

Climate Change-Related Temperature Impacts on Warm Season Heat Mortality: A Proof-of-Concept Methodology Using BenMAP

A. Scott Voorhees,* Neal Fann, Charles Fulcher, Patrick Dolwick, Bryan Hubbell, Britta Bierwagen, and Philip Morefield

United States Environmental Protection Agency (US EPA), 109 TW Alexander Drive, Research Triangle Park, North Carolina 27711, United States

ABSTRACT: Climate change is anticipated to raise overall temperatures and is likely to increase heat-related human health morbidity and mortality risks. The objective of this work was to develop a proof-of-concept approach for estimating excess heat-related premature deaths in the continental United States resulting from potential changes in future temperature using the BenMAP model. In this approach we adapt the methods and tools that the US Environmental Protection Agency uses to assess air pollution health impacts by incorporating temperature modeling and heat mortality health impact functions. This new method demonstrates the ability to apply the existing temperature–health literature to quantify prospective changes in climate-sensitive heat-related mortality. We compared estimates of future temperature with and without climate change and applied heat–mortality health functions to estimate relative changes in heat-related premature mortality. Using the A1B emissions scenario, we applied the GISS-II global circulation model downscaled to 36-km using MMS and formatted using the Meteorology–Chemistry Interface Processor. For averaged temperatures derived from the 5 years 2048–2052 relative to 1999–2003 we estimated for the warm season May–September a national U.S. estimate of annual incidence of heat-related mortality to be 3700–3800 from all causes, 3500 from cardiovascular disease, and 21 000–27 000 from nonaccidental death, applying various health impact functions. Our estimates of mortality, produced to validate the application of a new methodology, suggest the importance of quantifying heat impacts in economic assessments of climate change.

INTRODUCTION

The United States Environmental Protection Agency (US EPA) determined that greenhouse gases (GHG) in the environment endanger the public health and welfare of current and future generations.¹ Climate variability and change in the upcoming decades is likely, and rising temperatures are one manifestation of a warming planet. Heat waves and hot weather are expected to increase in frequency.² The intensity of heat events is forecast to increase, and air quality may worsen.³ Global average temperatures are projected to increase between 1.8 and 6.4 °C by the end of this century.⁴ On a continental scale, changes in land cover have already contributed to a surface warming of ~0.27 °C per century in the United States and ~0.05 °C per decade since 1978 in China.^{5–7} Heat was the primary weather-related cause of U.S. mortality in 1995, 1998, 1999, 2000, 2001, and 2002⁸ and was implicated in more than 3400 fatalities between 1999 and 2003, causing more deaths than hurricanes, lightning, tornadoes, and floods combined.⁹ Mortality risks increase with elevated temperatures, they are location dependent, and certain socioeconomic factors such as age and poverty impact health risk during a heat event.^{2,10,11} Increases in mortality risk occur as a result of heat waves and also as a result of high temperatures over longer time periods.¹² The Intergovernmental Panel on Climate Change (IPCC) states that hot days and nights, as well as heat waves, have become more frequent in recent years.¹³ Climate change is anticipated to both raise the overall temperature distribution and contribute to an increase in the frequency and intensity of heat waves.¹⁴ Demographic shifts in the United States are expected to produce a larger population with a higher mean age and heightened vulnerability to health risks.^{2,11}

Here we describe the US EPA's proof-of-concept approach to estimating excess heat-related premature deaths using the Environmental Benefits Mapping and Analysis Program (BenMAP) benefits model. BenMAP was designed to estimate the health impacts associated with a change in air quality using a damage function approach to calculate changes in the incidence of adverse health outcomes, assigning values and summing the values for nonoverlapping health end points to characterize total health impacts.¹⁵ This is a standard approach used in environmental cost–benefit analyses.^{16–22} We used BenMAP for the first time to treat temperature as a pollutant, comparing estimated changes in future temperature with and without climate change to present day temperatures, and apply heat–mortality health functions to estimate relative changes in mortality for the continental United States.

MATERIALS AND METHODS

The EPA relies on a damage function approach that relates changes in air pollution exposure to health and productivity impacts using health impact functions that quantify the incidence of pollution-related adverse health events

$$\Delta y = y_0 \cdot (e^{\beta \cdot \Delta x} - 1) \cdot \text{Pop}$$

where Δy is the change in the health or environmental effect, y_0 is the baseline incidence rate for the effect, the unitless coefficient

