Assessing the Performance of a Vulnerability Index during Oppressive Heat across Georgia, United States

GEORGE MAIER,* ANDREW GRUNDSTEIN,[+] WONCHEOL JANG,[#] CHAO LI,[@] LUKE P. NAEHER,[&]
AND MARSHALL SHEPHERD[+]

* School of City and Regional Planning, Georgia Institute of Technology, Atlanta, Georgia
[+] Department of Geography, The University of Georgia, Athens, Georgia
[#] Department of Statistics, Seoul National University, Seoul, South Korea
[@] Department of Epidemiology and Biostatistics, The University of Georgia, Athens, Georgia
[&] Department of Environmental Health Science, The University of Georgia, Athens, Georgia

ABSTRACT

Extreme heat is the leading weather-related killer in the United States. Vulnerability to extreme heat has previously been identified and mapped in urban areas to improve heat morbidity and mortality prevention efforts. However, only limited work has examined vulnerability outside of urban locations. This study seeks to broaden the geographic context of earlier work and compute heat vulnerability across the state of Georgia, which offers diverse landscapes and populations with varying sociodemographic characteristics. Here, a modified heat vulnerability index (HVI) developed by Reid et al. is used to characterize vulnerability by county. About half of counties with the greatest heat vulnerability index scores contain the larger cities in the state (i.e., Athens, Atlanta, Augusta, Columbus, Macon, and Savannah), while the other half of high-vulnerability counties are located in more rural counties clustered in southwestern and east-central Georgia. The source of vulnerability varied between the more urban and rural high-vulnerability counties, with poverty and population of nonwhite residents driving vulnerability in the more urban counties and social isolation/population of elderly/poor health the dominant factor in the more rural counties. Additionally, the effectiveness of the HVI in identifying vulnerable populations was investigated by examining the effect of modification of the vulnerability index score with mortality during extreme heat. Except for the least vulnerable categories, the relative risk of mortality increases with increasing vulnerability. For the highest-vulnerability counties, oppressively hot days lead to a 7.7% increase in mortality.

1. Introduction

Oppressive heat has the ability to cause large-scale loss of life. In 1980, a heat wave killed an estimated 10 000 Americans across the United States (Sheridan and Kalkstein 2004). Extreme heat killed over 700 people in Chicago, Illinois, in July of 1995 (Semenza et al. 1996). Heat waves in the summer of 2003 killed more than 52 000 people in Europe (Larsen 2006) and 1900 people in India (IFRC 2003). In July of 2010, heat waves and accompanying wildfires in Moscow and western Russia caused large increases in mortality as well (Dole et al. 2011), with some estimates indicating that excess mortality surpassed 15 000 (Masters 2012). In many places, such as North America, extreme heat is the leading weather-related killer (Pengelly et al. 2007). More people in the United States die annually from extreme heat than from hurricanes, lightning, tornadoes, floods, and earthquakes combined (NWS 2012).

Several factors may increase the risk for heat-related morbidity and mortality via changes in the frequency and magnitude of the hazard and/or changes in vulnerability. Warming of the climate system will likely result in an increase in extreme heat events (Meehl et al. 2000; Meehl and Tebaldi 2004). Additionally, increasing numbers of people are moving to urban environments (United Nations 2006; Luber and McGeehin 2008; National Research Council Committee on Urban Meteorology 2012), resulting in greater heat exposure from the urban heat island effect (Li and Bou-Zeid 2013; Zhou and Shepherd 2010; Stone et al. 2010; Tan et al. 2010;

Johnson et al. 2009; Hajat et al. 2007; Harlan et al. 2006; Lo and Quattrochi 2003). Indeed, an estimated 60% of the projected global population will live in cities by the year 2030 (United Nations 2006; Luber and McGeehin 2008). Finally, sociodemographic changes, such as an ageing population or increasing poverty in a region, may also heighten vulnerability to heat and therefore increase future heat mortality (Hajat and Kosatky 2010). These growing concerns for the health of current and future populations motivate researchers to target and evaluate the risks and possible mitigation strategies, for example, the System for Integrated Modeling of Metropolitan Extreme Heat Risk (SIMMER) project (NCAR 2012).

A variety of heat-watch warning systems (HWWS) have been utilized to provide warning about extreme heat. The U.S. National Weather Service, for instance, has a series of products to inform the public about the potential for hazardous weather conditions, including "excessive heat outlooks," "excessive heat watches," and "excessive heat warnings" (NWS 2012). Additionally, some cities have utilized synoptic-based systems, where oppressive conditions are locally defined based on past heat–health relationships, to help discern potentially hazardous conditions (Sheridan and Kalkstein 2004). More recently, Teng et al. (2013) have identified a wave pattern that may offer predictability of heat waves 3 weeks in advance of the event.

Of course, some populations are more sensitive or vulnerable to heat than others and identification of high-vulnerability subpopulations may be helpful in directing intervention strategies. Multiple studies have tried to identify these groups based on geographic (e.g., level of urbanization) and sociodemographic (e.g., education, poverty, race, gender, age) characteristics (e.g., Sheridan and Dolney 2003; Harlan et al. 2006; Reid et al. 2009; Rinner et al. 2010; Uejio et al. 2011; Reid et al. 2012a; Johnson et al. 2012; Chow et al. 2012). While broad-based vulnerability indices like the social vulnerability index (SoVI; Cutter et al. 2003) have been available for several years, indices or maps specifically focused on heat risk and heat vulnerability have only recently been proposed (e.g., Reid et al. 2009; Rinner et al. 2010; Johnson et al. 2012; Reid et al. 2012a; Harlan et al. 2013). Except for Reid et al. (2012a), all these studies have focused on quantifying vulnerability in urban settings. Yet, intriguing but not definitive results from Sheridan and Dolney (2003) suggest that rural populations may have greater mortality responses to oppressive heat than urban ones. More recent research in various locations around the world that include urban and rural landscapes shows conflicting results with some indicating that urban residents are more vulnerable (e.g., Gabriel and Endlicher 2011) and others less vulnerable (e.g., Wu et al. 2011) to

extreme heat. Henderson et al. (2013) observed greater mortality in response to extreme heat in a rural rather than an urban location but argue that the explanation may be multifaceted, including that the rural population largely lacks air-conditioning, has poorer overall health, and lives in a cooler climate where they are not well acclimated to heat. Broadly viewed, these results suggest that vulnerability to heat is a multivariable problem that aside from land use/land cover, which can affect heat exposure, involves factors such as sociodemographic characteristics of the population, access to medical care and air-conditioning, and even acclimatization.

