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Influence of heat wave definitions to the added effect of heat waves on daily mortality in Nanjing, China

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HIGHLIGHTS

- Significant added effects of heat waves on cause-specific mortality were found.
- Heat wave definitions had considerable impacts on these added effects.
- Modifying effect of age, gender and education was found under different definitions.

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ABSTRACT

Background: Few studies have explored the added effect of heat waves, especially in China. Moreover, no prior studies have assessed whether the choice of heat wave definitions affected this added effect. This study compared the associations between heat waves defined by different heat wave definitions (HWs) and cause-specific mortality in warm season in Nanjing, China.
Methods: A distributed lag model was applied to evaluate the differences in daily mortality during heat-wave days (defined using 15 HWs) compared with non-heat-wave days in Nanjing, during 2007 to 2013. For different HWs, model fits were examined by the Akaike Information Criterion for quasi-Poisson and effects were compared by stratified analysis and bootstrapping. In addition, we explored the effect modifications by individual characteristics under different HWs.
Results: Different HWs resulted in considerable differences in associations between heat waves and mortality. Heat waves defined as ≥4 consecutive days with daily average temperature >98th percentile had the best model fit and were associated with an increase of 24.6% (95% CI: 15.6%, 34.3%) total mortality, 46.9% (95% CI: 33.0%, 62.3%) cardiovascular mortality, 32.0% (95% CI: 8.5%, 60.5%) respiratory mortality, 51.3% (95% CI: 23.4%, 85.6%) stroke mortality, 63.4% (95% CI: 41.5%, 88.8%) ischemic heart disease mortality, and 47.6% (95% CI: 14.5%, 90.3%) chronic obstructive pulmonary disease mortality at lag day 2. Under different HWs, added effects of heat waves on mortality were higher for females versus males, the elderly versus young residents, and people with low education versus those with high education. Results were less sensitive to the inclusion of air pollutants.
Conclusions: Heat wave definition plays a critical role in the relationship between heat waves and mortality. Selecting an appropriate definition of heat waves is therefore important to design local heat warning systems and to reduce the burden of disease during heat waves.

1. Introduction

Epidemiological studies have found consistent effect of heat waves on mortality across various countries (Anderson and Bell, 2011; Bi et al., 2011; Conti et al., 2005; D'Ippoliti et al., 2010; Huang et al., 2010; Son et al., 2012). Under a changing climate, higher mortality risks from heat waves are expected since the intensity, frequency, and duration of heat waves may increase in the future (Meehl and Tebaldi, 2004; Wu et al., 2014). The health effect of heat stress during heat waves can be divided into two parts: (1) the "main effect", which is related to the independent effect of the high temperature, and (2) the "added effect" due to heat waves (Gasparrini and Armstrong, 2011; Hajat et al., 2006). However, few previous studies of heat waves and mortality have assessed whether the "added effect" existed (Zeng et al., 2014), ignoring the independent effect of high temperature in time-series or case-crossover methods (Kent et al., 2014; Tian et al., 2013; Tong et al., 2012).

There is no single, universal definition of heat waves. In general, heat wave definitions (HWs) differ in (1) the metric of temperature

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(e.g., daily average or daily maximum), (2) the threshold of temperature (e.g., a relative threshold or an absolute threshold), and (3) the duration of a heat wave (Smith et al., 2013). Previous heat-related epidemiological studies generally applied several heat wave definitions as sensitivity analyses. However, recent studies in Australia and the United States showed that the diversity of heat wave definitions resulted in substantial differences in mortality risk estimates (Hajat et al., 2010; Kent et al., 2014; Tong et al., 2010; Zhang et al., 2012), leading to confusions in determining the most appropriate definition for heat wave warning systems. Moreover, heat wave definitions can also have a large impact on heat wave mortality projections. A recent study conducted in the eastern United States found that heat wave definitions accounted for 22.2% of the uncertainty for mortality risks during future heat waves (Wu et al., 2014).

Studies have shown that the added effects of heat waves on mortality varied greatly by location (Anderson and Bell, 2011; Son et al., 2012; Tong et al., 2014), which might be due to differences in geography, climate, housing, and populations among different regions. Thus, research in different regions is crucial for designing local heat wave warning systems to reduce heat-related adverse health effects and to prepare residents for future heat waves. Although people in developing countries are more vulnerable to heat-related mortality risks (McMichael et al., 2008), most studies have investigated the impacts of heat waves on mortality in developed countries. Relatively few studies have examined the added effect of heat waves on mortality in China (Bai et al., 2014; Zeng et al., 2014). Moreover, no previous studies have investigated the influence of various heat wave definitions on the added effect of heat waves in China.

Additionally, the impact of heat waves on mortality can be modified by individual characteristics, such as age, gender, education, and death location (Breitner et al., 2014; Son et al., 2012; Zeng et al., 2014). A recent study in Beijing found that the duration of heat waves presented different coronary heart disease mortality risks in different age groups (Tian et al., 2013). Thus, different heat wave definitions based on duration may have an influence on the modifying effect of individual characteristics on heat wave mortality estimates.

In this study, we aimed to examine the influence of different heat wave definitions to the added effects of heat waves on daily mortality, and explore whether effect modifications by individual characteristics changed under different heat wave definitions in Nanjing, China.

2. Materials and methods

Nanjing, the capital of Jiangsu Province in China, is located in the Yangtze River Delta and held a population of 8.0 million by the end of 2010. Our study population includes all permanent residents living in the city. Nanjing has a subtropical humid climate with an annual average temperature of 16.2 °C in 2010. Known as one of the 'three furnace cities' in China, Nanjing always experiences hot summers. The highest ever maximum temperature in Nanjing was 43 °C on July 13, 1934.

