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Research Report

Racial and ethnic minorities disproportionately exposed to extreme daily temperature variation in the United States

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Abstract

In the history of *Homo sapiens*, well-populated habitats have featured relatively stable temperatures with generally small daily variations. As the global population is increasingly residing in highly disparate climates, a burgeoning literature has documented the adverse health effects of single-day and day-to-day variation in temperature, raising questions of inequality in exposure to this environmental health risk. Yet, we continue to lack understanding of inequality in exposure to daily temperature variation (DTV) in the highly unequal United States. Using nighttime and daytime land surface temperature data between 2000 and 2017, this study analyzes population exposure to long-term DTV by race and ethnicity, income, and age for the 50 states and the District of Columbia. The analysis is based on population-weighted exposure at the census-tract level. We find that, on average, non-White (especially Black and Hispanic) and low-income Americans are exposed disproportionately to larger DTV. Race-based inequalities in exposure to DTV are larger than income-based disparities, with inequalities heightened in the summer months. In May, for example, the DTV difference by race and ethnicity of 51 states is between 0.20 and 3.01 °C (up to 21.0%). We find that younger populations are, on average, exposed to larger DTV, though the difference is marginal.

Keywords: daily temperature variation, diurnal temperature range, health inequality, environmental justice, environmental inequality

Significance Statement

Evidence from across the globe demonstrates that large daily temperature variation is associated with higher mortality and morbidity. Yet, we lack basic insights into its sociodemographic patterning in the United States. Using satellite data, this study finds that exposure to daily temperature variation is extremely unequal by race and ethnicity, as well as by income. Racial and ethnic minorities and low-income populations in the United States are disproportionately exposed to larger daily temperature variation. This inequality is driven by the built environment, including blue and green space, which is a legacy of structural racism. This descriptive study reveals that the persistent inequality in the built environment manifests as inequality in yet another environmental risk factor—daily temperature variation.

The human body is a resilient, yet sensitive complex system whose homeostasis can be disrupted by unfavorable—and erratically changing—environmental conditions. In most human habitats, the temperature variation to which humans are exposed each day is relatively small compared to the historical temperature record (−89.2 to 56.7 °C) on the Earth's surface (1, 2). In the case of the two most populous cities in the United States, New York and Los Angeles, the annual temperature range is between −4 and 30 °C. The daily temperature variation (DTV) is even smaller, often within 2 to 10 °C (Fig. S1).

The DTV has long been of interest to the environmental science community, as it offers a comprehensive measure that is an important atmospheric indicator (3, 4). The ocean plays a major role in maintaining the relative stability of temperature on the Earth's surface—effectively precluding dramatic variability in a short-time frame (5). Globally, populous human habitats feature relatively small DTV (Fig. 1). If we trace back across the development of human societies, the favorable Oceanic Climate in Europe has given rise to densely populated cities, wherein the population enjoys relatively stable temperature in any single day (i.e. small DTV). Conversely, the Temperate Continental Climate common in Siberia and the Dry Desert Climate of Sahara Desert feature large DTV—and these unfavorable conditions arguably contribute to the continued sparse population in these settings.

Competing Interest: The authors declare no competing interest.
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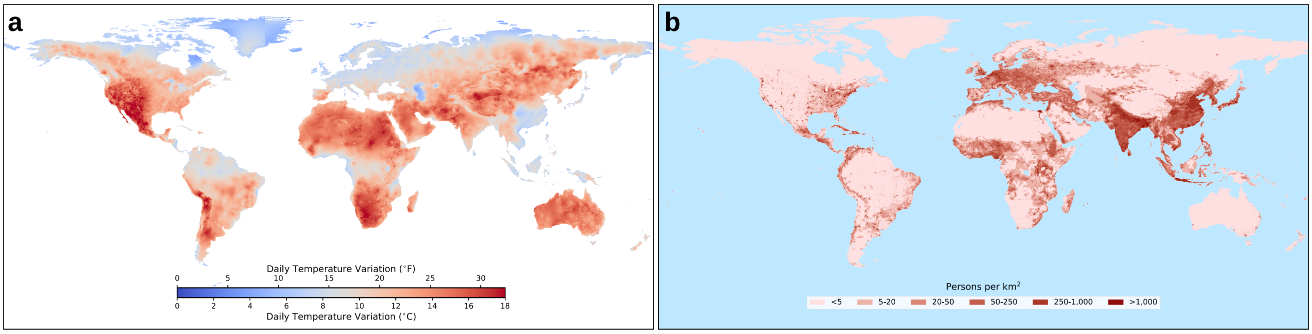

Fig. 1. Daily temperature variation (DTV, a) and population density in the world (b).

