

An Examination of Climate Change on Extreme Heat Events and Climate–Mortality Relationships in Large U.S. Cities

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ABSTRACT

This study examines the impact of a changing climate on heat-related mortality in 40 large cities in the United States. A synoptic climatological procedure, the spatial synoptic classification, is used to evaluate present climate–mortality relationships and project how potential climate changes might affect these values. Specifically, the synoptic classification is combined with downscaled future climate projections for the decadal periods of 2020–29, 2045–55, and 2090–99 from a coupled atmospheric–oceanic general circulation model. The results show an increase in excessive heat event (EHE) days and increased heat-attributable mortality across the study cities with the most pronounced increases projected to occur in the Southeast and Northeast. This increase becomes more dramatic toward the end of the twenty-first century as the anticipated impact of climate change intensifies. The health impact associated with different emissions scenarios is also examined. These results suggest that a “business as usual” approach to greenhouse gas emissions mitigation could result in twice as many heat-related deaths by the end of the century than a lower emissions scenario. Finally, a comparison of future estimates of heat-related mortality during EHEs is presented using algorithms developed during two different, although overlapping, time periods, one that includes some recent large-scale significant EHE intervention strategies (1975–2004), and one without (1975–95). The results suggest these public health responses can significantly decrease heat-related mortality.

1. Introduction

Excessive heat events (EHEs) are the leading cause of weather-related deaths in the United States [(National

Weather Service) NWS 2009]. However, the impacts of specific EHEs may be more widely recognized. For example, the loss of over 700 lives in Chicago to a 1995 EHE has been well documented (Klinenberg 2002; Semenza et al. 1996. Whitman et al. 1997) and is viewed as a critical moment in terms of increasing awareness of the potential health risks and impacts of EHEs in the United States. This awareness has been reinforced by the European EHE in August 2003 that was responsible for an estimated 40 000 deaths across central and western Europe (Valleron and Boumendil 2004). While it has been suggested that heat-related mortality in the United States

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has been declining in the last few decades (Davis et al. 2002, 2003a,b; Sheridan et al. 2009; Kalkstein et al. 2010), EHEs have still contributed to a significant and largely avoidable loss of life. In addition, some research (e.g., Sheridan et al. 2009) indicates this declining mortality trends may have stopped and may now be increasing again. At the same time, climate models generally project increasing average temperatures in the coming decades (Solomon et al. 2007). More focused studies that evaluate climate change impacts on future EHE trends have similarly concluded many regions of the United States can anticipate more frequent and severe EHEs (e.g., Meehl and Tebaldi 2004; O'Neill and Ebi 2009).

This study quantifies the potential impacts of climate on EHE-attributable mortality in 40 large U.S. cities under a “business as usual” greenhouse gas (GHG) emissions scenario and a scenario with GHG emissions controls. These results provide an update to earlier projections of the potential health impacts of climate change based on EHE impacts (e.g., Kalkstein and Greene 1997). Finally, a method is developed and applied to quantify the health benefit that recent improvements in EHE notification and response programs may provide in considering the future health impact of EHEs.

2. Data and methods

a. Mortality data

Developing the climate and EHE-attributable mortality relationships and estimates for the 40 U.S. cities under consideration began by extracting daily mortality record information including the date, cause, and county in which the deceased had passed away. Deaths from all causes are used as the mortality measure in this study as this has been shown to be a more robust measure for examining heat–mortality relationships than mortality totals for specific causes of death (Ebi et al. 2004). For the baseline portion of this study, these data were developed from 1 June to 31 August during 1975–95 [(National Center for Health Statistics) NCHS 2007]. Any population trends for the cities in these records have been removed using a standardization procedure used previously (Kalkstein et al. 2010). An analysis of intraseasonal trends was also undertaken to identify any significant changes in the daily mortality throughout the summer season. However, unlike in some European cities, for example Rome and Paris, where there is a pronounced decrease in acute daily mortality in early August as significant numbers of residents leave the city for summer vacations, no intraseasonal trends were found in the data for the U.S. cities, so no adjustment was necessary.

It should be noted that in estimating future EHE-attributable mortality we hold the exposed population

constant. In other words, no adjustments are made for potential changes in the size or composition (e.g., age distribution) of a city’s population. The nature of any bias this introduces is uncertain, as changes in the relative proportion of vulnerable individuals in a city would need to be accounted for along with changes in the response of these individuals to future EHE days to produce completely accurate forecasts. The data required for both of these adjustments is lacking over the time period of interest. However, since we can assume that the proportion of heat-vulnerable elderly individuals will likely rise, any estimates in this study may be considered conservative. Holding the population constant over time also helps highlight the impact of climate change over time by limiting the number of factors that contribute to EHE-attributable mortality estimates that are changing.

