stress as the air temperature increases. This is especially true for Chicago, Philadelphia, Washington, D.C., San Diego, and Los Angeles. In those cities, most pixels are in the far-right side of the histograms. This means that as the air temperature increases, most parts of those cities would be exposed to strong heat stress. Atlanta is different from other cities in that most pixels are in the left side of the histogram. This is because of the large tree canopy coverage (more than 46%) in

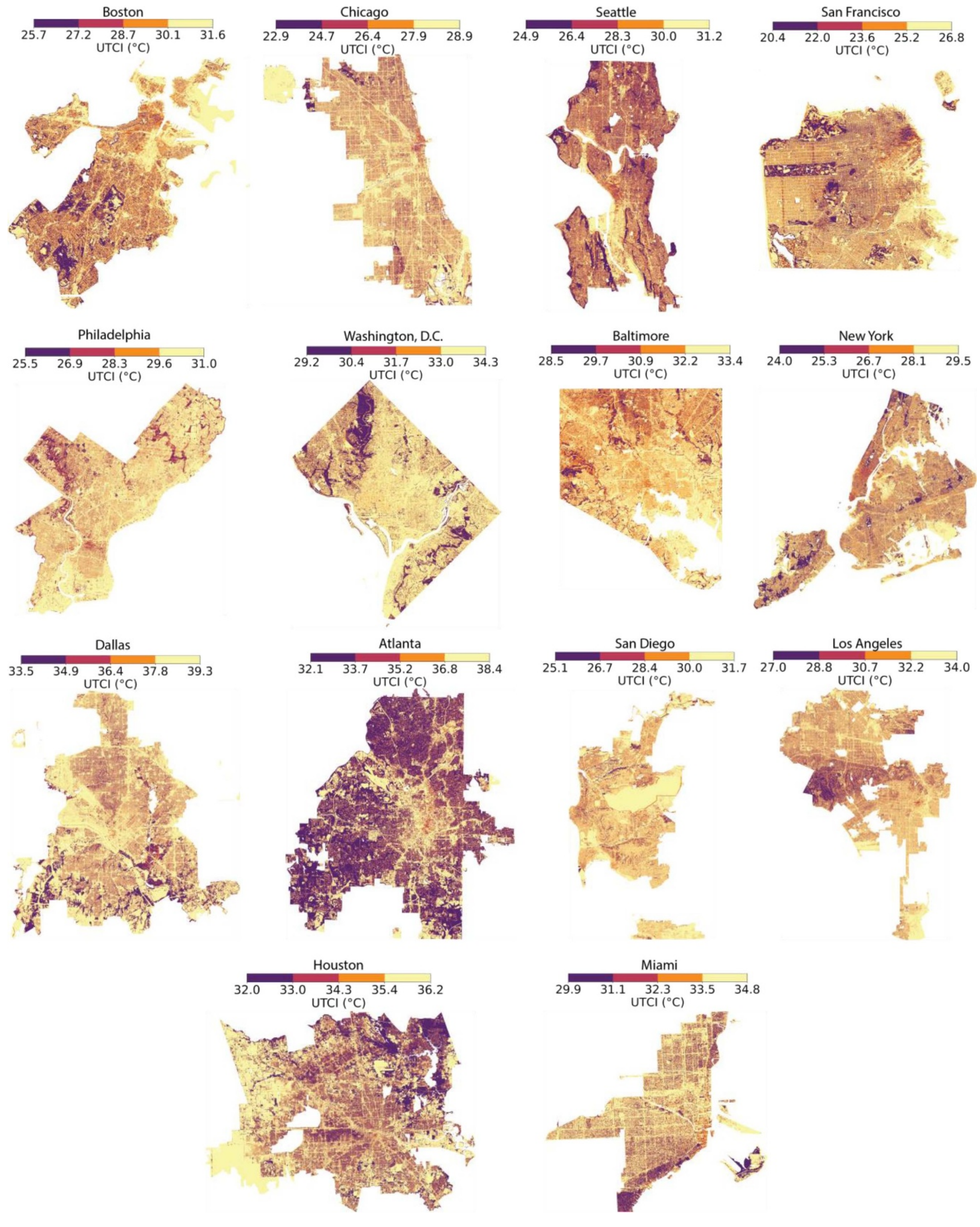


Figure 3. The spatial distributions of the hourly averaged UTCI (°C) in the hottest month of 2017 in different cities.

