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Climatic conditions and human mortality: spatial and regional variation in the United States

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Abstract Previous research on climatic conditions and human mortality in the United States has three gaps: largely ignoring social conditions, lack of nationwide focus, and overlooking potential spatial variations. Our goal is to understand whether climatic conditions contribute to mortality after considering social conditions and to investigate whether spatial non-stationarity exists in these factors. Applying geographically weighted regression to a unique nationwide county-level dataset, we found that (1) net of other factors, average July temperatures are positively (detrimentally) associated with mortality, while January temperatures mainly have a curvilinear relationship, (2) the mortality-climatic condition associations are spatially non-stationary, (3) the relationships between social conditions (e.g., social capital) and mortality are stable geographically, and (4) without a spatial approach to understanding the environment-mortality relationship, important spatial variations are overlooked. Our findings suggest that a universal approach to coping with the relationships between rapid climate changes and health may not be appropriate nor effective.

Keywords Environment · Health and mortality · Regional variation · US south · Climate · Geographically weighted regression

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Introduction

As an indicator of human population health, little is more central than mortality. Understanding systematic disparities in mortality has therefore been an abiding scientific enterprise, motivated by concern for basic human equity and the pursuit of better public health programs and policies. Accordingly, there is ample literature on how various socioeconomic, demographic, and geographic factors affect inequities in the risk of mortality (Kindig and Cheng 2013; Sparks et al. 2013). Previous studies have, for example, found persisting disparities in mortality with respect to gender, race/ethnicity, and geographic space (Yang and Jensen 2014; Yang, Jensen, & Haran 2011). Furthermore, extensive literature documents how characteristics of the natural environment affect human mortality (Curriero et al. 2002; Hajat et al. 2002; Kalkstein and Greene 1997; Kalkstein et al. 2008; Zanobetti and Schwartz 2008). Manifestly through extreme temperatures, drought, and other calamities, the natural environment is a primordial cause of death for human beings. Although mortality has improved due to the advance in living conditions and changing population features (e.g., urbanization) (Meijer et al. 2012), natural environmental factors remain as important determinants of mortality (Blaikie et al. 2014). The major contribution of this study is twofold: (1) to be the first nationwide study that explores the association between climatic conditions and mortality beyond urban areas and (2) to demonstrate that the relationships between climatic conditions and mortality vary geographically, contributing nuanced insight into the environment–mortality literature.

The impacts of heat and cold on mortality have been intensively studied (Curriero et al. 2002; Hajat et al. 2002; Kalkstein and Greene 1997; Kalkstein et al. 2008; Zanobetti and Schwartz 2008). This work documents excess mortality with the occurrences of heat waves or cold spells (Deschênes and Greenstone 2011; Donaldson et al. 1998; Huynen et al. 2001). Unusual hot and humid weather conditions burden human cardiovascular systems with excessive cooling demands (Davis, Knappenberger, Michaels, & Novicoff 2003; Marszalek 2000). By contrast, the relative risk of mortality increases when temperature decreases in winter (Curriero et al. 2002) and this association is generally attributable to the effect of cold on the human immune system (The Eurowinter Group 1997). While both heat and cold are important determinants of mortality (Chen et al. 2010; Gosling et al. 2009; Hajat and Kosatky 2010; Kovats and Hajat 2008; Medina-Ramon and Schwartz 2007; Metzger et al. 2010; O'Neill et al. 2009), previous studies have documented that heat is the most prominent weather-related cause of death in the United States (US) (Changnon et al. 1996; Davis et al. 2003).

The previous literature has provided invaluable evidence to support the association between temperature and human mortality, but three major shortcomings remain. First, the temperature–mortality association has been examined widely in metropolitan areas, but the question of whether the effect of heat or cold on mortality continues to hold elsewhere, particularly rural areas, remains unanswered. Mortality is heightened in the context of higher population density (Medina-Ramon and Schwartz 2007), proximity to the downtown core (Bassil et al. 2009; Dolney and Sheridan 2006; Reid et al. 2009), and urbanicity (Anderson and Bell 2009). In addition, evidence suggests that urban populations may be more susceptible to extreme heat (Smoyer et al. 2000), which may be the consequence of higher temperatures in urban than in rural areas. Specifically, high temperatures are common in urban areas with high building density, tall buildings, industrial land use, and limited green space (Balling and Brazel 1987; Hondula et al. 2012), as well as poor ventilation, localized heat sources (e.g., vehicles, air conditioning units) and great thermal storage capacity (Hajat and Kosatky 2010; Luber and McGeehin 2008). Given the important role of heat on urban mortality, we advance the literature by investigating whether heat is a generalized determinant of mortality or unique to urban areas.

The second shortcoming in the literature is that social conditions and social environments have been largely ignored. The health literature has suggested that social conditions have profound impacts on mortality as an individual's ability to improve health depends on such social conditions as employment and poverty and social ties (Kawachi et al. 1997; McLaughlin et al. 2007; Phelan et al. 2004; Wilkinson et al. 1998; Yang et al. 2009). However, few studies include both climatic and social conditions in the analysis and thus the support for the impacts of heat or cold on mortality in the literature may be overestimated. For example, low socioeconomic status contributes to excessive temperature-related mortality risk (Anderson and Bell 2009; Chen et al. 2010; Hondula et al. 2012; Johnson and Wilson 2009; Smoyer 1998; Yu et al. 2010) and minorities are more likely to die of extreme temperatures (Anderson and Bell 2009; Changnon et al. 1996; Johnson and Wilson 2009; O'Neill et al. 2003; Schwartz 2005). Controlling for social conditions is essential to better assess the relationship between temperature and mortality.

Third, and most important, weather is a space-dependent factor. People living near each other will exhibit similar behavioral and physiological reactions to weather such as increasing water intake and overburdened cardiovascular systems. Recent studies have reported that temperature declines are associated with all-cause and cardiovascular mortality increases in countries with warm winters, more so than in those with cold winters (Donaldson et al. 2003; Mercer 2003; The Eurowinter Group 1997). In the US, research shows that the temperature–mortality association is weaker in the southern cities compared to northern cities (Anderson and Bell 2009; Chestnut et al. 1998; Kalkstein and Greene 1997). These studies indicated that the impact of temperature on mortality may demonstrate a local, rather than global, pattern. However, previous literature provides little information on spatial variation in the impacts of climatic conditions on mortality, nor the mechanisms leading to spatial variation. As one's tolerance of extremely hot or cold temperatures may depend on where one lives (Basu and Samet 2002; Deschênes and Greenstone 2011), exploring whether and how the effect of temperature on mortality varies across geographic space is imperative for reducing weather-related deaths in the US.

