Disproportionate exposure to urban heat island intensity across major US cities

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Urban heat stress poses a major risk to public health. Case studies of individual cities suggest that heat exposure, like other environmental stressors, may be unequally distributed across income groups. There is little evidence, however, as to whether such disparities are pervasive. We combine surface urban heat island (SUHI) data, a proxy for isolating the urban contribution to additional heat exposure in built environments, with census tract-level demographic data to answer these questions for summer days, when heat exposure is likely to be at a maximum. We find that the average person of color lives in a census tract with higher SUHI intensity than non-Hispanic whites in all but 6 of the 175 largest urbanized areas in the continental United States. A similar pattern emerges for people living in households below the poverty line relative to those at more than two times the poverty line.
Built environments are commonly hotter than their neighboring rural counterparts. This phenomenon, commonly referred to as the urban heat island effect, contributes to a range of public health issues. Heat-related mortality in the USA, for example, causes more deaths (around 1500 per year) than other severe weather events. Heat exposure is also associated with several non-fatal health outcomes, including heat strokes, dehydration, loss of labor productivity, and decreased learning. Characteristics of the built environment (e.g., green space, urban form, city size, spectral reflectance) not only create temperature differentials between urban and surrounding rural areas but also contribute to intracity temperature variation. This variation has the potential to cause disparities in the distribution of the burden of adverse heat-related outcomes across sociodemographic groups.

Like other environmental stressors, such as air pollution, low-income or otherwise marginalized communities may experience disproportionately higher levels of heat intensity. Small-scale case studies have found disparities in the distribution of urban heat island intensity within single cities or differences in exposure among population groups within a few cities in different countries. Although evidence suggests that extreme heat-related morbidity and mortality in cities disproportionately affect marginalized groups, there has been little research showing whether these groups have systematic disproportionately high exposure to the heat island effect.

Instead, research linking intracity differences in heat exposure to sociodemographic factors has typically been done in an ad hoc manner for a small number of individual cities. Examining the relationship between the distribution of annual urban heat island exposure and income at the neighborhood level, find that the distribution tended to favor those with higher incomes in 18 out of 25 selected global cities. While illustrative, these results are difficult to generalize since the sociodemographic information comes from a variety of sources with distinct definitions and methods, and the sample of global cities was chosen in response to data constraints rather than random sampling. It also does not convey information about potential disparities for other US cities.

In 108 US cities, find that neighborhoods that were redlined in the 1930s have summer surface temperature profiles that are significantly higher than other coded residential areas (“redlining” refers to the historical practice of denying home loans or insurance based on an area’s racial composition). In light of substantial demographic changes and urban growth patterns over the past 90 years, however, the extent to which this finding translates into current racial or income disparities remains unclear.

While these studies are suggestive, it is difficult to extrapolate their results to a widespread or national level for several reasons. Varying methodological approaches to quantifying urban heat island intensity may lead to different conclusions, or analyses may not be representative. One obstacle to a more uniform approach has been the lack of consistent multicity delineations of urban and rural areas that are also comparable with the administrative areas of aggregation for which socioeconomic data are collected. Case studies may also reflect selection bias. Prior beliefs regarding inequitable distributions of heat exposure may have motivated such scientific inquiry for particular locations, such that the chosen cities may not be representative of the nation as a whole.

Combining high-resolution satellite-based temperature data with sociodemographic data from the US Census, we find that the average person of color lives in a census tract with higher summer daytime surface urban heat island (SUHI) intensity than non-Hispanic whites in all but 6 of the 175 largest urbanized areas in the continental United States. A similar pattern emerges for people living in households below the poverty line relative to those at more than two times the poverty line. In nearly half the urbanized areas, the average person of color faces a higher summer daytime SUHI intensity than the average person living below poverty, despite the fact that, on average, only 10% of people of color live below the poverty line. This last finding suggests that widespread inequalities in heat exposure by race and ethnicity may not be well explained by differences in income alone. While we do not observe major differences in SUHI intensity for very young or elderly populations in most major cities, when compared to the total population, we find that the same racial and ethnic disparities in SUHI for specific populations of color compared to non-Hispanic whites are also consistent for these age demographics.
using an inequality index to measure intragroup variation in SUHI intensity; and third, considering vulnerability according to age and race/ethnicity.

**Mean SUHI intensity across sociodemographic groups.** Table 1 (a) describes differences in exposure to SUHI by population groups defined by race/ethnicity and income (see “Methods” for demographic group definitions). We group urbanized areas by Köppen–Geiger climate zones: arid, snow, warm temperate (henceforth referred to as temperate), and equatorial. For total population, summer day SUHI intensity is lowest (0.40 ± 1.75 °C) for people of color and non-Hispanic whites in each climate zone, and the null hypothesis of equal means for people of color and non-Hispanic whites in each climate zone is not rejected. Slightly more cities expose populations under 5 to higher SUHI intensity, while populations over 65 are exposed to lower mean SUHI intensity. Restricting attention to the most vulnerable age groups in Fig. 1g does not alter the conclusion drawn from Fig. 1a; for both age groups people of color appear to have a worse SUHI distribution than non-Hispanic whites.

