GeoHealth

RESEARCH ARTICLE

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**Key Points:**

- Neighborhood-level temperatures within cities can differ by as much as 10°C, but acclimatization to neighborhood-level heat is unclear
- Heat-related deaths could be 10 times larger in hot neighborhoods if inhabitants are acclimatized to city-wide rather than local exposures
- Better understanding of acclimatization is needed to determine the utility of high-resolution temperature data and inform mitigation

**Supporting Information:**

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

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# Premature Deaths Due To Heat Exposure: The Potential Effects of Neighborhood-Level Versus City-Level Acclimatization Within US Cities

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**Abstract** For the population of a given US city, the risk of premature death associated with heat exposure increases as temperatures rise, but risks in hotter cities are generally lower than in cooler cities at equivalent temperatures due to factors such as acclimatization. Those living in especially hot neighborhoods within cities might therefore suffer much more than average if such adaptation is only at the city-wide level, whereas they might not experience greatly increased risk if adjustment is at the neighborhood level. To compare these possibilities, we use high spatial resolution temperature data to evaluated heat-related deaths assuming either adjustment at the city-wide or at the neighborhood scale in 10 large US cities. On average, we find that if inhabitants are adjusted to their local conditions, a neighborhood that was 10°C hotter than a cooler one would experience only about 1.0–1.5 excess heat deaths per year per 100,000 persons. By contrast, if inhabitants are acclimatized to city-wide temperatures, the hotter neighborhood would experience about 15 excess deaths per year per 100,000 persons. Using idealized analyses, we demonstrate that current city-wide epidemiological data do not differentiate between these differing adjustments. Given the very large effects of assumptions about neighborhood-level acclimatization found here, as well as the fact that current literature is conflicting on the spatial scale of acclimatization, more neighborhood-level epidemiological data are urgently needed to determine the health impacts of variations in heat exposure within urban areas, better constrain projected changes, and inform mitigation efforts.

**Plain Language Summary** Heat islands within urban areas cause some neighborhoods to be much hotter than others. However, epidemiological studies show that risk of premature death is generally lower in hot cities than in cooler cities based on city-wide average temperatures. Therefore it is not obvious if those living in hotter than average neighborhoods experience much greater risk of premature heat-related death than those in cooler areas, or if they will have adjusted to those conditions via physiological or behavior adaptation the way those in hotter cities have relative to those in cooler cities. We show that if inhabitants are adapted to their neighborhood's conditions, a heat island 10°C hotter than a cooler are would experience only about 1.0–1.5 excess heat deaths per year per 100,000 persons. If inhabitants are acclimatized to city-wide temperatures rather than neighborhood temperatures, the hotter neighborhood would experience about 15 excess deaths per year per 100,000 persons, with a markedly different distribution of deaths across urban areas relative to the assumption of adaptation to neighborhood-level temperatures. These results show the need for better understanding of the spatial scale of acclimatization to heat to determine the areas most affected by projected heat increases and inform mitigation efforts.

## 1. Introduction

The existence of large variations in surface air temperatures within cities is well documented (e.g., Hsu et al., 2021; Huang & Cadenasso, 2016). Increased heat exposure in specific neighborhoods within urban areas is correlated with a lack of vegetation, larger fractions of areas covered in impermeable surfaces, lower socio-economic status and larger proportion of populations from minority racial groups (e.g., Benz & Burney, 2021; Hsu et al., 2021; Huang & Cadenasso, 2016; Manware et al., 2022; Parsons et al., 2023). Exposure to heat extremes is associated with elevated risk of premature death (Ebi et al., 2021), and therefore the health impact of increased exposures in neighborhoods with strong urban heat islands is widely assumed to be damaging (Stevens et al., 2021) or

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modeled as damaging by applying the same superlinear exposure-response function to all populations in a region (Heaviside et al., 2016).

However, epidemiological research on health outcomes is limited at the neighborhood scale. A few studies have suggested increased death rates within urban heat islands for specific cities, most often for short duration heat waves (Johnson & Wilson, 2009; Laaidi et al., 2012) though sometimes for longer periods (Madrigano et al., 2015). However, others have found relationships that are quite weak in total (e.g., one excess death per million population (Lowe, 2016)) or found no substantive relationship between urbanization levels (across urban and rural areas) and heat-related death rates (Hattis et al., 2012). A study focused on local level adjustment found virtually no enhancement of premature heat-related death rates in urban heat island areas over many years in London, suggesting that populations had almost completely acclimatized to neighborhood-level conditions (Milojevic et al., 2016). Hence the relationship between increased exposures, which are clearly present, and large increases in premature death rates has not been robustly characterized. Investigating this relationship is important because although it may seem obvious that exposure to higher levels of heat would inherently lead to more damaging health impacts, evidence from across the US shows that the health impacts of exposure to an equivalent temperature are much smaller in cities with hotter summer climates than in cooler cities (Curriero et al., 2002; Weinberger et al., 2017, 2020). Additional studies report acclimatization at city to regional scales around the world (Burkart et al., 2021; Carleton et al., 2022). This regional relationship suggests that those living in hotter parts of the country or world tend to be acclimatized to warmer climates and are much less sensitive to temperature extremes of a specific level than those acclimatized to cooler climates.

More specifically, empirical evidence shows that premature heat-related deaths at the city scale generally follow the level of heat exposure above the 84th percentile of daily temperature averages for most mid-latitude cities (Honda et al., 2014; Vicedo-Cabrera et al., 2021). The 84th percentile corresponds to the minimum mortality risk in many mid-latitude locations and is therefore called the optimum temperature (OT), with many exposure-response functions from epidemiological studies describing the increase in relative risk compared with the value at the OT for temperatures above the OT. The varying OT across cities leads to similarly high temperatures having far more impact in a place with a low OT value than a high OT value. For example, a temperature of 32°C increases risk of premature mortality due to heat exposure relative to the minimum level by 50%–70% in New York and Chicago, with OTs in the range of 22–25°C, but only 5%–15% in Atlanta, Dallas, and Houston, with OTs in the range of 27–30°C (Weinberger et al., 2017). It is an open question as to whether the acclimatization that is clearly present at the city level is also present at the neighborhood level. If acclimatization were present at the neighborhood level, then the existence of urban areas within cities that are especially hot would be much less damaging to residents than if it were not. Specifically, if populations are adjusted to city-wide OT, then hot neighborhoods would be much more strongly affected by heat exposures than cooler ones, whereas if people are sensitive to daily temperature differences relative to their neighborhood-level OT then impacts would be more similar for everyone across neighborhoods within a city. Understanding this relationship has important implications for mitigating heat-related health impacts, which are projected to increase greatly as the world warms, all else being equal, using city-wide exposure response functions (Vicedo-Cabrera et al., 2021; World Health Organization, 2014).

