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Key Points:

- Sociodemographic disparities in heat exposure exhibit regional-scale variations across the United States
- At the local level, poverty is a more influential factor than race in determining heat exposure disparities
- Residents of nontraditional housing are more vulnerable to heat exposure

Supporting Information:

Supporting Information may be found in the online version of this article.

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Exploring the Spatial Patterning of Sociodemographic Disparities in Extreme Heat Exposure at Multiple Scales Across the Conterminous United States

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Abstract Climate change has led to an increase in heat-related morbidity and mortality. The impact of heat on health is unequally distributed amongst different socioeconomic and demographic groups. We use high-resolution daily air temperature-based heat wave intensity (HWI) and neighborhood-scale sociodemographic information from the conterminous United States to evaluate the spatial patterning of extreme heat exposure disparities. Assuming differences in spatial patterns at national, regional, and local scales; we assess disparities in heat exposure across race, housing characteristics, and poverty level. Our findings indicate small differences in HWI based on these factors at the national level, with the magnitude and direction of the differences varying by region. The starkest differences are present over the Northeast and Midwest, where primarily Black neighborhoods are exposed to higher HWI than predominantly White areas. At the local level, we find the largest difference by socioeconomic status. We also find that residents of nontraditional housing are more vulnerable to heat exposure. Previous studies have either evaluated such disparities for specific cities and/or used a satellite-based land surface temperature, which, although correlated with air temperature, does not provide the true measure of heat exposure. This study is the first of its kind to incorporate high-resolution gridded air temperature–based heat exposure in the evaluation of sociodemographic disparities at a national scale. The analysis suggests the unequal distribution of heat wave intensities across communities—with higher heat exposures characterizing areas with high proportions of minorities, low socioeconomic status, and homes in need of retrofitting to combat climate change.

Plain Language Summary Extreme heat exposure can result in severe health impacts such as heatstroke, respiratory issues, and heat exhaustion, and can even cause death. The areas and populations that are the most impacted by heat may be unable to mitigate the effects because they have fewer resources. This study evaluates the differences in exposure to extreme heat across race, housing characteristics, and poverty level. We evaluate these differences at the national, regional, and local levels in the United States. We find small differences in heat exposure based on these factors at the national level but the magnitude of the differences varies by region. At the local level, we find comparatively larger differences by socioeconomic status than race.

1. Introduction

Heat extremes have become more intense and frequent over the past few decades, and these trends are projected to continue in a warming climate (Perkins et al., 2012; Rastogi et al., 2020; Shiva et al., 2019; Tebaldi & Wehner, 2018). Extreme heat exposure poses serious health risks, including heatstroke, respiratory issues, and heat exhaustion, and can even cause death (Anderson & Bell, 2011; Gasparrini & Armstrong, 2011; Karl & Knight, 1997; Zhang et al., 2019). According to the United States Environmental Protection Agency, heat waves are one of the leading causes of weather-related deaths in the United States (EPA, 2016). According to the United States Centers for Disease Control and Prevention (CDC), an average of approximately 65,000 Americans visit the emergency department for acute heat-related illnesses every year (CDC, 2016). A total of 8,081 heat-related deaths were reported from 1999 to 2010 (CDC, 2017), and an average of 702 heat-related deaths were reported annually between 2004 and 2018 in the United States (Vaidyanathan et al., 2020). As the temperature increases during the extreme heat, the mortality risk also rises (Anderson & Bell, 2011; Kephart et al., 2022). For instance, in a study conducted in 43 U.S. communities, Anderson & Bell, 2011 found that with every 1°F increase in heat

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wave intensity (HWI), the mortality risk increased by 2.49%. Similarly, Kephart et al., 2022 found a 1.057 relative risk of death per 1°C rise in temperature during extreme heat events in Latin American cities.

Although extreme heat has implications for everyone, heat impacts people disproportionately, depending on their age, race, income, and housing conditions (Benz & Burney, 2021; Karner et al., 2015; Renteria et al., 2022; Stillman, J. H. 2019). These factors also affect the ability to gain access to and afford mitigation measures (e.g., air conditioning, higher utility bills, and personal vehicles) (Jessel et al., 2019). To date, most of the studies focusing on these disparities are generally limited to regional scales or specific cities (e.g., Dialesandro et al., 2021; Renteria et al., 2022). For instance, Renteria et al. (2022) found that neighborhoods with higher proportions of racial minorities and lower socioeconomic status are exposed to higher heat in the Northeastern United States. Similarly, using data from the San Francisco Bay area, Karner et al. (2015) found that people in low-income households and those without personal vehicles are disproportionately exposed to travel-related heat. A few recent studies have delved into heat exposures and associated disparities at national scales (e.g., Benz & Burney, 2021; Hsu et al., 2021). Benz and Burney (2021) found that the poorest and least educated census tracts (CTs) in the country are significantly hotter than the richest and most educated tracts. They further illustrate race-based disparities across the United States, where neighborhoods with higher Black, Hispanic, and Asian populations are hotter than those with higher White and non-Hispanic populations. However, these national-scale studies generally use satellite-based land surface temperature metrics to measure heat exposure. Although the land surface temperature is available at a very high spatial resolution and has been found to be statistically related to air temperature, it can overestimate the heat intensity and does not provide a true measure of heat exposure (Hsu et al., 2021; Mutiibwa et al., 2015). Contrarily, air temperature provides a more accurate way to identify heat extremes and measure direct heat exposure. Additionally, it is important to note that disparities evaluated at a national scale alone cannot paint a complete picture of the true impact of heat exposure across different socioeconomic groups. To obtain a comprehensive assessment, it is critical to perform a multi-scale study that accounts for local and regional variations within the national scale.

This study presents a comprehensive evaluation of disparities in exposure to air temperature–based extreme HWI (or heat exposure) at a national scale, which describes the spatial patterning of the association at both regional and local levels. Specifically, the objective is to answer the following two questions: (a) Are there neighborhood-level (CT) disparities in air temperature–derived heat exposure by race, socioeconomic status, and housing type in the conterminous United States (CONUS)?, and (b) If there are differences in heat exposure by socioeconomic status and housing type: Do these differences inequitably impact CTs with a high percentage of racial minorities? To answer these questions, we first describe the disparities at the CONUS national scale. We then drill down to the regional scale for a more in-depth look into the differences across various regions in the CONUS. National-level racial differences in heat exposure may be attributed to CT residential sorting that aligns with the latitudinal gradient, with roots dating back to post-Civil War Reconstruction (Massey et al., 2009). However, micro-level differences would suggest these disparities exist beyond geohistorical legacies. We sought to assess local-level differences in heat exposure to describe within state- and county-level differences in the association between sociodemographic characteristics of a CT and heat exposure. Therefore, to evaluate the spatial patterns of disparities in heat exposure over the CONUS and the difference in these patterns at state and county levels, we fit multiple statistical models using CT-level information on racial, socioeconomic, and housing characteristics, along with HWI derived from observation-based high-resolution gridded air temperature estimates.

