The spatial variability of heat-related mortality in Massachusetts

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Abstract

This study assesses heat-related mortality in Massachusetts during the months of May through September from 1990 to 2008. Daily maximum apparent temperature was interpolated across space via kriging, and aggregated to 29 municipality groups (MGs), a spatial unit composed of municipalities that was designed to have minimal variation in population. Death certificate data were analyzed to determine the spatial distribution of excess mortality on days that exceeded the 85th, 90th, and 95th percentiles of apparent temperature. We find that the average statewide mortality anomalies were 5.11, 6.26, and 7.26 deaths on days exceeding the 85th, 90th, and 95th percentiles of apparent temperature respectively. A linear stepwise regression showed that percent African–American population and percent elderly population (those above the age of 65) were positively associated with an MG’s mortality anomaly on days exceeding the 85th percentile of apparent temperature ($p < 0.05$). In spite of the urban heat island effect, our measure of urbanization was not associated with higher rates of heat-related mortality.

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Introduction

Heat events cause significant increases in mortality. The 2003 European heat wave is believed to have caused 14,947 excess deaths in France (Poumadère, Mays, Le Mer, & Blong, 2005). In the United States, heat exposure is considered to be the most deadly weather event (Changon et al., 1996). Between 1979 and 1999, 8015 deaths in the United States were classified as being caused by heat exposure (CDC, 2001). This amount, in all likelihood, is significantly understated because heat exposure often exacerbates pre-existing health conditions, and is thus often not classified as a direct cause of death. During heat events, many causes of death show significant increases, including cardiovascular disease, respiratory diseases, diabetes, stroke, accidents, suicide, and homicide (Ellis, 1972; McGeehin & Mirabelli, 2001).

Heat vulnerability varies significantly within populations, often along demographic and socio-economic lines (Reid et al., 2009). The elderly and infant age groups are at the highest risk for heat-related mortality (Basu & Samet, 2002), due to their physiological difficulties regulating heat, and their restricted mobility, which decreases their ability to access fluids when needed (CDC, 1993). Some evidence suggests that vulnerability also varies by ethnicity. A recent case control study found that African–Americans had the highest risk of heat-related mortality, and that Caucasians had a higher risk than Hispanics (Basu & Ostro, 2008). Income also may be an important factor. Jones et al. (1982) found that those in low-income census tracts were six times more likely to experience heat stroke during a heat event in St. Louis and Kansas City than those in upper-income census tracts. Some evidence suggests that education also might influence heat vulnerability. In a study of 50 United States cities, those without a degree above a high school diploma had a higher heat-related death rate than those with more education (Medina-Ramon, Zanobetti, Cavanagh, & Schwartz, 2006). Finally, social isolation has been identified as a factor that increases heat vulnerability. Living alone was found to be a strong risk factor for heat-related mortality in two case control studies of Chicago heat waves (Naughton et al., 2002; Semenza et al., 1996).

Much of the research on heat-related health impacts has focused on urban areas (Baccini et al., 2008; Davis, Knappenberger, Michaels, & Novicoff, 2003; Kalkstein & Davis, 1989; Smoyer, Rainham, & Hewko, 2000), where urban heat island effects tend to increase temperatures relative to surrounding locations. Some studies have found that heat waves generate greater mortality responses in cities than surrounding areas (Jones et al., 1982; Tan et al., 2010), and some future projections of heat-related health effects have focused primarily on urban areas. Tol (2002), for example, assumes that heat-related mortality due to cardiovascular disease will occur mainly in urban areas. However, a study of Ohio found that suburban and rural counties experienced a higher proportional increase in heat-related mortality than urban counties, although the difference was not statistically significant (Sheridan & Dolney, 2003).
This study seeks to advance this body of knowledge by assessing the relationship between heat and mortality in Massachusetts, in both its urban and rural areas. In doing so, this study attempts to answer the following research questions: (1) How does heat-related mortality vary across space in Massachusetts? (2) Can spatial patterns of heat-related mortality be explained by socio-demographic variables? (3) Do urban areas experience a higher level of heat-related mortality than non-urban areas?

Massachusetts was chosen as the study area because it contains a relatively diverse mix of urban, rural, and suburban areas, and it is located in the northeastern United States, a region where heat-related mortality may be especially problematic (McGeehin & Mirabelli, 2001).

