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Temperature and Mortality in 11 Cities of the Eastern United States

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Episodes of extremely hot or cold temperatures are associated with increased mortality. Time-series analyses show an association between temperature and mortality across a range of less extreme temperatures. In this paper, the authors describe the temperature-mortality association for 11 large eastern US cities in 1973–1994 by estimating the relative risks of mortality using log-linear regression analysis for time-series data and by exploring city characteristics associated with variations in this temperature-mortality relation. Current and recent days' temperatures were the weather components most strongly predictive of mortality, and mortality risk generally decreased as temperature increased from the coldest days to a certain threshold temperature, which varied by latitude, above which mortality risk increased as temperature increased. The authors also found a strong association of the temperature-mortality relation with latitude, with a greater effect of colder temperatures on mortality risk in more-southern cities and of warmer temperatures in more-northern cities. The percentage of households with air conditioners in the south and heaters in the north, which serve as indicators of socioeconomic status of the city population, also predicted weather-related mortality. The model developed in this analysis is potentially useful for projecting the consequences of climate-change scenarios and offering insights into susceptibility to the adverse effects of weather. *Am J Epidemiol* 2002;155:80–7.

aging; cause of death; climate; heat; mortality; weather

For centuries, the impact of weather on people has been a public health concern. Historically, researchers have noted that episodes of extremely hot or cold temperatures increase mortality (1), and contemporary time-series analyses show an association between temperature and mortality across the range of usual temperatures (2). These studies show that mortality tends to rise with increasingly hot or cold temperatures from an optimum temperature value. Global warming and other weather phenomena, such as El Niño, have sparked new interest in the weather-mortality relation. On the basis of climate-change scenarios, temperate regions such as North America are expected to warm disproportionately more than tropical and subtropical zones, and temperature variability will increase (3). According to an Intergovernmental Panel on Climate Change (IPCC) report, the frequency of extremely hot days in temperate climates approximately doubles for every 2–3°C increase in temperature during the average summer (3).

Heat waves cause excess deaths, many of which are due to increased demand on the cardiovascular system required for physiologic cooling (4). Data from US cities provide evidence that overall death rates increase during heat waves (5, 6), particularly when the temperature rises above the local population's threshold value. However, mortality rates show a strong seasonal pattern, peaking in the winter when epidemic respiratory infections, such as influenza, are most common.

We explored the weather-mortality relation in 11 of the largest metropolitan areas of the eastern United States to further characterize the weather-mortality relation across the full range of temperatures and latitudes. A number of similar studies have been published in recent years (1, 6–9). The present study extends these early analyses by incorporating contemporary methods of time-series analyses and by exploring city-specific factors that might explain variations in the temperature-mortality association across cities; a two-stage analytical approach was used. We developed a model of the weather-mortality relation that is potentially useful for projecting the consequences of climate-change scenarios. The model also offers a summary of these data as evidence about possible weather effects on mortality.

MATERIALS AND METHODS

Daily weather and mortality data for 1973–1994 were collected for 11 large metropolitan areas in the eastern United States (Chicago, Illinois; Boston, Massachusetts; New York, New York; Philadelphia, Pennsylvania; Baltimore, Maryland; Washington, DC; Charlotte, North

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Abbreviations: AIC, Akaike's Information Criterion; GAM, generalized additive model; MMT, minimum mortality temperature.

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Carolina; Atlanta, Georgia; Jacksonville, Florida; Tampa, Florida; and Miami, Florida). These metropolitan areas represent the principal population centers on the eastern seaboard plus Chicago, which was added to broaden the range of geographic coverage and weather. The data used were for the counties comprising these metropolitan areas. For New York City, we included its five counties and Yonkers. For Boston, we included only Suffolk County. Because the city of Baltimore is not part of Baltimore County, we combined the deaths for Baltimore City and Baltimore County to define the Baltimore location.

The mortality data were provided by the Division of Vital Statistics of the National Center for Health Statistics (Hyattsville, Maryland). These mortality data excluded persons who died in the study area but did not reside within that area and whose deaths were attributed to external causes. Information was used on underlying cause of death, coded according to the *International Classification of Diseases*, Ninth Revision, to classify deaths as due to cardiovascular disease (codes 390–459), respiratory disease (codes 460–519), and all other diseases. For selected analyses, the mortality data were stratified by age as less than 65, 65–75, and more than 75 years.