2.1. Data collection

Daily mortality data from January 1, 2007 to December 31, 2013 were collected from the Jiangsu Provincial Center for Disease Prevention and Control. Daily mortality counts were classified into the following categories using the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10): total (non-accidental) deaths (codes A00–R99), cardiovascular deaths (codes I00–I99), respiratory deaths (codes J00–J99), and deaths attributed to stroke disease (codes I60–I69), ischemic heart diseases (IHDs, codes I20–I25), and chronic obstructive pulmonary disease (COPD, codes J40–J47). We also investigated the effect of heat wave on total mortality modified by gender (male and female), age (0–64, 65–74, and ≥75 years old), education level (low: illiterate or primary school; high: high school or college), and death location (in hospital: ward or emergency room; out hospital: home or way to the hospital).

The daily average and maximum temperatures in Nanjing were provided by the China Meteorological Data Sharing Service System. Weather data were collected from a national principal weather station (Nanjing station). There were no missing data for the meteorological data. To adjust potential confounding effects of air pollutants, we obtained daily air pollution data for 2007–2013 from the nine monitoring stations of the Nanjing Environmental Monitoring Center. In accordance with China's air-quality monitoring standards, these monitoring stations were situated to avoid direct interference from vehicle exhaust and other sources. Monitors were set up approximately 3.5 m above ground level to measure daily air pollution levels. Daily mean concentrations of particulate matter with an aerodynamic diameter of 10 μm or less (PM_{10}), nitrogen dioxide (NO_2), and sulphur dioxide (SO_2) from nine stations were then averaged to derive the concentrations for Nanjing by simple mean. For all monitoring stations, only 2.0% data for SO_2, 1.3% data for NO_2, and 1.5% data for PM_{10} were missing for the whole period of analysis. There were no missing data for more than 2 consecutive days in all stations. The missing data in each station were then interpolated from data on the two adjacent days.

As in previous studies (Son et al., 2012; Tian et al., 2013; Zeng et al., 2014), the study period was restricted to the warm season (May–September) when heat waves generally occurred in Nanjing.

2.2. Heat wave definitions

Based on the differences of definitions in metric, threshold, and duration, fifteen HWs were identified from previous heat wave literature (Anderson and Bell, 2011; Peng et al., 2011; Son et al., 2012; Tian et al., 2013) and the definition used by the Chinese Meteorological Administration (Huang et al., 2010). These heat wave definitions are commonly used in heat wave studies and have been found to be significantly associated with daily mortality in different countries. Descriptions of these 15 HWs were shown in Table 1. Twelve HWs (HW01–HW12) were developed combining relative mean temperature thresholds (90th, 95th, 98th, and 99th) with duration of more than 2, 3, and 4 days. Daily maximum temperature with relative thresholds (HW13, 95th; HW14, 81st and 97.5th) or an absolute threshold (HW15, 35 °C) was also used to define heat waves.

2.3. Statistical analysis

In this study, we aimed to examine the added effect of heat waves on daily mortality. As daily mortality counts generally follow an overdispersed Poisson distribution, we used a distributed lag model (DLM) with a quasi-Poisson regression to evaluate the health effect of heat waves while adjusting for the effect of temperature at different lag days (Gasparrini, 2011). We controlled for long-term and seasonal time trends, relative humidity, daily average temperature, and day of the week. The DLM used the following formula:

$$\mathrm{Ln}E(Y_t) = \alpha + \beta HW_t + \varepsilon Cb.temp_l + ns(time) + ns(humidity) + \delta DOW \quad (1)$$

where $E(Y_t)$ is the expected daily mortality count at day t with $\mathrm{Var}(Y_t) = \varphi E(Y_t)$; φ is the overdispersion parameter; HW_t is a binary variable, which equals to 1 for heat-wave days and 0 for non-heat-wave days; $Cb.temp_l$ is a matrix obtained by applying to temperatures; l refers to the maximum lag days; β, ε, and δ are the coefficients for HW and DOW; the natural cubic spline function $ns()$ captures the non-linear relationships between the covariates (time and relative humidity) and mortality; and DOW is the dummy variable for day of the week. The DLM was fitted using a quadratic spline with 2 degrees of freedom per warm season (2 equally spaced knots) for temperature and a natural spline with 3 degrees of freedom for the lag (knots at

Table 1
Heat wave definitions and heat-wave days during 2007–2013 in Nanjing, China.

