Int J Public Health (2014) 59:923–931
DOI 10.1007/s00038-014-0611-5

ORIGINAL ARTICLE

Temperature variation between neighboring days and mortality: a distributed lag non-linear analysis

Jian Cheng · Rui Zhu · Zhiwei Xu · Xiangqing Xu · Xu Wang · Kesheng Li · Hong Su

Received: 30 May 2014 / Revised: 7 September 2014 / Accepted: 24 September 2014 / Published online: 4 October 2014

Abstract
Objectives To investigate whether a sudden temperature change between neighboring days has significant impact on mortality.
Methods A Poisson generalized linear regression model combined with a distributed lag non-linear models was used to estimate the association of temperature change between neighboring days with mortality in a subtropical Chinese city during 2008–2012. Temperature change was calculated as the current day's temperature minus the previous day's temperature.
Results A significant effect of temperature change between neighboring days on mortality was observed. Temperature increase was significantly associated with elevated mortality from non-accidental and cardiovascular diseases, while temperature decrease had a protective effect on non-accidental mortality and cardiovascular mortality. Males and people aged 65 years or older appeared to be more vulnerable to the impact of temperature change.
Conclusions Temperature increase between neighboring days has a significant adverse impact on mortality. Further health mitigation strategies as a response to climate change should take into account temperature variation between neighboring days.

Keywords Climate change · Temperature variation · Mortality · Time series

J. Cheng and R. Zhu are Co-first author.

Electronic supplementary material The online version of this article (doi:10.1007/s00038-014-0611-5) contains supplementary material, which is available to authorized users.

J. Cheng · X. Wang · K. Li · H. Su (✉)
Department of Epidemiology and Health Statistics, School of Public Health, Anhui Medical University, 81 Meishan Road, Hefei 230032, Anhui, China
e-mail: suhong5151@sina.com

R. Zhu
Department of Child and Maternal Health Care School of Public Health, Anhui Medical University, Hefei, Anhui, China

Z. Xu
School of Public Health and Social Work, Institute of Health and Biomedical Innovation, Queensland University of Technology Kelvin Grove, Brisbane, QLD, Australia

X. Xu
Maanshan Health Bureau of Huashan district, Maanshan, Anhui, China

Introduction

There is a widespread consensus that climate change is occurring and it is mainly caused by the emissions of anthropogenic greenhouse gases (WHO 2008). As projected by Intergovernmental Panel on Climate Change, global average temperature increase is likely to exceed 1.5 °C by the end of this century for all RCP scenarios except RCP 2.6 (IPCC 2013). Not only has the global average temperature increased, but the frequency and intensity of extreme temperatures (e.g., heat waves and cold spells) have also increased (IPCC 2013). Climate change has been recognized as an important threat to human health and well-being (WHO 2008; Kjellstrom and McMichael 2013).

Marked adverse effects of ambient temperature on morbidity and mortality have been demonstrated in various regions and climatic zones worldwide, and typical U-, V-, and J-shaped exposure–response relationships have been noted (Barnett 2007; Basu 2009; Guo et al. 2012, 2013; Yang et al. 2012; Green et al. 2010). Prior studies tended to use daily mean temperature, maximum temperature, minimum temperature, or apparent temperature as indicators of ambient temperature. As the climatic conditions continuously change, unstable weather patterns (e.g., an abrupt drop or increase in temperature) are also more likely to occur in the coming decades (Faergeman 2008; Epstein 2005). In recent years, there has been increasing interest in assessing the effect of temperature variation within 1 day or between neighboring days on human health. Defined as the difference between daily maximum temperature and minimum temperature, diurnal temperature range was found to be an independent risk factor for mortality (Lim et al. 2012; Yang et al. 2013; Cheng et al. 2014). However, to date, few data are available on the possible effect of temperature change between adjacent days on mortality (Lin et al. 2013; Guo et al. 2011). For example, in Brisbane, Australia, Guo et al. found an increase of more than 3 °C in temperature between neighboring days was associated with 35.3 % [95 % confidence interval (CI) 3.3–77.2 %] increase in cardiovascular mortality and people under 65 years were more vulnerable to the effects of temperature change (Guo et al. 2011). However, in Los Angeles, United States, a drop of more than 3 °C in temperature between neighboring days was found to be associated with 25.2 % (95 % CI 13.1–38.6 %) increase in cardiovascular mortality, and people aged 75 years or older were particular sensitive to the effects of temperature change (Guo et al. 2011).

Sudden short-term (days) temperature change is a source of additional environmental stress and may have acute or delayed adverse effects on human health, particularly to those with pre-existing chronic conditions (Lin et al. 2013). Therefore, we hypothesized that a sudden temperature change between neighboring days might pose a threat to human health. The association between temperature change among neighboring days and mortality has been examined by Lin and colleagues only in the Chinese coastland cities, and they found temperature increase was a risk factor of mortality (Lin et al. 2013). However, whether the adverse effect of temperature change on mortality exist in areas with different weather condition, population characteristics and socio-economic status needs to be further explored. In this study, we selected a Chinese inland city and attempted to address the following questions: (1) What is the relationship between temperature change among neighboring days and mortality? (2) Which groups are more vulnerable to the effects of temperature change? and (3) Is there a delayed effect of temperature change on daily mortality?