Both census and weather data were used as potential predictors for modeling mortality. Data from the 1980 and 1990 Census of Population and Housing were provided by the US Census Bureau (10–12). The weather data were extracted from the National Climatic Data Center EarthInfo CD2 database (13). These data included hourly readings for temperature and dew point reported in degrees Fahrenheit (°C = 5/9 × (°F − 32)).

As detailed further below, we estimated the weather-mortality relation by using generalized additive models (GAMs) with nonparametric smoothing functions (splines) to describe nonlinear relations (14, 15). We used Akaike's Information Criterion (AIC), a measure of fit, to select the smoothing parameters (16). Of the available weather variables for 1973–1994, we considered for each day the average temperature, dew point, nighttime (between 6 p.m. and 6 a.m.) temperature and dew point, and daytime (between 6 a.m. and 6 p.m.) temperature and dew point. In exploring the weather-mortality relation, we began with lagged predictor variables to allow for possible delayed effects of weather, starting with variables unlagged and lagged by 1–7 days.

Data for Philadelphia and Chicago were used for initial model development. For each city, a Poisson regression GAM was fit for mortality by using as the predictors smoothing spline functions of time, average daily temperature, and average daily dew point at several lags. For these and all other GAMs fit in the analysis, 44, 88, and 176 df were used in the smooth function of time, which is an average of 2, 6, and 8 df, respectively, per year over the 22 years of record. This approach controls for smooth seasonal variations in mortality without imposing a common seasonal pattern across all years or requiring separate models to be fit for each year. Functions of average temperature and average dew point were each given a total of 6 df.

The results of this initial analysis motivated us to construct additional variables intended to better capture the lagged effects of temperature and dew point. The new variables were constructed for both temperature and dew point: $T_{1\text{–}3}$ is the average temperature for the 3 days preceding the day on which mortality was recorded, while $T_{4\text{–}10}$ is the average temperature for days 4–10 preceding the recorded mortality. Similarly, variables $D_{1\text{–}3}$ and $D_{4\text{–}10}$ were constructed for dew point. Other variables were considered in the model but provided no additional understanding of the weather-mortality relation.

Our statistical analyses had two stages. In the first stage, a separate log-linear regression analysis for each city produced an estimated mortality relative risk curve as a smooth function of temperature. In the second stage, we summarized the shape of the smooth relative risk curve for each city and described how these summaries varied across cities as a function of latitude and other city-level variables. Each stage is described in more detail below.

Stage 1: city-specific log-linear regressions

Our primary goal was to characterize the shape of the mortality-temperature relation for shorter time scales while, to the extent possible, controlling for possible confounding due to longer-term trends in demographic characteristics, smoking, medical care, and seasonal health events, such as influenza epidemics. After substantial preliminary analysis in which several daily temperature variables were considered as predictors of mortality by using AIC, we focused our analysis on the daily mean values of temperature and dew point that were found to be the best or close to the best predictors for all 11 cities. On the basis of a preliminary analysis, we addressed the lagged dependence of mortality on weather by using same-day temperature T_0 and dew point D_0, average temperature and dew point over the preceding 3 days $T_{1\text{–}3}$, $D_{1\text{–}3}$, and average temperature and dew point temperature 4–10 days prior $T_{4\text{–}10}$, $D_{4\text{–}10}$. Because T_0, $T_{1\text{–}3}$, and $T_{4\text{–}10}$ (and D_0, $D_{1\text{–}3}$, and $D_{4\text{–}10}$) were highly correlated, and because our focus was on the shape of the temperature-mortality association and not on the lag structure, we orthogonalized the temperature predictor variables and included T_0, D_0; adjusted $T_{1\text{–}3}$ (adj $T_{1\text{–}3}$), which is $T_{1\text{–}3}$ adjusted for T_0 and D_0; adjusted $D_{1\text{–}3}$ (adj $D_{1\text{–}3}$), which is $D_{1\text{–}3}$ adjusted for T_0 and D_0; and $T_{4\text{–}10}$ and $D_{4\text{–}10}$ adjusted for T_0, D_0, $T_{1\text{–}3}$, $D_{1\text{–}3}$ (adj $T_{4\text{–}10}$, adj $D_{4\text{–}10}$). The adjusted lagged variables were taken as the residuals from regressing the lagged variable on the unlagged variables; for example, adj $T_{1\text{–}3}$ are the residuals from regressing $T_{1\text{–}3}$ on T_0 and D_0. Additionally, variables reflecting the difference between the average daytime and average nighttime temperatures were constructed at lag 0 (S_0) and for the averages of lags 1–3 ($S_{1\text{–}3}$) and lags 4–10 ($S_{4\text{–}10}$).