HW	Definition	Heat-wave days	Reference
HW01	Daily average temperature >90th percentile (30.6 °C) for ≥2 consecutive days	95	Anderson and Bell (2011)
HW02	Daily average temperature >95th percentile (31.9 °C) for ≥2 consecutive days	45	Anderson and Bell (2011)
HW03	Daily average temperature >98th percentile (32.7 °C) for ≥2 consecutive days	16	Anderson and Bell (2011)
HW04	Daily average temperature >99th percentile (33.5 °C) for ≥2 consecutive days	11	Anderson and Bell (2011)
HW05	Daily average temperature >90th percentile (30.6 °C) for ≥3 consecutive days	79	Son et al. (2012)
HW06	Daily average temperature >95th percentile (31.9 °C) for ≥3 consecutive days	35	Son et al. (2012)
HW07	Daily average temperature >98th percentile (32.7 °C) for ≥3 consecutive days	14	Son et al. (2012)
HW08	Daily average temperature >99th percentile (33.5 °C) for ≥3 consecutive days	9	Son et al. (2012)
HW09	Daily average temperature >90th percentile (30.6 °C) for ≥4 consecutive days	67	Tian et al. (2013)
HW10	Daily average temperature >95th percentile (31.9 °C) for ≥4 consecutive days	32	Tian et al. (2013)
HW11	Daily average temperature >98th percentile (32.7 °C) for ≥4 consecutive days	11	Tian et al. (2013)
HW12	Daily average temperature >99th percentile (33.5 °C) for ≥4 consecutive days	6	Tian et al. (2013)
HW13	Daily maximum temperature >95th percentile (36.4 °C) for ≥2 consecutive days	44	Anderson and Bell (2011)
HW14	Daily maximum temperature >97.5th percentile (37.3 °C) for ≥3 days, daily maximum temperature >81st percentile (34.0 °C) every day, the average of daily maximum temperature for all consecutive days >97.5th percentile (37.3 °C)	33	Peng et al. (2011)
HW15	Daily maximum temperature >35 °C for ≥3 consecutive days	84	Huang et al. (2010)

equally spaced values in the log scale of lags by default) (Petkova et al., 2014). A maximum lag of 6 days was used since previous studies showed that the heat effect usually lasted within a week (Bai et al., 2014; Wu et al., 2013). The 75th percentile of annual mean temperature (24.8 °C) was used as the reference value for calculating relative risk of temperature. Based on previous studies (Anderson and Bell, 2011; Son et al., 2012), 3 degrees of freedom per warm season for long-term time trends and 3 degrees of freedom for humidity were applied in this analysis. In order to examine the lag effects of heat waves on daily mortality, we evaluated the associations of daily mortality with heat waves at different lag structures (lag0–lag6). Based on the results of our primary analysis, we used the previous second day HW (lag2) in the DLM. The Akaike Information Criterion for quasi-Poisson (Q-AIC) values for models was applied to assess the best model fit among different heat wave definitions for Nanjing. This method has been used in a previous study to compare different heat wave definitions (Tian et al., 2013). To statistically test whether different HWs produced different estimates of association between mortality and heat waves, percentile-based bootstrapped confidence intervals were calculated. We calculated the 95% CIs using 1000 resampling and the bootstrap percentile method in the "boot" package in R software (Canty and Ripley, 2014). If a bootstrapped 95% CI did not include zero, then the difference between two estimates was considered to be significantly different (Kent et al., 2014).

To explore the influence of heat wave definitions on the modifying effect of these individual characteristics, analyses of heat wave effects on total mortality were conducted for different HWs. We used stratified models to examine whether the heat wave effects differed by gender, age, education level, and death location. Bootstrapped 95% CI was then calculated to test whether the effect modification was statistically significant.

Sensitivity analysis was conducted by using different choices of lag structures for temperature and heat waves. In addition, we investigated possible confounding effects of the same day air pollutants (i.e., PM_{10}, NO_2, and SO_2) since short-term exposure of these pollutants were also found to be associated with daily mortality in epidemiological studies (Chen et al., 2012). Sensitivity analyses were also conducted by changing the degrees of freedom for time trends and relative humidity in the DLM for different causes of deaths.

All analyses were conducted with R software (version 3.03; R Foundation for Statistical Computing, Vienna, Austria) and the "dlnm" package (Gasparrini, 2011).

3. Results

The highest maximum temperature and mean temperature during 2007 to 2013 in Nanjing was 40.1 °C and 34.6 °C, respectively (see the Supplementary Material, Table S1). The long-term time trend analysis showed an increasing trend for total, cardiovascular, respiratory, and IHD mortality, whereas stroke and COPD mortality presented a relatively stable trend during 2007 to 2013.

Table 1 shows that the number of heat-wave days during 2007–2013 in Nanjing varied under different heat wave definitions. As expected, less heat-wave days were identified as the relative threshold of daily average temperature increased from 90th percentile to 99th percentile (e.g., HW01–HW05), as well as the duration of heat waves increased (e.g., HW01, HW05, and HW09). Similar number of days were categorized as heat-wave days using the daily maximum temperature metric (HW13, 44 days) compared with using the daily average temperature metric (HW02, 45 days) in heat wave definitions.

Fig. 1 presents the health effect of heat wave on cause-specific mortality at lag 2 using all 15 HWs. A total of 15, 15, 9, 15, 4, and 6 HWs were statistically significantly associated with total, cardiovascular, respiratory, stroke, IHD, and COPD mortality, respectively. In all 15 HWs, the highest mortality risks were found in associations with heat waves defined by HW11 (daily average temperature >98th percentile for ≥4 consecutive days) with 24.6% increase in total mortality, 46.9% increase in cardiovascular mortality, 32.0% increase in respiratory mortality, 51.3% increase in stroke mortality, 63.4% increase in IHD mortality, and 47.6% increase in COPD mortality on heat-wave days compared with non-heat-wave days at lag day 2. Generally, associations with heat waves defined by HWs based on daily average temperature increased as the temperature threshold increased from the 90th percentile to the 98th percentile, and then decreased as the temperature threshold increased from the 98th percentile to the 99th percentile. HWs using different durations (e.g., HW05, HW06, HW07, and HW08 for ≥3 consecutive days) or different cause of deaths showed the same pattern. For duration, associations with heat waves defined by HWs based on daily mean temperature increased as minimum consecutive days increased from 2 days to 4 days. HWs using different temperature thresholds (e.g., HW02, HW06, and HW10 for 95th percentile) or different cause of deaths presented a similar pattern. Compared with definition using the mean temperature metric HW02, associations between mortality and heat wave definition using the maximum temperature metric with the same duration (HW13) were slightly smaller. Heat waves using the definition of the Chinese Meteorological Administration (HW15, daily maximum temperature >35 °C for ≥3 consecutive days) was significantly associated with total, cardiovascular, and stroke mortality, but not significantly associated with respiratory, IHD, and COPD mortality.