Data and methodology

This study employed three types of data: meteorological data from the National Climate Data Center (NCDC), mortality data from the Massachusetts Department of Public Health’s Registry of Vital Records and Statistics, and socio-demographic data from the U.S. Census Bureau.

Apparent temperature estimation

Apparent temperature, a variable that combines temperature and humidity, was used to measure heat exposure in this study (Steadman, 1984). Sub-hourly temperature and relative humidity data were obtained from NCDC’s Integrated Surface Hourly Database (NCDC, 2010) for all 2908 days in the study period (May 1st – September 30th for years 1990–2008). Fig. 1 shows the 102 temperature stations used in the analysis.

Temperature and relative humidity were used to calculate water vapor pressure, using the following equation:

\[
VP = \frac{RH}{100} \times 6.1121 e^{240.97 + \frac{T}{T}}
\]

where \(VP\) is water vapor pressure in hectopascals, \(T\) is temperature in °C, and \(RH\) is relative humidity (a percentage) (Buck, 1981). Using the calculated water vapor pressure, apparent temperature was derived using:

\[
AT = -1.3 + 0.92T + 2.2VP
\]

where \(AT\) is apparent temperature in °C, \(T\) is temperature in °C, and \(VP\) is water vapor pressure in kilopascals (Steadman, 1984).

Maximum daily apparent temperature, a commonly used heat exposure variable (Baccini et al., 2008; Smoyer et al., 2000), was calculated for each available weather station on each day in the study period. To ensure completeness, the sub-hourly data were first aggregated to the hour by deriving the mean apparent temperature within each hourly interval, and all stations that did not provide at least 18 hourly observations on a particular day were excluded. This exclusion was done to help assure that the maximum daily apparent temperature was reasonably representative of the conditions that occurred on that day. After removing days with an insufficient number of hourly readings, the highest hourly apparent temperature on each day was recorded as that day’s maximum apparent temperature.

This study used a geo-statistical approach to apparent temperature estimation. Based on the discrete point data from temperature stations, daily maximum apparent temperature was estimated across the entire state of Massachusetts for every day in the study period via kriging, a method of spatial interpolation that uses the spatial covariance structure of the data—how similar data points are at various distances from one another—to derive linear weights that produce a continuous surface estimate in raster format (Isaaks & Srivastava, 1989). Pixel size in the output raster surfaces was set at 330 m, which covered Massachusetts with 250,000+ pixels.

![Fig. 1. The locations of the 102 meteorological stations that provided temperature and relative humidity data.](image-url)
Fig. 2. The spatial distribution of the mean mortality anomaly per million population on hot days.

Fig. 3. The spatial distribution of the mean mortality anomaly per million population on very hot days.
Kriging models the spatial covariance structure of the data using a semivariogram (Isaaks & Srivastava, 1989). Due to the large number of days in the study period, the kriging procedure had to be automated, and to facilitate this automation, a uniform semivariogram model was selected for each daily surface. In order to choose the semivariogram model that would produce the most accurate estimates, a cross-validation procedure was performed to compare the accuracy of five semivariogram models available in the ArcGIS 9.3.1 Spatial Analyst tool: Spherical, Gaussian, Exponential, Circular and Linear. The cross-validation procedure used all data points (in this case, all weather stations) except one to create a continuous surface estimate. The value of the omitted data point was then compared to the value predicted at the corresponding location by the surface estimate to derive the error. This process was repeated for every weather station with an apparent temperature reading on a given day, and for a random sample of 100 days from the study period. The exponential semivariogram produced the lowest average standard error and was consequently chosen for use in the kriging procedure.

Unit of analysis

There is a tradeoff between geographical specificity and sample size when selecting a unit of analysis: larger units have greater population sample sizes and thus more statistical power per unit; on the other hand, increasing the size of the unit of analysis reduces the geographical specificity of the analysis, thus lessening the ability to discern variation across space. For this study, more statistical power per unit was desired than municipalities would provide, and more geographical specificity was desired than counties would provide. To resolve this tradeoff, Massachusetts was divided into 29 municipality groups (MGs), a unit created by combining municipalities in order to maximize the geographical specificity of the analysis, while ensuring that each unit had a 2000 Census population around 200,000, a figure that was expected to be large enough to provide meaningful results based on the experience of a similar study (Sheridan & Dolney, 2003). The 29 MGs, which can be seen in Figs. 2–5, all had 2000 Census populations around 200,000, with the exception of the Boston MG, which had a population of 589,141.