The existence of reduced sensitivity to temperatures of a particular value in warmer cities has been hypothesized to result from a combination of physiological adjustment to climate conditions and structural or personal habit differences across cities. For example, residents of warmer cities may know to drink more fluids on hot days, or there could be a greater penetration of air conditioning along with the establishment of "cooling centers" for those without air conditioning in warmer locations (Barreca et al., 2016; Ebi et al., 2021). It is unclear how these inter-city differences would relate to intra-city differences. Residents' bodies and behavior might adjust to their neighborhood "micro-climates." On the other hand, the presence of air conditioning (along with the resources to pay to use it) may not be correlated with increasing temperatures within a city the way it is between cities given the strong relationship between high heat exposure and lower incomes within cities (Benz & Burney, 2021; Hsu et al., 2021).

We therefore set out to test the impact of assuming that the neighborhood-level response to heat exposure is sensitive to the departure from the city-level versus the neighborhood-level OT. We explore the impact these differing heat responses would have on the distribution of deaths within a city, recognizing that the total increase in deaths for a given level of city-wide heat exposure is constrained by the epidemiological data. Our study does not intend to determine what level of acclimatization takes place, but rather to see how the current limited understanding

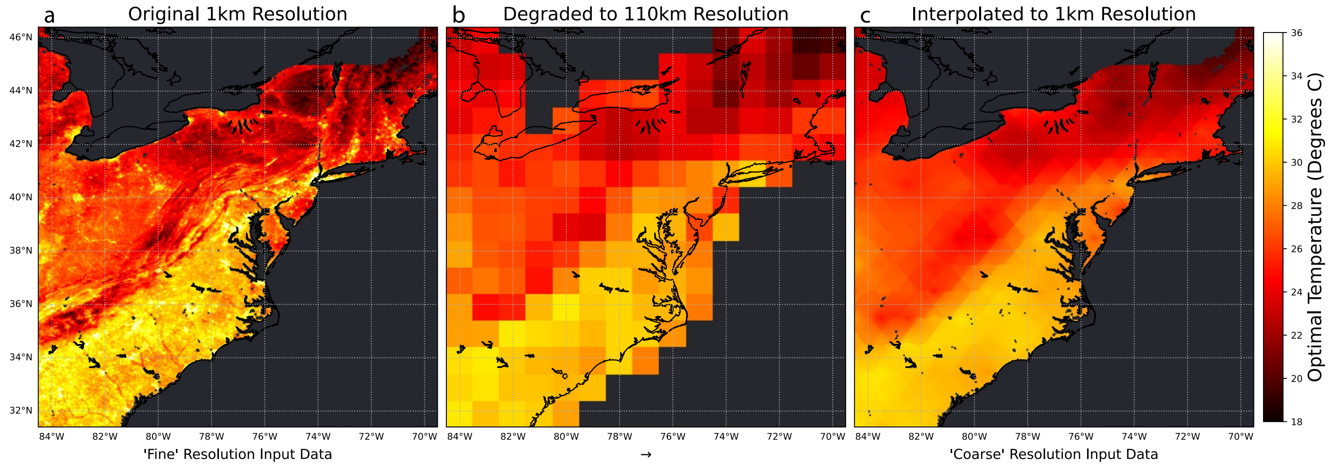


**Figure 1.** Example of the optimal temperature (OT) data's dependence on spatial resolution. The panels show OT at the original 1 × 1 km resolution (a), degraded to 110 × 110 km resolution (b), and the degraded data interpolated using distance weighted averaging back to 1 × 1 km resolution (c) over the northeastern US.

of this topic affects conclusions about the distribution of current and projected heat-related premature deaths. Ideally, revealing large effects of our limited knowledge regarding local acclimatization would motivate increased provision of high-resolution public health data to researchers. This study also attempts to help ascertain the value of applying high-resolution temperature data to health impact evaluations.

## 2. Methods and Data

We input local OT and daily surface air temperature data (year 2019) based on approximately 1 × 1 km horizontal resolution observations from the MODIS instrument (Zhang et al., 2022a). Those observations are adjusted from skin (ground surface) temperature to 2-m air temperature using the local differences between 2-m air temperature and skin temperature from fifth generation reanalysis (ERA) data (Hersbach et al., 2022) which is downscaled from its original 0.25° resolution to match the ∼1 × 1 km data using bilinear interpolation. These values are used to evaluate the impact of heat exposure on premature mortality based on empirical data for 10 US cities (Weinberger et al., 2017) as well as calculations using a generalized function developed previously based on those same empirical data (Shindell et al., 2020). The generalized risk function includes a dependence upon local summer mean temperature (SMT) as well as OT to capture the geographic differences across cities in the empirical data. Similar calculations are performed using 2018 data to test sensitivity. As the high-resolution temperature data are computationally intensive to analyze, the calculations evaluate the impacts of temperatures relative to that single year's OT. The empirical data are based on the OT averaged over 1985–2006; this time average is likely a better indicator of OT as structural and at least some physiological adjustments likely take time. Hence our results should be regarded as indicative values for the given calendar years rather than exact values, consistent with this study's goal of evaluating the sensitivity of results to various assumptions rather than establishing impact values for particular years.

All calculations use 1 × 1 km population data (CIESIN/FAO/CIAT, 2017) and are performed at the population grid's resolution (requiring a slight remapping of the MODIS data). We evaluate changes in all-cause premature deaths relative to daily baseline rates for the US (Global Burden of Disease Collaborative Network, 2021). To evaluate the impact of the OT being city or neighborhood level, we either input daily temperatures and OT both at 1 × 1 km resolution in the "fine" resolution case or we degrade OT (and SMT in the generalized case) to 110 × 110 km and then interpolate using distance weighted average interpolation to get the 1 × 1 km input for OT in the "coarse" case. This allows all calculations to be performed on an identical grid, but in the coarse resolution case, even though the data are at 1 × 1 km resolution, each neighborhood within a city essentially has the city-wide OT (Figure 1 and Figure S1 in Supporting Information S1). Similarly, to test the role of the high spatial resolution daily temperature data itself we also create a "coarse" version of the MODIS-based data set using the same spatial degradation process followed by distance weighted average interpolation. The epidemiological studies constrain the total city-wide deaths attributable to heat, and the calculations using coarse data for

