Published in final edited form as:

Environ Res. 2016 November ; 151: 610–617. doi:10.1016/j.envres.2016.08.029.

Study on the Association Between Ambient Temperature and Mortality Using Spatially Resolved Exposure Data

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Abstract

There are many studies that have posited an association between extreme temperature and increased mortality. However, most studies use temperature at a single station per city as the reference point to analyze deaths. This leads to exposure misclassification and usually the exclusion of exurban, small town, and rural populations. In addition, few studies control for confounding by PM_{2.5}, which is expected to induce upward bias. The high-resolution temperature and PM_{2.5} data at a resolution of 1 km² were derived from satellite images and other land use sources.

To capture the nonlinear association of temperature with mortality we fit a piecewise linear spline function for temperature, with a change in slope at -1°C and 28°C , the temperature threshold at which mortality in Georgia, North Carolina, and South Carolina increases due to cold and heat, respectively. We conducted stratified analyses by age group, sex, race, education, and urban vs nonurban, as well as sensitivity analyses of different temperature threshold and covariate sets.

We found a 0.19% (95% CI = $-0.98, 1.34\%$) increase in mortality for each 1°C decrease in temperature below -1°C and a 2.05% (95% CI = $0.87, 3.24\%$) increase in mortality for each 1°C increase in temperature above 28°C , a 79.8% larger effect size for heat compared to the station-based metric. The effect estimates relying on the monitoring stations were 0.09% (95% CI = $-0.79, 0.95\%$) and 1.14 % (95% CI = $0.08, 1.57\%$) for the equivalent temperature changes. The estimates were not confounded by PM_{2.5}. Children under 15 years of age had the largest percentage increase per 1°C increase in temperature (8.19%, 95% CI = -0.38 to 17.49%) followed by Blacks (4.35%, 95% CI = 2.22 to 6.53%). Higher education was a protective factor for the effect of extreme temperature on mortality. There was a suggestion that people in less urban areas were more susceptible to extreme temperature. The relationship between temperature and mortality was stronger when using exposure data with more spatial variability than using exposure data based on existing monitors alone.

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Conflict of Interest

The authors declare that they have no actual or potential conflict of interest.

Keywords

Acute effect; temperature; mortality; exposure error

1 Introduction

A body of literature has demonstrated an association between acute exposure to temperature and human morbidity and mortality^{1–4}. In such studies, exposure to temperature was determined by assigning the most representative monitoring stations to study subjects according to criteria such as the shortest distance between a given residence and a monitoring station or a corresponding jurisdiction. Although some regions have a relatively abundant number of weather monitoring stations⁵, the density of existing monitoring stations is not evenly distributed throughout the study area. In particular, rural areas have fewer weather monitoring stations per unit area than urban areas. Even the monitoring stations already installed are not enough to capture the dynamic temperature variations across a metropolitan area. The urban environment has the complex topography of the cityscape due to anthropogenic building materials and heat emissions from buildings and vehicles, which plays a critical role in re-radiating long wave radiation.^{6–9} Such factors contribute to thermal distribution, which can differ widely in the relatively small areas such as the urban heat island. Therefore, an ecological exposure with such potential for variation has introduced measurement error, which in turn has produced biased risk estimates with weaker power^{10,11}.

The reliance on the central or closest monitoring station has posed another limitation in terms of study area and population. Because most of the monitoring stations are located near cities, most studies are restricted to urban areas and populations, and thus providing little data on the effects in rural populations. There are limited data that suggest heat waves may have a bigger effect in rural areas^{1,12–14}.

Various approaches have been adopted to overcome this deficit in studies that deal with the ambient air temperature. Habeeb et al.¹⁵ used the Daymet data set to validate temperature observations from airport stations in regards to their accuracy for urban areas. However, the Daymet dataset is based on the interpolation of the weather station data and the digital elevation model (DEM). This univariate property of the model may not account for temperature variations due to other factors, such as land use. Li et al.¹⁶ applied the Weather Research and Forecasting (WRF) model in their study on the synergistic effect between urban heat islands and heat waves and validated their model using satellite temperature data from the Moderate Resolution Imaging Spectro-radiometer (MODIS). It provided daily estimates of surface temperature at a global level but with a high resolution of 1 km. Shi et al.¹⁷ calibrated temperature measurements based on remote sensing technology to the actual temperature data from the weather stations, and included considerations of other factors that influence temperature such as elevation, vegetation, and land use. As a result, the researchers achieved a high cross-validated R^2 (0.97) with little mean squared prediction error (1.38 °C).