2. Data and Methodology

2.1. Data

To identify heat waves, we obtain daily maximum temperatures (T_{max}) data from Daymet (Thornton et al., 1997, 2021, 2022), which is maintained by the Distributed Active Archive Center at the US Department of Energy's Oak Ridge National Laboratory. Daymet provides estimates of daily weather on a 1 km grid derived from ground-based observations. For each Daymet grid point, we define a heat wave as a period of at least three consecutive days when T_{max} is above a pre-defined threshold. We calculate the threshold by performing the following steps: (a) For each grid cell and index date, we extract the temperature values ±15 days from the index day across a 30-year period (1990–2020); (b) We then set the threshold for that grid cell and index date as the 90th percentile of observed T_{max} during that time frame, that is, for each day, T_{max} from a total of 930 days (31 days × 30 years) is used to calculate the threshold. Once the threshold is set, we identify heat waves for each year from 2008 to 2017 that occurred during May to September. The HWI in each grid cell is then calculated as the average T_{max} during the heat wave days and then average across the 10-year period. Finally, we calculate HWI for each CT by averaging HWI across all the 1 km grid cells that lie within the CT. HWI has been used in previous studies to evaluate risk arising from exposure to extreme heat (Anderson & Bell, 2011; Kephart et al., 2022).

We obtain sociodemographic characteristics from American Community Survey (ACS) 5-year estimates from 2011 to 2015. Specifically, we use the percentages of White alone (White), Black or African American alone (BAA), American Indian and Alaska Native alone (AI), Asian alone (Asian), and Native Hawaiian and other Pacific Islander alone (NH), Some other race alone (SORA) and Two or more races (TOMR) and the percentage of the population in a CT with income in past 12 months below the poverty line (poverty) from American Community Survey (ACS) 5-year estimates from 2011 to 2015 (ACS Race Estimates, 2015; ACS Poverty Status in Past 12 Months Estimates, 2015). We also obtain housing-type data at the CT level from ACS 5-year estimates from 2011 to 2015. We use the following variables: (a) Single-family—the proportion of total housing units in single-family detached dwellings, (b) Mobile homes, (c) Informal housing—housing not tied to land ownership including boat, recreational vehicle, and van, (d) Multi-family housing—the proportion of total housing units that are single-family attached dwellings or in buildings with 2 units, 3–4 units, or 5–9 units, and (e) Apartment complex—the proportion of total housing units in buildings with 10–19 units, 20–49 units, or 50 or more units (ACS Housing Characteristics Estimates, 2015).

2.2. Methodology

2.2.1. Statistical Models

To understand the overall association between HWI and the sociodemographic variables and how this association varies at micro- and meso- spatial scales, we fit a series of statistical models (Equations S1–S15 in Supporting Information S1) using CT-level data as follows: (a) We run a series of multivariable linear regression models at the CONUS level to evaluate the association between sociodemographic variables and HWI at the national scale (Equation S1–S5 in Supporting Information S1); (b) We stratify the linear regression models from Step 1 by geographic region over the seven US Geological Survey (USGS) adaptation regions to understand if the magnitude and direction of these associations vary across geographic region of the US; (c) We repeat all models from Steps 1 and 2 with state-level random effects to assess within-state differences in the association between HWI and sociodemographic factors at the national and regional scale (Equations S6–S10 in Supporting Information S1); and (d) We repeat all models from Steps 1 and 2 with county-level random effects to evaluate within-county differences in the association between HWI and sociodemographic factors at the national and regional scale (Equations S11–S15 in Supporting Information S1). We use standardized coefficients (mean = 0; SD = 1) to allow for comparison across measures.

3. Results and Discussion

3.1. CONUS-Level Disparities

Figure 1 shows distributions of HWI, poverty, race, and housing types across the CTs at the CONUS level. The HWI varies between 20°C and 46.5°C across the CTs with an average CONUS value of 34.3°C (Figure 1a). The poverty level also shows large variations across the CTs with a CONUS average of 17% (Figure 1b). Similarly, the race distributions vary across the CTs with average CONUS population by race: White (~73%), BAA (~14%), AI (<1%), Asian (~5%), NH (~0.12%), SORA (4.4%) and TOMR (3%) of total CT populations (Figure 1c). The distribution by housing type shows the highest average percentage of single-family detached housing (~62%) followed by multifamily living (~19%), and apartment complexes (12.5%); there are lower numbers of mobile homes (6%) and informal housing (0.1%) at CONUS level. However, the analyses show that these distributions vary across the CONUS, resulting in differences in heat exposure (Figure 1d). CTs that experience slightly higher HWI are often occupied by higher proportions of racial minority population for example, CTs with higher proportions of BAA and SORA population have HWIs that are higher by 0.2°C (BAA) and 0.53°C (SORA) on average during heat waves (Figure 2 and Table S1 in Supporting Information S1). Similarly, we find that CTs with higher poverty rates have slightly higher HWIs (by 0.3°C) (Figure 2, Table S2 in Supporting Information S1), and that relationship does not vary by race (Figure 2 and Table S4 in Supporting Information S1). Further, CTs with different housing distributions are found to have different levels of HWI exposure. For instance, CTs with higher percentages of mobile homes, informal housing, and apartment complexes have elevated HWIs by 0.2°C (mobile homes), 0.2°C (informal housing), and 0.1°C (apartment complexes), whereas those with a higher proportion of