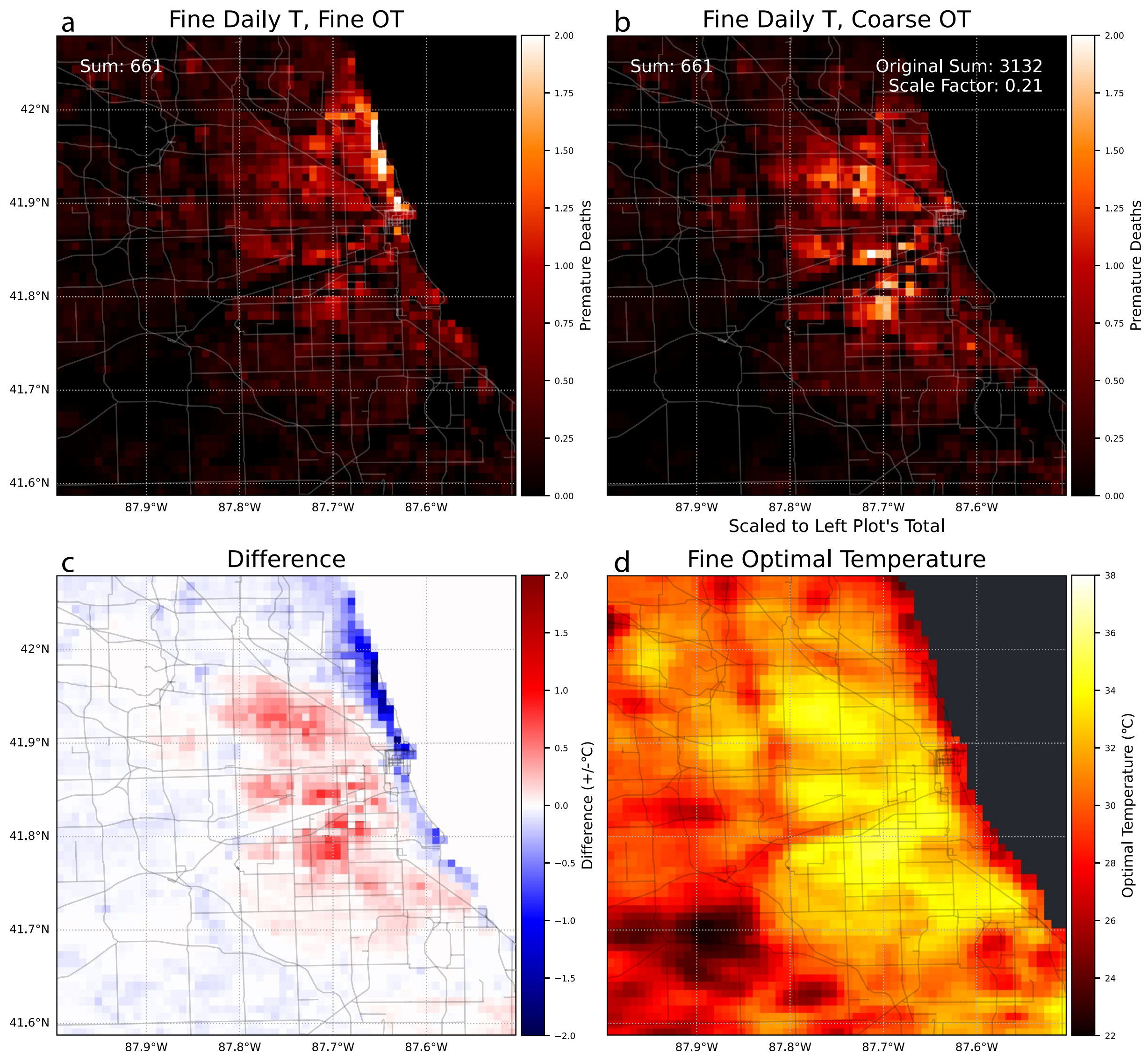


**Figure 2.** Premature deaths in Chicago attributable to heat exposure along with the local temperatures. Values are for 2019 and cover the 0.5 × 0.5° area around the city center and use the 1 × 1 km neighborhood-level OT in the fine case (a) and the city-wide OT interpolated from 110 × 110 km in the coarse case (b) with the difference between those (c) alongside the local optimum temperature (d). Values are calculated using the city-specific epidemiological function of Weinberger et al. (2017).

both daily temperatures and OT or fine data for both agree well with those empirical values (Shindell et al., 2020) (see also discussion below on Table S2 in Supporting Information S1), also indicating that the city-wide average is a reasonably good proxy for the station data used in the epidemiological study. Therefore, when using the coarse city-wide OT and fine daily temperatures, the otherwise much larger deaths for a given city and year are uniformly scaled down to match those from the fine case.

## 3. Results

### 3.1. Sensitivity of Heat-Related Death Rates to Spatial Scale of Acclimatization

We find that the distribution of premature heat-related deaths is highly sensitive to the use of city-wide or neighborhood-level OT. Using Chicago as an example, we find that premature deaths associated with heat exposure using neighborhood level OT are primarily located in areas along Lake Michigan with highest population density. By contrast, using city-wide OT, deaths are concentrated in hotter locations away from Lake Michigan (Figure 2). The use of city-wide OT represents the assumption that residents across the city are adapted to similar

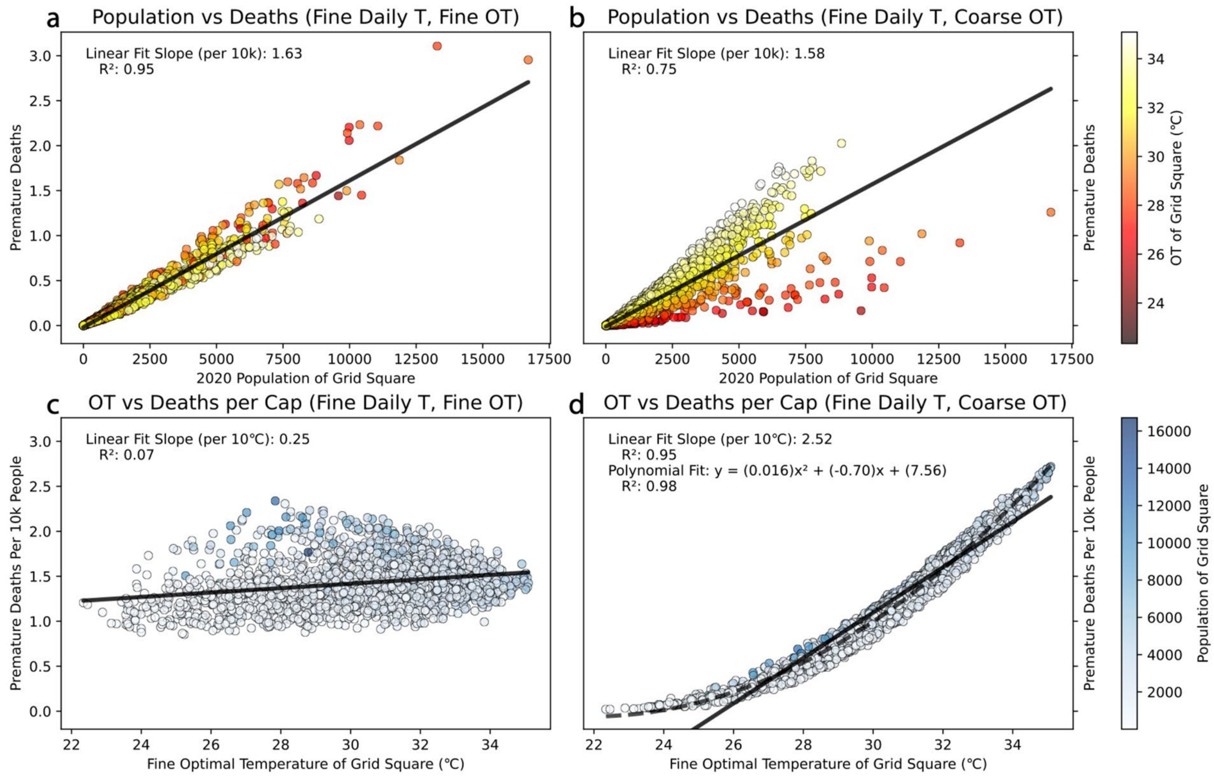


**Figure 3.** Relationship of 2019 premature heat-related mortalities to local optimum temperature and population for Chicago. Panels show deaths versus population (a and b) and deaths per 10,000 persons versus optimal temperature (OT; c and d) for each $1 \times 1$ km area using neighborhood-level OT in the fine case (a,c) and the city-wide OT interpolated from $110 \times 110$ km in the coarse case (b and d). Values are calculated using the city-specific epidemiological function of Weinberger et al. (2017).