Methods

Study area

This study was conducted in Maanshan, an inland city located in the East Anhui Province, China (East longitude: 117°53′–118°52′, North latitude: 31°24′–32°02′) (Fig. 1). This city covers 4,049 km^2 with a population of 1,366,302

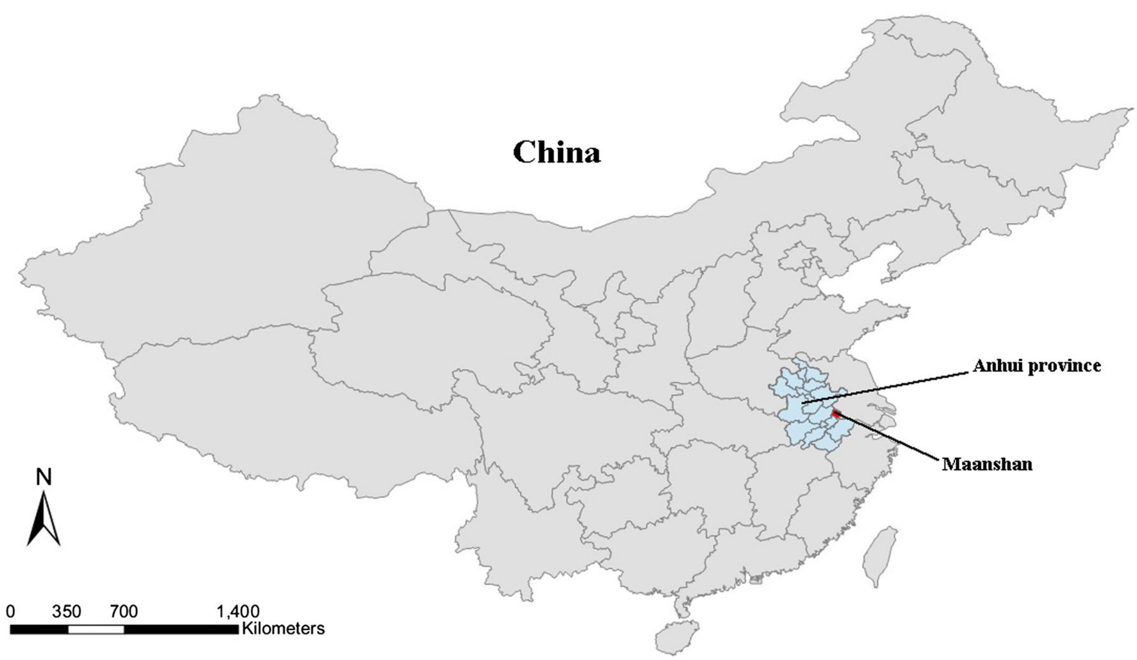

Fig. 1 The geographical location of the study area in China. The *light-blue polygons* represent the Anhui province and the *red polygon* represents Maanshan city

in 2010. It has a subtropical monsoon climate, experiencing four distinct seasons. The annual average temperature and rainfall is 15.7 °C and 1060 mm, respectively.

Data collection

Daily death counts between January 1st 2008 and December 31st 2012 were obtained from Maanshan Center for Disease Control and Prevention. The causes of mortality were coded according to the tenth version of the International Classification of Diseases (ICD-10). We classified the mortality into deaths due to all non-accidental causes (ICD-10: A00-R99), cardiovascular diseases (ICD-10: I00-I99) and respiratory diseases (ICD-10: J00-J99). Daily meteorological data, including daily maximum, minimum, and mean temperatures and relative humidity for the same period were collected from Maanshan Bureau of Meteorology. Temperature change between neighboring days, including mean temperature change (MeanTC), maximum temperature change (MaxTC), and minimum temperature change (MinTC), was calculated as the difference between the current day's mean/maximum/minimum temperature and previous day's mean/maximum/minimum temperature.

Ethical approval was obtained from the Ethics Committee of Anhui Medical University prior to the data collection.

Statistical analysis

As the count of daily death typically follows a Poisson distribution, we used the same analytical approach as Lin et al. (2013), namely, Poisson generalized linear regression model combined with a distributed lag non-linear model (DLNM), to estimate the effect of temperature change on mortality. DLNM is a modeling framework, which can flexibly model potential non-linear exposure–response dependencies and delayed effects in time series data (e.g., daily air pollutant, daily ambient temperature, and daily death number) (Gasparrini et al. 2010). This model is based on the definition of a "cross-basis", a bi-dimensional functional space, which describes simultaneously the shape of the relationship along both the space of the exposure and the lag dimension of its occurrence. Three-dimensional plots were finally built by building a series of grid of predictions for each lag and for suitable values of exposure to provide an overall picture of the effects of interest varying along the two dimensions.

In "cross-basis" function, we assumed a maximum lag of 21 days for the delayed effect of temperature change on mortality and used a natural cubic spline with three degrees of freedom (*df*) for the temperature change. A natural cubic spline with three *df* was used to adjust for mean temperature and relative humidity (Lin et al. 2013; Guo et al. 2011). Long-term trends and seasonal patterns were controlled using a natural cubic spline for time with seven *df* per year. Day of the week was controlled as a categorical variable. We did not control for the air pollutants, such as ozone (O3) and particulate matter less than 2.5 μm in aerodynamic diameter (PM2.5), because it is not available. The main model used to quantify the association of the temperature change and mortality was:

$$Yt \sim \text{Poisson } (ut)$$

$$\text{Log}(ut) = a + \text{ns}(\text{TC}t, 3) + \text{ns}(\text{Mean}Tt, 3) + \text{ns}(\text{RH}t, 3) + \text{ns}(\text{Time}t, 7) + \eta\text{DOW}t$$

where t is the day of the observation; Yt is observed daily death counts on day t; α is the model intercept; ns(.) denotes the natural cubic spline; TC is the temperature change, inclusion of MeanTC, MaxTC, and MinTC; MeanT is the daily mean temperature; η indicates the vector of coefficient for DOWt; DOWt is the categorical day of the week with a reference day of Sunday. In all cases, the Akaike information criterion (AIC) was used to measure goodness of fit and an analysis of residuals was examined to evaluate the adequacy of the model. We ran the above model with MeanTC, MaxTC, and MinTC being the independent variables separately and found the model with MaxTC generated the lowest AIC value, so we used MaxTC as the predicator to assess the association between temperature change between adjacent days and mortality.