b. Climatological data and methods

A large body of literature suggests that, rather than responding in isolation to individual weather elements (e.g., maximum temperature), human health is affected by the simultaneous interactions from a much larger suite of meteorological conditions (e.g., temperature, humidity, cloud cover, and wind speed). Much recent work on heat/health issues has relied on the utilization of a “synoptic climatological methodology,” which identifies weather situations that increase the incidence of adverse health outcomes (e.g., Kalkstein et al. 2008a; Sheridan and Kalkstein 2004; Kysely and Huth 2004). To account for this more holistic relationship between EHEs and daily mortality, the spatial synoptic classification (SSC; Sheridan 2002) method was used to categorize the representative weather conditions for each day in each city. The SSC examines a range of meteorological variables, and classifies each day at a particular location into one of several recognizable, homogeneous, weather types. Thus, in each city, each day is classified into one of six main airmass categories, or is considered a transition between the categories. The characteristics of the conditions in these airmass categories are as follows:

- Dry moderate (DM): A warm, comfortable air mass that occurs in the northeastern United States in summer.
- Dry polar (DP): The coolest and dry air mass, although still warm in the summertime. Usually occurs immediately after the passage of a cold front.
- Dry tropical (DT): The hottest air mass. For summer, temperatures usually exceed 95°F and sometimes exceed 100°F, or more in the hotter parts of the country. This air mass is also typically associated with low cloud cover humidity, which can lead to rapid dehydration.

- Moist moderate (MM): A cloudy, mild air mass that may sometimes be associated with fog and light rain.
- Moist polar (MP): While more typically a winter or shoulder season, rather than a summer, air mass, this situation is often associated with storms moving up the East Coast.
- Moist tropical (MT): Very warm and humid air mass, sometimes associated with summer thunderstorms. This air mass is associated with the highest apparent temperature values, and is often quite muggy and uncomfortable. Since MT is often quite prevalent in the summer, this hot and humid air mass is often subdivided to more closely establish the heat–mortality relationship.
 - Moist tropical plus (MT+): These are particularly hot and humid subsets of the MT air mass. Dewpoint temperatures are very high, temperatures are in the 90°s, and overnight temperatures are the warmest of any air masses.
- Transition (T): Associated with a rapid change between synoptic conditions. This can be associated with a frontal passage, when temperature, dewpoint, and other meteorological factors are rapidly changing.

Within this group, offensive air masses are those with a mean daily standardized mortality difference that are statistically significantly greater than 0 [refer to Sheridan and Kalkstein (2004) and Kalkstein et al. (2008b) for standardization procedures]. Based on prior analyses of the acute daily mortality–airmass relationship, it is clear that the DT and/or MT+ air mass are offensive airmass categories (Kalkstein et al. 2008a). Additional examples of the impacts of these categories come from notable past EHEs. For example many of the days in the 1995 Chicago Heat Wave were MT+ (Kalkstein and Greene 1997), while many days in France and Italy during the unprecedented European were DT (Kalkstein et al. 2008a). As a result, for this study, days in either the DT or MT+ categories with a mean daily standardized mortality difference greater than 0 are categorized as EHE days.

Once each day during the summer period is assigned to an airmass category, a mortality algorithm is developed that relates the variation in standardized mortality on all EHE days within a city to meteorological and environmental variables. The meteorological variables considered during the algorithm development include the following: maximum and minimum air temperature and maximum and minimum dewpoint temperature. The nonmeteorological variables considered are as follows: consecutive days of offensive airmass conditions, and time of season when the offensive air

mass occurs. These algorithms are developed using a stepwise multiple regression procedure, and care is taken to make certain that colinearity among independent variables is minimized.¹ For example, the following EHE-attributable mortality algorithm was developed using the historical weather and mortality data for St. Louis, Missouri:

$$\text{MORT} = 0.32t_{\text{max}} - 0.03T_{\text{OS}} - 7.76,$$

where MORT = excess mortality (defined here as mortality above the long-term adjusted baseline), T_{max} is the maximum temperature (°C), and T_{OS} is the time of season variable, where 1 June = 1, . . . , 31 August = 92). This example fits a common pattern shown in previous research (e.g., Greene and Kalkstein 1996; Kalkstein et al. 2010, and others), where maximum temperature is often the most important variable, and the nonmeteorological variables also show some importance. While the other variables have a positive relationship, the T_{OS} variable is negative, which shows a statistically significant decrease in sensitivity as the population acclimatizes over the course of the summer.

Table 1 lists the U.S. cities in this study, their 2000 census populations, the average number of EHE days they experienced each summer in the period 1975–95, and the corresponding average number of EHE-attributable deaths per summer during this period. The results in Table 1 are sorted in descending order based on the calculated average summertime EHE-attributable mortality rates per 100 000 city residents. These results show considerable variability by location. Cumulatively, the results indicate an EHE mortality impact of 1540 lives being lost to an average summer from among the roughly 37.5 million city residents covered in this study.

c. Climate model data and methods

For this study, the Parallel Climate Model (PCM) was used to complete climate simulations with the results then being downscaled to the appropriate location for each city. The PCM is a global coupled atmosphere–ocean general circulation model (AOGCM) developed at the National Center for Atmospheric Research (NCAR) that provides state-of-the-art simulations of the earth’s past, present, and future climate states. Included in the PCM is a series of submodels of the atmosphere, ocean, sea ice, and land. The atmospheric component is the parallel version of the NCAR Community Climate

¹ All models and algorithms shown in this paper are significant at the $\alpha = 0.05$ level.