Received: August 17, 2010

Accepted: December 20, 2010

Revised: December 16, 2010

Published: January 19, 2011

Table 1. Studies of Warm Season Mortality

study	functional form	temperature metric	threshold	relative risk (95% CI)	beta coefficient	standard error	mortality classification	study population/ study type
Basu, Feng, and Ostro ³⁸	conditional logistic regression	mean daily apparent T (May–Sept)	none specified	1.023 (1.01, 1.036) per 5.55 °C	0.0040972	0.0011683	nonaccidental	all ages, 9 California counties (1999–2003); time stratified case-crossover
Basu and Ostro ³⁷	conditional logistic regression	mean daily apparent T (May–Sept)	none specified	1.026 (1.013, 1.039) per 5.55 °C	0.0046248	0.0011649	cardiovascular disease	all ages, 9 California counties (1999–2003); time stratified case-crossover
				1.022 (1.0004, 1.04)	0.0039210	0.0017844	nonaccidental	≥65 yrs
Medina-Rámon and Schwartz ³⁵	conditional logistic regression	minimum daily T, 2-day cumulative (May–Sept)	>17 °C	1.0043 (1.0024, 1.0061) per 1 °C (O ₃ adjusted)	0.0042908	0.0009399	all cause	all ages, all counties in 42 cities across the United States (1989–2000); case-crossover
Zanobetti and Schwartz ³⁹	conditional logistic regression	mean daily apparent T (May–Sept)	none specified	1.018 (1.0109, 1.025) per 5.55 °C (PM _{2.5} and O ₃ adjusted)	0.0032	0.0006	nonaccidental	all ages, 9 cities across the United States (1999–2002); case-crossover
Basu, Dominici and Samet ²⁴	conditional logistic regression	mean daily apparent T (Jun–Aug)	none specified	1.15 (1.07, 1.24) per 5.55 °C	0.0251823	0.0067776	combined cardiovascular and respiratory	ages 65–99, 20 largest metropolitan areas of the United States (1992), southwest; time stratified case-crossover
				1.08 (0.92, 1.26)	0.0138669	0.0144555		ages 65–99, 20 largest metropolitan areas of the United States (1992), northwest; time stratified case-crossover
				1.01 (0.92, 1.11)	0.0017929	0.0086294		ages 65–99, 20 largest metropolitan areas of the United States (1992), midwest; time stratified case-crossover
				1.08 (1.02, 1.15)	0.0138669	0.0055138		ages 65–99, 20 largest metropolitan areas of the United States (1992), northeast; time stratified case-crossover
				1.10 (0.96, 1.27)	0.0171730	0.0128626		ages 65–99, 20 largest metropolitan areas of the United States (1992), southeast; time stratified case-crossover

beta (β) is derived from the relative risk (RR) associated with a change in exposure as expressed in concentration–response functions, Δx is the estimated change in exposure, and Pop is the exposed population. This approach is considered reasonable in spite of certain limitations.²³

Health Impact Functions. The literature was surveyed for studies linking temperature to premature mortality. We selected five studies which reported mortality impacts during the U.S. warm season (Table 1). The studies relied on the case-crossover approach, analyzing heat–mortality data using conditional logistic

regression to estimate the increased risk associated with elevated temperatures. Four studies adjusted for humidity. One study reported a 2-day cumulative function. Two of the five studies adjusted for ozone. Due to a RR value higher than those of the other four studies, we treated the Basu, Dominici, and Samet study²⁴ separately in a sensitivity analysis.

Population Data Sets. As described in Hubbell et al.,²⁵ the 2000 U.S. Census block-level data set²⁶ is the source of population data used by BenMAP. These population data are then projected to 2050 using growth factors based on an economic

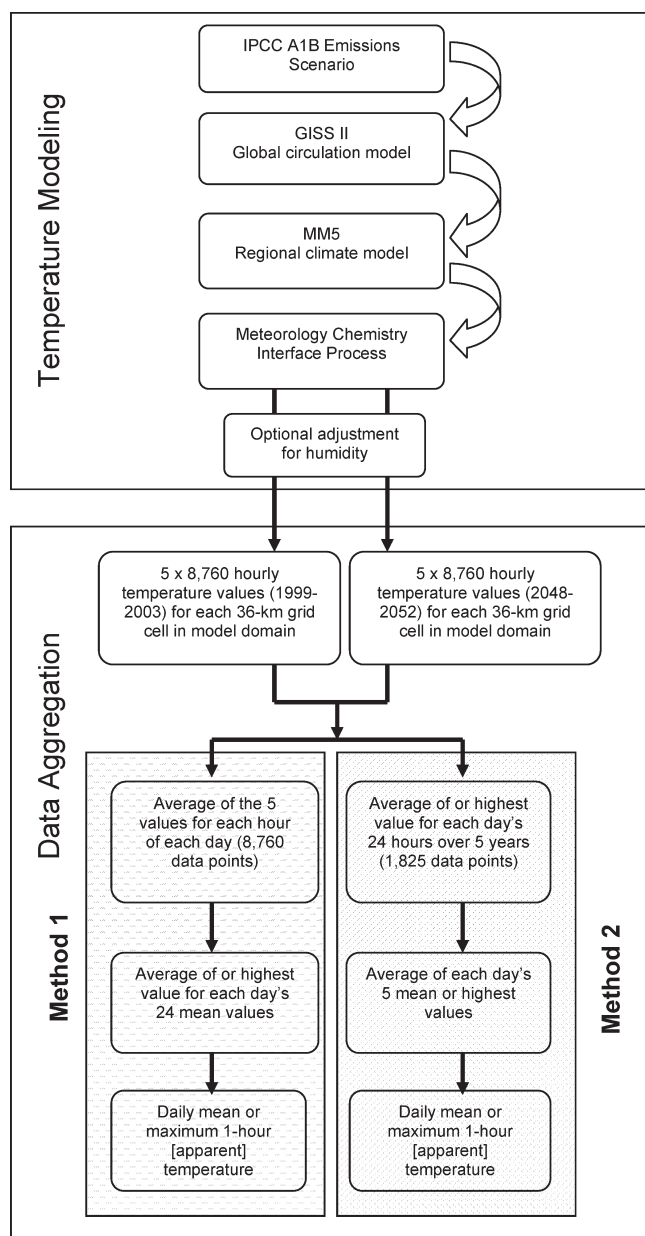


Figure 1. Temperature estimation algorithm.

forecasting model.²⁷ BenMAP allocated these population projections to the resolution of the air-quality model, in this case, with 36 km horizontal grid cell resolution.