Table 1(b) tests hypotheses that mean exposure is equal across selected groups. We reject (p < 0.01) both the null hypothesis of equal means for people of color and non-Hispanic whites in each climate zone, and the null hypothesis of equal means for people below and above two times the poverty line. Perhaps unsurprisingly, the average exposure of non-Hispanic whites is also significantly lower than the average exposure of people below poverty. Interestingly however, outside of arid climates, the Figure 1 illustrates these sociodemographic differences in exposure, comparing kernel density plots of the distribution of mean SUHI across the 175 cities for different population groups. The strongest differences appear between race, Fig. 1a, and income, Fig. 1b. In only a few cities (n = 17) are white populations exposed to a mean SUHI intensity greater than 2 °C, while the corresponding number of cities for people of color is 83. A similar number of cities (n = 82) expose below-poverty populations to more than 2 °C SUHI. Figure 1c shows that distributions for those below poverty and for people of color are practically identical. As shown in Fig. 1d, e, there are not large differences in the distributions for the very young (less than 5) or the elderly (greater than 65) and the rest of the general population. Slightly more cities expose populations under 5 to higher SUHI intensity, while populations over 65 are exposed to lower mean SUHI intensity. Restricting attention to the most vulnerable age groups in Fig. 1g does not alter the conclusion drawn from Fig. 1a; for both age groups people of color appear to have a worse SUHI distribution than non-Hispanic whites.

| Climate zone (number of urbanized areas) | Arid | Snow | Temperate | Equatorial | Total |
|-----------------------------------------|------|------|-----------|------------|-------|
| (a) Population-weighted means: Total   |      |      |           |            |       |
| (19) |      |      |           |            |       |
| 0.40 | 2.23 | 2.21 | 2.76      | 2.06       |       |
| (1.75) | (2.71) | (2.78) | (2.20) | (2.72) |
| By race/ethnicity: People of color      |      |      |           |            |       |
| Hispanic                                |      |      |           |            |       |
| 0.74 | 3.65 | 3.03 | 3.02      | 2.70       |       |
| (1.55) | (2.72) | (2.65) | (2.19) | (2.64) |
| Non-Hispanic Black                      |      |      |           |            |       |
| 0.74 | 3.71 | 3.04 | 3.74      | 3.12       |       |
| (1.59) | (2.33) | (2.76) | (1.91) | (2.67) |
| Non-Hispanic White                      |      |      |           |            |       |
| 0.11 | 1.67 | 1.54 | 1.93      | 1.47       |       |
| (1.86) | (2.58) | (2.65) | (2.06) | (2.60) |
| Non-Hispanic Other                      |      |      |           |            |       |
| 0.22 | 2.68 | 2.60 | 2.34      | 2.41       |       |
| (1.78) | (2.60) | (2.84) | (2.13) | (2.80) |
| By income: Below poverty                |      |      |           |            |       |
| 0.74 | 3.32 | 2.92 | 3.42      | 2.77       |       |
| (1.61) | (2.67) | (2.78) | (2.02) | (2.73) |
| 1–2× poverty                            |      |      |           |            |       |
| 0.69 | 2.87 | 2.64 | 3.32      | 2.50       |       |
| (1.62) | (2.69) | (2.72) | (2.03) | (2.67) |
| Above 2× poverty                        |      |      |           |            |       |
| 0.22 | 1.87 | 1.95 | 2.41      | 1.80       |       |
| (1.79) | (2.63) | (2.76) | (2.21) | (2.69) |
| (b) Difference in means: People of color — Non-Hispanic white |      |      |           |            |       |
| 0.54*** | 1.77*** | 1.39*** | 1.26*** | 1.30*** |
| Below poverty — 2× poverty              | (0.059) | (0.100) | (0.206) | (0.020) | (0.171) |
| People of color — below poverty         | (0.070) | (0.142) | (0.094) | (0.001) | (0.071) |
| Non-Hispanic white — below poverty      | (0.039) | (0.071) | (0.066) | (0.042) | (0.063) |

Source: Author calculations, based on data from US Census Bureau and ref. **Panel (a):** Population-weighted means of urbanized area SUHI intensity in °C. Standard deviation is given in parentheses. Panel (b): Difference in group means. Standard errors clustered by urban area are given in parentheses.

*p < 0.10, **p < 0.05, ***p < 0.01.

w= Hispanic is defined as all who report “Hispanic, Latino, or Spanish origin” as their ethnicity, regardless of race. People of color includes all Hispanic and all who do not identify as white alone. Black and white include all who identify as these races alone but not Hispanic. Other includes all other non-Hispanic races alone and more than one race.
average exposure of people of color is not significantly lower than the average exposure of people below poverty despite the fact that only 10% of people of color live below the poverty line.

The values in Table 1 are weighted by population, thus raising the possibility that a few exceptionally large urbanized areas may be driving the results. By illustrating the spatial distribution of significant city-level racial and income disparities in SUHI exposure, the maps in Fig. 2 visualize the geographic scope of the phenomenon presented in the table. For each comparison, circles and triangles identify which group has the higher average SUHI exposure in each city. Symbols with black outlines indicate cities for which the differences in means are statistically significant (p < 0.05). (Supplementary Table 1 displays city-level results used to generate these maps). In Fig. 2a, map shows that people of color have higher SUHI exposure than non-Hispanic whites in 97% of cities nationally, and that this difference is significant in three quarters of cities. By zone, this proportion ranges from 42% in arid climates to almost 90% in snow. In contrast, non-Hispanic whites have a significantly higher exposure in only a single city, McAllen, TX. In Fig. 2b, the map shows a similar pattern for income. For over 70% of cities people below poverty have a significantly higher exposure than people above twice the poverty line (and in no city do they have a significantly lower exposure). In only 7% of cities nationwide does the average person of color have a lower exposure than the average person living below the poverty line (Fig. 2c).

