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Spatiotemporal analysis of heat and heat wave effects on elderly mortality in Texas, 2006–2011

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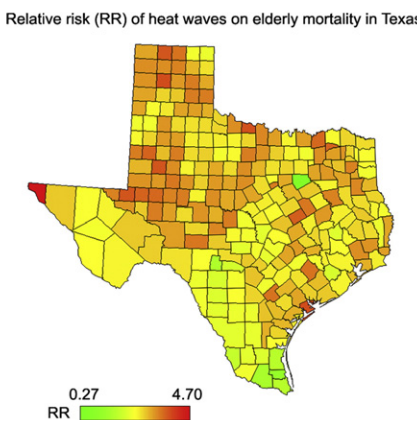
HIGHLIGHTS

- This study examines heat wave effects using a spatiotemporal analysis.
- This study addresses a state associated with varying climate.
- Heat wave effects on elderly mortality show strong geographical variations.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Heat and heat waves have been linked to the increased risk of deaths, hospital admissions, and emergency visits.
Objectives: This study presents a spatiotemporal analysis of heat and heat wave effects on elderly mortality (≥65 years) in Texas.
Methods: We compiled a six-year daily weather and mortality counts dataset from 254 counties in Texas during 2006–2011. Heat index (HI), a combination of temperature and relative humidity, was used as the exposure metric in this study. Associations between daily all-cause elderly mortality and daily maximum HI and heat waves (≥2 days of county-specific daily maximum HI > 95th percentiles) were examined using a quasi-Poisson regression. A Markov random field smoother was included in the model to account for spatial autocorrelations and spatial heterogeneity. The model also controlled for long-term trend and seasonality in mortality, and the effects of day of the week.
Discussion: On average, the lag effect of heat on elderly mortality risk lasted up to 10 days, and the cumulative heat effects started to increase rapidly when daily maximum HI exceeded the 90th percentile in Texas. Elderly living in Northwest Texas and parts of West Texas were at greater risk of elderly mortality attributable to heat

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waves, and the highest relative risk for elderly mortality occurred in El Paso County (4.70, 95% Confidence Interval = 4.33, 5.10).

Conclusions: Our study indicates strong geographical variations of heat wave effects on elderly mortality risk in Texas.

1. Introduction

The impact of ambient temperature on human health is a global public health threat. Exposures to hot and cold temperatures are associated with the increased risk of death, hospital admissions, and emergency room visits (Huynen et al., 2001). Recently, there has been an increase in the recognition of the potential risks to human health, well-being and survival posed by ambient temperature, with a consequent imperative for scientific evaluation and policy discussion about how to manage, reduce or avert these risks (McMichael, 2013). The elderly may be at high risk of extreme temperature-related illness, especially if they live alone or have medical conditions (Gamble et al., 2013). Frailty, limited mobility, and chronic diseases (e.g., cardiovascular diseases) can affect the elderly's ability to take adequate care of themselves in severe weather conditions, especially those that result in extreme cold and hot temperatures (Flynn et al., 2005). While evidence of the effect of extreme weather on the elderly exists, findings are inconsistent due to spatial variability (Astrom et al., 2011).

Previous research has shown that extreme heat poses a significant risk for mortality and morbidity in United States (U.S.) elderly (McGeehin and Mirabelli, 2001; Anderson and Bell, 2009), where spatial heterogeneity was only considered in the calculation of heat impact across cities; however, the impact of the actual location on human health during heat waves has not yet been evaluated. International studies have proven the existence of a locational effect between the association of high temperature and human health. For example, in a 2003 heat wave event in France, the geographic variations in mortality had a significant relationship with the number of very hot days, especially in elderly (Fouillet et al., 2006). An Australian study identified that the elderly living in Southwestern and Western Sydney are more vulnerable to heat-related mortality than those living in other areas of the city (Vaneckova et al., 2010). Similar studies have been published that use data from Germany, Britain, Canada and Taiwan (Gabriel and Endlicher, 2011; Tomlinson et al., 2011; Bassil et al., 2009; Wu et al., 2010). This evidence revealed that spatial variation exists in the associations between health and weather conditions; therefore, when analyzing data from a large area, spatial variation must be considered. So far a limited number of studies have dealt with spatial heterogeneity by using the geographic information system when modeling the effects of heat and heat waves on mortality. Until now, this method has been applied in the studies examining Asian dust storms (Yu et al., 2012) and dengue fever (Chien and Yu, 2014).

This study considered both complex nonlinear lag effects and spatial heterogeneity by simultaneously using a nonlinear statistical modeling approach with a spatial analytic method and geographic information systems. The research aims to: (1) examine complex associations among heat, heat waves, lags, and elder mortality; (2) explore the duration of cumulative impacts on elder mortality caused by heat and heat wave; and (3) investigate geographical variations of heat wave effects on elderly mortality risk. The critical hypothesis of this study is to reveal significant heat impacts on elder mortality in terms of lags and to identify vulnerable counties in Texas that may have excessive mortality risk among the elderly during heat wave days.