the city. However, in Atlanta most pixels have UTCI values higher than 32 °C. Although the large tree canopy covers help to lower the heat exposure level in Atlanta, the general heat exposure level is still too high for human thermal comfort.

Table 1 presents the numbers and percentages of population that are exposed to strong heat stress (UTCI larger than 32 °C) in different cities in the current situation and the scenario of air temperature 1 degree higher. In the current situation, about 98.1% of residents in Washington, D.C., 32.9% of residents in Baltimore, 100% of residents in Dallas, 100% of residents in Atlanta, 21.0% of residents in Los Angeles, 100% of residents in Houston, and 97.1% of residents in Miami, are exposed to strong heat stress. Residents in the rest of cities currently are not experiencing strong heat stress.

For the 1 °C warming scenario, 99.4% of residents in Washington, D.C. will be exposed to strong heat stress, an increase from 98.1% in the present-day scenario. The cities of Baltimore and Los Angeles have a large increase between the current situation

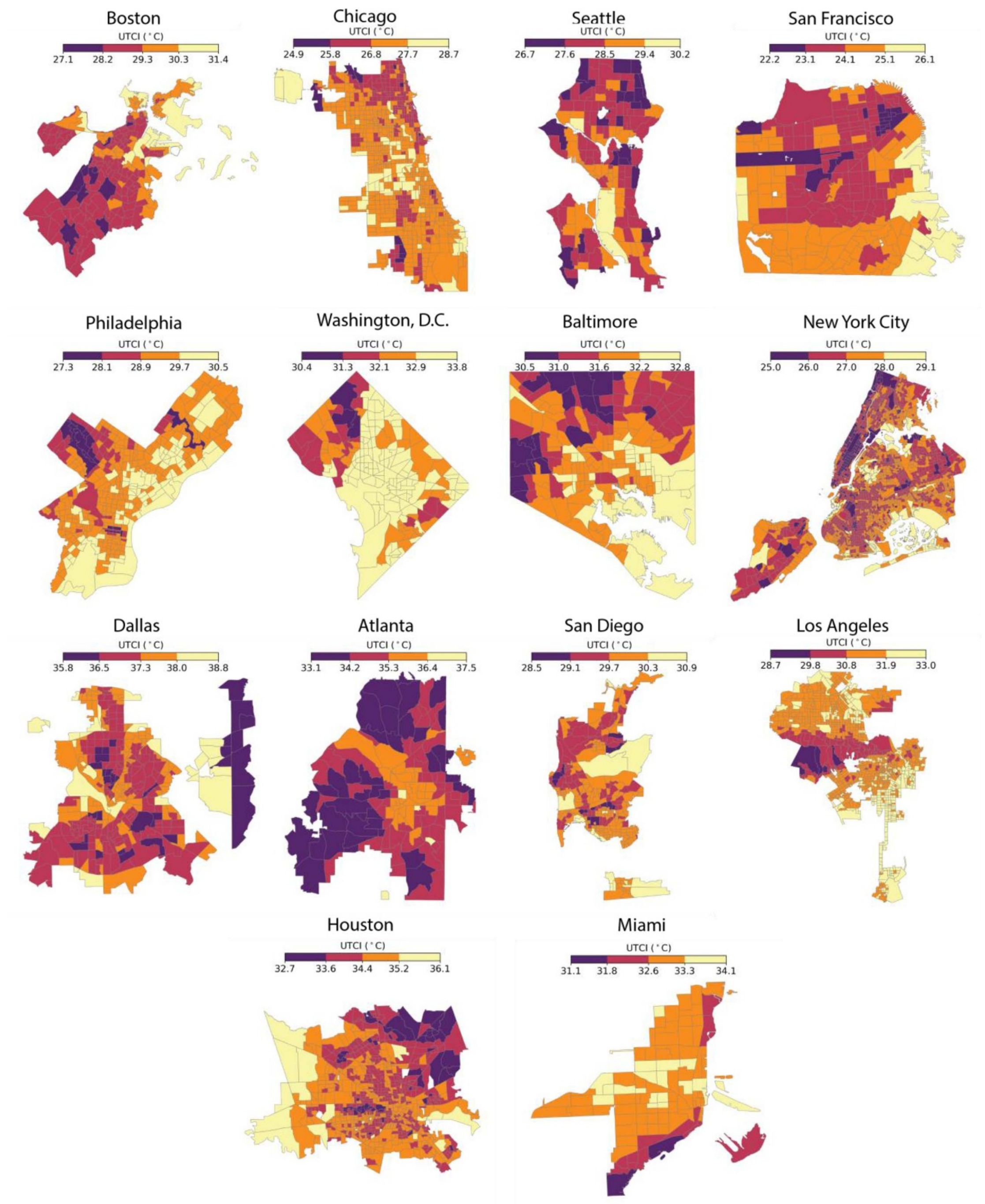


Figure 4. The spatial distributions of UTCI in the hottest month of 2017 in different cities at the census tract level. The UTCI value for each census tract is the average of all UTCI pixel values in each census tract after masking out the building pixels.

and the 1 °C warming scenario. 95.2% residents in Baltimore and 92.3% of residents in Los Angeles will be exposed to strong heat stress, increase from 32.9% and 21.0%, respectively in the current situation. In the 1 °C warming scenario, small population in Boston (0.2%) and San Diego (0.7%) starts to experience strong heat stress. The cities of Chicago, Seattle, San Francisco, Philadelphia, and New York City will not experience strong heat stress in the 1 °C warming scenario.

3.3. Correlations between the UTCI and socioeconomic and racial/ethnic variables

Figure 6 shows the correlation coefficients of the UTCI and different socioeconomic and demographic variables in different cities. Generally, the per capita income has a significant and negative correlation with the UTCI in all cities except Atlanta, Seattle, Baltimore, and Boston. The proportion of non-Hispanic white populations has a significant and negative correlation with the UTCI in Washington,