Baseline Incidence Rates. The BenMAP model contains county-level cause-specific mortality rates from the CDC-WONDER database.²⁸ Using census projections of mortality rates, BenMAP estimated the mortality rate in 5-year increments to the year 2050. BenMAP allocated these county mortality rates to each grid cell in the model domain using a spatial-weighting algorithm.

Temperature Estimation. We estimated the heat-related mortality occurring from modeled changes in temperature for the continental United States between two time periods; the “baseline” comprised of an average of temperatures between 1999 and 2003, and the “projected” comprised of an average of temperatures between 2048 and 2052. To apply the effect estimates reported in the health literature, it was necessary to

express temperatures using the same summary measurement metrics reported in the health studies. This process is outlined in Figure 1. For the IPCC A1B emissions scenario, the global circulation model GISS-II²⁹ was used to simulate climate for the period 1950–2055. In order to estimate the local scale impacts of global climate change, the simulations were downscaled from the 4×5 degree resolution to a 36-km horizontal grid cell resolution using MM5,^{30,31} part of a regional climate modeling exercise, referred to as the Climate Impact on Regional Air Quality (CIRAQ) project for current (ca. 2000) and future (ca. 2050) climate conditions.³² The Meteorology–Chemistry Interface Processor (MCIP)³³ was used to convert the regional climate MM5 modeling output into Community Multiscale Air Quality (CMAQ)³⁴ modeling inputs. Projecting future temperatures at local scales is a highly uncertain exercise. This analysis utilized a single future climate realization based on a single future emissions scenario and a single set of global–regional climate modeling. Alternate estimates of future temperatures would yield different estimates of health impacts.

Within each of the 15912 grid cells representing the continental United States, we generated 43 800 hourly temperature values for a five baseline year period (1999–2003) and for five projected years (2048–2052). We used 5 years of data to compensate for year-to-year variability due to local weather conditions and applied two data aggregation approaches (Figure 1). Method 1 involved averaging each hour’s value for each of 5 years and then for each day’s resulting 24 mean values, selecting the average and highest values. Method 2 involved first averaging or selecting the highest value for each day’s 24 h separately for each of the 5 years, followed by averaging each day’s resulting five mean or five high values. We generated temperature values for each day of each modeled year, but we reported BenMAP results only for the warm season (from May 1 to Sept 30).

RESULTS AND DISCUSSION

We generated 1-h maximum and 24-h mean temperature and humidity-adjusted “apparent” temperature values in each 36-km grid cell in the modeling domain (Table 2). Both 1-h maximum and 24-h mean values for the warm season (from May 1 to Sept 30) were approximately 2 °C higher in the future scenario. The range of 1-h maximum apparent temperatures shifted from between −3 and 33 °C in model years 1999–2003 to between −2 and 35 °C in model years 2048–2052. The range of 24-h mean apparent temperatures shifted from between −7 and 30 °C (present) to between −5 and 33 °C (future). The percentage of modeled grid cells with projected temperature values ≥ 29 °C rose from 3.4% (present) to 10% (future) for 24-h mean values and from 6.8% (present) to 15% (future) for 1-h maximum values. Median temperatures for modeled grid cells rose from 11.6 (present) to 13.8 °C (future) for 24-h mean values and from 15.6 (present) to 17.7 °C (future) for 1-h maximum values. Figure 2 illustrates the shift in the distribution of 24-h mean apparent temperature. On the high end, the number of grid cells with apparent temperatures in the range 29–31 °C rose from 547 to 820 and jumped from 0 to 850 for temperatures 31–33 °C.

For the 5 years 2048–2052 relative to 1999–2003, we estimated a typical year incidence of heat-related all-cause mortality to be 3700–3800 (95% CI 2300–5300) (0.094–0.098% of all cause mortality), heat-related cardiovascular disease mortality to be 3500 (95% CI 2000–5000) (0.86% of cardiovascular disease mortality), and heat-related nonaccidental mortality to be

Table 2. Temperature modeling results

	mean temperature, °C (low, high)		mean apparent temperature, °C (low, high)	
	method 1	method 2	method 1	method 2
1999–2003				
1-h max	15.92 (−2.58; 33.24)	16.44 (−1.79; 33.42)	15.45 (−3.32; 32.68)	16.01 (−2.77; 33.04)
24-h mean	12.63 (−6.17; 26.90)	12.63 (−6.17; 26.90)	12.21 (−6.53; 30.17)	12.21 (−6.53; 30.17)
2048–2052				
1-h max	17.83 (−1.06; 34.88)	18.36 (−0.33; 35.07)	17.65 (−2.21; 35.02)	18.23 (−1.64; 35.30)
24-h mean	14.59 (−4.23; 28.27)	14.59 (−4.23; 28.27)	14.45 (−5.04; 32.62)	14.45 (−5.04; 32.62)