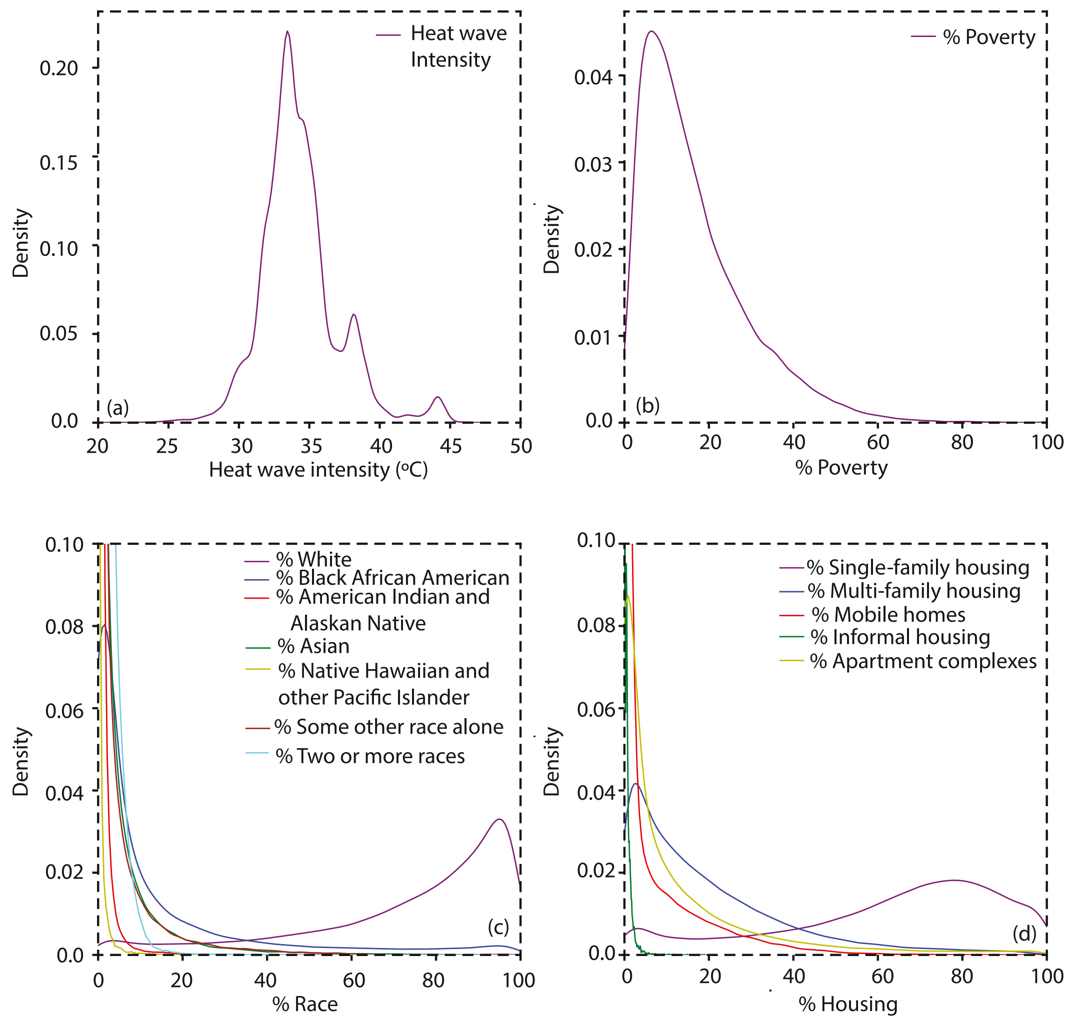

Figure 1. Probability density function plots for: (a) heatwave intensity, (b) percentage of population below poverty, percentage by (c) race, and (d) housing types for census tracts across the CONUS.

multifamily living have lower HWIs (Figure 2 and Table S3 in Supporting Information S1). HWIs are higher in CTs with higher percentages of BAA populations and mobile homes, as well as in areas with a high proportion of AI populations and apartment complexes (Figure 2 and Table S5 in Supporting Information S1).

Some of these effects at the CONUS scale are partially due to the latitudinal differences in HWIs, linking disparities to our geohistorical past (Rebbeck, 2022). For instance, higher instances of HWI in CTs with higher racial minority populations occur partly because the southern states experience high temperatures during heat waves (Figures 3 and 4). However, we are also interested in investigating whether these disparities persist across all geographical regions in the US and within states and counties.

3.2. Regional-Level Disparities

Regional-level differences in HWI are evident across the CONUS from the distributions of HWIs for each region (Figure 3). The South Central (37.4°C) and Southwest (36.7°C) regions exhibit the highest HWI, followed by the Southeast (34.8°C) and North Central (34°C) regions. The Northwest (31.5°C) exhibits the lowest HWI, followed by the Northeast (32.9°C) and Midwest (32.9°C) (Figure 3). Similarly, there are differences in the distribution of the percentage of the CT population by poverty level, race, and housing types between the regions (Figures 4 and 5). The Southeast (19.2%) and South Central (19%) have the highest average percentage of the CT population below the poverty level and the North Central (13.8%) has the lowest. The Southeast (23.4%) has the highest, and the Northwest (2.6%) has the lowest average percentage of BAA populations. The Southwest (11.2%) has the highest, and the Southeast has the lowest average percentage of the SORA population (Figure 4).