This study seeks to determine if counties in the state of Georgia, United States, with greater vulnerability, as defined by a heat vulnerability index (HVI), experience greater mortality during times of oppressive heat compared to counties with lesser vulnerability levels. Georgia provides an excellent study area for exploring the broader use of an HVI outside of metropolitan areas. The state is large (153 900 km^2) with 159 counties that display a wide range in land use/land cover types and sociodemographic characteristics. HVIs proposed by Reid et al. (2009) and Johnson et al. (2012) offer possible indices for use, as they were empirically validated against health outcome data for one or more metropolitan areas. Nevertheless, the HVI based on Reid et al. (2009) is used because it was designed to have wide geographic applicability and has been successfully tested against health outcome data in a variety of areas along the Pacific coast, New Mexico, and Massachusetts. This research expands on the work by Reid et al. (2012a) and Johnson et al. (2012) in a number of ways. Geographically, neither study has examined the use of an HVI versus health outcome data in the southern United States, incorporating both rural and urban locations. Second, several exposure metrics based on the multivariate apparent temperature, rather than ambient air temperature (Reid et al. 2012a) or land surface temperature (Johnson et al. 2012), are examined in an effort to better capture daily meteorological conditions that are oppressive to humans. Ultimately, if health outcome data can validate the Reid et al. (2009) HVI as a broadly applicable index, then it may be employed to guide intervention strategies across the state of Georgia and more widely across the southeastern United States.

2. Data and methodology

A variety of datasets are required in this study, including those relating to vulnerability (in construction of the HVI), meteorology (for indicating oppressive heat), and mortality (for representing negative health outcomes). Here, the HVI and oppressive heat indicator are predictor variables and the negative health outcome is the

TABLE 1. Summary of vulnerability variables included in construction of the HVI and statistics for Georgia counties.

Category	Data source	Year of survey	Variable	Mean(SD)	Range
Demographic	U.S. Census	2000	Percent population ≥65 years of age	12.04(3.36)	1.8–25.85
			Percent population ≥65 years of age and living alone	28.03(3.88)	18.82–38.66
			Percent population living in poverty	16.11(5.37)	3.8–28.6
			Percent population ≥25 years of age and does not hold a high school degree	29.29(7.54)	7.6–43.8
			Percent population of a race other than white	32.40(16.95)	1.7–78.70
			Percent population living alone	8.52(1.71)	1.75–13.96
Diabetes prevalence	BRFSS	2004	Percent population ever diagnosed with diabetes	9.12(1.43)	5.0–12.8
Land cover	NRSAL	2011	Percent county with land use/land cover described as urban	9.36(9.53)	2.44–60.62

response variable. Representative data were collected and analyzed for the state of Georgia from the years of 1995–2004 for the warm-season months of May–September. The study was limited to a 10-yr period centered on the year 2000 to minimize the effects of changes in land use/land cover and sociodemographic characteristics within the counties. Details on each of these datasets as well as the methodology involved are included below.

a. Vulnerability data

The HVI constructed in this study uses a combination of demographic, heath, and land use/land cover data that have been previously associated with increased vulnerability to heat (Table 1). With the exception of air-conditioning data, the approach of Reid et al. (2009) was followed. The first six variables that comprise the vulnerability index are based on demographic and socioeconomic characteristics; these include age, poverty, education, race/ethnicity, and living alone. These variables were gathered from the Censtats data made available by the U.S. Census Bureau (2011) for the year 2000 on the county level for the state of Georgia. Complete counts of Censtats data are recorded only every 10 years, so the year 2000 was chosen because it nearly bisected the study period of 1995–2004. Prevalence of the following variables were either directly downloaded or calculated from raw numbers: people 65 years of age or older; people 65 years of age or older who live alone; people living in poverty; people 25 years of age or older who do not hold a high school degree; people of a race other than white; and people living alone.

The percent of population ever diagnosed with diabetes was downloaded from the Centers for Disease Control and Prevention (CDC), following methodology by Reid et al. (2009). The year 2004 was selected because this was the first year county-level data are available and the only year that is in the study period. Prevalence data were estimated using data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS) and data from

the U.S. Census Bureau's Population Estimates Program. The BRFSS is a telephone survey conducted monthly by state on behavioral risk factors and preventative health practices. Participants were considered to have diabetes if they said yes when asked, "Has a doctor ever told you that you have diabetes?" Women who said yes only because they had diabetes during pregnancy were not included in the diabetes population (CDC BRFSS 2011).

Land use/land cover data from the Natural Resources Spatial Analysis Laboratory (NRSAL 2011) were used to assess percentage of urbanization. The closest available dataset to the study period is from 2001, and includes the following land cover types: beaches/dunes/mud, quarries/strip mines/rock outcrops, open water, low-intensity urban, high-intensity urban, clear-cut/sparse, deciduous forest, evergreen forest, mixed forest, row crops/pasture, forested wetland (saltwater), forested wetland (freshwater), and nonforested wetland (NRSAL 2011). The low-intensity urban and high-intensity urban types were combined to form one urban class, while all other land cover types are considered nonurban. The percentage of urban land use/land cover of each county in the state was included as the final vulnerability variable. It should be noted that Reid et al. (2009) used "not green space" as a variable, which was computed by subtracting out nondeveloped land use types (e.g., forest, pasture, crops, urban/recreational grasses, wetlands, etc.) from total land cover to estimate the amount of developed/urban land use. Our urban land use variable is similar but as described above, it is computed directly from observations in the NRSAL dataset.

Data on air-conditioning prevalence are not used in the construction of the modified HVI in this study, as these data are only available in major metropolitan regions from the American Housing Survey. This is a limitation in the study and remains a notable vacancy in rural heat vulnerability research, although the importance of including air-conditioning data may vary by region. In the Pacific and Northeast regions, for instance,

air-conditioning has become commonplace only recently and therefore may play a more important role in influencing heat mortality. In the southern United States, on the other hand, air-conditioning prevalence is said to have reached saturation, providing a nearly ubiquitous protective factor (Davis et al. 2003). Indeed, air-conditioning of some kind (including both central and separate units) for occupied housing units has been consistently high in recent years in major cities in the southeastern United States (e.g., Atlanta, Georgia; Charlotte, North Carolina; Memphis, Tennessee; New Orleans, Louisiana; U.S. Department of Commerce and U.S. Department of Housing and Urban Development 1997a,b,c,d, 2003, 2005a,b,c), achieving 98% prevalence by the early to mid-2000s.