2. Methods

2.1. Study area

Texas, the second largest state in the U.S., has a total population of 27.69 million (ranked second after California in 2015). The state's large size results in highly varied weather from multiple climatic zones. Although some snow events occur in North and West Texas each year, a high temperature over 32 °C is the most common climatic characteristic, especially in South Texas during the summer. Texas has the largest number of counties ($n = 254$) of any state in the U.S., providing a good fundamental unit to analyze the spatial heterogeneity of heat waves in such a vast area. Texas also has the highest number of heat-related deaths in the U.S., e.g., Texas had 46 deaths directly attributed to heat in 2011, which was higher than all other states (NWS, 2013).

2.2. Data sources

2.2.1. Mortality data

All-cause mortality data in Texas during 2006–2011 were used in this study. Original death records were obtained from the Texas Department of State Health Services (DSHS) and were aggregated for each day at the county level. This study was approved by the DSHS Institutional Review Board (IRB# 15-011) and the Committee for the Protection of Human Subjects of the University of Texas Health Science Center at Houston (HSC-SPH-14-0240).

2.2.2. Weather data

Hourly weather observations in Texas during 2006–2011 were downloaded from the National Climate Data Center (NCDC) through the Integrated Surface Database (ISD) (NCDC, 2014). A total of 239 weather stations were available during the study period. ISD weather data have been checked for extreme values, consistency between parameters, and continuity between observations through a rigorous quality control procedure developed by NCDC (Lott, 2014). We then calculated daily maximum, mean, and minimum temperatures as well as the heat index (HI), a composite index of temperature and relative humidity. The choice of HI is mainly due to two reasons: 1) HI simultaneously accounts for temperature and relative humidity, the two major weather parameters related to heat exposures; and 2) HI is used by National Weather Service (NWS) for issuing heat watches, advisories and warnings (NWS, 2014a). HI values were derived according to the equations representing different combination scenarios of temperature and relative humidity developed by NWS (NWS, 2014a). The maximum possible value of HI was set to 137 °F (58.33 °C) according to the NWS announced Heat Index Chart (NWS, 2014b).

We included all available weather stations and imputed weather parameters for those counties for which weather stations were unavailable during the study period or weather observations had missing values. This imputation was performed through a spatiotemporal Kriging technique that interpolates missing values by considering known values within local time and space neighborhoods (Kumar et al., 2013). Finally, for each of the 254 Texas counties, we used weather data from the single weather station that was considered to be the most representative of population exposure (e.g., airport weather station, close to the most populous city in the county, etc.) Imputed values for county centroids (center of a county) were based on 2010 U.S. Census data and were used to represent those counties for which weather stations were unavailable.

Because there is no consensus on the definition of “heat wave,” in this study, a heat wave was defined as HI that exceeds the 95th percentile of the county-specific maximum HI distribution during the study period for 2 or more consecutive days. This percentile-based definition has been widely used in previous studies (Zhang et al., 2012). The elderly population was defined as people greater than or equal to 65 years of age.

2.2.3. Socioeconomic data

Since 2005, the U.S Census Bureau has conducted a nationwide decennial survey, the American Community Survey (ACS), to collect the most updated information about the social and economic needs in each county of the U.S. Compared to the decennial census, the ACS estimates are more accurate due to the use of professional and highly trained interviewers every month (Mather et al., 2005). In order to match the data framework of this study in terms of county and year, we chose the 5-year socioeconomic data in 2011 to guarantee no missing value in each year.

2.3. Statistical methods

We divided the risks of temperature on mortality into two parts: the 'heat effect' defined as the independent effect attributed to daily HI, and the heat-wave effect associated with heat waves (Gasparrini and Armstrong, 2011; Zhang et al., 2014). HI was chosen as the exposure metric to heat in this study because NWS releases heat advisories and warnings based on HI. It is a challenge to introduce absolute HI values into spatiotemporal models given that Texas is a large state associated with different climates. Thus, we standardized the absolute HI into percentiles in each community following a method previously described (Guo et al., 2014), and defined this heat-mortality relationship on a relative scale. We interpreted it in terms of HI percentiles, which correspond to different community-specific absolute HI values.

To fully capture the non-linear and delayed effect of HI on elderly mortality, we used a flexible cross-basis function which is a core function of distributed lag nonlinear model (DLNM) to maximum HI (HI_{max}) percentiles. The cross-basis was defined by a b-spline for the space of standardized HI_{max} percentiles, and a b-spline with intercept for the space of lags, with the maximum lag up to 21 days. We placed three internal knots at 20th, 50th, and 80th percentiles of standardized HI_{max} and three internal knots at equally spaced log-values of lag (1.0, 2.8 and 7.6 days), respectively. The spline for standardized HI_{max} was centered at the 90th percentile, representing the average point of minimum mortality in preliminary analyses. A Vuong test was used to identify whether the use of an ordinary Poisson model was applicable to our count data, resulting a p-value < 0.0001 to reject the ordinary Poisson model due to over-dispersion. Therefore, a spatiotemporal quasi-Poisson model allowing for over-dispersion was used to examine the associations between heat, heat waves and elderly mortality:

$$\begin{aligned} Y_{ct} &\sim \text{Poisson}(\mu_{ct}) \\ \log(\mu_{ct}) &= \alpha + \beta \times YR + \gamma \times DOW + \eta \times SES \\ &\quad + f(HI_{max},\ lag) + f(t) + f_{spat}(c) \times HW + \log(pop) \end{aligned} \tag{1}$$

where county code c is from 1 to 254 and calendar time t is from 1 to 365 (or 366 for year of 2008). Y_{ct} was defined as the daily counts for elderly deaths at county c and time t. Three vectors, YR, DOW, and SES, indicated five dummy year variables (reference level is 2006), dummy day-of-the-week variables (reference level is Sunday), and four socioeconomic variables (Hispanics percentage, at least high school education percentage, health insurance coverage percentage and poverty percentage). The cross-basis function of standardized HI_{max} was denoted by f (HI_{max}, lag), and can be interpreted as relative risk (RR) in terms of standardized HI_{max} by using its 90th percentile as the baseline level. HW was a dummy indicator to represent 1 for heat waves days and 0 for non-heat wave days. A thin plate spline with 7 degrees of freedom in total was applied to time t to control for seasonality. The spatial function $f_{spat}(c)$ was estimated by the Markov random fields (MRF) smoother to not only take spatial autocorrelations into account, but also to carry out spatial heterogeneity. An offset 'log(pop)' was defined by the logarithm of elder population size at county level according to 2010 U.S. Census (U.S. Census Bureau, 2015). As opposed to random intercept, the MRF smoother uses a normally distributed conditional autoregressive prior to take care of neighborhood correlations according to whether a couple of counties share a common boundary, and the number of neighbors surrounding each county can also be considered in estimations:

$$f_{spat}(c')|c\neq c' \sim N\left(\sum_{c'\in\Omega_c} \frac{f_{spat}(c')}{N_c}, \frac{\sigma_c^2}{N_c}\right) \tag{2}$$

where c′ is one of a subset of adjacent counties (Ω_c) of the county c, the denominator N_c is the number of counties in the subset Ω_c, and σ_c^2 is an unknown variance parameter. Therefore, including a Markov random smoother in our model can advance the DLNM to a special type of the conditional autoregressive model. Thus, the exponential estimated spatial function can be interpreted as relative risk (RR) for elderly mortality in each county due to heat wave days compared to non-heat wave days.

Sensitivity analyses were performed to check the robustness of our results. We changed degrees of freedom for time (6–19 df per year). We increased the knots for HI_{max} (at 20th, 40th, 60th, and 80th percentiles of HI_{max}, or 10th, 40th, 60th, and 90th percentiles of HI_{max}).

We used SAS v9.3 (SAS Institute, Cary NC) for data cleaning and management. Spatiotemporal Kriging was implemented by using the *ltsk* package (version 1.0.3) (Kumar et al., 2013) in the R statistical software (R Development Core Team; http://R-project.org). Both DLNM and spatial analysis were performed by using the *dlnm* (Gasparrini et al., 2010) and *mgcv* (Wood, 2008) packages in R software version 3.1.2.

3. Results

Texas had large spatial variations in annual average daily HI_{max} across counties during 2006–2011 ranging from 24.57 °C to 26.18 °C. Each county included at least one heat wave day over the study period. The average number of heat wave days per county generally increased over the five-year period and reached the peak in 2011 (Fig. 1), e.g., the averages per county in August 2006 and 2011 were 5.64 and 17.44 days, respectively.

Three maps in Fig. 2 display varied geographic distributions of county-level daily maximum heat index, crude mortality per 100,000 elders and the total heat wave days during our study period, respectively. A higher average of daily maximum heat index clustered in South Texas, especially in Webb County, which had the highest average daily maximum heat index (31.75 °C ± 9.10 °C). Daily crude mortality among the elderly was higher in counties located in North Texas, but the highest risk appeared in El Paso County in West Texas by 6.00 ± 2.09 deaths per 10,000 elder populations. From 2006 to 2011, all Texas counties had at least 72 heat wave days, and Panola County, located in the border of Texas and Louisiana, had the most heat wave days with 106.

The 3-D plot in Fig. 3 shows the variation of RR along with the increase of HI_{max} percentile and lag, and we observed two greater elevations of RR in lower and higher HI_{max} percentiles. The rise of RR in some lags with HI_{max} lower than the 40th percentile can attribute to cold effects, while this study only focuses on heat effects, which were represented by four slice plots at the 95th and 99th HI_{max} percentiles and 1 and 10 lagged days in order to investigate more detailed variations of RR. Two slice plots on HI_{max} percentiles and lags indicated no evident short-term mortality displacement. At the 95th HI_{max} percentile, the RR slowly increased along with lagged days and significantly reached the highest level at lagged day 6 (RR = 1.0020, 95% CI = 1.0004, 1.0035), while no significant finding was found after lagged day 10. At the 99th HI_{max} percentile, lagged day 6 still had the greatest RR for elder mortality by 1.0053 (95% CI = 1.0008, 1.0097), which is nearly twice as much as the RR of the 95th HI_{max} percentile at the same lagged day. Similarly, the significant RR of the 99th HI_{max} percentile diminished