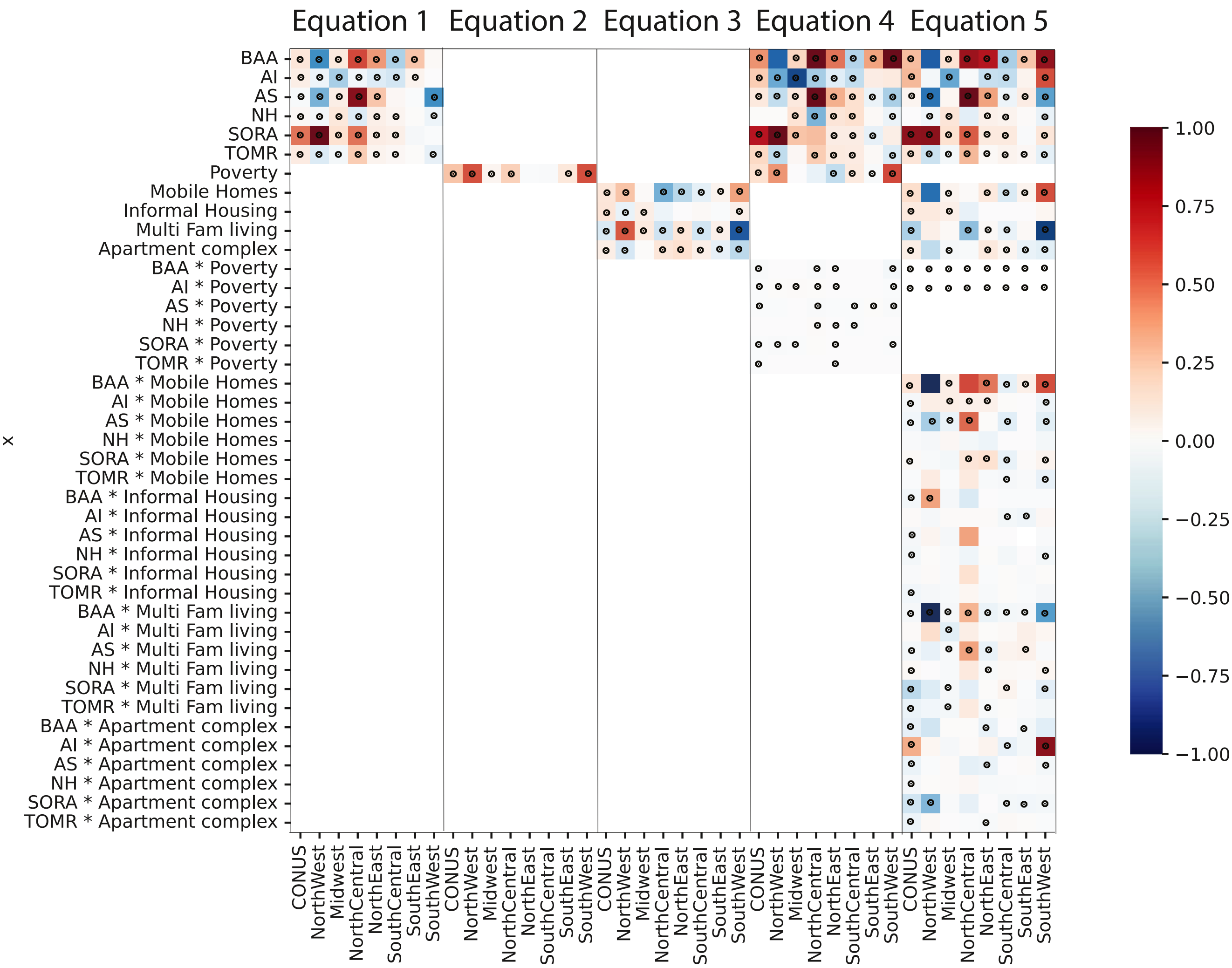

Figure 2. (a) Estimates from statistical models investigating differences at the national level (Equations S1–S5 in Supporting Information S1). Boxes marked with dots show coefficients that are significant at a 95% confidence level.

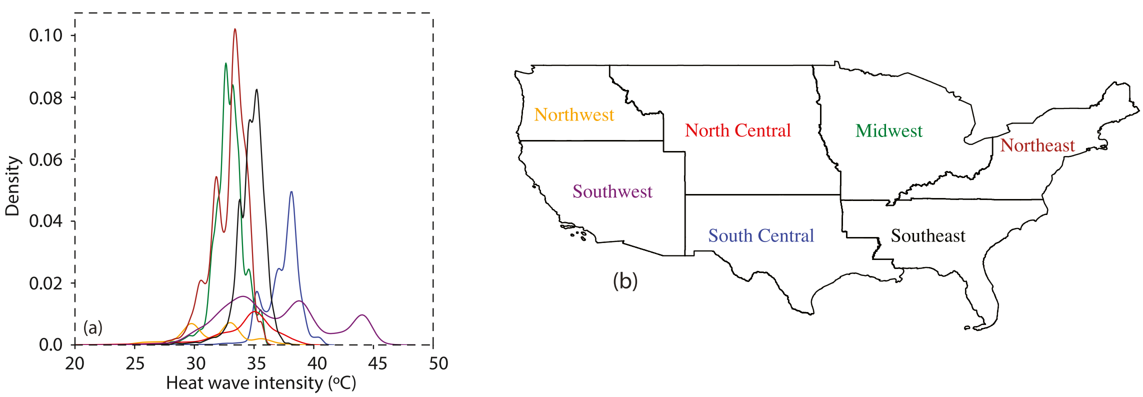

Figure 3. Probability density function plots at regional scale for: (a) heatwave intensity across census tracts in each of the seven US Geological Survey (USGS) adaptation regions (https://www.usgs.gov/programs/climate-adaptation-science-centers/casc-network-and-region-maps) shown in (b).