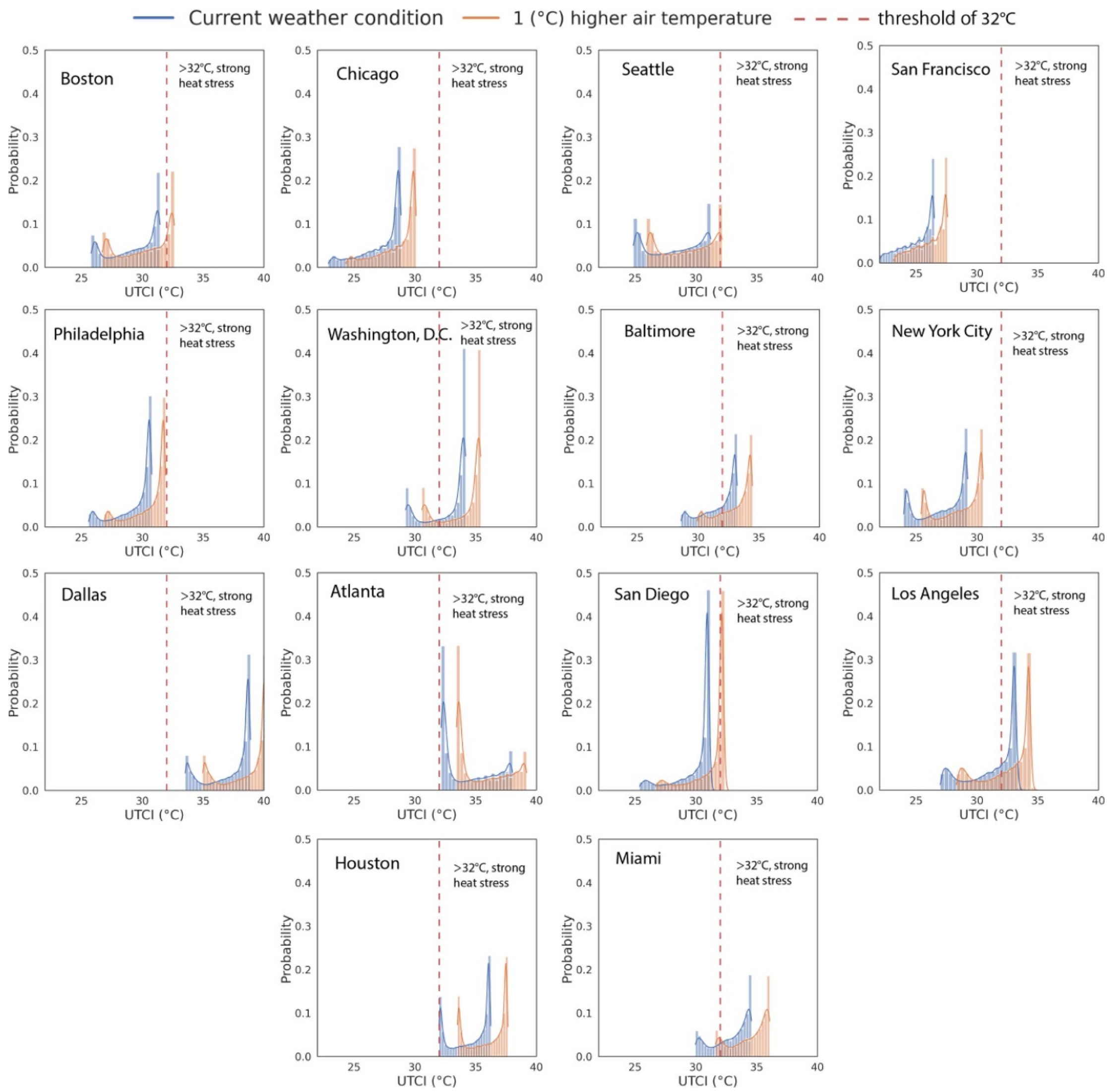