TABLE 1. Average number of summertime EHE days and EHE attributable-deaths/rates based on data from 1975 to 1995.

City	Population in 2000 (100 000s)	Avg No. of summertime EHE days (1975–95)	Forecast No. avg summertime EHE-attributable deaths from algorithm (1975–95 data)	Avg summertime EHE-attributable mortality rate per 100 000 residents (using algorithm 1975–95)
Hartford, CT	1.22	6	32	26.7
Newark, NJ	2.74	8	66	24.0
Providence, RI	1.74	7	40	22.9
Boston, MA	5.89	11	104	17.7
Greensboro, NC	2.24	8	36	16.3
Louisville, KY	2.56	8	39	15.3
Kansas City, MO	4.42	7	48	10.9
Birmingham, AL	2.43	5	24	10.0
Baltimore, MD	6.51	8	64	9.9
Cleveland, OH	4.78	5	45	9.4
Atlanta, GA	4.16	5	37	8.8
Denver, CO	5.55	9	46	8.3
Memphis, TN	6.50	9	54	8.3
Tampa, FL	3.03	3	25	8.2
St. Louis, MO	3.48	11	27	7.8
Buffalo, NY	2.93	3	23	7.7
Pittsburgh, PA	3.35	5	25	7.5
Detroit, MI	9.51	9	67	7.0
Minneapolis, MN	3.83	8	20	5.1
New Orleans, LA	4.85	5	24	5.0
Washington, DC	5.72	16	28	5.0
Philadelphia, PA	15.18	6	69	4.6
Dallas, TX	11.89	11	54	4.5
Jacksonville, FL	7.36	7	29	4.0
Chicago, IL	28.96	5	104	3.6
Cincinnati, OH	3.31	4	12	3.5
Indianapolis, IN	7.82	5	25	3.2
New York, NY	80.08	11	235	2.9
Portland, OR	5.29	4	14	2.6
Phoenix, AZ	13.21	7	33	2.5
Seattle, WA	5.63	2	13	2.3
San Antonio, TX	11.45	5	20	1.7
San Jose, CA	8.95	0	11	1.3
Salt Lake City, UT	1.82	0	2	0.9
Los Angeles, CA	36.95	1	25	0.7
Columbus, OH	7.11	5	4	0.6
San Diego, CA	12.23	1	6	0.5
San Francisco, CA	7.77	2	3	0.4
Houston, TX	19.54	1	6	0.3
Miami, FL	3.62	0	0	0.0
Tot	375.59		1540	

Model, version 3.2 (CCM3). This model includes the latest versions of radiation, boundary physics, and precipitation physics. It also contains submodels that consider soil physics and vegetation (Kiehl 2007; Kiehl et al. 1998; Collins et al. 2006; Dai et al. 2001). The historical estimates have been computed using the twentieth-century scenario (20C3M), which includes current estimates of twentieth-century total (anthropogenic + natural) forcing (Hayhoe et al. 2010). This incorporates observed historical emissions of carbon dioxide, methane, and other greenhouse gases. The projections for the future using the AOGCM are based on the Intergovernmental

Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES) higher (A1FI) and lower (B1) emissions scenarios (Nakićenović and Swart 2000). These scenarios set the future atmospheric carbon dioxide (CO₂) equivalent concentrations based upon estimates of a range of variables that could impact greenhouse gas emissions. These include estimates of future changes in population, demographics, and technology, among others.

The B1 scenario values are considered a proxy for stabilizing atmospheric CO₂ concentrations at or above 550 ppm by 2100, the atmospheric CO₂ equivalent

concentration for the higher A1FI scenario is approximately 1000 ppm (Nakićenović and Swart 2000). The estimates in this study do not explicitly model GHG emission control policies, but are considered an approximate surrogates for an intensive greenhouse gas emission control policy (B1), or a business-as-usual option (A1F1). The AOGCM simulations were then developed using these carbon equivalent values.

To account of any potential biases in the AOGCM scenario estimates, the values produced for the 1990s were compared to the actual data from that time period. Future estimates for the decades in the 2000s were standardized by the identified bias (e.g., difference between the estimated and observed values for the 1990s), so that any systematic errors in the model output would be minimized. Finally, once the 6-h instantaneous values for each of the necessary weather variables are available, a daily synoptic calendar for the future decades was developed.

