Science of the Total Environment 505 (2015) 535–544

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Impact of extreme high temperature on mortality and regional level definition of heat wave: A multi-city study in China

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HIGHLIGHTS

- High quality datasets were used in the present study.
- Regional characteristics of the five studied cities in China were considered.
- A general U-shaped temperature–mortality relationship with location-specific threshold temperatures was observed.
- Positive and short-term association between extreme high temperature and mortality was found.
- Regional level definition of heat wave for five cities in China was conducted.

ARTICLE INFO

Article history:
Received 22 March 2014
Received in revised form 28 September 2014
Accepted 10 October 2014
Available online 22 October 2014

Editor: Lidia Morawska

Keywords:
Extreme high temperature
Heat wave
Lag effects
Temperature–mortality relationships
Definition
Time-series models

ABSTRACT

Background: Few multi-city studies have been conducted to explore the regional level definition of heat wave and examine the association between extreme high temperature and mortality in developing countries.
Objectives: The purpose of the present study was to investigate the impact of extreme high temperature on mortality and to explore the local definition of heat wave in five Chinese cities.
Methods: We first used a distributed lag non-linear model to characterize the effects of daily mean temperature on non-accidental mortality. We then employed a generalized additive model to explore the city-specific definition of heat wave. Finally, we performed a comparative analysis to evaluate the effectiveness of the definition.
Results: For each city, we found a positive non-linear association between extreme high temperature and mortality, with the highest effects appearing within 3 days of extreme heat event onset. Specifically, we defined individual heat waves of Beijing and Tianjin as being two or more consecutive days with daily mean temperatures exceeding 30.2 °C and 29.5 °C, respectively, and Nanjing, Shanghai and Changsha heat waves as ≥3 consecutive days with daily mean temperatures higher than 32.9 °C, 32.3 °C and 34.5 °C, respectively. Comparative analysis generally supported the definition.
Conclusions: We found extreme high temperatures were associated with increased mortality, after a short lag period, when temperatures exceeded obvious threshold levels. The city-specific definition of heat wave developed in our study may provide guidance for the establishment and implementation of early heat-health response systems for local government to deal with the projected negative health outcomes due to heat waves.

1. Introduction

"Warming of the climate system is unequivocal", according to the fourth report of the Intergovernmental Panel on Climate Change (IPCC), the average temperature of the earth has increased by 0.74 °C since 1906 and is projected to rise by 1.1 to 6.4 °C during the next hundred years (IPCC, 2007; Medina-Ramón and Schwartz, 2007). As global warming continues, there is increasing evidence that extreme heat events are becoming more frequent, more intense and longer lasting.

Abbreviations: DLNM, distributed lag non-linear model; GAM, Poisson generalized additive model; AIC, Akaike's information criterion; RH, relative humidity; BP, barometric pressure; PM_{10}, particulate matter with aerodynamic diameter ≤10 μm; DOW, day of the week; df, the degrees of freedom; RR/RR(s), relative risk(s); CI, confidence interval.

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http://dx.doi.org/10.1016/j.scitotenv.2014.10.028
0048-9697/

Consequently, the incidence of heat-associated adverse health outcomes will escalate among vulnerable subpopulations, such as the elderly, young children, and people with preexisting medical conditions (Balbus and Malina, 2009; Peng et al., 2011; Smith et al., 2013). Unsurprisingly, in recent years, heat-related health disorders have become a major public health concern associated with global warming.

In 2003, western Europe experienced a record-breaking heat wave, resulting in an excess of over 70,000 heat-related deaths (Robine et al., 2008). In a severe heat wave in California in 2006, approximately 16,166 additional emergency department visits and 1182 additional hospitalizations occurred (Knowlton et al., 2009). These well-documented increases in heat wave-associated morbidity and mortality demonstrate the stunning lethality of extreme heat exposure. However, most of these studies focus on cities in high-income countries (e.g. Europe and USA), and relatively few studies have been conducted in developing countries, especially in Asia, where characteristics of climate, socioeconomic status and demographic pattern differ greatly from those in developed countries (Anderson and Bell, 2011; Baccini et al., 2011; Gasparrini and Armstrong, 2011; Ishigami et al., 2008; Peng et al., 2011).

As in other areas of the world, China has experienced noticeable changes in climate during the past 100 years (Development and Commission, 2007). The annual average temperature has risen by 0.5–0.8 °C, and this trend of climate warming is projected to intensify in the future (Kan, 2011). Heat waves are silent killers that are becoming a significant public health problem in China, and will be exacerbated by the synergistic effects of global warming, urbanization and a large aging population. To date, the few studies that have examined the temperature–mortality relationship in large Chinese cities (e.g. Beijing and Guangzhou) have generally observed that extreme high temperature is associated with increased risk of death, especially among the elderly (Liu et al., 2011; Wu et al., 2013; Yang et al., 2013). In light of the expected increase in frequency and severity of extreme heat events and the large aging population, it is crucial and essential to estimate the health consequences of extreme high temperature, and to explore how to best define heat waves properly in different regions in China.

In meteorological terms, extreme heat events are defined as extended periods of unusual warmth with high minimum temperatures (D'Ippoliti et al., 2010; Luber and McGeehin, 2008). However, to date, there is no uniform definition of heat wave for most countries, because it is generally accepted that geographical location, regional variability, and acclimatization of the local population play a significant role in determining the heat-related impact (Hajat et al., 2006; Hajat and Kosatky, 2010). Although no universal definition exists, numerous studies have used a combination of temperature (intensity) and duration to define heat waves (Huang et al., 2012; Smith et al., 2013; Son et al., 2012; Yang et al., 2013). Additionally, some researchers also suggest that the definition of a heat wave should be based on knowledge of cause–effect relationships between temperature and the health of a given population, and that regional differences and local characteristics should be taken into account (Kim et al., 2006; Montero et al., 2012, 2010).