Table 2 shows the evaluation results of model fits for 15 HWs using Q-AIC values. Small Q-AIC values suggest better fitted models. If the difference in Q-AIC values was >2, there was likely difference in model fits (Burnham and Anderson, 2004). Models using the definition

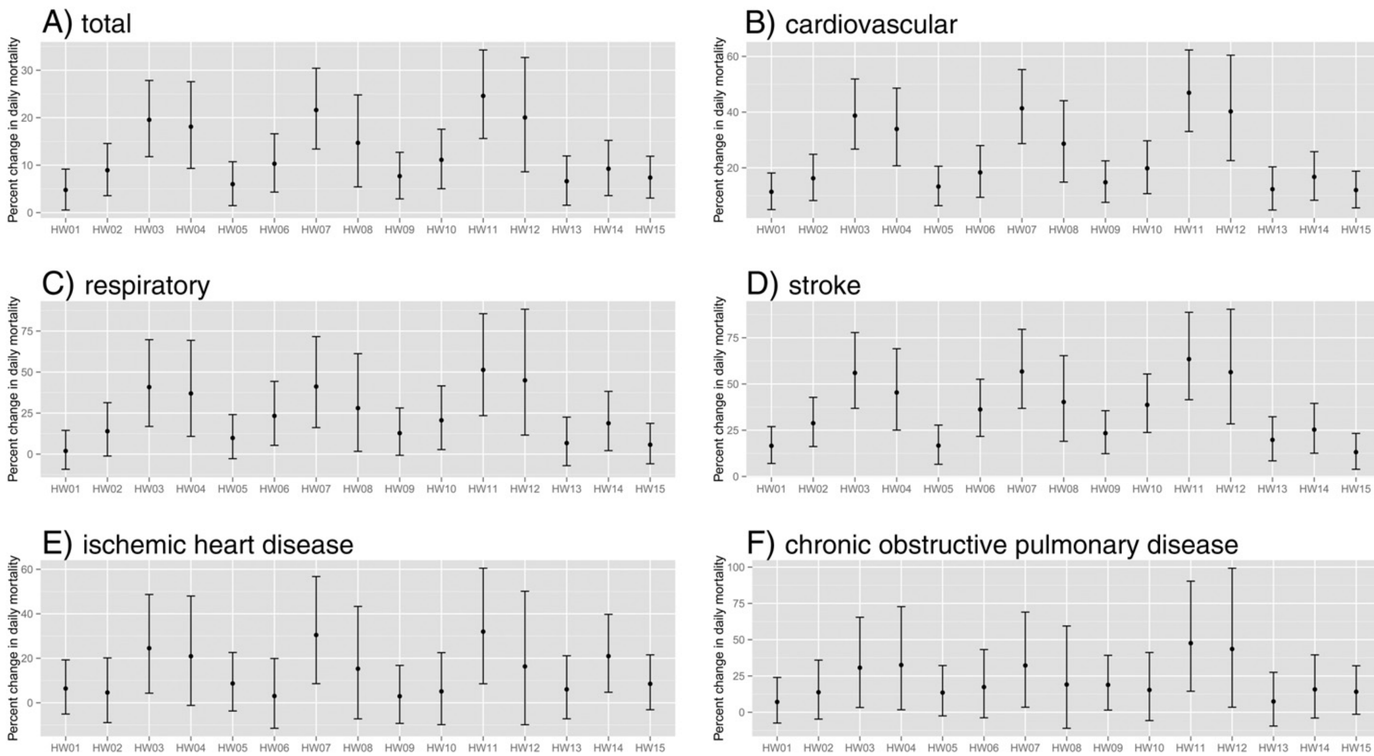

Fig. 1. Percent increase in estimated mortality risk on heat-wave days compared with non-heat-wave days at lag day 2 by 15 heat wave indexes in warm season (May to September) in Nanjing, China during 2007–2013.

of HW11 had the best model fits for all 6 causes of deaths in this study. Based on Q-AIC values, risk estimates, and different types of definitions, 4 HWs (HW11, HW02, HW03, and HW07) were selected to examine further.

Percentile-based bootstrapped CIs indicated that in total, cardiovascular, respiratory, stroke, and IHD mortality models, using HW02 generated significantly lower associations than those using HW03, HW07, or HW11 (Table 3). In total and cardiovascular mortality models, HW11 associations were significantly higher than estimates for HW03. For COPD mortality models, no significant difference was observed among these 4 HWs.