The initial results from the PCM were then downscaled using a statistical asynchronous regression technique (Dettinger et al. 2004; Cayan et al. 2008; Hayhoe et al. 2004; Vrac et al. 2007) to provide greater spatial resolution and to generate city-specific results for each of the simulated decades. The daily values from the PCM were interpolated to provide 6-h instantaneous values intervals (i.e., 0400, 1000, 1600, and 2200 UTC) for each day for the historic and future decades listed above. Values for the standard meteorological variables the SSC method requires to make daily airmass categorizations (e.g., temperature, dewpoint, wind speed and direction, sea level pressure, and cloudiness) were obtained from the downscaled data and used to develop daily airmass calendars for each decade and emission scenario simulated. The EHE-attributable mortality impact was then calculated for the future decades for each city using the mortality algorithms developed using the baseline data (i.e., 1975–95) while holding city populations constant as previously discussed. To more readily compare the EHE-related mortality impact among cities we also calculated the equivalent EHE-attributable mortality rate per 100 000 city residents for an average summer in each future period. Note that we have assumed that the relationships between the meteorological parameters and acute mortality during EHE will remain constant in the future. There has been some suggestion (Palecki et al. 2001; Fouillet et al. 2008) that there may be some acclimatization in cities. However, since there is no way of quantifying the specific direction and amount of such change, we have not included it in our analysis. We do note, however, that such potential acclimatization may increase the error bars associated with our estimates.

3. Results

Table 2 presents the average number of summertime EHE days in the cities in the different study periods and under the alternative climate change scenarios.

Recall that an EHE day is not merely a representation of “hot” weather, but represents those days where a particular location experiences airmass conditions that have been shown to increase daily mortality. Therefore, cities currently lacking evidence of a strong heat–mortality relationship, such as many Southeastern cities or cities that have minimal summertime weather variability (e.g., Phoenix, Arizona; Miami, Florida; Houston, Texas) do not have a relatively high number of EHE days under the current climate conditions, often despite having relatively hot summers. This linking of EHE days to mortality increases also explains why several cities with moderate summer climates (e.g., San Francisco, California; Seattle, Washington; Buffalo, New York) also appear in Table 2 with relatively few EHE days under current conditions.

Considering the impact of climate change with the A1 emission scenario results in Table 2 there is a fairly consistent increase in the number of EHE days across locations as time progresses. This result is consistent with previous studies (e.g., Solomon et al. 2007; Kalkstein and Greene 1997), which found that as the models estimate an increase in temperature, the number of EHE days increases as more days move into the offensive airmass categories based on existing characterization criteria. By the end of the twenty-first century, every city will experience an increase in the average number of summertime EHE days as compared to their values during 1975–95. In over half the cities (i.e., 23), this increase results in more than half of the average summertime days in the 2090s under the A1 scenario satisfying current EHE day criteria while in more than 25% of the cities (i.e., 11) more than 2/3 of future summertime days in this scenario satisfy current EHE criteria.

However, Table 2 also shows that these increases in EHE days do not always occur consistently over time in all locations. A careful examination of Table 2 shows the cities fall into three broad categories. The large majority of the cities fall into the first category, those that show a consistent increase in EHE days over time. These fit the expected pattern with a steady and significant increase in overall average temperature over time.

The second, smaller, group consists of those cities that show a reduction in the number of EHE days from present conditions to the early part of the twenty-first century (i.e., the 2020s) before experiencing a steady increase. Cities such as New Orleans, Louisiana, and Louisville, Kentucky, fall into this category. The

TABLE 2. Average number of summertime EHE days under baseline (1975–95) conditions and in future decades under alternative climate change scenarios.

City	Avg No. of EHE days 1975–95	Avg No. of EHE days 2020–29 A1	Avg No. of EHE days 2045–55 A1	Avg No. of EHE days 2090–99 A1	Avg No. of EHE days 2090–99 B1
Washington, DC	16	44	53	69	46
Boston, MA	11	43	51	71	51
St. Louis, MO	11	28	35	45	30
Dallas, TX	11	18	22	37	19
New York, NY	11	48	55	75	53
Memphis, TN	9	10	18	40	11
Denver, CO	9	85	88	77	76
Detroit, MI	9	13	15	36	12
Baltimore, MD	8	35	45	69	38
Minneapolis, MN	8	25	23	30	27
Newark, NJ	8	50	55	68	53
Louisville, KY	8	3	5	29	4
Greensboro, NC	8	50	59	70	50
Kansas City, MO	7	31	38	48	35
Phoenix, AZ	7	82	84	75	71
Jacksonville, FL	7	14	24	43	14
Providence, RI	7	32	38	63	41
Philadelphia, PA	6	46	54	73	51
Hartford, CT	6	25	31	58	33
Pittsburgh, PA	5	45	52	59	42
Atlanta, GA	5	51	48	58	37
Cleveland, OH	5	4	5	17	3
Birmingham, AL	5	17	24	56	17
Indianapolis, IN	5	19	22	32	18
Chicago, IL	5	14	18	33	17
Columbus, OH	5	3	4	16	5
San Antonio, TX	5	19	23	30	22
New Orleans, LA	5	1	8	54	1
Portland, OR	4	37	42	51	41
Cincinnati, OH	4	18	22	30	20
Tampa, FL	3	32	36	59	30
Buffalo, NY	3	1	3	15	1
Seattle, WA	2	51	54	57	47
San Francisco, CA	2	70	66	54	64
Houston, TX	1	4	5	13	3
Los Angeles, CA	1	45	60	88	57
San Diego, CA	1	32	39	61	36
Salt Lake City, UT	0	0	0	0	0
San Jose, CA	0	2	4	4	1
Miami, FL	0	2	14	55	2

explanation for the pattern in these cities is the difference between the actual data for the latter twentieth century, and the model estimates for the twenty-first century. That is, the model estimates are lower than the actual number of EHE days. However, the expected pattern of increased EHE days associated with higher temperatures toward the middle and latter part of the twenty-first century still holds for these locations.