Table 1 Summary statistic for daily weather variables and daily mortality cases in Maanshan, China, from 2008–2012

Variables	Mean	SD	Min	Percentile			Max
				25	50	75	
MaxTC (°C)	0	3.06	−12.50	−1.90	0.2	1.90	13.80
MinTC (°C)	0	2.44	−13.20	−1.30	0.1	1.40	8.7
Mean temperature (°C)	17.75	8.98	−3.90	10.35	19.25	25.40	34.50
Relative humidity (%)	67.99	15.64	16.00	57.00	69.00	80.00	99.00
Total mortality (non-accidental)	4.44	2.42	0	3.00	4.00	6.00	16.00
Male	2.84	1.77	0	2.00	3.00	4.00	11.00
Female	1.59	1.39	0	1.00	1.00	2.00	10.00
Age <65 years	1.30	1.15	0	0.0	1.00	2.00	7.00
Age ≥65 years	3.14	2.05	0	2.00	3.00	4.00	15.00
Cardiovascular mortality	0.57	0.80	0	0	0	1.00	4.00
Respiratory mortality	0.89	0.97	0	0	1.00	1.00	6.00

MaxTC Maximum temperature change between adjacent days, *MinTC* Minimum temperature change between adjacent days

Effects of the temperature change on mortality were estimated and presented as relative risk (RR, with 95 % CI of temperature increase/drop (1, 5, 25, 75, 95, and 99 % percentiles of temperature changes) along specific lag days with 0 °C as the reference. A stratified analysis was also conducted to explore the association across age, gender, and cause of death.

All data analysis was conducted using the R statistical environment (version 2.15.3) with the "dlnm" package to fit the regression model (Gasparrini 2013). To check our findings, additional sensitivity analyses were performed by varying the *df* for time, mean temperature, and relative humidity.

Results

Characteristics of mortality and meteorological variables

A total of 8,111 deaths were identified during the study period of 2008–2012. Table 1 showed the summary statistics for daily weather conditions and mortality. There were, on average, 4.44 daily non-accidental deaths in Maanshan, China. The average value of MaxTC and MinTC were 0 °C (ranged from −12.5 to 13.8 °C) and 0 °C (ranged from −13.2 to 8.7 °C), respectively. The average values of mean temperature and relative humidity were 17.75 and 67.99 %, respectively.

Association between temperature change and mortality

The three-dimension plot showed the relationships between MaxTC and mortality from non-accidental, cardiovascular, and respiratory diseases for different lags, with 0 °C as the reference (Fig. 2). Overall, the estimated effect of MaxTC on mortality was non-linear. Large temperature increases have delayed adverse effects on mortality from non-accidental and cardiovascular diseases. Figure 2 showed a protective effect of temperature decrease, and the risk of death decreased with the decreased temperature.

Figure 3 showed the gender-specific risk curve at lag 10 due to the effects of extremely high MaxTC (6.9 °C) on mortality peaked at 10 days lag. It suggested that risk of death increase significantly above a MaxTC of 0 °C, with

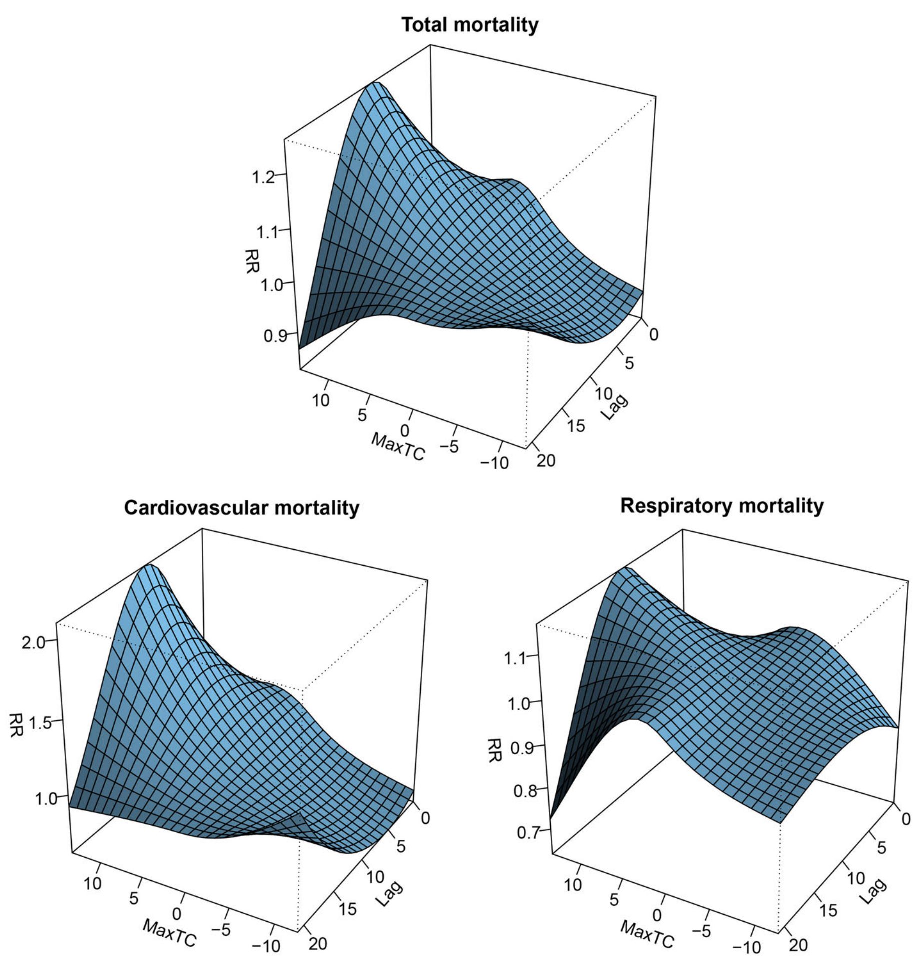

Fig. 2 3D graph of MaxTC effect on mortality from non-accidental, cardiovascular and respiratory diseases, with 0 °C as the reference in Maanshan, China, during 2008–2012. *RR* relative risk, *MaxTC* maximum temperature change between neighboring days