Several models were fit with the new lag-combination variables. Comparing the AIC values for all models, we found that those including same-day temperature and dew point, as well as previous 3-day temperature and dew point (lag 1–3 variables), fit best. Because the models with same-day and 3-day lag variables also have the advantage of simplicity, the lag 4–10 variables were not included. The daily spread in temperature variables (S_0, $S_{1\text{–}3}$, $S_{4\text{–}10}$) did not seem to improve the model fit and were also excluded. To avoid giving undue priority to same-day variables, we also considered models with T_{1-3}, D_{1-3} and T_0, D_0 adjusted for T_{1-3}, D_{1-3} as predictors.

In a standard log-linear regression (17), log mortality is assumed to be a linear function of temperature and other predictors. In our study, we assumed that log mortality is a smooth but not necessarily linear function. We estimated this smooth function by using a GAM (14), which fits a cubic spline function of temperature. Instead of summarizing the temperature-mortality association with a single relative risk value for all temperatures, we obtained a relative risk estimate that was a smoothly changing function of temperature. GAMs or cubic splines are widely available in most statistical software packages (e.g., S-PLUS (18) and SAS (19)). The degree of smoothness of the estimated mortality-temperature relative risk curve is controlled by its number of degrees of freedom. A linear function has 1 df for its one slope; a quadratic curve has 2 df for its slope and curvature, among other variables. To allow for highly nonlinear shapes, we used 6 df to describe the association of mortality with each weather variable.

Finally, the regression of mortality on weather may also be affected by key potential effect modifiers including longer-term changes in population characteristics, health behaviors (particularly smoking), trends in medical practices or access to health care, and potential seasonal-related confounders. All but the last change slowly, but not necessarily linearly, over time. Therefore, these variables can be adjusted by including a smooth function of calendar time as a predictor. Acute events affecting health, such as influenza epidemics, occur seasonally, as does temperature variation. Since detailed data on such events were not available, they were more difficult to control for without removing some or all of the temperature effects. Thus, we relied on a smooth function of calendar time to adjust for potential seasonal confounders as best as was possible. To explore the effects of this adjustment on our results, we used 44, 88, and 176 df (average of 2, 6, and 8 df, respectively, per year) for the smooth function of calendar time.

Hence, the final log-linear model for a given city has the form:

$$\text{log expected mortality}_{(t)} = S(t;\lambda_1) + S(T_0,6) + S(D_0,6) + S(\text{adj } T_{1-3},6) + S(\text{adj } D_{1-3},6) \quad (1)$$

where $S(\bullet,\lambda)$ represents a smooth relative risk function with λ degrees of freedom for the variable indicated, and t denotes calendar time. We considered $\lambda_1 = 44$, 88, and 176 df over the 22 years.

Stage 2: variation in relative risk curves for temperature across cities

The goal of the second-stage analysis was to describe variation in the shape of the mortality-temperature relative risk curve across cities in relation to latitude and other city-specific characteristics, such as percentage of elderly persons and percentage of homes with heating and/or air-conditioning. We summarized the relative risk curves for mortality in relation to T_0 with three variables: the temperature at which the estimated relative risk curves from the GAM achieved their minimum or minimum mortality temperature (MMT), the average slope of the estimated relative risk curves at temperatures lower than the MMT (cold slope), and the average slope of the curves at temperatures higher than the MMT (hot slope) (figure 1). The cold slopes and hot slopes were found by fitting a linear regression line through those points in the fitted relative risk curve from the GAM before and after the turning point (MMT), respectively.

We used a random-effects linear regression model (e.g., Diggle et al. (20)) in the second stage to describe the linear associations of the MMT and the cold and hot slopes with city characteristics while accounting for both the statistical error in estimating the characteristics of these three city-specific relative risk curves and the natural variation in their true values about the regression on predictor variables. The model has the form

$$Y_i = \beta_{0_i} + \beta_1 X_i + \varepsilon_i \quad (2)$$

where Y_i is the estimated MMT, cold slope, or hot slope; X_i is a vector of predictors, for example, latitude and percentage of the population more than 65 years of age; β_{0_i} is a city-specific random effect that reflects natural variation from the model prediction $\beta_1 X_i$ among cities; β_1 represents the dependence of Y on X; and ε_i is the statistical error. We assumed that β_{0_i} and ε_i were independent, approximately Gaussian variates with variances τ^2 and σ_i^2, respectively.