The goal of this study is to address these shortcomings by answering three research questions: (1) Are the effects of climatic conditions on mortality independent from those of social conditions? (2) If yes, do these climatic effects vary spatially in the US? (3) If there are spatial variations of climatic associations in the US, how are they distributed? To answer these questions, we create a unique dataset by combining both social and climatic covariates for continental US counties using various data resources, analyze them with both ordinary least squares (OLS) regression and geographically weighted regression (GWR) to compare the results, and then map the results with geographic information systems (GIS). The purpose of analyzing the data with both OLS and GWR is to fully explore whether spatial analysis outperforms the traditional regression approach and yields reliable estimates. The details are described in the next sections.

Data, measures, and methodology

Mortality

The Compressed Mortality Files (CMF) for 1989–1998 and 1999–2003 from the National Center for Health Statistics (NCHS) are used to calculate five-year (1998–2002) mortality rates (NCHS 2003, 2006) standardized by the 2000 US age–sex population structure. Race/ethnicity is not included, because CMF only categorizes races into three groups: white, black, and others. Therefore, we have chosen to keep the rate unstandardized by race, but to control for three race/ethnic composition variables that includes Hispanics as a separate category in the analysis. Specifically, the percent of the county population that is Hispanic, the percent black, and the percent "other races" are used in the analysis. It should be noted that CMF contains all death counts in the US, including the deaths of marginal populations that are more susceptible to climatic conditions (Ramin and Svoboda 2009), such as the homeless.

Climatic conditions

The county-level heat-related variables are from the 2003 Area Resource File (ARF) and are assumed to be stable over time in the analysis. The data were collected from county weather stations. For those counties without a weather station, the US Weather Bureau extrapolated the data from other similar counties (ARF 2003). We adopt four variables: the average July temperature, the average January temperature, the mean relative summer humidity, and the mean hours of sunlight in January. To avoid small coefficient estimates, these variables are centered on their national means. Furthermore, in order to capture the potential curvilinear effects of temperatures on mortality, we include the squared terms of weather-related variables. Thus, the analysis includes eight climatic variables.

Social conditions

To capture county social conditions, we use variables reflecting social affluence and concentrated disadvantage. Following Sampson, Raudenbush, and Earls (1997), we create these two social condition measures using a principal components factor analysis to reduce variables and eliminate multicollinearity. The social affluence measure is comprised of the following: the log of per capita income (factor loading is .88); the percent of population aged 25 years or older with a bachelor's degree or higher (.93); the percent of the population employed in professional, administrative, and managerial positions (.78); and the percent of families with incomes over $75,000 (.92). One factor emerged that explained 78 % of the variance and hence a single factor score is used to represent the degree of social affluence. A higher value on this factor indicates higher social affluence.

In contrast, concentrated disadvantage consists of the following covariates: the poverty rate (.89), the percent of persons receiving public assistance (.85), the unemployment rate (.87), and the percent of households that are female-headed with children (.78). Combined, these are considered as one indicator of concentrated disadvantage, because the principal components factor analysis indicates these variables share 72 % of the variance. Similar to the social affluence factor, higher values represent higher levels of county disadvantage.

In addition to these measures of social structure, recent research has identified social capital as a determinant of health (Hawe and Shiell 2000; Lochner et al. 2003; Petrou and Kupek 2008). We draw on endeavors by Rupasingha et al. (2006), who have developed a social capital index for US counties that considers a range of variables, including association density (.77), the percentage of voters participating in presidential elections (.73), the county-level response rate to the decennial census (.86), and the number of tax-exempt non-profit organizations (.81). Extracting the first principal component out of these four variables creates a single social capital index (Rupasingha et al. 2006).

Along with this index, we use two additional measures of social capital: neighborhood crime and residential stability. Neighborhood crime is believed to reflect the absence of mutual trust and a lack of a sense of safety (Kennedy et al. 1998). Neighborhood crime is a factor score based on the following crimes: embezzlement (.59), forgery/counterfeiting (.82), fraud (.60), and total part I property crimes (.76). To reduce random variation, five-year average rates are calculated for 1998–2002 from the Uniform Crime Reports (Uniform Crime Reports 2000).

Previous studies have found that social capital (defined as organization membership) is higher among homeowners (Glaeser et al. 2002), implying that a stable neighborhood may facilitate residents' interaction and the development of social capital. Hence, we include a residential stability index that is created by combining the percent of county population living at the same address since 1995, the percent of owner-occupied housing units, and the percent of people living in mobile homes, respectively, and then averaging the three z-scores. The 2000 Census of Population and Housing SF3 Files enable the calculation of residential stability (US Census Bureau 2000).[1]

[1] The US decadal censuses aim to include all populations. As such, the US Census Bureau has sought to minimize potential errors when collecting data by using specialized procedures to count people without conventional housing (e.g., homeless).

Rurality

Studies have found that rurality has important implications for mortality differentials in the US (McLaughlin et al. 2001, 2007; Yang et al. 2011). To fully explore the association between climate and mortality beyond urban areas, we include this concept in the analysis. This study measures rurality with six variables extracted from the 2000 Census of Population and Housing SF3. Factor analysis indicates that the six variables can be summarized into three dimensions of rurality, namely natural resources dependency, population concentration, and exogenous economic integration (EEI). We calculate the factor scores with the regression method and use them as indicators of rurality.

The first dimension, natural resources dependency, loads on one variable: the percent of the population employed in farming, forestry, and fishing (factor loading is .934). While in the past few decades the industrial structure of rural areas in the US has changed substantially, natural resources dependency remains one of the characteristics of the US rural population. It should be noted that the factor loadings of other indicators are all below 0.4, suggesting that it is inappropriate to include them in this dimension.

The second dimension, population concentration, consists of three variables related to total population of a county: population density (total population divided by land area, factor loading is .931), road density (the length of major roads per squared kilometer, factor loading is .800), and percent of workers commuting by public transportation (factor loading is .947). This dimension reflects the ecological facet of rurality in the literature (Willits and Bealer 1967), and higher scores reflect greater population concentration and lower level of rurality.