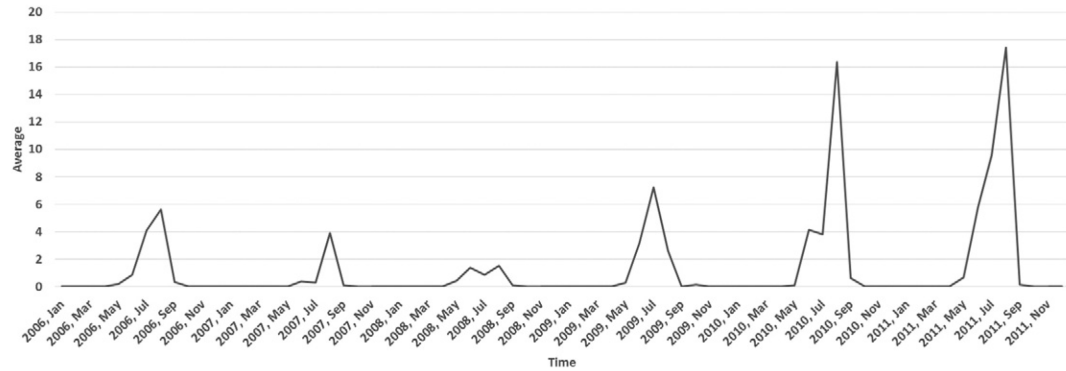

Fig. 1. The average number of heat wave days per county in Texas by months from 2006 to 2011.

at lagged day 11. Compared to RR associated with exposures on the present day, RR for elder mortality appeared to be statistically significant from lagged day 1 as the HI_{max} percentile is >90, while no significant finding was identified since lagged day 11. Thus, we conclude that extreme higher heat index (i.e., >90th percentile) may only cause significant risk of elder mortality up to lagged day 10. Additionally, while accumulating all lag effect from present day to lagged day 21 in terms of the HI_{max} percentile, the overall RR of heat on elderly morality was significantly elevated from 1 as the HI_{max} was over 90th percentile (Fig. 4).

The spatial impact during heat wave days varied across counties in Texas shown in Fig. 5(a), demonstrating that most counties with RR >1 were more likely clustered in Northwest Texas and part of West Texas. Among 163 of 254 counties with RR >1, only 16 counties can be defined as vulnerable to elder mortality in terms of heat wave days because those counties had a statistically significant RR above 1. Their locations are presented in white in Fig. 5(b). In particular, two of the largest five cities in Texas are located in Bexar County (San Antonio) and El Paso County (El Paso). In addition, El Paso County was found to have the greatest RR, showing that the risk of elder mortality during heat wave days was 4.70 times (95% CI = 4.33, 5.10) as likely to occur, compared to non-heat wave days, in this far west county.

Possible explanations for the 'protective' effects in some areas may include changed behavior, improvement of housing structures, installation of air conditioners, and establishment of heat-warning systems. Future studies are needed to explore these and other possible reasons.

Sensitivity analyses were performed to test the robustness of our results. When we modified the degrees of freedom for time (6–10 df) and changed the knots for HI_{max}, we did not observe apparent differences from our main findings.

4. Discussion

As global warming presents a great threat to human health, more epidemiological studies related to heat and heat waves have been conducted (Gronlund, 2014; Ye et al., 2012; O'Neill and Ebi, 2009; Basu, 2009). Based on a spatiotemporal analysis, our findings can be summarized by the following points: 1) the minimum-mortality HI_{max} percentile was discovered at the 90th percentile; 2) the lag effects of heat on elderly mortality in Texas last up to 10 days; and 3) during heat wave days, the excessive risk of elder mortality was more concentrated in Northwest and West Texas.

The minimum-mortality HI_{max} percentile, where deaths are lowest, occurred at the 90th percentile in Texas. A multi-country study of 12 countries/regions reported that the minimum-mortality temperatures ranged from the 66th percentile (Taiwan) to the 80th percentile (United Kingdom) (Guo et al., 2014). Although these studies are not directly comparable because our HI_{max} was calculated using both temperature and relative humidity, a possible explanation for the higher minimum-mortality HI_{max} percentile may be that the residents in Texas are more acclimated to hot weather. In addition, the significant heat lag effect in Texas lasted up to 10 days, longer than that shown in previous research, has reported. This may be because people living in Texas are more adaptive and resistant to extremely hot weather conditions, but this finding additionally reflects longer care for elderly in hot days.