The final, smallest, group of cities are those that show an increase in EHE days for most of the century, and then show a drop toward the latter part of the twenty-first century. Denver, Colorado, and Phoenix, Arizona, are examples of these cities, while Salt Lake City, Utah,

shows 0 days throughout the period. An explanation for these anomalies would be pure conjecture, but model uncertainty and variability certainly may play a role for the counterintuitive results that we see in this small subset of the study locations. However, for these cities, even though there is a decrease in EHE days toward the end of the twenty-first century, they still show a significant increase over the period from the present-day conditions.

Table 2 also shows the substantial impact that aggressive GHG emissions controls could have on future EHE days. These results show that in over half the cities (i.e., 24) the A1 scenario results in at least 50% more

TABLE 3. Estimates of average summertime EHE-attributable deaths in future periods under alternative climate change scenarios, using Algorithm 1.

City	EHE-attributable deaths per summertime using 1975–95 algorithm for years 2020–29	EHE-attributable deaths per summertime using 1975–95 algorithm for years 2045–55	EHE-attributable deaths per summertime using 1975–95 algorithm for years 2090–99	EHE-attributable deaths per summertime using 1975–95 algorithm for years 2090–99
	Scenario: A1	Scenario: A1	Scenario: A1	Scenario: B1
Detroit, MI	255	291	701	234
New York, NY	221	251	344	245
Louisville, KY	178	327	548	234
Dallas, TX	175	224	371	194
Chicago, IL	143	185	300	165
Denver, CO	138	145	144	125
Atlanta, GA	124	114	123	92
Minneapolis, MN	119	112	142	131
Cleveland, OH	103	139	463	95
Boston, MA	85	111	132	102
Philadelphia, PA	83	97	133	94
Memphis, TN	81	150	335	88
Hartford, CT	78	99	174	98
Washington, DC	71	80	98	43
Newark, NJ	68	74	92	72
Baltimore, MD	67	87	137	73
St. Louis, MO	67	109	189	79
Kansas City, MO	64	80	99	73
Birmingham, AL	57	65	110	56
Greensboro, NC	47	57	68	58
Buffalo, NY	45	70	112	54
Jacksonville, FL	44	84	182	45
Pittsburgh, PA	41	45	45	37
Phoenix, AZ	40	48	100	69
Providence, RI	40	50	85	52
New Orleans, LA	38	40	92	31
Indianapolis, IN	37	41	65	33
Los Angeles, CA	26	38	59	35
San Antonio, TX	21	27	34	25
Cincinnati, OH	19	23	31	21
Columbus, OH	19	30	112	33
Seattle, WA	15	14	18	13
Houston, TX	14	19	28	14
Tampa, FL	13	11	14	12
San Jose, CA	11	13	15	13
Portland, OR	8	10	13	9
San Francisco, CA	7	6	9	6
San Diego, CA	3	4	8	4
Salt Lake City, UT	3	3	5	3
Miami, FL	0	0	0	0
Tot	2668	3373	5730	2860

EHE days than with the B1 scenario. Alternatively, in most cities the number of EHE days in the 2090s falls in the range of the estimated number of days for the 2020s and the period 2045–55 under the A1 scenario.

Table 3 presents the estimates of average summertime EHE-attributable mortality in the future periods under these climate change scenarios. Figure 1 presents these results in terms of the equivalent EHE-attributable mortality rates for the different periods with the A1 emissions scenario.

The results in Table 3 are sorted in descending order based on the average number of estimated summertime EHE-attributable deaths in the period 2020–29 under the A1 scenario. Cumulatively, these results show the average number of summertime EHE-attributable deaths would be expected to more than double from the value in the 2020–29 period to the results in the 2090–99 period under the A1 emissions scenario. These results represent increases of nearly 1100 and 4200 EHE-attributable deaths per year compared to the baseline estimates from

