HHS Public Access
Author manuscript
Ecohealth. Author manuscript; available in PMC 2019 September 01.

Published in final edited form as:
Ecohealth. 2018 September ; 15(3): 485–496. doi:10.1007/s10393-018-1363-0.

Climate Change and Heat-Related Excess Mortality in the Eastern US

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Abstract

Climate change will increase extreme heat related health risks. To quantify the health impacts of mid-century climate change, we assess heat-related excess mortality across the eastern United States. Health risks are estimated using the US Environmental Protection Agency's Environmental Benefits Mapping and Analysis Program (BenMAP). Mid-century temperature estimates, downscaled using the Weather Research and Forecasting model, are compared to 2007 temperatures at 36 km and 12 km resolutions. Models indicate the average apparent and actual summer temperatures rise by 4.5° and 3.3 °C, respectively. Warmer average apparent temperatures could cause 11,562 additional annual deaths (95% Confidence Interval, CI: 2,641–20,095) due to cardiovascular stress in the population aged 65 years and above, while higher minimum temperatures could cause 8,767 (95% CI: 5,030–12,475) additional deaths each year. Modeled future climate data available at both coarse (36 km) and fine (12 km) resolutions predict significant human health impacts from warmer climates. The findings suggest that currently available information on future climates is sufficient to guide regional planning for the protection of public health. Higher resolution climate and demographic data are still needed to inform more targeted interventions.

Keywords

heat wave; heat stress; climate modeling; health impact assessment; downscaling; scenario; climate change

1.0 Introduction and Purpose

Climate change poses numerous threats to human health, most directly through extreme heat exposures. Higher temperatures are linked with elevated mortality in many parts of the world

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(Rupa Basu 2009). In the US, an average of 658 deaths are classified as directly attributable to heat-related causes annually (Centers for Disease Control and Prevention 2013). The total impact is likely greater because heat-related deaths are routinely classified under other causes (Donoghue et al. 1997). In the US, extreme heat events cause more deaths each year than all other extreme weather events combined (Luber and McGeehin 2008). Elevated greenhouse gas concentrations are expected to increase the variability of summer temperatures globally (Diffenbaugh 2005). Along with increases in mean air temperatures, enhanced climatic variability is predicted to lead to more frequent, persistent, and intense heat waves (Meehl 2004; Goodess 2013; Luber and McGeehin 2008).

Epidemiologic studies indicate that chronic (seasonal) exposure to elevated temperatures presents a significant health risk to populations (R. Basu 2002; Rupa Basu 2009). Estimates of the mortality impacts of long-term temperature change vary substantially by region due to differences in exposure patterns and adaptive capacities in populations (Kovats and Hajat 2008). One US study found stronger exposure-response effects in cities with a greater temperature variability (Braga, Zanobetti, and Schwartz 2001; O'Neill 2005).

The accurate assessment of future exposures to warmer temperatures is a challenge in health impact assessment. We attempt to improve estimates of mid-century climatic conditions by using a constrained dynamical downscaling approach with a coupled global-regional climate model and focusing on a single future summer (Harkey and Holloway 2013; Abel et al. 2018). Constraining the downscaled climate simulation to a parent dataset minimizes departures from the underlying projection, while allowing for a physically consistent and continuous representation of climate at a finer scale than the parent data. This method improves upon the spatial estimates of temperature previously applied in studies of climate change, ambient air temperatures, and health risks in the US (Voorhees et al. 2011).

We consider the effects of long-term changes in seasonal temperatures on mortality risks, rather than the health effects of acute heat waves. While elevated average temperatures increase health risks on acute time scales (Filleul et al. 2006; Matsueda 2011), adverse effects on human health for exposures over longer time horizons are also clear (R. Basu 2002; Zanobetti and Schwartz 2008; Kovats and Hajat 2008). There is a high likelihood that climate change will amplify the severity and duration of future heat waves, but disagreement among climate models as to the mid-century temperature profile of the study region (Harkey and Holloway 2013; Abel et al. 2018).

2.0 Methods

2.1 Study Region

Our area of analysis contains much of the eastern United States (Figure 2). Studies of the temperature–mortality relationship suggest that urban populations in this region could experience a high number of heat-related deaths in response to increases in summer temperatures due to high population density and demographic trends (McGeehin and Mirabelli 2001; Greene et al. 2011).

2.2 Modeling Climate Change

While climatic patterns are generally considered as thirty-year averages, high-resolution regional models are too computationally demanding to support the temporal scope of the health impact assessment presented here. Calculating the effects of long-term temperature change on health requires the selection of a baseline scenario for comparison. We chose the summer of 2007 as the baseline scenario because it adequately simulates presentday summer temperature and air pollution exposure patterns across the study region and corresponds to a parallel climate impacts downscaling study (Harkey and Holloway 2013). Present-day summer temperature patterns across the study region were simulated using North American Regional Reanalysis (NARR) data (Mesinger et al. 2006). NARR data comprise long term datasets that simulate land–atmosphere interaction on a 36 km grid, are output every three hours from January 1979 to the present, and provide a dynamically consistent meteorology based on observations, with no discontinuities or gaps as might exist in an observational data set. In 2007, summer temperatures were near normal in the northeast, and above normal in the southeast and midwest (Harkey and Holloway 2013).