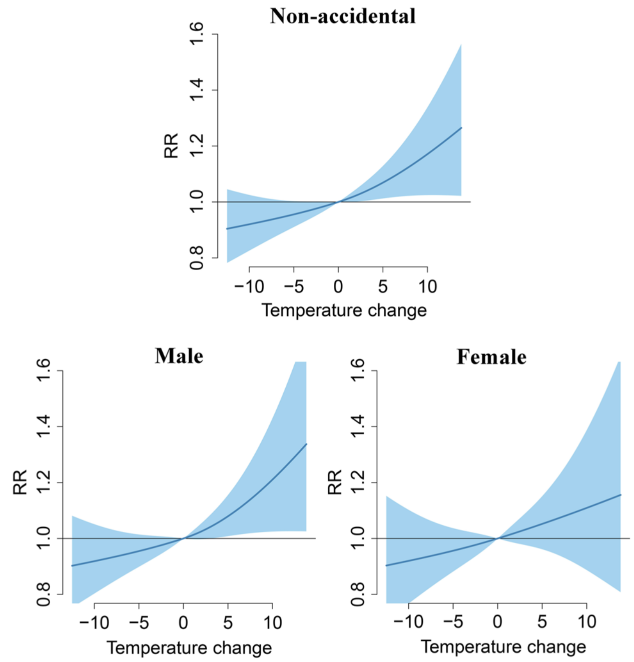

Fig. 3 Association between temperature change between neighboring days (MaxTC, Lag 10) and sex-specific mortality in Maanshan, China, during 2008–2012 (reference = 0 °C). *RR* relative risk, *MaxTC* maximum temperature change between neighboring days; the *solid steel blue line* and *shade area* represent the RR and its 95 % confidence interval

males exhibiting the greater susceptibility than females. A 5 °C increase in MaxTC was associated with 6.9 % (95 % CI 1.3–12.9 %) increase in total, 7.9 % (95 % CI 0.8–15.6 %) increase in male and 5.2 % (95 % CI −3.9–15.1 %) increase in female mortality, respectively.

The effects of MaxTC on cause-specific mortality at specific lag days (0, 1, 2, 3, 7, 14, and 21 days) and at specific temperature changes (−7.9, −5.1, −1.9, 1.9, 4.7, and 6.9 °C), which corresponded to approximately the 1, 5, 25, 75, 95, and 99 % percentiles of MaxTC, were presented in Table 2. We found moderate temperature change (including positive and negative) had the greatest effect on mortality at lag0. Regarding the effects of temperature increase on mortality, the moderate MaxTC (1.9 °C), high MaxTC (4.7 °C) and extremely high temperature MaxTC (6.9 °C) could significantly increase the non-accidental and cardiovascular mortality. For example, a 1.9 °C increase in MaxTC was found to be associated with 3 % (95 % CI 0–5 %, lag0) and 8 % (95 % CI 2–15 %, lag0) increase in non-accidental mortality and cardiovascular mortality, respectively. Meanwhile, season-specific analysis showed that the effects of temperature change were greater in cool season (January–April and November–December) than those in warm season (May–October) (Fig. 4). In contrast, temperature drop was found to be followed with decreased mortality.

Table 3 showed the effects of temperature changes on mortality stratified by age and gender. It indicated that MaxTC was more likely to affect mortality among males and people aged 65 years or older. Temperature drop was associated with decreased mortality, while temperature increase could increase the risk of death. A 1.9 °C drop in MaxTC was found to be associated with 4 % (95 % CI 1–6 %, lag0) and 3 % (95 % CI 1–6 %, lag0) decrease in mortality among males and people aged 65 years or older, respectively. However, 1.9 °C increase in MaxTC corresponded to a 3 % increase at lag 0 (95 % CI 0–6 %) and lag 3 (95 % CI 1–5 %) in mortality among males and people aged 65 years or older, respectively.

Sensitivity analysis

We also examined the relationship between MinTC and mortality. Significant relationship between MinTC and mortality among males and mortality due to cardiovascular diseases were also observed. With a moderate and high temperature increase in MinTC (1.4 and 3.9 °C), the risk of death among males elevated by 3 % (95 % CI 0–6 %) and 8 % (95 % CI 1–16 %) on the current day, respectively. Meanwhile, a high and extremely high temperature increase in MinTC (3.9 and 5.8 °C) has the acute maximum effects at lag day 0 on mortality due to cardiovascular diseases (percent change: 23 %, 95 % CI 5–43 %; 41 %, 95 % CI 8–83 %).

To check our findings, we also changed the *df* (6–10 per year) for time to control for long-term trends and seasonal patterns. We also varied the *df* (4–7) for mean temperature and relative humidity, the estimated results changed a little (supplementary Fig. 1 and supplementary Fig. 2).

Discussion

This study examined the impact of temperature change between neighboring days on mortality in a subtropical city of China. Large temperature drops between neighboring days were found to be significantly linked with decreased non-accidental and cardiovascular mortality, while temperature increases were associated with elevated risk of mortality from non-accidental and cardiovascular diseases. These findings suggested that individual physiological reactions to temperature fluctuations between adjacent days might depend on the direction and degree of the temperature change.