Meanwhile, there is not unanimous agreement on whether PM_{2.5} confounds the temperature-mortality association^{18–21}. Many studies failed to assess it mostly due to the lack of data^{22,23}.

High temperature also accelerates the formation of secondary particles in the atmosphere through gas-to-particle conversions. Therefore, PM_{2.5} may produce an upward bias in the direct health effects of temperature. However, studies controlling for PM_{2.5} have been limited since the number of PM_{2.5} monitoring stations is smaller than that of weather stations and measurement of PM_{2.5} is not always made on a daily basis.

As part of efforts to overcome these limitations, Shi et al.¹⁷ and Lee et al.²⁴ have modeled daily temperature and PM_{2.5} at a 1 km² resolution, respectively, for seven adjacent states located in the southeastern United States. Using these spatially resolved exposure metrics, we assessed the association between acute exposure to ambient temperature and nonaccidental mortality, controlling for PM_{2.5}.

2 Data and methods

2.1 Outcome

We obtained nonaccidental mortality data from the departments of public health in Georgia, North Carolina, and South Carolina for the years 2007 through 2011. The data include variables such as the date of death, age, sex, race, education, and zip code for residence. Our research was exempt from the IRB review by the office of human research administration at the Harvard T. H. Chan School of Public Health.

2.2 Exposure

We used the modeled air temperature at 1 km² resolution on a daily basis produced by Shi et al.,¹⁷ because they captured the spatial variation of temperature well by incorporating remote sensing measurement of temperature and other land-use factors such as elevation, vegetation, and the percentage of urbanicity. Using satellite-derived surface temperature measurements and other land use predictors, Shi et al.¹⁷ modeled the daily mean temperature with the high-resolution temperature for seven states in the United States (North Carolina, South Carolina, Georgia, Tennessee, Alabama, Mississippi, and Florida) from the year 2000 through 2014. They calibrated satellite surface temperature to ground-monitored temperature measurements based on a mixed linear model framework with daily slopes. Regression against nearby monitors and spatiotemporal smoothing was applied where satellite measurements were not available. As a result, an out-of-sample cross-validated R^2 of 0.95 was obtained. Also, the high-resolution temperature modeled by Shi et al. agreed well with the Modern-Era Retrospective Analysis for Research and Applications (MERRA) from NASA ($R^2 = 0.97$, a mean squared prediction error = 1.38 °C).

2.3 Ambient temperature and dew point from ground-level monitoring stations

Shi et al.¹⁷'s model does not model humidity. Therefore, we used weather data available online from the National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center (NCDC, 2010). In the study area, 318 monitoring stations were operated and centroids of zip codes were matched to the closest weather station for each day. The variables for the mean temperature and the mean dew point were available and the dew point variable was used to control for humidity²⁵.

2.4 Covariates

To control for the effect of PM_{2.5}, we used modeled PM_{2.5} at 1 km² resolution on a daily basis. Lee et al.²⁶ modeled the relationship between the Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth (AOD) data from the Aqua satellite and other meteorological and land-use predictors as well as ground-level PM_{2.5} measurements from the Environmental Protection Agency (EPA) and Interagency Monitoring of Protected Visual Environments (IMPROVE) monitoring networks. Three different models were fitted for three subregions within the study area because of the large area involved. Mean cross-validated R^2 values for regions 1, 2, 3 were 0.77, 0.81, and 0.70, respectively, with the corresponding root of the mean squared prediction errors of 2.89, 2.51, and 2.82 µg/m³. The slopes between the observations and results were also almost 1. We note that region 2, the best performance region, covers North Carolina, South Carolina, and a part of Georgia. Details have been elaborated elsewhere²⁶.