In addition to its relevance as a valuable atmospheric indicator, more recently, scientists studying the climate-human health nexus have recognized DTV's relevance to population health. Although the vast literature on the climate-human health nexus has focused on the adverse consequences of extreme absolute temperature, a small but growing literature outlines an association between large DTV and poor human health (6). For example, a recent study contends that 2.5% of the total mortality between 1972 and 2013 is attributable to DTV in 308 cities from 10 countries across 5 continents (7). Moreover, in 95 communities across the United States, larger DTV is associated with increased nonaccidental mortality, with older adults most vulnerable (8). The association between DTV and elevated mortality has also been documented in the United Kingdom (9), East Asian cities (10), and other parts of the world (11–13). Higher DTV also leads to higher risks of morbidity, with evidence of hospital admissions and emergency department visits in the United States, Spain, Thailand, South Korea, and China (14–18), as well as childhood illness in Australia (19).

Despite growing recognition of the adverse health consequences of high DTV, we lack basic insights into population exposure to DTV in the United States, and whether it corresponds with other social and demographic inequalities. Exposure to environmental risk factors is often unequal across population groups. Globally, there are socioeconomic disparities in exposure to harmful climate conditions, like particulate matter and nitrogen dioxide, and to beneficial ones, like access to green space (20–22). In the United States, racial and ethnic minorities, in addition to low-income populations, have been exposed historically to higher particulate matter and nitrogen dioxide (23, 24). In terms of temperature, specifically, global studies have shown similarly unequal exposure to, and effects of, extreme heat (25, 26). Similarly, in the United States, historically marginalized racial and ethnic groups, as well as lower-income groups, also bear an out-sized burden of extreme heat and urban heat islands (27, 28). Even so, few studies have analyzed temperature exposures other than heat, despite a burgeoning literature showing poor health outcomes associated with extreme cold and large DTV (7, 8, 29). Except for one city-specific study of Los Angeles (30), no study has described the population prevalence, nor inequality, in DTV exposure in the United States.

Such descriptive research is valuable given the social and demographic correlates of DTV remain unclear. Given recent evidence that DTV is actually decreasing in some global contexts, partly due to urbanization and climate change (31), it is possible that less advantaged populations, which tend to concentrate in urban areas, are actually exposed to smaller DTV. However, within an urban area, the local DTV is affected by the urban landscape. The US features unequal exposure to green space, which partly explains the unequal exposure to extreme heat (32, 33). Trees can reduce temperature via transpiration—a process more intense during daytime—and trees can trap long-wave radiation in the atmosphere under the canopy at night, which can lead to increased night-time temperature (34–36). Moreover, water has a high heat capacity that can minimize changes in temperature (37). As such, with limited access to neighborhood green space and blue space, less advantaged populations could experience larger DTV, on average, even despite declining trends in urban areas more generally. This study analyzes DTV exposure across population groups in the United States. Using monthly night-time and daytime land surface temperature data from satellites, we estimate the population-weighted exposure to DTV at the census tract level of the 50 states and the District of Columbia (hereinafter referred to as 51 states). We analyze inequality by three sociodemographic characteristics: race and ethnicity, income, and age.

Results

Figure 2 visualizes the distributions of DTV exposure of the non-White population (in red) and White population (in blue) for each state (see Fig. S5 for individual race and ethnicity). These DTV exposures are scaled to the mean of the White population. If the exposure to DTV is equal across population groups, the distributions would show the same shape. Yet, as shown, there is a clear difference in DTV exposure between the White and non-White populations, with some states more evident, such as Rhode Island, Connecticut, and Massachusetts in New England. We use the KS test to measure the distance between the two distributions. The KS distance ranges between 0 and 1; the larger the distance, the larger difference in DTV exposure between the two populations.