Our findings on the effects of heat waves on elderly mortality are generally consistent with a few earlier studies. A time series study using data from 43 U.S. cities during the years 1987–2005 analyzed weather and mortality associations with a definition based on the 95th percentile of temperature and 2 days of duration, and reported

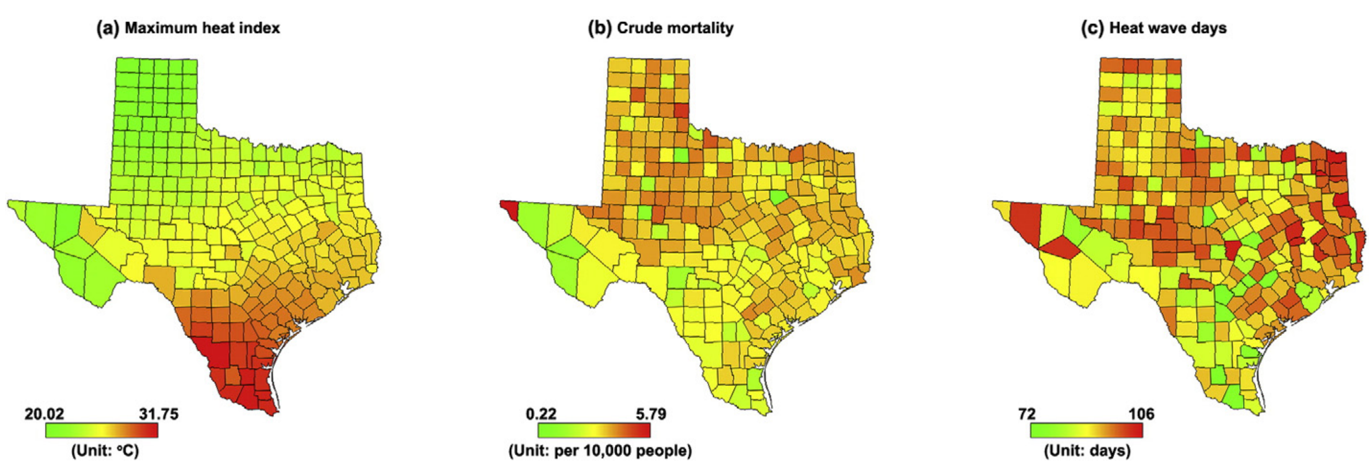

Fig. 2. Geographic distributions of (a) average daily maximum heat index, (b) daily crude mortality in the elderly, and (c) summation of heat wave days from 2006 to 2011 in Texas.