Common epidemiologic approaches, used to investigate the health effects of temperature, are of 2 types — the distributed lag non-linear model (DLNM) and the Poisson generalized additive model (GAM). The DLNM was developed to simultaneously examine non-linear and delayed effects of temperature on morbidity or mortality, and describes a bi-dimensional exposure–response relationship along the dimensions of temperature and lag (Armstrong, 2006; Gasparrini et al., 2010; Goldberg et al., 2011). The GAM has been widely used in environmental epidemiology to adjust for air pollution, day of the week, and long-term trends when performing time-series analysis, and characterizes temperature–mortality associations (Kim et al., 2006; Tong et al., 2012; Wood, 2006).

In the present study, we first used the DLNM to quantify and characterize the effects of daily mean temperature on non-accidental mortality in five Chinese cities from 2006 through 2011. Then we used the GAM to explore the city-specific definition of heat wave by analyzing the temperature–mortality relationship and evaluating the Akaike's information criterion (AIC) values. Finally, we performed a preliminary comparative analysis to evaluate the suitability of the definition. To our knowledge, this is the first multi-city study to explore the definition of heat wave on a local basis in China. Results from this study will improve our understanding about the heat-related health effects in different latitudes and climate zones of China, and contribute to the development and implementation of regional early heat-warning systems and heat-health prevention plans in the future.

2. Materials and methods

2.1. Study settings

We conducted the study in the urban districts of five cities (Beijing, Tianjin, Nanjing, Shanghai and Changsha) with different characteristics in China (Fig. 1). Beijing and Tianjin are located on the North China Plain, along the coast of the Bohai Gulf, and typically have a warm, temperate, semi-humid continental monsoon climate. Nanjing and Shanghai are located on the Yangtze River Delta and along China's eastern coastal areas and have a subtropical, humid monsoon climate, while Changsha is located in the south-central China and has a subtropical, continental monsoon climate.

All of the selected settings are the densely populated cities in China. According to the *China City Statistical Yearbook 2012*, at the end of 2011, the population in the urban districts of Beijing, Tianjin, Nanjing, Shanghai and Changsha were 12.07 million, 8.16 million, 5.52 million, 13.51 million and 2.97 million, respectively. Our study areas included all of the urban districts of each city, and the target population included all permanent residents living in the areas. We chose the study settings on the following basis: first, taking into account the data availability and completeness, the suburban districts of the five cities were excluded from our analysis due to the poor quality of mortality data and inadequate weather monitoring stations in those areas. Second, the five cities were selected as the study areas because they are representative of the different climatic characteristics and latitudes in China.

2.2. Data sources

Daily mortality data from January 1st, 2006 to December 31st, 2011 was obtained from the Chinese Center for Disease Control and Prevention for the five cities. The causes of death were coded according to the 10th International Classification of Diseases (ICD-10). Only the non-accidental mortality data (ICD-10: A00-R99) were analyzed, while deaths resulting from external causes, such as poisoning and injury, were excluded (World Health Organization, 2011).

Daily meteorological data of all the chosen cities was obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn) for the same period. City-specific variables included daily maximum, minimum, and mean temperatures (°C), relative humidity (RH, %) and barometric pressure (BP, kPa). Daily city-specific concentrations of respirable particulate matter with aerodynamic diameter ≤10 μm (PM_{10}) covering the study period was collected from the local Environmental Monitoring and Protection Bureaus.

2.3. Statistical analysis

Studies suggested that the counts of daily mortality typically followed a Poisson distribution, and the relationship between temperature and mortality might be non-linear with a lag effect (Son et al., 2012; Xie et al., 2013). Thus, in the present study, we made use of the DLNM to simultaneously investigate non-linear and delayed dependencies in the association between daily mean temperature and mortality for each city. This methodology is based on a “cross-basis” function that describes a bi-dimensional association along the dimensions of temperature and lag days, which not only allows for examination of the relationships between temperature and mortality at each lag period,

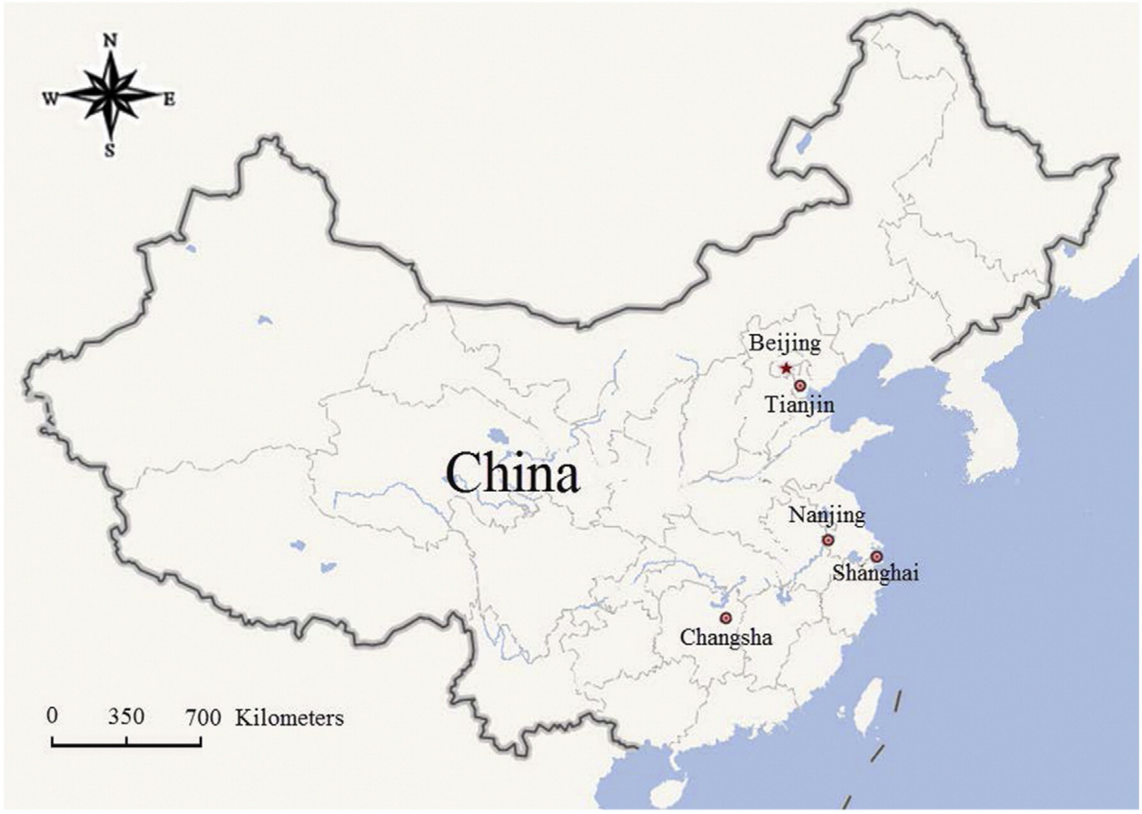

Fig. 1. Geographical distribution of the five studied cities in China.