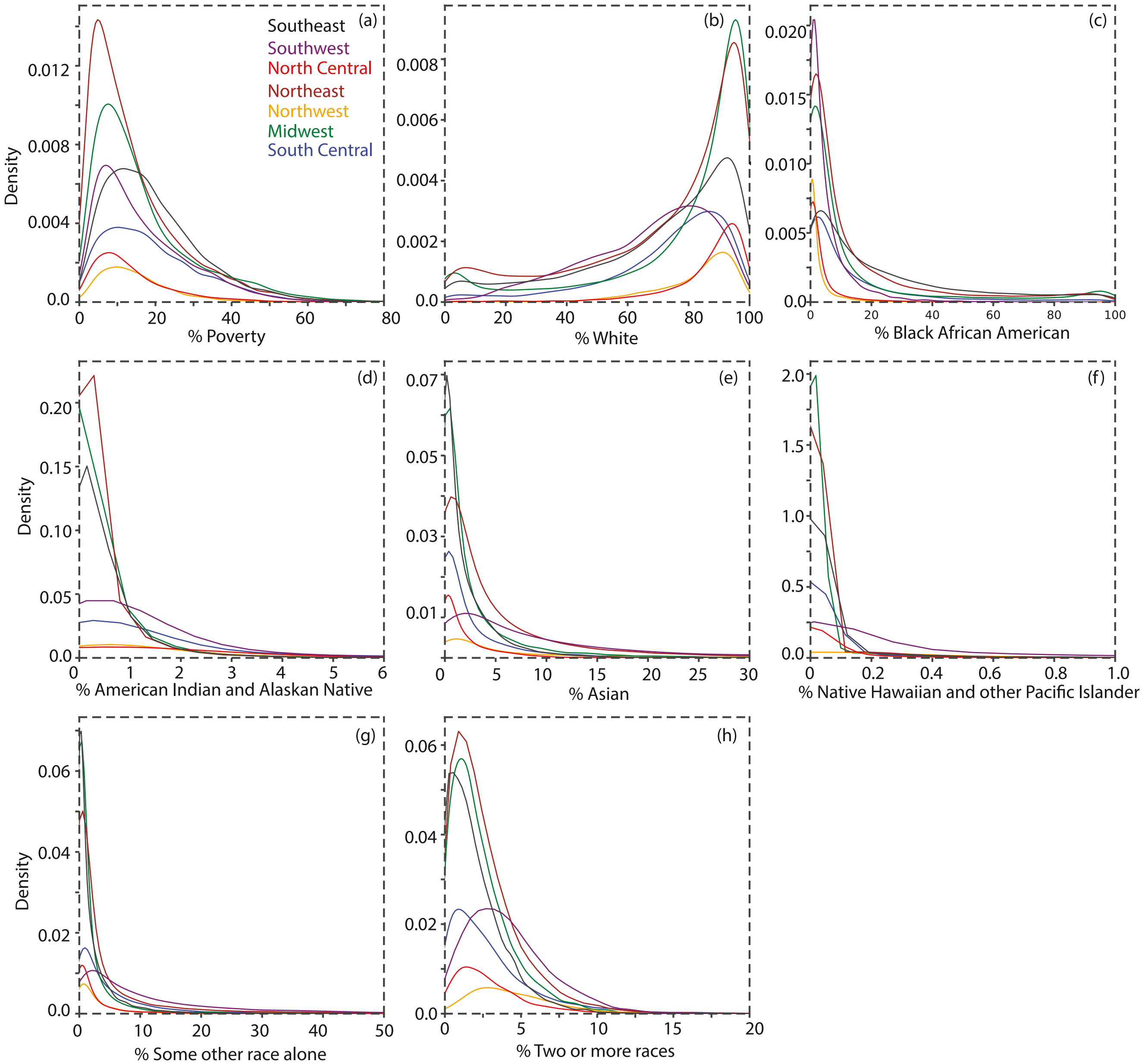

Figure 4. Probability density function plots at regional scale for: (a) percentage of population below poverty, percentage of (b) White, (c) Black African American, (d) American Indian and Alaska Native, (e) Asian, and (f) Native Hawaiian and Pacific Islander (g) Some other race alone and (h) Two or more races population across Census Tracts in each of the seven USGS adaptation regions.

There is evidence of regional-level disparities in HWI exposure by race (Figures 2 and 6b–6e). The CTs with higher proportions of BAA population have higher HWIs, with the largest differences witnessed over the North Central and Northeast followed by the Southeast (Figure 2 and Table S6 in Supporting Information S1). For instance, the average HWI over the North Central region is 34.8°C, whereas CTs with higher proportions of BAA and Asian population have HWIs that are higher by 0.9°C (BAA) and 1°C (Asians) on average. Similarly, the average HWI over the Northeast is 32.8°C, whereas CTs with higher proportions of BAA and Asian population are exposed to HWIs that are higher by 0.5°C (BAA) and 0.3°C (Asians). Over the Southeast, the HWI is higher by 0.3°C for CTs with higher proportions of BAA population, but no significant differences are noted for CTs with larger Asian populations (Table S6 in Supporting Information S1). Although CTs with high proportions of BAA and Asian population show slightly higher HWI over the Midwest, larger BAA and Asian populations are not associated with higher HWIs over the South Central and Southwest regions. The CTs with higher proportions

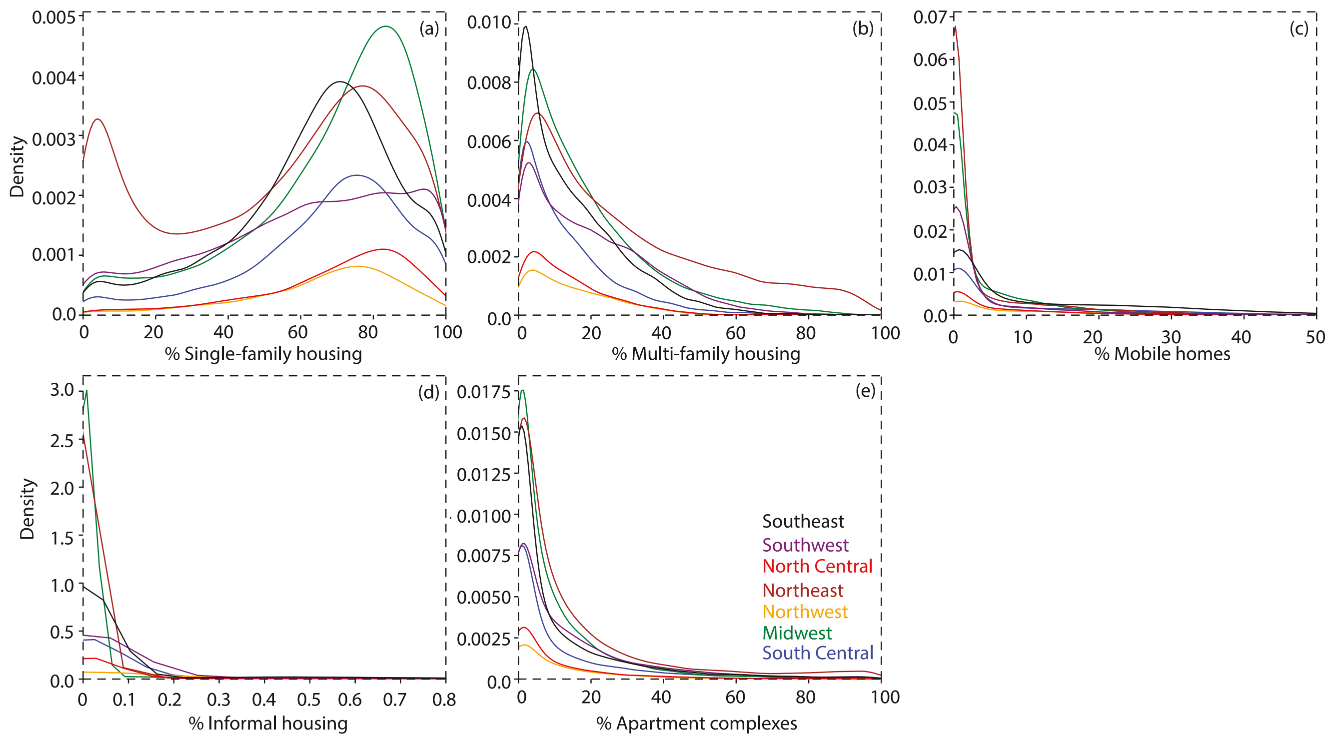

Figure 5. Probability density function plots at regional scale for percentage of housing types including (h) single-family detached, (k) multifamily living, (m) mobile homes, (o) informal housing, and (q) apartment complexes across census tracts in each of the seven USGS adaptation regions.

