

Re-examining Mortality Impacts of Urban Heat Islands in United States Cities

Chad Milando

cmilando@bu.edu

Boston University <https://orcid.org/0000-0001-6340-7754>

Yirong Yuan

Boston University <https://orcid.org/0009-0001-3299-4922>

Nikolaus Bates-Haus

Boston University <https://orcid.org/0009-0005-3030-1415>

Alexis Arlak

Boston University

Ruth Engel

World Resources Institute

M Patricia Fabian

Boston University School of Public Health

Gregory Wellenius

Boston University <https://orcid.org/0000-0003-0427-7376>

Lucy Hutyra

Boston University

Article

Keywords: Urban heat island, mortality, health, cities, extreme temperature

Posted Date: September 10th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10132845/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: **Yes** there is potential Competing Interest. Dr. Wellenius serves as a consultant for the Health Effects Institute (Boston, MA) and Climate Resilience for All (Washington, DC).

Abstract

Recent research has suggested that in many cities, mitigation of urban heat islands (UHI) would result in net increases in temperature-related mortality, as the additional cold temperature deaths surpass the expected lives saved. Given the profound policy implications of these conclusions, we re-examined the predicted impact of UHI removal on mortality in 49 major United States cities using observed temperature data to estimate the UHI intensity and Bayesian inference to recreate published temperature and mortality models with high precision. Half of the 49 cities showed no change in net mortality following UHI removal. Among the remainder, increases in net mortality were < 1% of total mortality and < 5% of temperature-related mortality, changes several-fold smaller than those previously reported. While temperature-related mortality is a critical metric, it provides an incomplete assessment of urban climate health impacts: there is more to living than not dying. To safeguard vulnerable populations from both hot and cold thermal extremes, comprehensive urban climate policies must move towards approaches that integrate exposure metrics, vulnerabilities, and the feasibility of transformative infrastructure modifications.

Main

Cities are often warmer than surrounding regions because local land surface modification alters the surface energy balance, a phenomenon known as the urban heat island (UHI).^{1,2} Substantial evidence links higher temperatures in cities to an array of adverse health outcomes, including increases in summertime all-cause mortality³⁻⁵ and cardiovascular and respiratory emergency department visits.^{6,7} In response, adaptation to and mitigation of UHI have been a public health focus for cities. Common mitigation strategies include tree planting, which provides cooling through evapotranspiration and shading, and modification of surface albedo through 'white' roofs. By increasing the fraction of reflected shortwave radiation, these surfaces reduce absorbed radiation and the energy available to drive air temperature increases (sensible heat flux).^{8,9} While these modifications are expected to be beneficial to health during warm seasons, questions have been raised about unintended detrimental impacts during cold seasons.¹⁰

Under some definitions of UHI, temperatures in urban areas are similarly elevated compared to reference locations in both the warm and cold seasons.¹¹ Given the "U-shaped" relationship between temperature and mortality (where the relative risk of death increases with both cold and warm temperature extremes),⁵ increased temperature would be associated with higher heat-related mortality in the warm season but lower cold-related mortality in the cool season. By extension, reducing the UHI would decrease urban temperatures throughout the year, plausibly decreasing heat-related mortality but increasing cold-related mortality. Moderately cold days are thought to be the largest contributor to temperature-related mortality in many climates,⁵ suggesting that policy strategies to reduce UHI may paradoxically result in a net *increase* in mortality in some settings because the number of days of moderate cold would increase.¹²⁻¹⁴ Yang and Bou-Zeid posited that the UHI can shelter cities against

extreme cold events, with beneficial implications for health.¹² Wang et al. recently estimated that efforts to reduce the UHI may *increase* temperature-related mortality by up to 40% in some US cities.¹³ Finally, Macintyre et al. estimated that in the West Midlands of the United Kingdom, the winter UHI effect could prevent around 266 cold-related deaths, which is about 15% of the total cold-related mortality during roughly 11 weeks in winter.¹⁴ If confirmed, these findings have the potential to dramatically shape implementation of urban heat mitigation strategies.

However, the conclusions of Yang and Bou-Zeid and others^{12–14} are sensitive to analytic choices which may inflate the impact of the UHI on mortality. First, most definitions of UHI use contemporaneous temperature measurements at urban and reference sites, but differences in the choice of urban/reference boundary can yield reference conditions that are substantially colder than their urban counterparts, thus inflating the UHI effect and estimated health impacts.^{1,2} Second, using gridded air temperature reanalysis products rather than measured data can introduce biases that can be similar to estimated temperature differences in urban microclimates, thus distorting the estimates of UHI. For example, the gridded temperature data product used by Wang et al.¹³ has a mean absolute error of 1.44°C in daily maximum temperature in North America,¹⁵ which is a large enough error to undermine the validity of UHI estimates (other US UHI estimates include a remotely-sensed average daily max effect of 2.9°C from Imhoff et al.¹⁶ and a gridded daily min effect of 0.37 C from Debbage et al.¹⁷). Third, local fine-scale mortality data are optimal for estimation of the fatal impacts of UHI, but in some cases such data are difficult to obtain, so proxy measures are used that can add further uncertainty. For example, Wang et al.¹³ used seminal work by Gasparrini et al.⁵ to estimate temperature-mortality relationships for cities around the world; however, these mortality estimates were extrapolated from a subset of only 4 points within each temperature distribution, rather than the smoothed underlying model form and uncertainties. Given the potential importance of the resulting estimates to urban planning and urban heat mitigation strategies, it is essential to critically re-examine the extant estimates of the net impacts of UHI mitigation on mortality using approaches that address the above uncertainties.

In this study, we modeled the impact of UHI removal on mortality in 49 cities in the United States using methodologies that minimize critical uncertainties for estimating UHI and the temperature-mortality relationship in each city (Fig. 1). We delineated urban regions using the Global Human Settlement Layer (GHSL) database¹⁸ and created a reference area for each city using a 10 km buffer around each city polygon (**Fig. S1**). UHI was assessed using quality-controlled available weather station observations within each buffered area, avoiding the substantial uncertainties in estimated urban temperatures using reanalysis products. (Fig. 2a). We gathered weekly mortality data for each city, which we then downscaled to the daily level (Fig. 2b). These data are used to scale estimated excess deaths. We developed a process for re-creating model coefficients and variance-covariance matrices from published exposure-response curves⁵ with high fidelity (Fig. 2c). This is a key innovation of our work that allows us to accurately recreate the temperature-mortality model without access to the local mortality data. We then estimated the mortality impacts of UHI removal (Fig. 2d), evaluating both warm-season heat and cool-season cold impacts to determine the net annual health effect attributable to UHI (Fig. 2e).

Throughout our analysis, we compare our findings to recent and comprehensive assessment of the UHI impact on mortality in cities globally: Wang et al.¹³ Our analysis provides improved estimates of UHI-modified temperature exposure and a clear accounting of the seasonal offset between increased heat risk and reduced cold risk.

Characterizing UHI Intensity

To estimate UHI intensity, we compared daily mean temperature measurements in strictly defined urban settlement boundaries and the 10km buffer outside each boundary. We queried all urban areas in the United States defined in the Global Human Settlement Layer,¹⁸ and defined reference areas to be the 10 km buffer surrounding the urban area,¹⁹ excluding other urban areas and permanent water. We then assembled weather observation data for 2023 in each urban and reference area from the Meteorological Assimilation Data Ingest System (MADIS) station network.²⁰ We restricted the cities to those in which at least 5 urban and 5 reference stations consistently passed quality control for the entire study period, with many cities having many more than 5 urban and reference stations (**Fig. S1**). The minimum threshold of 5 stations per network were set by observing trends in the stability of the UHI estimate (**Fig. S2**). See additional consideration in **Methods**.

In most regions, the UHI effect was as expected – urban areas were largely warmer than the surrounding reference areas (**Tbl. 1**). Most cities showed median UHI between 0 and 0.5°C, with city-specific medians ranging from – 0.74 to 0.82°C), and the UHI impact was statistically significantly different than zero for 90% of cities (44 of 49) using the Mann-Whitney U-test with $\alpha = 0.05$. The magnitude and sign of the UHI reflects the highly varied urban and surrounding topography, microclimate impacts such as sea-breeze, and varying land cover and uses surrounding cities. The UHI impact was positive (indicating a warming impact) in the Midwest, Northeast, Northwest, Southeast, and Southern Great Plains regions, while in the Southwest region, 7 cities showed that urban areas were cooler than the reference areas. We tested the sensitivity of these findings to expansions of the rural buffer from 10 km to 30 and 50km, with smaller changes in UHI magnitude (**Fig. S3**).

We assessed summer and winter UHI impacts, hypothesizing that while deciduous trees are effective in summer cooling, they do not have a significant impact on winter temperatures (given their loss of leaves in the winter season). Results varied by region; summer and winter UHI were significantly different than zero in 78% of cities (38 of 49) using the Mann-Whitney U-test with $\alpha = 0.05$. In the Northeast, New York and Boston showed no difference between winter and summer UHI intensity, while winter UHI was larger than summer UHI in Baltimore, Philadelphia, Pittsburg, and Washington. In the Midwest, all differences between seasonal UHI intensities were statistically significant, but not all were in the same direction. For example, in Detroit, the summer UHI intensity was nearly twice the winter UHI intensity, while for all other cities in the Midwest the winter UHI intensity was stronger. This again reflects variation in urban topography and geography.