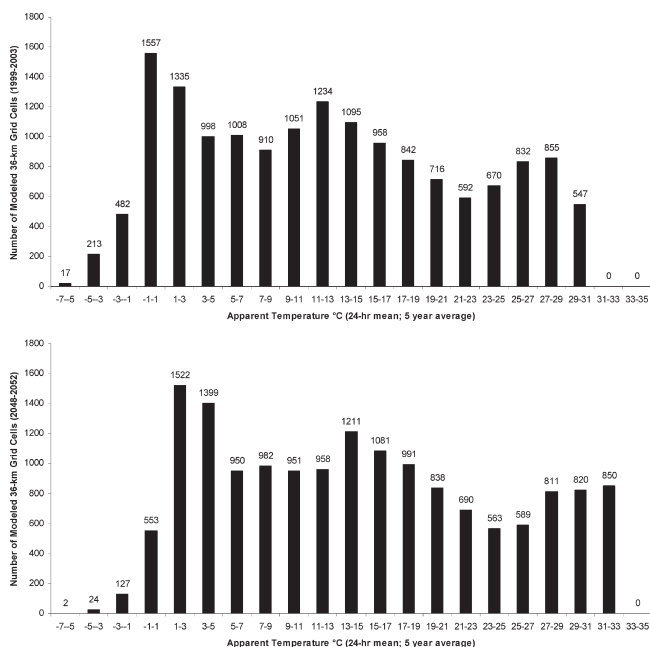


Figure 2. Modeled 24-h mean apparent temperature for two 5-year periods, 1999–2003 (top) and 2048–2052 (bottom), for the continental United States during warm season months of May–September.

21 000–27 000 (95% CI 14 000–40 000) (0.57–0.73% of non-accidental mortality). These results, shown in Figure 3, are independent estimates of heat-related mortality and as such should not be treated as additive. These results represent the differences in temperature between the future and the present in the absence of climate change mitigation activities. The wide variation in mortality estimates reflects the variability in the underlying concentration–response functions which were derived from different populations, locations, and time periods.

Sensitivity and Scenario Analyses. We conducted sensitivity and scenario analyses to evaluate the interaction among each of the three principal analytical inputs: temperature, health function, and population. Starting with temperature, we found that the results are fairly insensitive to unadjusted and apparent temperature (Figure 3). Estimating mortality impacts using risk estimates from Medina-Ramón and Schwartz³⁵ and incorporating an exposure estimate based on apparent temperature produced a result 9% higher than the daily mean temperature. The key difference between apparent and daily temperature is that apparent temperature adjusts for humidity. However, the underlying temperature data are highly correlated (see discussion

in ref 8). This finding is consistent with Anderson and Bell, who concluded that the various temperature metrics will produce similar results.³⁶

In the next sensitivity analysis, we applied five region-specific heat-related mortality impact functions based on risk estimates from Basu et al.²⁴ The resulting national incidence estimate of excess heat-related all-cause mortalities in one averaged year in the future scenario compared to the present scenario (3.1% of all cause mortality) was more than double our estimate applying a Basu and Ostro³⁷ risk estimate function to the same 65+ age cohort. Basu et al.²⁴ relied on a single year’s data, whereas the other studies used data sets of 4 years or longer. Basu et al.²⁴ relied on mortality data for the hottest months of June, July, and August, whereas the other studies analyzed mortality data from May to September. Even with application of risk estimate functions with the same functional form, the same temperature metric, the same mortality end points, and the same warm season duration, the results will differ as the RR differs. This occurred with Basu et al.³⁸ versus Zanobetti and Schwartz,³⁹ where the epidemiological study areas differed and the study duration differed, the RR values were 1.023 and 1.018, respectively, and our estimated nonaccidental heat-related premature mortality incidence was 28% higher with Basu et al.³⁸

Next, we considered the influence of other key inputs including the demographic variables by performing a scenario analysis. To account for the extended time horizon, we projected population and baseline mortality rates. To account for the interaction between climate change and the size and distribution of population growth over time, we utilized four alternative population projections generated by the Integrated Climate and Land-Use Scenarios (ICLUS) project.⁴⁰ This analysis estimated the future size and distribution of the U.S. population based on U.S. Census Bureau population and immigration projections and four social, economic, and demographic storylines adapted from the IPCC Special Report on Emission Scenarios (SRES).⁴¹ The ICLUS project uses high, medium, and low domestic and international migration rates in a demographic model to generate scenarios consistent with the primary SRES storylines. The SRES describe storylines across two axes: economic versus environmentally driven development (A–B) and global versus regional focus (1–2).⁴¹ Each of the four scenarios (A1, A2, B1, and B2) corresponds to different assumptions regarding economic development, fertility, and migration. These factors, in part, determine the levels of GHG emissions projected by climate models. While the ICLUS scenarios are consistent with the SRES storylines, climate or GHG emissions are not explicitly included in the ICLUS scenarios. We therefore included the ICLUS population projections in order to differentiate the effect of demographically and spatially resolved population scenarios.