To assign the exposure to temperature and PM_{2.5} to the study subjects (with their zip code addresses), the modeled temperature and PM_{2.5} at a 1 km² resolution were aggregated by zip code and day, by averaging them by the zip code in which the 1 km grid cells falls for each day.

To depict the spatial locations of the deceased and match them with the relevant temperature and PM_{2.5} exposures based on spatial locations, we used the polygon data for zip code Tabulation Areas (ZCTA) in Smart Data Compression (SDC) format from ESRI® Data & Maps 2004.

We downloaded the shape file that describes metropolitan and micropolitan statistical areas in the U.S. from the U.S. Census Bureau website. If the centroid of the zip code area falls in a metropolitan or micropolitan statistical area, the zip code is defined as an urban zip code, otherwise it is defined as a rural zip code.

2.5 Statistical analyses

For the dew point temperature variable, we allocated the closest monitoring stations by Euclidean distance between the centroid of the ZCTA for the deceased and a specific day.

A case-crossover design was used to evaluate the acute effect of temperature on mortality. We selected the time-stratified sampling to select the reference periods because it has been demonstrated to produce the most unbiased results compared to other methods and to be comparable with the time-series analysis²⁷. In doing so, the reference period was restricted to the same month in which death occurred to control for seasonal confounding. Control days were chosen every third day away from the case day to reduce temporal correlation between temperature²⁸.

The association was analyzed using conditional logistic regression. To accommodate the expected U-shaped dose-response relationship between temperature and mortality risk, we used linear splines to fit different slopes for low, medium, and high temperatures. To test the linearity and choose the appropriate threshold temperatures for each effect, we fitted a conditional logistic model with a penalized spline term for temperature (degree of freedom =

4) controlling for PM_{2.5} and the day of the week. Visual observation suggested that a piecewise linear model with knots at -1 °C and 28 °C captured the curve well. The use of linear slopes within each category of temperature allows straightforward examination of effect modification. The temperature of previous days was controlled as well in the form of a linear term for the sake of the parsimony of the model. Specifically, a piecewise conditional logistic regression was fitted as follows,

$$\begin{aligned} \text{Logit}(p_i) = & \beta_{0i} + \beta_1 \text{PredTemp}_{jk} + \beta_2 \left(\text{PredTemp}_{jk} - (-1^*) \right)_+ + \beta_3 \\ & \left(\text{PredTemp}_{jk} - (28^*) \right)_+ + \beta_4 \text{PM}_{2.5jk} + \beta_5 \text{Temp_lag1}_{jk} + \beta_6 \text{Temp_lag2}_{jk} \\ & + \beta_7 \text{Temp_lag3}_{jk} + \beta_8 \text{Tuesday} + \dots + \beta_{13} \text{Sunday}, \end{aligned}$$

where $(x)_+$ is a function that equals x when is positive and equals 0 otherwise. p_i is the probability of death for the i^{th} person, PredTemp_{jk} is the modeled temperature in zip code j on day k , $\text{PredPM}_{2.5jk}$ is the modeled PM_{2.5} level in zip code j on day k , Temp_lag1_{jk} is the 1-km temperature on the previous day, Temp_lag2_{jk} is the modeled temperature 2 days prior to death, Temp_lag3_{jk} is the modeled temperature 3 days prior to death, and the rest are dummy variables for day of the week.

To see if there is an effect modification between PM_{2.5} and high temperature, we added a multiplicative interaction term between the temperature above 28 °C and PM_{2.5}. If the sign of the estimate for the term is positive and statistically significant, we determined there was a synergistic interaction between PM_{2.5} and high temperature in mortality.

One of our interests was to assess the performance of the zip-code level temperature and determine if it reduces measurement error in temperature and PM_{2.5}. Therefore, we compared the result with another from the same model but based on nearest monitor stations for temperature and PM_{2.5}. AIC values from both models were used to determine the preference on the exposure metric where the lower value is given preference.

Various stratified analyses were conducted by age group, sex, race, residence, and education to identify vulnerable populations. For education level, we assessed the effect by race to see if race is a confounder. Subgroup analyses by race were conducted for each residence to see if the residence effect is confounded by other social factors such as race.