A future summer for analysis was chosen after reviewing historic simulations of conditions from all available datasets within the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al. 2009). NARCCAP includes a suite of global and regional climate model pairs. NARCCAP data, built on a series of atmosphere-ocean general circulation models and regional climate models, provide a range of regional projections for 2041–2070 at a 50 km resolution. All model pairs within NARCCAP assume the A2 emissions scenario of the Intergovernmental Panel on Climate Change, a trajectory that mirrors current trends (Nakicenovic et al. 2000) Based on its correlation with NARR data for summers from 1981–1995, we selected the Weather Research Forecast-Canadian Community System Model (WRF-CCSM) pairing. From the future WRF-CCSM simulations, we selected a year (2069) representing the highest average summer (June-August) temperature for the region. This scenario demonstrates a potential upper bound for health risks associated with exposure to higher summer temperatures (Harkey and Holloway 2013). We refer to this future year as a mid-century estimate, because 2069 reflects sampling from model data spanning 2041–2070. To calculate effects of long-term temperature change on health risks, future summer temperatures were compared to the year 2007. For more information on the selected climate. change scenario summer and modeling methods, see (Abel et al. 2018).

NARR data were run through the WRF model using the same constraining technique as was used to downscale NARCCAP data. Because neither the NARR nor NARCCAP data are archived with sufficient spatial or temporal resolution to support our health impact analysis, we calculated baseline and future air temperatures at 2 meters above ground level using the Advanced Research WRF (WRF-ARW) core of the National Center for Atmospheric Research Weather Research and Forecasting model. WRF simulations employed dynamical downscaling to maximize agreement with the input data (NARR for 2007; NARCCAP for 2069) at 36 km and 12 km resolution. This downscaling technique, in which the entire study domain is constrained to coarser resolution parent climate data, offers more consistent and readily comparable results (see Harkey and Holloway 2013). Although we focus on a single future year, by constraining to the NARCCAP projections, we can evaluate results in the context of a multi-year, multi-model climate ensemble. Minimum and average 2-m air temperature data at 36 km and 12 km resolution were exported from WRF, averaged at the grid level, and then used as exposure inputs for the heat stress mortality analysis. Average daily apparent temperature data (which take into account the effect of humidity on the experience of heat (Steadman 1984)) and minimum daily temperature data were calculated in both present-day and future modeling domains.

2.3 Health Impact Modeling

We quantify heat-related excess mortality using modeled average minimum daily and average daily apparent temperature data from WRF as direct inputs into the Benefits Mapping and Analysis Program (BenMAP), which considers environmental, demographic, health incidence, and concentration-response relationships (US Environmental Protection Agency 2010; Fann et al. 2012; Grabow et al. 2012). This method treats temperature as an exposure analogous to air pollution within a quantitative epidemiologic framework (Voorhees et al. 2011; Stone Jr et al. 2014; Vargo et al. 2016). Our modeling improves upon previous work by incorporating 12 km resolution data (compared to 36 km), considering a distinct mid-century climate change exposure scenario drawn from NARCCAP, and encompassing a broader geographic study area. Changes in temperature metrics are linked to health responses (quantified changes in relative risk, with associated measure of uncertainty) using relative risk estimates derived from epidemiologic studies and baseline health incidence information at the county level. Because the underlying health response functions deployed within BenMAP are based on epidemiologic analyses that consider confounding in their quantitative findings, we do not adjust our results for any additional potentially confounding variables or possible effect modifiers, such as present-day or future air pollution exposures. We considered two temperature metrics as inputs within BenMAP: (1) the minimum temperature as the lowest average 2-m air temperature experienced in each grid cell over the entire summer, and (2) the average apparent temperature, also in each grid cell over the entire summer, extracted from WRF (Skamarock et al. 2005). These metrics align with the exposure-response functions applied to estimate health risks.

2.4 Population

To calculate changes in annual morbidity outcomes, BenMAP version 4.0.67 includes population data from the US Census Bureau. These data include information on the age, sex, and racial composition of each grid cell. BenMAP includes decadal estimates of future population counts from an economic forecasting model (Woods and Poole Economics, Inc. 2001). To calculate population-wide exposures, we apply a projected population for 2040 as an input, the best-available projection available most consistent with a mid-century exposure scenario (Charles Fulcher, personal communication, March 17, 2014).

2.5 Baseline and Future Mortality Rates

The spatial specificity of baseline mortality rate input data in the US varies by health outcome and location. BenMAP mortality data is based on 2004–2006 data for the entire US. This information includes individual-level death information, including county, age at death, month of death, and underlying cause (International Classification of Disease, ICD-10 codes). For each exposure-response function, we selected the baseline rate or combination of rates that most closely matched the epidemiologic study endpoint definition (US Environmental Protection Agency 2010). More information on BenMAP inputs and baseline and projected age-, cause-, and county-specific mortality rates can be found in documentation (Abt Associates 2010).