Table 2
Differences in Akaike Information Criterion for quasi-Poisson (Q-AIC) values for models examining daily mortality risk on heat wave days at lag day 2 by 15 heat wave definitions in warm season (May–September) in Nanjing, China during 2007–2013.[a]

HW	Total	Cardiovascular	Respiratory	Stroke	IHD	COPD
HW01	40.675	53.462	17.74	37.377	8.062	8.089
HW02	31.342	47.908	13.9	23.989	8.904	6.776
HW03	8.024	7.433	2.944	0	2.465	3.925
HW04	21.804	32.026	8.093	24.483	5.406	4.498
HW05	37.697	50.123	15.163	39.031	7.214	6.098
HW06	30.021	47.051	9.594	17.108	9.238	6.212
HW07	4.005	5.259	4.042	2.84	0	3.896
HW08	33.036	46.339	12.693	33.366	7.424	7.517
HW09	32.657	47.428	13.759	28.776	9.163	4.008
HW10	27.751	43.963	11.424	13.458	8.913	6.806
HW11	0	0	0	0.812	0.628	0
HW12	29.279	39.952	9.018	29.502	7.878	4.202
HW13	37.976	55.989	16.765	37.126	8.459	8.227
HW14	32.007	48.708	11.85	31.704	1.362	6.412
HW15	30.445	51.509	16.81	42.965	7.058	5.664

[a] Differences in Q-AIC values are calculated as the differences between each heat wave definition and the definition which had the lowest Q-AIC values (HW11 for total, cardiovascular, respiratory, and COPD mortality, HW03 for stroke mortality, HW07 for IHD mortality). IHD: ischemic heart disease; COPD: chronic obstructive pulmonary disease.

Fig. 2 revealed similar patterns in lag effects of heat waves on daily mortality among 4 HWs. The risk estimates in models using HW03, HW07, and HW11 were generally greater at lag day 2 than those at lag day 0 for all causes of deaths. In general, associations between heat waves and daily mortality became insignificant at lag day 6.

Effect modifications of individual characteristics were shown in Fig. 3. For heat waves defined by HW11, estimated heat wave effects on total mortality were higher for female (30.3%, 95% CI: 18.7%, 43.2%) than for male (18.4%, 95% CI: 7.5%, 30.4%), for people ≥75 years old (38.7%, 95% CI: 26.9%, 51.6%) than for people 0–64 years old (4.8%, 95% CI: −90.1%, 20.7%) or people 65–74 years old (6.3%, 95% CI: −9.5%, 24.7%), for those with low education level (35.0%, 95% CI: 24.3%, 46.6%) than for those with high education level (0.2%, 95% CI: −12.8%, 15.1%), and for out-of-hospital deaths (29.3%, 95% CI: 18.8%, 40.6%) than for in-hospital deaths (6.8%, 95% CI: −6.5%, 21.9%). Heat waves defined by HW02, HW03, and HW07 generated similar results. Percentile-based bootstrapped 95% CIs indicated that the effect modification of gender, age, and education was statistically significant for all 4 HWs, whereas death location was a significant effect modifier using HW11.

Associations between heat waves and daily mortality with and without adjusting for air pollutants (PM_{10}, NO_2, and SO_2) remained similar in Nanjing (Table 4). For HW11, estimated heat wave effects on total mortality were consistent before adjusting for air pollutants (24.6%, 95% CI: 15.6%, 34.3%) and after adjusting for PM_{10} (24.6%, 95% CI: 15.6%, 34.3%), NO_2 (24.4%, 95% CI: 15.4%, 34.1%), or SO_2 (24.6%, 95% CI: 15.6%, 34.3%). Estimated heat wave effects in Nanjing were higher for subcategory mortality (i.e., stroke, IHD, and COPD) than for cardiovascular or respiratory mortality with and without adjusting for air pollutants. Using the definition of HW11, estimated percent increase was 51.3% (95% CI: 23.4%, 85.6%) in stroke mortality, 63.4% (95% CI: 41.5%, 88.8%) in IHD mortality, and 47.6% (95% CI: 14.5%, 90.3%) in COPD mortality respectively.

Our sensitivity analysis indicated that the risk estimates were not substantially changed using different combinations of lag structures

Table 3
Bootstrapped percentile-based 95% Confidence Intervals (CIs) for the difference between mortality risk estimates using different heat wave definitions (HW02, HW03, HW07, and HW11).

Mortality	HW	HW03	HW07	HW11
Total	HW02	**(−19.86, −3.18)**	**(−22.65, −5.60)**	**(−26.82, −8.49)**
	HW03		(−7.82, 0.00)	**(−14.01, −0.69)**
	HW07			(−10.57, 0.22)
Cardiovascular	HW02	**(−36.22, −12.83)**	**(−41.03, −15.45)**	**(−47.66, −22.19)**
	HW03		(−9.69, 0.00)	**(−21.14, −2.65)**
	HW07			(−16.75, 0.00)
Respiratory	HW02	**(−53.07, −3.68)**	**(−59.74, −5.43)**	**(−72.11, −10.12)**
	HW03		(−13.90, 5.38)	(−35.70, 0.30)
	HW07			(−28.24, 0.00)
Stroke	HW02	**(−48.65, −10.99)**	**(−52.30, −12.45)**	**(−63.26, −19.65)**
	HW03		(−8.98, 2.63)	(−32.57, 3.30)
	HW07			(−27.33, 5.74)
Ischemic heart disease	HW02	**(−46.18, −0.66)**	**(−53.59, −5.33)**	**(−55.28, −4.46)**
	HW03		(−19.77, 0.00)	(−34.23, 17.09)
	HW07			(−27.95, 21.72)
Chronic obstructive pulmonary disease	HW02	(−58.61, 14.59)	(−64.05, 13.25)	(−91.24, 4.33)
	HW03		(−20.63,6.14)	(−54.80, 0.17)
	HW07			(−44.1, 0.0)

for mean temperature and heat wave (see the Supplementary Material, Fig. S1). Changing the degrees of freedom (3–6) for time trends yielded similar results (see the Supplementary Material, Fig. S2). For HW02, HW03, HW07, and HW11, estimated mortality risks were robust when the degrees of freedom for relative humidity increased from 2 to 5 (see the Supplementary Material, Fig. S3).