While acknowledging that there are many previous estimates of UHI intensity for US cities,^{16,17} we directly compared our seasonal estimates of UHI intensity for US cities with those in a recent and comprehensive UHI health impacts study, Wang et al.,¹³ see Fig. 3. For most regions, our estimates of UHI intensity were similar to those of Wang et al. and below 1°C. However, our results differed sharply from those of Wang et al. in several cities in the Northwest and Southwest regions. For example, Wang et al. estimates a UHI of 6.5°C for Boulder, CO as compared to our estimate of 0.01°C.

Other estimates of UHI intensity in the US vary considerably, reflecting differences in temperature metrics, urban and reference area definitions, and the temporal scale of analysis.^{12,16,17} Imhoff et al. reported a mean annual surface UHI intensity of about 2.9°C across U.S. biomes, with values averaging 4.3°C in summer and 1.3°C in winter.¹⁷ Using a canopy air-temperature metric, Debbage and Shepherd reported a much smaller mean annual UHI intensity of 0.37°C across the 50 largest U.S. metropolitan areas.¹⁸ Winter-focused studies have generally reported more modest magnitudes. Yang and Bou-Zeid found that nighttime UHI intensity increased by $1.32 \pm 0.78^\circ\text{C}$ during cold waves across 12 U.S. cities.¹³

Mortality impacts associated with UHI

We estimated the baseline temperature-attributable mortality in each of the 49 cities, and the change in mortality expected in a counterfactual scenario without UHI. Gasparrini et al.⁵ presents city-specific temperature-mortality models derived from local daily mortality data in the form of figures that describe the non-linear relationship between daily temperature and the relative risk of mortality. The model coefficients and variance-covariance matrix describing the exposure-response function are required to apply these functions to a different time-series of temperature – for example, the counterfactual time-series of city temperatures without the UHI effect. These model parameters are not published in Gasparrini et al.,⁵ and the underlying daily mortality data are not accessible to recalculate exposure response curves for this analysis. Accordingly, we developed a methodology to reconstruct the model coefficients and variance co-variance matrix in Gasparrini et al.⁵ using image analysis, Bayesian inference, and publicly available weekly mortality records (**Methods**). Briefly, we extracted the relative risk curve estimate and confidence intervals with high fidelity (root mean squared error, [RMSE], on relative risk curves < 0.01 for images with resolutions higher than 300 dpi, **Fig. S4**), and used Bayesian inference to reconstruct a plausible model variance co-variance matrix, allowing similarly high precision in re-estimated values of attributable number (RMSE on daily attributable mortality < 0.10, **Fig. S5**). This approach differs from that of Wang et al. who derived linear relationships of the per 1 °C change in mortality relative risk at specific temperature percentiles (defined the minimum risk, the 5th percentile, the percentile of minimum mortality risk, 95th percentile, and the maximum risk).¹³ These linear relationships were then used to update estimates of daily mortality under temperature scenarios with a different number of days within each temperature percentile bin. This approach does not include estimates of empirical confidence intervals or incorporate non-linearity that occurs within each bin.

We estimate that total (the sum of heat- and cold-attributable mortality) temperature-attributable mortality was between 2.5 and 8% of total mortality, largely driven by cold-related attributable mortality, which is consistent with previous literature.⁵ Chicago had the largest number of cold-related deaths, and Los Angeles had the largest number of heat-related deaths (Fig. 4).

Estimated changes in temperature-attributable mortality associated with the hypothetical removal of UHI were mostly below 5% (Fig. 5a), with 53% (26 of 49) cities showing changes in temperature-related mortality where the confidence intervals include the null (0% change between UHI and no UHI scenarios). Only Tampa and Los Angeles had more than a 10% increase in temperature-related mortality following the removal of the UHI. In 22 of 49 cities, the removal in the UHI was associated with less than 5% increase in net temperature-related mortality. Only two cities showed a slight reduction in temporal-related mortality (< -5%) following UHI removal: Mesa, AZ and Austin, TX. These findings stand in stark contrast to those in a comparable study of UHI effects in US cities, Wang et al.,¹³ who found that many cities in the US have a greater than 20% increase in temperature-related mortality following the removal of the UHI (Fig. 2 therein). The magnitudes that we find are at least 4 times smaller in most cases.

Presenting the modeled change in mortality relative to total deaths rather than temperature-related deaths provides further context to our findings (Fig. 5b). In most (n = 44) cities, elimination of the UHI changed total mortality by -0.25% to 0.25%. In four cities (Washington, Tampa, Atlanta, and San Francisco) elimination of the UHI led to an increase of total mortality between 0.25% and .5%. And one city (Los Angeles) had a median increase in mortality of greater than 0.5% (an increase of 0.7%).

Rationale for harmonizing definitions of UHI

UHI intensity is appealing as a single metric for estimating the potential impact of climate change on human health, but has substantial limitations. Estimation of UHI intensity depends significantly on how urban and reference areas are defined, and there is not an established demarcation of the urban/non-urban boundary. A key consequence of this ambiguity is that reference sites may not appropriately estimate the impact of human activity independent of the built environment, or they may be drawn from areas that are environmentally distinct from the baseline conditions in cities due to varied topography or coastal effects. Accordingly, UHI estimates can be based on estimated reference temperatures that are substantially lower than those measured in urban areas. In our work, we defined urban areas using the Global Human Settlement Layer (GHSL) Urban polygons.¹⁸ The GHSL provides a broadly accepted definition of urban area that takes both land cover and population into account, and recent comparisons of GHSL and other urban boundary definitions showed higher accuracy of GHSL in defining urban areas.²¹ Reference areas were defined as the 10 km buffers around GHSL polygons.¹⁹ We believe this approach more accurately reflects the concept of the UHI because it allows us to estimate the impact of modifying the built environment for temperature mitigation without entirely removing the impacts of human activity in the surrounding areas. In some cities, though, diverse environments and microclimates still create biases in the delineation of urban and reference areas.

However, not all literature follows this near-urban reference convention. Some studies define urban extent using Global Urban Boundary (GUB) polygons, impervious-surface thresholds, U.S. Census urbanized areas, or metropolitan statistical areas.^{10,22} Others select references based on broad buffer zones or product-specific “non-urban” classes; these approaches are often well-suited to large-scale mapping or to the goals of a particular study, but they can also shift what is being measured.^{16,17} Changing which places count as “urban” and which serves as reference can influence both the composition of the comparison groups and the resulting estimate of UHI intensity.²³ For example, in Wang et al.¹³ the urban location is defined by a GUB;²² these urban extents are very large (typically more than double the area of the corresponding GHSL urban area) and as a result contain a larger variety of land cover and elevation. Wang et al. define the reference as the region between 10km and 50km buffers beyond the GUB. However, given the large urban extent defined by the GUB, this reference typically excludes the suburban region, thereby combining the effects of modifying the built environment and modifying human activity.²⁴ This discrepancy is one of the likely drivers of the higher UHI intensities found in Wang et al, in some cities greater than 100x higher than our estimates.

The temperature data products used also play a role in the different estimates of UHI. We chose observed surface air temperature at weather stations as the most direct measure of urban heat because it captures the ambient ground-level temperature that populations were directly exposed to in both the urban and reference areas, which allows the most direct assessment of the impact of temperature on human health.¹⁰ While individual weather station observations have limited reliability, recent analyses show that networks of stations can provide robust estimates of hourly and daily urban air temperature.²⁵

Our approach using networks of monitoring stations is contrasted by other approaches that use gridded temperature reanalysis data products, which aggregate data from multiple sources to model temperature with broad spatial coverage.^{15,17} Although gridded products provide spatially continuous temperature fields, they are generated by combining station observations with satellite data and other covariates such as elevation, land cover, or model outputs.^{15,17,26} As a result, their accuracy depends on factors such as station density, interpolation methods, and retrieval conditions, including cloud cover.²⁷ There are also well-known biases in reanalysis gridded products, e.g., the Zhang et al. 2022 surface air temperature product used in Wang et al.¹³ has overall mean absolute error for daily maximum temperature of 1.22°C.¹⁵ These biases can be exacerbated in urban areas, where global reanalysis products do not account for diverse intra-urban morphology and land use.²⁸ For UHI intensities < 2°C, this reanalysis product may not have adequate sensitivity to accurately represent the small differences in temperature that occur between urban and suburban reference locations.

Temperature is not the only climatic variable affected by urban form and relevant to human health.^{29–32} Humidity also plays a critical role in health outcomes because it affects how effectively our bodies cool through sweating.^{33–36} In urban areas, humidity can be influenced by features of the built environment, including the amount of land covered by pavement, the presence of vegetation and tree canopy, nearby water bodies, building density and height, airflow, heat storage, and human-generated heat and

moisture.^{37–40} Therefore, urban heat-mitigation strategies may profitably target human thermal comfort more broadly rather than temperature alone. Even then, broad measures of thermal stress such as wet-bulb globe temperature may not fully capture what individuals actually experience, since personal heat exposure can vary depending on time-activity patterns and hyperlocal conditions, including shade, wind or ventilation, and the comfort of indoor environments.^{33,34,37}

An alternative approach is to directly assess of the impact of proposed changes in urban form (cool surface, tree canopy, etc.) on multiple heat-stress indicators (e.g., surface air and wet bulb globe temperatures) within the urban area, rather than between an urban area and a rural reference. This approach maintains realistic, often-desirable dense urban form, and can help identify strategies that can reduce exposure and health disparities on the neighborhood level where people live today.⁴¹ This approach can also help estimate urban heat mitigation impacts for locations where no meaningful reference area can be defined, such as those surrounded by water, extremely low population density, varying land use, or substantial changes in elevation or climate. We have performed such impact analyses in Boston, MA,⁴² showing how the integration of specific regions of tree canopy expansion and albedo improvement on the 30m scale across Boston could reduce air temperature exposure for urban populations.