In accordance with previous studies (Goldberg et al. 2011; Lin et al. 2013; Guo et al. 2011), we found the significant association of temperature change between neighboring days and mortality from non-accidental and cardiovascular diseases. The increased risk of death due to

Table 2 The effects of temperature changes (1, 5, 25, 75, 95, and 99 % percentiles) on non-accidental and cause-specific mortality at different lag days in Maanshan, China, during 2008–2012 (reference = 0 °C)

Death cause	RR (95 % CI)					
	−7.9 °C	−5.1 °C	−1.9 °C	1.9 °C	4.7 °C	6.9 °C
Non-accidental						
Lag0	0.91 (0.82–1.00)	0.93 (0.88–0.98)*	0.97 (0.95–0.99)*	1.03 (1.00–1.05)*	1.03 (0.98–1.08)	1.00 (0.91–1.09)
Lag1	0.91 (0.83–0.99)*	0.93 (0.88–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.03 (0.99–1.08)	1.01 (0.94–1.10)
Lag2	0.91 (0.84–0.99)*	0.93 (0.89–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.04 (1.00–1.09)	1.03 (0.96–1.11)
Lag3	0.91 (0.84–0.98)*	0.94 (0.89–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.05 (1.00–1.09)*	1.05 (0.98–1.12)
Lag7	0.92 (0.86–0.99)*	0.95 (0.90–0.99)*	0.98 (0.96–1.00)*	1.03 (1.01–1.05)*	1.06 (1.01–1.11)*	1.09 (1.02–1.18)*
Lag14	1.03 (0.96–1.10)	0.97 (0.93–1.01)	0.99 (0.97–1.01)	1.01 (1.00–1.03)	1.04 (1.00–1.09)	1.07 (1.00–1.15)*
Lag21	1.03 (0.96–1.10)	1.01 (0.98–1.04)	1.00 (0.98–1.02)	1.00 (0.98–1.01)	0.98 (0.94–1.02)	0.95 (0.88–1.02)
Cardiovascular						
Lag0	0.76 (0.58–1.00)*	0.82 (0.70–0.95)*	0.92 (0.86–0.98)*	1.08 (1.02–1.15)*	1.15 (1.00–1.32)	1.15 (0.91–1.46)
Lag1	0.76 (0.59–0.97)*	0.82 (0.71–0.94)*	0.92 (0.87–0.97)*	1.08 (1.02–1.15)*	1.16 (1.02–1.32)*	1.18 (0.96–1.46)
Lag2	0.75 (0.60–0.94)*	0.82 (0.72–0.93)*	0.92 (0.87–0.97)*	1.09 (1.03–1.14)*	1.18 (1.05–1.32)*	1.22 (1.00–1.47)*
Lag3	0.75 (0.61–0.92)*	0.82 (0.72–0.92)*	0.92 (0.87–0.96)*	1.09 (1.03–1.14)*	1.19 (1.06–1.32)*	1.25 (1.04–1.50)*
Lag7	0.75 (0.61–0.92)*	0.82 (0.72–0.93)*	0.92 (0.88–0.97)*	1.09 (1.03–1.15)*	1.23 (1.08–1.39)*	1.35 (1.11–1.65)*
Lag14	0.86 (0.72–1.05)	0.90 (0.80–1.01)	0.96 (0.91–1.01)	1.06 (1.00–1.11)*	1.16 (1.03–1.32)*	1.28 (1.05–1.56)*
Lag21	1.17 (0.98–1.39)	1.08 (0.99–1.18)	1.02 (0.97–1.06)	0.99 (0.95–1.04)	0.98 (0.88–1.10)	0.97 (0.79–1.20)*
Respiratory						
Lag0	0.92 (0.74–1.15)	0.97 (0.85–1.09)	1.00 (0.94–1.05)	0.99 (0.94–1.04)	0.93 (0.83–1.04)	0.86 (0.71–1.05)
Lag1	0.93 (0.76–1.13)	0.97 (0.86–1.08)	0.99 (0.95–1.04)	0.99 (0.95–1.04)	0.95 (0.85–1.05)	0.89 (0.75–1.06)
Lag2	0.93 (0.77–1.12)	0.96 (0.87–1.07)	0.99 (0.95–1.04)	1.00 (0.95–1.04)	0.96 (0.87–1.06)	0.92 (0.78–1.08)
Lag3	0.93 (0.78–1.10)	0.96 (0.87–1.07)	0.99 (0.95–1.03)	1.00 (0.96–1.04)	0.98 (0.89–1.08)	0.95 (0.82–1.11)
Lag7	0.93 (0.79–1.10)	0.96 (0.87–1.06)	0.99 (0.95–1.03)	1.01 (0.97–1.06)	1.04 (0.94–1.15)	1.06 (0.90–1.25)
Lag14	0.93 (0.80–1.08)	0.95 (0.86–1.04)	0.98 (0.94–1.02)	1.03 (0.98–1.07)	1.06 (0.96–1.17)	1.09 (0.93–1.27)
Lag21	0.91 (0.78–1.06)	0.93 (0.86–1.00)	0.97 (0.93–1.00)	1.02 (0.98–1.06)	0.99 (0.91–1.08)	0.92 (0.78–1.09)

RR relative risk, *CI* confidence interval

* $P < 0.05$

short-term temperature variation highlights the importance of not only focusing on absolute temperature (e.g., daily mean daily temperature, maximum temperature, and daily minimum temperature), but also sudden temperature change (e.g., MaxTC and MinTC), when assessing the climate change related to human health. Currently, the exact mechanism by which exposure to a large temperature can increase the risk of mortality remains largely unknown. Normally, human body regulates the heat exchange between body and ambient temperature by physiological control (Guo et al. 2012). When a sudden temperature increase exceeds the limits people could bear, the automatic thermo-regulation system might not well adapt to such a sudden change, particularly for those with some chronic diseases (Zanobetti et al. 2012). Sudden temperature changes has found to be associated with increased blood cholesterol levels, blood pressure, plasma fibrinogen concentrations, peripheral vasoconstriction, heart rate, platelet viscosity, and reduced the immune system's resistance (Schneider et al. 2008; McGeehin and Mirabelli 2001). The dehydration, salt depletion, and increased surface blood circulation (Bouchama and Knochel 2002) may be also related to the potential mechanism, through which a sudden temperature change induced the occurrence of death.