2.6 Applying Exposure-Response for Exposure to Extreme Heat

In contrast to prospective cohort study data applied in BenMAP for modeling of long-term exposures to air pollution, exposure-response estimates utilized for heat stress are largely derived from case-crossover studies. These studies explore associations between changes in daily temperature exposures and health, and by design allow adjustment for known and unknown time-invariant confounding variables—as a result, we do not adjust for any additional potential confounding or effect modifying variables, such as air pollution exposures (Maclure 1991; Bateson and Schwartz 2001).

Three epidemiologic exposure-response estimates for heat stress mortality identified by US EPA for their external validity are used to estimate the burden of heat-related excess mortality (Table 1) (Rupa Basu, Domini, and Samet 2005; Zanobetti and Schwartz 2008; Medina-Ramón and Schwartz 2007). Variation in risk estimates between these studies is due to exposure-response relationships derived from different source populations, study locations, and time periods. Two of these studies examined the effects of changes in mean summer apparent temperature between May-September, while Medina-Ramón and Schwartz assessed risks posed by changes in the minimum summer temperature; both metrics are common in the literature (Basu 2008; R. Basu and Ostro 2008; Medina-Ramón and Schwartz 2007; Zanobetti and Schwartz 2008; Rupa Basu, Domini, and Samet 2005). To estimate the combined cardiovascular and respiratory effects in the population aged 65–99 over our study region and reduce the influence of spatial variation in risk and adaptive capacity, we applied a regional risk estimate from Basu, Dominici and Samet for the northeastern US.

2.7 Spatial Analysis of Health Impacts

To quantify geographic patterns of heat-related health risks, we analyze output at the county scale. Mortality estimates associated with summer temperature data for the 12 km and the 36 km WRF output are compared to determine if urban areas are disproportionately vulnerable to heat-related mortality risks compared to rural ones. Using a modified version of the National Center for Health Statistics' Urban-Rural Classification Scheme for counties (Centers for Disease Control and Prevention 2014) we apportion county-level mortality risks among four urbanization categories: core metropolitan (urban centers with populations >1 million), suburban (large fringe metropolitan counties), periurban (small and medium metropolitan counties), and rural areas (micropolitan and noncore counties).

3.0 Results

3.1 Monthly Temperature Data

Climate modeling resulted in hourly temperature estimates for June-August in 2007 and 2069 at 36 km and 12 km resolutions. In comparing modeled current and future temperatures, average monthly temperatures are distributed fairly uniformly over time, with higher anticipated apparent and minimum temperatures expected in the future (Table 2). Temperatures generally rise over the course of the summer, though in some cases, August temperatures are slightly cooler than July temperatures. Because we consider conditions in 2007 and 2069, we do not present data for any of the intervening years.

3.2 Average Summer Temperatures

Summer temperature averages are presented in Table 3. The average apparent summer temperature increased by 4.5 °C (12 km) and 5.4 °C (36 km) and the average minimum summer temperature rose by 3.3 °C (12 km) and 2.2 °C (36 km) over the same period. For average apparent temperature estimates, the 36 km data for 2069 were slightly warmer than the 12 km estimates. For the average minimum temperature values, temperature increases were slightly higher at the 12 km scale.

Figure 1 shows the distribution of average actual and apparent temperatures in the baseline (2007) and comparison (2069) years. Modeled apparent temperatures are generally higher than ambient temperatures at mid-century, but not currently. The warmest temperature values in 2069 exceed those in 2007, and the standard deviation (SD) of 12 km temperature values is also lower in 2069 (SD 2.4 °C for apparent temperature, 3.4 °C for minimum) compared to 2007 (4.9 °C for apparent temperature, 4.7 °C for minimum).

The spatial distribution of mid-century temperatures suggests that warming will be substantial across the study region. Figure 2 displays the change in summer average apparent temperature (Panels A and B) and average minimum temperature (Panels C and D) between 2007 and 2069 at 36 km and downscaled 12 km resolution. Northern latitudes generally experience the greatest change in summer temperatures in 2069, while the southernmost areas analyzed experience moderate cooling or little change from 2007. While 36 km data indicate substantial warming in certain highly-populated regions, the 12 km scale confines the greatest areas of warming to smaller areas. As a result, exposure classification may be a limitation of high-resolution modeling, potentially resulting in an overestimation of temperatures and associated health impacts.

3.3 Health Impacts

Results of heat-related excess mortality (above the expected baseline level of heat-related mortality) using the downscaled temperatures ranged from 5,870–11,562 (Table 4). For our analysis using mean apparent temperature at a 12 km scale, we calculated between 5,870 (95% Confidence Interval, CI: 3,725–8005) and 6,736 (4,277–9,182) deaths for the entire population in the study region in the future (242.5 million). For the analysis of the population aged 65 and older (48.6 million), we calculated 11,562 (2,641–20,095) excess deaths due to extreme heat experienced over the summer. The change in mortality rate is an order of magnitude higher for the elderly population (20.20 excess deaths per 100,000 individuals) compared to the population at-large (2.40–3.23 per 100,000). Because each health impact calculation is based on a unique combination of seasonal temperature exposure estimates, exposure thresholds, and non-overlapping mortality outcomes from distinct epidemiologic studies that adjust for potentially confounding and effect-modifying variables such as air pollution exposures, these estimates should be interpreted as independent projections rather than additive ones. The estimated number of additional deaths did not vary significantly across climate model resolutions or health impact function utilized.