In sensitivity analyses, we evaluated how the choice of knots affects the model results. We changed the placement of knots from 28 °C to 26 °C and 30 °C, keeping the cold knot constant as -1 °C. Then, we changed the place of knots from -1 °C to -3 °C and 1 °C, keeping the knot for heat constant as 28 °C.

Last, we tested to find out whether the health effect of temperature is sensitive to the deletion of PM_{2.5} or the addition of the variable of dew point into the model.

Data manipulation and statistical analyses were carried out using the survival package in R version 3.2.0 for windows (R Foundation for Statistical Computing, Vienna, Austria), ArcGIS 10.3.1 for Desktop (Copyright © 2015 Esri, Redlands, CA, USA), and Base SAS

software, version 9.4 of the SAS system for windows (Copyright © 2015 SAS Institute Inc., Cary, NC, USA).

3 Results

There were 848,270 deaths from natural causes recorded in North Carolina, South Carolina, and Georgia from 2007 to 2011 (Table 1). The fraction of these deaths by state was North Carolina (42%), Georgia (37%), and South Carolina (21%). The mean age at death was 73, with a standard deviation (SD) of 17. Of those deceased, 71% were older than 65 years of age and 27% were between 15 and 65 years of age. Only 2% of deaths were of people younger than 15 years of age. The distribution of sex was almost even. In regards to race, 75% of the population was white and 24% were black. The most common education level was a high school education (years = 12 years), accounting for 27%, although 24% of the education records were missing. Age and education level were independent of living within metropolitan areas or not; 74% of the deceased were classified as living in a zip code in an urban area. (Table A1 in Appendix).

During the same period, the average modeled temperature was 17 °C with a SD of 8 °C, consistent with the study area being in a warm region. Figure 1 describes the distribution of the temperature in the study area 2007 through 2011. Across the years and zip codes, the lowest daily mean temperature was -12.9 °C and the highest was 33.2 °C (Table 2). It is worth noting that Shi et al.¹⁷ restricted the NCDC temperature observations to -40 °C to 50 °C, because they regarded the temperature observations over 50 °C as measurement error, which may affect the overall modeling on other readings. For modeled PM_{2.5}, the average was 11.1 µg/m³ (SD: 4.4 µg/m³) ranging from 0 to 138 µg/m³.

For the heat effect (temperature > 28 °C), we found a 2.05% increase (95% CI = 0.52 to 2.91%) in mortality per 1 °C increase in temperature. On cold days (temperature < -1 °C), death increased 0.19% (95% CI = -0.98 to 1.34%) per 1 °C drop. In contrast, the effect estimates from the same model but relying on the monitoring stations were 0.09% (95% CI = -0.79, 0.95%) for cold and 1.14 % (95% CI = 0.08, 1.57%) for heat. Figure 2 compares these results with what we would have obtained if we had used only NCDC monitoring data. The solid line represents the dose-response curve for the main model with temperature at a 1-km level resolution. The dotted line depicts the dose-response curve for the same model with temperature from the monitoring stations. Each effect estimate from a different exposure metric functions as the slopes for the graphs. The results based on the high-resolution temperature showed stronger effects. Particularly, the difference was prominent for heat (temperature > 28 °C) with a 79.8% larger effect size than that from the station-based metric.

The AIC value (3869691.6) from the main model was lower than that from the model based on spatially discrete observations from weather stations (3869931.5).

There was a suggestion of interaction between high temperature (> 28 °C) and PM_{2.5} (0.3 % per 10 µg/m³ increase in PM_{2.5}), however it was not statistically significant (*p*-value = 0.68).