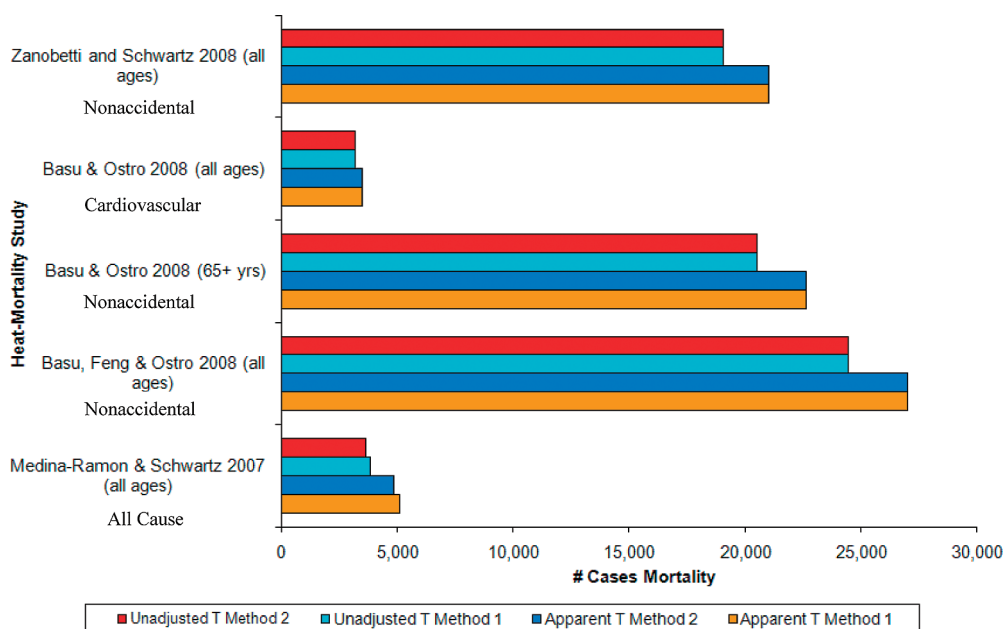


Figure 3. Estimated increases in heat-related premature mortality in a BenMAP model-projected 2048–2052 climate scenario relative to 1999–2004 using modeled mean daily or minimum daily humidity-adjusted (apparent) and unadjusted temperature; heat impact functions taken from different regional population studies. Method 1 is the 24-h mean or 1-h maximum for each hour’s temperatures, followed by averaging for each day. Method 2 is averaging for each day, followed by the 24-h mean or 1-h maximum across years.

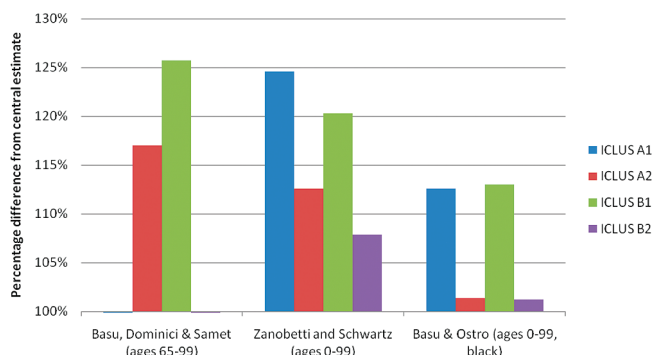


Figure 4. Sensitivity of temperature–mortality estimates to four population projections for three temperature–mortality risk estimates. Each of the four population projections reflects different assumptions regarding the relationship between climate change and economic development, fertility, and migration. The three temperature–mortality risk estimates are based on risk estimates drawn from three different studies of different demographic groups.

Estimated health impacts vary significantly across the four ICLUS population projections and the three selected temperature–mortality estimates (Figure 4). In this portion of the analysis we selected risk estimates from studies that considered specific regions and demographic groups to characterize the interaction between alternate population projections and risk among specific groups. The results indicate that the mortality estimates are highest under scenarios A1 and B1, irrespective of the concentration–response function applied or demographic group considered. The combination of a low fertility rate and high international migration led to a population structure that is older nationwide but particularly in the southeastern United States. This results in a greater number of older, heat-sensitive individuals in areas of the United States with large temperature increases. To identify the influence of population projections on our results,

we selected the most inclusive all-ages health function reported by Zanobetti and Schwartz³⁹ to which we applied both ICLUS and Woods and Poole projections. The ICLUS data produced estimates of mortality ranging from 108% (B2 scenario) to 125% (A1 scenario) above the Woods and Poole central-case scenario. This scenario analysis demonstrates the influence of population projections, assumptions about migration, and distribution of different age groups on projected temperature-related mortality impacts.

Several studies have projected environmental or health impacts from increasing temperatures in future years (Table 3). For three Canadian cities, Doyon et al.⁴² estimated an increase in heat–mortality for the summertime. Hayhoe et al.⁴³ compared annual heat-related deaths for California cities in the 1990s to the mid and late 21st century and concluded that heat-related mortality would increase up to seven times. Deschênes and Greenstone⁴⁴ suggest that under a “business as usual” future scenario there will be a small increase in the overall U.S. mortality rate by the end of the 21st century but that there may be meaningful increases in heat-related mortality rates for some sensitive groups, especially infants. For the New York metropolitan area, current and future climates were simulated, and estimated future year increases in heat-related premature mortality ranged from 47% to 95%, with acclimatization (i.e., biophysical desensitization) effects reducing the increases by about 25%. Adjusting for acclimatization was accomplished by using a response function derived from two U.S. cities with present day observed temperatures similar to those the researchers projected for the 2050s in the New York region. The researchers concluded that acclimatization may not completely mitigate the premature mortality effects of climate change.⁴⁵ Doyon et al.⁴² presented their results in a format similar to our present study, projecting that heat would account for 2% and 0.5% of nonaccidental mortality for 3 Quebec cities for the year 2020. We estimated 0.57–0.73% for nonaccidental mortality in 2048–2052. The large number of variables associated with a

Table 3. Studies Reporting Future Year Temperature–Mortality Impacts^a

study	emissions	mortality impact	models	dates	study population
Doyon et al. ⁴²	A2 and B2	2% and 0.5% (all cause except injury) (2020); 10% and 3% (2080)	HadCM3/SDSM	2010–2039; 2040–2069; 2070–2099	3 Québec cities
Hayhoe et al. ⁴³	B1 and A1fi	2–7× increase in heat related	Parallel Climate Model/ Hadley Centre Climate Model	2020–2049; 2070–2099	California
Deschênes and Greenstone ⁴⁴	A1F1 and A2	0.5–1.7% increase in heat related	HadCM3; CCSM	end of 21st century	United States
Knowlton et al. ⁴⁵	A2 and B2	65–295% increase in heat-related (A2); 33–201% increase in heat-related (B2)	GISS/MMS	five summers of 2050s compared to 1990s	31 county New York metropolitan area
present study	A1B	0.099–0.10% (all cause); 0.86% (cardiovascular); 0.57–0.73% (nonaccidental)	GISS-II/MMS/CMAQ	May–Sept 1999–2003; May–Sept 2048–2052	United States