The eight variables indicating vulnerability were inserted into a matrix (8×159) to achieve county-specific vulnerability scores. A principal component analysis (PCA) was used to transform the observed variables into new and independent factors. The PCA was rotated using the varimax technique to simplify interpretation of the components by concentrating high loadings on as few variables as possible on each principal component. The methodology for variable selection as well as analysis for inclusion of variables into a vulnerability index was followed as in Reid et al. (2009). Factors were selected on the basis of eigenvalues >1, an apparent separation in values in a scree test, and the percentage of variance from each factor. This yielded three factors. Factor scores were then calculated for each of the factors for every county in Georgia. Factor scores were normalized to have a mean of 0 and a standard deviation (SD) of 1. Each factor was then divided into six categories based on standard deviations with category 1 ≥ 2 SD below the mean, factor 2 = 1–2 SD below the mean, factor 3 < 1 SD below the mean, factor 4 < 1 SD above the mean, factor 5 = 1–2 SD above the mean, and factor 6 ≥ 2 SD above the mean. A value of 1 represents the least vulnerable score for that factor in the respective county, while a value of 6 represents the highest value of vulnerability. Because there is no detailed understanding of the impact of each factor on vulnerability, all factors were weighted equally when summing them for the final vulnerability score (Reid et al. 2009). The three factor scores are combined to assign each county a vulnerability score between 3 (low vulnerability) and 18 (high vulnerability).

b. Atmospheric data

The apparent temperature (AT) is used as a metric for assessing environmental heat stress. The term AT, which incorporates both humidity and temperature, is a more complete descriptor of human thermal comfort than any single meteorological measurement (Davis et al. 2002; Steadman 1979, 1984) and therefore has been widely used in studies of heat-related mortality (e.g., Smoyer 1998; Smoyer et al. 2000; Davis et al. 2002, 2003; Sheridan and Dolney 2003; Hajat et al. 2006; Baccini et al. 2008; Basu and Ostro 2008; Zanobetti and Schwartz 2008; Michelozzi et al. 2009).

Maximum and minimum daily AT data were obtained from the National Climatic Data Center (U.S. Heat Stress Index; available online at http://www.ncdc.noaa.gov/temp-and-precip/heat-stress.html) for the 1995–2004 period for the following cities: Athens, Atlanta, and Macon, Georgia; Jacksonville, Florida; Savannah, Georgia; Tallahassee, Florida; and Chattanooga, Tennessee (Fig. 1). An additional city, Augusta, Georgia, was added to the AT dataset by calculating maximum and minimum AT values from hourly air temperature and humidity observations. To assign AT values to each county in Georgia, a spatial interpolation of the time series data was performed. AT values for each day were gridded to a $0.25° \times 0.25°$ resolution across the state using a scheme based on inverse distance weighting (Willmott et al. 1985). Each county in Georgia was assigned the most central AT grid value that fell inside its border.

Oppressive heat was defined using 90th and 95th percentiles of both maximum and minimum ATs for the warm season (May–September) and by month (Basu 2009). Percentiles were used rather than a fixed threshold because they account for local adaptation in each area. Also, greater vulnerability to heat oftentimes exists early in the summer because people are able to acclimate to hot temperatures over the course of a season (Basu and Samet 2002). Thus, we used monthly percentiles to account for intraseasonal acclimatization to heat. In total, we consider eight different approaches for quantifying extreme heat.

c. Mortality data

County-level mortality data for Georgia, from 1995–2004, were obtained from the National Center for Health Statistics (NCHS). Heat-related mortality is examined during the warm-season months (May–September) when heat stress is most likely to occur. These data include the cause of death as well as demographic information, such as race, age, and gender. Unlike Reid et al. (2012a), who stratify deaths by cause (e.g., cardiovascular and respiratory) in their analysis, we only consider total or all-cause mortality. In contrast to metropolitan areas, many rural counties have small populations with few deaths per day, which makes mortality stratification difficult. A variety of studies have demonstrated that mortality rates from many different causes increase during unusually hot conditions (Kalkstein and Davis 1989; Kalkstein 1991). Moreover, the etiology of heat-related deaths can be difficult to determine because heat has the potential to exacerbate preexisting medical conditions and is oftentimes
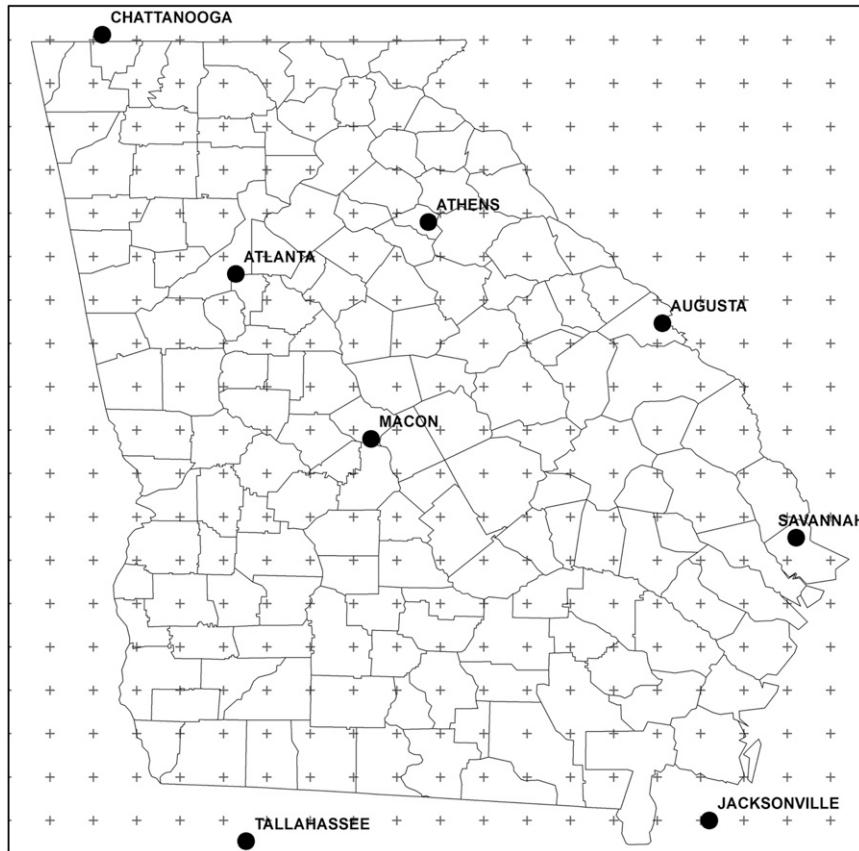
FIG. 1. Locations of surface-observing stations where data for computing AT were obtained. Crosses represent a 0.25° × 0.25° interpolated grid of AT values.