Impact of methods for estimating temperature-attributable mortality

We, like Wang et al.,¹³ used widely-cited estimates of the relationship between daily temperature and mortality published by Gasparrini et al.⁵ However, Wang et al.¹³ used interpolation between 4 data points to estimate the non-linear exposure response function in each city while we developed and applied a method to more faithfully recreate the published exposure response curves and confidence intervals. Macintyre et al. used a similar linear interpolation approach for calculating the attributable fraction of deaths associated with changes to the UHI.¹⁴

Assumptions about the shape of the temperature-mortality exposure-response curve also play a critical role in determining estimated impacts.^{5,43} For example, Wang et al. conceptualized the effect of UHI as a change in temperature exposure: urban overheating raises temperature, increasing heat-related risk above the minimum mortality temperature or percentile, while reducing cold-related risk below it.⁴⁴ This approach is similar to much of the UHI health-impact literature, including studies by where urban or mitigation scenarios change the temperature exposure distribution while the underlying exposure-response function is held fixed.^{3,14,45} We are uncertain whether removal of the UHI would cause the exposure response curve to “hinge” around the minimum mortality temperature, as is suggested by Fig. 1 of Wang et al. A “hinge” effect suggests that the minimum mortality temperature (or minimum mortality percentile) would not change in response to shifts in the temperature distribution (**Fig. S6a**). However, it is also plausible that the exposure-response relationship would “shift”, such that the entire curve is translated along the temperature axis and the minimum mortality temperature occurs at a lower (or higher) point than in the present day (**Fig. S6b**). In either case, changes in these curves would reflect

changes in physiological acclimatization, adaptation interventions (e.g. increased air conditioning), built environment modification (albedo and tree cover interventions), and health services availability, all of which would be changing at different rates over years or decades.^{3,46–48} The amount of modification would also be impacted by whether absolute or percentile temperatures are used to evaluate the changes in health impacts.

Only a limited literature has examined whether UHI or urban environmental context modifies the exposure-response curve itself. Milojevic et al., for example, used a shifted-spline framework in London to test whether UHI-related acclimatization displaced the temperature-mortality function.⁴⁷ Other studies have examined whether UHI intensity or local urban thermal context modifies temperature-related mortality or morbidity risks,^{49–51} suggesting that UHI may affect health not only by moving people along an existing exposure-response curve, but also by changing the curve through adaptation, susceptibility, or local environmental conditions. More evidence is required about how the exposure response curve itself changes in following changes to the UHI.

Considerations for modeling of temperature-related health impacts

The present research also highlights the limitations in the conceptualization of the temperature-mortality relationship as “U-shaped.” A key feature of the current modeling system is a single inflection point of minimum risk (the so-called minimum mortality temperature or optimal temperature), which implies a single temperature at which risks are minimized. Given this conceptualization, the increased magnitude of cold impacts relative to warm impacts is in part reflects the finding that in most locations the optimal temperature does not occur at the 50th percentile. Gasparrini et al. bring attention to this fact by specifically identifying “extreme cold” and “extreme heat” health impacts, which each are roughly ~ 1% of total mortality. However, when viewed across the temperature distribution, the largest contributor to attributable mortality was days of moderate rather than extreme cold.⁵ An alternative conceptualization of the temperature-mortality relationship could be as a “flat-bottomed” curve where there is a range of safe temperatures and a heat-and cold minimum mortality temperatures (**Fig. S7**). Such a combined framework might eliminate some of the weight currently given to moderate cold in estimating the attributable impacts of ambient temperature.

Reconciling UHI modeling with the reality of urban heat mitigation in cities

There is a disconnect between how removing UHI from a city in a model changes temperature and the reality of how urban heat mitigation strategies are implemented. Rather than wholesale replacement of the built environment factors that contribute to the UHI, mitigation strategies such as increasing tree cover change or surface albedo^{52–54} are rolled out at different points in space and time depending on city plans and budgets. While we often consider the UHI as a metric that benchmarks urban heat and contextualizes the changes that development has made to the environment, the idea of removing the

UHI is an extreme and unrealistic counterfactual in considering health outcomes. Realistic urban infrastructure strategies to mitigate the UHI can reduce local temperatures, but scaling these interventions across a city would require extreme investment. In considering citywide health outcomes, scaling the effects of UHI removal according to achievable, policy-relevant benchmarks⁵⁵ would produce substantially lower increases in temperature-related mortality than even the low effects we see here.

Additionally, little is known about how implementation of these strategies would affect wintertime temperatures in practice given lower solar angles, existing high albedo due to snow cover in some cities, and the deciduous character of most urban trees. Most studies investigating wintertime impacts are simulations, with results that reflect monotonicity in underlying physical models.^{56,57} More multi-city and multi-season field measurements of UHI mitigation interventions are required to substantiate simulated results.

We question whether the finding of net mortality offset from increased cold days would persist in practice given projected future warming and the time horizon for acclimatization. Temperatures are projected to rise globally in coming decades,^{58,59} which in some regions may increase net mortality due to much warmer summers but only slightly milder winters.¹⁴ Thus, there is a temporal mis-alignment in the finding of net-mortality offset, the trend of increasing global temperatures, the shape of the exposure response function at the high temperature extreme, and the time it would take to implement any UHI intervention.

Using mortality impacts alone to frame whether to mitigate the UHI effect ignores the multitude of non-fatal impacts of UHIs such as increased risk of injury, illness, and discomfort, and reduced productivity, among others. Non-fatal impacts may not share the same “U-shaped” relationship with temperature as does mortality. Notably, emergency department visits show a near monotonic exposure response curve for temperature.^{60–66} For this outcome and others, warmer temperatures in any season could be associated with more frequent illnesses, resulting in greater healthcare utilization especially among vulnerable populations. In calculating of the health impacts of urban heat islands, there is simply more to living than not dying.

Finally, and perhaps most important, framing urban heat mitigation policies as a choice that could be paused to reduce net mortality is not in line with public health practice of protecting the most vulnerable populations. We should not pause mitigation efforts that *in practice* reduce deaths during extreme heat because deaths during moderate cold may *in theory* become more numerous. This framing fails to acknowledge common strategies to reduce risk during both temperature extremes: improving shelter, reducing energy insecurity, and improving individual economic ability to adapt can all help vulnerable populations withstand the dangers of extreme temperatures. Policy targets should be set to reduce total deaths rather than to minimize net mortality, by focusing on season- and city-specific solutions to the problems that vulnerable groups face and addressing those directly.

Conclusions

Our results run counter to claims that removing the UHI would be associated with large net increases in mortality. Rather we show that theoretical removal of the UHI in 26 of 49 major cities would have negligible net impacts, and in the remaining cities UHI removal would at most be associated with increases of < 1% of total mortality and < 5% of temperature-related mortality. The stark differences between the our work and previous studies highlight the importance of using heat health indicators beyond mortality impacts to guide selection of UHI mitigation policies. Specific methodology points that warrant further assessment include (i) the definition of the UHI intensity and (ii) the method used for estimating the attributable number of temperature-related health impacts in the absence of local-scale data. The disparity in estimated temperature and temperature-related mortality between these various methods gives rise to an opportunity: future work can explore standardized and improved ways of estimating the impact of real-world interventions geared to improving the built environment, urban microclimate, and human health.

Methods

We examined the health impacts of UHIs, focusing on temperature-related mortality across 49 cities in the United States. We estimated the UHI effect in each city, then extracted exposure response curves from the published literature,⁵ and used mortality data obtained from the Centers for Disease Control (CDC) to estimate the change in mortality attributable to the removal of the UHI. Data processing and analysis were conducted using R (versions 4.4.3 and 4.5.1)⁶⁷, STAN,⁶⁸ and Python (version 3.12.12).⁶⁹ The code and data to reproduce our results are available at: https://github.com/yiryuan/heat_UHI.

Monitored temperature data

We queried all urban areas in the United States defined in the Global Human Settlement Layer (GHSL).¹⁸ GHSL is a broadly accepted definition of urban area that considers both land cover and population. Following Venter et al.,⁷⁰ we defined reference areas to be the 10 km buffer surrounding the urban area, excluding other urban areas. Thus, the reference areas were similar to each urban area in elevation, land cover, and proximity to coast, but excluded the most densely populated and intensely developed areas.

We then queried monitored temperate data in each urban and reference area from the Meteorological Assimilation Data Ingest System (MADIS) station network, a federally managed network. MADIS assimilates weather station data from multiple networks, providing a uniform data format and quality control metrics. Only the first non-null surface air temperature observation from each hour was retained. From this network we obtained hourly surface air temperature observations for 2023.

Station data quality was assessed using CrowdQC+, an R package that provides automated quality checks to monitored weather station data.²⁵ Quality checks included: multiple stations at the same location, outlier temperatures outside the highest and lowest 1% of measured values, readings from a station for a month if the station has less than 20% valid temperature readings for the month, readings

from a station for a day if the minimum correlation coefficient between the station and other stations was less than 90%, all readings from a station for a day if the station has less than 70% (17 hours) of readings for the day. We imputed single missing air temperature observations with a linear interpolation between adjacent observations. For a given urban area, all urban stations and reference stations were checked together, and the resulting surface air temperature including interpolated values was used as the hourly station temperature. We also checked that stations were not near permanent water as defined by European Space Agency (ESA) Land Cover Climate Change Initiative (CCI) static map of open water bodies at 150m resolution for the year 2000.⁷¹ Quality checks were defined to fail for a station if a 100m buffer around the station location touched permanent water. Urban elevation was calculated as the median of elevations returned by CrowdQC + for all urban stations that ever passed the quality checks.