The third dimension, EEI, captures the economic influence by neighboring counties, and it consists of two variables: percent of workers traveling over an hour to work (factor loading is .866) and percent of workers employed outside their county of residence (.821). A more integrated county is expected to have a higher score and would be more economically dependent on adjacent counties.

Analytic strategy

As discussed previously, this study uses both aspatial and spatial analytic results to yield a thorough picture of how natural and social environments matter. We begin with the OLS regression, which is a widely used method in the scientific community. However, this approach assumes that the errors are independent and homoscedastic. The OLS regression can be written as:

$$y_i = \beta_0 + \sum_{n=1}^{k} \beta_n x_{ni} + \varepsilon_i,$$

where y_i is the mortality rate for county i, β_0 indicates the global (i.e., same for all counties) intercept, β_n represents the global estimated effect of variable n, and x_{ni} represents a set of explanatory variables ($n = 1, \ldots, k$) for county i.

One major shortcoming of OLS is that it provides one set of estimates that fit all counties. As discussed previously, the relationship between temperature and mortality varies by locations and thus OLS fails to investigate heterogeneity across space. Arguably, GWR is the most commonly used tool to explore spatial heterogeneity and it extends OLS by taking spatial structures into account and estimating local, rather than global, parameters (Fotheringham et al. 2003). This model is written as:

$$y_i = \beta_{0i}(u_i, v_i) + \sum_{n=1}^{k} \beta_{ni}(u_{i,}v_i)x_{ni} + \varepsilon_i,$$

where (u_i, v_i) denotes the coordinates of the centroid of county i, and β_{0i} and β_{ni} represent the local estimated intercept and effect of variable n for county i, respectively. To calibrate this formula, the bi-square weighting kernel function is used (Brunsdon et al. 1996). The counties near to i have a stronger influence in the estimation of $\beta_{ni}(u_{i,}v_i)$ than do those located farther from i. This model demonstrates one of the strengths of GWR—localized parameters can be obtained for any point across space. Specifically, a continuous surface of parameter values can be created and the spatial variability (non-stationarity) can be assessed (Fotheringham et al. 2003). The Akaike Information Criterion (AIC) (Akaike 1974) is used to compare OLS with GWR. As a rule of thumb, when the difference between two AICs is greater than 10, the model with the smaller AIC is preferred and fit the empirical data better than other (Burnham and Anderson 2003). We implemented the analyses with the iteratively reweighted least squares method in the software of *GWR 3.0*.

To assess whether the GWR parameter estimates vary across space, we adopt a Monte Carlo significance test (Hope 1968). For a given relationship between mortality and an independent variable k at a given location i, the GWR yields a parameter estimate of $\beta_k(u_{i,}v_i)$. Suppose there are m observations within the weighting kernel of i, we can have m values of the parameter estimate and thus, calculate the standard deviation of the m parameter estimates, say S_k. The next stage is to determine whether the observed variation (S_k) is sufficient to reject the null hypothesis that the parameter ($\beta_k(u_{i,}v_i)$) is spatially invariant. A Monte Carlo approach allows us to randomly permute the observed data and obtain the variance of each permutation m-1 times. In doing so, we are able to compare S_k with $m - 1$ simulated variances and obtain the p value of this test. For the Monte Carlo significance test, the null hypothesis is that $\beta_k(u_{i,}v_i)$ does not vary by location (i) and this test is specific to the independent variable k. *GWR 3.0* conducts the test for each independent variable included in the regression model (Brunsdon et al. 1998). If the p value is below .05, we then have sufficient support to reject the null hypothesis and conclude that the effect of variable k on mortality varies spatially (Brunsdon et al. 1996).

It should be noted that the observed data are used repeatedly in GWR, which may raise the concern about multiple testing. While there is no consensus on how to address this concern (Fotheringham et al. 2003), the aforementioned Monte Carlo significance test uses the permutation approach and provides robust testing results for spatial non-stationarity (Brunsdon et al. 1998).

As discussed previously, an understanding of spatial variation in associations between the mortality and independent variables can be generated with GWR estimates. For brevity,[2] our approach is to create maps using GIS and the GWR estimates, particularly for climatic conditions, to fully explore the associations between climate and mortality in the US. It should also be noted that visualizing the GWR results is the most efficient and effective way to make sense of the large volume of output from GWR (Fotheringham et al. 2003).

Before the complex analyses above are implemented, a preliminary descriptive analysis is included to provide a thorough picture of our data. Moreover, since the data structure is a composite of both social and climatic conditions, multicollinearity might be a problem. To generate valid statistical inferences, the variance inflation factor (VIF) is used to ensure that multicollinearity does not bias our results. In general, a VIF greater than 10 is indicative of a severe multicollinearity problem and hence further actions need to be taken, i.e., dropping or standardizing variables (Kutner et al. 2004).

Results

Following the analytic plan, in this section, we first present the descriptive statistics of the variables in this study, followed by the OLS (aspatial) results. The last part focuses on the GWR (spatial) results and compares them with the aspatial findings.

Descriptive analysis

Table 1 displays the descriptive statistics and VIFs of the variables. The range of the standardized mortality rate among the US counties is wide. On average, there are almost 890 deaths per 100,000 population, but the highest rate is more than double this number. Moreover, the distributions of racial groups are not even. While a county, in general, has a racial/ethnic composition of 8.7 % Black, 6.1 % Hispanic, and 3.5 % other races, the standard deviations of these variables are greater than the means. The uneven distribution of minorities has relevance here to the extent that there is also race/ethnic variation in mortality. Compared to non-Hispanic whites, African Americans have a higher risk of death (Rogers et al. 2000). However, Hispanics persistently demonstrate a lower mortality rate despite the fact that their socioeconomic profiles are similar to those of African Americans (Abraido-Lanza et al. 1999). The countervailing effects on mortality are provocative and suggest that race/ethnic composition is a crucial factor for understanding the relationship between climate and mortality rates that should not be ignored.

[2] The total number of parameter estimates is the product of total number of observations and number of variables (including the intercept). It is more feasible to summarize these estimates into maps than in tables (Fotheringham et al. 2003).