misclassified (Luber and McGeehin 2008). Finally, extraction of accidental deaths was not performed because research has shown that some types of accidental deaths typically increase during stressful weather conditions as well (Larsen 1990; Kalkstein and Greene 1997). Mortality values will be compared with meteorological data for an evaluation of death rates increased by heat stress. Oppressive heat is known to cause acute health responses among vulnerable populations, and therefore heat mortality generally occurs very shortly after exposure (Kalkstein and Valimont 1987; Sheridan and Dolney 2003). We examined both zero day and 1-day lags but found no statistically significant lag relationship. This is likely due to small daily mortality in rural counties.

d. Mortality model

A Poisson mixed effect model with natural splines was utilized to execute the second two objectives of this paper. This model will reveal 1) if oppressively hot days, as identified by various meteorological metrics, respond with greater mortality than days that were not oppressively hot; and 2) if counties with greater vulnerability,

as characterized by the HVI, respond with greater increases in mortality on oppressive days than non-oppressive days than counties with lower HVI values. This model utilizes multiple Poisson regression to analyze mortality in Georgia, with mortality as the response variable and the HVI and oppressive heat as the predictor variables. Poisson regression was chosen because it is commonly used when the response variable is a rate or count, such as in this case. The coefficients of the predictors in this model are used to describe the natural log of the relative risk (RR). The RR is the ratio of the event occurring (death) in the exposed group (population on oppressively hot days) to the event occurring in an unexposed group (population on nonoppressive days). Days that are oppressively hot are hypothesized to produce greater mortality than days that are not oppressively hot, while vulnerability level is hypothesized to act as an effect modifier of this relationship.

The model notation involves letting Y_{it} denote the total number of deaths on day t in county i, and assuming that Y_{it} follows a Poisson distribution with mean μ_{it}. The county-level model is given as follows:

$$Y_{it} \sim \text{Poisson}(\mu_{it})$$

$$\ln(\mu_{it}/N_{i,\text{year}}) = \beta_{0i} + \beta_1 x_{it} + \beta_2 v_i + \beta_3 x_{it} \cdot v_i$$
$$+ \text{ns}(\text{year}, df),$$

where $N_{i,\text{year}}$ is the yearly population for county i, β_{0i} is a random intercept term, x_{it} is the indicator of oppressive days in i county on day t, v_i is the vulnerability index value, and ns (year, df = 3) is a natural cubic spline function of time year with 3 df. The $(\mu_{it}/N_{i,\text{year}})$ term represents the number of deaths over the total population. The term β_0 is used to allow each county to have different mortality estimates even if they share the same HVI and oppressive indicator value. Without this term, mortality would be determined simply by the HVI and oppressive heat indicator. The second term in the model, β_1, is the slope of the oppressive heat indicator. It is the estimated regression coefficient (ERC) associated with oppressive heat. The oppressive heat indicator is a binary term, where 1 represents days that are defined as oppressive and 0 as nonoppressive days. The third term in the model is β_2, which is the slope of the HVI value— that is, the estimated regression coefficient associated with the HVI. The next term is an interaction term, β_3, which includes both the oppressive indicator value as well as the HVI value. Last, the term ns (year, df) is included, which is a natural cubic spline function of time year with 3 df to control for unidentified possible confounders and overdispersion. We initially considered ns (date, df) rather than ns (year, df), but it fit poorly because of low daily mortality in the rural counties and we found only the yearly effect is statistically significant. Using Poisson distribution assumes that the mean and the variance are the same; however, the variance is oftentimes larger than the mean. In cases such as this, a statistical problem arises known as overdispersion; the ns (year, df) term accounts for this problem. Alternatively one can add individual random effects to account for overdispersion. We estimate the overdispersion parameter with our model and our model plus the individual random effect, and found the estimates are similar (2.0 vs 1.7). Note that with our generalized linear mixed model, these are approximated estimates. Assuming the latter model allows for overdispersion, we believe closing to the (approximated) overdispersion by the latter model shows robustness of our model. We also tried to fit a negative binomial model but failed to do that (the maximum likelihood estimator did not converge) because of low mortality in rural counties.

Finally, we should note that many models of health impacts of heat on morbidity and mortality have included ozone as a variable, variously considered a confounder,

TABLE 2. Rotated factor loadings for heat vulnerability variables for the three retained factors based on data from 159 counties.

	Factor 1	Factor 2	Factor 3	Uniqueness
Poverty	0.3220	0.7634	0.4438	0.1165
Less than high school diploma	0.3911	0.3239	0.7098	0.2383
Race other than white	0.0949	0.9239	−0.1092	0.1254
Live alone	0.8442	0.3784	0.0264	0.1434
Age ≥65	0.9370	−0.0172	0.2691	0.0492
Age ≥65 and living alone	0.2228	0.6017	0.5098	0.3284
Diabetes	0.6833	0.5202	0.1784	0.2305
Urban	−0.1043	0.0553	−0.8846	0.2035

an effect modifier, a coexposure, or a causal intermediate (Reid et al. 2012b). Our study does not include air quality data in the heat-mortality model, as these data are not widely available outside of urban areas. In heat vulnerability studies such as ours that cannot control for air quality, some of the deaths that occur during extreme heat may be falsely attributed to extreme heat alone. The unmeasured comorbidities that oftentimes assist heat in killing, therefore, should be acknowledged as limitations, and care must be taken in interpreting results.

3. Results

a. Heat vulnerability index

A heat vulnerability index based on an approach by Reid et al. (2009) was developed from a suite of eight demographic, health, and land use variables. Summary statistics of these variables are presented in Table 1. The variable "race other than white" had by far the greatest range among counties (1.7–78.7); however, the variable "percent land cover described as urban" also had a large range (2.4–60.6). These two categories observed much greater standard deviations from the mean compared to the other variables. Conversely, the standard deviations of "living alone" and "diagnosed with diabetes" were much smaller, having much less variation among different counties. Counties had an average of almost 30% for a population "that does not hold a high school degree" and 28% for those "≥65 years of age and living alone."