Exposure to DTV differs significantly between White and non-White populations (Fig. 2). Among the 51 states, 47 of them show a KS distance larger than 0.1; among which, 8 states show a KS distance larger than 0.3 and 14 states with a KS distance larger than 0.2. Figure S5 shows the comparison of mean exposure among the four racial and ethnic groups, which indicates that the difference is due to the larger DTV exposure among Black and Hispanic populations; DTV exposure among Asian Americans is higher than Whites, however, not as dramatically so. Unequal exposure to DTV is also observed between low-income and high-income populations, though to a lesser degree (Fig. S2). Of the 51 states, 6 states show a KS distance larger than 0.3, 13 states show a KS distance larger than 0.2, and 20 states show a KS distance larger than 0.1 between the DTV

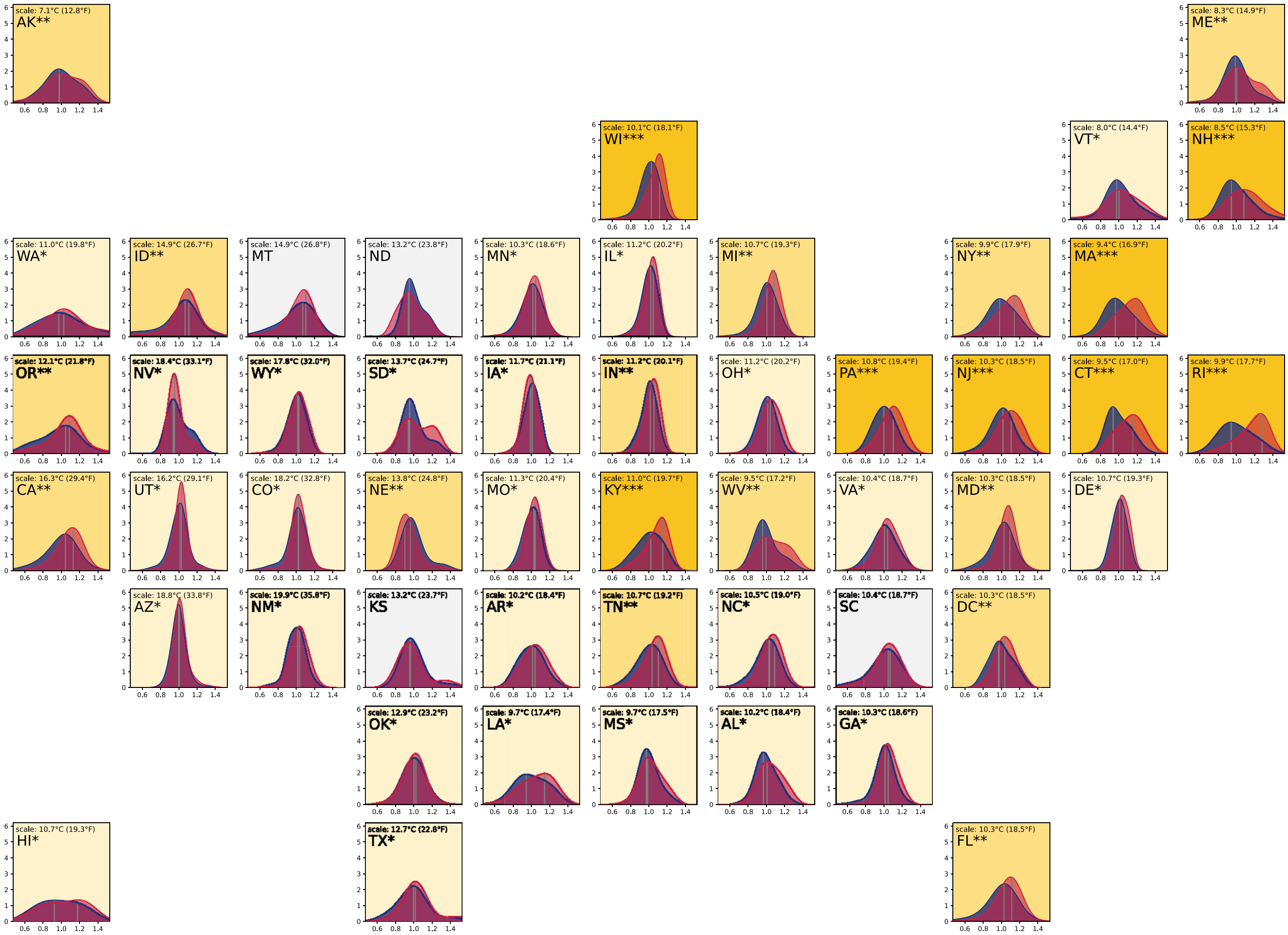

Fig. 2. Distribution of the exposure to daily temperature variation (DTV) of White and non-White populations. The values are averaged from all 2000–2017 data. Each state shows the kernel density estimation for the White (in blue) and the non-White population (in red). The x-axis is relative DTV exposure, which is obtained by dividing the mean exposure of the White population (the scale factor). The y-axis is population percentage. The gray line marks the peak of each distribution. The two distributions are compared using the KS distance. distance ≥0.1: state abbreviation marked with * (background in light yellow ◆); distance ≥0.2: state abbreviation marked with ** (background in moderate yellow ◆); distance ≥0.3: state abbreviation marked with *** (background in yellow ◆). Figure S5 shows a more detailed comparison using the four racial and ethnic groups, which shows that Black and Hispanic populations are exposed to generally higher DTV than the Asian population, yet the Asian population exposure is also higher than the White population. As such, the non-White and White comparisons showcased here would be even more dramatic if studying only Black and Hispanic populations to their White counterparts.

exposures of low-income and high-income populations (household income less than US$15,000 vs. greater than US$200,000). Exposure to DTV is the least unequal by age. Of the 51 states, none show a KS distance larger than 0.2 and only 15 states show a KS distance larger than 0.1 between the distributions of old-age (aged 65+) and young-age (aged 0–4) populations—the two age groups with the lowest and highest DTV exposure (Fig. S3).