Stratified analyses for heat by age groups revealed that children younger than 15 years of age had the largest percentage increase in deaths, although it was not statistically significant (Fig. 3). Especially, the age group of between 1 and 5 years of age showed the largest effect size (17.42%, 95% CI = -11.84 to 55.38%), followed by the age group between 6 and 10 years of age (15.71%, 95% CI = -18.24 to 63.75%), and the one from 11 to 15 years of age (7.64%, 95% CI = -24.19 to 52.82). Figure 4 represents the results of the stratified analyses by sex, race, and whether (or not) living in the metropolitan statistical areas (MSA). Males were more susceptible to heat (2.57%, 95% CI = 0.86 to 4.31%) than females (0.9%, 95% CI = -0.75 to 2.58%) for the heat effect. By race, blacks showed higher risk (4.35%, 95% CI = 2.22 to 6.53) than whites (0.6%, 95% CI = -0.84, 2.07%), and the difference was statistically significant (p -value = 0.010). People living outside of an MSA showed a slightly higher risk of death associated with higher temperature after 28 °C (2.11%, 95% CI = -0.48 to 4.77%) compared with those in an MSA (1.60%, 95% CI = 0.26 to 2.95%), however it was not statistically significant. The same analysis for race resulted in similar patterns (Table A2 in Appendix).

We observed an inverse trend of decreasing effect of high temperatures as education level increases (Fig. 5). The least educated group (fewer than 8 years) showed the highest increase in mortality (6.16%, 95% CI = 2.81 to 9.62%), and the linear trend was statistically significant (p -value < 0.001).

To examine if effect modification by education level was confounded by race, we conducted separate analyses. As a result, similar patterns were observed in the white and black groups, as illustrated in Appendix A (Fig. A1–A2).

We also tested effect modification for the cold effect; the results revealed patterns similar to those from the heat effect but with decreased magnitude of effect size. More details are illustrated in Appendix A (Fig. A3).

Our data-driven analysis revealed that mortality start to increase at -1 °C as respects cold and 28 °C as respects heat in Georgia, North Carolina, and South Carolina. By changing the knot points, we found that the knot points of -1 °C and 28 °C were optimal, with a lower AIC value than any of the other choices, which implies a better model fit.

In Table 4, the model without control for PM_{2.5} resulted in a lower temperature slope for cold days (< -1 °C) (0.17%, 95% CI = -0.99, 1.33%) compared to the main model (0.19%, 95% CI = -0.98, 1.34%). The slope for hot days (> 28 °C), however, increased from 2.05% (95% CI = 0.87, 3.24%) to 2.09% (95% CI = 0.91, 3.28%) when the PM_{2.5} covariate was removed from the model. Both of these changes were small and well within the noise of the estimates. The addition of the dew point temperature variable barely changed the cold effect (0.19%, 95% CI = -0.97, 1.35%) and slightly increased the heat effect, which was 2.07% (95% CI = 0.89, 3.26%).

4 Discussion

In this study, we have examined the association between acute exposure to ambient temperature and mortality in three southeastern U.S. states, Georgia, North Carolina, and

South Carolina, controlling for PM_{2.5} and using the high-resolution temperature at a fine geographic scale.

We found that both high and low temperatures were associated with an increase in mortality. It appeared that the cold effect was much smaller than the heat effect in both terms of the effect size and the statistical significance. It may be because these states have too few days of low temperatures and too few locations. Indeed, the days and ZCTA areas with temperature less than -5 °C make up only 1.4% of the entire study area and period. In terms of the rareness of the event and adaptation, one can argue that cold has a greater effect on residents of these warm states. However, the absolute number of the sample size appears to be too small to detect any signal that would exist in the data. It may also be partially related to the exposure time window for cold. If we had used a longer-range window to examine lagged effects, the cold effect may have been stronger.

Meanwhile, the heat effect still occurs in states that have warm summer temperatures, where adaptation has presumably occurred. This indicates that such adaptation has not been able to eliminate the effects of heat, even below the level of heat waves. Key factors of this study are that it included rural populations: used fine-scale exposure: and assessed effect modification by age (including children), rural location, education, race, sex, and sensitivity to control for PM_{2.5}, which was also assessed on a fine scale.

In a similar study, Guo et al.²⁹ found that spatiotemporal models yielded a slightly better model fit. We speculate that this may be attributable to the reduced exposure error, the likely result of a better characterization of the spatial variation in temperature. The high-resolution temperature captures the variability of temperature at the zip-code level, whereas the observations from monitoring stations vary less and become irrelevant as the distance between the monitor and the location of outcome increases.

It is well known that the use of widely spaced monitoring stations as an exposure metric in environmental epidemiology induces bias, which underestimates the effect size in many cases^{30,31}. And this appears more prominent in a case where the exposure of interest dynamically changes in space, as occurs for temperature distribution within a city³². The results from our study support the hypothesis wherein a reduction in measurement error leads to the stronger effect estimate.