There are many strong cross correlations between the eight input variables. For instance, in a precursor analysis (not shown), we found that poverty is highly associated with most of the other vulnerability variables, including having less than a high school diploma, being a race other than white, being 65 years of age or older and living alone, and having diabetes. Thus, a principal component analysis was used for data reduction. Three orthogonal variables were retained that explain 82% of the variability. Factor 1, in particular, explains by far the
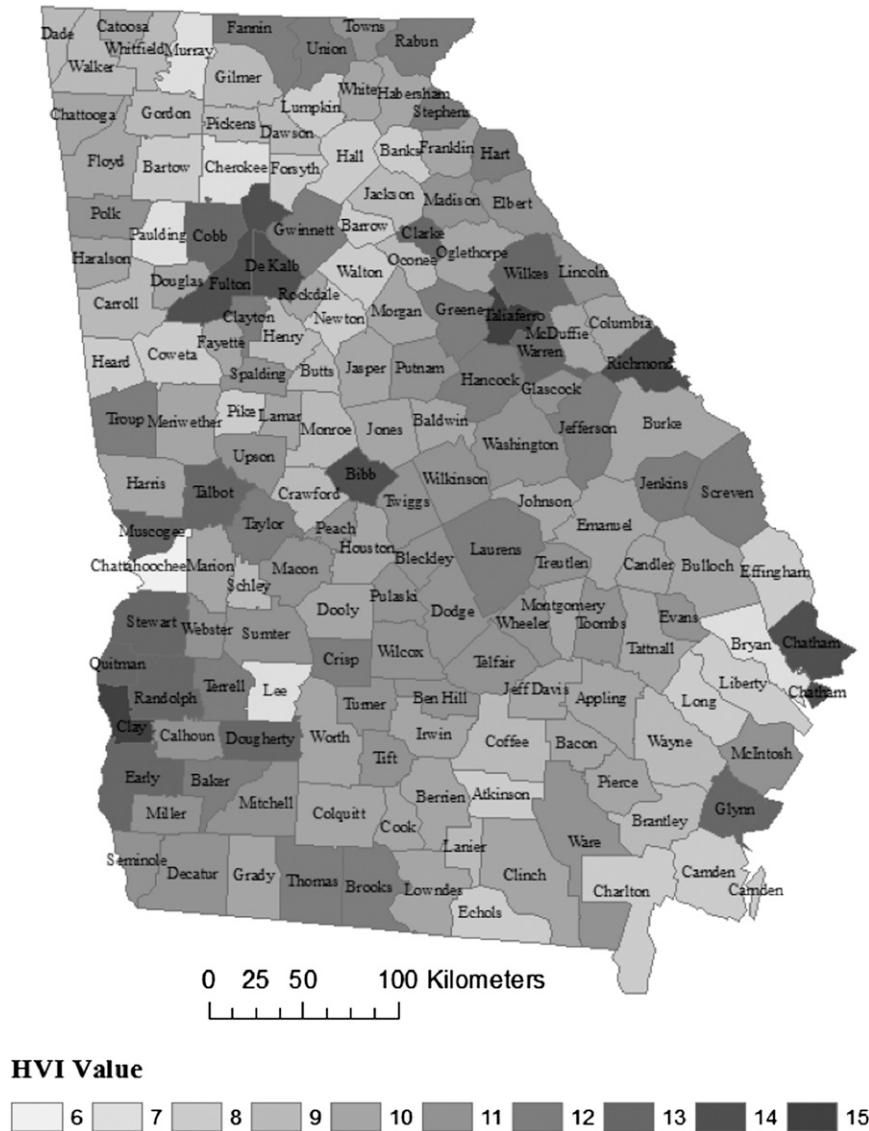
FIG. 2. Total vulnerability level by county as indicated by the HVI. Greater values indicate increased vulnerability to heat.

greatest percentage of variability with nearly 53.7%. Factors 2 and 3, explaining 15.5% and 12.8% of the variability, respectively, were the only remaining factors with eigenvalues >1 and were consequently included in the vulnerability index. Based on the factor loadings (Table 2), factor 1 can be characterized as accounting for social isolation/prevalence of elderly/poor health (diabetes); factor 2 may be characterized as accounting for poverty/proportion of people of a race other than white; and factor 3 represents education/land use.

HVI scores ranged from a low of 6 (Chattahoochee) to a high of 15 (Clay, Taliaferro) across the state (Fig. 2). No county achieved the lowest (3) or highest (18)

possible value for vulnerability. The mode for all counties was 10, of which 42 of the 159 counties observed. An examination of the 19 most vulnerable counties (HVI ≥ 13) shows that about half (9/19) occur in more urban counties that contain larger cities and half (10/19) in rural counties (Table 3). These more urban counties have an average urban cover percentage of 35% (range = 16%–61%) and include Fulton and DeKalb Counties with Atlanta; Richmond County with Augusta; Muscogee County with Columbus; Chatham County with Savannah; Clarke County with Athens; Bibb County with Macon; and Dougherty County with Albany. Interestingly, in all nine "urban" counties, the high vulnerability is driven by

TABLE 3. Vulnerability scores for high-vulnerability counties. The maximum value for each factor is 6, and HVI represents the sum of all three factors. Urban land cover (%) is rounded to the nearest whole number.

	County	Factor 1	Factor 2	Factor 3	HVI	Urban cover (%)
Urban	DeKalb	3	6	5	14	61
	Cobb	1	6	6	13	57
	Fulton	3	6	5	14	48
	Clarke	3	6	4	13	32
	Muscogee	3	6	4	13	28
	Richmond	4	6	4	14	28
	Bibb	4	5	5	14	25
	Chatham	4	5	5	14	20
	Dougherty	4	5	4	13	16
Rural	Glynn	4	4	5	13	10
	Warren	5	4	4	13	5
	Taliaferro	6	4	5	15	4
	Wilkes	5	3	5	13	4
	Early	5	4	4	13	4
	Talbot	5	4	4	13	4
	Clay	6	4	5	15	3
	Randolph	6	4	3	13	3
	Quitman	5	3	5	13	3
	Stewart	5	4	4	13	2

factor 2, which is associated with poverty and/or race other than white, followed by moderate–high values for factor 3. These counties had only moderate scores for factor 1, with an average of score of 3.22 out of a maximum of 6. The remaining counties, including clusters in east-central and southwest Georgia have very little urban coverage, averaging about 4% (range = 2%–10%). In all but one of these counties (90%), the high score is driven by factor 1, associated with social isolation/prevalence of elderly/poor health, and only moderate scores for factors 2 and 3. The upshot is that more urbanized counties are not unique among the locations with the highest vulnerability. However, there does appear to be a strong pattern related to the source of the vulnerability between high-vulnerability urban and rural counties in Georgia. Counties with the lowest HVI scores, on the other hand, are generally in the northwest portion of the state, as well as the far southeast region proximal to the Atlantic coast.