In present study, based on the analytical approach of Lin et al. (2013), we found that people with cardiovascular diseases were more vulnerable to temperature change than those with respiratory diseases. Likewise, Lin et al. (2013) have also observed temperature change had adverse effect on cardiovascular disease, but not on respiratory disease in Taishan, China. Previous studies have shown that temperature was associated with physiological changes in the circulatory system, including blood pressure, heart rate, blood cholesterol levels, plasma fibrinogen concentrations, peripheral vasoconstriction, and platelet viscosity (Schneider et al. 2008; Carder et al. 2005), which are directly associated with cardiovascular function. The

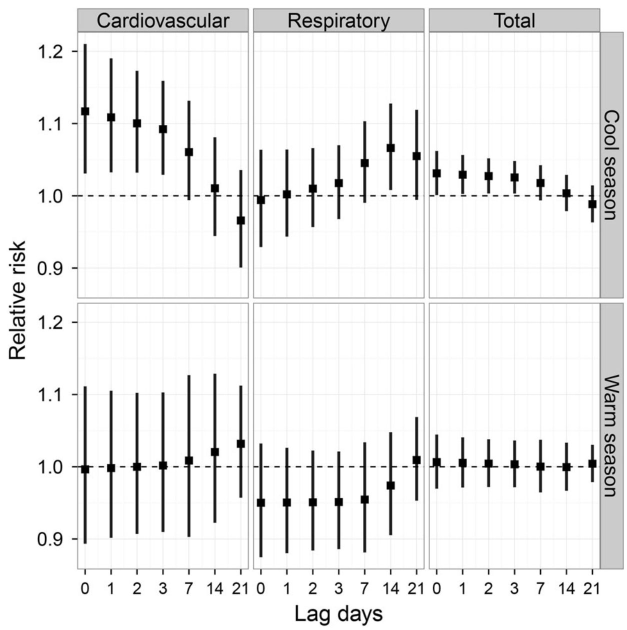

Fig. 4 Season-specific effects of MaxTC on non-accidental, cardiovascular and respiratory mortality in Maanshan, China, during 2008–2012 (reference = 0 °C). Relative risk and 95 % confidence interval associated with moderate MaxTC (1.9 °C); *MaxTC* maximum temperature change between neighboring days; the *squares* and *long solid lines* indicate the relative risk and its 95 % confidence interval; the *short dashed lines* indicate that the value of relative risk is 1

respiratory mortality is generally due to the immune system's resistance to respiratory infections caused by exposure to cold or hot temperatures (Curriero et al. 2002). Therefore, compared with people with respiratory diseases, those with cardiovascular disease might be particularly sensitive to temperature change.

The gender- and age-specific analyses also showed that males and people aged 65 years or older were more likely to be affected by temperature change. Lin et al. (2013) have found that temperature increase between neighboring days was significantly associated with increased mortality among males, but not among females in Guangzhou, China and no difference was found in both males and females in Taishan, China. Basu et al. (2009) have pointed out that the differences of the impact of temperature on males and females were dependent on location and population. For instance, the impact of hot temperature on mortality was higher for males in São Paulo, but higher for females in Mexico City (Bell et al. 2008). Compared with younger population, the elderly have a lower ability to regulate body temperature and an elevated sweating threshold (Kenney and Hodgson 1987). When exposed to a large temperature increase, the elderly would be a more vulnerable group.

In this study, the effect of temperature change on mortality increased rapidly above 0 °C at lag10, particularly above large temperature change (Fig. 3). In Maanshan, China, during 2008–2012, people were exposed to the risk of high temperature change (4.7 °C) for more than 90 days, and extreme high temperature change (6.9 °C) for 20 days. In terms of lag structure of effects of extreme high temperature increase on mortality, we found the effect started at lag5, peaked at lag10 and then declined gradually, which was inconsistent with previous findings. In Guangzhou, China, using the same analytical approach, Lin et al. (2013) found the acute effects of extreme temperature increase on non-accidental and cardiovascular mortality, while delayed effects were observed on respiratory mortality, with the greatest effects occurred at around lag10. Meanwhile, delayed effects on non-accidental mortality were also found in Taishan, China, and the effects could last for at least 15 days. However, in Brisbane, Australia, Guo et al. (2011) observed that a large temperature change (more than 3 °C) had the acute effects on cardiovascular mortality and people under 65. It suggests that furthers research is needed to explore whether the lag structure of effects of extreme temperature change on mortality vary with location and death cause.

With respect to the effects of temperature decrease on mortality, analogous results that temperature drop was accompanied with the decrease in risk of death due to non-accidental and cardiovascular diseases were reported by Lin and coworkers (Lin et al. 2013). We should also pay attention to temperature decrease between neighboring days, because a large temperature drop between adjacent days has been found associated with elevated mortality in a study in Brisbane, Australia (Guo et al. 2011). The inconsistence might be partly due to the differences in population characteristics (e.g., adaptive capacity, socioeconomic status, lifestyles, and access to health care) and weather condition. Therefore, local policy makers should fully take into account the direction and magnitude of short-term temperature variation when developing or updating the public health mitigation strategy as a response to current climate change.

Several limitations should be considered when interpreting the findings from our study. First, this was an ecological study, and therefore, some bias due to exposure misclassification may be inevitable. Second, only one city was included in the present study, the results of this study may not be generalized to population in other areas. Third, some other time-varying factors, such as O_3 and $PM_{2.5}$, which might confound the relationship between temperature change and mortality, were not controlled in our study due to its non-availability. Fourth, previous studies have showed acute adverse effects of high temperature on human health (Huang et al. 2012; Zhang et al. 2014), which may modify the relationship between temperature change among neighboring days and mortality. It is necessary for

Table 3 Gender- and age-specific effects of temperature changes (1, 5, 25, 75, 95, and 99 % percentiles) on mortality at different lag days in Maanshan, China, during 2008–2012 (reference = 0 °C)