Table 1 Descriptive statistics and variance inflation factors of the variables (N = 3108)

Variables	VIF[a]	Minimum	Maximum	Mean	Std. Deviation
Dependent variable					
Mortality (per 100,000 population)	N.A.	0.000	1977.700	889.876	137.665
Race/ethnicity					
Black	2.811	0.000	86.078	8.712	14.505
Hispanic	2.345	0.000	98.104	6.140	12.083
Other races	1.762	0.000	93.583	3.494	6.758
Rurality					
Population concentration	1.369	−0.605	28.704	0.000	1.000
EEI	1.541	−1.918	4.535	0.000	1.000
Natural resources dependency	1.535	−2.891	8.652	0.000	1.000
Social conditions					
Affluence	2.404	−2.428	6.011	0.000	1.000
Disadvantage	3.667	−2.536	9.056	0.000	1.000
Social capital index	2.416	−4.063	7.656	0.004	1.293
Stability	1.839	−4.152	1.701	0.000	0.589
Crimes	1.408	−1.370	12.119	0.000	1.000
Climatic conditions (original means)					
January temperature (32.900)	5.937	−31.800	33.900	0.000	12.015
January sunlight (151.572)	1.833	−103.572	114.428	0.000	33.130
July temperature (75.857)	5.172	−20.357	17.843	0.000	5.351
July humidity (56.125)	4.006	−42.125	23.875	0.000	14.610
Squared January temperature	1.399	0.000	1149.204	144.321	178.412
Squared January sunlight	1.555	0.183	13093.751	1097.242	1872.820
Squared July temperature	1.949	0.002	414.401	28.628	42.384
Squared July humidity	2.704	0.016	1774.556	213.394	306.527

[a] VIFs are obtained based on the full OLS model

We used factor analysis to create the three measures of rurality, and so they all had a mean of zero and a standard deviation of one. A similar statistical treatment was imposed on the covariates of social conditions so their distributions were centered on zero.

Regarding climatic conditions, we centered these variables so that their means were zero. The national average January temperature is 32.9° Fahrenheit, and as shown in Table 1 the lowest and highest average January temperatures are 1.1° and 66.8°. Regarding July temperatures, the national average is 75.9°, and the lowest and the highest average July temperature are 55.5° and 93.7°. Furthermore, the original average hours of sunlight in January is 151.6 and the relative humidity is 56.1. Similar to temperatures, these two weather-related features differ greatly across the US counties. It should be noted that we visualized these variables and the maps are available upon request.

The VIFs in Table 1 indicate that multicollinearity was not a problem in our data, as the largest VIF observed was 5.9 for January temperature. Hence, no further actions were required.

OLS (aspatial) results

The OLS regression estimates and the diagnostic statistics for model fit are presented in Table 2. We estimated five nested models where race/ethnicity, rurality, social conditions, and climatic conditions were included sequentially. We summarize the important findings below. First, as expected, racial/ethnic composition contributes to mortality. Specifically, the concentration of blacks and other races is positively associated with mortality, whereas the percentage Hispanic has a negative relationship with mortality. Rurality measures do not alter the associations of racial/ethnic composition variables with mortality substantially (Model II); however, when social conditions are considered (Model III), the magnitude of the relationships of Black and other races with mortality drops greatly, and the beneficial association between Hispanics presence and mortality becomes even stronger. This phenomenon not only echoes the Hispanic paradox (Abraido-Lanza et al. 1999), but also suggests that social conditions do, in part, explain racial mortality differentials.

Second, while the three measures of rurality are all significant in Model II, taking social conditions into account eliminates the association between population concentration and mortality, indicating that the ecological dimension of rurality is unrelated to mortality. Nonetheless, counties with high natural resources dependency tend to have low mortality. More importantly, natural resources dependency appears confounded with climatic conditions. By comparing Model III with Model V, we find that the magnitude of the effect of natural resources dependency shrinks over 50 %. This reduction is not unexpected since primary industries, i.e., farming, are highly correlated with weather.

Moreover, we find a positive relationship between exogenous economic integration and mortality. Specifically, a high level of economic dependence on neighboring areas is associated with high mortality in US counties. These findings suggest that the association between rurality and mortality is complex and population concentration may not reflect such complexity (Yang et al. 2011).

Third, we find social conditions to be significant determinants of county mortality when modeling the association without consideration for spatial relationship. This finding echoes the fundamental cause hypothesis—social conditions are the major causes of disease and poor health (Phelan et al. 2004). The adjusted R-square almost doubles from Model II (0.292) to Model III (0.547). Social affluence and concentrated disadvantage have stronger associations with the 5-year mortality measure than any other social condition variables. According to Model V, a one-unit increase in the affluence score is associated with 35 fewer deaths per 100,000 county population. Similarly, a one-unit increase in the disadvantage score is associated with 43 more deaths per 100,000 county population. It should also be noted that the dramatic change in the adjusted R-square is not observed in the GWR analysis, and this consistency suggests that controlling for the spatial structure may

Table 2 Regression estimates and diagnostic information for OLS and GWR models ($N = 3108$)

Variables	Model I		Model II		Model III		Model IV		Model V	
	ß	S.E.	ß	S.E.	ß	S.E.	ß	S.E.	ß	S.E.
Intercept	843.781	3.030***	839.004	2.997***	889.585	3.126***	898.855	3.311***	919.029	4.007***
Race/ethnicity										
Black	4.531	0.149***	4.463	0.148***	1.231	0.163***	0.167	0.178	0.498	0.179**
Hispanic	−0.880	0.178***	−0.344	0.182	−2.104	0.167***	−2.348	0.193***	−1.910	0.196***
Other races	3.441	0.317***	4.033	0.313***	0.730	0.312*	1.152	0.310***	1.480	0.304***
Rurality										
Population concentration			−15.705	2.129***	1.584	1.871	0.867	1.840	−2.488	1.813
EEI			21.255	2.118***	14.172	2.005***	10.674	1.949***	7.314	1.923***
Natural resources dependency			−10.202	2.174***	−21.927	1.909***	−15.006	1.931***	−10.551	1.919***
Social conditions										
Affluence					−41.799	2.479***	−35.082	2.459***	−34.571	2.401***
Disadvantage					40.107	3.011***	44.228	3.039***	43.026	2.967***
Social capital index					−14.171	1.814***	−6.311	1.868**	−6.708	1.862***
Stability					−24.700	3.539***	−22.526	3.650***	−22.530	3.565***
Crimes					15.545	1.942***	13.531	1.871***	13.217	1.838***
Climatic conditions										
January temperature							0.968	0.261***	1.374	0.314***
January sunlight							−0.321	0.064***	−0.212	0.063**
July temperature							4.946	0.494***	3.051	0.658***
July humidity							0.713	0.149***	0.517	0.212*
Squared January temperature									−0.110	0.010***
Squared January sunlight									−0.004	0.001***
Squared July temperature									−0.019	0.051

Table 2 continued

Variables	Model I		Model II		Model III		Model IV		Model V	
	ß	S.E.	ß	S.E.	ß	S.E.	ß	S.E.	ß	S.E.
Squared July humidity									−0.030	0.008***
OLS adjusted R^2	0.254		0.292		0.547		0.586		0.606	
GWR adjusted R^2	0.590		0.592		0.672		0.680		0.682	
OLS AIC	38,528.234		38,366.958		36,983.647		36,712.007		36,555.737	
GWR AIC	36,844.473		36,867.033		36,142.494		36,133.588		36,105.251	

* Significant at 5 % level; ** Significant at 1 % level; *** Significant at 0.1 % level

generate more stable estimates. In other words, the similarities in these associations between proximate counties are likely rendering the aspatial regression unstable.