b. Heat vulnerability model

Each of the eight oppressive heat approaches was tested to see whether it indicated increased mortality by using the mortality model. Only the 95th percentile warm-season maximum AT approach showed a statistically significant effect on mortality in Georgia and was therefore used as the threshold for oppressive conditions. The relative risks for oppressive and nonoppressive days show increased mortality under both conditions with increases in vulnerability, but at a greater rate on oppressive days. Thus, there was a 13.4% increase in

mortality for every increase of 1 HVI value on oppressive days compared with a 12.4% increase in mortality for every increase of one unit on the HVI for nonoppressive days.

The results of the HVI mortality model indicate a progressively greater heat-related mortality effect with greater HVI values (Table 4). No statistically significant relationship between the HVI and mortality was observed on oppressive days for counties with low HVIs of 6 and 7. Those with HVIs ≥8, however, show positive, statistically significant relationships between HVI and mortality on oppressively hot days. Here, the relative risk becomes greater than one, signifying that the number of mortalities on oppressive days is greater than the number of mortalities on nonoppressive days. As the HVI increases, the proportion of deaths on oppressive days to

TABLE 4. Output from the HVI model for all 10 values. CI is the confidence intervals.

HVI	ERC	RR for oppressive heat	95% CI
6	−0.013611	0.9865	(0.9390–1.0364)
7	−0.003884	0.9961	(0.9554–1.0386)
8	0.005843	1.0059	(0.9717–1.0412)
9	0.015570	1.0157	(0.9880–1.0442)
10	0.025297	1.0256	(1.0035–1.0482)
11	0.035024	1.0356	(1.0176–1.0541)
12	0.044751	1.0458	(1.0285–1.0634)
13	0.054478	1.0560	(1.0357–1.0767)
14	0.064205	1.0663	(1.0404–1.0929)
15	0.073932	1.0767	(1.0438–1.1107)

deaths on nonoppressive days increases as well. For example, there is a 4.6% (RR = 1.0458) increase in mortality for days that were oppressive compared to days that were not oppressive in areas with an HVI of 12 compared with a 7.7% (RR = 1.0767) increase for areas with an HVI of 15. Thus, the models indicate that counties with greater vulnerability, as characterized by the HVI, respond with greater increases of mortality rates on oppressive days than counties with less vulnerability.

4. Discussion and conclusions

This study provided a new application of the HVI with regard to scale: county-level data in the state of Georgia. The HVI was then mapped for visual evaluation, which included a range of 10 levels across the state. Among the most vulnerable counties, about half were more urban counties containing the larger cities in Georgia, such as Atlanta, Augusta, Macon, Savannah, Columbus, and Albany. The remaining high-vulnerability counties were more rural and clustered in southwest and east-central Georgia. Interestingly, the source of vulnerability varied between the high-vulnerability urban and rural counties with poverty and nonwhite populations the primary driver for more urban counties, while social isolation/prevalence of elderly/poor health were the most prominent factors in the more rural counties.

A variety of metrics were tested with mortality data to determine which definition could successfully represent oppressive heat. For modeling purposes, the warm-season 95th percentile max AT was used as a threshold, above which daily conditions were considered thermally oppressive. This approach showed greater increases in mortality per increase in HVI on oppressive days (13.4%) than nonoppressive days (12.4%).

When coupled with mortality data, the HVI was modeled as an effect modifier of oppressive heat. The oppressive heat indicator and HVI values were used as predictor variables, and mortality data were used as the response variable. HVI values of 6 and 7 actually showed more mortality on nonoppressive days than oppressive days, but the difference was not statistically significant. The fact that there was no statistically significant difference in mortality between oppressive and nonoppressive days, however, is important because it suggests some protective effects in low-vulnerability counties. For HVIs ≥8, the RR increased with HVI, indicating that on oppressively hot days, populations with greater heat-related vulnerability become increasingly susceptible to heat-related mortality. For example, on oppressively hot days, lower-vulnerability counties with an HVI = 8 had a 5.8% increase in deaths compared to a 7.7% increase for the most vulnerable counties with an HVI = 15.

This study demonstrates that the modified HVI can be applied outside of metropolitan areas in a southern state and can accurately identify vulnerable populations based on health outcome data. Application of the modified HVI to rural areas is warranted in our study region as air-conditioning prevalence is high. However, use of the modified HVI without inclusion of air-conditioning data may not be appropriate in areas with less air-conditioning prevalence. By extending the HVI across the state, public safety officials may be able to target the most vulnerable populations in an attempt to save lives during dangerously hot conditions.

Further, our study builds geographically on the work of Reid et al. (2012a) and demonstrates that the Reid et al. (2009) HVI is a useful indicator for public health officials. At this point, the HVI has been empirically tested in California, Washington, Oregon, New Mexico, Massachusetts, and now Georgia, indicating wide applicability in regions with diverse climates, land use, and sociodemographic characteristics. We also observed similar findings as Reid et al. (2012a), with increasing mortality responses to extreme heat with increasing heat vulnerability while using different heat metrics. This strengthens the generalizability of the index, in that the results are not constrained to use of a certain measure of heat.

There are several possible areas for future research. First, the modified HVI can be tested in other regions of the country such as the Midwest, which has not yet been empirically examined. A second area for future research is that thresholds of temperatures or other metrics of oppressive conditions, above which mortality increases, may vary by vulnerability level. It is well known that thresholds for increased heat mortality vary geographically, with lower thresholds in more northern cities and higher thresholds in more southern cities (Curriero et al. 2002). It is possible that there may be lower thresholds for populations with greater vulnerability. Identification of these thresholds implies that HWWS may need to be adapted for different geographic locations with different vulnerabilities.

REFERENCES

Baccini, M., and Coauthors, 2008: Heat effects on mortality in 15 European cities. *Epidemiology,* **19,** 711–719.