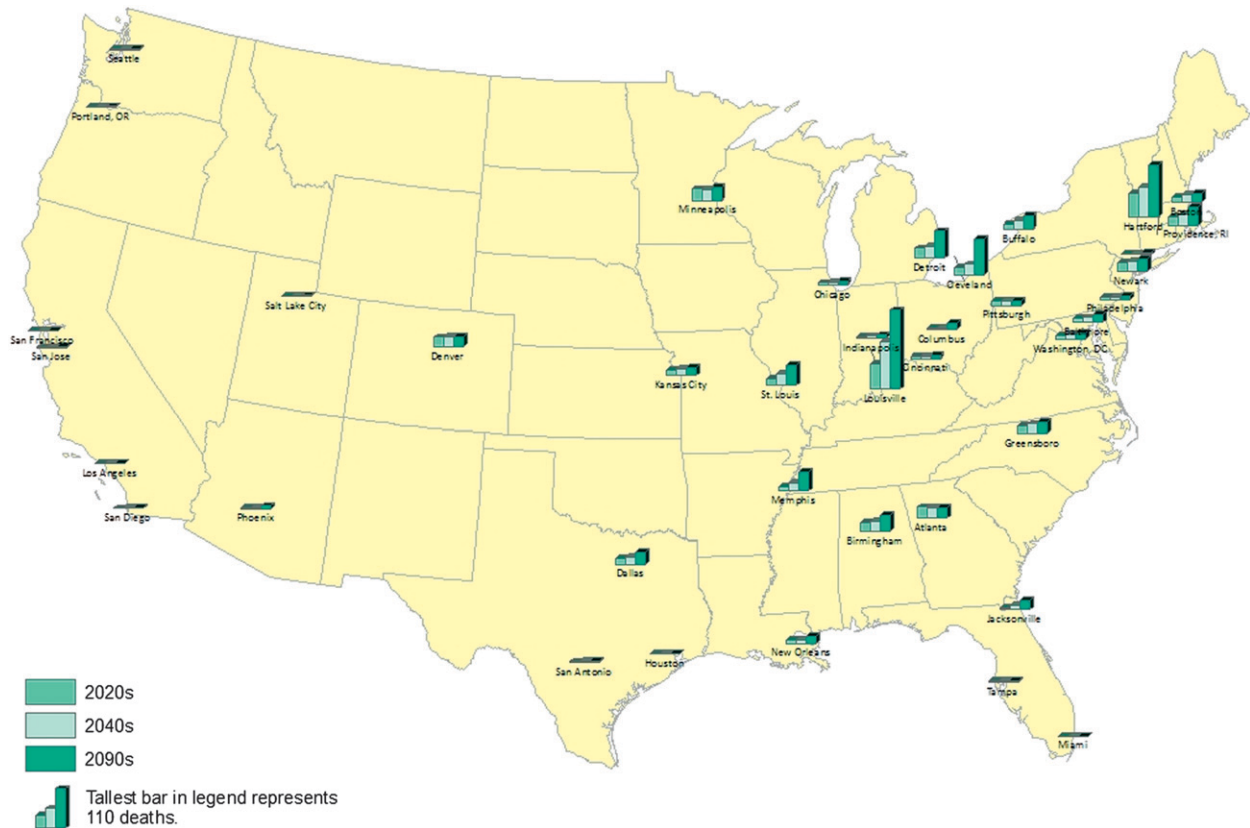


FIG. 1. EHE-attributable mortality rates under the A1 scenario in future periods.

the period 1975–95. The growth in the city-specific results over time under the A1 scenario in Table 3 is a reflection of both the anticipated increase in the number of EHE days and the initial sensitivity of the city to those days. More EHE days will, by definition, result in more EHE-attributable mortality in a location. The sensitivity of the location to these days also strongly influences the absolute size of the increase. As with Table 2, there are a few cities that do not show the expected steady increase over time. Seattle, Washington, and Tampa Bay, Florida, are examples that show a small drop and then revert back to the expected pattern of an increase with time. In addition to climate model error, one explanation for this pattern is that the reduction of leveling of EHE days for some cities for certain time periods will also result in a small decrease for in heat-related mortality in some instances. However, it noteworthy that in a broad evaluation of this type there is an intuitive mortality response in the preponderance of cities.

The contrast in results in Table 3 between the A1 and B1 scenarios for an average year in the 2090s is also notable. Under the B1 scenario there would be roughly half as many anticipated EHE-attributable deaths as in the A1 scenario. This represents a potential benefit of

roughly 2800 fewer lives lost in an average summer as a result of the greater emissions controls in the B1 scenario relative to the A1 scenario.

Figure 1 provides the A1 scenario results from Table 3 in terms of their equivalent EHE-attributable mortality rates per 100 000 city residents. The 2020 results in this figure provide a rough indication of current EHE vulnerability while the series shows how this vulnerability is expected to change over time. The general pattern of these results is consistent with results of previous studies that show the strongest regional EHE-attributable mortality response in northeastern and midwestern cities (e.g., Anderson and Bell 2009; Medina-Ramon and Schwartz 2007; Sheridan et al. 2009). This pattern is also consistent with results from with past studies (e.g., Chestnut et al. 1998; Greene and Kalkstein 1996; Sheridan et al. 2009) that concluded the risk of EHE-related mortality increases with increasing inter- and intraseasonal climate variability. Previous studies found the area from Minneapolis, Minnesota, and Kansas City, Missouri, eastward experiences the greatest intraseasonal synoptic climatological variability (Greene and Kalkstein 1996), and virtually all the highest EHE-attributable mortality rates are found in this area.