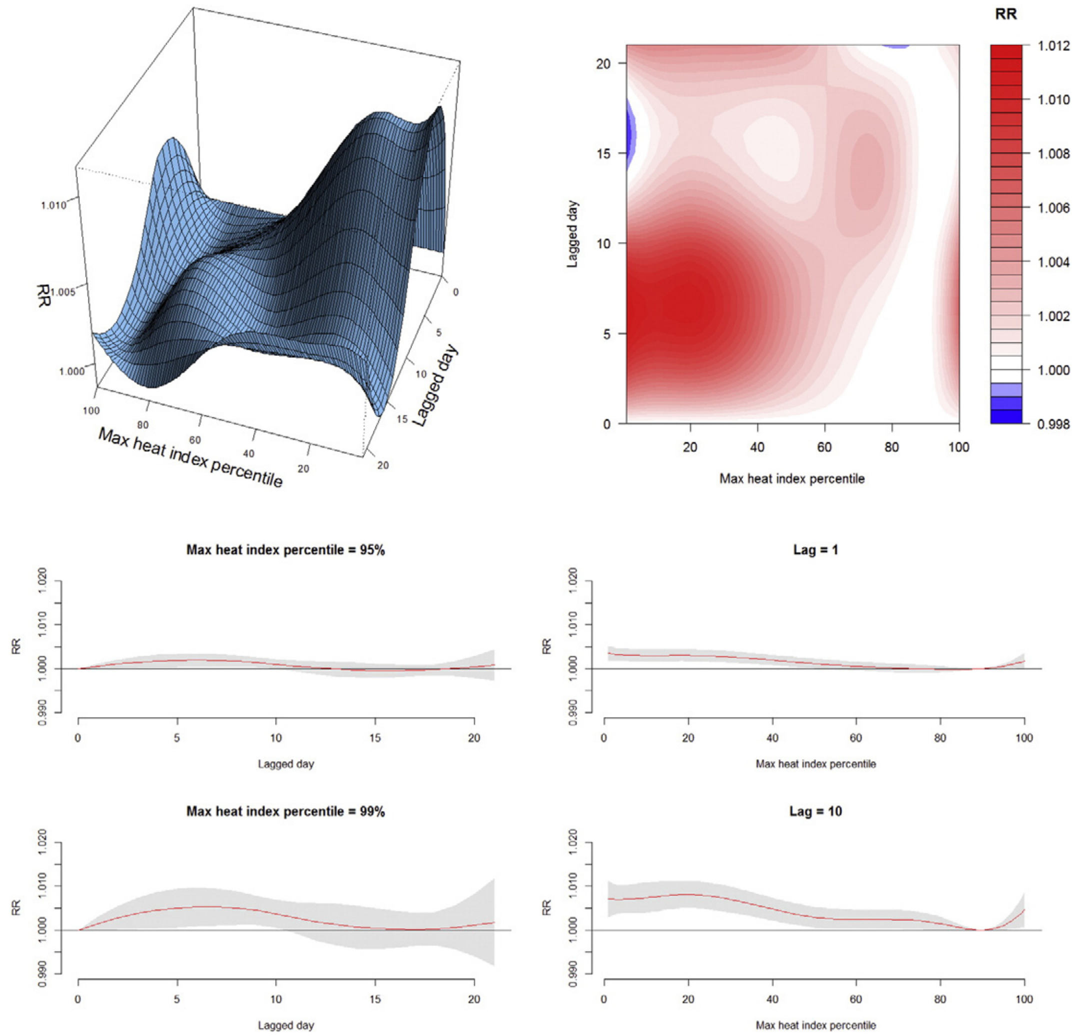

Fig. 3. 3D and contour graphs with selected slice plots showing the relative risk of heat on elderly mortality at lagged days along with maximum heat index percentile, where the reference levels are the 90th percentile of maximum heat index and present day (lag 0).

an average increase of 1.8% (95% CI: −0.1%, 3.8%) in mortality in the southern U.S. region (Anderson and Bell, 2011). An analysis of heat wave effects on mortality in U.S. during 1987–2005 showed an average increase of 0.3% (95% CI: −0.5%, 1.1%) in mortality across 108 cities using a definition based on the 97th percentile of temperature lasting at least two days (Gasparrini and Armstrong, 2011). Our recent study showed that the 2011 heat wave, the most severe heat wave in Texas since 1895, resulted in a 5.8% increase in elderly mortality risk (95% CI: −6.8%, 20.1%) (Zhang et al., 2015). Additionally, the lack of evidence of short-term mortality displacement suggests negligible harvest effects, which is consistent with a study examining the impact of the 2003 heat wave on mortality in France (Le Tertre et al., 2006).

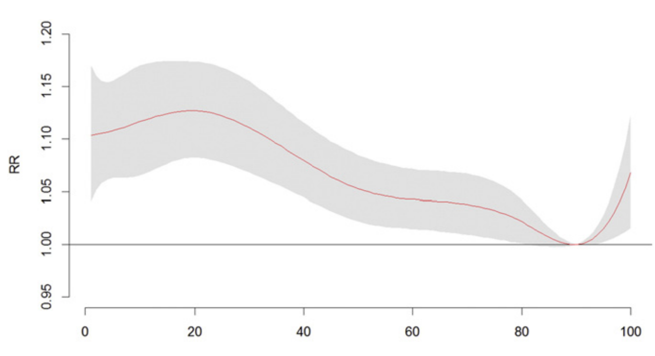

Fig. 4. The overall cumulative relative risk of heat index on elder mortality over 0–21 lagged days.

Within Texas, heat waves have the lowest impact of elderly mortality in South Texas. The Northwestern and Western regions have a colder climate (colder winters and more temperate summers) than other regions, particularly the coastal and valley regions, e.g., the annual average temperature in Texas during 1981–2010 ranged from 11 °C in Northwestern Texas to 20 °C in the southernmost tip of South Texas and coastal regions, while relative humidity generally decreased with increased distance from the Gulf of Mexico (Texas Water Development Board 2012). This pattern is also confirmed by annual average heat indexes, which range from 20.02 °C (Northwest Texas) to 31.75 °C (South Texas) (Fig. 2a). The spatial pattern of heat wave effects on mortality in Texas is generally consistent with that in the U.S. shown by Anderson and Bell (2011): heat wave mortality impacts are higher in colder regions (the Northeast and Midwest) than subtropical regions (the South). Spatial variations of heat wave mortality impacts in Texas may be explained by three possible reasons: 1) the North and East regions have higher elderly mortality rates than other Texas regions (see Fig. 3b); 2) the residents in the coastal, valley and East regions are more acclimated to hot weather; and 3) air conditioning systems are likely more commonly used in the coastal, valley and east regions, e.g., approximately 98.5%, 99.0% and 97.5% of residences in Houston,