4. Discussion

In this study, we examined which of the 15 HWs was the best definition to capture the added heat wave effects on cause-specific mortality in Nanjing during 2007 to 2013. Compared with non-heat-wave days, heat waves defined by HW11 (daily average temperature >98th percentile for ≥4 consecutive days) had the highest mortality risk estimates and the best model fits for all four causes of deaths. The estimated impacts of heat waves on mortality remained similar after controlling air pollutants (PM_{10}, NO_2, and SO_2). We also found that women, the elderly, and people with low education level were more susceptible to heat wave effects. The effect modifications by age, gender, and education were robust to different heat wave definitions.

In the present study, we found evidence of statistically significant added effect of heat waves on total mortality, which is consistent with previous studies in the United States (Anderson and Bell, 2011; Gasparrini and Armstrong, 2011), Europe (Hajat et al., 2006), and Korea (Son et al., 2012). Compared with non-heat-wave days, the increased total mortality during heat-wave days at lag0 was 3.74% (95% CI: 2.29%, 5.22%) using HW02 in 43 cities in the United States (Anderson and Bell, 2011), 8.4% (95% CI: 0.1%, 17.3%) using HW03 in Seoul (Son et al., 2012), 4.3% (95% CI: 0.8%, 7.9%) in London and 7.9% (95% CI: 3.6%, 12.4%) in Budapest using HW04 (Hajat et al., 2006), and 2.8% (95% CI: 0.4%, 5.3%) using HW12 in 108 communities in the United States (Gasparrini and Armstrong, 2011). Our results showed slightly higher estimates of total mortality risk on heat-wave days compared with non-heat-wave days at lag0, which was 10.3% (95% CI: 4.9%, 16.0%), 12.9% (95% CI: 5.4%, 20.9%), 10.2% (95% CI: 1.9%, 19.2%), and 8.4% (95% CI: −2.3%, 20.2%) using HW02, HW03, HW04, and HW12 respectively.

More than 19% of total mortality in Nanjing during 2007 to 2013 was caused by stroke disease (see the Supplementary Material, Table S1). As the world's second leading cause of death in 2010, stroke poses a high burden of disease in China, accounting for about one fifth of total mortality (Kim and Johnston, 2011; Lozano et al., 2013). We found a higher risk of stroke mortality during heat waves than total, cardiovascular, and respiratory mortality, suggesting that more effective measures should be taken to reduce the burden of stroke during heat waves in Nanjing. It is difficult to directly compare our results with previous studies since very few studies have explored the added effect of heat waves on stroke mortality. However, previous studies have confirmed a strong health effect of heat waves on stroke mortality. An episode analysis of the 2003 heat wave in Shanghai showed a 21% (95% CI: 6.0%, 39.0%)

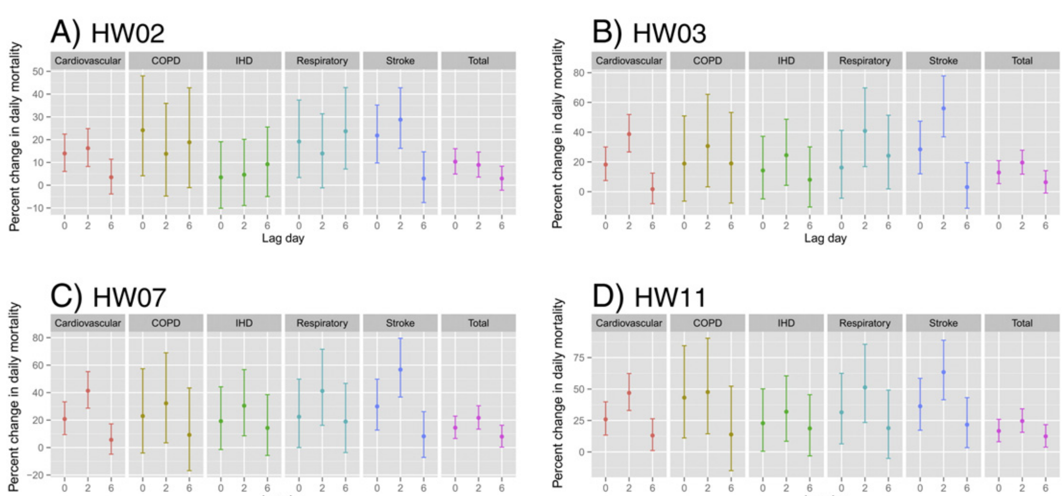

Fig. 2. Percent increase in daily mortality risk on heat-wave days compared with non-heat-wave days for different lag structures using HW02, HW03, HW07, and HW11.