We also excluded cities with too few stations per hour that passed quality checks. Hourly urban network size was calculated as the minimum of the number of urban stations that pass the quality checks in each hour. Hourly reference network size was calculated as the minimum number of reference stations that pass the quality checks in each hour. Daily network size is the minimum of hourly urban network size and hourly reference network size on each day, from local midnight to local midnight. Target network size is the desired minimum number of stations in the station network; we selected 5 as the target network size. Network gap length is the number of consecutive days that the daily network size is less than the target network size. The maximum network gap length is the maximum network gap length for the year. For the present analysis, we chose to exclude urban areas with a maximum network gap length greater than 10.

Adjusted hourly station temperature was calculated for both urban stations and reference stations by multiplying the difference between station elevation as returned by CrowdQC + and urban elevation by an adiabatic lapse rate of $-0.0065^{\circ}\text{C} \cdot \text{m}^{-1}$, and subtracting the result from the hourly station temperature. Hourly urban temperature was calculated as the mean of adjusted hourly station temperatures for all urban stations that passed the quality checks in that hour. Hourly reference temperature was calculated as the mean of adjusted hourly station temperature for all reference stations that passed the quality checks in that hour. Daily mean urban temperature was calculated as the mean of hourly urban temperatures on each day, from local midnight to local midnight. Daily mean reference temperature was calculated as the mean of hourly reference temperatures on each day, from local midnight to local midnight. Daily UHI intensity was calculated as the difference between the daily mean urban temperature and the daily mean reference temperature.

We restricted the final analysis to those urban areas with observations from at least 5 urban and 5 reference weather stations for at least 300 days of the year, and no interval longer than 10 days with observations from fewer than 5 stations each in the urban and reference area. This resulted in the 49 US cities selected in this analysis (Fig. 1), distributed across National Climate Assessment regions.

We used the non-parametric Wilcoxon-Mann Whitney U test to determine if distribution of daily differences in temperature was different than 0 or different between summer and winter months (defined as June, July, August and December, January, February respectively).

Mortality data

For each city, we obtained weekly all-cause mortality data from the Centers for Disease Control weekly mortality database at the county level.⁷² Each record contains the state–county FIPS code and mortality counts reported by Morbidity and Mortality Weekly Report epidemiologic week. Any suppressed weekly counts were replaced using linear interpolation. We downscaled these data to the daily level by dividing each weekly count by 7 and distributing across each day following week. These data are not used to create the temperature mortality relationships but instead serve to quantify the health impacts of reducing the UHI.

Exposure response functions

The exposure response curve reconstruction occurred in two parts: (1) extracting the curve data from an image and (2) using Bayesian statistics to reconstruct the variance-covariance matrix of each curve.

Image extraction

Each city-specific SVG panel from Gasparrini et al. was parsed using custom Python scripts. Axis tick labels were identified from text elements along the plot margins, and SVG coordinate transformations were reconstructed to convert SVG coordinates into the original temperature and relative risk (RR) scales. The exposure-response curves were identified by classifying path colors (blue and red strokes) and distinguishing them from confidence intervals regions, which are identified as filled path elements within the plot clipping region. All path geometries were coded as cubic or quadratic Bézier segments, resampled into dense point sequences and then transformed into data coordinates. Confidence intervals bands were reconstructed by binning transformed CI points along the temperature axis (default width 0.05°C) and taking the minimum and maximum RR values within each bin. Blue and red curves were reconstructed by merging stroke segments and summarizing them within narrow temperature bins. For each city, the script produced a CSV file containing temperature, RR (blue and red curves), and confidence interval bounds, along with a reproduced plot for visual inspection. For application to other studies, users should verify whether the RR axis is linear or logarithmic, as log-scaled axes would require a modified coordinate transformation,

After data extraction, exposure response curves were recentered to the reported MMT. Specifically, the extracted curve minimum was identified, the temperature axis was shifted so that this minimum aligned with the reported MMT, and the curve was then rescaled so that $RR = 1$ at the MMT. The same scaling was applied to the extracted confidence interval bounds, preserving the overall curve shape while correcting small extraction-related misalignment.

We performed a validation tests analysis for these methods showing how across image resolutions this code precisely estimates the centerline and confidence interval of images in the style of Gasparrini et al: across image resolutions the root mean squared error (RMSE) for RR was < 0.01 (**Fig. S4**).

Bayesian methods

To calculate the model coefficients and variance-covariance matrix for each city's model, we used Bayesian methods and leverage what is written in Gasparrini et al⁵ about the specific structure of the models that were used. In that manuscript's text, the model structure is described as such:

Specifically, we modelled the exposure-response curve with a quadratic B-spline with three internal knots placed at the 10th, 75th, and 90th percentiles of location-specific temperature distributions, and the lag-response curve with a natural cubic B-spline with an intercept and three internal knots placed at equally spaced values in the log scale

Although we cannot re-create the lag dimension of the matrix (because only the "cross-reduced" exposure dimension is shown in the supplemental figures), from this text we can create an exposure basis matrix, X , using the monitored temperature time-series for each city and following the same methods as described by Gasparrini et al. (i.e., a quadratic B-spline with internal knots at the 10th, 75th, and 90th percentiles). We can then use matrix inversion to estimate the cross-reduced model coefficients, β , from the exposure basis matrix, X , and the relative risk estimate, RR , extracted from the images:

$$\beta = X^{-1} \times \log RR$$

To reconstruct the variance-covariance matrix of each city-specific exposure response curve, S , we used Bayesian inference. We wrote STAN code⁶⁸ to find the positive definite variance-covariance matrix that would most likely produce the relative risk estimate and confidence intervals extracted from the given outcome time-series, observed temperature time-series, and model structure. The target object of the STAN code was the log of the upper bound of CI_{RR} . The STAN parameters corresponded to the variance-covariance matrix that would result in that observed upper bound. Validation tests data shows that this reconstruction method recreates attributable mortality with high precision (RMSE on daily attributable mortality < 0.10, **Fig. S5**); methods to estimate attributable mortality are described below.

Attributable Mortality

Finally, we estimated the change in total- and temperature-attributable mortality following the reduction of the UHI in each city. In short, the attributable mortality represents the number of deaths that occur due to the temperature being greater than (or less than) a counterfactual comparison temperature. In the case of mortality, most cities have a "U-shaped" exposure response curve, which roughly means that there is a point of minimum excess mortality, called the minimum mortality temperature or MMT, at which the risk of mortality due to changes in temperature is minimized. The MMT is one choice of a counterfactual comparison temperature (although there are others). Heat-attributable mortality is

therefore the estimate of the sum of deaths that occur *solely due to the change in temperature* for all temperatures *above* the MMT. Cold-attributable mortality has a similar interpretation – the estimate of the sum of deaths that occur *solely due to the change in temperature* for all temperatures *below* the MMT.

To estimate the empirical confidence interval on the attributable number in each city, we followed established methods.⁴³ We simulated $N = 1000$ draws from a multi-variate normal distribution defined by β and S . We then used a recentered exposure basis and the downscaled daily time-series of deaths in each city to estimate the empirical confidence interval for heat- and cold-attributable mortality for each city under observed conditions and under the counter-factual scenario of each city not having an UHI.

We produced three outputs from these calculations: (1) the UHI attributable mortality in each city, (2) the UHI attributable mortality as a percentage of total mortality in each city, and (3) the UHI attributable mortality as a percentage of total temperature-related mortality in each city. These metrics allow us to compare our estimates to those previously estimated. Using the variance-covariance matrix for each city, we calculated empirical confidence intervals of each estimate.

Limitations and Strengths of the modeling system

Our findings are limited to a subset of the cities that have a published exposure-response function in Gasparrini et al. These curves are made for daily mean temperatures, which might not reflect the health effects of extreme cold or extreme heat. We also created estimates for a single year of data (2023) – including more years of data would permit greater stability. Although our estimates of attributable number have high precision, there may be some bias in some locations where the monitored data diverge greatly from the temperature data products used in comparable literature.

Declarations

Acknowledgements

This study was made possible in part due to the data made available to the National Oceanic and Atmospheric Administration as part of the MADIS network.

Data availability

The code and data to reproduce our results are available at: https://github.com/yiryuan/heat_UHI.

Funding attribution

This work was funded by Wellcome Foundation Climate Impact Award 311886/Z/24/Z. The content of this report is solely the responsibility of the authors and does not necessarily represent the official views of the sponsoring agencies.

Conflicts of Interest

Dr. Wellenius serves as a consultant for the Health Effects Institute (Boston, MA) and Climate Resilience for All (Washington, DC).