As expected, OLS estimates suggest social capital plays an important role in understanding county-level mortality differentials. Counties where residents actively participate in public affairs and have higher association densities (i.e., social capital index) have lower mortality rates than those whose residents are less socially engaged. In addition, higher percentages of home ownership and lower turnover rates characterize counties with low mortality rates. By contrast, to an extent, high crime rates correlate with higher death rates.

Of special importance here is the fact that the four climatic variables in Model IV are all significant predictors of mortality rates across space, even after taking into account social conditions. July temperature demonstrates the strongest association with county-level mortality. In general (in Model IV), 1° Fahrenheit above the national mean of July temperatures (75.9) is associated with almost five additional deaths per 100,000 county population. Somewhat surprisingly, January temperatures and county mortality are also *positively* associated. Specifically, every 10° Fahrenheit over the national average (32.9) could be related to an increase of 10 deaths. This finding is further elaborated below.

With regard to humidity, a one-percent increase in humidity is associated with an increase of nearly 6 county-level deaths per 100,000 population.[3] And the measure of average January sunlight hours is negatively correlated with county mortality. Given a 10-h difference in sunlight, the mortality differential could be as wide as 3.2 deaths per 100,000, *ceteris paribus.*

With regard to the positive association between January temperature and county-level mortality in Model IV, we had simply anticipated that higher January temperatures were related to lower mortality but in fact this relationship is much more complicated than our expectation in two ways. First, when considering the square of January Temperature in Model V, we find that the marginal effect of January temperature on mortality (i.e., partial derivative of January temperature) was negative.[4] Specifically, a 30° Fahrenheit increase in January temperature is related to 2 fewer deaths per 100,000 county population ($1.374 - 0.11 \times 30 = -1.926$). This negative relationship in Model V supports our expectation.

Second, the Intergovernmental Panel on Climate Change (IPCC) reported that climate change will not evenly affect population (IPCC 2014) and a recent report further argued that southern counties will experience a larger increase in mortality than others because the number of extreme-high-temperature days will increase substantially (Houser et al. 2015). This knowledge stream leads us to speculate that the positive relationship between January temperature and mortality is driven by southern counties. To examine this potential explanation, we added a dummy variable (southern counties coded 1, otherwise 0) to Model V and found that the positive relationship between January temperature and mortality disappears in the

[3] We tested an interaction term between July temperature and humidity in the analysis, but it was not statistically significant.

[4] The marginal effect of January temperature (based on Model V) is 1.374-0.11*January temperature. We use the term "marginal effect" without any causal implication.

new model, while all other salient estimates—notably that for July temperature—remain substantively unaltered (see Appendix 1).[5] The marginal effect of January temperature on mortality remains negative in this new model.

The discussion above carries three implications. One is that the negative relationship between January temperature and mortality is embedded in the squared term, namely the marginal effect. The other implication is that the significant and positive association between January temperature and mortality in Model IV may be driven by the southern counties, a regional relationship with mortality. Finally, the subtle and intertwined relationships among mortality, January temperature, and the squared January temperature suggest that a local perspective would further improve our understanding of how climatic conditions matter and underscores the importance of spatially rigorous analysis.

To capture the potential curvilinear relationships between climatic conditions and mortality, squared terms for the weather-related variables are introduced in Model V. Except for the squared July temperature, the estimated associations of other squared variables are all negative and significant, indicating their global curvilinear associations were concave downward. The four plots in Fig. 1 illustrate the parameter estimates of Model V using the mean values of other covariates. Specifically, the county-level mortality would reach its maximum (921 deaths per 100,000 population) when the average January temperature was 39.1° Fahrenheit (6.25° higher than the national average). After which, January temperature increases are associated with mortality decreases, which corresponds to the aforementioned marginal effect. January sunlight hours and July humidity can be interpreted in the same vein. Nonetheless, we note that the theoretical maximum mortality rate (almost 1040 deaths per 100,000 population) associated with the average July temperature is reached when the July temperature is 80° Fahrenheit higher than the national average (almost 156°), which is practically impossible (the highest average July temperature is 94° in our data) and may explain why the estimated coefficient for the squared July temperature is not statistically significant in Model V.

The aforementioned findings drawn from the OLS can only be interpreted as the *general* case for US counties as a whole. It remains unclear whether the associations discussed previously vary across the contiguous US, although the significance of "South" as indicated in Appendix 1 suggests important regional variation.

Geographically weighted regression (spatial) results

The Monte Carlo significance test results for the independent variables in different models are presented in Table 3. Recall that GWR estimates a regression model for every county to yield a thorough understanding of the relationships between mortality and independent variables across space. Using the permutation approach, the Monte Carlo test examines whether the observed spatial variation in the local

[5] More importantly, our sensitivity analysis considered an interaction term between January temperature and south but this interaction term was not significant (results available upon request) and other estimates were comparable to the model in "Appendix 1".