Basu, R., 2009: High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. *Environ. Health,* **8,** Article 40, doi:10.1186/1476-069X-8-40.

——, and J. M. Samet, 2002: Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. *Epidemiol. Rev.,* **24,** 190–202.

——, and B. D. Ostro, 2008: Populations vulnerable to mortality associated with high ambient temperature in California. *Amer. J. Epidemiol.,* **168,** 632–637.

CDC BRFSS, cited 2011: Prevalence and trends data. [Available online at http://apps.nccd.cdc.gov/brfss/.]

Chow, W. T., W. Chuang, and P. Gober, 2012: Vulnerability to extreme heat in metropolitan Phoenix: Spatial, temporal, and demographic dimensions. *Prof. Geogr.,* **64,** 286–302.

Curriero, F. C., K. S. Heiner, J. M. Samet, S. L. Zeger, L. Strug, and J. A. Patz, 2002: Temperature and mortality in 11 cities of the eastern United States. *Amer. J. Epidemiol.,* **155,** 80–87.

Cutter, S., B. Boruff, and W. L. Shirley, 2003: Social vulnerability to environmental hazards. *Soc. Sci. Quart.,* **84,** 242–261.

Davis, R. E., P. C. Knappenberger, W. M. Novicoff, and P. J. Michaels, 2002: Decadal changes in heat-related human mortality in the eastern United States. *Climate Res.,* **22,** 175–184.

——, ——, P. J. Michaels, and W. M. Novicoff, 2003: Changing heat-related mortality in the United States. *Environ. Health Perspect.,* **111,** 1712–1718.

Dole, R., and Coauthors, 2011: Was there a basis for anticipating the 2010 Russian heat wave? *Geophys. Res. Lett.,* **38,** L06702, doi:10.1029/2010GL046582.

Gabriel, K. M., and W. R. Endlicher, 2011: Urban and rural mortality rates during heat waves in Berlin and Brandenburg, Germany. *Environ. Pollut.,* **159,** 2044–2050.

Hajat, S., and T. Kosatky, 2010: Heat-related mortality: A review and exploration of heterogeneity. *J. Epidemiol. Community Health,* **64,** 753–760.

——, and Coauthors, 2006: Impact of high temperatures on mortality: Is there an added heat wave effect? *Epidemiology,* **17,** 632–638.

——, R. S. Kovats, and K. Lachowycz, 2007: Heat-related and cold-related deaths in England and Wales: Who is at risk? *Occup. Environ. Med.,* **64,** 93–100.

Harlan, S. L., A. J. Brazel, L. Prashad, W. L. Stefanov, and L. Larsen, 2006: Neighborhood microclimates and vulnerability to heat stress. *Soc. Sci. Med.,* **63,** 2847–2863.

——, J. H. Declet-Barreto, W. L. Stefanov, and D. B. Petitti, 2013: Neighborhood effects on heat deaths: Social and environmental vulnerability in Maricopa County, Arizona. *Environ. Health Perspect.,* **121,** 197–204.

Henderson, S. B., V. Wan, and T. Kosatky, 2013: Differences in heat-related mortality across four ecological regions with diverse urban, rural, and remote populations in British Columbia, Canada. *Health Place,* **23,** 48–53.

IFRC, 2003: India: Heat wave. Information Bull. 1/2003. [Available online at http://www.ifrc.org/docs/appeals/rpts03/indiaheatwave03a1.pdf.]

Johnson, D. P., J. S. Wilson, and G. C. Luber, 2009: Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int. J. Health Geogr.,* **8,** Article 57, doi:10.1186/1476-072X-8-57.

——, A. Stanforth, V. Lulla, and G. Luber, 2012: Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. *Appl. Geogr.,* **35,** 23–31.

Kalkstein, L. S., 1991: A new approach to evaluate the impact of climate on human mortality. *Environ. Health Perspect.,* **96,** 145–150.

——, and K. M. Valimont, 1987: Effects on human health. *Appendix B: Potential Effects of Future Climate Changes on Forest and Vegetation, Agriculture, Water Resources, and Human Health,* D. A. Tirpak, Ed., Vol. 5, *Assessing the Risks of Trace Gases That Can Modify the Stratosphere,* EPA 400/1-87/001E, U.S. EPA, 122–152.

——, and R. E. Davis, 1989: Weather and human mortality: An evaluation of demographic and interregional responses in the United States. *Ann. Assoc. Amer. Geogr.,* **79,** 44–64.

——, and J. S. Greene, 1997: An evaluation of climate/mortality relationships in large U.S. cities and the possible impacts of a climate change. *Environ. Health Perspect.,* **105,** 84–93.

Larsen, J., 2006: Setting the record straight: More than 52,000 Europeans died from heat in summer 2003. Earth Policy Institute. [Available online at http://www.earth-policy.org/plan_b_updates/2006/update56.]

Larsen, U., 1990: Short-term fluctuations in death by cause, temperature, and income in the United States 1930-1985. *Soc. Biol.,* **37,** 172–187.

Li, D., and E. Bou-Zeid, 2013: Synergistic interactions between urban heat islands and heat waves: The impact in cities in larger than the sum of its parts. *J. Appl. Meteor. Climatol.,* **52,** 2051–2064.

Lo, C. P., and D. A. Quattrochi, 2003: Land-use and land-cover change, urban heat island phenomenon, and health implications: A remote sensing approach. *Photogramm. Eng. Remote Sens.,* **69,** 1053–1063.

Luber, G., and M. McGeehin, 2008: Climate change and extreme heat events. *Amer. J. Prev. Med.,* **35,** 429–435.

Masters, J., 2012: Over 15,000 likely dead in Russian heat wave; Asian monsoon floods kill hundreds more. [Available online at http://www.wunderground.com/blog/JeffMasters/comment.html?entrynum=1571.]

Meehl, G. A., and C. Tebaldi, 2004: More intense, more frequent, and longer lasting heat waves in the 21st century. *Science,* **305,** 994–997.

——, F. Zwiers, J. Evans, T. Knutson, L. Mearns, and P. Whetton, 2000: Trends in extreme weather and climate events: Issues related to modeling extremes in projections of future climate change. *Bull. Amer. Meteor. Soc.,* **81,** 427–436.

Michelozzi, P., and Coauthors, 2009: High temperatures and hospitalizations for cardiovascular and respiratory causes in 12 European cities. *Amer. J. Respir. Crit. Care Med.,* **179,** 383–389.