temperatures, leading to greater impacts in hot neighborhoods. The relationship between the assumed scale of adjustment and impacts can be seen clearly by comparing premature heat-related deaths with local temperature and population (Figure 3). In the fine case using neighborhood-level (fine) OT, deaths track population very closely ($R^2 = 0.96$ regressing population against deaths at each grid cell; Figure 3a). There is a weak correlation between higher temperatures and total deaths as well ($R^2 = 0.11$), but this weak relationship appears to primarily reflect generally higher populations in hotter neighborhoods as per-capita deaths show minimal relationship with local temperatures ($R^2 = 0.07$; Figure 3c). In contrast, in the case using city-level acclimatization (city-wide OT) the correlation with population, while still strong, is greatly decreased and there is an extremely strong relationship between per-capita deaths and temperature and an order of magnitude increase in sensitivity relative to using local OT as well as an increase in the correlation to $R^2 = 0.95$ (Figure 3d). Optimum temperatures across Chicago range from about 23 to 35°C (Figure 3), and the deaths/temperature slope is 2.5 deaths per 10,000 persons per 10°C warming. This slope indicates that the hottest neighborhoods are likely to experience approximately 3 extra deaths per 10,000 persons relative to the coolest neighborhoods when assuming city-wide OT, a rate 10 times larger than the value of about 0.3 excess deaths per 10,000 persons using the assumption of adaptation to neighborhood-level OT.

Geographically, using city-wide OT the increased deaths are shifted to the hottest neighborhoods (>32°C OT; >17°C annual average) whereas death rates in the cooler (<28°C OT; <15°C annual average) neighborhoods decrease (Figure 3; Figure S2 in Supporting Information S1). Though there is clearly increased sensitivity at higher OT values, a linear relationship nonetheless provides a fairly good representation of the increased death rate as OT increases and allows easy comparison of sensitivities across the methods (Figure 3d, where a quadratic fit is provided as well). Hence using the adjustment to neighborhood-level temperatures, nearly all neighborhoods have similar death rates between 1 and 2 premature deaths per 10,000 persons per 10°C warming. In contrast, assuming acclimatization to city-wide temperatures, death rates in cooler neighborhoods drop to near zero whereas they increase up to about 2.7 in the hottest locations (Figure 3), accounting for the shifts seen in the spatial patterns

**Table 1**
*Premature Deaths per Million Persons for 2019 Conditions in the 15th Percentile Hottest and Coldest 1 × 1 km Areas*

15th percentile high and low OT areas versus estimated 2019 per capita premature deaths due to heat exposure (city-specific functions)

| City (0.5° × 0.5°) | Premature deaths per 1 million people in the coldest 15th percentile grid boxes | | Premature deaths per 1 million people in the hottest 15th percentile grid boxes | |
|---|---|---|---|---|
| | All fine inputs | Fine daily T, coarse OT (scaled) | All fine inputs | Fine daily T, coarse OT (scaled) |
| Chicago | 157 | 35 | 143 | 221 |
| Los Angeles | 77 | 1.0 | 78 | 172 |
| Houston | 74 | 9.4 | 82 | 109 |
| New York | 63 | 14 | 70 | 137 |
| Atlanta | 58 | 10 | 68 | 135 |
| Miami | 41 | 9.7 | 45 | 63 |
| Dallas | 15 | 1.3 | 19 | 28 |
| Philadelphia | 31 | 5.2 | 39 | 55 |
| DC | 64 | 8.1 | 79 | 120 |
| Boston | 60 | 9.5 | 80 | 107 |
| Average | 64 | 10 | 70 | 115 |

(Figure 2). Across all 10 cities, the assumption of acclimatization to neighborhood (fine OT) or city-wide (coarse OT) temperatures shifts heat-related death distributions in a similar way. Examining totals (rather than per 10°C warming), 2019 values are similar in the hottest neighborhoods (70 per million population) to those in the coolest areas (64 per million) using neighborhood-level acclimatization, but these death estimates shift to 115 and 10 for the hottest and coldest areas, respectively, using city-wide acclimatization (Table 1). Therefore assuming that adjustment is at the city-wide level leads to more than an order of magnitude larger impacts in urban heat island areas.

As annual average temperature data are likely much more readily available than OT values, we also examine the relationship between per-capita premature deaths rates and local annual average temperatures. We find that results are similar using annual averages rather than OT values to characterize neighborhoods (Figure S2 in Supporting Information S1). Using annual average temperatures, death rates for Chicago increase 0.29 per 10°C per 10,000 persons using all fine inputs, almost identical to the value of 0.25 per 10°C using local OT, and rates increase 3.6 per 10°C per 10,000 persons using coarse OT as an input, compared to 2.5 per 10°C using local OT to order neighborhoods. Note that if we use coarse daily temperature data as well as coarse OT, death distributions become virtually identical to the fine case (Figure S3 in Supporting Information S1) and deaths per unit area become almost completely dependent upon population ($R^2 = 1.00$) with per-capita deaths showing no relationship with OT (slope = 0.0 deaths per 10°C per 10,000 persons; $R^2 = 0.12$). In that case, virtually all persons experience the same temperature and are adjusted to the same OT.

Using fine data for all inputs gives values that are typically 20%–80% larger than using coarse data for all inputs (Table S1 in Supporting Information S1). These values are often within the uncertainty range of the exposure-response functions and therefore difficult to evaluate against published epidemiology studies. Results for 2019 are similar to those interpolated between 1997 and 2050 values from prior work (Weinberger et al., 2017), with no obvious better match using fine versus coarse inputs (Table S2 in Supporting Information S1). In contrast, using fine daily temperatures but city-wide OT gives much larger values and hence, as noted previously, those results have been normalized to match the fine case (e.g., Figure 2).