3.4 Spatial Distribution of Health Impacts

Overall, core metropolitan counties experience the greatest increases in ambient temperatures between the 2007 summer and mid-century estimate compared to rural counties (see Table 4). Due to relatively greater increases in summer temperatures from 2007 to mid-century and high population densities, urbanized areas experience a disproportionately large heat stress mortality rate (for the elderly population, 26.53 deaths per 100,000 in core metropolitan counties compared to 20.55 per 100,00 in rural counties). Mortality rates in core metropolitan counties are between 4–51% higher than in rural counties, though differences are not statistically significant. There are inconsistent patterns in mortality rates when comparing core metro, suburban, periurban and rural counties across exposure spatial resolutions and temperature metrics. Figure 3 depicts the spatial distribution of health impacts at a county scale for the age 65+ group. Here, population-weighted death rates categorized by quintile show the greatest changes in heat-related excess death rates in northern latitudes, consistent with the temperature results presented in Figure 2. Many of the most urbanized counties are expected to experience the greatest heat-related health impacts in the future, indicating that these areas warrant special consideration in climate adaptation and health system planning to avoid adverse health outcomes and improve the resilience of urban communities to extreme heat exposures.

4.0 Discussion

Results are consistent with published estimates of anticipated future heat-related mortality, though cross-study comparisons are complicated by distinct exposure scenarios, exposure data resolution, and regions of analysis (Voorhees et al. 2011; Doyon, Belanger, and Grosselin 2008; Deschênes and Greenstone 2007). In a national study employing similar modeling methods and mid-century temperature estimates, Voorhees et al. found larger mortality estimates overall; impacts were slightly elevated when apparent temperature was considered. While direct quantitative comparisons to other studies are difficult due to different exposure and health metrics, a consistency with patterns in heat-mortality projections is apparent. A study considering a business-asusual emissions scenario found a 3% rise in the age-adjusted mortality rate in 2100 in response to changes in daily temperatures, and identified subpopulations particularly vulnerable to extreme heat exposures not studied here, including infants (Deschênes and Greenstone 2007). Moreover, in modeling extreme heat event days, (Greene et al. 2011) projected spatial trends in mortality impacts consistent with our analysis, as the northeastern US experiences elevated risks that rise as warming accelerates by the end of the century. Heat-related mortality rates are higher at northern latitudes (Figure 3), consistent with the largest anticipated temperature changes by mid-century.

For health impacts related to chronic heat stress, uncertainty in exposure-response estimates applied in BenMAP appears to outweigh uncertainty in exposure classification from coarse model resolution. Our use of temperature data at a 12 km scale resulted in health impacts that were 10–13% lower than when calculated using 36 km exposure data, though this difference was not statistically significant (see Table 4). Like Thompson et al. (2014), we found that higher spatial resolution modeling in BenMAP led to lower health impacts than coarse resolution simulations, although we examine heat stress instead of air pollution (Thompson, Saari, and Selin 2014).

Several factors explain variation between our calculated mortality impacts and those of other studies of anticipated climatic effects on harmful exposures to extreme heat. Our analysis is geographically restricted to the eastern US, with a climate projection downscaled from a national dataset (Abel et al. 2018). This focus highlights differences in temperature estimates between distinct regional climate and atmosphere-ocean general circulation models. Specifically, the average and minimum temperatures for the entire domain in WRF were higher for 36 km data compared to dynamically downscaled 12 km data (see Figure 2, Tables 2 and 3). While the downscaled data more adequately represents spatial variation in exposure to extreme heat, the overall lower temperature values reduced ultimate impacts on mortality. Our selection of a subset of epidemiologic studies as used in Voorhees et. al (Table 1) allows for direct comparability of mortality estimates, however the application of additional exposure-response functions in BenMAP could yield substantially different results, depending on the temperature metric and threshold applied.

The magnitude of health impacts in any given year depends on interannual variability in meteorology, and the selection of a particular mid-century estimate of warming from NARCCAP allows us to contextualize heat-related health impacts. Relative to temperature data analyzed in Harkey and Holloway (2013), 2069 reflects a slightly smaller temperature increase from 2007 than the difference in the modeled climatic means for 1979–1999 and 2041–2070, respectively. The particular model combination and future year applied here is the warmest future summer simulated by the WRF-CCSM combination, a model pairing which best represented past conditions (Harkey and Holloway 2013; Abel et al. 2018). As a result, the health impact estimates presented represent a potential upper bound of annual excess heat mortality by the middle of the century.

We observed comparable impacts when applying changes in summer (chronic) average apparent temperatures and minimum temperatures, even though increases in the average apparent temperatures were greater than the increases in actual minimum temperatures. Variation in excess mortality estimates reflects the current substantial, but still emerging, knowledge in epidemiologic literature as to the impacts of temperature exposures on human health. Findings suggest the importance of multiple risk factors (such as age, race, and location) operating in tandem on different temporal trajectories to confer health risks.