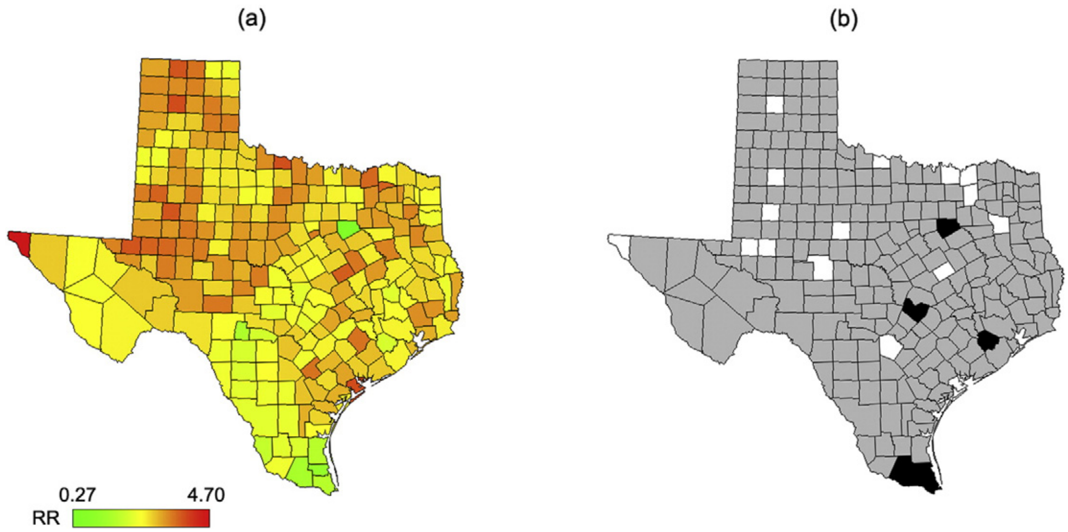

Fig. 5. Maps for each county in Texas according to the estimated spatial function. Map (a) shows the relative risk (RR) of heat waves from small (green) to large (red) on elderly mortality compared to non-heat wave days. Map (b) shows the significance of each county determined by the 95% confidence interval of RR, where white represents significant RR > 1, black represents significant RR < 1 and grey represents non-significant RR.

Austin and San Antonio, respectively, were equipped with either central air conditioning or room units (U.S. Census Bureau, 2015).

To the best of our knowledge, this is the first spatiotemporal analysis in a heat-related epidemiological study simultaneously accounting for spatial correlation and nonlinear lag effects. The same study design which was used in dengue fever research uncovered a new finding: that locational impacts should be taken into account in lag effect studies, especially in a large study area (Chien and Yu, 2014). Nonetheless, our study implemented an advanced analysis to construct an interactive spatial function for examining heat wave effects while considering spatial correlations across counties. This finding can further explain excessive risk of mortality in the elderly during heat wave days, and could be combined with the knowledge of other place-specific conditions (e.g., weather forecasts and local knowledge of historical weather) for use in heat wave and warning systems (Zhang et al., 2014).

This study has several limitations. First, heat exposure misclassification could exist when we assigned heat exposures to exposed persons in each county using the measurements at limited weather stations. Personal heat exposure measurements would be ideal, but this is unfortunately not feasible for a population-based epidemiological study. Second, some potential confounders such as ozone could not be controlled because ozone monitor coverage is sparse and focuses primarily on urban and suburban areas. Third, estimating DLNM with a spatial function in a large number of counties is extremely computation-intensive, particularly when more smoothers, cross-basis functions and spatial functions are included or when interacting with a continuous confounding variable. An advanced methodological development is needed to simplify complex high-dimensional computations in the DLNM.

5. Conclusion

A spatiotemporal analysis was conducted to investigate the effects of heat and heat waves on elderly mortality risk in Texas by simultaneously accounting for spatial heterogeneity and non-linear lagged effects. Our investigation showed that the 90th daily HI_{max} was a cut-off point in Texas where relative risk of heat effects on elderly mortality started to increase sharply, and heat waves had a greater impact on Northwest Texas and part of West Texas. Our findings provide insight for local decision-makers and other stakeholders to strengthen preparedness and design more effective interventions for future heat waves, particularly among elderly.

Competing financial interests

The author(s) declare that they have no competing interests.

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References

Anderson, B.G., Bell, M.L., 2009. Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiology 20, 205–213.
Anderson, G.B., Bell, M.L., 2011. Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. Environ. Health Perspect. 119, 210–218.
Astrom, D.O., Bertil, F., Joacim, R., 2011. Heat wave impact on morbidity and mortality in the elderly population: a review of recent studies. Maturitas 69, 99–105.
Bassil, K.L., Cole, D.C., Moineddin, R., Craig, A.M., Wendy Lou, W.Y., Schwartz, B., et al., 2009. Temporal and spatial variation of heat-related illness using 911 medical dispatch data. Environ. Res. 109, 600–606.
Basu, R., 2009. High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ. Health 8, 40.
Chien, L.-C., Yu, H.-L., 2014. Impact of meteorological factors on the spatiotemporal patterns of dengue fever incidence. Environ. Int. 73, 46–56.
Flynn, A., McGreevy, C., Mulkerrin, E., 2005. Why do older patients die in a heatwave? QJM 98, 227–229.
Fouillet, A., Rey, G., Laurent, F., Pavillon, G., Bellec, S., Guihenneuc-Jouyaux, C., et al., 2006. Excess mortality related to the August 2003 heat wave in France. Int. Arch. Occup. Environ. Health 80, 16–24.
Gabriel, K.M.A., Endlicher, W.R., 2011. Urban and rural mortality rates during heat waves in Berlin and Brandenburg, Germany. Environ. Pollut. 159, 2044–2050.
Gamble, J.L., Hurley, B.J., Schultz, P.A., Jaglom, W.S., Krishnan, N., Harris, M., 2013. Climate change and older Americans: state of the science. Environ. Health Perspect. 121, 15–22.
Gasparrini, A., Armstrong, B., 2011. The impact of heat waves on mortality. Epidemiology 22, 68–73.
Gasparrini, A., Armstrong, B., Kenward, M.G., 2010. Distributed lag non-linear models. Stat. Med. 29, 2224–2234.
Gronlund, C., 2014. Racial and socioeconomic disparities in heat-related health effects and their mechanisms: a review. Curr. Epidemiol. Rep. 1, 165–173.
Guo, Y., Gasparrini, A., Armstrong, B., Li, S., Tawatsupa, B., Tobias, A., et al., 2014. Global variation in the effects of ambient temperature on mortality: a systematic evaluation. Epidemiology 25, 781–789.