Since our summary-statistics MMT, cold slope, and hot slope were calculated from nonparametric regressions, we used a standard statistical method—bootstrapping (21)—to estimate the statistical variance σ_i^2 for each city. Bootstrapping is a computer-intensive resampling method for estimating variances. From the original sample of N days, we randomly drew a new sample, also of size N, with replacement. By using this new sample, we refit the model and obtained a new set of estimates of the MMT, cold slope, and hot slope. This process was repeated 100 times, and σ_i^2 was estimated by the variance among these 100 replications of the summary measure (e.g., cold slope) of interest. We estimated τ^2 by using the method of moments and then used iteratively reweighted least squares to estimate β_1 with weights $\text{var}(Y_i) = (\hat{\tau}^2 + \hat{\sigma}_i^2)^{-1}$, $i = 1, \ldots 11$. The city-specific predictor variables, averaged from the 1980 and 1990 US Censuses, were the fractions of persons 1) more than age 65 years, 2) more than age 65 years who were disabled, 3) more than age 25 years who did not have a high school degree, and 4) living in poverty; and the fraction of occupied homes with 5) heating and 6) air-conditioning. The heating variable included homes equipped with some form of heat source (gas, oil, electric, etc.). The air-conditioning variable included homes with central air or homes with one or more wall units. Air-conditioning data were available from the 1980 US Census only, so these percentages were used in the analysis. Similarly, the fraction of persons more than age 65 years who were disabled was recorded in the 1990 US Census only; therefore, these numbers were used (10–12).