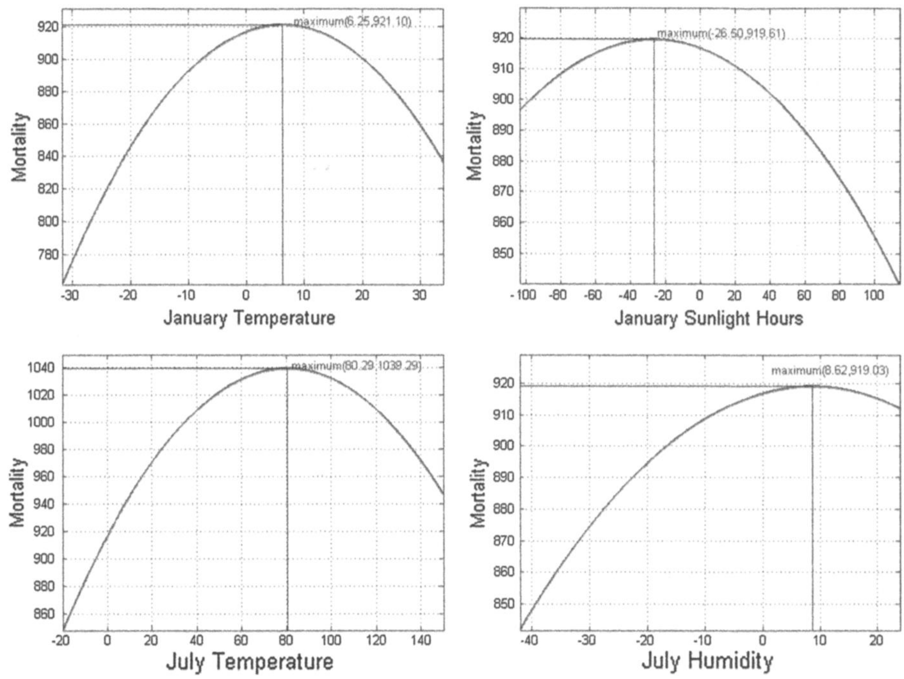

Fig. 1 Curvilinear associations between mortality and climatic conditions

estimates of a certain variable is statistically significant. We first compare the goodness of fit between OLS and GWR first and then focus our discussion on Model V.

The AIC diagnostic statistics reported in Table 2 indicate that the GWR models are always preferred in contrast to the OLS models. The adjusted R^2 increased and the AIC decreased from Models I-V, implying that the inclusion of different sets of variables consistently explained the variation of county mortality rates. Since GWR generated coefficient estimates for each county, it is not feasible to present all GWR results. Following Fotheringham et al. (2003), the best approach to presenting the GWR results is to visualize the local coefficients and their significance level. We use a recently developed method (Matthews and Yang 2012) to create the maps and examine the spatially varying effects of climatic conditions on mortality.

Among the eleven race/ethnicity, rurality, and social environment variables, only five demonstrate spatially varying associations with county-level mortality. By contrast, all the relationships of climatic conditions with mortality are found to vary geographically. That is, as expected, the associations between mortality, temperature, humidity and sunlight hours vary across the nation—suggesting that the estimation of a single coefficient to illustrate this association misses important spatial patterning.

It should be emphasized that the Monte Carlo significance test was used to examine whether the association of an independent variable with mortality differs by location, and the test results should not be interpreted as to whether or not the

Table 3 Monte Carlo significance tests for spatial variability of parameters

Variables	Model I	Model II	Model III	Model IV	Model V
Intercept	***	***	***	***	***
Race/Ethnicity					
Black	***	***	***	***	***
Hispanic	***		***	***	*
Other races	***	***	***	n/s	n/s
Rurality					
Population concentration		***	***	***	***
EEI		***	*	*	*
Natural resources dependency		***	***	n/s	n/s
Social environment					
Affluence			***	**	**
Disadvantage			n/s	n/s	n/s
Social capital index			*	n/s	n/s
Stability			*	n/s	n/s
Crimes			n/s	n/s	n/s
Climatic conditions					
January temperature				***	***
January sunlight				***	***
July temperature				***	***
July humidity				***	***
Squared January temperature					***
Squared January sunlight					***
Squared July temperature					***
Squared July humidity					***

n/s not significant

* Significant at 5 % level; ** Significant at 1 % level; *** Significant at 0.1 % level

effect was statistically significant in GWR models (which will be included in the maps).

The maps of spatial heterogeneity for the climatic variables and their squared terms are shown in Figs. 2 and 3, respectively. The colored areas are where the local estimates are significant at the 0.05 level (or lower) and the GWR results suggest a strong level of spatial heterogeneity for each climatic variable. For example, we find that county mortality rates are positively associated with January temperature although this relationship does not hold for counties in the New England, Middle Atlantic, South Atlantic, East North Central, and East South Central regions. The strongest association between January temperature and mortality (darkest color) is found in Texas, Wisconsin, Minnesota, South Dakota, and North Dakota. The spatial variation corresponds to the potential regional/South effect in the OLS results. Note that the statistically significant local estimates cover both positive and

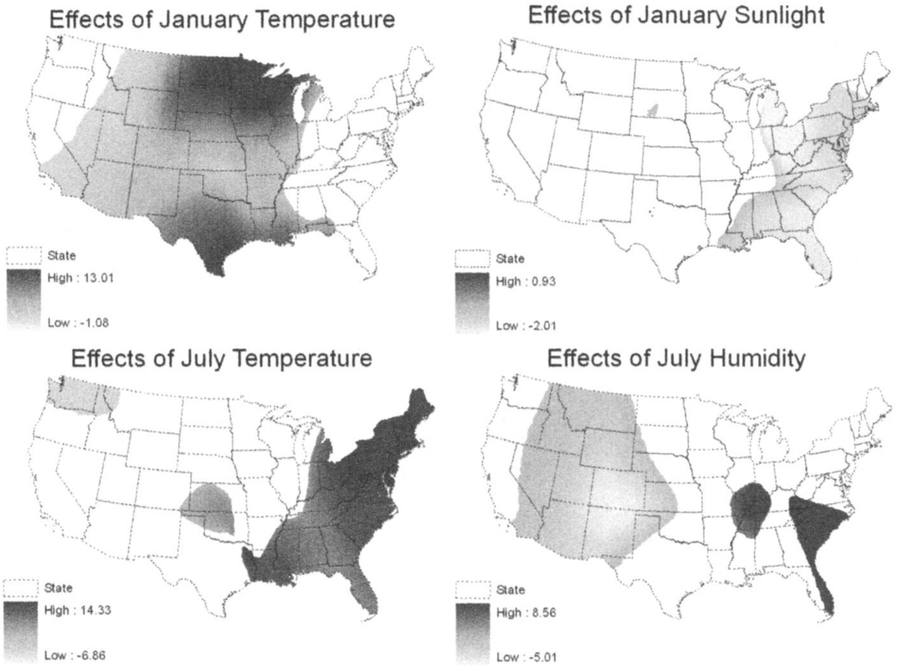

Fig. 2 The linear effects of climatic conditions on mortality in the US

negative relationships, indicating that a local perspective is essential to better understand how temperature matters.