### Intragroup variation in SUHI intensity

A potential drawback to focusing on average exposures by demographic group is it can mask the existence of potential hotspots, geographic areas in which individuals are exposed to elevated levels of the hazard. Hotspots are particularly problematic when comparing exposures across groups if the additional damage caused by an incremental temperature increase grows as temperatures rise. In such cases, even if two groups were to hypothetically face the same average exposure, a group in which half of individuals were exposed to a temperature of, say, 38 °C and half were exposed to 32 °C, would suffer higher adverse effects than a group in which all individuals were exposed to 35 °C.

The Kolm–Pollak (KP) inequality index (see “Methods”) is a tool for ranking group distributions of exposures when there are potential differences in dispersion of outcomes within each group (e.g., hotspots). Table 2(a) summarizes the average KP inequality index values for each city by population group and climate zone. A higher value corresponds to a less equal distribution of SUHI exposures within each group, with zero indicating a perfectly equal exposure (i.e., no within-group variation).

In general, cities in arid climates tend to have the lowest intragroup variation, and cities in snow and temperate zones have the highest. Within a given zone, however, index values are remarkably similar across population groups. Table 2(b) evaluates the hypothesis that index values vary significantly by demographic groups. Differences, measured in °C, are small in magnitude and not generally significant. Taken together, results in Table 2 suggest that the group means presented in Table 1 do not mask significant differences in variation within demographic groups. That is, the presence of relative hotspots is not likely to be higher among people living below the poverty line, for example, than people living at more than twice the poverty line. Consequently, for the remainder of this analysis we focus on average exposure levels for each group.

### Vulnerability

Analyzing vulnerability is a relevant factor in considering the implications of the difference in mean exposures presented in Table 1. Since SUHI intensity is more damaging to people over the age of 65 years, the fact that all people of color might be exposed to higher average SUHI than non-Hispanic whites may not be problematic, for example, if its vulnerable (over 65) subpopulations are not exposed in the same way. Map in Fig. 2d indicates that people over 65 have lower SUHI exposures than those under 65 in 86% of US cities. While this difference is significant for only 16% of cities, there are no cities in which they have a significantly higher exposure. Table 3(a) presents mean SUHI exposure levels by race and ethnicity, restricting attention to two particularly vulnerable subpopulations: those over 65 years old and those below the age of 5 years. Comparing the exposure levels of these ages in Table 3(a) with group-wide exposure in Table 1(a), we see that for people of color exposure levels are nationally the same or higher for these vulnerable groups: 2.76 ± 2.64 °C for those below 5 and 2.88 ± 2.77 °C for...
For non-Hispanic whites, however, these vulnerable populations have slightly lower exposures: 1.45 ± 2.53 °C for those below 5 and 1.44 ± 2.60 °C for those above 65, compared to 1.47 ± 2.60 °C for the entire white population. Table 3(b) compares mean exposures of these vulnerable ages across racial/ethnic groups. The patterns are almost identical to results in Table 1(b): people of color in each age group have significantly higher exposure levels than their white peers in each climate zone.

Discussion

Framework for understanding inequalities in SUHI. This analysis provides a framework for quantifying the intercity and intracity distribution of SUHI intensity by race, income, and age that considers both the intensity of the exposure as well as the inequality of distribution for different population subgroups. We find that the distributions of summer daytime SUHI intensity, taking into account both the mean and dispersion, is worse for both people of color and the poor, compared to white and wealthier populations in nearly all major US cities. As illustrated in Fig. 2, this pattern holds not only at the national level, but in almost all major urban areas regardless of geographical location or climate zones, with a particularly intense difference in the Northeast and upper Midwest of the continental United States. These findings provide comprehensive evidence supporting the narrative presented by earlier case studies that minority and low-income communities bear the brunt of the urban heat island effect, air temperature, and heat stress in individual or multicity studies.

Although age presents a vulnerability to SUHI, and elderly individuals aged 65 and older comprise a substantial percentage (39%) of heat-related deaths in the USA, our finding that populations over 65 are on average slightly less exposed (1.84 °C versus 2.06 °C for those under 65) could have several explanations. Because SUHI intensity and greenness (as measured by normalized difference vegetation index) are negatively correlated, cooler areas tend to be greener. There is evidence that populations over the age of 65 tend to live in suburban areas, which are typically greener than denser urban areas, except in arid climates. Considering the intersection of race and age demographics, however, the same racial and ethnic disparities in SUHI intensity for specific populations of color compared to non-Hispanic whites are also consistent for both very young and elder populations, meaning non-white populations over the age of 65 or less than 5 are still exposed to higher levels of SUHI than their white counterparts. The fact that older people of color have a slightly higher SUHI exposure than all people of color suggests that they may be less able to escape the heat by changing location than their white counterparts.

The Intergovernmental Panel on Climate Change has identified the “increasing frequency and intensity of extreme heat, including
the urban heat island effect” as a relevant hazard for certain age groups (i.e., elderly, the very young, people with chronic health problems), which creates a risk of increased morbidity or mortality during extreme heat periods. Relating intercity SUHI disparities to health outcomes is challenging due to both prevalence of confounding factors in the populations groups, as well as the differences between land surface temperature (LST) and more comprehensive metrics of heat stress. There is, however, evidence of disparities in heat-related health outcomes across the USA and for individual cities. For example, ref. found higher heat-related mortality rates among non-Hispanic American Indians/Alaska Natives and Blacks than for non-Hispanic whites at the national level.