National Research Council Committee on Urban Meteorology, 2012: *Urban Meteorology: Forecasting, Monitoring, and Meeting Users' Needs.* The National Academies Press, 176 pp.

National Weather Service, cited 2012: Heat: A major killer. [Available online at http://www.nws.noaa.gov/os/heat/index.shtml.]

NCAR, cited 2012: SIMMER project. [Available online at http://www.ral.ucar.edu/projects/simmer/team/.]

NRSAL, cited 2011: Georgia land use trends. [Available online at http://narsal.uga.edu/glut.]

Pengelly, L. D., M. E. Campbell, C. S. Cheng, C. Fu, S. E. Gingrich, and R. Macfarlane, 2007: Anatomy of heat waves and mortality in Toronto: Lessons for public health protection. *Can. J. Public Health,* **98,** 364–368.

Reid, C. E., M. S. O'Neill, C. J. Gronlund, S. J. Brines, D. G. Brown, A. V. Diez-Roux, and J. Schwartz, 2009: Mapping community determinants of heat vulnerability. *Environ. Health Perspect.,* **117,** 1730–1736.

——, and Coauthors, 2012a: Evaluation of a heat vulnerability index on abnormally hot days: An environmental public health tracking study. *Environ. Health Perspect.,* **120,** 715–720, doi:10.1289/ehp.1103766.

——, J. M. Snowden, C. Kontgis, and I. B. Tager, 2012b: The role of ambient ozone in epidemiologic studies of heat-related mortality. *Environ. Health Perspect.,* **120,** 1627–1630.

Rinner, C., D. Patychuk, K. Bassil, N. Shiraz, S. Gower, and M. Campbell, 2010: The role of maps in neighborhood-level heat vulnerability assessment for the city of Toronto. *Cartogr. Geogr. Inf. Sci.,* **37,** 31–44.

Semenza, J. C., C. H. Rubin, K. H. Falter, J. D. Selanikio, W. D. Flanders, H. L. Howe, and J. L. Wilhelm, 1996: Heat-related deaths during the July 1995 heat wave in Chicago. *N. Engl. J. Med.,* **335,** 84–90.

Sheridan, S. C., and T. J. Dolney, 2003: Heat, mortality, and level of urbanization: Measuring vulnerability across Ohio, USA. *Climate Res.,* **24,** 255–266.

——, and L. S. Kalkstein, 2004: Progress in heat watch–warning system technology. *Bull. Amer. Meteor. Soc.,* **85,** 1931–1941.

Smoyer, K. E., 1998: A comparative analysis of heat waves and associated mortality in St. Louis, Missouri—1980 and 1995. *Int. J. Biometeor.,* **42,** 44–50.

——, G. C. Rainham, and J. N. Hewko, 2000: Heat-stress-related mortality in five cities in southern Ontario: 1980–1996. *Int. J. Biometeor.,* **44,** 190–197.

Steadman, R. G., 1979: The assessment of sultriness. Part I: A temperature–humidity index based on human physiology and clothing science. *J. Appl. Meteor.,* **18,** 861–884.

——, 1984: A universal scale of apparent temperature. *J. Climate Appl. Meteor.,* **23,** 1674–1687.

Stone, B., J. J. Hess, and H. Frumkin, 2010: Urban form and extreme heat events: Are sprawling cities more vulnerable to climate change than compact cities? *Environ. Health Perspect.,* **110,** 1425–1428.

Tan, J., and Coauthors, 2010: The urban heat island and its impact on heat waves and human health in Shanghai. *Int. J. Biometeor.,* **54,** 75–84.

Teng, H., G. Branstator, H. Wang, G. A. Meehl, and W. M. Washington, 2013: Probability of US heat waves affected by a subseasonal planetary wave pattern. *Nat. Geosci.,* **6,** 1056–1061, doi:10.1038/ngeo1988.

Uejio, C. K., O. V. Wilhelmi, J. S. Golden, D. M. Mills, S. P. Gulino, and J. P. Samenow, 2011: Intra-urban societal vulnerability to extreme heat: The role of heat exposure and built environment, socioeconomics, and neighborhood stability. *Health Place,* **17,** 498–507.

United Nations, 2006: World urbanization prospects: The 2005 revision. Population Division, Department of Economic and Social Affairs, United Nations, Working Paper ESA/P/WP/200, 196 pp.

U.S. Census Bureau, cited 2011: Censtats databases. [Available online at http://censtats.census.gov.]

U.S. Department of Commerce and U.S. Department of Housing and Urban Development, 1997a: American housing survey for the Atlanta metropolitan area in 1996. Current Housing Rep. H170/96-21, 258 pp.

——, 1997b: American housing survey for the Charlotte metropolitan area in 1995. Current Housing Rep. H170/95-63, 220 pp.

——, 1997c: American housing survey for the Memphis metropolitan area in 1996. Current Housing Rep. H170/96-8, 218 pp.

——, 1997d: American housing survey for the New Orleans metropolitan area in 1995. Current Housing Rep. H170/95-30, 258 pp.

——, 2003: American housing survey for the Charlotte metropolitan Area in 2002. Current Housing Rep. H170/02-63, 348 pp.

——, 2005a: American housing survey for the Atlanta metropolitan area in 2004. Current Housing Rep. H170/04-21, 356 pp.

——, 2005b: American housing survey for the Memphis metropolitan area in 2004. Current Housing Rep. H170/04-8, 356 pp.

——, 2005c: American housing survey for the New Orleans metropolitan area in 2004. Current Housing Rep. H170/04-30, 356 pp.

Willmott, C. J., C. M. Rowe, and W. D. Philpot, 1985: Small-scale climate maps: A sensitivity analysis of some common assumptions associated with grid point interpolation and contouring. *J. Amer. Cartogr.,* **12,** 5–16.

Wu, P. C., C. Y. Lin, S. C. Lung, H. R. Guo, C. H. Chou, and H. J. Su, 2011: Cardiovascular mortality during heat and cold events: Determinants of regional vulnerability in Taiwan. *Occup. Environ. Med.,* **68,** 525–530.

Zanobetti, A., and J. Schwartz, 2008: Temperature and mortality in nine U.S. cities. *Epidemiology,* **19,** 563–570.

Zhou, Y., and J. M. Shepherd, 2010: Atlanta's urban heat island under extreme heat conditions and potential mitigation strategies. *Nat. Hazards,* **52,** 639–668.