of SORA populations have higher HWI over all regions except the Southeast and the Southwest. For instance, CTs with higher proportions of SORA have HWIs that are higher by 1°C over the Northwest and 0.53°C over the North Central (Figure 2). Areas with high proportions of AI population are generally not associated with higher heat exposures except over the Southeast. Areas with higher proportions of TOMR population have HWI higher by 0.3°C over the North Central whereas they have either slightly higher or are not associated with higher heat exposures over the other regions (Figure 2 and Table S6 in Supporting Information S1).

HWI has a strong association with poverty across many regions (Figures 2, Figure 6a, and Table S7 in Supporting Information S1). For instance, CTs with higher poverty levels in the Southwest, Northwest, and North Central regions have HWIs that are higher by 0.62°C (Southwest), 0.61°C (Northwest), and 0.26°C (North Central). There are also higher HWIs in areas with higher poverty levels in the Southeast (0.15°C) and Midwest (0.06°C), although the differences are smaller. No significant poverty-based associations with HWIs are observed over the South Central and Northeast regions. The association of HWIs with poverty does not vary by race at the regional level (Figure 2 and Table S9 in Supporting Information S1).

CTs with higher proportions of mobile homes have higher exposure to HWIs in the Southwest and Northwest regions. In the Midwest and Southwest, CTs with higher proportions of informal housing have higher HWIs. CTs with higher proportions of multifamily housing have higher HWIs over the Northwest, Midwest, Northeast, and Southeast, whereas CTs with higher proportions of apartment complexes have higher HWIs over the Northeast, North Central, and South Central regions (Figures 2 and 7, and Table S8 in Supporting Information S1). CTs with high BAA populations and higher proportions of mobile homes have high HWIs across all regions except the Northwest and South Central. Several other racial differences in the association between housing type and HWI are observed and are summarized in Figure 2 and Table S10 in Supporting Information S1.

3.3. Local Disparities at the State and County Levels

The local differences in heat exposure within states and counties and their association with sociodemographic and housing characteristics of CTs are summarized in Figure 8 and Tables S11–S30 in Supporting Information S1. The analyses show that state and county account for 68% and 92% of the variance in CT-level HWI, respectively

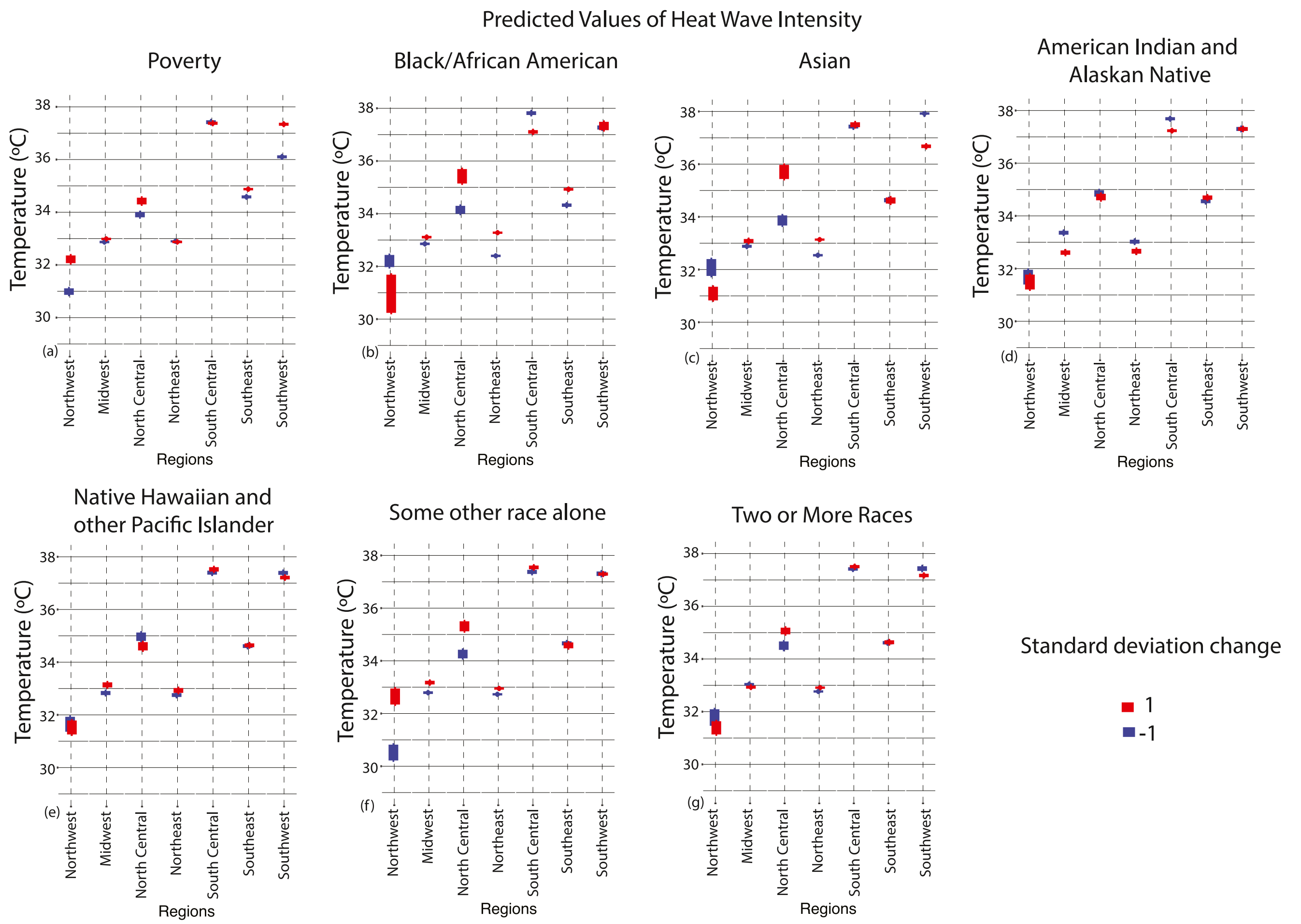

Figure 6. Predicted values of heat wave intensity for one standard deviation change in: (a) poverty levels, and (b–g) race at the regional level.