The statewide daily apparent temperature surfaces were aggregated to the MGs by deriving the mean pixel value within each MG polygon. This task was done with the Zonal Statistics tool in ArcGIS 9.3.1. Daily apparent temperature categories

Based on the apparent temperature estimates, each MG received a daily classification of hot, very hot, extremely hot, or not hot. Hot days were operationally defined as those that exceeded the 85th percentile apparent temperature in a given MG; very hot and extremely hot days were likewise defined as days that exceeded the 90th and 95th percentiles, and all other days were classified as not hot. These thresholds were chosen because mortality often increases significantly beginning at the 85th percentile apparent temperature (Gaffen & Ross, 1998). This method determines the daily classification based on a comparison between the maximum apparent temperature experienced on a given day in a given MG, to the maximum apparent temperatures experienced in that MG throughout the entire study period. As a result, the minimum apparent temperature at which a day was classified as hot, very hot, or extremely hot varied between MGs. This method was used instead of applying uniform apparent temperature thresholds across the entire state because Massachusetts experiences some variation in climate due to its coastal position. The mean maximum daily apparent temperature during the study period ranged from 22.77 °C in an MG including Cape Cod, to 24.89 °C in southwestern Massachusetts. With this variation in climate, some parts of Massachusetts might be slightly better acclimated to heat than others, and it thus was determined that what is considered hot, very hot, and extremely hot was relative and could vary between MGs.

Fig. 4. The spatial distribution of the mean mortality anomaly per million population on extremely hot days.
Calculating mortality anomaly

Death certificate data from the Massachusetts Department of Public Health’s Registry of Vital Records and Statistics was used to obtain the number of deaths in each MG on each day in the study period (Massachusetts Department of Public Health, 2010). All-cause mortality was used because a wide variety of causes of death are elevated during heat events (Ellis, 1972). A daily mortality anomaly was then calculated using the following equation (Sheridan & Dolney, 2003):

\[
MA = D - ED
\]

where \( MA \) is the mortality anomaly, \( D \) is the number of deaths on a given day in a given MG, and \( ED \) is the number of deaths expected on a given day in a given MG, which is equal to the average number of daily deaths in the MG that year during the months of May through September.

The average mortality anomaly per million population was then calculated separately for hot, very hot and extremely hot days for each MG. The Local Indicators of Spatial Association (LISA) tool in Geoda was used to test for spatial clustering of mortality anomalies on these days (Anselin, 1995).

There is frequently a lag between a heat event and its associated mortality response. People may initially get sick on a hot day, and then die as a result on a later day. Studies have found the strongest associations between a heat event and the mortality response ranging from the same day to 3 days following the heat event (Basu & Samet, 2002). Results presented in this paper are for a 0-day lag, because a 0-day lag was found to have the strongest correlation (measured by a Pearson’s correlation coefficient) between apparent temperature and the mortality anomaly.

Testing statistical significance of mortality anomalies

A randomization procedure was used to test whether the mortality anomaly was statistically significantly elevated on days classified as hot, very hot, and extremely hot (Sheridan & Dolney, 2003). This involved randomly sampling the series of mortality anomalies in each MG 10,000 times (using a uniform distribution so that each day was equally likely to be chosen), with each iteration selecting a number of samples equal to the number of days that were categorized as hot, very hot, or extremely hot. The percentage of random samples with mean mortality anomalies exceeding the observed mortality anomaly on the classified days determined the statistical significance (Sheridan & Dolney, 2003). For example, if the Boston MG had 250 days classified as very hot, and the mean mortality anomaly on those days was +1.5 deaths, then each iteration would first randomly select 250 mortality anomalies in the Boston MG. The average mortality anomaly from the random sample would then be compared to the observed mortality anomaly on the days classified as very hot (in this case +1.5 deaths). If 4 percent of the mortality anomaly samples had means greater than 1.5 deaths, then the derived \( p \) value would be 0.04.