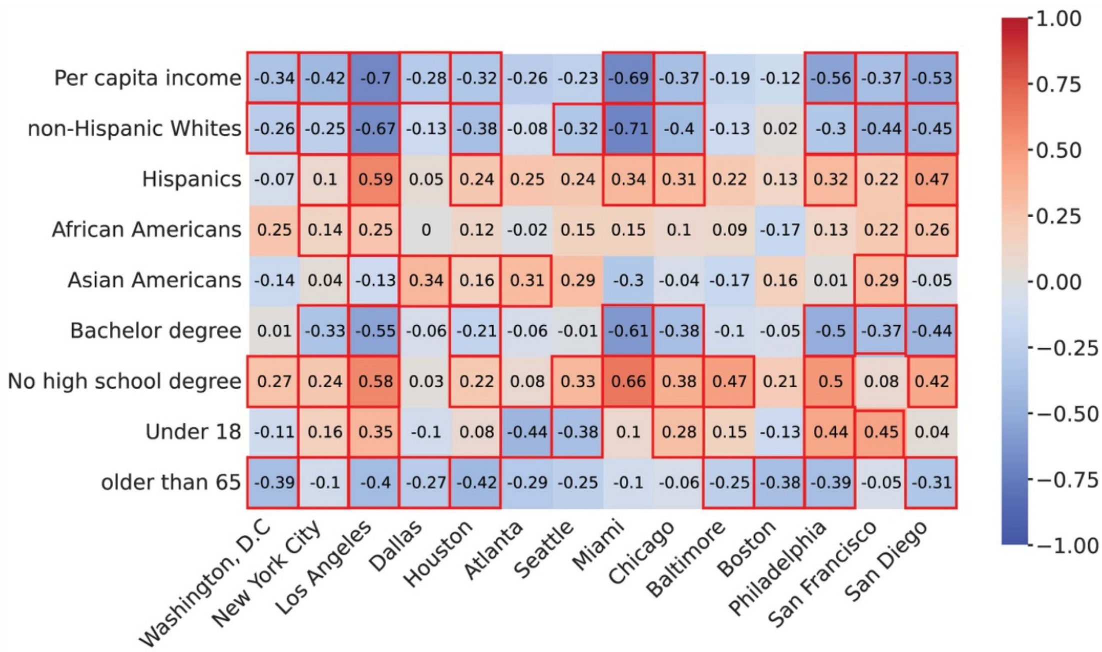