Locally-tailored SUHI mitigation strategies. In addition to evaluating the general scope of potential heat-related environmental inequality concerns, the metrics developed in our study can identify precisely in which cities specific sociodemographic groups are most adversely exposed to SUHI intensity and to potential heat-related health effects for vulnerable groups. These data can thereby assist policy makers in designing interventions to address this exposure differential, as well as facilitate analysis of different scenarios to select the most appropriate strategy to mitigate exposure in an equitable manner. According to ref. 47, many cities do not take into consideration the spatial location of the most exposed populations in climate mitigation planning and whether areas that present increased sociodemographic vulnerabilities, such as age or high minority populations, are coincident with areas exposed to higher temperatures.

Consideration of background climate differences, which have been found to strongly modulate the thermodynamics of SUHI intensity, are critical for adapting city-specific intervention strategies to reduce both total exposure and disparities in its distribution. Because we use a globally consistent dataset derived from satellite remote sensing, our data allow for comparison of SUHI given differences in background climates and sociodemographics. Decision-makers and urban planners can utilize this information as a starting point to identify best practices and strategies for mitigating the overall SUHI as well as inequalities in its distribution, although there are certainly localized, context-specific factors that must be considered when determining SUHI management strategies. Studies have demonstrated the importance of coproduction (i.e., involving citizens in the production of knowledge and planning decisions) in developing tailored urban environmental policies. who used similar globally consistent satellite-derived data to evaluate drivers of SUHI in 30,000 cities around the world, acknowledge that these data can provide a first-order analysis to understand base-level SUHI exposures and differences to complement more fine-grained data on local factors that influence the SUHI (see “Study limitations” section for more discussion on data issues).

For example, the presence (or absence) of urban vegetation is often proposed as a strategy to reduce the urban heat island effect, climate change more generally, and for their other co-benefits. Access to green space has been found to be inversely correlated with median income. Actions such as planting trees in low-income and minority neighborhoods, which has been shown to reduce summertime afternoon temperatures by as much as 1.5 °C, can increase property values and housing...

### Table 2 Kolm-Pollak inequality index of summer daytime surface urban heat island intensity (SUHI) by climate zone and sociodemographic group.

| Climate zone | Arid | Snow | Temperate | Equatorial | Total |
|--------------|------|------|-----------|------------|-------|
| (a) Population-weighted index means: Total | 0.12 | 0.29 | 0.27 | 0.20 | 0.26 |
| (0.09) | (0.11) | (0.12) | (0.03) | (0.13) |
| By race/ethnicity*: People of color | 0.10 | 0.24 | 0.23 | 0.19 | 0.22 |
| (0.07) | (0.08) | (0.12) | (0.02) | (0.11) |
| Hispanic | 0.09 | 0.25 | 0.21 | 0.20 | 0.19 |
| (0.06) | (0.08) | (0.11) | (0.02) | (0.11) |
| Non-Hispanic Black | 0.09 | 0.19 | 0.22 | 0.15 | 0.21 |
| (0.05) | (0.07) | (0.08) | (0.01) | (0.08) |
| Non-Hispanic White | 0.14 | 0.27 | 0.27 | 0.18 | 0.26 |
| (0.12) | (0.11) | (0.12) | (0.04) | (0.12) |
| Non-Hispanic Other | 0.13 | 0.25 | 0.27 | 0.20 | 0.26 |
| (0.08) | (0.11) | (0.17) | (0.03) | (0.16) |
| By income: Below poverty | 0.10 | 0.25 | 0.24 | 0.17 | 0.23 |
| (0.08) | (0.10) | (0.11) | (0.02) | (0.11) |
| 1–2 × poverty | 0.10 | 0.26 | 0.24 | 0.17 | 0.22 |
| (0.08) | (0.11) | (0.11) | (0.02) | (0.11) |
| Above 2 × poverty | 0.13 | 0.28 | 0.27 | 0.21 | 0.26 |
| (0.10) | (0.11) | (0.13) | (0.04) | (0.13) |
| (b) Difference in mean index values: People of color – Non-Hispanic white | −0.04 | −0.04 | −0.04 | 0.01 | −0.04* |
| (0.055) | (0.031) | (0.030) | (0.018) | (0.023) |
| Below poverty – 2 × poverty | −0.03 | −0.02 | −0.03 | −0.04 | −0.03 |
| (0.048) | (0.032) | (0.029) | (0.014) | (0.023) |
| People of color – below poverty | 0.00 | −0.02 | −0.01 | 0.02* | −0.01 |
| (0.038) | (0.027) | (0.026) | (0.007) | (0.020) |

Source: Author calculations, based on data from US Census Bureau. Panel (a): Population-weighted mean of urban area Kolm-Pollak indexes in °C with moderate inequality aversion. Standard deviation is given in parentheses. Panel (b): Difference in group means. Robust standard errors are given in parentheses.