but also allows for the estimation of non-linear effects across lags (Gasparrini et al., 2010; Goldberg et al., 2011). Moreover, to capture the non-linear and delayed temperature–mortality association, the lag-stratified natural cubic spline (NS) was adopted, and in order to control for potential confounders, the RH, BP, long-term and seasonal trends, day of the week (DOW), public holidays and atmospheric pollutants (PM_{10}) were introduced into the model simultaneously. For each city, the relationship between daily mean temperature and mortality was described using the following model:

$$\begin{aligned}&Y_t \sim Poisson\,(\mu_t)\\&Log\,(\mu_t) = \alpha + \beta T_{t,l} + NS(RH_t, df) + NS(BP_t, df) + NS(PM_{10t})\\&\qquad + NS(Time_t) + \eta DOW_t + \upsilon Holiday_t\end{aligned}$$

where t refers to the day of the observation; Y_t is the observed daily number of non-accidental deaths on day t; α is the intercept; β is the coefficient for $T_{t,l}$, $T_{t,l}$ represents a matrix obtained by applying the DLNM to temperature, and l is the number of lag days; $NS(\cdots)$ is a natural cubic spline for the non-linear variables; RH_t, BP_t and PM_{10t} denote the daily RH, BP and PM_{10} on day t, respectively, and the degrees of freedom (df) for each were 2, which was chosen by minimizing the AIC values (Akaike, 1974; Gasparrini et al., 2010). $NS(Time_t)$ is the natural cubic spline of a variable representing time to adjust for secular trends and seasonality confounding; DOW_t is day of the week on day t, and η is the vector of coefficients; $Holiday_t$ is a binary variable where the value is "1" if day t was a public holiday, and υ is the coefficient.In order to choose the df (knots) for daily average temperature and lag in the NS models, we used the AIC for quasi-Poisson models, and found that natural cubic splines with 5 df for the daily mean temperature and 4 df for lag stratification produced the best model fitting (Gasparrini et al., 2010; Peng et al., 2006). According to previous studies, in order to completely capture the overall city-specific temperature effects on mortality and adjust for any potential harvesting, we assumed a maximum lag of 27 days between exposure and death (Armstrong, 2006; Guo et al., 2011).

We examined the relative risk (RR) of daily average temperature on mortality along lag days with the median value of city-specific temperature distribution as the baseline reference value (the centered value of the temperature basis variables). We plotted RRs against temperature and lags to show the entire relationship between daily mean temperature and mortality for each city, and the cumulative 27-day overall effect of temperature on morality was also plotted. Then we compared the temperature–mortality association between daily mean and maximum temperature to identify the characteristics of exposure–response relationships when different temperature indices were chosen.

After characterizing the effects of daily mean temperature on non-accidental mortality, and visually describing the shape of the temperature–mortality association by substantial analysis of the DLNM, we used a Poisson GAM to define the heat wave in a city-specific manner by modeling the natural logarithm of the expected daily mortality as a function of the predictor variables. To control for possible confounders, we used the penalized cubic regression spline that allows for potential non-linear confounding factors to model temperature effects, and we simultaneously included DOW and public holidays in the model as dummy variables. The GAM model used in this analysis was given by:

$$\begin{aligned}Log[E(Y_t)] &= \alpha + s(T_t, df)\\&\quad + \sum s\left(x_{j_t}, df\right) + s(Time_t, df) + DOW_t + Holiday_t\end{aligned}$$

where t denotes the day of the observation; $E(Y_t)$ is the expected number of non-accidental deaths on day t; α is the intercept; and $s(\cdots)$ refers to the smooth cubic spline function used in GAM models to fit the non-linear relationship between independent and dependent variables (Wood, 2006). T_t is the average temperature on day t; x_j represents the covariates RH, BP and PM_{10}; and $Time_t$ refers to both seasonal and long-term trends.

For the GAMs of each city, we chose the *df* for the smoothing terms in the model simultaneously as part of model fitting by minimizing the generalized cross-validation criteria of the whole model (Wood, 2006, 2000). The ranges of lags for temperature exposure and other covariates in the model were chosen on the basis of the aforementioned DLNM analysis. Then the city-specific threshold temperature defining the heat wave was estimated by visually inspecting the original graphs of the DLNM analysis and an evaluation of AIC values for models with different thresholds. AIC values were iteratively calculated for the GAMs of each city using one degree increments in city-specific daily mean temperatures from 20 °C to the 99th percentile of the city's temperature distribution, which was selected based on the visual inspection of the forenamed plots. The mean temperature and lags corresponding to the model with the lowest AIC value were selected as the threshold temperature (intensity) and lag days (duration) to define the heat wave for each city. A similar method has been performed in many previous studies (Chung et al., 2009; Yu et al., 2010, 2011).

Finally, we conducted a preliminary comparative analysis to illustrate the effectiveness of our definition of heat wave for each city. We compared city-specific mortality between the heat wave period, identified by our definition, and the non-heat wave control period that was selected from the study period to examine whether the definition was appropriate and helpful for regional level early heat-related health warnings. To minimize potential confounders, we selected a near-term control period with the same duration and the same distribution of days of the week of the month for the analysis. It was hypothesized that the mortality during the identified heat wave period would be higher than the control period.