Figure 5. The histograms of the UTCI in different cities in the present-day climate (of 2017) and the hypothetical 1 °C warming scenario.

Table 1. The number and percentage of residents experiencing strong heat stress (UTCI higher than 32 °C) for present-day climate and a hypothetical 1 °C warming scenario in different cities.

	Population exposed to strong heat stress (UTCI higher than 32 °C)			
	Present-day climate		Hypothetical 1 °C warming scenario	
Cities	Population number	Percentage	Population number	Percentage
Boston	0	0	1020	0.2%
Chicago	0	0	0	0
Seattle	0	0	0	0
San Francisco	0	0	0	0
Philadelphia	0	0	0	0
Washington, D.C.	671 534	98.1%	680 305	99.4%
Baltimore	202 008	32.9%	585 324	95.2%
New York City	0	0	0	0
Dallas	1501 499	100%	1501 499	100%
Atlanta	479 854	100%	479 854	100%
San Diego	0	0	10 817	0.7%
Los Angeles	865 935	21.0%	3811 325	92.3%
Houston	4774 220	100%	4774 220	100%
Miami	439 885	97.1%	453 211	100%



	Washington, D.C	New York City	Los Angeles	Dallas	Houston	Atlanta	Seattle	Miami	Chicago	Baltimore	Boston	Philadelphia	San Francisco	San Diego
Per capita income	-0.34	-0.42	-0.7	-0.28	-0.32	-0.26	-0.23	-0.69	-0.37	-0.19	-0.12	-0.56	-0.37	-0.53
non-Hispanic Whites	-0.26	-0.25	-0.67	-0.13	-0.38	-0.08	-0.32	-0.71	-0.4	-0.13	0.02	-0.3	-0.44	-0.45
Hispanics	-0.07	0.1	0.59	0.05	0.24	0.25	0.24	0.34	0.31	0.22	0.13	0.32	0.22	0.47
African Americans	0.25	0.14	0.25	0	0.12	-0.02	0.15	0.15	0.1	0.09	-0.17	0.13	0.22	0.26
Asian Americans	-0.14	0.04	-0.13	0.34	0.16	0.31	0.29	-0.3	-0.04	-0.17	0.16	0.01	0.29	-0.05
Bachelor degree	0.01	-0.33	-0.55	-0.06	-0.21	-0.06	-0.01	-0.61	-0.38	-0.1	-0.05	-0.5	-0.37	-0.44
No high school degree	0.27	0.24	0.58	0.03	0.22	0.08	0.33	0.66	0.38	0.47	0.21	0.5	0.08	0.42
Under 18	-0.11	0.16	0.35	-0.1	0.08	-0.44	-0.38	0.1	0.28	0.15	-0.13	0.44	0.45	0.04
older than 65	-0.39	-0.1	-0.4	-0.27	-0.42	-0.29	-0.25	-0.1	-0.06	-0.25	-0.38	-0.39	-0.05	-0.31

Figure 6. The correlation coefficients matrix between the UTCI and different socioeconomic and demographic variables in different cities (the red enclosed grids are statistically significant, $p = 0.01$).