The differences in monthly DTV exposure between population groups by race and ethnicity, income, and age of 51 states are shown in Fig. 3. The values are calculated as the subtraction between the maximum and minimum DTV of the population groups (i.e. absolute difference). If the DTV exposure is truly equal across populations, the difference should be marginal with a darker color. However, in most states, the difference is large and visible by race and ethnicity; however, they are only somewhat visible by income, and barely visible by age. Summer months generally have the largest DTV difference, with the absolute DTV differences up to 3.0 °C (5.4 °F) in May for some states. Note that we also show a version of this figure with the actual difference in Fig. S7. We manually plot the difference between the two groups with the largest DTV gap on average. In all 46 out of 51 states, 44 out of 51 states and 47 out of 51 states, non-White, low-income, and young-age populations are exposed to higher DTV, respectively.

To further convey the scale of demographic inequality in exposure to DTV, the mean DTV differences by race and ethnicity, income, and age along with standard deviations in May from ten representative states are shown in Table 1. We chose May because most states have the largest DTV during this month. The 10 states include six of the most populous states (California, Texas, Florida, New York, Pennsylvania, and Illinois) and four additional states (Washington, Massachusetts, Connecticut, and Rhode Island) that exhibited large DTV differences by race and ethnicity or income from the previous findings. For the 10 representative states, the maximum differences by race and ethnicity are between 0.93–3.01 °C, or 7.2–21.0% of the DTV exposure of the White population. The maximum difference by income is between 0.20–2.33 °C, or 1.3–17.1% of the DTV exposure of the White population. The difference by age is marginal, especially at older ages. Rhode Island has the largest DTV difference by race and ethnicity and by income among all states. Figure S5 shows the mean and standard deviation of annual DTV exposure for all 51 states, which show a consistent finding drawn from the 10 representative states.