References

1. Martin-Vide J, Sarricolea P, Moreno-García MC (2015) On the definition of urban heat island intensity: the rural reference. *Front Earth Sci* 3. 10.3389/feart.2015.00024
2. Wang ZH (2022) Reconceptualizing urban heat island: Beyond the urban-rural dichotomy. *Sustainable Cities Soc* 77:103581. 10.1016/j.scs.2021.103581
3. Heaviside C, Macintyre H, Vardoulakis S (2017) The Urban Heat Island: Implications for Health in a Changing Environment. *Curr Envir Health Rpt* 4(3):296–305. 10.1007/s40572-017-0150-3
4. Tong S, Prior J, McGregor G, Shi X, Kinney P (2021) Urban heat: an increasing threat to global health [Internet]. 25. 10.1136/bmj.n2467
5. Gasparrini A, Guo Y, Hashizume M, Lavigne E, Zanobetti A, Schwartz J et al (2015) Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *Lancet* 386(9991):369–375. 10.1016/S0140-6736(14)62114-0 PubMed PMID: 26003380
6. Bobb JF, Obermeyer Z, Wang Y, Dominici F (2014) Cause-Specific Risk of Hospital Admission Related to Extreme Heat in Older Adults. *JAMA* 312(24):2659–2667. 10.1001/jama.2014.15715
7. Sun S, Weinberger KR, Nori-Sarma A, Spangler KR, Sun Y, Dominici F et al (2021) Ambient heat and risks of emergency department visits among adults in the United States: time stratified case crossover study. *BMJ* e065653. 10.1136/bmj-2021-065653
8. Morgenroth J, Doick K, Hauer R, Locke DH, Barona CO, Roman LA et al (2025) Urban tree cover targets: The good, the bad and the SMART. *Urban Forestry Urban Green* 112:128979. 10.1016/j.ufug.2025.128979
9. US EPA O Heat Island Community Actions Database [Data and Tools] [Internet]. 2014 [cited 2026 Mar 11]. Available from: <https://www.epa.gov/heatislands/heat-island-community-actions-database>
10. Stewart ID (2011) A systematic review and scientific critique of methodology in modern urban heat island literature. *Int J Climatol* 31(2):200–217. 10.1002/joc.2141
11. Yang C, Yan F, Zhang S (2020) Comparison of land surface and air temperatures for quantifying summer and winter urban heat island in a snow climate city. *J Environ Manage* 265:110563. 10.1016/j.jenvman.2020.110563
12. Yang J, Bou-Zeid E (2018) Should Cities Embrace Their Heat Islands as Shields from Extreme Cold? *J Appl Meteorol Climatology* 57(6):1309–1320. 10.1175/JAMC-D-17-0265.1
13. Wang S, Zhan W, Zhou B, Tong S, Chakraborty T, Wang Z et al (2025) Dual impact of global urban overheating on mortality. *Nat Clim Chang* 15(5):497–504. 10.1038/s41558-025-02303-3
14. Macintyre HL, Heaviside C, Cai X, Phalkey R (2021) The winter urban heat island: Impacts on cold-related mortality in a highly urbanized European region for present and future climate. *Environ Int* 154:106530. 10.1016/j.envint.2021.106530

15. Zhang T, Zhou Y, Zhao K, Zhu Z, Chen G, Hu J, et al. A global dataset of daily maximum and minimum near-surface air temperature at 1 km resolution over land (2003–2020). *Earth System Science Data*. 2022;14(12):5637–49. doi:10.5194/essd-14-5637-2022
16. Imhoff ML, Zhang P, Wolfe RE, Bounoua L (2010) Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sens Environ* 114(3):504–513. 10.1016/j.rse.2009.10.008
17. Debbage N, Shepherd JM (2015) The urban heat island effect and city contiguity. *Computers, Environment and Urban Systems*. ;54:181–94. 10.1016/j.compenvurbsys.2015.08.002
18. Pesaresi M, Schiavina M, Politis P, Freire S, Krasnodębska K, Uhl JH et al (2024) Advances on the Global Human Settlement Layer by joint assessment of Earth Observation and population survey data. *Int J Digit Earth* 17(1):2390454. 10.1080/17538947.2024.2390454
19. Venter ZS, Chakraborty T, Lee X (2021) Crowdsourced air temperatures contrast satellite measures of the urban heat island and its mechanisms. *Sci Adv* 7(22):eabb9569. 10.1126/sciadv.abb9569
20. NCEP Meteorological Assimilation Data Ingest System (MADIS)
21. Liu Z, Huang S, Fang C, Guan L, Liu M (2024) *Sci Data* 11:1359. 10.1038/s41597-024-04195-y PubMed PMID: 39695247; PubMed Central PMCID: PMC11655987 Global urban and rural settlement dataset from 2000 to 2020
22. Li X, Gong P, Zhou Y, Wang J, Bai Y, Chen B et al (2020) Mapping global urban boundaries from the global artificial impervious area (GAIA) data. *Environ Res Lett* 15(9):094044. 10.1088/1748-9326/ab9be3
23. Yang Q, Xu Y, Tong X, Hu T, Liu Y, Chakraborty TC et al (2023) Influence of urban extent discrepancy on the estimation of surface urban heat island intensity: A global-scale assessment in 892 cities. *J Clean Prod* 426:139032
24. Liu H, He B, jie, Gao S, Zhan Q, Yang C (2023) Influence of non-urban reference delineation on trend estimate of surface urban heat island intensity: A comparison of seven methods. *Remote Sens Environ* 296:113735. 10.1016/j.rse.2023.113735
25. Fenner D, Bechtel B, Demuzere M, Kittner J, Meier F (2021) CrowdQC+—A Quality-Control for Crowdsourced Air-Temperature Observations Enabling World-Wide Urban Climate Applications. *Front Environ Sci* 9. 10.3389/fenvs.2021.720747
26. White-Newsome JL, Brines SJ, Brown DG, Dvonch JT, Gronlund CJ, Zhang K et al (2013) Validating satellite-derived land surface temperature with in situ measurements: a public health perspective. *Environmental health perspectives* [Internet]. [cited 2026 May 21];121(8):925. Available from: <https://pmc.ncbi.nlm.nih.gov/articles/PMC3734495/>
27. Li ZL, Wu H, Duan SB, Zhao W, Ren H, Liu X et al (2023) Satellite Remote Sensing of Global Land Surface Temperature: Definition, Methods, Products, and Applications. *Rev Geophys* 61(1):e2022RG000777. 10.1029/2022RG000777
28. Jacobs A, Top S, Vergauwen T, Suomi J, Käyhkö J, Caluwaerts S (2024) Filling gaps in urban temperature observations by debiasing ERA5 reanalysis data. *Urban Clim* 58:102226.

10.1016/j.uclim.2024.102226

29. Heo S, Bell ML, Lee JT (2019) Comparison of health risks by heat wave definition: Applicability of wet-bulb globe temperature for heat wave criteria. *Environ Res* 168:158–170
30. Ebi KL, 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. 10.1016/S0140-6736(21)01208-3 PubMed PMID: 34419205
31. Spangler KR, Liang S, Wellenius GA (2022) *Sci Data* 9(1):326. 10.1038/s41597-022-01405-3. Wet-Bulb Globe Temperature, Universal Thermal Climate Index, and Other Heat Metrics for US Counties, 2000–2020
32. Ibsen PC, Mchale MR, Desouza P, Steinharter L, Green C Jr, Diffendorfer JE et al (2026) Moving toward a more human-oriented analysis of urban heat: examining differences of heat exposure intensity at busy commuting locations. *Environ Research: Health* 4(1):015016
33. Steadman RG The Assessment of Sultriness. Part I: A Temperature-Humidity Index Based on Human Physiology and Clothing Science. *Journal of Applied Meteorology* (1962–1982) [Internet]. 1979 [cited 2022 Jun 7];18(7):861–73. Available from: <https://www.jstor.org/stable/26179216>
34. Baldwin JW, Benmarhnia T, Ebi KL, Jay O, Lutsko NJ, Vanos JK (2023) Humidity’s Role in Heat-Related Health Outcomes: A Heated Debate. *Environ Health Perspect* 131(5):055001. 10.1289/EHP11807
35. Raymond C, Matthews T, Horton RM (2020) The emergence of heat and humidity too severe for human tolerance. *Sci Adv* 6(19):eaaw1838. 10.1126/sciadv.aaw1838
36. Park K, Baik JJ, Jin HG, Tabassum A (2024) Changes in urban heat island intensity with background temperature and humidity and their associations with near-surface thermodynamic processes. *Urban Clim* 58:102191. 10.1016/j.uclim.2024.102191
37. Zhang K, Cao C, Chu H, Zhao L, Zhao J, Lee X (2023) Increased heat risk in wet climate induced by urban humid heat. *Nature* 617(7962):738–742
38. Sailor DJ (2011) A review of methods for estimating anthropogenic heat and moisture emissions in the urban environment. *Intl J Climatology* 31(2):189–199. 10.1002/joc.2106
39. Hao M, Liu X, Li X (2025) Quantifying heat-related risks from urban heat island effects: A global urban expansion perspective. *Int J Appl Earth Obs Geoinf* 136:104344
40. Huang X, Song J (2023) Urban moisture and dry islands: spatiotemporal variation patterns and mechanisms of urban air humidity changes across the globe. *Environ Res Lett* 18(10):103003
41. Rahmani N, Sharifi A (2025) Urban heat dynamics in Local Climate Zones (LCZs): A systematic review. *Build Environ* 267:112225. 10.1016/j.buildenv.2024.112225
42. Smith IA, Li D, Fork DK, Wellenius GA, Hutyra LR (2025) Integrated tree canopy expansion and cool roofs can optimize air temperature and heat exposure reductions in Boston. *Commun Earth Environ* 6(1):507. 10.1038/s43247-025-02462-3