D.C., New York City, Los Angeles, Houston, Seattle, Miami, Chicago, Philadelphia, San Francisco, and San Diego, while for other cities, there is no significant correlations. The proportion of Hispanic population has significant and positive correlation with the UTCI in the cities of New York City, Los Angeles, Houston, Miami, Chicago, Philadelphia, and San Diego. The proportion of African Americans generally has no significant correlation with the UTCI, except the significant and positive correlation in the cities of New York City, Los Angeles, and San Diego. The proportion of Asian Americans has significant and positive correlation with the UTCI in the cities of Dallas, Houston, Atlanta, and San Francisco, while there is a significantly negative correlation in Los Angles, and no significant correlation in the other cities.

The educational variables have relatively consistent correlation in sign with the UTCI in different cities, as neighborhoods with more people of higher education have lower UTCI, and neighborhoods with higher proportion of people without high school degree tend to have higher UTCI. However, such correlations are not significant for all cities.

The proportion of people under 18 years of age has a significant and positive correlation with the UTCI for New York City, Los Angeles, Chicago, Philadelphia, and San Francisco, while in Atlanta, Seattle the correlation is negative. There is no significant correlation for the other cities. The proportion of people older than 65 has a consistently and significantly negative correlation with UTCI in the cities of Washington, D.C., New York City, Los Angeles, Dallas, Houston, Baltimore, Boston, Philadelphia, and San Diego, while there is no significant correlation for the other cities.

3.4. Regression analysis results

Figure 7 shows the regression analysis results of the UTCI and different socioeconomic and racial/ethnic variables in different cities. The SAR_{lag} models results show a similar pattern with the OLS regression models results after controlling the spatial dependence. Generally, the per capita income has a consistently and significantly negative association with the UTCI in most cities, except the cities of Seattle, Chicago, Baltimore, Boston, and San Francisco.

The proportion of Hispanic population has a significantly positive association with the UTCI in the cities of Los Angeles, Houston, Seattle, Miami, Chicago, Baltimore, Philadelphia, San Francisco, and San Diego, while for New York City and Dallas, the association is negative and significant. For the other cities, there is no significant association.

The proportion of African Americans has a significant and positive association with UTCI in Los Angeles, Houston, Miami, and Chicago, but a negative and significant association with UTCI in Dallas, Atlanta, Boston, and Philadelphia. For all other cities, there is no significant association between the proportion of African Americans and UTCI.

The proportion of Asian Americans has a significantly positive association with the UTCI in the cities of Dallas, Houston, Seattle, Miami, Chicago, and San Francisco, while for the rest of cities, there is no such significant association.