A currently unanswered question is whether the potential benefits of the recent growth in interest in EHE notification and response programs can be estimated when considering the meteorological impacts of climate change? The impact of these intervention activities was estimated by developing a second EHE-attributable mortality algorithm for each city. The first algorithm, as previously described, was developed using data for the period 1975–95. This represents a “baseline” period before the presumed increase in EHE awareness and intervention following the severe EHEs in the summer of 1995. The second algorithm uses daily mortality and weather data for the years 1975–2004, which includes the period during 1996–2004 when general public awareness of the health risks of EHEs increased and more rigorous EHE notification and response programs were implemented in a number of cities following the 1995 EHE in Chicago. Rather than using the much shorter time period of 1995–2004, when intervention activities were instituted, we decided to utilize the entire time frame to increase sample size and allow for a full pre- and postintervention comparison. Because this period is dominated by the years before we assume there was a substantial increase in efforts to develop and implement EHE programs, indications of these programs reducing EHE-attributable mortality in this longer period likely present a conservative estimate of the programs’ true benefits. Results using the algorithm from this longer period can be compared with estimates using the algorithm from the shorter period to calculate changes in EHE-attributable mortality that may be attributable to the increase in public awareness of EHE risks and a greater interest in EHE programs over this longer period. To estimate these benefits, new EHE-attributable mortality algorithms were developed along with estimates of EHE-attributable mortality under each of previously described time periods and climate change scenarios using the previously described methods.

Table 4 provides a summary of the resulting EHE-attributable mortality estimates using this longer data series. Similarly, Table 5 presents the estimated number of lives saved as a result of the presumed increase in public awareness of EHEs and interest in EHE notification and response programs. These results are calculated by subtracting the EHE-attributable mortality results by city, period, and scenario in Table 4 from the equivalent results in Table 3.

Combined, Tables 4 and 5 show that using the algorithms developed with data from the period where we assume there was considerable growth in EHE awareness and EHE notification and response programs results in lower EHE-attributable mortality across all scenarios and periods when the results across cities are

aggregated. These estimates of avoided EHE-attributable deaths range from over 600 in the study cities in the average year in the 2020s under the A1 scenario to over 1100 in the average year in the 2090s in the same scenario. The 2090’s results for the B1 scenario are large and similar to those observed for the 2020s in the A1 scenario with an estimate of over 600 avoided deaths.

However, the results in Table 5 also highlight some of the potential complications with this simple approach as several of cities (i.e., 8) produce estimates that suggest there was no benefit from increased awareness or development of heat programs as evidenced by negative values. No clear characteristic can be readily identified to link these cities. For example, they are not clustered geographically as the group includes Boston, Massachusetts; Tampa, Florida; and Portland, Oregon. One possibility is that there were important differences in the nature of the EHE days in the periods in these locations compared to other study cities. While a small number of random anomalous results should be expected in an evaluation of this kind a more comprehensive explanation is currently lacking and remains an area for potential future investigation.

4. Summary and conclusions

While this analysis provides an insight into the potential impacts of a changing climate on heat-related mortality, there are nevertheless some caveats that need to be considered when evaluating the results.

As mentioned previously, this study does not consider any potential changes in the demographic patterns of the cities. Considerable research has shown that the elderly represent a more vulnerable population in terms of negative health impacts of heat (O’Neill et al. 2008; Gronlund et al. 2008; O’Neill and Ebi 2009). As the anticipated demographic trend in the United States is toward an older population, our mortality estimates may understate the future impact of heat on acute mortality.

Our results also assume that current threshold conditions for EHE days and the future health response to these days will remain unchanged. Thus, we have not changed the attributes of the airmass types; the same meteorological criteria lead to the same airmass types throughout this analysis. While society’s future response to specific weather conditions may vary from what is currently observed, the nature of this response is difficult to predict. At the same time, holding this response constant over time helps highlight the risks associated with projections of future climates under different scenarios as well as the potential benefits of climate change mitigation efforts.

These are both strong assumptions. In particular, the assumption about the consistent response to warming

TABLE 4. Estimates of average summertime EHE-attributable deaths in future periods under alternative climate change scenarios.