With respect to January sunlight, this measure does not demonstrate statistical significance with county-level mortality for most of the country, including the Pacific, Mountain, West North Central, and West South Central regions. However, for those counties in the Middle Atlantic, South Atlantic, and East South Central regions, more sunlight hours in January is correlated with lower mortality rates.

Perhaps more interestingly, the strongest positive associations of July temperature with mortality are found in the New England, Middle Atlantic, and part of South Atlantic areas. These regions generally have mild summer climates, which echoes the finding that residents in areas with mild summers are less likely to be able to adapt to high summer temperature than their counterparts in areas with typically hot summers (Basu and Samet 2002; Deschênes and Greenstone 2011). July temperature is not a determinant of mortality in the West South Central and Mountain regions, i.e., Texas, New Mexico, and Arizona.

July humidity is more complicated than other climatic variables. Its positive associations (dark color, increasing mortality) are observed along the coast of Florida, Georgia, South Carolina, and North Carolina, as well as Kentucky, western Tennessee, and northern Mississippi. Nonetheless, July humidity is negatively related to mortality (light color) in Midwest and West regions. Specifically, high July humidity is associated with low mortality in Colorado, New Mexico, and their neighboring states. In general, these regions have relatively low humidity in contrast

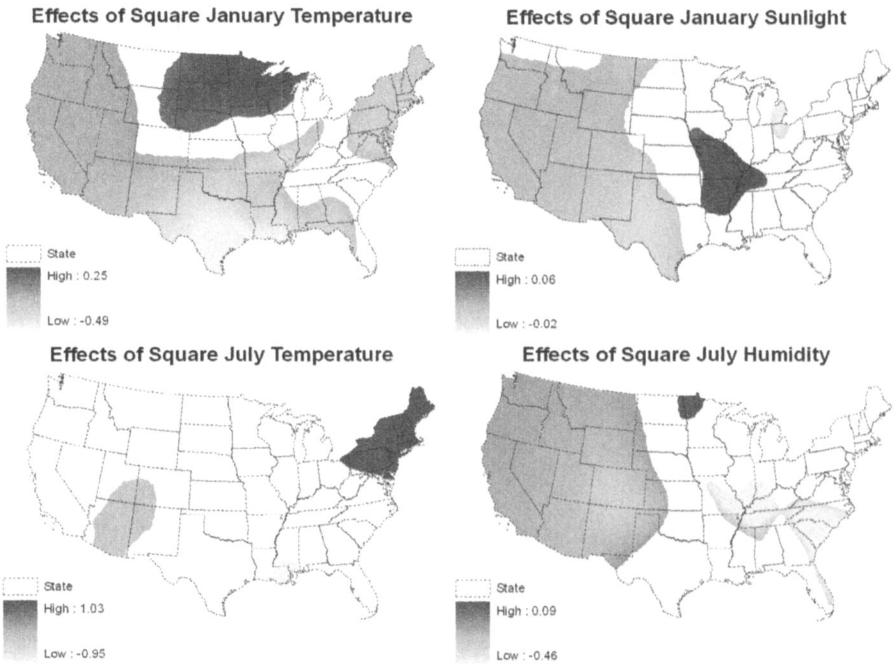

Fig. 3 The effects of squared climatic conditions on mortality in the US

to others and contain the major deserts (e.g., Great Basin Desert and Mojave Desert) in the US. Increasing humidity may in fact provide a more comfortable environment that reduces mortality.

Figure 3 shows the local estimates of the squared climatic variables. Although the linear effect of January temperatures is not significant in New England and the Middle Atlantic areas, the relationship of the squared January temperature with mortality is significant for the counties in these regions. As discussed in the OLS results, the relationship between January temperature and mortality is embedded in the curvilinear term and the map further bolsters this finding. Moreover, it should be noted that the local effects in West North Central and upper Mountain regions are positive, whereas the relationship between the squared January temperature and mortality is negative in other regions. The map of the local effects of the squared January sunlight hours presents a similar story. An area where the squared January sunlight is positively related to mortality is concentrated on Missouri, Tennessee, and Arkansas. Most of the counties in the west show a negative relationship between the squared January sunlight. By contrast, most of the counties in the east are not statistically significant. Coupled with the map of January sunlight in Fig. 2, the associations between January sunlight and mortality in the east seem captured in the linear term, whereas the squared term better explains how January sunlight is related to mortality in the rest of the country.

In Table 2, the global OLS association of the squared July temperature with mortality is not significant, which is reflected in the map in Fig. 3. Most of the counties do not show significant relationships except for three zones in the map. Counties in the northeastern region exhibit positive associations between mortality and the squared July temperature, while the counties near the mouth of Mississippi River in the Gulf of Mexico and those close to the Four Corners[6] have a negative association between mortality and the squared July temperature. One explanation for the latter may be the concentration of Native American reservations in this region, but the data do not afford a separate analysis of this sub-population.

Regarding the relationship between the squared July humidity and mortality, its pattern is similar to the map in Fig. 2. The squared July humidity is negatively related to mortality in the Mountain and Pacific regions, and the strongest associations are observed in the Four Corners area. By contrast, the eastern counties are mostly unrelated to the squared July humidity. However, a conspicuous zone, extending from the Atlantic coast through the Appalachian area to Missouri, suggests that the squared July humidity is negatively correlated with mortality. It is worth noting that the effect of July humidity in this zone is positive (see Fig. 2). Combining the linear and curvilinear spatial variations, the GWR findings indicate that in this conspicuous zone, the marginal effect of July humidity on mortality decreases with the increase in humidity, which may be related to the high tolerance of humidity among residents in this zone.

In all, geographically weighted regression demonstrates important regional variation in county-level associations between natural environmental factors and mortality rates. The Monte Carlo tests indicate that the relationships between social environment variables and mortality are relatively stable. This distinction between social and natural environment factors has not been reported elsewhere, and more important, our findings confirm that a local perspective is essential to fully explore the health–environment relationship.

Discussion and conclusion

To our knowledge, little research, if any, has considered both weather-related and social covariates in exploration of variations of mortality, and even less has employed GWR to detail how the effects of temperature vary geographically. This paper offers such a contribution.