All statistical tests were two-sided and values of $P < 0.05$ were considered statistically significant. The DLNM and MGCV packages in R software Version 2.14.2 (R Development Core Team, 2012, http://www.r-project.org/) were used to fit all the models and perform all the statistical analysis and graphical representation.

3. Results

Table 1 presents the summary statistics of daily mortality, weather variables and air pollution for the five selected cities during the study period. The average daily deaths varied from 109.5 to 315.0, with Shanghai having both the largest population and the most non-accidental mortality. The detailed distributions of temperature for specific cities are described, with average daily temperatures ranging between 12.5 °C and 18.0 °C, showing that the higher latitude, the lower the average temperature.

3.1. The entire temperature–mortality association

The RR of daily non-accidental mortality associated with city-specific average temperature was examined. Fig. 2 depicts the general pattern of RRs, as a function of lag and temperature, by showing the city-specific three-dimensional plots of the RR along temperature and 27 lag days. Overall, the estimated effect of temperature was non-linear for mortality, with higher RRs at hot temperatures. Fig. 2 also suggested that there was a positive association between extreme high temperature and same-day non-accidental mortality. For example, when the daily mean temperature reached as high as 30.0 °C at lag 0 day, the RRs of mortality for Beijing, Tianjin, Nanjing, Shanghai and Changsha were RR = 1.17 (95% CI: 1.12–1.25), RR = 1.18 (95% CI: 1.10–1.26), RR = 1.31 (95% CI: 1.21–1.41), RR = 1.14 (95% CI: 1.06–1.24) and RR = 1.25 (95% CI: 1.13–1.39), respectively. However, the effects of extreme high temperatures declined rapidly, and after a 20-day lag the RRs of all cities were close to 1 across the entire range of temperatures.

3.2. The 27-day cumulative RR for daily mean temperature

Fig. 3 illustrates the overall consecutive daily lag effects of temperature on mortality. For each city, a U-shaped association between daily mean temperature and mortality was generally observed, with "mild" temperature ranges where the RRs of mortality were close to 1. Although the ranges associated with the lowest mortality risk varied among cities, the heat thresholds of all cities generally ranged from 20 °C to 35 °C, and above which the negative effects of temperature on mortality were significant.

3.3. Temperature–mortality association with daily mean and maximum temperatures

For each city, although the daily maximum temperature caused higher RRs for mortality than the mean temperature, both temperature indices showed a similar exposure–response association with mortality (Fig. 4). Harmful effects of the two temperature indices were generally observed between 0 to 3 days after exposure, with insignificant or

Table 1
Descriptive statistics of daily mortality, weather conditions, air pollutants and selected characteristics of the studied cities between 2006 and 2011 in China.

Variables	Beijing	Tianjin	Nanjing	Shanghai	Changsha
Latitude, °N	39.9	39.1	32.1	31.2	28.2
Non-accidental mortality Mean ± SD	269.9 ± 40.1	164.9 ± 27.1	113.22 ± 19.1	315.0 ± 44.0	109.5 ± 27.7
Temperature (°C)					
Mean ± SD	12.5 ± 11.7	13.8 ± 11.5	16.7 ± 9.1	17.1 ± 8.0	18.0 ± 9.5
P_0 min[a]	−12.7	−13.7	−6.5	−3.9	−3.4
P_{25}	2.2	2.6	8.3	9.9	10.2
P_{50} median	15.1	14.7	18.1	18.9	20.0
P_{75}	24.3	24.0	25.0	25.2	26.6
P_{95}	30.2	29.5	30.4	30.6	32.0
P_{96}	31.2	31.0	31.9	31.5	33.1
P_{97}	32.7	32.9	33.0	32.3	34.5
P_{98}	34.0	34.2	35.4	33.9	36.7
P_{99}	36.1	36.4	36.3	35.5	37.7
P_{100} max	37.6	37.6	37.3	37.5	38.8
Relative humidity (%)					
Mean ± SD	52.5 ± 20.1	58.0 ± 18.1	71.9 ± 13.1	69.1 ± 12.5	71.5 ± 12.7
Barometric pressure (kPa)					
Mean ± SD	102.4 ± 1.4	102.2 ± 1.5	101.7 ± 0.3	101.3 ± 0.8	101.2 ± 0.9
PM_{10} (μg/m^3)					
Mean ± SD	67.1 ± 21.3	76.9 ± 32.1	74.6 ± 32.1	64.5 ± 24.2	70.9 ± 28.0

SD: standard deviation.
[a] The percentiles (P_0–P_{100}) of temperature distribution during the study period.