*Hispanic is defined as all who report “Hispanic, Latino, or Spanish origin” as their ethnicity, regardless of race. People of color includes all Hispanic and all who do not identify as white alone. Black and white include all non-Hispanics identifying as these races alone. Other includes all other non-Hispanic races alone and more than one race.
Complexity in disentangling race, income, and SUHI. The effect of historical practices of real estate, urban development, and planning policies that promoted spatial and racial segregation in US cities, as well as the fact that people of color tend to have lower income than white populations in the USA makes it difficult to disentangle purely economic reasons for the unequal distribution of SUHI intensity exposure to those based upon racial factors. We can, however, shed light on the complex relationships between race, poverty, and urban heat by comparing the distribution of SUHI intensity exposure to those based upon race.

While there is some overlap of individuals belonging to both groups, such individuals are a minority; according to the 2017 5-year ACS, only about 10% (ranging from 0.4 to 18.9%) of people of color live below the poverty line in these major urbanized areas. If income were to determine local summer daytime SUHI intensity exposure by sociodemographic group are not all the same across the entire sample the mean SUHI exposure of a person of color (2.77 ± 2.70 °C) is practically identical to that of a person living below poverty (2.77 ± 2.73 °C). The distribution of temperature differentials across cities is also similar for these two groups (Fig. 1). Nationally, we observe few cities (about 10%) with statistically significant differences between the mean SUHI intensities for these groups (Fig. 2c).

### Illustrative examples

While the SUHI distributions for below poverty and people of color are nearly identical (Fig. 1), patterns of exposure by sociodemographic group are not all the same between cities. Figure 3 provides an illustrative example, contrasting the cases of Baltimore, MD, and Greenville, SC. In Baltimore, the temperature exposure of the average person of color is about 0.7°C cooler than the average person in poverty, whereas the opposite is true for Greenville. Figure 3a, b shows that in Greenville, the Black population is highly concentrated in the warmest census tracts, while the poor population is more widely dispersed to cooler areas away from the city center. In Baltimore by contrast, Fig. 3c, d indicates that the poorest census tracts tend to be the warmest, while the Black population is much more evenly spread through the city.

As these illustrative examples of Greenville, SC, and Baltimore, MD, show, while many factors might explain our observed difference in below poverty and minority populations' SUHI exposure in these two cities, prior research on residential housing markets in the USA has shown that racial and ethnic segregation, among factors other than consumer preference alone, determine where certain groups live.

### Future challenges

The patterns of systematically higher SUHI exposure for low-income populations and communities of color...
Fig. 3 Distribution of surface urban heat island intensity (SUHI) by race and income in Greenville, SC, and Baltimore, MD. The correlation between SUHI intensity (dark orange and red) and census tracts that are predominantly non-Hispanic Black (in dark purple) and low-income areas (in dark teal) differs across cities. Hispanic is defined as all who report “Hispanic, Latino, or Spanish origin” as their ethnicity, regardless of race. a Greenville, SC: SUHI and income. b Greenville, SC: SUHI and income. c Baltimore, MD: SUHI and race. d Baltimore, MD: SUHI and income.

We assume every individual residing in a census tract has the same temperature exposure. In reality, temperatures and demographic characteristics may vary within a tract, and exposures can depend on individual behavior or conditions (home air conditioning, time spent outdoors, etc.). Our analysis also assumes that people pass the entire day in their census tract, abstracting from the possibility that they spend work or leisure time in other locations with distinct SUHI profiles.

Methods

Study limitations. While the SUHI database used in this study has been validated against other published estimates35, we recognize limitations of its use as a metric to identify which groups may be more vulnerable to heat stress within cities. Our environmental equity analysis assumes that SUHI intensity is harmful. While this assumption is likely to be justified in the summer periods evaluated in this study, the effect may be beneficial in cities exposed to extreme winter cold76. Although in theory the association between SUHI intensity and income and race could imply less extreme cold-related stress in poorer and predominantly non-white neighborhoods, other research suggests that these winter benefits may not materialize35. Nonetheless, intracity variation should be taken into account while planning strategies both to reduce mean SUHI and to address environmental disparities in its exposure within cities.

Heat stress also depends on factors other than LST and air temperature, including humidity, wind speed, and radiation77. SUHI intensity, however, is still a useful proxy for the urban contribution to local heat stress35. Our analysis relies on satellite-based estimates, which could overestimate UHI magnitude compared to in situ weather stations, particularly during daytime78, when shade from tree canopies or buildings reduce air temperature in a way that is not captured from a satellite’s vantage point. Our estimates, therefore, likely slightly overestimate the absolute measures of UHI (in °C), but in lieu of dense, widely accessible ground-based air temperature networks, satellite-derived estimates represent the best available data source.

We assume every individual residing in a census tract has the same temperature exposure. In reality, temperatures and demographic characteristics may vary within a tract, and exposures can differ across cities. Hispanic is defined as all who report “Hispanic, Latino, or Spanish origin” as their ethnicity, regardless of race. This dataset uses global LST products from NASA’s MODIS sensor82 and the land cover product from the European Space Agency83. It calculates SUHI intensity at the census tract level by combining the land cover data with the census tracts that intersect US urbanized areas, as defined by the US Census Bureau84.

We use the simplified urban extent method85 to define the SUHI intensity of an urban census tract as the difference between the tract’s mean LST and the mean
temperature of the rural reference r, the nonurban, nonwater land cover pixels within the tract’s urbanized area

\[ \text{SUHI}_r = \text{LST}_r - \text{LST}_c, \]

(1)

Urbanized area boundaries do not necessarily coincide with those of census tracts. In such cases, we adjust the approach to include only pixels within the urbanized area of a census tract to calculate LST. For more details, see ref. 33. The distributional analysis thus implicitly assumes no one resides in the nonurbanized portion of those adjoining tracts.