We found different responses to temperature in various subgroups. Interestingly, children showed the largest percent increase in mortality in relation to temperature among the age groups, however their baseline mortality rate was lowest and the result was not statistically significant. The wide, and thus insignificant, confidence intervals for the large effect size appear to originate from the small sample size or other factors. The mortality rate among infants and children is very low in developed countries such as the U.S. Indeed, the average age of the decedents in the study area is 73 years and the population younger than 15 years of age only makes up 2% of them. It is well known that both the young and old are more susceptible to extreme temperatures due to the lack of the control of body temperature. Children are highly susceptible to heat stress because of higher surface-area-to-body mass ratio, a lower sweat rate per gland, and high metabolism, etc.³³ Preexisting clinical

conditions are also a likely part of the picture and as such, death and hospital admissions due to heat should be investigated separately. Further studies on hospital admissions or emergency room visits are needed to assess the underlying health conditions in young age groups.

Many studies on the similar topic have mainly focused the elderly as a vulnerable subpopulation and called for public interventions for them³⁴. Benmarhnia et al.³⁵ identified the need for studies to clarify if young population is also susceptible to extreme temperature in the perspective of public health interventions. The result of this study suggests that children should also be given more active public policy interventions. Parents, day care centers, and schools should be advised to take precautions on days of unusual temperature.

In our study, males and females displayed different patterns in response to cold and hot temperatures. Men were more adversely affected by hot temperature than women, whereas they were less affected by cold temperature. However, these differences were marginal and many studies have been indecisive about gender differences in response to extreme temperature^{36–39}.

Most studies of acute temperature effects have focused on cities, with little data on rural areas, and have relied on weather stations, which are sparse in rural areas. By including the entire area of three states, we were able to address this. As a result, we found that the effect of hot days was 31% higher in rural areas, although it was not statistically significant. This is in accordance with previous studies^{12,13}, which found that rural areas have a similar or a higher level of temperature-related death rate as compared to urban areas. And the results were not confounded by race.

Blacks were more adversely affected by heat than whites, and this difference was statistically significant. We also found strong effect modification by education level. Overall, as the education level increased, the heat-related mortality risk decreased. This phenomenon was not confounded by race. Whites and blacks showed the same pattern as the whole group analysis. Our result is consistent with previous research where blacks and people with low educational attainment have been identified as being susceptible to extreme temperature^{13,40,41}. Although we suspected this pattern could be related to level of income, we were unable to evaluate the hypothesis because the income variable was not available in the mortality data from the state departments.

In the sensitivity analysis, the lack of controlling for PM_{2.5} had little effect. The heat effect size increased from 2.05% (95% CI = 0.87, 3.24%) to 2.09% (95% CI = 0.91, 3.28%) when removing the PM_{2.5}. In contrast, the absence of the control for PM_{2.5} produced a slightly smaller cold temperature effect. Neither of these differences was significant or large. One of the potential reasons for the small cold effect could be relatively low PM_{2.5} levels in this region. This area is not very industrialized and has lower levels of PM_{2.5} compared to those in other industrialized regions in the U.S.⁴² Our model was robust in controlling for dew point temperature, retrieved from the closest monitoring stations.

We found the optimal threshold temperatures that increase mortality associated with cold and heat for the specific region, warm and southeastern three states. The penalized spline

model indicated that 28 °C was the approximate threshold temperature where heat-related mortality begins to increase substantially. This is higher than the threshold in colder locations⁴³, which was usually around 20 ~ 25 °C. We believe this finding is directly related to the characteristics of the study area. Since the study area is warm, it appears that subjects in this study area are adapted to warm temperature behaviorally or physiologically. The normally warm temperatures of the study area lead to a higher threshold for excessive deaths when compared to normally cooler areas of the U.S, such as New England. This is in accord with the results from the sensitivity analysis of change in the location of the threshold temperature. When the threshold temperature for the heat effect was lowered from 28 °C to 26 °C, the effect size decreased from 2.05% (95% CI = 0.87, 3.24%) to 0.77% (95% CI = -0.40, 1.95%) and the statistical significance also disappeared. Warnings for extreme temperature should be adjusted by regional climate, and threshold temperature needs to be scientifically explored.