While our analysis is confined to a three-month summer period, BenMAP estimates reflect annualized excess heat-related mortality estimates. The use of BenMAP and seasonal temperature data from WRF allows for more readily interpretable results, but also implies a regional consistency in conditions that may not reflect the pattern of future exposures and may obscure the more acute health effects of extreme heat exposures. As an increase in summer temperature-related mortality is consistently anticipated in studies of climate change, so are decreases in cold-related deaths. Modeling of future summer and winter climate scenarios for New York City and Europe indicates that the net effect of future warming will be an increase in the number of annual deaths (Li, Horton, and Kinney 2013; McMichael, Woodruff, and Hales 2006).

While the modeled future summer indicates an earlier onset of warmer temperatures and a July temperature peak (Table 2), the effects of unusually early warmer temperatures are not captured in modeling of seasonal temperature change using BenMAP. There is evidence to suggest that the timing and sequence of heat waves are significant predictors of mortality, with early events presenting a disproportionately high risk (Anderson and Bell 2011). As a result of this limitation, we may underestimate the mid-century summer burden of heat-related mortality. Our modeling indicates earlier warmer temperatures, but we did not analyze data for May, during which the largest marginal impacts of high temperatures would be expected based on current evidence (Hajat et al. 2002).

Analysis at the 12 km scale is a nine-fold improvement over published estimates at 36 km (Voorhees et al. 2011; Li, Horton, and Kinney 2013), but is still limited by use of ambient temperature as a personal exposure surrogate. Exposure misclassification resulting from this assumption is tied to the degree of correlation between ambient and microenvironmental temperatures (Kloog et al. 2012) and could increase over time along with adaptive responses to climate change by mid-century. Modeling at a 12 km scale, while capturing a portion of the urban temperature profile and disproportionate health impacts in cities, is still too coarse to identify neighborhood-level microclimates which pose especially high health risks to vulnerable populations and the characteristics of cities which ultimately determine risk (Harlan et al. 2006; Kinney et al. 2008).

Other key risk factors predisposing certain populations to heat stress vulnerability, such as socioeconomic status, social isolation, and lack of mobility (Semenza et al. 1996; Vandentorren et al. 2006; Hajat, O’Connor, and Kosatsky 2010; Yardley, Sigal, and Kenny 2011) are not addressed in BenMAP modeling. We lack adequate spatiallyresolved information about adaptive measures such as air conditioning prevalence in the study region, the effect of which is only partially captured using region-specific exposure-response functions in BenMAP (Medina-Ramón and Schwartz 2007).

5. Conclusion

Modeled future climate data available at both coarse and fine resolutions predict significant human health impacts from a warmer climate, and many of the most urbanized counties are expected to experience the greatest heat-related health impacts. Findings suggest that currently available information on future climates is sufficient to guide regional planning for the protection of public health.

Acknowledgments:

Research was supported by the U.S. National Institute of Environmental Health Sciences (NIEHS) grant 1R21ES020232–01. V.L. was also supported by NSF grant DGE-0549407, an Integrative Graduate Education and Research Traineeship (IGERT) titled “Vulnerability and Sustainability in Coupled Human-Natural Systems.” TH and MH were also supported by the NASA Air Quality Applied Sciences Team (AQAST). We acknowledge the North American Regional Climate Change Assessment Program (NARCCAP) and the National Climatic Data Center (NCDC) for providing the data used in this paper. NARCCAP is funded by the National Science Foundation, the U.S. Department of Energy, the National Oceanic and Atmospheric Administration, and the U.S. Environmental Protection Agency Office of Research and Development. The NCDC provided North American Regional Reanalysis (NARR) data from the National Centers for Environmental Prediction (NCEP), a division of NOAA/National Weather Service.