Since previous studies have demonstrated the importance of background climate in modulating the SUHI intensity15,16, we also examine the relationship between disparities in SUHI exposure and the Köppen–Geiger climate zone69. The possible impact of background climate has policy implications, since it constrains what city planners can do to mitigate the city-specific SUHI and its distributional impacts.

Demographic data. We assign the same SUHI intensity to every individual living in a given census tract. Demographic group averages are calculated as weighted means across census tracts, in which the weights correspond to the number of people of a given group residing in a tract. Census tract level demographic data come from the 2017 ACS 5-year Data Profile68,69. We collect data on race, ethnicity, poverty status, age, and age by race for all 46,346 census tracts in the 175 census–defined urbanized areas that contain more than 250,000 residents (Supplementary Fig. 2). Our set of urbanized areas ranges from 43 to 4470 tracts, with a median of 582 (Supplementary Table 2). Responses to race include options for single race (e.g., Black only) as well as multiple races. Hispanic is an ethnicity reported in addition to race (e.g., Black only and Hispanic). Regardless of race, it is defined as any who respond “yes” to the Census question asking whether the person is “of Hispanic, Latino, or Spanish origin”68. For the total population, we generate categories for two non-Hispanic single race groups (Black, white), Hispanic of any race, and “Other”. Other includes non-Hispanics of other single races, including Black or African American, Asian, American Indian and Alaska Native, Native Hawaiian and other Pacific Islander, and non-Hispanics reporting two or more races. We also create a People of Color category that includes all Hispanic and all who do not identify as White alone. For age categories, we use the same race and ethnicity groupings to develop under 5 and over age 65 categories. Since ACS age data do not differentiate Black by Hispanic ethnicity, however, Black Hispanics appear in both the Black and Hispanic categories in Table 3 only.

The ACS reports poverty status as household income relative to the poverty line. This income is not measured in dollars since the poverty line depends on the number of individuals in the household. We use these data to generate three income categories: at or below the poverty line, from one to two times the poverty line, and at or above two times the poverty line (the highest recorded category). Since ACS data were collected from the US Census Bureau 2017 5-year ACS via the API at https://api.census.gov/data/2017/acs/acs5/variables.html.

Code availability

SUHI intensity data are available for exploration on an interactive Google Earth Engine platform tool, available at https://datadrivenlab.users.earthengine.app/view/usuhiappand also for download at https://data.mendeley.com/datasets/x9mv4krnm2/2. Sociodemographic data were collected from the US Census Bureau 2017 5-year ACS via the API at https://api.census.gov/data/2017/acs/acs5/variables.html.

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References

1. Oke, T. R. The energetic basis of the urban heat island. Q. J. R. Meteorolog. Soc. 108, 1–24 (1982).
2. Strand, R. A. & Cutter, S. L. Spatial patterns of natural hazards mortality in the United States. Int. J. Health Geogr. 7(1), 64 (2008).
3. Eunice Lo, Y. T. et al. Increasing migration ambition to meet the Paris Agreement’s temperature goal avoids substantial heat-related mortality in U.S. Cities. Sci. Adv. https://doi.org/10.1126/sciadv.aau4373 (2019).
4. NOAA. Weather Related Fatality and Injury Statistics. https://www.weather.gov/oh/heat (2018).
5. Anderson, G. B. & Bell, M. L. Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U. S. counties. Environ. Health Perspect. 119, 210–218 (2011).
6. Graff-Zivin, J. & Neidell, M. Temperature and the allocation of time: implications for climate change. J. Labor Econ. 32, 1–26 (2014).
7. Heil, G. & Park, J. Reflections—temperature stress and the direct impact of climate change: a review of an emerging literature. Rev. Environ. Econ. Policy 10, 347–362 (2016).
8. Heaviside, C., Macintyre, H. & Vardoulakis, S. The urban heat island: implications for health in a changing environment. *Carr. Environ. Health Rep.* 5, 296–305 (2019).

9. Park, J., Goodman, J., Hurwitz, M. & Smith, J. Heat and learning. *Am. Econ. J.: Econ. Policy* 12, 306–39 (2020).

10. Shahmohamadi, P., Che-Ani, A. I., Etessam, I., Maulud, K. N. A. & Tawil, N. M. Healthy environment: the need to mitigate urban heat island effects on human health. *Proc. Eng.* 20, 61–70 (2011).

11. Tan, J. et al. The urban heat island and its impact on heat waves and human health in Shanghai. *Int. J. Biometeorol.* 54, 73–84 (2010).

12. Peng, S. et al. Surface urban heat island across 419 global big cities. *Environ. Sci. Technol.* 46, 16–28 (2012).

13. Zhou, B., Rybski, D. & Kropp, J. P. The role of city size and urban form in the surface urban heat island. *Sci. Rep.* 7, 1–9 (2017).

14. Chakraborty, T. & Lee, X. A simplified urban-extension algorithm to characterize surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. *Int. J. Appl. Earth Observ. Geoinf.* 74, 269–280 (2019).

15. Zhao, L., Lee, X., Smith, R. B. & Olsson, K. Strong contributions of local background climate to urban heat islands. *Nature* 511, 216–219 (2014).