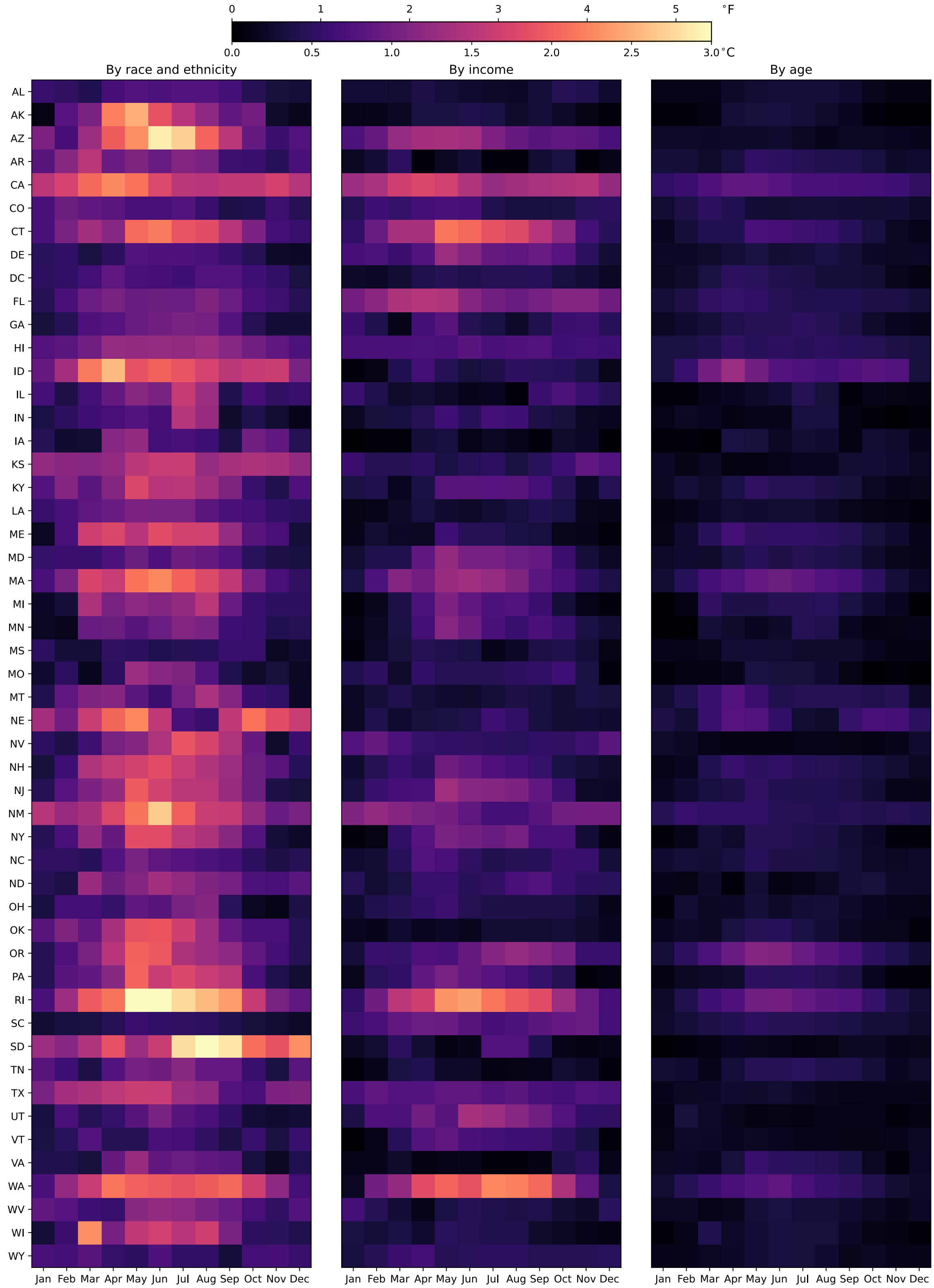

Fig. 3. From left to right: monthly DTV differences of the 51 states by race and ethnicity, income, and age. The difference is between the maximum DTV and minimum DTV of the population groups. If the DTV exposure is truly equal across population groups, the difference should be marginal (darker color). X-axis: month from January to December.

Because Rhode Island has the largest DTV difference by race and ethnicity and income, we visualize its DTV, non-White population percentage, median household income, and green space at the census tract level (Fig. 4). The area with the largest DTV is Providence, the state's most populous city, with a concentration of the state's non-White population. Providence shows a relatively low median household income compared to the surrounding areas. It is also the area with the smallest green space exposure.

Table 1. DTV differences (°C) in May by race and ethnicity, income, and age in 10 representative states (standard deviation shown in brackets).