Socio-demographic determinants of heat-related mortality

Socio-demographic data were obtained from the 2000 U.S. Census (U.S. Census, 2010a), which was conducted approximately midway through the study period. The following socio-demographic variables were calculated for each MG: (1) mean household income, defined as the average income per household; (2) percent African—American, defined as the percent of population who classified themselves as African—American; (3) percent elderly, defined as the percent of population above the age of 65; (4) percent infant, defined as the percent of population below the age of 1; (5) percent single person households, defined as the percent of occupied households with only one person; and (6) percent without high school diploma, defined as the percent of population above 25 without a high school diploma. These variables were chosen because previous studies have linked the underlying phenomena with heat-related mortality (see Section 1). Correlation analysis and linear regression were performed to determine the relative importance of these socio-demographic variables in explaining the variance in the mortality anomaly between the MGs.
Urbanization and heat-related mortality

There are several ways to operationalize urbanization. One option is to use the U.S. Census Bureau’s urban/non-urban classifications. Individuals are classified by the U.S. Census as living in an urban area if their residence lies within an urban cluster (a densely settled area with a population between 2500 and 50,000 people) or an urbanized area (a densely settled area with a population greater than 50,000 people) (U.S. Census, 2010b). One downside of this method is that it is a binary scale, which may be problematic because it does not capture any variation between areas classified as urban or non-urban. This may be problematic for our purposes because the urban heat island effect may be more severe in a place like Boston than in Pittsfield, a relatively small city located in western Massachusetts that is also classified as urban by the U.S. Census.

An alternative to this binary approach is to use a continuous variable, like population density, as a proxy for urbanization. However, using population density may not always represent the urbanization of an area. Consider an area that has within it a small densely populated city, as well as a large mountain range, where few people live. Deriving the population density of this entire area would underestimate the urbanization of the population because it does not capture any variation between areas classified as urban or non-urban. This may be problematic for our purposes because the urban heat island effect may be more severe in a place like Boston than in Pittsfield.

To resolve this issue, a weighted average procedure was used to create a modified population density value for each MG. This was done in three steps: (1) The population density of each census block group within each MG was obtained; (2) these population densities were multiplied by the percent of population they represented of the entire MG; and (3) these values were summed. The equation for this procedure is shown below:

\[
\text{Modified Population Density}_{BG} = \frac{\sum_{BG} \left( \frac{\text{Pop}_{BG}}{\text{Pop}_{MG}} \times \frac{\text{Area}_{BG}}{\text{Area}_{MG}} \right)}{n}
\]

Where BG is a given block group within an MG, n is the total number of block groups within the given MG, Pop is population, and Area is the land area in square miles.

Correlation analysis and linear regression were performed to determine whether the degree of urbanization (measured by modified population density) was associated with increased heat-related mortality.

Results

Total heat-related mortality in Massachusetts

A summary of the characteristics of heat-related mortality in Massachusetts is presented in Table 1. As expected, the mean mortality anomaly increased with the temperature threshold: the mean mortality anomaly statewide was 5.11 deaths on hot days, 6.26 deaths on very hot days, and 7.26 deaths on extremely hot days. As the temperature classification became more stringent, the sample size of days meeting each category decreased, and as a consequence, lower number MGs exhibited significant increases in their mortality anomalies.

The spatial distribution of heat-related mortality

Figs. 2–4 show the spatial distribution of the average mortality anomaly per million population on hot, very hot, and extremely hot days. The MGs are labeled by the largest municipality they contain in terms of population, according to the 2000 U.S. Census. The spatial distribution of heat-related mortality was similar on hot, very hot, and extremely hot days. The greatest heat-related mortality was generally experienced in southwest/south-central Massachusetts (in the Southbridge and Springfield MGs), southeast Massachusetts (in the Brockton and New Bedford MGs) and in some municipalities in and around Boston (for example, the Boston and Framingham MGs). LISA tests found significant clustering of high mortality anomaly values in southwest/south-central Massachusetts on hot and very hot days. A LISA test on extremely hot days showed significant negative spatial autocorrelation centering in the Framingham MG.

Explaining the variation in heat-related mortality across space

Correlation analysis and linear regression were performed to determine the extent to which socio-demographic variables and urbanization could explain the variation in heat-related mortality between the MGs. The results reported here use the average mortality anomaly on hot days per million population as the dependent variable (referred to hereafter as the mortality anomaly on hot days), because this classification contained the largest sample size of days, and is thus expected to show the most reliable variations in heat-related mortality.