43. Gasparrini A, Leone M (2014) Attributable risk from distributed lag models. *BMC Med Res Methodol* 14(1):55. 10.1186/1471-2288-14-55
44. Wang S, Zhan W, Zhou B, Tong S, Chakraborty TC, Wang Z et al (2025) Dual impact of global urban overheating on mortality. *Nat Clim Chang* 15(5):497–504. 10.1038/s41558-025-02303-3
45. Huang WTK, Masselot P, Bou-Zeid E, Fatichi S, Paschalis A, Sun T et al (2023) Economic valuation of temperature-related mortality attributed to urban heat islands in European cities. *Nat Commun* 14(1):7438
46. lungman T, Cirach M, Marando F, Barboza EP, Khomenko S, Masselot P et al (2023) Cooling cities through urban green infrastructure: a health impact assessment of European cities. *Lancet* 401(10376):577–589
47. Milojevic A, Armstrong BG, Gasparrini A, Bohnenstengel SI, Barratt B, Wilkinson P Methods to estimate acclimatization to urban heat island effects on heat-and cold-related mortality. *Environmental health perspectives* [Internet]. 2016 [cited 2026 May 21];124(7):1016. Available from: <https://pmc.ncbi.nlm.nih.gov/articles/PMC4937865/>
48. Barreca AI (2012) Climate change, humidity, and mortality in the United States. *J Environ Econ Manag* 63(1):19–34
49. Cleland SE, Steinhardt W, Neas LM, West JJ, Rappold AG (2023) Urban heat island impacts on heat-related cardiovascular morbidity: A time series analysis of older adults in US metropolitan areas. *Environ Int* 178:108005
50. Wicki B, Flückiger B, Vienneau D, de Hoogh K, Rössli M, Ragettli MS (2024) Socio-environmental modifiers of heat-related mortality in eight Swiss cities: A case time series analysis. *Environ Res* 246:118116. 10.1016/j.envres.2024.118116
51. Ho JY, Shi Y, Lau KK, Ng EY, Ren C, Goggins WB (2023) Urban heat island effect-related mortality under extreme heat and non-extreme heat scenarios: A 2010–2019 case study in Hong Kong. *Sci Total Environ* 858:159791
52. Chakraborty T, Venter ZS, Qian Y, Lee X (2022) Lower Urban Humidity Moderates Outdoor Heat Stress. *AGU Adv* 3(5). e2022AV000729
53. Krayenhoff ES, Broadbent AM, Zhao L, Georgescu M, Middel A, Voogt JA et al Cooling hot cities: a systematic and critical review of the numerical modelling literature. *Environmental Research Letters* [Internet]. 2021 [cited 2026 Mar 11];16(5):053007. Available from: <https://iopscience.iop.org/article/10.1088/1748-9326/abdcf1/meta>
54. Santamouris M Cooling the cities—a review of reflective and green roof mitigation technologies to fight heat island and improve comfort in urban environments. *Solar energy* [Internet]. 2014 [cited 2026 Mar 11];103:682–703. Available from: https://www.sciencedirect.com/science/article/pii/S0038092X12002447?casa_token=ZZ-lwIA7c-oAAAAA:-OJQTP-mEKyNPkNWQvd6rdiGn0--6Qw3PnsVwMEIsXk_dnFfWhg3Tu1-QaISvjTs8yMKhECc_w

55. Wesley EJ, Mackres E, Shickman K, Janssen CW, Mulder M, Wong T Mapping Scenarios and Estimating the Potential for Heat-Resilient Infrastructure in Cities [Internet]. 2026 Mar 16 [cited 2026 May 12]. Available from: <https://www.wri.org/research/mapping-scenarios-and-estimating-potential-heat-resilient-infrastructure-cities>
56. He C, Zhao J, Zhang Y, He L, Yao Y, Ma W et al (2020) Cool Roof and Green Roof Adoption in a Metropolitan Area: Climate Impacts during Summer and Winter. *Environ Sci Technol* 54(17):10831–10839. 10.1021/acs.est.0c03536
57. Zhang T, Fu X, Qi F, Shen Y, Xu P, Tao Y et al (2025) Optimizing pedestrian thermal comfort in urban street canyons for summer and winter: Tree planting or low-albedo pavements? *Sustainable Cities Soc* 120:106143. 10.1016/j.scs.2025.106143
58. O'Neill BC, Tebaldi C, van Vuuren DP, Eyring V, Friedlingstein P, Hurtt G et al (2016) The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci Model Dev* 9(9):3461–3482. 10.5194/gmd-9-3461-2016
59. Hansen J, Sato M, Ruedy R, Lo K, Lea DW, Medina-Elizade M (2006) Global temperature change. *Proceedings of the National Academy of Sciences*. ;103(39):14288–93. 10.1073/pnas.0606291103
60. Weinberger KR, Haykin L, Eliot MN, Schwartz JD, Gasparrini A, Wellenius GA (2017) Projected temperature-related deaths in ten large U.S. metropolitan areas under different climate change scenarios. *Environ Int* 107:196–204. 10.1016/j.envint.2017.07.006
61. Zhang Y, Yan C, Kan H, Cao J, Peng L, Xu J et al (2014) Effect of ambient temperature on emergency department visits in Shanghai, China: a time series study. *Environ Health* 13(1):100. 10.1186/1476-069X-13-100
62. Sun X, Sun Q, Yang M, Zhou X, Li X, Yu A et al (2014) Effects of temperature and heat waves on emergency department visits and emergency ambulance dispatches in Pudong New Area, China: a time series analysis. *Environ Health* 13(1):76. 10.1186/1476-069X-13-76
63. Gould CF, Heft-Neal S, Heaney AK, Bendavid E, Callahan CW, Kiang M et al Temperature Extremes Impact Mortality and Morbidity Differently [Working Paper] [Internet]. National Bureau of Economic Research; 2024 [cited 2024 Jul 29]. (Working Paper Series). Available from: <https://www.nber.org/papers/w32195> 10.3386/w32195
64. Kingsley SL, Eliot MN, Gold J, Vanderslice RR, Wellenius GA (2016) Current and Projected Heat-Related Morbidity and Mortality in Rhode Island. *Environ Health Perspect* 124(4):460–467. 10.1289/ehp.1408826
65. Kim J, Lim Y, Kim H (2014) Outdoor temperature changes and emergency department visits for asthma in Seoul, Korea: A time-series study. *Environ Res* 135:15–20. 10.1016/j.envres.2014.07.032
66. Zhao Q, Zhang Y, Zhang W, Li S, Chen G, Wu Y et al (2017) Ambient temperature and emergency department visits: Time-series analysis in 12 Chinese cities. *Environ Pollut* 224:310–316. 10.1016/j.envpol.2017.02.010
67. R Core Team R Foundation for Statistical Computing, Vienna, Austria. 2017. R: A language and environment for statistical computing

68. Stan Development Team. Stan Reference Manual, Version 2.34.0 [Internet] (2024) Available from: <https://mc-stan.org>

69. Python Software Foundation. Python Language Reference, Version 3.12 [Internet] (2023) Available from: <https://www.python.org>

70. Venter ZS, Chakraborty T, Lee X (2021) Crowdsourced air temperatures contrast satellite measures of the urban heat island and its mechanisms. Sci Adv 7(22):eabb9569. 10.1126/sciadv.abb9569

71. Lamarche C, Santoro M, Bontemps S, D’Andrimont R, Radoux J, Giustarini L et al (2017) Compilation and Validation of SAR and Optical Data Products for a Complete and Global Map of Inland/Ocean Water Tailored to the Climate Modeling Community. Remote Sens 9(1). 10.3390/rs9010036

72. Provisional Mortality S (2018) through Last Week Request [Internet]. [cited 2026 Mar 11]. Available from: <https://wonder.cdc.gov/mcd-icd10-provisional.html>