16. Chakraborty, T., Hsu, A., Manya, D. & Sheriff, G. A spatially explicit surface heat island vulnerability and risk mapping in Helsinki, Finland. *Environ. Sci. Technol.* 51, 1498–1507 (2017).

17. Bruinsma, J., Che-Ani, A. I., Etesam, I., Maulud, K. N. A. & Tawil, N. M. Healthy environment: the need to mitigate urban heat island effects on human health. *Proc. Eng.* 20, 61–70 (2011).

18. Park, J. Hot temperature and high stakes performance. *J. Health Sci. Technol.* 15, 678–703 (2012).

19. Zhou, B., Rybski, D. & Kropp, J. P. The role of city size and urban form in the surface urban heat island. *Sci. Rep.* 7, 1–9 (2017).

20. Zitter, C. D., Pedersen, E. J., Kucharik, C. J. & Turner, M. G. Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. *Proc. Natl Acad. Sci. USA* 116, 7757–7765 (2019).

21. Clark, L. P., Millet, D. B. & Marshall, J. D. National patterns in environmental injustice and inequality: outdoor NO2 air pollution in the United States. *PloS ONE* 9, e94431 (2014).

22. Park, J., Bangalore, M., Hallegatte, S. & Sandhoefner, E. Households and heat stress: estimating the distributional consequences of climate change. *Environ. Dev. Econ.* 23, 349 (2018).

23. Voelkel, J., Hellman, D., Sakuma, R. & Sandhas, V. Assessing vulnerability to urban heat: a study of disproportionate heat exposure and access to refuge by socio-demographic status in Portland, Oregon. *Int. J. Environ. Res. Public Health* 15, 640 (2018).

24. Johnson, D. P., Wilson, J. S. & Luber, G. C. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int. J. Health Geogr.* 8(1), 57 (2009).

25. Seppänen, O., Fisk, W. J. & Lei, Q. H. Effect of Temperature on Task Performance in Office Environment (Lawrence Berkeley Natl Lab., 2006).

26. Deschénes, O. & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the U.S. Am. Econ. J.: Appl. Econ. 3, 152–85 (2011).

27. Johnson, D. P., Wilson, J. S., & Luber, G. C. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int. J. Health Geogr.* 8(1), 57 (2009).

28. Johnson, D. P., Wilson, J. S. & Luber, G. C. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int. J. Health Geogr.* 8(1), 57 (2009).

29. Uejio, C. K. et al. Intra-urban societal vulnerability to extreme heat: the role of exposure to urban heat in lower-income neighborhoods: a multi-city framework for reducing urban vulnerability to extreme heat. *Environ. Lett.* 5, 014021 (2020).

30. O’Lenic, C. R. et al. Urban heat and air pollution: a framework for integrating population vulnerability and indoor exposure in health risk analyses. *Sci. Total Environ.* 660, 715–733 (2019).

31. Kenny, G. P., Yardley, J., Brown, C., Sigal, R. J. & Jay, O. Heat stress in older individuals and patients with common chronic diseases. *CMAJ* 182, 1053–1060 (2010).

32. McGehee, M. A. & Mirabelli, M. The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. *Environ. Health Perspect.* 109, 185–189 (2001).

33. Clinton, N. & Gong, P. MODIS detected surface urban heat islands and sinks: global locations and controls. *Int. J. Biometeorol.* 54, 73–84 (2010).

34. Huang, G., Zhou, W. & Cadenasso, M. L. Is everyone hot in the city? Spatial stability. *Environ. Sci. Technol.* 51, 1498–1507 (2017).

35. Raisänen, A., Heikkinen, K., Pihlaja, N. & Juhola, S. Zoning and weighting in urban heat island vulnerability and risk mapping in Helsinki, Finland. *Reg. Environ. Change* 19, 1481–1493 (2019).

36. Estoque, R. C. et al. Heat health risk assessment in Philippine cities using remotely sensed data and social–ecological indicators. *Nat. Commun.* 11, 1–12 (2020).

37. Johnson, D. P., Wilson, J. S. & Luber, G. C. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int. J. Health Geogr.* 8(1), 57 (2009).

38. Seppänen, O., Fisk, W. J. & Lei, Q. H. Effect of Temperature on Task Performance in Office Environment (Lawrence Berkeley Natl Lab., 2006).

39. Deschénes, O. & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the U.S. Am. Econ. J.: Appl. Econ. 3, 152–85 (2011).

40. Graf-Zivin, J. & Shadel, J. Temperature extremes, heat, and human capital. *Future Child.* 26, 31–50 (2016).

41. Wang, C. et al. Nonlinear relationship between extreme temperature and mortality in different temperature zones: a systematic study of 122 communities across the mainland of China. *Sci. Total Environ.* 586, 96–106 (2017).

42. Kottke, M., Griesser, J., Reck, C., Rudolf, R., & Rubel, F. World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift.* 15, 259–263 (2006).

43. Joint Center for Housing Studies of Harvard University. *Projections and Implications for Housing a Growing Population: Older Households 2015–2035* (Joint Center for Housing Studies, 2016).

44. Nitisalwisai, S. A., Duninker, P. N. & Bush, P. G. A review of drivers of diversity in suburban areas: research needs for North American cities. *Environ. Rev.* 24, 471–483 (2016).

45. Hanssen, A. J. et al. Effects of exurban development on biodiversity: patterns, mechanisms, and research needs. *Ecol. Appl. 15*, 1893–1905 (2005).