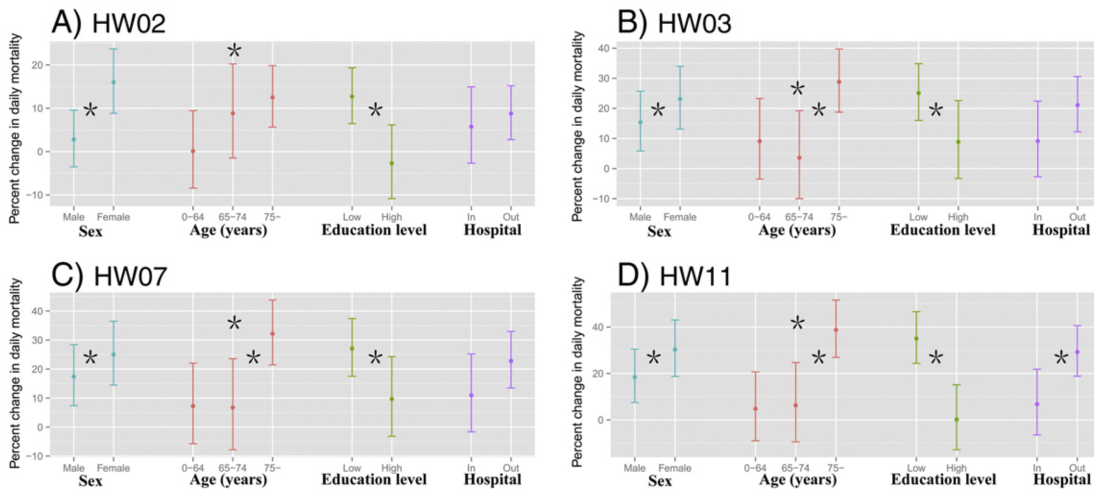

Fig. 3. Percent increase in total mortality risk on heat-wave days compared with non-heat-wave days at lag day 2 by individual characteristics using HW02, HW03, HW07, and HW11. * indicates statistical significance at $p < 0.05$ based on the bootstrapped percentile-based confidence intervals.

increase in stroke mortality, which was higher than in total (13%, 95% CI: 6.05, 20.0%) and cardiovascular mortality (19.0%, 95% CI: 8.0%, 32.0%) (Huang et al., 2010). Stroke mortality was found to account for 6% to 52% of the excess mortality during heat waves (Kilbourne, 1997). A case-only study in the United States also found a higher risk of stroke mortality compared with cardiovascular mortality during heat waves (Medina-Ramón et al., 2006). In addition, we also observed a significantly high risk of IHD mortality during heat waves, which is in accordance with previous studies in China (Tian et al., 2013) and Germany (Zacharias et al., 2014).

Our results shows that HWs based on daily mean temperature (HW01–HW12) generally had higher mortality risks than those based on daily maximum temperature (i.e., HW13, HW14, HW15). This suggests that mean temperature is more predictive of daily mortality than maximum temperature in the present study, which is in accordance with previous studies (Barnett et al., 2010; Hajat et al., 2006; Vaneckova et al., 2011). We examined one definition based on the absolute threshold of maximum temperature (HW15, daily maximum temperature >35 °C for ≥3 consecutive days), which generally had lower mortality risks than definitions based on the same duration (HW05–HW08, ≥3 consecutive days). Heat waves defined by HW15 also had non-significant associations with respiratory, IHD, and COPD mortality. In addition, bootstrapped 95% CI indicated that heat waves defined by HW15 generated significantly lower associations with cause-specific mortality than those defined by HW03, HW07, and HW11 (data not shown). This finding implies that the official definition of the Chinese Meteorological Administration (HW15) may not be an ideal indicator to protect public health during heat waves in Nanjing.

Table 4
Percent increase in estimated mortality risk on heat-wave days (using 4 heat wave definitions: HW02, HW03, HW07, and HW11) compared with non-heat-wave days at lag day 2 with and without adjusting for air pollutants in Nanjing, China during 2007–2013.

	Unadjusted	$+PM_{10}$	$+NO_2$	$+SO_2$
HW02				
Total	8.9 (3.6, 14.6)	8.9 (3.5, 14.6)	8.9 (3.5, 14.5)	8.9 (3.6, 14.6)
Cardiovascular	16.2 (8.2, 24.8)	16.3 (8.3, 24.9)	16.2 (8.2, 24.8)	16.4 (8.3, 25.0)
Stroke	13.9 (−1.2, 31.4)	13.7 (−1.4, 31.1)	13.8 (−1.3, 31.2)	13.6 (−1.5, 30.9)
IHD	28.8 (16.2, 42.8)	28.9 (16.2, 42.9)	28.8 (16.2, 42.8)	29.0 (16.4, 43.1)
Respiratory	4.6 (−8.9, 20.1)	4.5 (−9.0, 20.1)	4.5 (−9.1, 20.0)	4.6 (−9.0, 20.1)
COPD	13.8 (−4.7, 35.9)	13.8 (−4.8, 36.0)	13.6 (−4.9, 35.8)	13.4 (−5.1, 35.5)
HW03				
Total	19.5 (11.8, 27.8)	19.5 (11.8, 27.9)	19.4 (11.6, 27.7)	19.6 (11.8, 27.9)
Cardiovascular	38.7 (26.7, 51.9)	38.9 (26.9, 52.1)	38.6 (26.5, 51.7)	39.0 (26.9, 52.2)
Stroke	40.9 (16.9, 69.7)	40.4 (16.5, 69.3)	40.3 (16.4, 69.2)	40.3 (16.4, 69.1)
IHD	56.0 (36.8, 77.8)	56.2 (37.0, 78.1)	56.2 (37.0, 78.1)	56.4 (37.2, 78.4)
Respiratory	24.5 (4.3, 48.7)	24.4 (4.2, 48.6)	23.9 (3.7, 48.0)	24.5 (4.3, 48.7)
COPD	30.7 (3.2, 65.4)	30.7 (3.2, 65.6)	30.1 (2.7, 64.8)	30.2 (2.8, 64.8)
HW07				
Total	21.6 (13.4, 30.4)	21.6 (13.4, 30.4)	21.5 (13.2, 30.3)	21.7 (13.4, 30.5)
Cardiovascular	41.4 (28.7, 55.3)	41.6 (28.9, 55.5)	41.2 (28.5, 55.1)	41.7 (28.9, 55.6)
Stroke	41.2 (16.2, 71.6)	40.7 (15.7, 71.1)	40.7 (15.7, 71.0)	40.5 (15.6, 70.8)
IHD	56.7 (36.8, 79.6)	57.0 (37.0, 79.9)	56.9 (36.9, 79.8)	57.3 (37.2, 80.2)
Respiratory	30.5 (8.6, 56.7)	30.4 (8.5, 56.7)	29.8 (8.0, 56.0)	30.5 (8.6, 56.9)
COPD	32.2 (3.5, 69.0)	32.3 (3.4, 69.2)	31.7 (2.9, 68.4)	31.6 (2.9, 68.3)
HW11				
Total	24.6 (15.6, 34.3)	24.6 (15.6, 34.3)	24.4 (15.4, 34.1)	24.6 (15.6, 34.3)
Cardiovascular	46.9 (33.0, 62.3)	47.2 (33.2, 62.6)	46.8 (32.8, 62.1)	47.1 (33.2, 62.6)
Stroke	51.3 (23.4, 85.6)	50.8 (22.9, 85.0)	50.7 (22.9, 84.9)	50.7 (22.9, 84.9)
IHD	63.4 (41.5, 88.8)	63.7 (41.7, 89.1)	63.7 (41.7, 89.1)	63.8 (41.8, 89.2)
Respiratory	32.0 (8.5, 60.5)	31.9 (8.4, 60.5)	31.2 (7.9, 59.7)	32.0 (8.5, 60.6)
COPD	47.6 (14.5, 90.3)	47.7 (14.5, 90.6)	47.0 (13.9, 89.6)	47.0 (14.0, 89.6)