^a CCSM = National Center for Atmospheric Research's Community Climate System Model; CMAQ = Community Multiscale Air Quality atmospheric chemistry model; GISS = Goddard Institute for Space Studies; HadCM3 = Hadley Centre 3rd Ocean-Atmosphere General Circulation Model; MMS = Penn State/National Center for Atmospheric Research Mesoscale Model S; SDSM = Statistical DownScaling Model.

heat–mortality analysis makes cross-study comparisons difficult. Choices made among IPCC scenarios, temperature–mortality functions, global and regional climate models, dates of analyses, and study populations all influence the results. Advantages of the present analysis include use of accepted climate models, detailed population estimates, and a range of heat–mortality functions. The successful use of BenMAP to estimate heat–mortality suggests the viability of adapting an air pollutant impact model to a heat–morbidity analysis.

Uncertainties. Similar to estimating the impacts of air pollutants, BenMAP does not factor in changes in heat-related dose–response over time. In future work, it would be illustrative to make use of health functions reflective of adaptation or to devise a discount factor to reduce mortality estimates from levels derived using unacclimatized health functions. Region-specific results acknowledging the geographic heterogeneity of heat–mortality responses would add an important dimension to this analysis. We addressed this in our sensitivity analysis using the Basu, Dominici, and Samet region-specific functions.²⁴ Curriero et al. also found a strong association of temperature–mortality with latitude.⁴⁶

With the inclusion of four epidemiological studies, this methodology encompasses several recognized risk influences including age, mortality type, time (lag time, warm season), threshold, and compounding impacts of air pollutants. Not addressed here but of potential importance are population cohorts based on gender, education, race, and income. Other influences that may affect the impact of elevated temperature include acclimatization, adaptation and displacement, morbidity, and productivity effects. The regional differences in reaction to heat are also of importance. This study does not assign regional heat–mortality functions to geographic regions. This will tend to overstate the number of projected cases, given the evidence that residents of warm regions exhibit a lesser sensitivity to heat than observed in colder regions.

The science of modeling climate change-related impacts is evolving. Emissions of GHG are still rising. Future analyses would benefit from applying observed 20th century GISS-generated temperature estimates in BenMAP. Temperature sensitivity has been observed in many if not all people, with the elderly and infants at particular risk. The proportion of the U.S. population over 65 years of age is growing over time and is expected to reach 13% by 2010 and 20% by 2030.² Other subpopulation sensitivities are recognized, and recent analyses point to combinations of characteristics—lower education/higher

poverty/higher proportion people of color/lower green space, higher social isolation, lack of air conditioning, higher proportion elderly/diabetes—as leading to disproportionate impacts.⁴⁷ Spatial variability of the heat–mortality impact is well documented. Recent work to map disparate vulnerabilities across the United States demonstrated higher vulnerability in the Northeast and along the Pacific Coast and in inner city urban areas.⁴⁷ Heat events early in the warm season produce greater mortality results than later events. These various sensitivities emphasize the continued importance of targeted public health responses, such as the U.S. National Weather Service's heat watches and warnings.

For the warm season months May–September with averaged temperatures derived from the 5 years 2048–2052 relative to 1999–2003, our proof-of-concept approach successfully produced typical year estimates for the United States of heat-related all-cause mortality to be 3700–3800, heat-related cardiovascular disease mortality to be 3500, and heat-related nonaccidental mortality to be 21 000–27 000. Numbers of this magnitude, produced to validate the application of a new methodology, suggest the importance of quantifying heat impacts in economic assessments of climate change. Economic valuation was not assigned in this preliminary exercise but would be an important addition to future studies that compare benefits of reducing GHG to potential implementation costs. Future applications of the methodology introduced here should consider a range of climate futures in their estimates of the health impacts of warmer temperatures.

As we discuss above, the limited extent of the current literature inhibited our ability to fully consider in this proof-of-concept analysis the synergistic impacts of temperature and air pollutant exposure, morbidity impacts, spatial heterogeneity of impacts, or changes in cold season health impacts in the United States. We anticipate that as the literature continues to evolve, additional studies will provide useful inputs to future analyses of climate-related health impacts.

■ AUTHOR INFORMATION

Corresponding Author

*Address: US Environmental Protection Agency, Mail Code C504-04 4930 Page Road, Durham, NC 27703; phone: (919) 541-5348; fax: (919) 541-5598; e-mail: voorhees.scott@epa.gov.

ACKNOWLEDGMENT

We thank Drs. Rupa Basu and Kristie Ebi for their technical editing and Drs. Carey Jang, Chris Nolte, and Sharon Phillips for assistance in acquiring the CMAQ meteorological input data. We thank Ms. Lara Reynolds for calculating the apparent temperature using MCIP Model data. The opinions expressed in this article are solely those of the authors and do not necessarily represent those of the US EPA. The authors declare that they have no competing financial interests. No grants or other funding support were used in the preparation of this manuscript.