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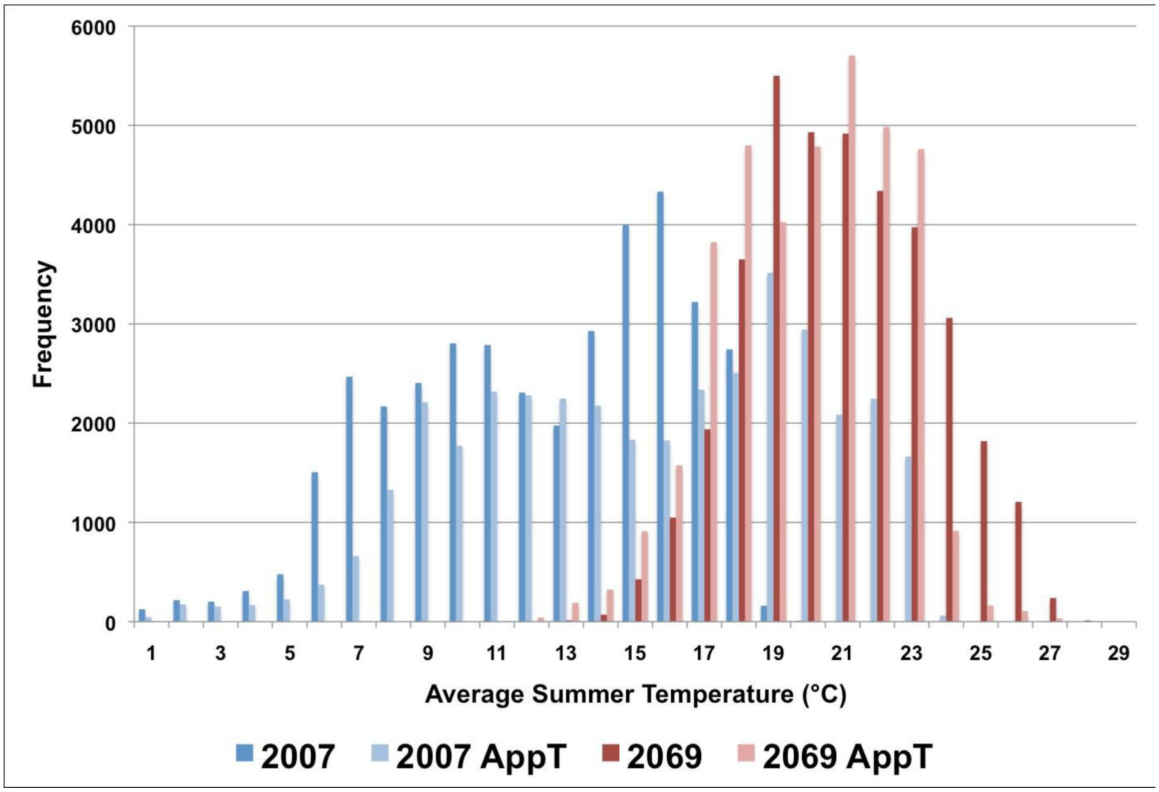

Figure 1:
Frequency of daily average actual and apparent summer temperature values at 12 km scale applied in BenMAP grid cells for baseline (2007, blue bars) and future (2069, red bars) scenarios.

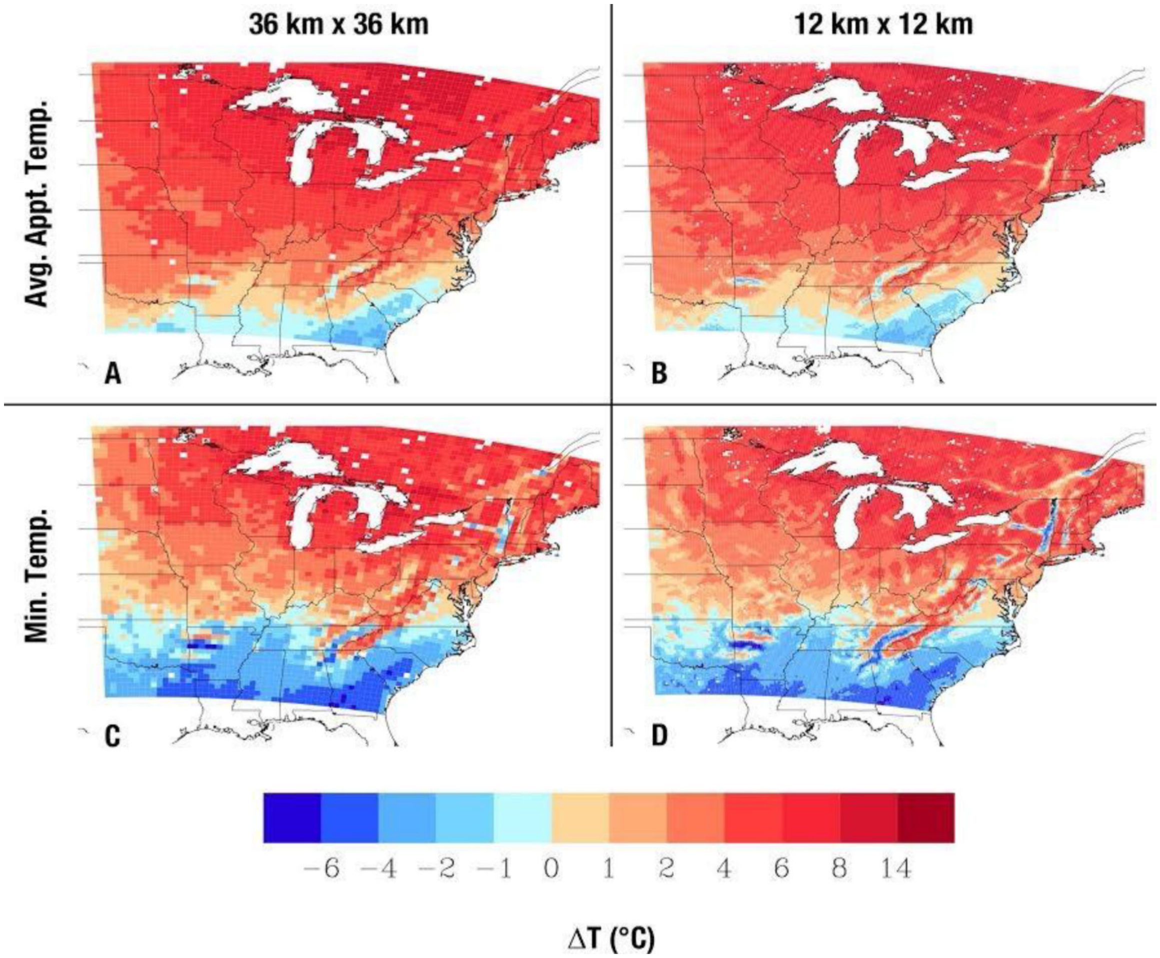

Figure 2:

Change in summer temperatures (°C) between 2007–2069. Average apparent temperature at the (A) 36 km and (B) 12 km resolution. Minimum temperature change at the (C) 36 km and (D) 12 km resolution.