(i.e., the correlation in HWI between two CTs randomly drawn from within a particular state would be 0.68, and between two CTs drawn from within a particular county would be 0.92).

At the CONUS scale, there are small but significant within-state positive differences in HWIs for CTs with high BAA and SORA populations and high poverty levels (Figure 8, Tables S11 and S12 in Supporting Information S1). Additionally, regional variations are seen in the within-state differences in HWIs. For instance, the CTs with higher percentages of BAA populations have higher HWIs in the Northeast (by 0.3°C) and Southeast (by 0.3°C), and to a smaller extent in Midwest (by 0.1°C). Similarly, areas with higher percentages of Asians in the North Central and the Northeast regions have higher HWIs. This effect is also seen over the Southeast and Midwest but to a smaller extent (Figure 8a, Table S16 in Supporting Information S1). Similarly, the CTs with higher percentages of SORA populations have higher HWIs in the Northwest (by 1.2°C) and North Central (by 0.5°C), and to a smaller extent over other regions (by 0.02–0.3°C). Areas with high poverty levels are exposed to high HWIs across all the regions, but the magnitude of this effect shows regional variations: the Southwest (by 0.5°C) and Northwest (by 0.4°C) exhibit the highest, and the Midwest (by 0.05°C) shows the lowest differences (Figure 8a, Table S17 in Supporting Information S1). Regional differences are also found in housing-based disparities within states. For example, in the North Central and Northeast regions, and to a small extent over the Midwest, areas within states with higher numbers of apartment complexes have higher heat exposure. Similarly, areas with higher numbers of multifamily homes have higher heat exposure in the Northwest (by 0.5°C) and Northeast (by 0.2°C) and, to a lesser extent, in the Southeast and Midwest (Figure 8a, Table S18 in Supporting Information S1). Moreover, in the Northeast and Southwest, areas with higher numbers of mobile homes as well as high BAA populations show high HWI disparities. A similar effect is seen over the Midwest and Southeast but with a lower magnitude (Table S20 in Supporting Information S1).

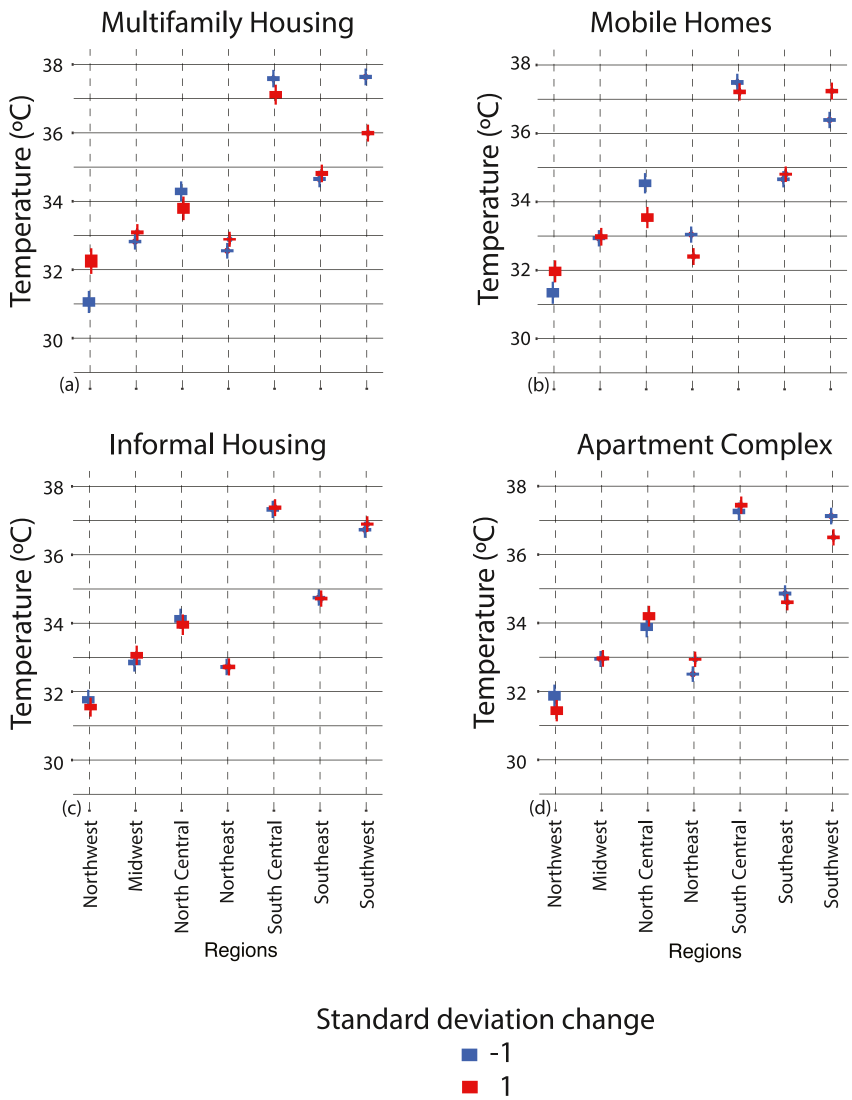

Figure 7. Predicted values of heat wave intensity by one standard deviation of change in housing types at the regional level.

At the CONUS scale, there is no evidence of net within-county differences in HWI for areas with high BAA population levels. There are very small positive differences in HWI for areas with high SORA, AS, and AI populations and high poverty levels. Similarly, areas with higher proportions of mobile homes and multifamily housing show very small differences in HWI (Figure 8b, Tables S21–S25 in Supporting Information S1). There are also small regional-scale variations in the within-county differences. For instance, there are small positive differences in HWI (small but significant) in areas with higher SORA populations over the Northwest (0.2°C) and North Central (0.2°C). A similar effect is evident for areas with high AS populations in the North Central region. Similarly, there are differences in HWI associated with housing types for certain regions, but the size of the effect is generally small. There are within-county differences for CTs with high poverty levels across all regions. Although these poverty-based differences are comparatively small (<0.2°C), they are significant across all the regions (Figure 8, Tables S26–S30 in Supporting Information S1).