Figures

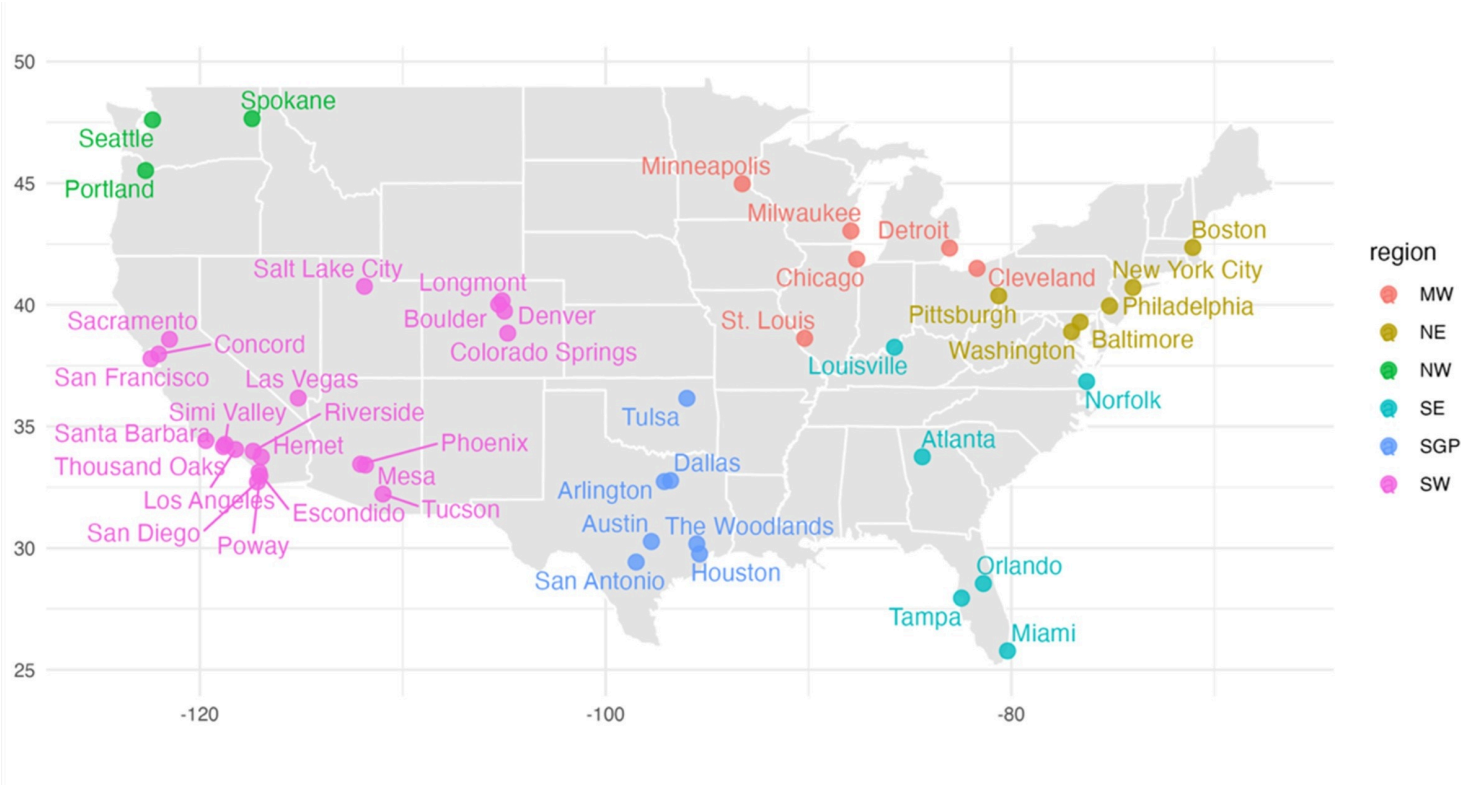


Figure 1

US Cities(N=49) with points, colored to denote geographic regions as defined in the Fourth National Climate Assessment (NCA4): Midwest (MW), Northeast (NE), Northwest (NW), Southeast (SE), Southern Great Plains (SGP), and Southwest (SW).

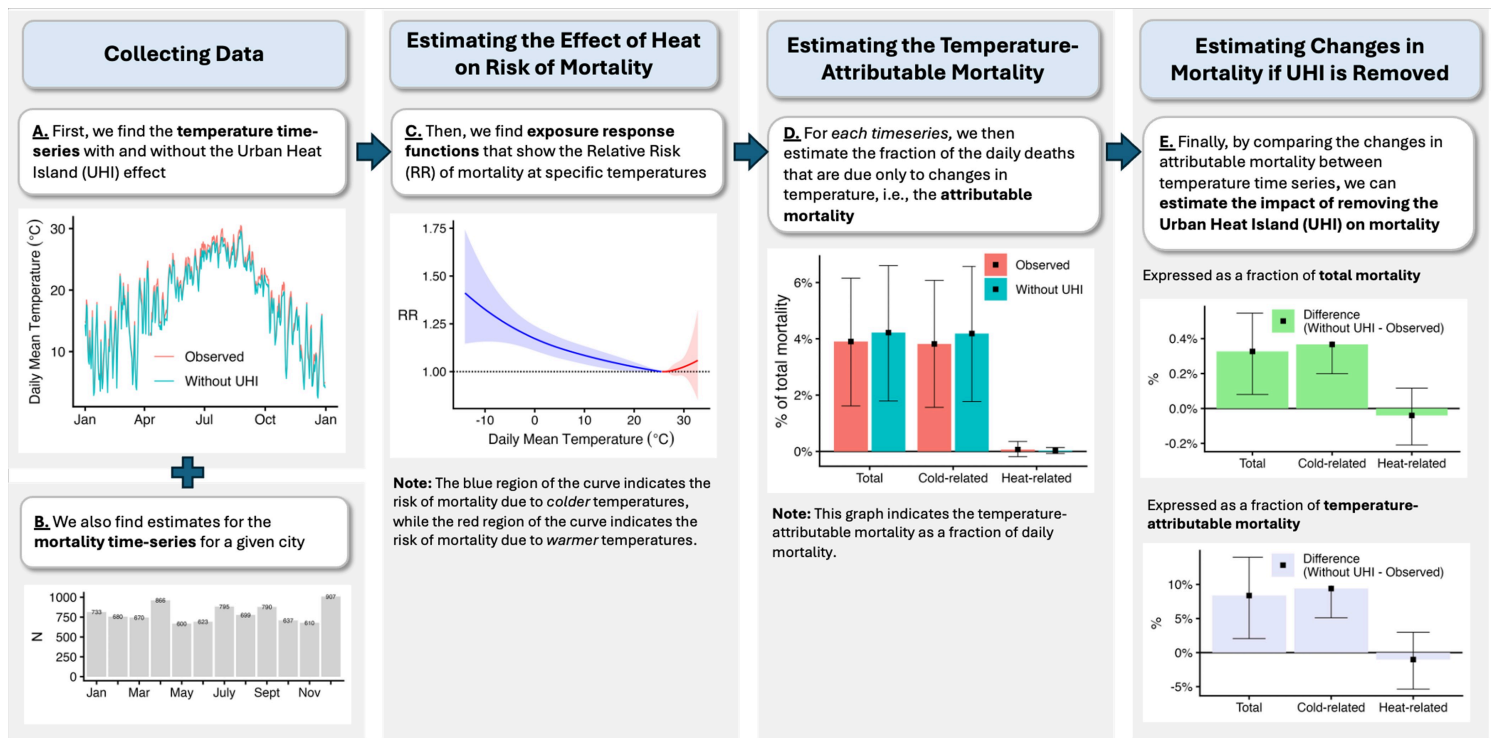


Figure 2

Conceptual diagram of the process for estimating the impact of urban heat islands (UHI) on mortality. The example data shown in this figure are for the city of Atlanta, GA. We (A, B) collect data on UHI exposures and mortality, (C) re-create the exposure response functions in Gasparrini et al., (D) find the temperature-attributable mortality, and (E) estimate the differences in temperature-attributable mortality that are associated with removing the UHI.

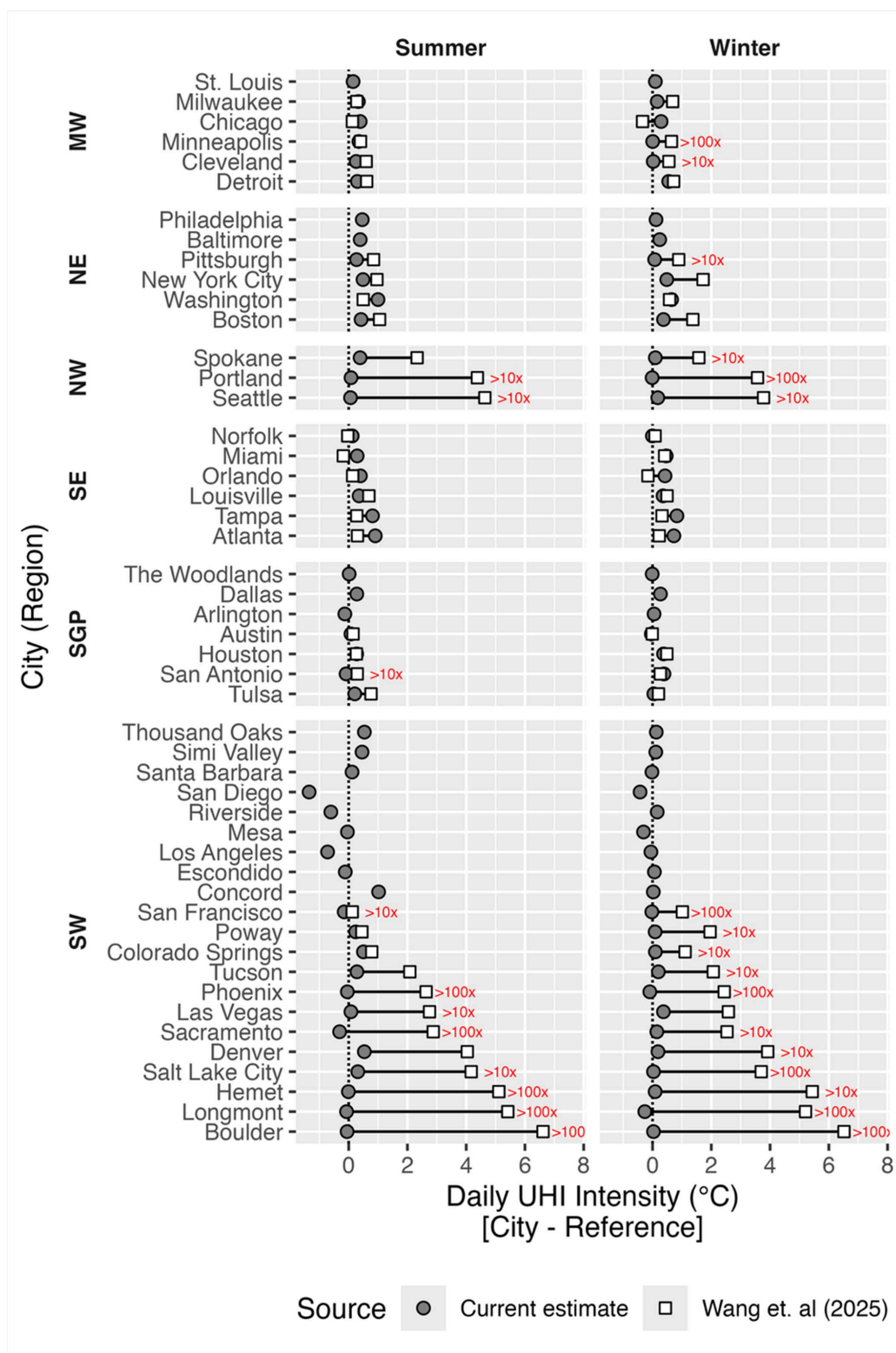


Figure 3

Absolute and relative differences in UHI intensity (unit: °C) during summer (hot season) and winter (cold) season in US cities within US Climate Regions: Midwest (MW), Northeast (NE), Northwest (NW), Southeast (SE), Southern Great Plains (SGP) and Southwest (SW). The text to the right of each line describes the magnitude of ratio between the Wang et al (2025) estimate and the current estimate, with ratios > 10 and 100x indicated. Cities with no square indicator do not have an estimate in Wang et al

(2025). Cities are sorted by increasing summer ratio. For the ratio calculation, UHI values below 0 were replaced with 0.01.