Our study has limitations. We still anticipate a random measurement error in the modeled temperature, which led to bias of the effect estimates and overestimated standard error. Moreover, zip code designations were the finest resolution of location that we could obtain. Therefore, the temperature and PM_{2.5} exposure assessments still leave room for measurement error despite the improvement over observations from sparsely located weather stations in counties or cities.

A potentially influential error is that we use outdoor temperature as our exposure base, and people spend most of their time indoors. We were unable to obtain indoor temperatures, but public interventions, such as heat warnings or advisories, are based on outdoor temperatures, and thus it is useful to know how they relate to mortality. Still, our study would benefit from efforts to gain more comprehensive data on temperature exposure that includes the indoor environment or the environment on an individual level⁴⁴⁻⁴⁶.

Daily mean temperature was used as exposure for our study. The minimum or the maximum temperature on a given day might be more directly related to mortality⁴⁷. Since those numbers were not available, we were not able to assess the hypothesis. Lastly, the effects of the minimum or the maximum temperature data from monitoring stations were not evaluated because those outliers were excluded during temperature modeling to minimize their effect on the general results from the model.

Due to the absence of possible data at a fine scale on a daily basis, we could not include covariates such as ozone and other weather variables. During the sensitivity analyses, we used the dew point temperature from monitoring stations, but our model was robust to the influence of the dew point temperature.

In conclusion, we applied exposure metrics with a fine resolution to an epidemiologic study on the acute effect of temperature controlling for the confounding effect of PM_{2.5}. As a result, we obtained a 79.8% larger effect size using high-resolution temperature metric compared to the station-based metric. In similar fashion, the use of fine-scale PM_{2.5} enabled us to achieve much better control of potential confounding and effect modification by PM_{2.5}.

These spatially and temporally continuous exposures and/or covariates have much potential for use in prospective studies.

Acknowledgments

This publication was made possible by USEPA grant RD 83479801, NIEHS grant R21ES024012, and NIEHS grant ES000002. Its contents are solely the responsibility of the grantee and do not necessarily represent the official views of the USEPA. Further, USEPA does not endorse the purchase of any commercial products or services mentioned in the publication.

Appendix A

Fig. A1.
Heat effect (daily mean temperature > 28 °C) by education level in whites

Fig. A2.
Heat effect (daily mean temperature > 28 °C) by education level in blacks

Fig. A3.
Subgroup analyses on the association between cold (daily mean temperature < -1 °C) and mortality

Table A1

Distribution of age and education by residence

	MSA	No MSA
Age		
Mean	72.6	73.2
Standard Deviation	17.7	16.8
Minimum	0	0

	MSA	No MSA
Maximum	116.0	110.0
Education (%)	Spearman Correlation=0.056	
0 – 8 yr	78,835 (67.7)	37,702 (32.3)
9 – 11	78,647 (70.8)	32,478 (29.2)
12	166,664 (74.3)	57,599 (25.7)
13 – 15	84,393 (78.5)	23,119 (21.5)
16	60,989 (80.5)	14,745 (19.5)
Missing	150,432 (74.1)	52,473 (25.9)

Table A2Percent increase in Mortality by heat[†] by residence

	MSA	No MSA
White	0.58 (−1.04, 2.23)	0.72 (−2.44, 3.99)
Black	4.24 (1.85, 6.70) [*]	4.64 (0.05, 9.43) [*]

[†]Heat is defined as daily mean temperature > 28 °C.