		California	Washington	Texas	Illinois	New York	Florida	Pennsylvania	Massachusetts	Connecticut	Rhode Island
By race and ethnicity	Hispanic	22.21 (2.71)	17.23 (4.06)	15.08 (3.72)	16.70 (1.70)	15.16 (2.41)	13.77 (1.96)	16.05 (2.34)	15.98 (2.02)	15.53 (2.16)	17.35 (2.26)
	Black	21.98 (2.84)	15.92 (2.78)	13.45 (2.41)	15.98 (1.69)	16.11 (2.33)	13.90 (1.68)	15.86 (2.10)	16.17 (1.99)	15.68 (1.83)	17.35 (2.48)
	Asian	21.01 (2.74)	15.35 (2.77)	13.88 (2.28)	16.23 (1.47)	15.57 (2.29)	13.32 (1.94)	15.30 (2.06)	15.24 (2.11)	14.22 (1.95)	16.05 (2.73)
	Non-White	21.81 (2.84)	16.18 (3.63)	14.65 (3.47)	16.32 (1.72)	15.54 (2.41)	13.77 (1.87)	15.73 (2.20)	15.75 (2.11)	15.31 (2.10)	17.01 (2.51)
	White	20.09 (3.51)	15.23 (3.89)	13.64 (3.28)	15.52 (2.15)	14.26 (2.32)	12.97 (2.32)	14.01 (1.88)	14.05 (2.09)	13.60 (1.86)	14.34 (2.63)
By income	<15,000	21.09 (3.36)	16.07 (3.88)	14.31 (3.51)	15.60 (2.11)	15.12 (2.49)	13.46 (2.14)	14.91 (2.29)	15.27 (2.32)	15.18 (2.20)	15.97 (2.92)
	15,000–34,999	21.24 (3.31)	16.06 (3.96)	14.30 (3.51)	15.69 (2.15)	14.86 (2.44)	13.44 (2.15)	14.52 (2.16)	14.74 (2.31)	14.72 (2.16)	15.51 (2.81)
	35,000–99,999	21.07 (3.25)	15.62 (3.84)	14.21 (3.41)	15.76 (2.09)	14.67 (2.41)	13.27 (2.20)	14.29 (2.04)	14.48 (2.25)	14.30 (2.09)	14.99 (2.79)
	100,000–199,999	20.60 (3.18)	14.85 (3.55)	13.94 (3.21)	15.83 (1.95)	14.51 (2.38)	12.79 (2.28)	14.11 (1.84)	14.18 (2.15)	13.71 (1.89)	14.18 (2.59)
	200,000 +	19.54 (3.25)	14.04 (3.35)	13.45 (2.85)	15.63 (1.78)	14.05 (2.45)	11.99 (2.40)	13.86 (1.70)	13.99 (2.01)	13.04 (1.63)	13.64 (2.66)
By age	0–4	21.46 (3.08)	15.83 (3.77)	14.35 (3.45)	15.90 (2.01)	14.86 (2.42)	13.55 (2.03)	14.59 (2.15)	14.74 (2.20)	14.36 (2.15)	15.52 (2.80)
	5–19	21.41 (3.14)	15.74 (3.92)	14.30 (3.47)	15.86 (2.02)	14.67 (2.43)	13.48 (2.06)	14.46 (2.11)	14.49 (2.17)	14.15 (2.14)	15.14 (2.90)
	20–34	21.33 (3.09)	15.87 (3.67)	14.34 (3.37)	15.90 (1.99)	14.97 (2.42)	13.51 (1.99)	14.67 (2.12)	15.02 (2.28)	14.57 (2.11)	15.48 (2.91)
	35–64	21.05 (3.25)	15.31 (3.80)	14.12 (3.39)	15.81 (2.05)	14.62 (2.43)	13.28 (2.17)	14.27 (2.05)	14.35 (2.19)	14.00 (2.07)	14.84 (2.80)
	65 +	20.60 (3.45)	15.09 (3.99)	14.10 (3.53)	15.66 (2.12)	14.53 (2.42)	13.02 (2.42)	14.17 (1.99)	14.12 (2.18)	13.89 (2.01)	14.52 (2.75)

Discussion

Extending the long-running interest in how extreme temperature adversely affects human health, a small but growing literature outlines that the range of temperature to which humans are exposed is another source of climate vulnerability. That is, exposure to higher DTV has been linked to higher rates of population morbidity and mortality across various age groups in diverse global contexts—above and beyond the absolute temperatures driving the DTV (7). Despite this recognition, we still lack fundamental insights into exposure to DTV in the United States, and its possible inequality between sociodemographic groups. Our analysis shows that there is unequal exposure to DTV across racial and ethnic groups, as well as income groups. The difference is larger by race and ethnicity than by income, with minimal differences observed across age groups. Non-White (especially Black and Hispanic) populations, as well as low-income populations, are disproportionately exposed to higher DTV. Although we identify regional differences, the DTV differences by race and ethnicity appear to be driven by intra-urban differences due to the urban landscape, as illustrated in the case of Rhode Island.