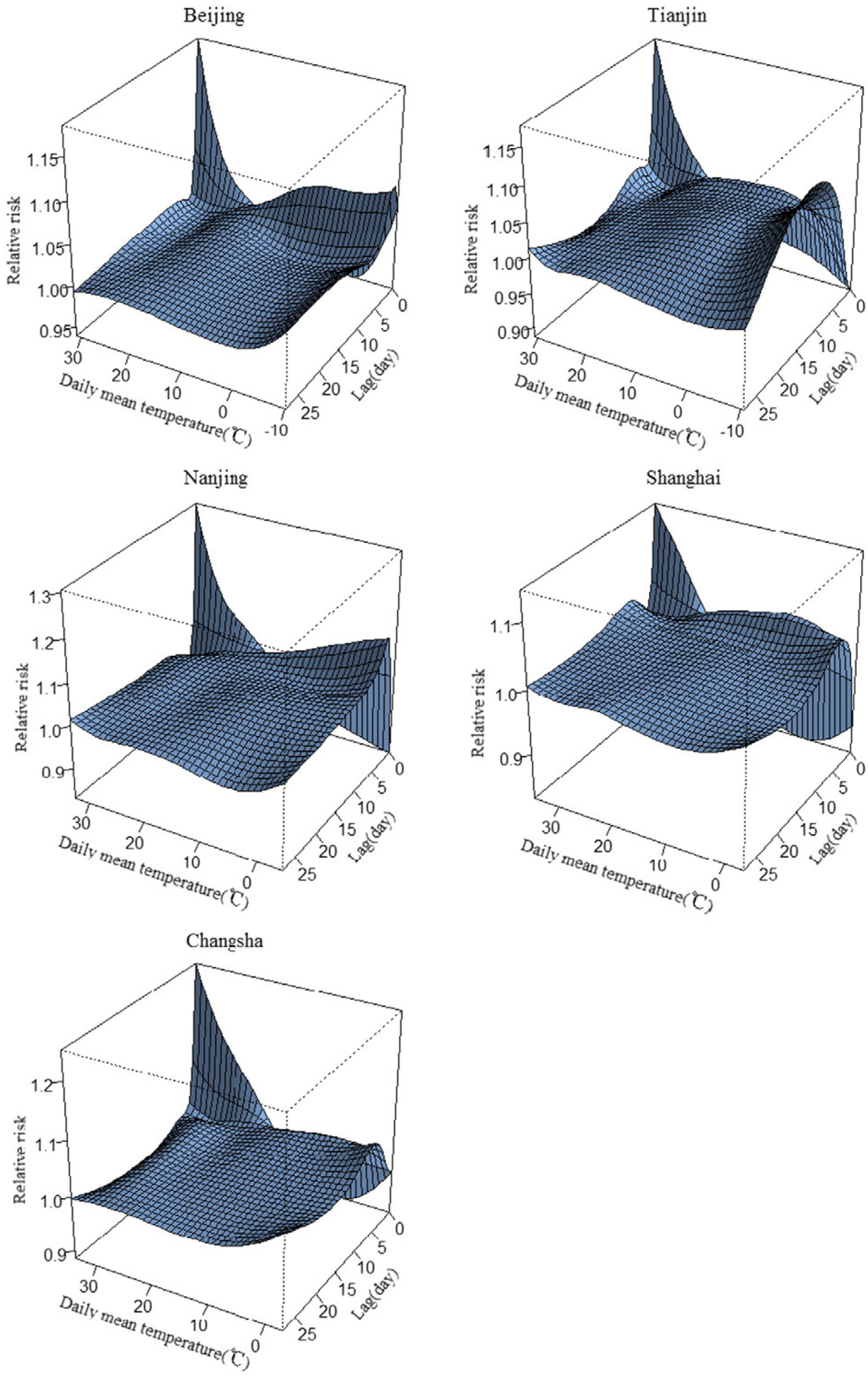

Fig. 2. City-specific relative risks of daily non-accidental mortality by average temperature along 27 lag days, adjusting for city-specific RH, BP, PM_{10}, DOW, public holidays and long-term and seasonal trends.

even protective effects found after a lag of 4–23 days, and a tendency to increase starting after a lag of 25 days.

3.4. Definition of heat wave

According to the above DLNM analysis, for each city, the daily high temperature extreme positively associated with the same-day non-accidental mortality (Fig. 2), and the effects of heat had threshold temperatures above which the RRs of mortality increase (Fig. 3). In addition, the daily mean and maximum temperatures have a similar exposure–mortality association, and the negative effects of extreme high temperature were generally observed between 0 and 3 days after exposure (Fig. 4). Consequently, the city-specific effects of extreme high temperature on mortality were estimated by introducing appropriate terms of exposure into the GAM model—in our case, based on the visual inspection of the forenamed plots, 0- to 7-day lags for temperature exposure and other covariates in the model, and 20 °C to the 99th percentile of the city-specific daily mean temperature distribution were selected and iteratively introduced into the GAM to calculate the AIC values.