The patterns of shifting spatial distributions and increased sensitivity to temperature are similar examining other cities (e.g., Figure 4; Figures S4 and S5 in Supporting Information S1). Specifically, averaged over all 10 cities, the slope and correlations between premature deaths per 10,000 persons and OT using fine inputs are 0.13 deaths per 10°C and $R^2 = 0.12$, with similarly weak relationships using all coarse inputs, whereas using fine daily temperatures but city-level OT these values shift to 1.44 deaths per 10,000 persons per 10°C and $R^2 = 0.89$ (Table 2). Therefore the sensitivity to temperature is roughly an order of magnitude greater in the city-wide OT case. This behavior is similar when regressing death rates against annual average temperatures rather that OT (Table S3 in Supporting Information S1), as was shown above for Chicago. Variations in annual average temperatures across neighborhoods

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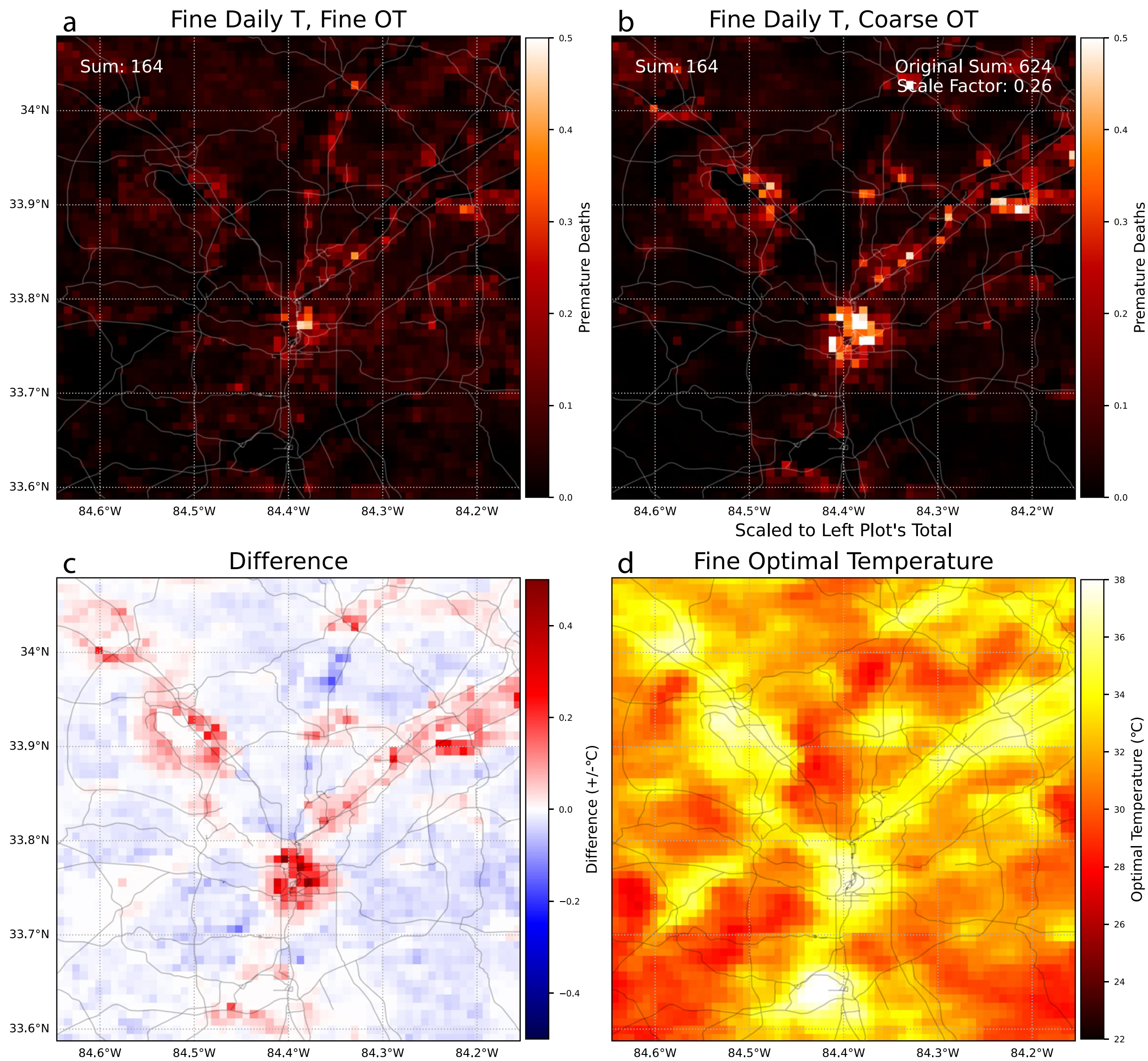


**Figure 4.** Premature deaths attributable to heat exposure in 2019 as in Figure 2 but for Atlanta.

are slightly weaker than variations in OT (e.g., for Chicago about 7°C for annual average compared with about 12°C for OT), so that the slightly larger slope per 10°C corresponds to similar sensitivity. The fact that results seem largely insensitive to the use of local OT or local annual average temperature may substantially ease data requirements because annual average neighborhood temperature data are likely to be much more readily accessible to most people than the 84th percentile (OT). Additional analyses indicate that results at the large scale (most individual cities and certainly the 10-city average) are not greatly sensitive to the year selected for the input temperature data (Table S1 in Supporting Information S1). We also note that results are quite similar when using the nationwide generalized equation developed in our prior work (Shindell et al., 2020), as shown in the Supplemental Information (Tables S4–S6 in Supporting Information S1). Using our generalization that includes a dependence of the risk function on the summer mean temperature (capturing the observed increase in risk in cooler climates) hotter neighborhoods would actually see slightly less risk on average than cooler ones, counterintuitively (Table S5 in Supporting Information S1).

### 3.2. Idealized Comparison of Exposure-Response Function

We also performed idealized calculations to test whether the empirical data for the total city-wide risk increase relative to temperature above the city-wide OT is able to distinguish between uniform sensitivity across the city and increased sensitivity in hotter neighborhoods. In other words, we see how use of local temperature data affects the

**Table 2**
*Regression Between 1 × 1 km Premature Death Rates and Population or Temperature (OT) for the Indicated Input Data Cases*