Huynen, M.M., Martens, P., Schram, D., Weijenberg, M.P., Kunst, A.E., 2001. The impact of heat waves and cold spells on mortality rates in the Dutch population. Environ. Health Perspect. 109, 463–470.
Kumar, N., Liang, D., Comellas, A., Chu, A.D., Abrams, T., 2013. Satellite-based PM concentrations and their application to COPD in Cleveland, OH. J. Expo. Sci. Environ. Epidemiol. 23, 637–646.
Le Tertre, A., Lefranc, A., Eilstein, D., Declercq, C., Medina, S., Blanchard, M., et al., 2006. Impact of the 2003 heatwave on all-cause mortality in 9 French cities. Epidemiology 17, 75–79.
Lott, J.N., 2014. The quality control of the integrated surface hourly database. http://www1.ncdc.noaa.gov/pub/data/inventories/ish-qc.pdf ([accessed 14.08.14]).
Mather, M.R., Kerri, L., Jacobsen, L.A., 2005. The American community survey. Popul. Bull. 60, 1–20.
McGeehin, M.A., Mirabelli, M., 2001. The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. Environ. Health Perspect. 109, 185–189.
McMichael, A.J., 2013. Globalization, climate change, and human health. N. Engl. J. Med. 368, 1335–1343.
NCDC (National Climatic Data Center), 2014. Integrated Surface Database. http://www.ncdc.noaa.gov/isd ([accessed 14.04.14]).
NWS (National Weather Service), 2013. NWS weather fatality, injury and damage statistics. Available: http://www.nws.noaa.gov/om/hazstats.shtml ([accessed 04.05.13]).
NWS (National Weather Service), 2014a. Heat Index Chart. http://www.nws.noaa.gov/os/heat/heat_index.shtml ([accessed 14.08.14]).
NWS (National Weather Service), 2014b. Heat Index Equation. http://www.hpc.ncep.noaa.gov/html/heatindex_equation.shtml ([accessed 14.08.14]).
O'Neill, M.S., Ebi, K.L., 2009. Temperature extremes and health: impacts of climate variability and change in the United States. J. Occup. Environ. Med. 51, 13–25.
Texas Water Development Board, 2012. Water for Texas. https://www.twdb.texas.gov/waterplanning/swp/2012/index.asp ([accessed 24.04.15]).
Tomlinson, C.J., Chapman, L., Thornes, J.E., Baker, C.J., 2011. Including the urban heat island in spatial heat health risk assessment strategies: a case study for Birmingham, UK. Int. J. Health Geogr. 10, 42.
US Census Bureau, 2015. Metropolitan summary tables - American housing survey 2013. http://www.census.gov/programs-surveys/ahs/data/2013/metropolitan-summary-tables—ahs-2013.html ([accessed 23.04.15]).
Vaneckova, P., Beggs, P.J., Jacobson, C.R., 2010. Spatial analysis of heat-related mortality among the elderly between 1993 and 2004 in Sydney, Australia. Soc. Sci. Med. 70, 293–304.
Wood, S.N., 2008. Fast stable direct fitting and smoothness selection for generalized additive models. J. R. Stat. Soc. B 70, 495–518.
Wu, P.-C., Lin, C.-Y., Lung, S.-C., Guo, H.-R., Chou, C.-H., Su, H.-J., 2010. Cardiovascular mortality during heat and cold events: determinants of regional vulnerability in Taiwan. Occup. Environ. Med. http://dx.doi.org/10.1136/oem.2010.056168.
Ye, X.F., Wolff, R., Yu, W.W., Vaneckova, P., Pan, X.C., Tong, S.L., 2012. Ambient temperature and morbidity: a review of epidemiological evidence. Environ. Health Perspect. 120, 19–28.
Yu, H.-L., Chien, L.-C., Yang, C.-H., 2012. Asian dust storm elevates Children's respiratory health risks: a spatiotemporal analysis of Children's clinic visits across Taipei (Taiwan). PLoS One 7, e41317.
Zhang, K., Rood, R.B., Michailidis, G., Oswald, E.M., Schwartz, J.D., Zanobetti, A., et al., 2012. Comparing exposure metrics for classifying 'dangerous heat' in heat wave and health warning systems. Environ. Int. 46, 23–29.
Zhang, K., Chen, Y.H., Schwartz, J.D., Rood, R.B., O'Neill, M.S., 2014. Using forecast and observed weather data to assess performance of forecast products in identifying heat waves and estimating heat wave effects on mortality. Environ. Health Perspect. 122, 912–918.
Zhang, K., Chen, T.H., Begley, C.E., 2015. Impact of the 2011 heat wave on mortality and emergency department visits in Houston, Texas. Environ. Health 15, 11.