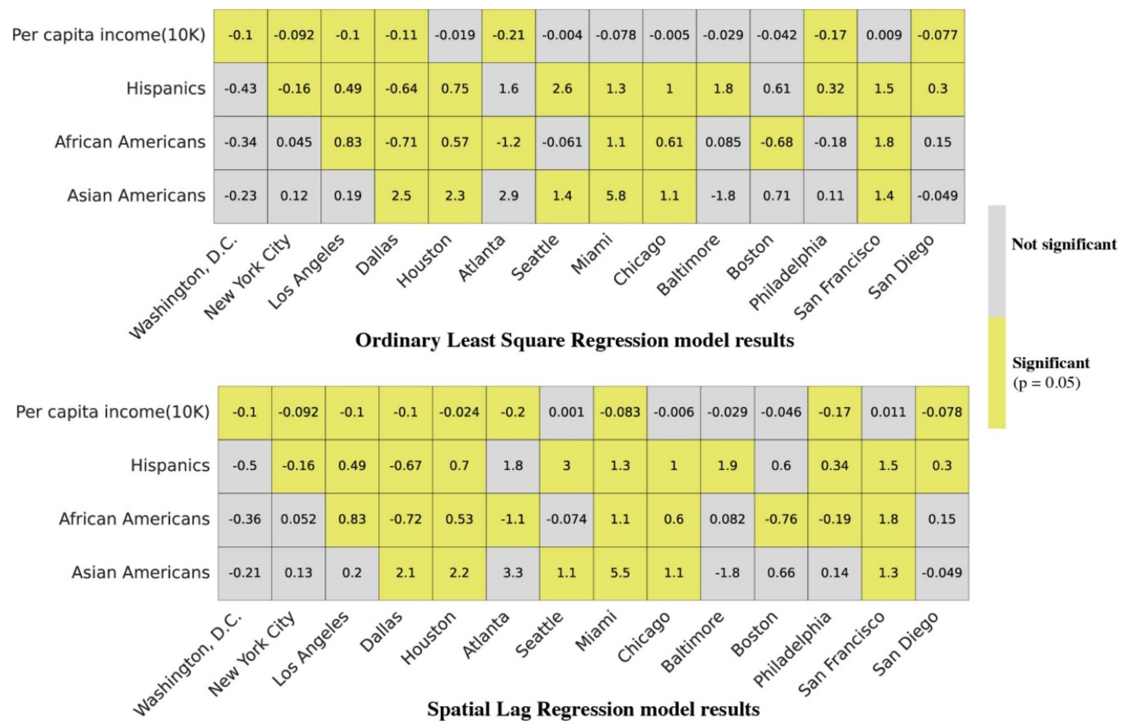


Figure 7. The regression analysis results of the UTCI and different socioeconomic variables in different cities.

4. Discussion

This study investigated the heat distributions in major US cities at hyperlocal level (1 m) using urban microclimate modeling. Different from the widely used LST, the UTCI was used to map and indicate how residents are exposed to heat over space in different cities. The UTCI is a more complete metric to indicate human heat stress level (Blazejczyk *et al* 2012, Bröde *et al* 2012) since it accounts for air temperature, radiation, humidity, and wind speed. The fine level UTCI maps make it possible to examine the spatial distributions of human outdoor heat exposure at multiple scales. By averaging the UTCI values for non-roof pixels in each census tract, the aggregated census tract level UTCI maps can better indicate how residents of different socio-economic and demographic characteristics are exposed to outdoor heat. In addition, it is possible to examine the city-wide heat exposure along the sidewalks, around public transit stations, and within playgrounds and parks. The fine-level heat maps also provide more actionable insights at local scale for heat mitigation practices, such as increasing tree canopies and placing shade in the right places, especially in those areas where human activities take place but have high UTCI values.

Through microclimate modeling, we also conducted a sensitivity analysis of the heat stress change for a hypothetical 1 °C warming to examine the heat exposure change in future higher air temperature scenarios. The histograms of all UTCI pixels for the present-day climate and for the 1 °C warming scenario were used to understand how the air temperature increase would shift the heat exposure levels in different cities. Different cities show different sensitivities to rising air temperature and several cities are on the brink of strong heat stress level. In the current situation, the cities of Washington, D.C., Dallas, Atlanta, Houston, and Miami are under strong heat stress already. The cities of Baltimore and Los Angeles are partly exposed to strong heat stress in current situation and increasing greatly in 1 °C higher scenario. The cities of Boston and San Diego are not currently exposed to strong heat stress and slightly exposed to strong heat stress in 1 °C higher scenario. However, the more skewed histogram of San Diego shows that more areas in San Diego will experience strong heat stress with air temperature increase. The cities of Chicago, Seattle, San Francisco, Philadelphia, New York City are not exposed to strong heat stress in the current situation and 1 °C higher scenario. However, because of the skewed distributions of UTCI histograms in Chicago, San Francisco, and Philadelphia, with the increase of air temperature in future climate scenarios or during extreme weather events with high air temperature, a large proportion of those cities will experience strong heat stress. This would make those cities more vulnerable to extreme heat events in a warming climate.