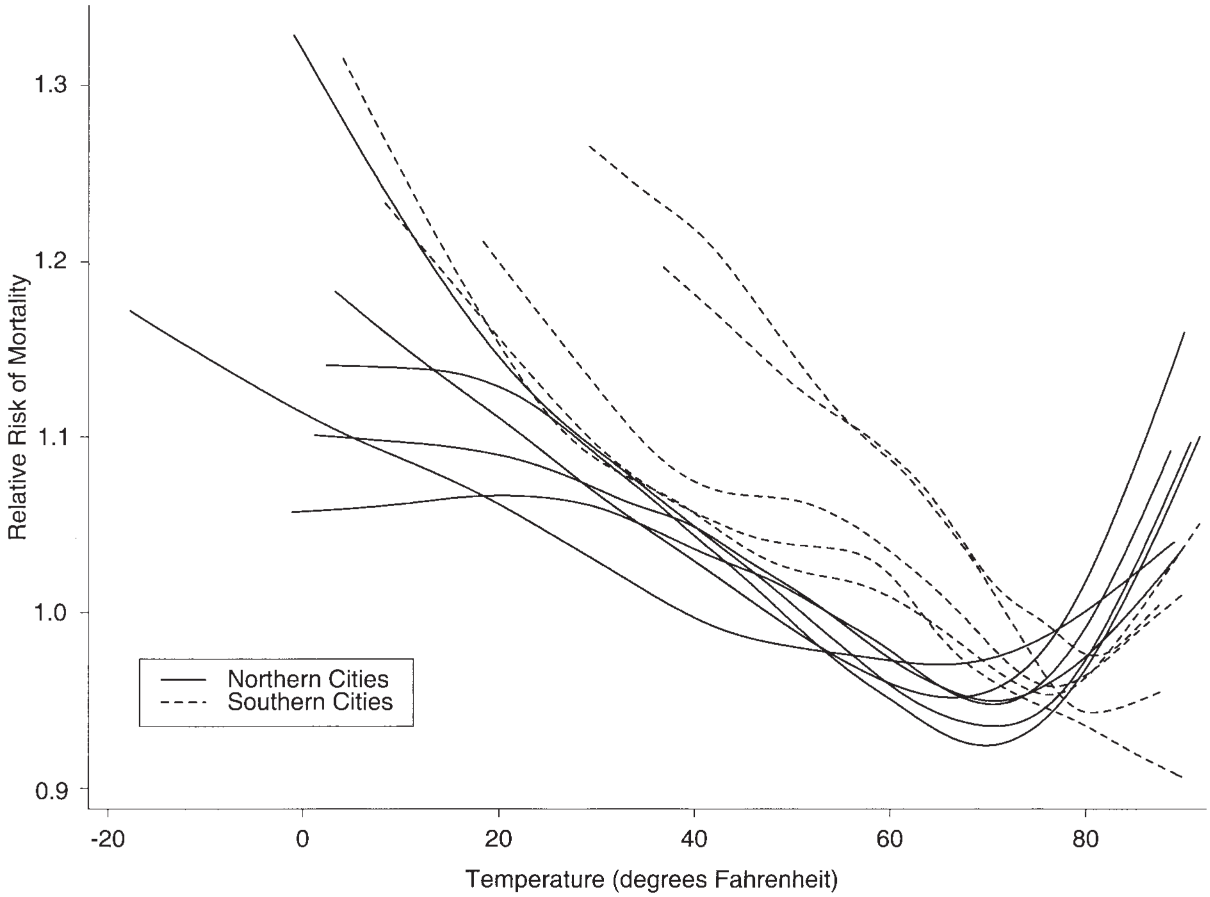

FIGURE 1. Temperature-mortality relative risk functions for 11 US cities, 1973–1994. Northern cities: Boston, Massachusetts; Chicago, Illinois; New York, New York; Philadelphia, Pennsylvania; Baltimore, Maryland; and Washington, DC. Southern cities: Charlotte, North Carolina; Atlanta, Georgia; Jacksonville, Florida; Tampa, Florida; and Miami, Florida. ˚C = 5/9 × (˚F – 32).

We first regressed each of the summary scores (MMT, cold slope, and hot slope) on each predictor alone and then on latitude with each of the city-specific variables. We used this approach to estimate the effect modification by these city-specific variables over and above the apparent effect modification due to latitude. S-PLUS statistical software (18) was used for all analyses.

RESULTS

Table 1 provides summary characteristics of those cities included in the analysis, listed from the northernmost to the southernmost. Figure 1 shows the temperature (T_0)-mortality relative risk function $S(T_0,6)$ estimated for each of the 11 cities by using log-linear regression model 1. We focused on T_0 because it was by far the strongest term in the regression model: it was stronger than D_0 because temperature is a much stronger predictor than either dew point or adj $T_{1–3}$ and adj $D_{1–3}$, the variables constructed to be approximately uncorrelated with T_0 and D_0.

We found that the effect of temperature on mortality varied among cities. For all cities, mortality risk decreased as temperature increased from the coldest temperatures. For the northern cities, mortality risk began to rise as the temperature increased from a certain temperature, producing a J-shaped relation. For the southern cities, the temperature-risk relations did not have a hooklike shape but tended to flatten at warmer temperatures, indicating little increase in mortality risk for the hottest days. With colder temperatures, the curves for the southern cities had steeper slopes than those for the northern cities. These findings were similar when the analysis was limited to winter. During the spring and fall, a slight increase in mortality risk occurred with colder temperatures, especially in the southernmost cities. In the summer, the effect of extreme heat on mortality was evident, increasing almost 40 percent over the baseline average in the northernmost cities. The results shown in figure 1 are from a model in which we controlled for trends by using a smooth function of time with 176 df over the 22 years. The findings were qualitatively similar when we used 44 or 88 df.

We next explored the association between weather and mortality for four different time periods—1973–1979, 1980–1984, 1985–1989, and 1990–1994—fitting model 1 to each period. Fits for each period were similar to those described earlier for the entire period (figure 1). Thus, it

TABLE 1. Population, mortality, and temperature summaries for 11 selected US cities*

City	Latitude	1980 population (× 10^3)	Average daily no. of deaths	Average no. of cardiorespiratory deaths	Average temperature (˚F†)	
					Summer	Winter
Boston, Massachusetts	42˚35´	625.4	15	8	71.0	31.5
Chicago, Illinois	41˚83´	5,253.6	117	69	71.9	25.6
New York, New York	40˚78´	7,938.2	195	117	73.8	34.5
Philadelphia, Pennsylvania	39˚95´	1,688.2	43	23	75.1	34.2
Baltimore, Maryland	39˚30´	1,442.3	21	11	75.1	35.4
Washington, DC	38˚90´	6,383.0	16	8	75.7	36.0
Charlotte, North Carolina	35˚23´	4,042.0	7	4	77.2	42.4
Atlanta, Georgia	33˚75´	589.9	12	7	77.8	44.0
Jacksonville, Florida	30˚36´	571.0	12	7	79.8	53.9
Tampa, Florida	27˚95´	646.9	14	8	81.3	61.0
Miami, Florida	25˚76´	1,625.7	40	23	82.3	68.7

* Mortality and average daily temperatures, 1973–1994.
† ˚C = 5/9 × (˚F – 32).

seems that over the total period of 1973–1994, the effects of weather on mortality were qualitatively consistent.