() is the 95% confidence interval

^{*} is statistically significant at $\alpha=0.05$ **Table A3**

Comparison of effect estimates by exposure metric

	Model	Remote Monitor [*]
Cold [†]	0.28 (−1.49, 2.01)	−0.03 (−1.5, 1.43)
Heat [‡]	3.48 (1.08, 5.94)	2.02 (0.76, 3.30)

^{*} Closest monitor > 20 km[†] Cold is defined as daily mean temperature < −0.1 °C[‡] Heat is defined as daily mean temperature > 28 °C

() is the 95% confidence interval

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Highlights

- Temperature estimates based on satellite imagery enabled us to study their acute effect on mortality to the entire population of three southeastern states in the U.S at zip code level.
- Even in an area well acclimatized to heat, temperatures above 28 °C increased mortality.
- The aged, black, and the uneducated were identifies as vulnerable population.
- We found neither confounding nor effect modification by PM_{2.5}.
- The use of sparse weather stations led to underestimation of the temperature effects.

Fig. 1.
Spatial distribution of the daily mean temperature in the study area from 2007–2011

Fig. 2.

Comparison of dose-response curves between high-resolution temperature and monitor-based temperature. Each effect estimate from a different exposure metric represents the slopes for the graphs. -1°C and 28°C are the temperature threshold at which mortality in Georgia, North Carolina, and South Carolina increases due to cold and heat, respectively.

Fig. 3.
Heat-related death (daily mean temperature > 28 °C) by age group in years

Fig. 4. Subgroup analyses on the association between heat (daily mean temperature > 28 °C) and mortality

Fig. 5.
Heat effect (daily mean temperature > 28 °C) by education level (years)

Table 1

Descriptive statistics of the study population

	Total
Deaths, No. (%)	848,270 (100)
Georgia	311,831 (37)
North Carolina	357,915 (42)
South Carolina	178,524 (21)
Age, mean (SD), yr	73 (17)
< 15 yr, No. (%)	13,617 (2)
15–65	231,010 (27)
> 65	603,600 (71)
Missing	43 (< 1)
Sex, No. (%)	
Male	409,408 (48)
Female	438,847 (52)
Missing	15 (1)
Race, No. (%)	
White	631,701 (75)
Black	206,226 (24)
Other	9,202 (1)
Missing	1,141 (1)
Education, No. (%)	
0 – 8 yr	118,283 (14)
9 – 11	112,699 (13)
12	227,791 (27)
13 – 15	109,018 (13)
16	77,187 (9)
Missing	203,292 (24)
Living in MSA [*] , No. (%)	
Yes	619,960 (73)
No	218,116 (26)
Missing	10,194 (1)

^{*} MSA: metropolitan statistical area

Table 2

Summary statistics for temperature and PM_{2.5} by season across Georgia, North Carolina, and South Carolina from 2007 to 2011

	Spring	Summer	Fall	Winter
Temperature (°C)				
Mean	16.8	25.8	17.1	7.3
Standard Deviation	5.3	2.1	6.0	5.5
Minimum	-8.8	14.2	-5.6	-12.9
Maximum	29.7	33.2	30.7	22.7
PM_{2.5} (µg/m³)				
Mean	10.9	13.3	10.1	9.8
Standard Deviation	4.2	4.4	3.7	3.5
Minimum	0.0	1.5	0.0	0.1
Maximum	80.2	86.2	60.0	55.0

Table 3

Sensitivity analysis on the variation in threshold temperature

Threshold Temperature for Cold (°C)	Threshold Temperature for Heat (°C)	Percent Increase in Mortality by Cold (95% CI)	Percent Increase in Mortality by Heat (95% CI)
-1	26	0.19 (1.34, -0.98)	0.77 (-0.40, 1.95)
-1	30	0.22 (1.37, -0.95)	1.60 (0.42, 2.78)
-3	28	1.85 (5.47, -1.9)	2.05 (-1.72, 5.95)
1	28	-0.01 (0.55, -0.59)	2.04 (1.46, 2.62)

-1 °C and 28 °C were the temperature threshold at which mortality in Georgia, North Carolina, and South Carolina increases due to cold and heat from the original piecewise regression analysis.

Table 4

Sensitivity analysis by a covariate set

	Percent Increase in Mortality by Cold (95% CI)	Percent Increase in Mortality by Heat (95% CI)
Main Model	0.19 (1.34, -0.98)	2.05 (0.87, 3.24)
Main Model – PM2.5	0.17 (1.33, -0.99)	2.09 (0.91, 3.28)
Main Model + Dew Point	0.19 (1.35, -0.97)	2.07 (0.89, 3.26)