The findings can be used to answer the three research questions posed at the outset. We first asked whether the effects of climatic conditions on mortality are independent from those of social conditions, and whether the associations between climatic variables and morality vary spatially. The answer to these questions is yes—climatic variables are predictive of county-level mortality controlling for social conditions, and climate effects differ by region. On the other hand, the

[6] The region in the US surrounding the geographic point where Colorado, Utah, Arizona, and New Mexico come together.

associations between county-level mortality and social conditions are largely stable across space.

Our third question concerned the spatial association between climatic conditions and county-level mortality rates. The GWR results indicate that (1) the January temperature has a bimodal pattern, as the strongest associations are observed in southern Texas and the areas near Lake Superior and Lake Michigan; (2) the negative relationship between January sunlight hours and mortality is concentrated on the Atlantic coast, while most of the counties east of Appalachian region are unaffected by January sunlight hours; (3) July temperature is positively associated with mortality and the strongest relationships are found in the New England, Middle Atlantic, and South Atlantic regions, while the county mortality rates in Texas, New Mexico, and Arizona are not correlated with July temperature; and (4) the associations of July humidity with mortality demonstrate a complex geographic pattern. Mortality is positively related to July humidity in the counties in South Atlantic region; however, in the Mountain and Pacific regions, high July humidity is associated with low mortality.

Studies in the US and Europe have concluded that the effects of low temperature on mortality are stronger in countries or areas with typically warm winters than in those with cold winters (Basu and Samet 2002; Deschênes and Greenstone 2011) and that the relationships of high temperature with mortality are weaker in those places with hot summers than their counterparts with mild summers (Kalkstein and Greene 1997). The relatively high tolerance of heat in warm areas may help residents to adapt to high temperatures. The GWR results presented here could inform future research using individual data within fine geographic scales to identify the factors resulting in the spatial inequalities. For example, some scholars found that the relationships between environment factors and outmigration are highly localized and sensitive to geographic scale (Hunter et al. 2012; Hunter et al. 2015) and applying GWR to other research topics may generate important insight into extant literature.

While this study cannot establish causal connections between climatic conditions and mortality (particularly at the individual level), several plausible explanations may be used to understand the relationships. First, individuals adapt to climatic changes. When the cardiovascular system cannot normally balance body temperature and external temperature (Davis et al. 2003), it may lead to diseases and high mortality (Hondula et al. 2012; Kalkstein et al. 2008). Second, from a sociological perspective, urban isolation or segregation may exacerbate the adverse effect of climatic changes on mortality (Klinenberg 2015). Explicitly, the lack of access to support or resources may expose the vulnerable or marginal populations to a high risk of death when climatic conditions change rapidly. For example, Klinenberg (2015) found that blacks were more likely to die in the 1995 Chicago heat wave than whites. Third, poor understanding of the potential health threats posed by climatic changes may be related to high mortality as people may not take appropriate actions to protect against climatic conditions.

Several limitations of this study must be noted. First, we used average climate conditions to explain mortality variations at the county level. Caution should be used when attempting to generalize the findings to other analytic units (e.g., census tracts or states). Averages also do not allow for investigation of the effects of sudden extreme climate changes, such as heat waves or cold surges, on human health. Furthermore, other factors implicated in the weather–mortality relationship, such as green space (Maas et al. 2006) should be included. The Area Resource File did not include minimal and maximal temperature nor indicators of air pollutants, and there are no readily available data on climate change awareness at the county level. These data limitations preclude us from taking these factors into account. Finally, the complicated relationships among the South, January temperature, and the squared January temperature should be further examined with finer regional and longitudinal data. Doing so would advance our understanding of the determinants of observed regional differences.

With these caveats in mind, our findings suggest the following policy implications. First and foremost, since the associations of weather-related factors with mortality differ by locations, it is important to take a local perspective to develop the threshold of issuing severe weather alerts, such as heat warnings. For example, the National Weather Service currently uses 105° (for the north) and 110° (for the south) as thresholds to issue a heat warning. Given our finding that the northeastern region of the US (an area with mild summers) is more sensitive to high July temperature, the current criteria may be further refined. The GWR maps illustrate an approach that may be useful in informing local policies and programs designed to reduce climate vulnerabilities. Even so, the associations between mortality and disadvantage, social capital, residential stability, and crimes are geographically stationary. As such, policies that promote social capital or facilitate community development might usefully be formed and implemented nationwide.

In sum, using nationwide data and advanced spatial analysis techniques, we demonstrate that (1) social environment and climatic conditions both account for the variation in mortality across US counties; (2) spatially informed models fit the data better than aspatial OLS, indicating that the variation in county-level mortality can be better explained with a local analytic perspective; and (3) all the effects of climatic conditions on mortality are spatially varying, but the relationships between social environment and mortality are relatively stable across space. This study is the first to focus on nationwide data (i.e., beyond urban areas) and to demonstrate the importance of both social and environmental factors in mortality risk, and the critical need to consider geographic variation within climate–health research.

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Appendix 1

See Table 4.

Table 4 Sensitivity analysis results of the model with the dummy variable "South."

Variables	Model V		Model V + South	
	ß	S.E.	ß	S.E.
Intercept	919.029	4.007***	899.994	4.616***
Race/ethnicity				
Black	0.498	0.179**	0.488	0.177**
Hispanic	−1.910	0.196***	−1.850	0.194***
Other races	1.480	0.304***	1.515	0.301***
Rurality				
Population concentration	−2.488	1.813	−1.395	1.799
EEI	7.314	1.923***	5.539	1.916***
Natural resources dependency	−10.551	1.919***	−10.731	1.899***
Social conditions				
Affluence	−34.571	2.401***	−33.776	2.379***
Disadvantage	43.026	2.967***	42.416	2.937***
Social capital index	−6.708	1.862***	−5.546	1.848**
Stability	−22.530	3.565***	−23.458	3.531***
Crimes	13.217	1.838***	10.013	1.862***
Climatic conditions				
January temperature	1.374	0.314***	0.634	0.325
January sunlight	−0.212	0.063**	−0.210	0.063**
July temperature	3.051	0.658***	2.069	0.663**
July humidity	0.517	0.212*	0.569	0.212*
Squared January temperature	−0.110	0.010***	−0.111	0.010***
Squared January sunlight	−0.004	0.001***	−0.003	0.001***
Squared July temperature	−0.019	0.051	−0.063	0.051***
Squared July humidity	−0.030	0.008***	−0.033	0.008***
South (1 = yes, 0 = no)			42.739	5.302***

* Significant at 5 % level; ** Sgnificant at 1 % level; *** Significant at 0.1 % level

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