REFERENCES

- (1) U.S. Environmental Protection Agency. *Endangerment and Cause or Contribute Findings For Greenhouse Gases Under Section 202(a) of the Clean Air Act; Final Rule*; EPA: Washington, DC, 2009.
- (2) O'Neill, M. S.; Ebi, K. L. Temperature extremes and health: Impacts of climate variability and change in the United States. *J. Occup. Environ. Med.* **2009**, *51* (1), 13–25.
- (3) In *Global Climate Change Impacts in the United States*; Karl, T. R., Melillo, J. M., Peterson, T. C., Eds.; Cambridge University Press: New York, 2009.
- (4) Intergovernmental Panel on Climate Change. Climate change 2007: The physical basis of climate change, 8.2.2.1. In *Intergovernmental Panel on Climate Change Fourth Assessment Report*; Working Group I Chapter 8 Human Health Section: 2007.
- (5) Kalnay, E.; Cai, M. Impact of urbanization and land-use change on climate. *Nature* **2003**, *423*, 528–531.
- (6) Patz, J. A.; Campbell-Lendrum, D.; Holloway, T.; Foley, J. A. Impact of regional climate change on human health. *Nature* **2005**, *438*, 310–317.
- (7) Zhou, L. M.; Dickinson, R. E.; Tian, Y.; Fang, J.; Li, Q.; Kaufmann, R. K.; Tucker, C. J.; Myneni, R. B. Evidence for a significant urbanization effect on climate in China. *Proc. Natl. Acad. Sci. U.S.A.* **2004**, *101* (26), 9540–9544.
- (8) Kinney, P. L.; O'Neill, M. S.; Bell, M. L.; Schwartz, J. Approaches for estimating effects of climate change on heat-related deaths: Challenges and opportunities. *Environ. Sci. Policy II* **2008**, 87–96.
- (9) Kalkstein, L. S.; Greene, J. S. An analysis of potential heat-related mortality increases in US cities under a business-as-usual climate change scenario. *Environ. Am.* **2007**; Available at http://www.environmentamerica.org/uploads/Js/tF/JstFEsHrsQjiSifIA931Q/Heat-Mortality_Report_.pdf.
- (10) Basu, R.; Samet, J. Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. *Epidemiol. Rev.* **2002**, *24* (2), 190–202.
- (11) Ebi, K. L.; Mills, D. M.; Smith, J. B.; Grambsch, A. Climate change and human health impacts in the United States: An update on the results of the US national assessment. *Environ. Health Perspect.* **2006**, *114* (9), 1318–1324.
- (12) Hajat, S.; Armstrong, B.; Baccini, M.; Biggeri, A.; Bisanti, L.; Russo, A.; Paldy, A.; Menne, B.; Kosatsky, T. Impact of high temperatures on mortality: Is there an added heat wave effect? *Epidemiology* **2006**, *17* (6), 632–638.
- (13) Intergovernmental Panel on Climate Change. *Climate Change 2007: Synthesis Report 2007*. Intergovernmental Panel on Climate Change Fourth Assessment Report. Available at http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf.
- (14) Climate Change Science Program. *Weather and Climate Extremes in a Changing Climate. Regions of Focus: North America, Hawaii, Caribbean, and US Pacific Islands. A Report by the US Climate Change Science Program and the Subcommittee on Global Change Research*; Karl, T. R., Meehl, G. A., Miller, C. D., Hassol, S. J., Waple, A. M., Murray, W. L., Eds.; Department of Commerce: Washington, DC, 2008.
- (15) Davidson, K.; Hallberg, A.; McCubbin, D.; Hubbell, B. Analysis of PM_{2.5} using the environmental benefits mapping and analysis program (BenMAP). *J. Toxicol. Environ. Health, Part A* **2007**, *70* (3), 332–346.
- (16) Kunzli, N.; Kaiser, R.; Medina, S.; Studnicka, M.; Chanel, O.; Filliger, P.; Herry, M.; Horak, F., Jr.; Puybonnieux-Textier, V.; Quenel, P.; et al. Public health impact of outdoor and traffic-related air pollution: A European assessment. *Lancet* **2000**, *356* (9232), 795–801.
- (17) Levy, J. I.; Carrothers, T. J.; Tuomisto, J. T.; Hammitt, J. K.; Evans, J. S. Assessing the public health benefits of reduced ozone concentrations. *Environ. Health Perspect.* **2001**, *109* (12), 1215–1226.
- (18) Ostro, B.; Chestnut, L. Assessing the health benefits of reducing particulate matter air pollution in the United States. *Environ. Res.* **1998**, *76* (2), 94–106.
- (19) U.S. Environmental Protection Agency. *Final Regulatory Analysis: Control of Emissions From Nonroad Diesel Engines*; EPA 420/R-04-007. EPA: Washington, DC, 2004.
- (20) U.S. Environmental Protection Agency. *Regulatory Impact Analysis For the Final Clean Air Interstate Rule*; EPA 452/R-05-002. EPA: Washington, DC, 2005.
- (21) U.S. Environmental Protection Agency. *Final Regulatory Impact Analysis: PM-2.5 NAAQS*; EPA: Washington, DC, 2006.
- (22) U.S. Environmental Protection Agency. *Final Ozone NAAQS Regulatory Impact Analysis*; EPA 452/R-08-003. EPA: Washington, DC, 2008.
- (23) National Research Council. *Estimating the Public Health Benefits of Proposed Air Pollution Regulations*; National Academies Press: Washington, DC, 2002.
- (24) Basu, R.; Dominici, F.; Samet, J. Temperature and mortality among the elderly in the United States. *Epidemiology* **2005**, *16* (1), 58–66.
- (25) Hubbell, B.; Hallberg, A.; McCubbin, D. R.; Post, E. Health-related benefits of attaining the 8-hr ozone standard. *Environ. Health Perspect.* **2005**, *113* (1), 73–82.
- (26) GeoLytics Inc. *Geolytics CensusCD 2000 Short Form Blocks*, CD-ROM Release 1.0; GeoLytics, Inc.: East Brunswick, NJ, 2002; Available at <http://www.geolytics.com/>.
- (27) Woods and Poole Economics, Inc. *Population by Single Year of Age CD*; Woods & Poole Economics, Inc.: Washington, DC, 2001.
- (28) Centers for Disease Control and Prevention. *CDC Wonder*. US Department of Health and Human Services: Atlanta, GA, 2009; Available at <http://wonder.cdc.gov/>.
- (29) Mickley, L. J.; Jacob, D. J.; Field, B. D.; Rind, D. Effects of future climate change on regional air pollution episodes in the United States. *Geophys. Res. Lett.* **2004**, *31* (24), L24103.
- (30) Cooter, E. J.; Gilliam, R.; Benjey, W.; Nolte, C.; Swall, J.; Gilliland, A. Examining the impact of changing climate on regional air quality over the US. In *Developments in Environmental Science*; Borrego, C., Renner, E., Eds.; Elsevier Press: New York, 2007; Vol. 6 (Air Pollution Modeling and its Application XVIII).
- (31) Gustafson, W. L.; Leung, L. R. Regional downscaling for air quality assessment—a reasonable proposition? *Bull. Am. Meteor. Soc.* **2007**, *88* (8), 1215–1227.
- (32) Nolte, C. G.; Gilliland, A. B.; Hogrefe, C.; Mickley, L. J. Linking global to regional models to assess future climate impacts on surface ozone levels in the United States. *J. Geophys. Res.* **2008**, *113*, D14307.
- (33) Otte, T. L. *Using MMS Version 2 With Models-3/CMAQ: A User's Guide and Tutorial*; EPA-600/R-99/065; EPA: Washington, DC, 1999.
- (34) Byun, D. W.; Schere, K. L. Review of the governing equations, computational algorithms, and other components of the models-3 Community Multi-scale Air Quality (CMAQ) modeling system. *Appl. Mech. Rev.* **2006**, *59* (2), 51–77.
- (35) Medina-Ramón, M.; Schwartz, J. Temperature, temperature extremes, and mortality: A study of acclimatization and effect modification in 50 United States cities. *Occup. Environ. Med.* **2007**, *64* (12), 827–833.
- (36) Anderson, B. G.; Bell, M. L. Weather-related mortality: How heat, cold, and heat waves affect mortality in the United States. *Epidemiology* **2009**, *20* (2), 205–213.
- (37) Basu, R.; Ostro, B. A multicounty analysis identifying the populations vulnerable to mortality associated with high ambient temperature in California. *Am. J. Epidemiol.* **2008**, *168* (6), 632–637.