| Population/Temperature versus estimated 2019 premature heat-related deaths (city-specific functions) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Population versus 2019 calculated deaths | | | | | | Optimal temperature versus 2019 calculated deaths per 10k People | | | | | |
| | All fine inputs | | All coarse inputs | | Fine daily T, coarse OT | | All fine inputs | | All coarse inputs | | Fine daily T, coarse OT | |
| City (0.5° × 0.5°) | Slope (per 10k people) | $R^2$ | Slope (per 10k people) | $R^2$ | Slope (per 10k people) | $R^2$ | Slope (per 10°C) | $R^2$ | Slope (per 10°C) | $R^2$ | Slope (per 10°C) | $R^2$ |
| Chicago | 1.63 | 0.96 | 1.49 | 1.00 | 1.58 | 0.75 | 0.25 | 0.07 | −0.05 | 0.12 | 2.53 | 0.95 |
| Los Angeles | 0.67 | 0.85 | 0.68 | 0.99 | 0.70 | 0.38 | −0.14 | 0.03 | 0.01 | 0.00 | 2.50 | 0.72 |
| Houston | 0.81 | 0.95 | 0.74 | 1.00 | 0.95 | 0.86 | 0.11 | 0.03 | −0.07 | 0.24 | 1.36 | 0.86 |
| New York | 0.76 | 0.96 | 0.68 | 1.00 | 0.67 | 0.78 | 0.14 | 0.07 | −0.05 | 0.06 | 1.42 | 0.88 |
| Atlanta | 0.69 | 0.93 | 0.65 | 1.00 | 1.00 | 0.68 | 0.17 | 0.08 | −0.01 | 0.02 | 2.10 | 0.92 |
| Miami | 0.48 | 0.97 | 0.46 | 1.00 | 0.49 | 0.80 | 0.05 | 0.06 | −0.01 | 0.01 | 0.70 | 0.96 |
| Dallas | 0.19 | 0.92 | 0.18 | 1.00 | 0.22 | 0.82 | 0.08 | 0.15 | 0.01 | 0.04 | 0.39 | 0.84 |
| Philadelphia | 0.39 | 0.98 | 0.35 | 1.00 | 0.54 | 0.87 | 0.12 | 0.31 | 0.00 | 0.02 | 0.67 | 0.92 |
| DC | 0.80 | 0.96 | 0.76 | 1.00 | 0.99 | 0.84 | 0.26 | 0.16 | −0.01 | 0.06 | 1.62 | 0.94 |
| Boston | 0.81 | 0.96 | 0.74 | 1.00 | 1.05 | 0.90 | 0.29 | 0.29 | 0.00 | 0.00 | 1.15 | 0.92 |
| Average | 0.72 | 0.94 | 0.67 | 1.00 | 0.82 | 0.77 | 0.13 | 0.12 | −0.02 | 0.06 | 1.44 | 0.89 |

*Note.* Values are calculated over all areas within the 0.5 × 0.5° box around the city center.

shape of the relative risk curve. In our prior study (Shindell et al., 2020) we fit a second-order polynomial to each of the 10 cities' empirical response curves. This fit matches the empirical data well (Figure 5) and we therefore use it to allow us to evaluate risk at the hotter levels encountered in the local data relative to those in the empirical city-wide data based on an airport monitor. For Chicago, the OT was 25°C (1985–2006) in the empirical study and the maximum was 33°C for city-wide temperatures. In our first idealized test, we represent neighborhood-to-neighborhood variability by adding variations around the city-wide mean that are distributed symmetrically. We compute the average relative risk at a given temperature by averaging over 81 cases in which the local temperature is perturbed by −4, −3.9, −3.8, …, 3.9, 4.0°C. That is, the risk at 30°C is averaged over all neighborhoods with the first using the risk at 26°C, the second using risk at 26.1°C, and so on, through to the last evaluating risk at 34°C. This is equivalent to a Monte-Carlo estimate with an even distribution across the given temperature range. The result is then scaled to provide a RR of 1 at the OT. This test produces a curve that is indistinguishable from the original (Figure 5).

In a second idealized test, we evaluate the case for which the city-wide OT, determined at an airport, is less than the average in the more urban areas. To represent this case, we impose a similar set of temperature perturbations but this time ranging from −2 to +6°C rather than −4 to +4°C. This asymmetric case produces a curve different in magnitude with higher risk for any given temperature above the OT (Figure 5). However, as the empirical data constrains the total number of deaths, the more important factor is the shape of the risk curve, which is in fact quite similar to the original. This comparison implies that using a scaled version of the same second-order fit could still match the empirical results based on city-wide OT very well. For example, if we scale the risk enhancement (RR-1) from this asymmetric case by 0.4 and then plot the total RR we see a fairly similar shape of the risk curve, one that fits within the uncertainty in the empirical analysis (Weinberger et al., 2017) (Figure 5). These idealized analyses therefore imply that the empirical city-wide data is unable to distinguish between uniform sensitivity across the city and increased sensitivity in hotter neighborhoods. Given the lack of consistency in the aforementioned studies that have looked directly at the distribution of heat-related premature deaths, it appears that current epidemiological results provide very limited information on the spatial scale of acclimatization.

## 4. Conclusions

Residents of cities are in general adapted to their regional climates, and here we test the impacts of city versus neighborhood level acclimatization on estimates of heat-related mortality. Our analysis shows that assuming

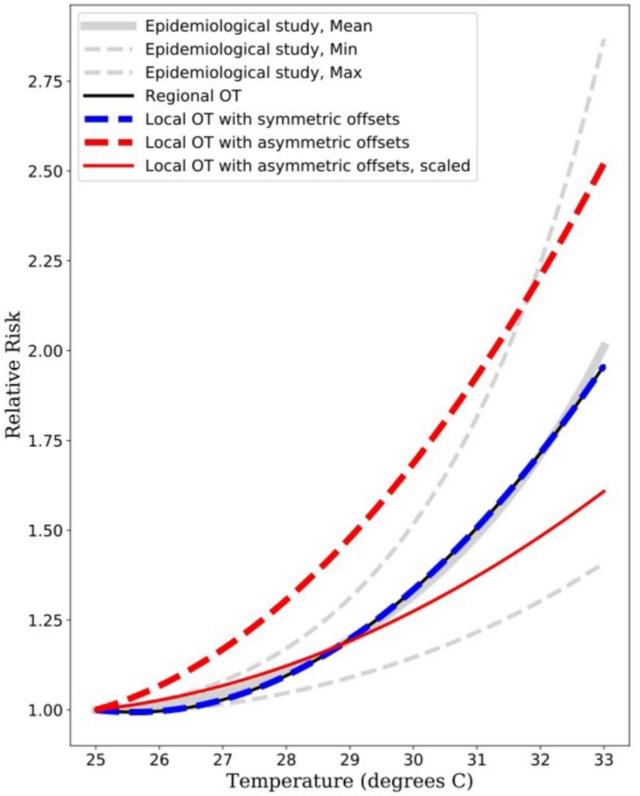


**Figure 5.** Idealized tests of the effect of acclimatization at alternate spatial scales against empirical data. The plot shows the shape of the risk function using the curve fit to the empirical data and regional OT (thin black line) and with the application of variation of local T around regional OT (symmetric and asymmetric in dashed blue and red lines, respectively) in comparison with the original ERF (thick solid gray line shows mean, dashed gray lines show ERF uncertainty range; data from (Weinberger et al., 2017)). Also shown is the asymmetric response scaled uniformly down by 0.4 ($RR = ((RR - 1) \times 0.4) + 1$) (thin solid red line).

local populations are adapted to their neighborhood's heat levels leads to fairly uniform per-capita deaths across cities with only modestly greater impacts in urban heat islands. In contrast, assuming populations are acclimatized to larger-scale (city-wide) temperatures leads to far greater per capita death rates in hot neighborhoods relative to cooler neighborhoods within the same city. Based on our idealized analyses, it appears that existing city-wide epidemiological data cannot readily distinguish between these possibilities. Studies of neighborhood-level impacts in individual locales are also inconsistent. While some of those studies suggest that local hot spots within cities lead to increased death rates, the larger-scale applicability of these studies are limited in that they typically cover single heat wave events in single cities. For example, a study in Philadelphia found evidence for greater heat-related mortalities in the hottest neighborhoods during a heatwave (Johnson & Wilson, 2009), but interpreting this single city's results is difficult as there can be greater deaths in hot neighborhoods in a single city even when assuming neighborhood-level acclimatization. For instance, our results show Philadelphia would experience ~25% higher mortality in the hottest neighborhoods even assuming neighborhood-level adjustment (fine OT) (Table 1). On average cities show minimal differences under this assumption, but 9 of 10 cities show at least moderately larger impacts in hotter areas even when using fine OT. Other studies of neighborhood-level impacts show little difference in sensitivity between hotter and cooler neighborhoods, but are also limited in their coverage, including a single metropolitan area (Milojevic et al., 2016) or one region of the Northeast US (Hattis et al., 2012). Therefore we conclude that it is important to determine not only that there are increased heat-related impacts in hotter neighborhoods with epidemiological studies, but to compare those with simulations such as those shown in this study to evaluate acclimatization at the neighborhood level.