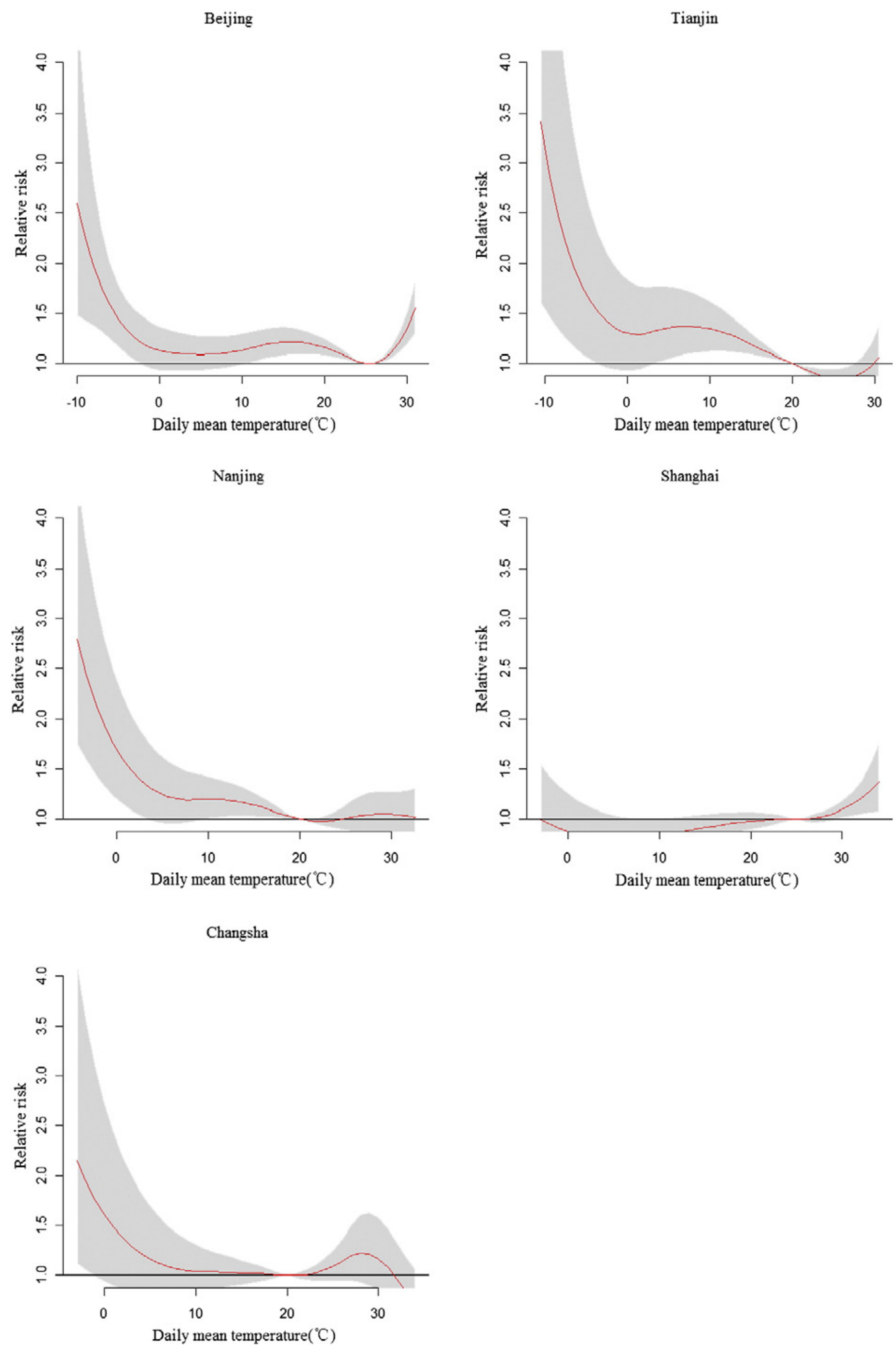

Fig. 3. 27-day cumulative effects of daily mean temperature on non-accidental mortality in the studied cities, controlling for the daily city-specific averages of RH, BP, PM_{10}, DOW, public holidays, and long-term and seasonal trends. RRs were estimated by using the DLNM. The maximum likelihood estimate of RRs is shown as smooth red lines and the pointwise 95% confidence intervals are shown in the gray regions.

Based on the plots and AIC values, the threshold temperature (intensity) and lag days (duration) of the best fit model were selected to define the heat wave for each city. Specifically, we defined the heat waves of Beijing and Tianjin as being two or more consecutive days when the daily mean temperatures exceeded 30.2 °C and 29.5 °C, respectively, representing the 95th percentile of the city-specific daily mean temperature distribution during the study period. Similarly, the heat waves of Nanjing, Shanghai and Changsha were defined as ≥3 consecutive days with daily mean temperature above 32.9 °C, 32.3 °C and 34.5 °C, respectively, which comprised the 97th percentile of the city-specific daily mean temperature distribution.

3.5. Illustration of the heat wave definition obtained from the models

We used the above definition to identify the heat waves for each city. Then we compared mortality between the heat wave periods and the selected non-heat wave control periods in each city to illustrate the effectiveness of the heat wave definition. The result of our comparative analysis showed that the non-accidental mortality during the identified heat wave periods were generally higher than the corresponding control periods in all the studied cities except Shanghai, because no appropriate control period could be found during the study period (figure not presented).