46. Anderson, G. B., Bell, M. L. & Peng, R. D. Methods to calculate the heat index as an exposure metric in environmental health research. *Environ. Health Perspect.* 121, 1111–1119 (2013).

47. Rosenthal, J. K., Kinney, P. L. & Metzger, K. B. Intra-urban vulnerability to heat-related mortality in New York city, 1997–2006. *Health Place* 30, 45–60 (2014).

48. Georgescu, M., Morefield, P. E., Bierwagen, B. G. & Weaver, C. P. Urban adaptation can roll back warming of emerging megapolitan regions. *Proc. Natl Acad. Sci. USA* 111, 2909–2914 (2014).

49. Satorras, M., Ruiz-Mallen, I., Mondero, A. & March, H. Co-production of urban climate planning: insights from the Barcelona Climate Plan. *Cities* 106, 102587 (2020).

50. Manoli, G. et al. Magnitude of urban heat islands largely explained by climate and population. *Nature* 573, 55–60 (2019).
61. Cui, Y. Y. & De Foy, B. Seasonal variations of the urban heat island at the surface and the near-surface and reductions due to urban vegetation in Mexico City. J. Appl. Meteorol. Climatol. https://doi.org/10.1175/JAMC-D-11-0104.1 (2012).

62. Hubau, W. et al. Asynchronous carbon sink saturation in African and Amazonian tropical forests. Nature 579, 80–87 (2020).

63. Dadvand, P. et al. Green spaces and cognitive development in primary schoolchildren. Proc. Natl Acad. Sci. USA 112, 7937–7942 (2015).

64. Fong, K. C., Hart, J. E. & James, P. A review of epidemiologic studies on greenness and health: updated literature through 2017. Curr. Environ. Health Rep. 5, 77–87 (2018).

65. Engemann, K. et al. Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence to adulthood. Proc. Natl Acad. Sci. USA 116, 5183–5193 (2019).

66. Iyer, H. S. et al. The contribution of residential greenness to mortality among men with prostate cancer: a registry-based cohort study of black and white men. Environ. Epidemiol. 4, e007 (2020).

67. Nesbitt, L., Meitner, M. J., Girling, C., Sheppard, S. R. J. & Lu, Y. Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 U.S. cities. Landsc. Urban Plan. 181, 51–79 (2019).

68. Rosenfeld, A. H., Akbari, H., Romm, J. I. & Pomerantz, M. Cool communities: strategies for heat island mitigation and smog reduction. Energy Build. 28, 51–62 (1998).

69. Wolch, J. R., Byrne, J. & Newell, J. P. Urban green space, public health, and environmental justice: the challenge of making cities ‘just green enough’. Landsc. Urban Plan. 125, 234–244 (2014).

70. Jennings, V., Gaither, C. J. & Gragg, R. S. Promoting environmental justice through urban green space access: a synopsis. Environ. Justice 5, 1–7 (2012).

71. Klaiber, H. A., Abbott, J. K. & Smith, V. K. Some like it (less) hot: extracting temperature/emissivity product.

72. Ring, D. L. & Tester, G. The complexities and processes of racial housing discrimination. Soc. Probl. 56, 49–69 (2009).

73. Islam, N. & Winkel, J. Climate Change and Social Inequality. Number 152 in Department of Economic and Social Affairs Working Paper (Organization for Economic Cooperation and Development, 2017).

74. Yang, J. & Bou-Zeid, E. Should cities embrace their heat islands as shields from extreme cold? J. Appl. Meteorol. Climatol. 57, 1309–1320 (2018).

75. Olson, K. W. et al. Interactions between urbanization, heat stress, and climate change. Clim. Change 129, 525–541 (2015).

76. Zehner, P., Bouma, L., Irwin, M. L., Wolfe, R. E. & Thome, K. Comparison of MODIS land surface temperature and air temperature over the continental U.S.A. meteorological stations. Can. J. Remote Sens. 40, 110–122 (2014).

77. Banzhaf, S., Ma, L. & Timmins, C. Environmental justice: the economics of race, place, and pollution. J. Econ. Perspect. 33, 185–208 (2019).

78. Cao, B. et al. A review of Earth surface thermal radiation directionality observation and modeling: historical development, current status and perspectives. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2019.113104 (2019).

79. Colmer, J., Hardman, I., Shumshack, J. & Voorheis, J. Disparities in PM2.5 air pollution in the United States. Science 369, 575–578 (2020).

80. Wang, Z. New refinements and validation of the collection-6 MODIS land-surface temperature/emissivity product. Remote Sens. Environ. 140, 36–45 (2014).

81. Bontemps, S. et al. Consistent global land cover maps for climate modelling communities: current achievements of the ESA’s land cover CCI. In Proc. ESA Living Planet Symposium 2015. (Edinburgh, UK) 9–13 (Ecological Society of America, 2013).

82. U.S. Census Bureau. 2010 Census Urban and Rural Classification and Urban Area Criteria. www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html. (U.S. Census Bureau, 2020).

83. Rubel, F. & Kottek, M. Observed and projected climate shifts 1901–2100 depicted by world maps of the Köppen-Geiger climate classification. Meteorol. Z. 19, 135–141 (2010).

84. U.S. Census Bureau. American Community Survey, 2017 5-year Estimates, Tables B03002 and C17002. factfinder.census.gov. (U.S. Census Bureau, 2020).