Existing projections of the large-scale impacts of increasing future heat exposure as the climate continues to warm generally omit urban heat islands entirely (Carleton et al., 2022; Ebi et al., 2018; World Health Organization, 2014). This omission may yield realistic results if acclimatization is at the neighborhood level, at least for relatively modest warming levels. In fact, if acclimatization takes place largely at the neighborhood level, use of high-resolution temperature data is not needed to derive accurate heat-impact results. However, as our results show, if acclimatization takes place at only the city-wide level, as opposed to the neighborhood level, high-resolution data is very important as impacts in hotter neighborhoods can be an order of magnitude larger than those in cooler areas. Indeed, some studies for single cities have related impacts directly to neighborhood-level temperatures, implicitly assuming there is no local adjustment (Rohat et al., 2019; Varquez et al., 2020), the other end of the spectrum from the studies neglecting heat islands. As studies have clearly shown that historically disadvantaged areas are up to 7°C warmer than other neighborhoods within US cities (Hoffman et al., 2020), these differences may have substantial environmental justice implications. Hotter areas could also experience greater impacts from heat if acclimatization to neighborhood-level conditions was partial rather than complete, as might be expected under rapid warming. Although it is clear that people living in hotter neighborhoods generally have fewer resources to cope with heat stress owing to socioeconomic factors (e.g., Benz & Burney, 2021; Lim & Skidmore, 2020; Parsons et al., 2023; Wang et al., 2018), not knowing the extent to which they may also be more vulnerable directly because of their increased heat exposure limits our ability to most efficiently mitigate heat impacts.

Our analysis does not account for local variations in baseline mortality rates due to lack of daily baseline mortality data at $1 \times 1$ km resolution. Higher baseline mortality rates in hotter, poorer neighborhoods would likely further exacerbate differences between heat-related deaths in those areas relative to city-wide averages, regardless of acclimatization (Ebi et al., 2021). Additionally, elevated levels of air pollution are often co-located with urban heat islands (Heaviside et al., 2016). Ideally, risk functions should be developed that account for this compound risk.

Improved understanding of the interaction between health and urban heat islands is especially important as urban areas are projected to experience greater warming relative to their regional warming levels under business-as-usual trajectories (Zhao et al., 2021). There is therefore a need for additional high-resolution health impact analyses evaluating how much residents of hot neighborhoods have adjusted to those conditions compared with how much they are more severely affected than residents of cooler areas. Without such data, it is difficult to efficiently plan interventions to mitigate the effects of projected increases in heat exposure. While it may seem obvious to focus efforts on the hottest neighborhoods, and certainly that is required in places approaching physiological limits to the body's ability to cool itself (Sherwood & Huber, 2010), this is actually not clear at the city level based on the epidemiological studies discussed in the Introduction. At the national level, focusing climate intervention efforts on the hottest locations might even erroneously imply that we do not need to worry about the generally cooler northern cities when in fact heat waves have been far more damaging in northern than southern cities in both the US and Europe (Ebi et al., 2021). In the US, agencies such as the National Institute of Health, the Centers for Disease Control and Prevention, and state or local governments should support access to geolocated health data needed to support local analyses, with appropriate privacy safeguards, to facilitate improved understanding of the role of neighborhood-level acclimatization. The stark differences found here between city-wide and neighborhood level acclimatization suggest both that acclimatization levels may be relatively easy to determine and that they are extremely important for understanding how health risks vary across cities.

## Conflict of Interest

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

## Data Availability Statement

All data used in this analysis are publicly available. MODIS skin temperatures is available at Zhang et al. (2022b), 2m and skin temperatures at Hersbach et al. (2022), population data at CIESIN/FAO/CIAT (2017), and vulnerability data at Global Burden of Disease Collaborative Network (2021). This study used software from the Open Source Geospatial Foundation (2023) and Schulzweida (2022).

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## References

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), 105–159. https://doi.org/10.1086/684582

Benz, S. A., & Burney, J. A. (2021). Widespread race and class disparities in surface urban heat extremes across the United States. *Earth's Future*, *9*(7), e2021EF002016. https://doi.org/10.1029/2021ef002016

Burkart, K. G., Brauer, M., Aravkin, A. Y., Godwin, W. W., Hay, S. I., He, J., et al. (2021). Estimating the cause-specific relative risks of non-optimal temperature on daily mortality: A two-part modelling approach applied to the Global Burden of Disease Study. *Lancet*, *398*(10301), 685–697. https://doi.org/10.1016/s0140-6736(21)01700-1

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *Quarterly Journal of Economics*, *137*(4), 2037–2105. https://doi.org/10.1093/qje/qjac020

CIESIN/FAO/CIAT. (2017). Gridded population of the world: Future estimates, 2017 (GPWv4): Population grids [Dataset]. Socioeconomic Data and Applications Center (SEDAC). Retrieved from http://sedac.ciesin.columbia.edu/gpw

Curriero, F. C., Heiner, K. S., Samet, J. M., Zeger, S. L., Strug, L., & Patz, J. A. (2002). Temperature and mortality in 11 cities of the eastern United States. *American Journal of Epidemiology*, *155*(1), 80–87. https://doi.org/10.1093/aje/155.1.80

Ebi, K. L., Capon, A., Berry, P., Broderick, C., de Dear, R., Havenith, G., et al. (2021). Hot weather and heat extremes: Health risks. *Lancet*, *398*(10301), 698–708. https://doi.org/10.1016/s0140-6736(21)01208-3

Ebi, K. L., Hasegawa, T., Hayes, K., Monaghan, A., Paz, S., & Berry, P. (2018). Health risks of warming of 1.5°C, 2°C, and higher, above pre-industrial temperatures. *Environmental Research Letters*, *13*(6), 063007. https://doi.org/10.1088/1748-9326/aac4bd

Global Burden of Disease Collaborative Network. (2021). Global Burden of Disease Study 2019 (GBD 2019) air pollution exposure estimates 1990–2019 [Dataset]. Institute for Health Metrics and Evaluation. Retrieved from https://ghdx.healthdata.org/

Hattis, D., Ogneva-Himmelberger, Y., & Ratick, S. (2012). The spatial variability of heat-related mortality in Massachusetts. *Applied Geography*, *33*(1), 45–52. https://doi.org/10.1016/j.apgeog.2011.07.008