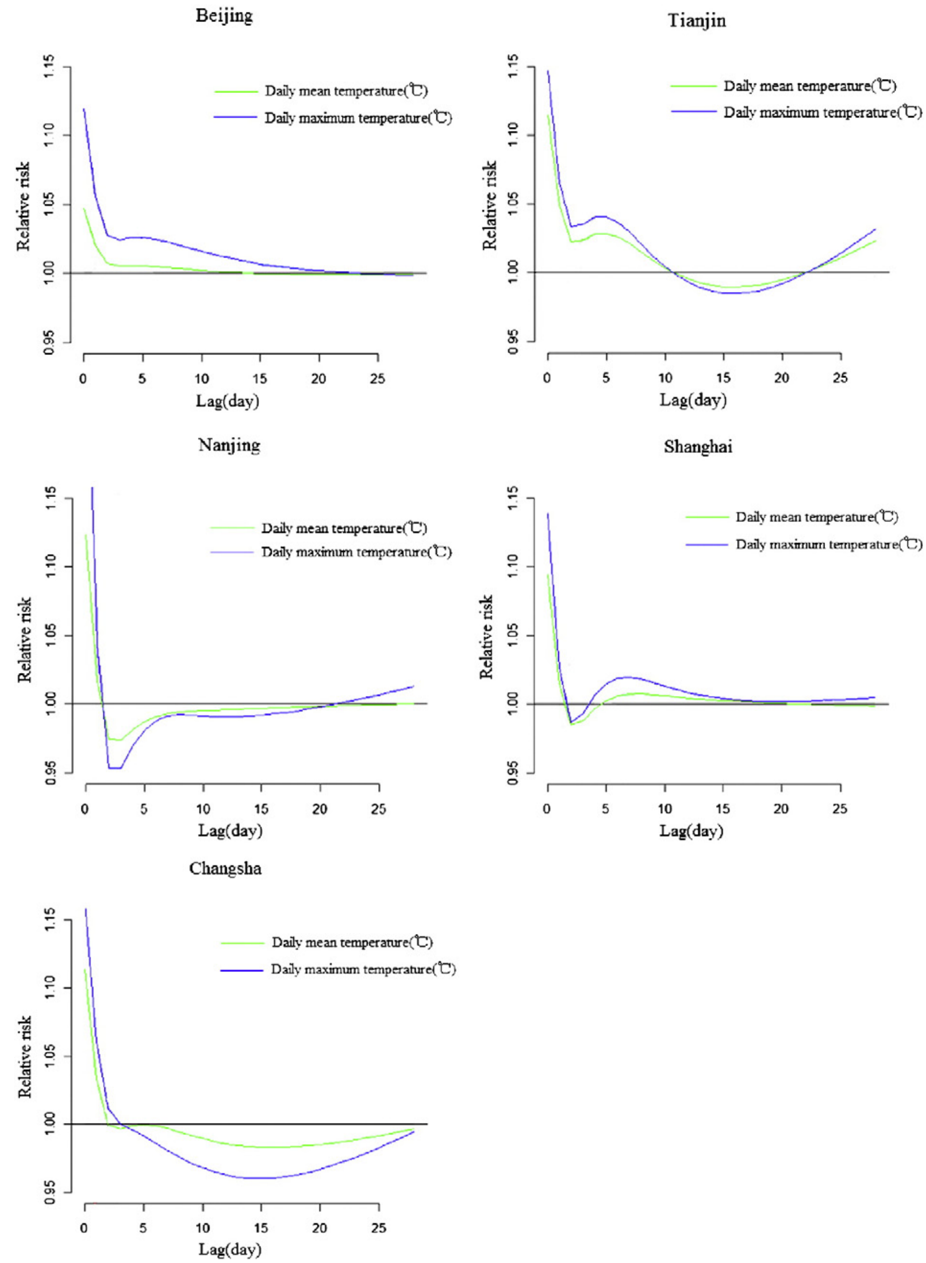

Fig. 4. Effects of city-specific daily mean and maximum temperatures on non-accidental mortality along 27 lag days, with the median value of city-specific temperature as the reference, and adjusting for city-specific RH, BP, PM_{10}, DOW, public holidays, and long-term and seasonal trends.

4. Discussion

In the present study, we first visually characterized the association between city-specific daily mean temperature and non-accidental mortality. Then we defined the heat wave for each city, in terms of temperature and duration, and conducted a comparative analysis to evaluate the suitability of our definition. To date, this is the first multi-city study to explore the regional level definition of heat wave by using sophisticated models in different latitudes in China.

4.1. Models in the present study

Recently, DLNM and GAM methods have been used increasingly to examine heat-related health effects. The DLNM is a more flexible and biologically plausible method that provides a detailed representation of the time course of the non-linear exposure–response relationship, while avoiding problems related to co-linearity among lagging exposure variables, especially at short lag times (Gasparrini et al., 2010; Xie et al., 2013). It has been frequently applied in numerous studies to describe the effects of temperature on mortality (Barnett et al., 2012; Lin et al., 2012; Xie et al., 2013). The GAM adopted in this study allows researchers to explore temperature effects without making strong assumptions about the shape of the association curve, which has also been effectively used in a variety of studies to characterize temperature–mortality relationships (Kim et al., 2006; Liu et al., 2011; Yu et al., 2011).

4.2. Selection of temperature indices

To date, various temperature indicators and meteorological indices (e.g. mean or maximum temperature, apparent temperature, diurnal temperature ranges and heat index) have been employed to assess the association between temperature and mortality (Hajat et al., 2006; Lin et al., 2013; Yu et al., 2011). However, no uniform criteria have been established to determine which indicator is superior to others for the prediction of mortality (Barnett et al., 2010; Hajat et al., 2010). Some studies have compared the performance of a variety of temperature indicators and concluded that because of the strong correlation among different measures of temperature, mean temperature performed similarly to other meteorological indices and could be used interchangeably among different indicators (Barnett et al., 2010; Vaneckova et al., 2011; Yu et al., 2011). In addition, other studies suggest that mean temperature is a more accurate predictor of heat-related mortality, since mean temperature is a simple indicator that goes through the whole day and night and provides more easily interpreted results in a policy context, while maximum temperature or heat index only reflects the exposure for a short period and is hardly manageable because of the complexity of the measure (Anderson and Bell, 2009; Guo et al., 2011; Lin et al., 2012; Lin et al., 2011).

In this study, the effects of daily mean and maximum temperature show similar exposure–response curves. However, when taking the sensitivity and timeliness of the response into account, mean temperature appears more appropriate for early heat-health warning. Therefore, only city-specific daily mean temperatures were chosen to examine the effects of temperature on mortality and explore the definition of heat wave in the present study.

4.3. Selection of mortality indices

In the present study, non-accidental mortality was chosen as the measure of the harm caused by extreme high temperature, since the most recent analysis shows it to be the factor that maintains the most stable relationship with temperature (Montero et al., 2012; Smith et al., 2013; Wu et al., 2013; Yang et al., 2013). To our knowledge, ambient temperature is mainly associated with non-accidental deaths (total mortality minus external causes), especially deaths from cardiovascular, cerebrovascular and respiratory causes (Kravchenko et al., 2013; Son et al., 2012; Wu et al., 2013). Additionally, a study has indicated that 90–97% of road traffic injuries (accidental deaths) are attributable to people, vehicles and road situation (Naci et al., 2009). In China, almost all of the accidental deaths from external causes are related to injury (mainly from road traffic injury) and production accidents, which have little correlation with temperature (Ma et al., 2012; Wang et al., 2008). Accordingly, the real exposure–response relationship between temperature and mortality would be underestimated when the deaths from external causes were included. This is the reason why only the non-accidental mortality was included in our study.

4.4. The association between temperature and mortality

Previous studies conducted in high-income countries suggest a J-, V-, or U-shaped association between temperature and mortality, with an optimum range of temperatures corresponding to the lowest point ("threshold" or "turning point") in the exposure–response effect curve, meaning there is a positive association for temperatures above the threshold (Anderson and Bell, 2009; Baccini et al., 2011; Huang et al., 2012; Kim et al., 2006; Revich and Shaposhnikov, 2008). Consistent with those reports, after adjusting for potential confounders, we find a generally U-shaped temperature–mortality relationship in all five studied cities, with a location-specific heat threshold above which increased risk of mortality is observed. Additionally, although the association of temperature–mortality quantitatively differs among the five cities, the city-specific extreme high temperature generally had a short-term and acute impact on mortality, with the highest effects occurring within 3 days after the onset of the extreme heat event, and then diminishing rapidly, in agreement with the previous findings (Gasparrini and Armstrong, 2011; Guo et al., 2011; Wu et al., 2013).

We also observed that the city-specific threshold of heat wave temperatures varied by climatic zones and geographical location. In general, the thresholds were usually higher in southern or lower latitudinal cities, suggesting that residents of colder regions or higher latitudes of the northern hemisphere are more susceptible to heat waves or extreme high temperature, possibly due to acclimatization and adaptation of the local populations. This phenomenon has also been reported by many other studies (Anderson and Bell, 2011; Kim et al., 2006; Kravchenko et al., 2013; Wu et al., 2013). Accordingly, these findings of city-specific threshold temperatures and the magnitude of the effects of high temperatures suggest that any assessment of the public health impact of temperature should take regional differences into account.