The association between weather and mortality from various causes was examined (results not shown), with cardiovascular disease and respiratory disease grouped together because of small numbers of deaths from respiratory diseases. As in the models for all causes of death, mortality risk for cardiovascular and respiratory disease decreased as temperature increased, although the cold-weather slopes were steeper than those for all disease types combined (figure 1). As for total mortality, the slopes of the curves before the turning point were steeper for the southern cities than those for the northern cities; after the turning point, the slopes for the northernmost cities were steeper. The Other disease category included mainly cancer deaths. For the Other category, the curves representing the effects of the temperature lag 0 variable were relatively flat compared with the curve for cardiovascular and respiratory disease.

To explore the possibility of differing weather-mortality relations for each age group, we stratified the mortality data into three different age categories: less than 65, 65–75, and more than 75 years. In each age group, we observed a qualitatively similar relation between weather and mortality (results not shown), although the temperature effect was smallest for the youngest age group and largest for the group aged 75 years or more.

We summarized the relative risk curves for mortality in terms of MMT, cold slope, and hot slope (table 2). As is apparent in figure 1, the cold slope was steeper (more negative) for the southernmost cities, and the hot slopes were steeper (more positive) for the northernmost cities. The MMT increased the farther south the city's location. There was a surprisingly large difference in hot slope between Baltimore and Washington, DC, two nearby cities with almost identical weather patterns. The curve representing Charlotte never turned, making it impossible to estimate a corresponding hot slope.

In the second stage of the analysis, we first regressed each of the three summary characteristics of cold slope, hot slope, and MMT on the city-specific variables in univariate models. We then added latitude to the model. The results are pre-

TABLE 2. Summary scores* for temperature-mortality relation, by US city,† 1973–1994

City	Minimum mortality temperature (MMT)‡	Cold slope‡,§	Hot slope‡,¶
Boston, Massachusetts	69.71	−4.34	5.83
Chicago, Illinois	65.17	−2.25	2.45
New York, New York	66.42	−3.59	6.28
Philadelphia, Pennsylvania	70.58	−4.37	6.11
Baltimore, Maryland	70.46	−2.65	6.56
Washington, DC	70.56	−3.13	3.67
Charlotte, North Carolina	90.38	−3.27	NA#
Atlanta, Georgia	76.29	−2.91	5.41
Jacksonville, Florida	76.75	−3.76	3.71
Tampa, Florida	80.71	−7.12	1.43
Miami, Florida	80.92	−5.46	4.01

* Refer to the Materials and Methods section of the text for a description of these scores.
† Cities are listed by decreasing latitude.
‡ Percentage change in mortality per (˚C = 5/9 × (˚F – 32)).
§ Cold slope = average slope of the estimated relative risk curves at temperatures lower than MMT.
¶ Hot slope = average slope of the estimated relative risk curves at temperatures higher than MMT.
# NA, not available because the curve has no turning point.

sented in table 3. Comparison of the univariate and bivariate regressions indicates the extent to which the associations of the city-specific variables reflect latitude.

Without adjustment for latitude, the percentage of the population aged 65 years or more (%65+) significantly predicted the cold slope. A 10 percent increase in the population aged 65 years or more was associated with an estimated increase in the steepness of the cold slope (negative coefficients make the cold slope more negative) corresponding to an approximately 4.0 percent higher risk of mortality per 10˚F decrease in temperature. When we adjusted for latitude, the %65+ coefficient changed little and remained statistically significant. Although not significant, the percentage of homes with heating (%Heating) was associated with a reduction in the steepness of the cold slope. After we controlled for latitude, the effect of the %Heating variable was reduced more substantially, since this variable is closely related to latitude.

For the hot slopes, significant pairwise associations were found with percentages of persons not completing high school (%NoHS), persons living in poverty (%Poverty), and homes with air conditioners (%Air Cond). A 10 percent increase in %Poverty, the strongest predictor, was estimated to increase mortality risk by approximately 4.3 percent per 10˚F increase in temperature, at temperatures higher than the MMT. Adjusting for latitude had little impact on these significant associations. For MMT, only %Air Cond showed a significant association, and this association was reduced substantially by adjusting for latitude, since this variable is closely related to latitude.

DISCUSSION

The objective of this research was to use analytical techniques—in particular, GAMs—to characterize the relation between weather and mortality in large eastern US cities. These models offer flexibility and are descriptive, without making strong prior assumptions about the shape of the relative risk curve. In general, our findings were consistent with prior findings. Many of the previous reports used conventional linear regression techniques that would be less appropriate for discrete data and correlated variables (7, 22).