Heaviside, C., Vardoulakis, S., & Cai, X. M. (2016). Attribution of mortality to the urban heat island during heatwaves in the West Midlands, UK. *Environmental Health*, *15*(S1), S27. https://doi.org/10.1186/s12940-016-0100-9

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., et al. (2022). ERA5 hourly data on pressure levels from 1940 to present [Dataset]. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.bd0915c6

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

Honda, Y., Kondo, M., McGregor, G., Kim, H., Guo, Y. L., Hijioka, Y., et al. (2014). Heat-related mortality risk model for climate change impact projection. *Environmental Health and Preventive Medicine*, *19*(1), 56–63. https://doi.org/10.1007/s12199-013-0354-6

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

Huang, G. L., & Cadenasso, M. L. (2016). People, landscape, and urban heat island: Dynamics among neighborhood social conditions, land cover and surface temperatures. *Landscape Ecology*, *31*(10), 2507–2515. https://doi.org/10.1007/s10980-016-0437-z

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

Laaidi, K., Zeghnoun, A., Dousset, B., Bretin, P., Vandentorren, S., Giraudet, E., & Beaudeau, P. (2012). The impact of heat islands on mortality in Paris during the August 2003 heat wave. *Environmental Health Perspectives*, *120*(2), 254–259. https://doi.org/10.1289/ehp.1103532

Lim, J., & Skidmore, M. (2020). Heat vulnerability and heat island mitigation in the United States. *Atmosphere*, *11*(6), 558. https://doi.org/10.3390/atmos11060558

Lowe, S. A. (2016). An energy and mortality impact assessment of the urban heat island in the US. *Environmental Impact Assessment Review*, *56*, 139–144. https://doi.org/10.1016/j.eiar.2015.10.004

Madrigano, J., Ito, K., Johnson, S., Kinney, P. L., & Matte, T. (2015). A case-only study of vulnerability to heat wave-related mortality in New York City (2000–2011). *Environmental Health Perspectives*, *123*(7), 672–678. https://doi.org/10.1289/ehp.1408178

Manware, M., Dubrow, R., Carrión, D., Ma, Y., & Chen, K. (2022). Residential and race/ethnicity disparities in heat vulnerability in the United States. *Geohealth*, *6*(12), e2022GH000695. https://doi.org/10.1029/2022gh000695

Milojevic, A., Armstrong, B. G., Gasparrini, A., Bohnenstengel, S. I., Barratt, B., & Wilkinson, P. (2016). Methods to estimate acclimatization to urban heat island effects on heat- and cold-related mortality. *Environmental Health Perspectives*, *124*(7), 1016–1022. https://doi.org/10.1289/ehp.1510109

Open Source Geospatial Foundation. (2023). Geospatial Data Abstraction software Library (GDAL/OGR): May 10, 2023 release (version 3.6.4) [Software]. Zenodo. https://doi.org/10.5281/zenodo.5884351

Parsons, L. A., Lo, F., Ward, A., Shindell, D., & Raman, S. R. (2023). Higher temperatures in socially vulnerable US communities increasingly limit safe use of electric fans for cooling. *GeoHealth*, *7*(8), e2023GH000809. https://doi.org/10.1029/2023gh000809

Rohat, G., Wilhelmi, O., Flacke, J., Monaghan, A., Gao, J., Dao, H., & van Maarseveen, M. (2019). Characterizing the role of socioeconomic pathways in shaping future urban heat-related challenges. *Science of the Total Environment*, *695*, 133941. https://doi.org/10.1016/j.scitotenv.2019.133941

Schulzweida, U. (2022). Climate Data Operators User Guide, Oct. 4, 2022 (version 2.1.0) [Software]. Zenodo. https://doi.org/10.5281/zenodo.7112925

Sherwood, S. C., & Huber, M. (2010). An adaptability limit to climate change due to heat stress. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(21), 9552–9555. https://doi.org/10.1073/pnas.0913352107

Shindell, D., Zhang, Y., Scott, M., Ru, M., Stark, K., & Ebi, K. L. (2020). The effects of heat exposure on human mortality throughout the United States. *Geohealth*, *4*(4), e2019GH000234. https://doi.org/10.1029/2019gh000234

Stevens, L. E., Maycock, T. K., & Stewart, B. C. (2021). Climate change in the human environment: Indicators and impacts from the fourth national climate assessment. *Journal of the Air & Waste Management Association*, *71*(10), 1210–1233. https://doi.org/10.1080/10962247.2021.1942321

Varquez, A. C. G., Darmanto, N. S., Honda, Y., Ihara, T., & Kanda, M. (2020). Future increase in elderly heat-related mortality of a rapidly growing Asian megacity. *Scientific Reports*, *10*(1), 9304. https://doi.org/10.1038/s41598-020-66288-z

Vicedo-Cabrera, A. M., Scovronick, N., Sera, F., Royé, D., Schneider, R., Tobias, A., et al. (2021). The burden of heat-related mortality attributable to recent human-induced climate change. *Nature Climate Change*, *11*(6), 492–500. https://doi.org/10.1038/s41558-021-01058-x

Wang, Y., Nordio, F., Nairn, J., Zanobetti, A., & Schwartz, J. D. (2018). Accounting for adaptation and intensity in projecting heat wave-related mortality. *Environmental Research*, *161*, 464–471. https://doi.org/10.1016/j.envres.2017.11.049

Weinberger, K. R., Harris, D., Spangler, K. R., Zanobetti, A., & Wellenius, G. A. (2020). Estimating the number of excess deaths attributable to heat in 297 United States counties. *Environmental Epidemiology*, *4*(3), e096. https://doi.org/10.1097/ee9.0000000000000096

Weinberger, K. R., Haykin, L., Eliot, M. N., Schwartz, J. D., Gasparrini, A., & Wellenius, G. A. (2017). Projected temperature-related deaths in ten large US metropolitan areas under different climate change scenarios. *Environment International*, *107*, 196–204. https://doi.org/10.1016/j.envint.2017.07.006

World Health Organization. (2014). *Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s*. World Health Organization.

Zhang, T., Zhou, Y., Zhu, Z., Li, X., & Asrar, G. R. (2022a). A global seamless 1 km resolution daily land surface temperature dataset (2003–2020). *Earth System Science Data*, *14*(2), 651–664. https://doi.org/10.5194/essd-14-651-2022

Zhang, T., Zhou, Y., Zhu, Z., Li, X., & Asrar, G. R. (2022b). A global seamless 1 km resolution daily land surface temperature dataset (2003–2020) [Dataset]. MODIS. Retrieved from https://modis.gsfc.nasa.gov/data/dataprod/mod21.php

Zhao, L., Oleson, K., Bou-Zeid, E., Krayenhoff, E. S., Bray, A., Zhu, Q., et al. (2021). Global multi-model projections of local urban climates. *Nature Climate Change*, *11*(2), 152–157. https://doi.org/10.1038/s41558-020-00958-8