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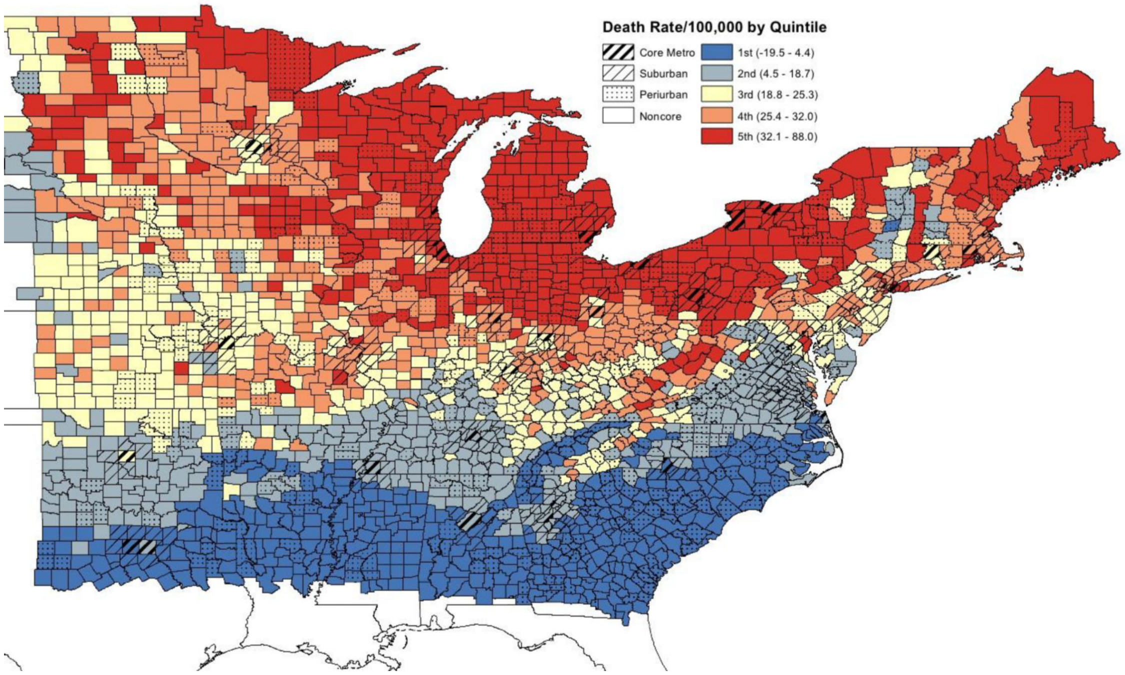

Figure 3:

Heat-related mortality rate per Change in heat-related mortality rate per 100,000 by 2069 by quintile in the age 65 + group as calculated in BenMAP, aggregated by county.

Table 1:

Exposure-response functions for long-term changes in ambient temperature applied in BenMAP.

Study	Study Type	Health Outcome	Functional Form	Temperature Metric	Threshold	Relative Risk (95% CI)
Basu, Dominici and Samet (Rupa Basu, Domini, and Samet 2005)	Case-Crossover	Combined cardiovascular and respiratory deaths, ages 65–99, northeastern US	Conditional logistic regression	Mean daily apparent T (June-August)	None	1.08 (1.02, 1.15) per 5.5 °C
Zanobetti and Schwartz (Zanobetti and Schwartz 2008)	Case-crossover	Non-accidental deaths, all ages	Conditional logistic regression	Mean daily apparent T (May-September)	None	1.018 (1.0109, 1.025) per 1 °C
Medina-Ramón and Schwartz (Medina-Ramón and Schwartz 2007)	Case-crossover	All-cause deaths, all ages	Conditional logistic regression	Minimum daily T, 2day cumulative (May-September)	>17 °C	1.0043 (1.0024, 1.0061) per 1 °C

Table 2:

Monthly summer temperature metrics for baseline (2007) and future (2069) scenarios at a 12 km and 36 km resolution.

Year	Month	Average Apparent Temperature (Standard Deviation) (°C)		Average Minimum Temperature (Standard Deviation) (°C)	
		12 km	36 km	12 km	36 km
2007	June	21.4 (3.9)	20.8 (4.9)	16.3 (4.3)	16.3 (4.3)
	July	23.2 (3.7)	23.1 (4.5)	18.0 (4.5)	18.1 (4.5)
	August	24.3 (4.5)	24.6 (5.6)	19.1 (5.2)	19.2 (5.3)
2069	June	26.8 (3.5)	26.7 (3.5)	19.9 (4.2)	19.9 (4.2)
	July	29.1 (2.7)	29.0 (2.6)	22.0 (3.3)	22.0 (3.2)
	August	28.9 (2.6)	28.8 (2.6)	21.2 3.4)	21.3 (3.3)

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Table 3:

Summer temperature metrics for baseline (2007) and future (2069) scenarios.