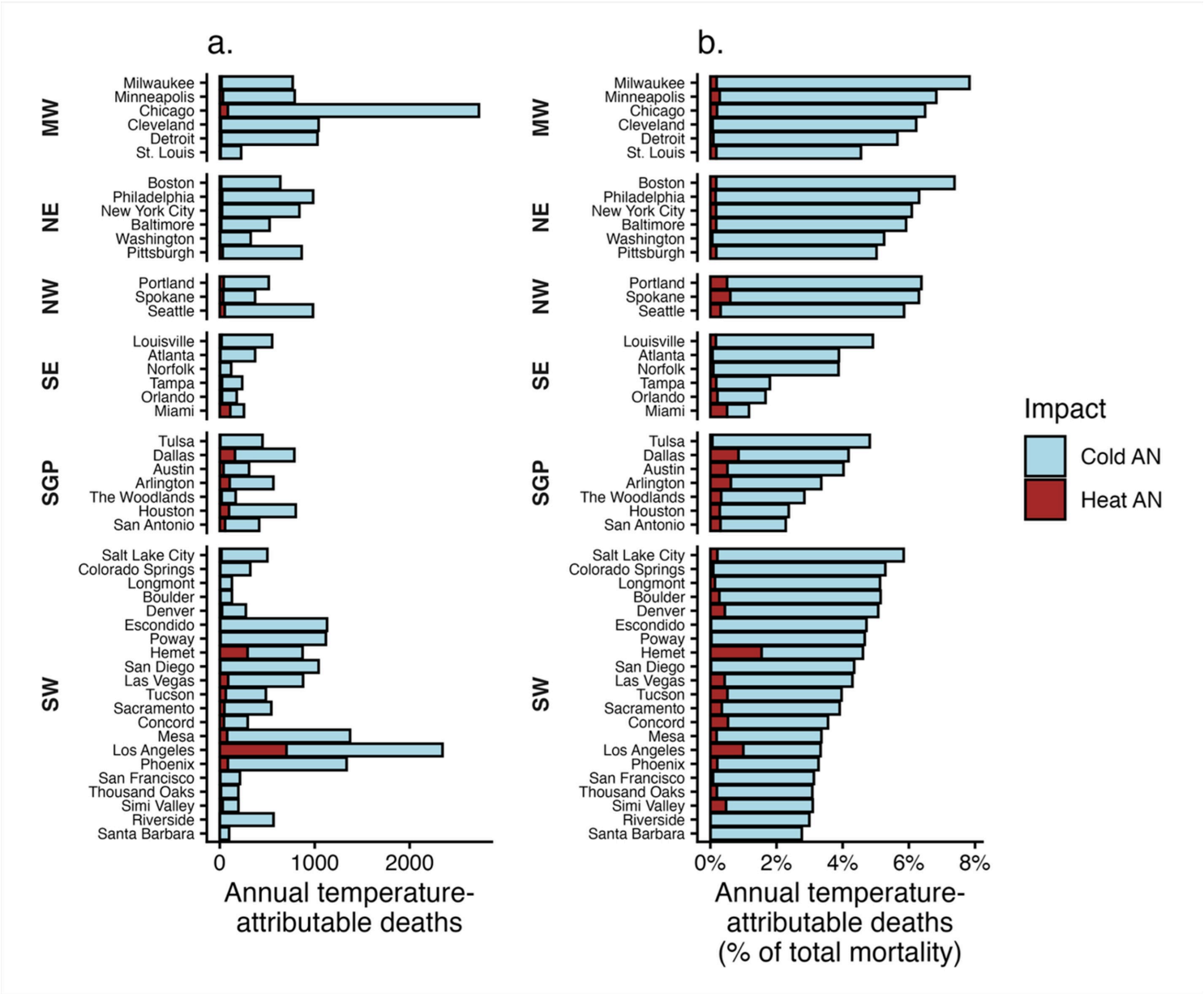


Figure 4

Mortality associated with extreme temperature in 49 US cities, expressed as the median attributable number (AN) of annual temperature-attributable deaths expressed (a) directly and (b) as a percentage of total mortality. Cities are grouped by US Climate Regions: Midwest (MW), Northeast (NE), Northwest (NW), Southeast (SE), Southern Great Plains (SGP) and Southwest (SW).

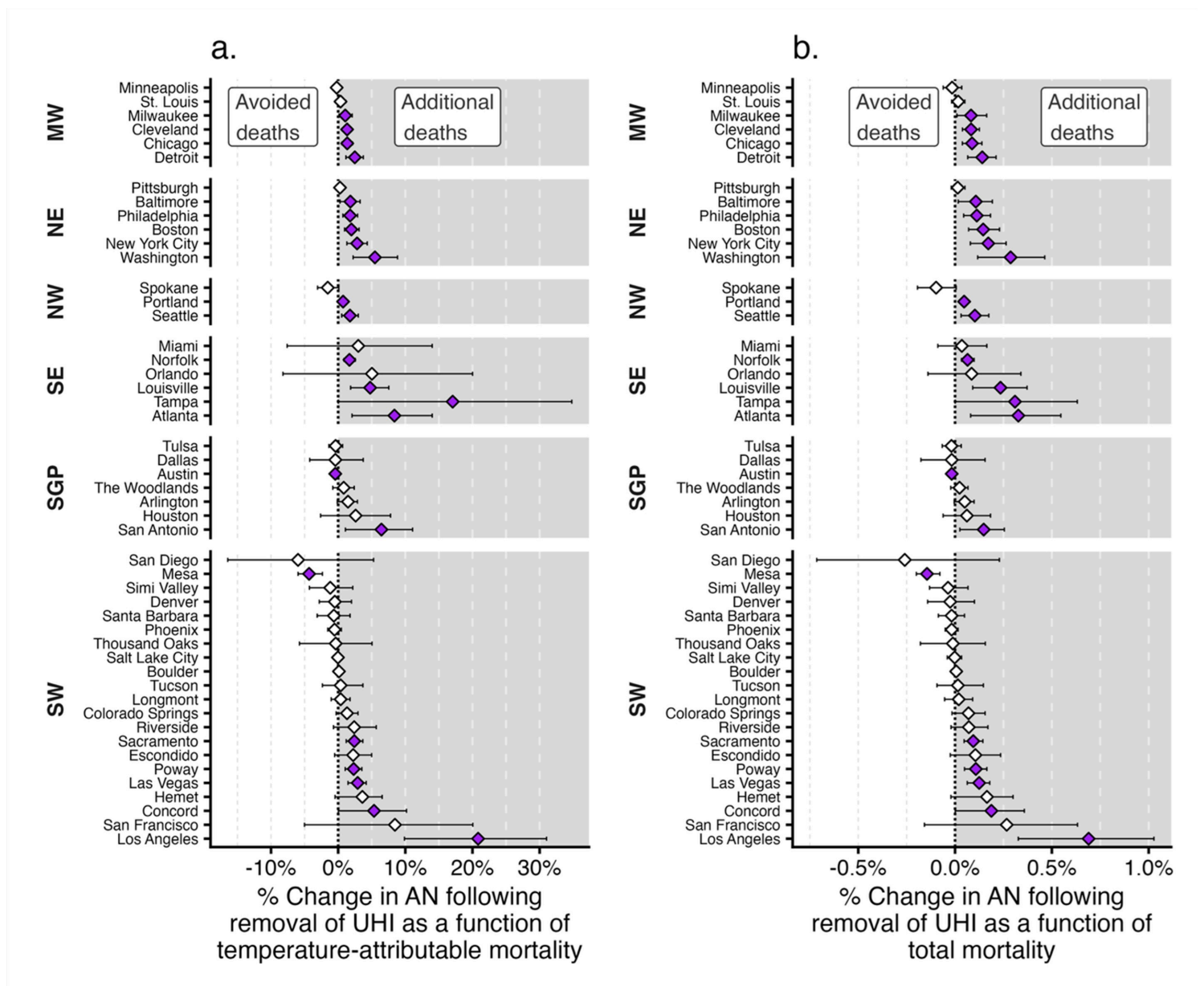


Figure 5

Estimated changes in mortality associated with the theoretical removal of the Urban Heat Island in 49 US cities, expressed as % changes in attributable number (AN) and 95% confidence interval as a function of (a) temperature-attributable mortality and (b) total mortality. Positive numbers indicate more deaths estimated under the counterfactual scenario of no UHI compared to the present-day observed values. Cities are grouped by US Climate Regions: Midwest (MW), Northeast (NE), Northwest (NW), Southeast (SE), Southern Great Plains (SGP) and Southwest (SW).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementalFigures.docx](#)