The magnitude of DTV difference by race/ethnicity and income is 0.20–3.01 °C, or up to 21.0% of the DTV exposure of White or high-income populations. This magnitude of difference by race and ethnicity and by income is larger than the difference in exposure to the urban heat island (28). According to Lee et al. (38) with evidence from air temperature, DTV could contribute to 6% of the total mortality in the United States by 2,100. Based on our study, facing up to 3 °C larger DTV exposure in land surface temperature than their White or high-income peers, DTV is a critical dimension of how racial and ethnic minorities and low-income populations will continue to face higher health risks in the era of climate change.

Although our goal is to offer a nationally-representative descriptive overview, our deeper analysis of Providence, Rhode Island suggests that the local variation in exposure to DTV is driven by unequal urban landscapes. During daytime, trees can reduce daytime temperature via transpiration; at night, the tree canopy, paradoxically, prevents heat loss. As a result, trees work to suppress DTV. Similarly, water (i.e. blue space) has higher specific heat capacities, meaning it is more resilient to the changing temperature. Yet, poor urban communities tend to lack access to both adequate green and blue space.

This inequality in the built urban environment can be understood as a legacy of structural racism that undergirds persistent neighborhood segregation and housing inequality. First, houses in prime locations are already occupied by the White population. Due to historical redlining, racial and ethnic minorities tend to live in areas with inferior access to green space and blue space (39–42). Prime suburbs with green space were occupied by White population since the 1950s (i.e. White flight), but racial and ethnic minorities were excluded by law (e.g. G.I. Bill). The persistent racial and ethnic segregation—even with reductions in income disparities—leads to persistent inequalities in access to climatically healthy neighborhoods. Second, and related, home ownership may also play a role. Additional analyses confirm that renters are, in general, exposed to larger DTV (Fig. S8). Non-White populations are more likely to be renters and thus live in multifamily units rather than in single-family homes (43). Multifamily residences tend to concentrate in compact, urban environments lacking trees relative to more ample green space offered by single family neighborhoods.

Even as this study offers a first, foundational overview of DTV in the United States, it comes with limitations. The land surface

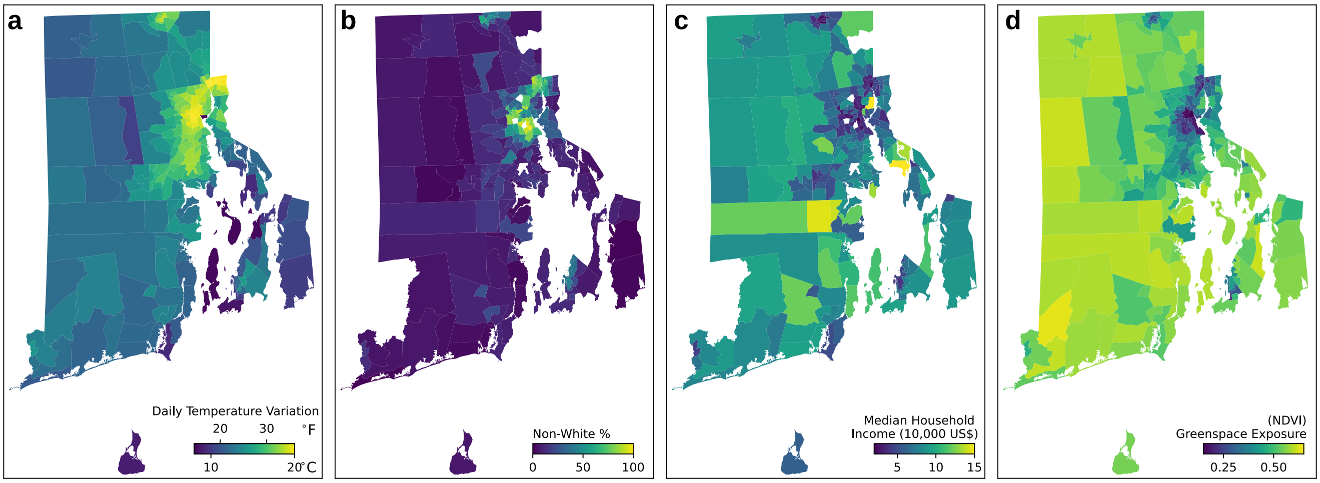

Fig. 4. Daily temperature variation in May a), non-White population percentage b), median household income c), and green space d) at census tracts in Rhode Island.