Summer Year (June-August)	Average Apparent Temperature (Standard Deviation) (°C)		Average Minimum Temperature (Standard Deviation) (°C)	
	12 km	**36 km**	**12 km**	**36 km**
2007	22.9 (4.9)	22.8 (4.9)	17.7 (4.7)	17.9 (4.6)
2069	27.4 (2.4)	28.2 (2.6)	21.0 (3.4)	21.1 (3.3)
Change in average between 2007 and 2069	*+4.5*	*+5.4*	*+3.3*	*+3.2*

Table 4.

Distribution of Mid-Century Temperature Changes, Excess Heat Stress Mortality, and Changes in Mortality Rates per 100,00 Population by County Urbanization Class.

Metric	Basu, Domenici & Samet, 2005 (Mean Apparent Temperature)		Zanobetti & Schwartz, 2008 (Mean Apparent Temperature)		Medina-Ramón & Schwartz, 2007 (Minimum Temperature)	
	12 km	36 km	12 km	36 km	12 km	36 km
2007–2069 Change in Temperature, °C (Min., Mean, Max.)	−2.61 3.44 12.03	−2.95 4.21 16.39	−2.61 3.43 12.02	−2.94 4.21 16.46	−4.51 2.06 10.24	−4.53 2.14 12.44
Urban class (# counties):						
Rural/noncore (1,459)	−2.61 3.47 12.03	−2.95 4.35 16.39	−2.61 3.47 12.02	−2.94 4.35 16.46	−4.51 2.18 10.24	−4.31 2.16 12.44
Periurban (499)	−2.43 3.13 9.38	−2.48 3.75 13.36	−2.43 3.12 9.6	−2.42 3.75 13.36	−4.24 1.52 7.51	−4.53 1.8 9.54
Suburban (289)	−0.33 3.67 9.53	−0.88 4.15 12.07	−0.27 3.66 9.46	−0.87 4.15 12.02	−2.3 2.26 8.08	−2.62 2.46 10.08
Core metro (40)	0.05 4.44 8.98	−0.29 5.01 11.88	0.06 4.44 8.93	−0.3 5.01 11.88	−2.45 3.37 8	−2.16 3.55 9.22
Population	48,603,337	48,603,337	242,534,475	242,534,475	242,534,475	242,534,475
Urban class (# counties):						
Rural/noncore (1,459)	10,374,823	10,374,823	44,638,833	44,638,833	44,638,833	44,638,833
Periurban (499)	14,170,419	14,170,419	70,730,896	70,730,896	70,730,896	70,730,896
Suburban (289)	16,200,902	16,200,902	81,654,315	81,654,315	81,654,315	81,654,315
Core metro (40)	7,857,193	7,857,193	45,510,431	45,510,431	45,510,431	45,510,431
Additional Deaths (95% Confidence Interval)	11,562 (2,641, 20,095)	13,177 (3,027, 22,818)	5,870 (3,725, 8,005)	6,736 (4,277, 9,182)	8,767 (5,030, 12,475)	9,739 (5,590, 13,856)
Urban class (# counties):						
Rural/noncore (1,459)	2,283 (522, 3,967)	2,559 (588, 4,433)	1,138 (722, 1,552)	1,285 (816, 1,751)	1,423 (817, 2,024)	1,487 (853, 2,115)
Periurban (499)	2,877 (657, 5,001)	3,355 (770, 5,815)	1,480 (939, 2,018)	1,739 (1,104, 2,370)	1,789 (1,027, 2,544)	2,181 (1,252, 3,103)
Suburban (289)	4,061 (926, 7,068)	4,619 (1,060, 8,005)	2,051 (1,301, 2,797)	2,344 (1,488, 3,196)	3,441 (1,973, 4,899)	3,783 (2,170, 5,384)

Metric	Basu, Domenici & Samet, 2005 (Mean Apparent Temperature)		Zanobetti & Schwartz, 2008 (Mean Apparent Temperature)		Medina-Ramón & Schwartz, 2007 (Minimum Temperature)	
	12 km	**36 km**	**12 km**	**36 km**	**12 km**	**36 km**
Core metro (40)	2,341 (536, 4,060)	2,644 (610, 4,565)	1,202 (763, 1,638)	1,369 (869, 1,865)	2,114 (1,213, 3,007)	2,289 (1,314, 3,254)
Change in Mortality Rate (per 100,000)	20.20	24.32	2.40	2.89	3.23	3.35
Urban class (# counties):						
Rural/noncore (1,459)	20.55	25.34	2.53	3.12	3.51	3.53
Periurban (499)	18.22	21.42	2.06	2.41	2.27	2.56
Suburban (289)	20.95	23.48	2.33	2.63	3.31	3.63
Core metro (40)	26.53	29.57	2.52	2.81	4.43	4.67