Correlation analysis

Table 2 shows a bivariate Pearson’s correlation matrix, which contains the dependent variable (mortality anomaly on hot days),
along with all of the socio-demographic variables described in Section 2.6, and the modified population density variable described in Section 2.7. Percent African—American and percent elderly were both positively correlated with the mortality anomaly on hot days, and were significant at the p < 0.1 and p < 0.05 levels respectively. Additionally, many of the independent variables exhibited strong correlations with one another. For example, mean household income was strongly negatively correlated with percent without high school diploma (r = −0.773), and modified population density displayed a strong positive correlation with percent single person households (r = 0.747).

Linear regression

Several diagnostic tests were used to assess whether our data conformed with the assumptions of linear regression: A Jarque-Bera procedure was undertaken to test for non-normality (Jarque & Bera, 1987), a Breusch–Pagan test was undertaken to test for heteroskedasticity (Breusch & Pagan, 1979), and Moran’s I tests were used to test for spatial autocorrelation in the regression variables and residuals (Moran, 1950). None of these tests showed statistically significant deviations from the regression assumptions, so no adjustments were made.

Table 3 shows the results of three linear regression models. Model 1 included all seven independent variables (the socio-demographic variables described in Section 2.6, and the modified population density variable described in Section 2.7). Only percent African—American was statistically significant (p = 0.005). For Model 2, a stepwise regression procedure was used with all the independent variables from Model 1. Percent African—American and percent elderly were found to be positively associated with the mortality anomaly on hot days (p values of 0.011 and 0.006 respectively). Model 3 used the two variables included in the stepwise procedure (percent African—American and percent elderly), along with modified population density as independent variables. Percent African—American and percent elderly were still positively associated with the mortality anomaly on hot days (p values of 0.005 and 0.006 respectively), but here the modified population density coefficient was negative, although still statistically insignificant (p = 0.147). As shown in Table 2, modified population density showed a slight, statistically insignificant bivariate correlation of 0.066 with the mortality anomaly on hot days (p = 0.734).

Linear regression residuals

As is apparent in Table 2, the three regression models had Moran’s I values that were either negative (although none of these values were statistically significant) or close to 0. Fig. 5 shows the residuals for Model 2 (with all coefficients statistically significant). We could not identify any missing explanatory variables that could explain the spatial pattern of the residuals.

Discussion and conclusions

This study is one of only several to our knowledge that has analyzed the spatial distribution of heat-related mortality in relation to both urbanization and relevant socio-demographic variables. Mortality statewide was elevated on days that exceeded the apparent temperature thresholds. The reported figures, however, may be overstated. Previous studies indicate that high apparent temperatures are associated with pollution episodes, which also impact mortality (Kovats & Hajat, 2008). For example, a study of Mexico City found that controlling for air pollution and respiratory epidemics decreased the impact of apparent temperature on mortality by 50% (O’Neill et al., 2005). As a result, failure to account for pollution may produce results that overestimate the impact of apparent temperature on mortality. However, it should be noted that higher temperatures increase the concentrations of many air pollutants, including Ozone and Volatile Organic Compounds (Bernard, Samet, Grambsch, Ebi, & Romieu, 2001).

Previous investigations have found significantly elevated heat-related mortality in urban areas relative to surrounding rural/suburban areas (Jones et al., 1982; Tan et al., 2010). However, neither of these studies reported results after controlling for relevant socio-economic variables. This study found a very slight positive (but statistically insignificant) correlation between an MG’s modified population density and its mortality anomaly on hot days. However, after controlling for the two statistically significant variables from the stepwise regression (percent African—American, and percent elderly), a negative relationship was present between modified population density and the mortality anomaly on hot days (this also was statistically insignificant). These results suggest that, at least in Massachusetts, an area’s demographics may be more important to its heat-related mortality than its level of urbanization, at least as captured by the specific variables used in this study.

The comparative vulnerability of urban and rural areas appears to vary greatly by location and heat event. Up until this point, little research has been done on heat vulnerability in rural areas. It is conceivable that the vulnerability of rural areas may be influenced by drivers that have little importance in urban areas. For example, heat vulnerability in rural areas may be influenced by the prevalence of outside laborers (Sheridan & Dolney, 2003). Further research is needed to determine the factors that affect heat-related mortality in rural areas, especially in light of expected temperature increases.

References