Therefore, regional specific definitions based on relative temperature threshold are needed to design effective local heat warning systems.

The health effect of heat waves defined by mean temperature increased as the threshold increased from the 90th percentile to the 98th percentile in the present study. Consistently, a study in four communities of Guangdong Province (China) found that the heat wave definition based on a mean temperature threshold of 97th percentile had a stronger relationship with total mortality than that based on a mean temperature threshold of 95th percentile for the same minimum duration of 2 days (Zeng et al., 2014). Higher temperature threshold $\leq$98th percentile was also found to be associated with greater heat wave effect on mortality in Brisbane, Australia (Tong et al., 2010; Vaneckova et al., 2011). However, associations between mortality and heat waves defined by mean temperature declined as the threshold increased from the 98th percentile to the 99th percentile in our study, whereas these associations continued to increase in other studies in western countries (Anderson and Bell, 2009; Hajat et al., 2006). In line with our finding, a study in Korea also observed lower effect of heat waves on total mortality using HW08 (mean temperature >99th percentile for $\geq$3 consecutive day) compared with HW07 (mean temperature >98th percentile for $\geq$3 consecutive day) (Son et al., 2012). This difference may be due to the small number of heat-wave days using the 99th percentile (Son et al., 2012).

Consistent with other studies, heat wave definitions with longer minimum duration had higher mortality risks (Anderson and Bell, 2009; Son et al., 2012). This is plausible since heat waves with longer duration generally resulted in a greater added effect on daily mortality (Anderson and Bell, 2011).

In this study, we found stronger associations among females than males, older people than young people, residents with low education than those with high education, and those dying out of hospitals than those dying in hospitals. These patterns did not change under different heat wave definitions (Fig. 3). In accordance with our findings, women and the elderly were found to be more vulnerable to the impact of heat waves in previous studies (Son et al., 2012; Tong et al., 2014; Zeng et al., 2014). This may be due to different physiopathological responses to heat stress (Bell et al., 2008; Stafoggia et al., 2006) and differences in social and living conditions (D'Ippoliti et al., 2010; Hajat et al., 2007) between different age and gender groups. The greater mortality estimates for people with low education and those dying outside of hospitals have also been demonstrated in other studies (Medina-Ramón et al., 2006; O'Neill et al., 2003; Reid et al., 2009). The effect modifications of education and place of death on heat wave impacts may reflect limited access to health care and poor housing conditions such as lack of air conditioning for those with low education and dying outside of hospitals (Son et al., 2012).

To the best of our knowledge, this study is the first attempt to explore the influence of various heat wave definitions on the added effect of heat waves on cause-specific mortality in China. Moreover, it is one of the few studies to examine the added effects of heat waves on stroke, IHD, and COPD mortality. Further, a strength of this study is adjusting for the possible confounding effects of relative humidity and several air pollutants (PM_{10}, NO_2, and SO_2).

One limitation of this study is that we only focused on a single city. Our findings may not be applicable to other areas with different climates, housing systems, and demographics. However, the importance of heat wave definitions to the impact of added effects of heat waves on mortality we found is consistent with the conclusion of a previous U.S. multicity study on the overall effects of heat waves (Kent et al., 2014). Further multicity study is needed to confirm our findings. Another limitation is that, as in most heat wave studies, we were unable to control the modifying effect of air conditioning (Anderson and Bell, 2009; O'Neill et al., 2005) since no data were available in Nanjing. Besides, we only used air pollution data from outdoor fixed monitoring stations and weather data from a single site, which might result in inevitable measurement errors. Also, misclassification of causes of death might occur. Finally, due to data availability, the potential role of ozone played during high temperatures and heat waves was not considered in this study.

5. Conclusions

We found that different heat wave definitions had considerable impacts on the added effects of heat waves. The modifying effect of individual characteristics, such as age, gender, and education, remained the same under different heat wave definitions. These findings suggests that regional-specific heat wave definitions are crucial for designing local heat warning systems and reducing the heavy burden of heat-related diseases.

Conflict of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2014.10.092.

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