(38) Basu, R.; Feng, W.-Y.; Ostro, B. D. Characterizing temperature and mortality in nine California counties. *Epidemiology* **2008**, *19* (1), 138–145.

(39) Zanobetti, A.; Schwartz, J. Temperature and mortality in nine US cities. *Epidemiology* **2008**, *19* (4), 563–570.

(40) U.S. Environmental Protection Agency. *Land-Use Scenarios: National-Scale Housing-Density Scenarios Consistent with Climate Change Storylines*; EPA/600/R-08/076F. EPA: Washington, DC, 2009.

(41) In *Special Report On Emissions Scenarios*; Nakicenovic, N., Swart, R., Eds.; Cambridge University Press: Cambridge, U.K., 2000.

(42) Doyon, B.; Bélanger, D.; Gosselin, P. The potential impact of climate change on annual and seasonal mortality for three cities in Québec, Canada. *Int. J. Health Geogr.* **2008**, *7* (1), 23.

(43) Hayhoe, K.; Cayan, D.; Field, C. B.; Frumhoff, P. C.; Maurer, E. P.; Miller, N. L.; Moser, S. C.; Schneider, S. H.; Cahill, K. N.; Cleland, E. E.; et al. Emissions pathways, climate change, and impacts on California. *Proc. Natl. Acad. Sci. U.S.A.* **2004**, *101* (34), 12422–12427.

(44) Deschênes, O.; Greenstone, M. Climate change, mortality and adaptation: Evidence from annual fluctuations in weather in the US. Working Paper 07-19; Massachusetts Institute of Technology: Cambridge, MA, 2007.

(45) Knowlton, K.; Lynn, B.; Goldberg, R. A.; Rosenzweig, C.; Hogrefe, C.; Rosenthal, J. K.; Kinney, P. L. Projecting heat-related mortality impacts under a changing climate in the New York City region. *Am. J. Public Health* **2007**, *97* (11), 2028–2034.

(46) Curriero, F. C.; Heiner, K. S.; Samet, J. M.; Zeger, S. L.; Strug, L.; Patz, J. A. Temperature and mortality in 11 cities of the eastern United States. *Am. J. Epidemiol.* **2002**, *155* (1), 80–87.

(47) Reid, C. E.; O'Neill, M. S.; Gronlund, C. J.; Brines, S. J.; Brown, D. G.; Diez-Roux, A. V.; Schwartz, J. Mapping community determinants of heat vulnerability. *Environ. Health Perspect.* **2009**, *117* (11), 1730–1736.