Given only same-day average temperature and average dew point, temperature was the index of weather that most strongly predicted mortality (AIC comparison not shown in results). However, we found that same-day dew point provided an additional explanation for mortality. With regard to time response, daily temperature at lag 0 and the average of daily temperatures at lags 1, 2, and 3 were more strongly associated with mortality than further lagged variables were. The weather more than 4 days prior was at best weakly associated with mortality once the more recent weather was taken into account. Within the selected cities, mortality risk decreased as temperature increased from the coldest days; however, after a certain critical temperature threshold, mortality risk increased in most of the cities as temperature increased.

Although this J-shaped relation was present for most cities, there were noticeable differences in the temperature-mortality response among the cities (table 2). These results are consistent with the work of others (5, 23). Generally, populations in warmer regions tend to be most vulnerable to cold (24), and those residing in cold climates are most sensitive to heat (23). In temperate regions, mortality rates are highest during the winter. When analyzing data for the Netherlands, Kunst et al. (6) also observed the decline in mortality with temperature for low and moderate temperatures and increased mortality with temperature at high average daily temperatures, that is, the J-shaped relation. We

TABLE 3. Summary results from regressing the cold slopes, hot slopes, and minimum mortality temperatures on city-specific predictor variables with and without adjusting for latitude, United States, 1973–1994†

Predictor‡	Model	Cold slope§	Hot slope¶	Minimum mortality temperature (MMT)
%65+	Unadjusted	−3.97* (1.27)	0.71 (2.47)	1.66 (8.08)
	Adjusted	−3.96* (1.17)	1.63 (2.45)	5.34 (5.22)
%NoHS	Unadjusted	0.10 (0.83)	3.13* (0.95)	−5.95 (4.16)
	Adjusted	−0.46 (0.71)	2.78* (1.01)	−3.46 (2.67)
%Poverty	Unadjusted	0.03 (0.10)	4.26* (0.46)	−6.05 (5.06)
	Adjusted	−0.39 (0.83)	4.26* (0.42)	−2.56 (3.50)
%65+ Disability	Unadjusted	1.20 (1.70)	1.47 (2.72)	0.41 (9.30)
	Adjusted	0.85 (1.48)	1.14 (2.67)	6.78 (5.73)
%Air Cond	Unadjusted	−0.22 (0.22)	−0.77* (0.32)	2.54* (0.79)
	Adjusted	0.44 (0.35)	−1.40* (0.56)	0.46 (1.64)
%Heating	Unadjusted	2.38 (1.60)	0.22 (2.92)	−9.08 (8.21)
	Adjusted	0.74 (1.96)	−2.82 (3.40)	5.33 (6.83)

* Statistically significant at the p = 0.05 level.

† Expressed as log-relative rates (× 1,000), which are approximately the percentage change in mortaliity per 10˚F (˚C = 5/9 × (˚F – 32)) per 10-unit change in the predictor variable; their corresponding standard errors are enclosed in parentheses. The regressions for each predictor were performed both without including latitude (unadjusted) and including latitude (adjusted) as a second predictor.

‡ Percentage of the population aged 65 years or more, not completing high school, living in poverty, aged 65 years or more and disabled, living in homes with air-conditioning, and living in homes with heating, respectively.

§ Cold slope = average slope of the estimated relative risk curves at temperatures lower than MMT.

¶ Hot slope = average slope of the estimated relative risk curves at temperatures higher than MMT.

found a strong dependence of the configuration of the temperature-mortality relation on latitude (figure 1). For the more-northern cities, the MMT was generally lower and the hot slope steeper; for the more-southern cities, the MMT was generally higher and the cold slope steeper. This pattern is consistent with more effective adaptation to colder temperatures in more-northern cities and to hotter temperatures in more-southern cities. For example, the 1980 US Census showed that the prevalence of air-conditioning ranged from 65 percent in Chicago and 35 percent in Boston to 96 percent in Miami.

We found other predictors of the shape of the mortality-temperature relation (table 3). Mortality associations with colder temperatures were larger for cities with higher proportions of elderly and smaller for cities with a higher fraction of heating systems. The elderly have long been considered physiologically susceptible to temperature extremes (4). A study of the 1980 heat wave in Texas found relative death rates to be highest among males, the elderly, Blacks, and those persons engaged in heavy activity. Compared with earlier heat waves in the same region, the number of 1980 heat-related deaths was not as high, most likely because of increased use of air-conditioning (7). A case-control study of the 1995 Chicago heat wave concluded that select groups of people were at greater risk of death; these groups included persons with known medical problems, those confined to bed, persons who did not leave home each day, and those who lived alone or on the top floor of a building (8).