	RR (95 % CI)					
	−7.9 °C	−5.1 °C	−1.9 °C	1.9 °C	4.7 °C	6.9 °C
Male						
Lag0	0.88 (0.78–1.00)*	0.92 (0.86–0.98)*	0.96 (0.94–0.99)*	1.03 (1.00–1.06)*	1.05 (0.99–1.12)	1.05 (0.94–1.17)
Lag1	0.89 (0.79–0.99)*	0.92 (0.86–0.98)*	0.97 (0.94–0.99)*	1.03 (1.01–1.06)*	1.06 (1.00–1.12)	1.06 (0.96–1.17)
Lag2	0.89 (0.81–0.99)*	0.92 (0.87–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.06)*	1.06 (1.01–1.12)*	1.07 (0.98–1.17)
Lag3	0.90 (0.81–0.98)*	0.93 (0.88–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.07 (1.01–1.12)*	1.08 (1.00–1.18)
Lag7	0.90 (0.83–1.00)	0.94 (0.89–1.00)*	0.98 (0.95–1.00)*	1.03 (1.00–1.05)*	1.08 (1.02–1.14)*	1.12 (1.03–1.23)*
Lag14	0.97 (0.89–1.06)	0.98 (0.92–1.03)	0.99 (0.97–1.01)	1.02 (0.99–1.04)	1.05 (0.99–1.11)	1.08 (0.99–1.18)
Lag21	1.05 (0.97–1.14)	1.02 (0.98–1.06)	1.00 (0.98–1.02)	1.00 (0.97–1.02)	0.97 (0.92–1.01)	0.93 (0.84–1.02)
Female						
Lag0	0.95 (0.81–1.12)	0.95 (0.87–1.04)	0.97 (0.94–1.01)	1.02 (0.98–1.06)	0.99 (0.91–1.08)	0.93 (0.80–1.07)
Lag1	0.95 (0.82–1.10)	0.95 (0.87–1.03)	0.97 (0.94–1.01)	1.02 (0.99–1.06)	1.00 (0.92–1.08)	0.95 (0.83–1.08)
Lag2	0.95 (0.83–1.08)	0.95 (0.88–1.03)	0.97 (0.94–1.00)	1.02 (0.99–1.05)	1.01 (0.94–1.08)	0.96 (0.85–1.09)
Lag3	0.94 (0.83–1.07)	0.95 (0.88–1.02)	0.97 (0.95–1.00)	1.02 (0.99–1.05)	1.01 (0.95–1.08)	0.98 (0.88–1.09)
Lag7	0.94 (0.82–1.06)	0.95 (0.88–1.03)	0.98 (0.95–1.01)	1.02 (0.99–1.05)	1.04 (0.96–1.12)	1.05 (0.93–1.18)
Lag14	0.94 (0.84–1.06)	0.96 (0.90–1.04)	0.99 (0.96–1.02)	1.01 (0.98–1.05)	1.04 (0.97–1.12)	1.07 (0.95–1.20)
Lag21	0.98 (0.88–1.10)	0.99 (0.94–1.05)	1.00 (0.97–1.02)	1.00 (0.97–1.03)	1.00 (0.94–1.07)	1.00 (0.88–1.13)
Age <65 years						
Lag0	0.97 (0.81–1.15)	0.95 (0.86–1.05)	0.97 (0.93–1.01)	1.04 (1.00–1.08)	1.08 (0.99–1.19)	1.10 (0.94–1.29)
Lag1	0.97 (0.83–1.14)	0.96 (0.87–1.05)	0.97 (0.94–1.01)	1.03 (1.00–1.07)	1.07 (0.99–1.17)	1.09 (0.95–1.26)
Lag2	0.98 (0.84–1.13)	0.96 (0.88–1.05)	0.98 (0.94–1.01)	1.03 (0.99–1.07)	1.06 (0.98–1.15)	1.08 (0.95–1.23)
Lag3	0.98 (0.85–1.12)	0.97 (0.89–1.05)	0.98 (0.95–1.01)	1.03 (0.99–1.06)	1.06 (0.98–1.14)	1.07 (0.95–1.21)
Lag7	1.00 (0.87–1.15)	0.99 (0.91–1.08)	0.99 (0.96–1.03)	1.01 (0.98–1.05)	1.03 (0.94–1.12)	1.04 (0.91–1.18)
Lag14	1.04 (0.91–1.18)	1.02 (0.94–1.10)	1.00 (0.97–1.03)	1.00 (0.97–1.04)	1.00 (0.92–1.09)	1.00 (0.88–1.14)
Lag21	1.09 (0.97–1.24)	1.03 (0.97–1.10)	1.00 (0.97–1.03)	1.01 (0.98–1.04)	1.00 (0.93–1.08)	0.99 (0.86–1.13)
Age ≥65 years						
Lag0	0.88 (0.78–0.99)*	0.92 (0.86–0.98)*	0.97 (0.94–0.99)*	1.02 (1.00–1.05)	1.01 (0.95–1.07)	0.96 (0.87–1.07)
Lag1	0.88 (0.79–0.98)*	0.92 (0.87–0.98)*	0.97 (0.94–0.99)*	1.02 (1.00–1.05)	1.02 (0.96–1.08)	0.98 (0.90–1.08)
Lag2	0.88 (0.80–0.97)*	0.92 (0.87–0.97)*	0.97 (0.95–0.99)*	1.03 (1.00–1.05)*	1.03 (0.98–1.09)	1.01 (0.93–1.10)
Lag3	0.88 (0.81–0.97)*	0.92 (0.87–0.97)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.04 (0.99–1.09)	1.04 (0.96–1.12)
Lag7	0.89 (0.81–0.98)*	0.93 (0.88–0.98)*	0.97 (0.95–0.99)*	1.03 (1.01–1.05)*	1.08 (1.02–1.14)*	1.12 (1.03–1.22)*
Lag14	0.93 (0.86–1.01)	0.95 (0.91–1.00)	0.98 (0.96–1.00)	1.02 (1.00–1.04)	1.06 (1.01–1.12)*	1.11 (1.02–1.21)*
Lag21	1.00 (0.92–1.08)	1.00 (0.96–1.04)	1.00 (0.98–1.02)	0.99 (0.97–1.01)	0.97 (0.92–1.01)	0.94 (0.86–1.02)

RR relative risk, *CI* confidence interval

* $P < 0.05$

further studies to check whether there was an interaction between temperature change and mean temperature on human health.