temperature data were acquired at times not exactly corresponding to daily minimum and maximum temperatures (see Methods section). The DTV calculated is, as such, an estimate. Further, we used land surface temperature to estimate the population exposure here, which, while strongly correlated with air temperature, is not identical and tends to be more extreme. Existing evidence on the temperature-health nexus is mostly based on studies relying on air temperature, even as a growing number of studies are examining temperature-health nexus using land surface temperature (44, 45). But DTV (a relative measure) as the difference between daily maximum and minimum temperatures should be less subject to this limitation. Further, the harmonized land surface temperature products do not have data on water, and due to the 1-km spatial resolution, some small, coastal census tracts lack valid temperature values from the data. Even so, this study represents the most sophisticated approach to estimating DTV with current data constraints. By offering foundational insights into inequality in DTV exposure in the United States, this study will act as a springboard for growing efforts to consider DTV as a fundamental source of climate-induced health disparities.

Estimation of daily temperature variation

Long-term DTV is proxied from the monthly Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) dataset (46). This dataset harmonized the MODIS LST data in 2000–2017 into monthly daytime and night-time products. The spatial resolution of the products is 1 km. Due to the polar-orbiting, sun-synchronous nature of the two MODIS satellites (Terra, Aqua), the data acquisition time is always around 10:30 am and pm local time for Terra and 1:30 am and pm for Aqua (47). For each census tract, temperature exposure is determined by averaging all of the observations (pixels) within its geographical boundary. We did this using ArcGIS separately for daytime and night-time data each month. After calculating the respective mean daytime and night-time temperature, DTV was calculated at the census tract level. Exposure to DTV was then calculated in a population-weighted fashion explained later.

Demographic and socioeconomic data

Demographic data are from the 2017 American Community Survey (ACS) 5-year estimates. A total of 57,796 census tracts in 51 states were analyzed after excluding those without valid temperature or population estimates. All individuals within the same census tract were assigned the same temperature exposure. Race and ethnicity were aggregated into five categories: Hispanic, Black, White, Asian, and Others. Hispanics are those who identified as "Hispanic", regardless of race. White, Black, and Asian are single-race non-Hispanic. "Other" includes American Indian and Alaska Native, Native Hawaiian and other Pacific Islanders, and those who identified as "other race" or two or more races. The non-White population in this article means all other populations except for non-Hispanic White. Five-year age groups were aggregated into five categories: 0–4, 5–19, 20–34, 35–64, and 65 +, corresponding to young children, youth, young adults, middle-age adults, and older adults. Annual household income data (in US$) was collapsed into five categories: 0–14,999, 15,000–34,999, 35,000–99,999, 1,00,000–1,99,999, and over 2,00,000.

Population-weighted exposure

For the ith census tract, suppose its DTV is t_i, and its population of a specific group k is p_i^k, for a collection of N census tracts within a state, the population-weighted exposure E^k for the specific population k can be calculated as

$$E^k = \frac{\sum t_i \times p_i^k}{\sum p_i^k}. \tag{1}$$

In the case of household income, due to data availability, the estimate is based on the number of households (not individual): DTV exposure by income is technically a household-weighted exposure.

Comparing distributions of DTV exposure

We used the two-sample KS test to determine if two distributions of DTV exposure by population group differs significantly in Fig. 2. The KS test determines if two distributions are drawn from the same probability distribution and is commonly used in studies of environmental inequality [details shown in Fig. S6 in the supplementary materials] (48).

Acknowledgments

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Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

Author Contributions

S.L. designed research and performed research. S.L. and E.S.G. analyzed data and wrote the article.

Data Availability

The code for reproducing the figures in this study is available at https://skrisliu.com/dtvus. Data used in this work are publicly available from sources included in the manuscript. The monthly Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) dataset is publicly available (46). Demographic and socioeconomic data from the 2017 American Community Survey (ACS) 5-year estimates are publicly available at https://www.census.gov/programs-surveys/acs/data.html. The world's annual mean of daily temperature variation data used in Fig. 1 is from the WorldClim v2 dataset for 1970–2000 and publicly available on their website (49). The population density data is from the NASA Center for International Earth Science Information Network (CIESIN) at Columbia University. We use the gridded population of the world v4 for 2000–2020 (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

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