City	EHE-attributable deaths per summertime using 1975–2004 algorithm for years 2020–29 Scenario: A1	EHE-attributable deaths per summertime using 1975–2004 algorithm for years 2045–55 Scenario: A1	EHE-attributable deaths per summertime using 1975–2004 algorithm for years 2090–99 Scenario: A1	EHE-attributable deaths per summertime using 1975–2004 algorithm for years 2090–99 Scenario: B1
Detroit, MI	160	185	454	148
New York, NY	159	182	249	178
Louisville, KY	138	257	376	171
Dallas, TX	91	115	190	99
Chicago, IL	110	142	250	127
Denver, CO	91	94	83	81
Atlanta, GA	25	24	29	18
Minneapolis, MN	99	93	121	107
Cleveland, OH	99	133	486	91
Boston, MA	129	154	213	152
Philadelphia, PA	49	57	78	55
Memphis, TN	70	130	293	77
Hartford, CT	32	40	76	43
Washington, DC	47	57	73	25
Newark, NJ	63	69	86	67
Baltimore, MD	64	83	127	70
St. Louis, MO	47	82	137	58
Kansas City, MO	71	89	112	81
Birmingham, AL	23	32	75	23
Greensboro, NC	36	47	52	48
Buffalo, NY	20	51	92	25
Jacksonville, FL	64	111	199	64
Pittsburgh, PA	29	33	38	27
Phoenix, AZ	36	44	91	63
Providence, RI	44	53	87	57
New Orleans, LA	28	29	68	24
Indianapolis, IN	45	51	73	41
Los Angeles, CA	22	29	47	30
San Antonio, TX	21	27	35	26
Cincinnati, OH	17	21	28	19
Columbus, OH	29	42	155	47
Seattle, WA	8	9	12	7
Houston, TX	12	16	27	10
Tampa, FL	22	25	41	21
San Jose, CA	11	13	15	13
Portland, OR	15	17	21	17
San Francisco, CA	6	5	8	5
San Diego, CA	3	4	7	4
Salt Lake City, UT	3	3	4	3
Miami, FL	0	0	0	0
Tot	2038	2648	4608	2222

conditions provides the possibility, all else remaining equal, for a potentially significant underestimation of the impact of health intervention strategies on future EHE-attributable mortality as future conditions increasingly resemble the extremes under the current climate.

Overall, our results show extreme heat events representing a source of increased health risk and impacts for many cities across the United States. The AOGCM-estimated changes show an overall increase in summer temperature with often significant increases in the number of future EHE days in most of our study cities. Thus,

this represents a significant potential increase in the risk that heat will pose to human health in the twenty-first century, as substantial increases in heat-related mortality are projected in the future. In addition, the results suggest that already vulnerable cities in the Northeast and Midwest will bear the brunt of large mortality increases if the weather warms as the models indicate.

It appears that an intervention and mitigation strategy with respect to greenhouse gas emissions could have a noticeable impact on future EHE-attributable mortality, as the estimated deaths associated with the lower

TABLE 5. Estimates of potential average summertime EHE-attributable deaths avoided as a result of increased public awareness of EHE risks and adoption of EHE notification and response programs during the period 1996–2004.

City	Estimate of avg summertime EHE-attributable deaths avoided in the 2020–29 period Scenario: A1	Estimate of avg summertime EHE-attributable deaths avoided in the 2045–55 period Scenario: A1	Estimate of avg summertime EHE-attributable deaths avoided in the 2090–99 period Scenario: A1	Estimate of avg summertime EHE-attributable deaths avoided in the 2090–99 period Scenario: B1
Detroit, MI	95	106	247	86
New York, NY	62	69	95	67
Louisville, KY	40	70	172	63
Dallas, TX	84	109	181	95
Chicago, IL	33	43	50	38
Denver, CO	47	51	61	44
Atlanta, GA	99	90	94	74
Minneapolis, MN	20	19	21	24
Cleveland, OH	4	6	–23	4
Boston, MA	–44	–43	–81	–50
Philadelphia, PA	34	40	55	39
Memphis, TN	11	20	42	11
Hartford, CT	46	59	98	55
Washington, DC	24	23	25	18
Newark, NJ	5	5	6	5
Baltimore, MD	3	4	10	3
St. Louis, MO	20	27	52	21
Kansas City, MO	–7	–9	–13	–8
Birmingham, AL	34	33	35	33
Greensboro, NC	11	10	16	10
Buffalo, NY	25	19	20	29
Jacksonville, FL	–20	–27	–17	–19
Pittsburgh, PA	12	12	7	10
Phoenix, AZ	4	4	9	6
Providence, RI	–4	–3	–2	–5
New Orleans, LA	10	11	24	7
Indianapolis, IN	–8	–10	–8	–8
Los Angeles, CA	4	9	12	5
San Antonio, TX	0	0	–1	–1
Cincinnati, OH	2	2	3	2
Columbus, OH	–10	–12	–43	–14
Seattle, WA	7	5	6	6
Houston, TX	2	3	1	4
Tampa, FL	–9	–14	–27	–9
San Jose, CA	0	0	0	0
Portland, OR	–7	–7	–8	–8
San Francisco, CA	1	1	1	1
San Diego, CA	0	0	1	0
Salt Lake City, UT	0	0	1	0
Miami, FL	0	0	0	0
Tot	630	725	1122	638

emissions scenario are less than half of those projected to occur under higher emissions scenarios by the 2090s. However, the proportionality of these differences is less likely to exist in earlier periods as the impact of emissions control increases over time in these scenarios.

Similarly, the comparison of results using the two different mortality algorithms suggests that advances in EHE notification and response that have occurred during the period 1996–2004 have had a significant impact in

reducing EHE-related mortality. Projecting these benefits into the future highlights the importance of these advances in a warming climate. The magnitude of the resulting estimates shows the potential health benefits that could be realized by continuing to improve these efforts.

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