Two indicators of socioeconomic status—percentage of persons without a high school education and percentage of those living in poverty—were associated with increased mortality effects of high temperature, even after adjustment for latitude. A higher percentage of homes with air-conditioning was associated with small, but significant effects of hot temperature on mortality. We examined four time periods: 1973–1979, 1980–1984, 1985–1989, and 1990–1994. For all periods, we were surprised to observe similar relations between the weather variables and mortality, in spite of increasing penetration of air-conditioning and rising awareness of the effect of temperature on mortality.

When the data were stratified by cause of death, the same J-shaped relation was found for the cardiovascular and respiratory disease strata but not for Other causes (mainly cancer). The greater effects of temperature on cardiorespiratory deaths are consistent with prior reports (25). Mechanisms for the effects of temperature on cardiovascular mortality have been postulated. For example, blood viscosity and cholesterol levels have been found to increase with high temperatures (26), whereas blood pressure and fibrinogen levels increase during winter, although outdoor temperature does not seem to determine the seasonal variation in fibrinogen (27).

Larsen (9) reported that the effects of weather on mortality are noticed immediately. Kunst et al. (6) observed effects within a week of the weather event. Our results indicate that the effects can be observed within 3 days for a cold-weather event and within 1 day for a hot-weather event. As in our data, Machenbach et al. (28) also found greater mortality in the winter months.

Our results were based on daily mortality counts that did not exclude deaths attributed to specific health events such as influenza (29). Because sufficient data from such events rarely exist for these cities, we addressed these potential confounding effects by using different degrees of freedom in the time component of the model; we found that the temperature-mortality relative risk curves were qualitatively similar for various functions of time, including those sufficiently flexible to capture, for example, influenza epidemics. However, because temperature varies so smoothly with season, it was not possible to set aside all of the information about season and still reliably estimate a relative risk function for temperature. Hence, residual confounding by seasonal variables may have occurred. One possibility for future consideration is seasonal migrations of elderly persons from northern to southern cities. Proper adjustment for potential seasonal time confounders remains a limitation of these types of analyses because of the lack of city-specific data.

Other studies, for example, Kunst et al. (6), have considered wind speed as well as temperature and dew point. In these studies and ours, such predictors compete for explanatory effect. Future studies might use "apparent temperature," which combines temperature, wind speed, and dew point and considers "synoptic" or air mass climate analyses (30). Weather variability could be emphasized more. We constructed a temperature-range variable accounting for the difference between average daytime and average nighttime temperature; however, this variable did not significantly predict mortality. Perhaps daily range, minimum and maximum temperatures during winter and summer months, or other carefully constructed measures reflecting sharp temperature declines in the winter months and the absence of cooling during the summer months could help predict mortality. Nighttime minimum temperatures are anticipated to increase disproportionately according to global climate-change projections (31).

From these analyses, it would seem that public health programs to prevent heat- and cold-related mortality would best be directed at the elderly and those persons with cardiovascular and respiratory diseases. Although persons should use caution during any extreme weather event, whether hot or cold, those in the northernmost cities are more vulnerable during a warm temperature period and those in the southernmost cities are most vulnerable during cold periods. Earlier we pointed out a large difference in the hot slope between Baltimore and Washington, DC, two cities with virtually identical weather. Identifying differences between these two cities that affect their responses to weather, whether in housing stock or in weather watch/warning protocols, might lead to better public health prevention strategies.

Substantial additional investigation of this association remains. We did not address in detail how the temperature-mortality association changes by gender, age, race, and many other factors. Future research should study an aggregate weather variable that incorporates temperature, dew point, and wind speed; control for seasonal confounders such as influenza epidemics; and further consider weather variability. For example, in temperate climates, climatologists project that a 2–3°C increase in average summer temperatures doubles the frequency of extreme heat waves (32). Additional investigation of the effects of air-conditioning and heating on the association between weather and mortality may also be useful, as would a nationwide study on the effects of weather on mortality in large metropolitan areas. The types of models that we developed are also applicable to estimating weather-related mortality given various future climate scenarios.

An important public health question is whether the increased mortality associated with temperature largely occurs among the very frail persons who were likely to die in the short term absent stressful temperatures. This "harvesting" can be tested by using methods developed for air pollution studies (33, 34), for which this same issue has arisen.

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