Statistical analyses results show that per capita income has a relatively consistent and significantly negative association with the UTCI in most cities, which indicates that richer people tend to live in relatively cooler neighborhoods. This is similar to previous studies on the relationship between urban heat island intensity indicated by LST and income level (Huang *et al* 2011, Chakraborty *et al* 2019, McDonald *et al* 2021). This is mainly because low-income people tend to live in neighborhoods with less tree canopies (Schwarz *et al* 2015, McDonald *et al* 2021), and the shade provision of trees is one of the major factors determining UTCI (Li 2021). The proportion of Hispanic population is significantly associated with stronger heat stress in the cities of Los Angeles, Houston, Seattle, Miami, Chicago, Baltimore, Philadelphia, San Francisco, and San Diego. There is no consistently significant association between the proportion of African Americans and the heat stress level for all cities. The proportion of African Americans has significant association with higher heat stress levels only in the cities of Los Angeles, Houston, Miami, Chicago, and San Francisco, while in Dallas, Atalanta, Boston, and Philadelphia the association is negative and in other cities the association is not significant. Neighborhoods with high Asian American populations experience consistently stronger summer heat stress in the cities of Dallas, Houston, Seattle, Miami, Chicago, and San Francisco. Since the cities of Dallas and Houston are experiencing strong heat stress or even very strong heat stress level in summertime, this situation is even worse for the Asian American communities in those cities.

Although this study generated hyperlocal outdoor urban daytime heat maps for cities based on fine level multispectral aerial images and LiDAR data with spatial resolution of 1 m, there are still several limitations in this study. First, this study only computes the daytime and outdoor heat exposure in those cities. However, the nighttime and indoor heat stress level also have meaningful impact on human wellbeing. Therefore, future studies should also focus on indoor and nighttime heat exposure. This study only used the average monthly UTCI maps to indicate the general heat exposure distribution, and future studies should also examine maximum UTCI values at a higher temporal resolution to indicate the extreme conditions during the heat waves.

In this study, we only tested the sensitivity to a hypothetical 1 °C warming scenario. During extreme heat events, the air temperature would increase much higher and the rising air temperature is usually compounded with different humidity levels impacting human thermal comfort. Future study should also examine the sensitivity of urban UTCI to realistic warming and the compound effects and feedback due to other meteorological factors.

The census data used in this study only indicate the residence of urban residents, while this is usually not the place where all human activities happen, particularly during daytime. Future studies should also consider the human mobility pattern to better estimate actual human exposure to extreme heat.

5. Conclusion

This study conducted microclimate modeling and examined the vulnerability and sensitivity to heat extremes in major cities across the United States. The hyperlocal and more human-centric heat metrics generated by efficient modeling provide an efficient tool to examine the impacts of heat extremes and actionable insights for heat mitigation. The cities of Washington, D.C., Baltimore, Atlanta, Dallas, Los Angeles, Houston, and Miami are suffering from strong heat stress during summer days. Boston and San Diego are on the brink of strong heat stress, and with potential future increases in air temperature, more residents will be exposed to strong outdoor heat stress.

Generally, people with higher income tend to live in neighborhoods with less heat stress level, especially in those cities that are suffering from relatively strong heat stress level, while in the cities of marine, cold, and very cold climate zones, the associations are not significant. Generally, the proportion of Hispanic and Asian American populations both tend to have a significantly positive association with the higher heat stress in summertime, while the association between the proportion of African Americans heat stress levels is mixed in different cities.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://xiaojianggis.github.io/heatexpo/. Data will be available from 10 March 2025.

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