In conclusion, we found that temperature increase between neighboring days may be a risk factor of mortality from non-accidental and cardiovascular diseases, particularly for males and people aged 65 years or older. Along with the continuing climate change, unstable weather patterns (e.g., a sudden drop or increase in temperature) are more likely to occur in the coming decades, it will be necessary to develop effective adaption strategies to protect vulnerable groups from being adversely affected by the sudden temperature change.

Acknowledgments This work was funded by Anhui Natural Science Fund (No. 1408085MH159). We thank Jian Song, Yangyang Zhou, and Liangliang Guo for their valuable comments.

Conflict of interest The authors report no conflict of interest.

References

Barnett AG (2007) Temperature and cardiovascular deaths in the US elderly: changes over time. Epidemiology 18(3):369–372

Basu R (2009) High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ Health 8:40

Bell ML, O'Neill MS, Ranjit N, Borja-Aburto VH, Cifuentes LA, Gouveia NC (2008) Vulnerability to heat-related mortality in Latin America: a case-crossover study in Sao Paulo, Brazil, Santiago, Chile and Mexico City Mexico. Int J Epidemiol 37(4):796–804

Bouchama A, Knochel JP (2002) Heat stroke. N Engl J Med 346(25):1978–1988

Carder M, McNamee R, Beverland I, Elton R, Cohen GR, Boyd J, Agius RM (2005) The lagged effect of cold temperature and wind chill on cardiorespiratory mortality in Scotland. Occup Environ Med 62(10):702–710

Cheng J, Xu Z, Zhu R, Wang X, Jin L, Song J, Su H (2014) Impact of diurnal temperature range on human health: a systematic review. Int J Biometeorol. doi:10.1007/s00484-014-0797-5

Curriero FC, Heiner KS, Samet JM, Zeger SL, Strug L, Patz JA (2002) Temperature and mortality in 11 cities of the eastern United States. Am J Epidemiol 155(1):80–87

Epstein PR (2005) Climate change and human health. N Engl J Med 353(14):1433–1436

Faergeman O (2008) Climate change, disease and public health. Ugeskr Laeger 170(35):2667–2668

Gasparrini A (2011) Distributed lag linear and non-linear models in R: the package dlnm. J Stat Softw 43(8):1–20

Gasparrini A (2013) Distributed lag non-linear models in R: the package dlnm. http://cran.r-project.org/web/packages/dlnm/vignettes/dlnmOverview.pdf. Accessed 17 Mar 2014

Gasparrini A, Armstrong B, Kenward MG (2010) Distributed lag non-linear models. Stat Med 29(21):2224–2234

Goldberg MS, Gasparrini A, Armstrong B, Valois MF (2011) The short-term influence of temperature on daily mortality in the temperate climate of Montreal Canada. Environ Res 111(6):853–860

Green RS, Basu R, Malig B, Broadwin R, Kim JJ, Ostro B (2010) The effect of temperature on hospital admissions in nine California counties. Int J Public Health 55(2):113–121

Guo Y, Barnett AG, Yu W, Pan X, Ye X, Huang C, Tong S (2011) A large change in temperature between neighbouring days increases the risk of mortality. PLoS One 6(2):e16511

Guo Y, Punnasiri K, Tong S (2012) Effects of temperature on mortality in Chiang Mai city, Thailand: a time series study. Environ Health 11:36

Guo Y, Barnett AG, Tong S (2013) Spatiotemporal model or time series model for assessing city-wide temperature effects on mortality ? Environ Res 120:55–62

Huang C, Barnett AG, Wang X, Tong S (2012) Effects of extreme temperatures on years of life lost for cardiovascular deaths: a time series study in Brisbane Australia. Circ Cardiovasc Qual Outcomes 5(5):609–614

IPCC (2013) Summary for policymakers. In: Climate change 2013: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge

Kenney WL, Hodgson JL (1987) Heat tolerance, thermoregulation and ageing. Sports Med 4(6):446–456

Kjellstrom T, McMichael AJ (2013) Climate change threats to population health and well-being: the imperative of protective solutions that will last. Glob Health Action 6:20816

Lim YH, Park AK, Kim H (2012) Modifiers of diurnal temperature range and mortality association in six Korean cities. Int J Biometeorol 56(1):33–42

Lin H, Zhang Y, Xu Y, Xu X, Liu T, Luo Y, Xiao J, Wu W, Ma W (2013) Temperature changes between neighboring days and mortality in summer: a distributed lag non-linear time series analysis. PLoS One 8(6):e66403

McGeehin MA, 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(Suppl 2):185–189

Schneider A, Schuh A, Maetzel FK, Ruckerl R, Breitner S, Peters A (2008) Weather-induced ischemia and arrhythmia in patients undergoing cardiac rehabilitation: another difference between men and women. Int J Biometeorol 52(6):535–547

WHO (2008) (World Health Organization) Protecting Health from Climate Change—World Health Day 2008

Yang J, Ou CQ, Ding Y, Zhou YX, Chen PY (2012) Daily temperature and mortality: a study of distributed lag non-linear effect and effect modification in Guangzhou. Environ Health 11:63

Yang J, Liu HZ, Qu CQ, Lin GZ, Zhou Q, Shen GC, Chen PY, Guo Y (2013) Global climate change: impact of diurnal temperature range on mortality in Guangzhou, China. Environ Pollut 175:131–136

Zanobetti A, O'Neill MS, Gronlund CJ, Schwartz JD (2012) Summer temperature variability and long-term survival among elderly people with chronic disease. Proc Natl Acad Sci USA 109(17):6608–6613

Zhang Y, Li S, Pan X, Tong S, Jaakkola JJ, Gasparrini A, Guo Y, Wang S (2014) The effects of ambient temperature on cerebrovascular mortality: an epidemiologic study in four climatic zonesin China. Environ Health 13(1):24