4.5. Definition of heat wave

To date, various definitions of heat wave have been proposed and adopted in numerous studies and heat-health warning plans. However, many of them set the threshold temperature either by directly using a statistical–meteorological criterion taken by other countries, or by using a given percentile of temperature distribution without explaining the reasons for choosing this over another, and do not consider the relationship between temperature and local mortality (Anderson and Bell, 2011; Montero et al., 2010, 2012; Son et al., 2012; Yang et al., 2013).

In addition, although some studies suggest that heat waves earlier in the summer or year are associated with higher mortality than are later heat waves, and that the first heat wave of the summer or year has a greater impact than do later heat waves, taking the convenience of practical application and sensitivity and efficiency of the development and implementation of early heat–health warning systems into account, to date, the existing studies conducted to explore the definition of heat wave all employ the methodology that only combines intensity and duration (Anderson and Bell, 2011; Huang et al., 2012; Smith et al., 2013; Son et al., 2012).

Accordingly, consistent with previous studies, in the current study, we use a combination of intensity and duration to define city-specific heat wave, taking regional patterns of the cause–effect association between temperature and mortality into account. Additionally, regional differences and local weather characteristics of the study areas are also considered, as suggested by previous studies (Kravchenko et al., 2013; O'Neill et al., 2009). It should therefore be stressed that our regional level definitions of heat wave may play a role in developing and implementing early threshold-based heat-warning systems, which can alert regional policy-makers to extreme heat risks and help them know when and at what level heat wave prevention plans should be activated to protect the health of their local population.

4.6. Illustration of the heat wave definition

Because of the relatively small number of city-specific heat waves identified by our definition and the limitation requiring selection of non-heat wave control periods during the present study period, the hypothesis test of the difference of mortality between the heat wave periods and non-heat wave control periods cannot be conducted. However, the comparative analysis shows that both the city-specific trends of mortality patterns and number of deaths toward the differences between the identified case period and selected control period in all the studied cities except Shanghai. Consequently, these results preliminarily suggest that our regional level heat wave definition is appropriate.

The forenamed comparative analysis and Fig. 2 also suggest the higher RRs of mortality and larger number of deaths in Nanjing and Changsha, compared to other studied cities, are possibly due to the following reason: in general, as the municipalities directly under the Central Government of China, Beijing, Tianjin and Shanghai are all at a relatively higher socio-economic level, with more developed health care systems and larger improvements of living conditions, all of which may play a role in the mitigation and adaptation to heat waves associated with climate change. For example, Tan et al. reported that improvements in living conditions in Shanghai, such as larger living areas, increased use of air conditioning, and increased urban green space, were responsible for the lower levels of human mortality in the 2003 heat wave compared to the 1998 heat wave (Tan et al., 2007).

4.7. Strengths and limitations

This study has several strengths. Firstly, to the best of our knowledge, this is the first multi-city study to explore the regional level definition of heat wave for cities located in different latitudes and climatic zones in China. Secondly, our analysis takes into account the acclimatization of the local population to its own climate, by defining heat waves based on the percentiles of city-specific daily mean temperature distribution, and the choice of threshold temperatures based on the AIC values and plots of regional temperature–mortality relationships. Thirdly, the datasets used in the present study are quite comprehensive with high quality, since the data are all collected by the national surveillance systems. Moreover, in contrast with other studies that only choose several districts, within a single city, to serve as study regions for investigating temperature–mortality relationships, our study areas include all the urban districts of each city, which means that the findings presented herein are more likely to be representative of the actual situation of the studied cities. Finally, sophisticated statistical models were adopted and developed to examine the lagging and cumulative effects of city-specific daily mean temperature on mortality, and the possible confounding effects of RH, BP, PM_{10}, and DOW as well as long-term trends were controlled.

Some limitations of the present study should also be acknowledged. First, in the current study, the heat wave is defined by using a combination of intensity and duration, but other factors, such as timing during the season, were not considered. Some reports show that higher mortality risk is observed from heat waves that occur earlier in summer, when the population has not yet become acclimatized to hot weather (Anderson and Bell, 2011; Barnett et al., 2012; Son et al., 2012). Second, even though we adjusted for the potential confounding by the PM_{10}, we did not control for other air pollutants, especially ozone and nitrogen dioxide, because the necessary data was unavailable. However, previous studies suggest that temperature effects on health outcomes are generally robust or even independent of air pollution (Anderson and Bell, 2009; Kim et al., 2006; Lin et al., 2011). Third, although the differences of city-specific mortality between the identified case periods and selected control periods were suggested by our preliminary comparative analysis, due to the limited numbers of heat waves identified by our definition, we were not able to investigate whether the differences are statistically significant. Finally, it is plausible that the association between temperature and mortality could be modified by other time-varying factors such as socioeconomic status, educational level, improvements of living conditions, and the availability of air-conditioning, which were not considered in our analysis because the data was not available at the time of the present study (Tan et al., 2007; Kravchenko et al., 2013; Yang et al., 2013). Further research is needed to address these issues.

5. Conclusion

In summary, this study reports a general U-shaped association between city-specific daily mean temperature and non-accidental mortality in five Chinese cities. We demonstrate that the effects of extreme high temperature are acute with clear threshold temperatures. Additionally, the city-specific definition of heat wave explored in our study has the dual advantage of taking both local characteristics and temperature–mortality association into account. Considering the likelihood of increasing incidence and severity of extreme heat events, findings from this study will be useful in providing guidance for local policymakers and service-providers to deal with the projected negative health outcomes due to extreme high temperature and heat waves, and contribute to the development and implementation of appropriate regional intervention strategies and early heat-health response systems that could yield both financial and health-related wellbeing for a majority of the population.

Conflict of interest

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

Acknowledgments

We thank Dr. Stanley Lin and Jan Bian for providing language help, the Chinese Center for Disease Control and Prevention for providing the mortality data, and the respective local Environmental Monitoring and Protection Bureaus for providing air pollution data.

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