4. Summary and Discussion

In this study, we fit multiple statistical models using HWIs derived from high-resolution air temperature and sociodemographic information at the CT level to understand the disparities in extreme heat exposure across the United States. We evaluate these differences at national and regional scales and investigate within state- and county-level differences.

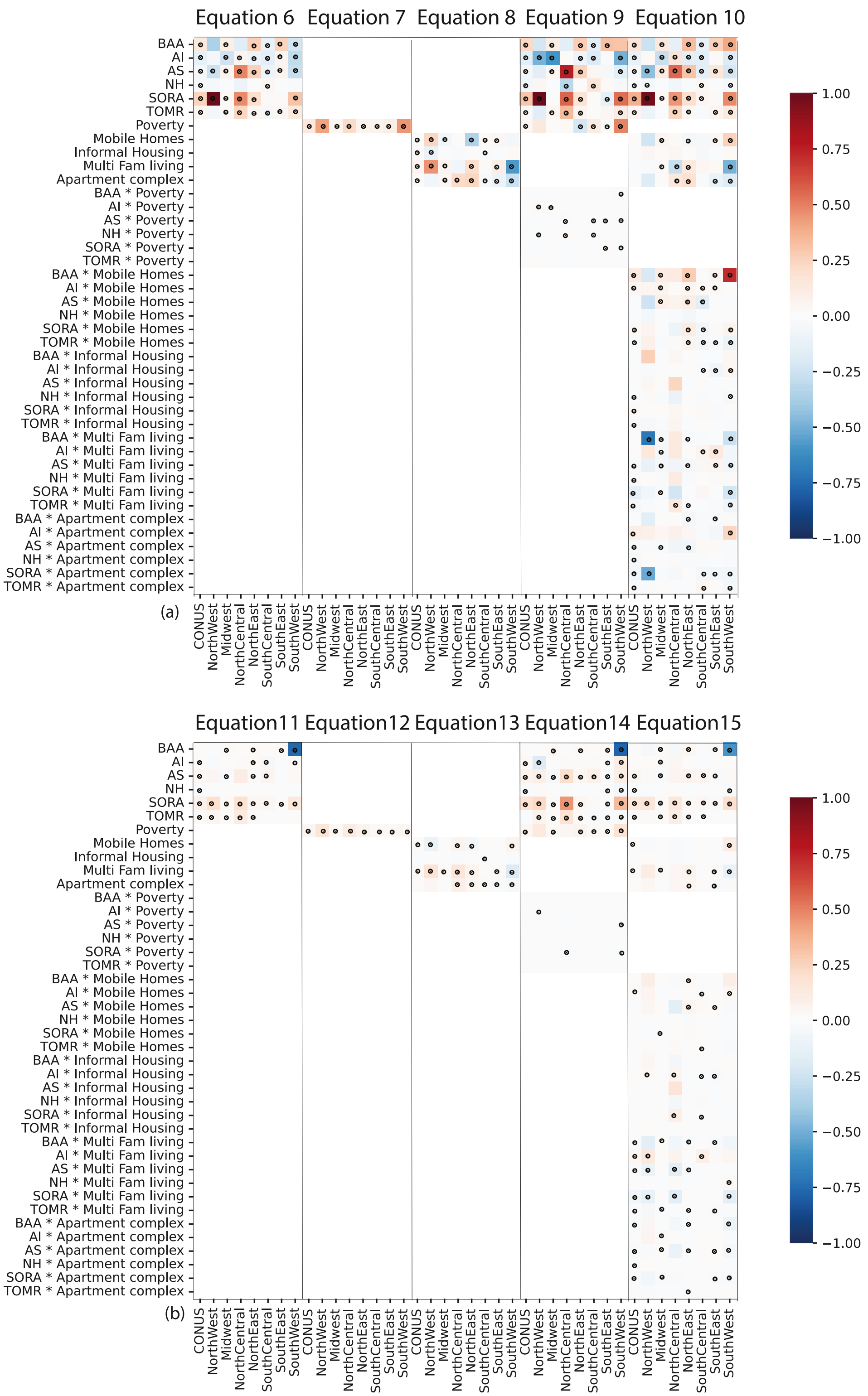

Figure 8. Estimates from the statistical models referred to in (a) Equations S6–S10 in Supporting Information S1, within-state differences, and (b) Equations S11–S15 in Supporting Information S1, within-county differences. Boxes marked with dots show coefficients that are significant at a 95% confidence level.

We find small disparities in HWI based on race, income, and housing type at a national level; but the magnitude and direction of the disparities vary by region across the United States. For instance, some regions have larger differences in HWI between CTs with high poverty levels than in CTs with low poverty levels. CTs with a higher proportion of mobile homes and informal housing have higher heat exposure at the national scale; the disparities in HWI based on these housing types also vary by region (Figure 2). These nontraditional homes are not heat-efficient, so implementing heat mitigation measures in them is costlier than in traditional homes. The residents of these nontraditional homes are generally economically disadvantaged, placing them at higher risk of heat exposure, especially over the Southwest where HWI is higher relative to other regions, and CTs with higher proportions of non-traditional homes are also exposed to higher HWI.

The in-depth analysis at the regional scale also reveals that there is evidence of race-based disparities in heat exposure beyond the latitudinal divide. In areas with comparatively cooler temperatures (e.g., North Central and Northeast regions), the hottest areas are found to have a higher percentage of the BAA and SORA population (Figure 4). Contrarily, in the southern regions, there may not be disparities associated with minority populations, but these regions overall witness the highest temperatures during heat waves (Figure 3) and are occupied by higher percentages of minorities. Moreover, these regions already have some of the highest health disparities in the United States (Rebbeck, 2022). Local-level differences for heat exposure are also seen, that is, for CTs within states and counties, but their magnitude is comparatively small. There are also regional-scale variations in the differences in heat exposure. Further, at the county level, poverty, not race, is the dominant decider of heat exposure.

Overall, the analysis suggests the unequal distribution of HWIs across communities—with higher heat exposures characterizing areas with high proportions of minorities, low socioeconomic status, and homes in need of retrofitting to combat climate change. These findings have implications that disparities in heat exposure and the vulnerability of disadvantaged populations to heat exposure may further increase as global warming continues and will be the focus of future studies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The Daymet observations data are publicly available (from https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=2129). The American Community Survey data are publicly available (from https://www2.census.gov/programs-surveys/acs/summary_file/2015/data/5_year_entire_sf/).

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