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The temperature–mortality relationship in China: An analysis from 66 Chinese communities

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ABSTRACT

Background: Previous studies examining temperature–mortality associations in China focused on a single city or a small number of cities. A multi-city study covering different climatic zones is necessary to better understand regional differences in temperature risk on mortality in China.
Methods: Sixty-six communities from 7 regions across China were included in this study. We first used a Distributed Lag Non-linear Model (DLNM) to estimate community-specific effects of temperature on non-accidental mortality during 2006–2011. A multivariate meta-analysis was then applied to pool the estimates of community-specific effects.
Results: A U-shaped curve was observed between temperature and mortality at the national level in China, indicating both low and high temperatures were associated with increased mortality risk. The overall threshold was at about the 75th percentile of the pooled temperature distribution. The relative risk was 1.61 (95% CI: 1.48–1.74) for extremely cold temperature (1st percentile of temperature), and 1.21 (95% CI: 1.10–1.34) for extreme hot temperature (99th percentile of temperature) at lag 0–21 days. The temperature–mortality relationship is different for different regions. Compared with north China, south China had a higher minimum mortality temperature (MMT), and there was a larger cold effect in the more southern parts of China and a more pronounced hot effect in more northern parts.
Conclusions: Both cold and hot temperatures increase mortality risk in China, and the relationship varies geographically. Our findings suggest that public health policies for climate change adaptation should be tailored to the local climate conditions.

1. Introduction

There have been numerous epidemiological studies to investigate the health impacts of extreme temperatures, especially in developed countries (Analitis et al., 2008; Anderson and Bell, 2009; Armstrong et al., 2011; Basu, 2009; Martin et al., 2012). Generally, the temperature–mortality relationship is found to be V-, U- or J-shaped, with increased mortality at temperatures below or above a temperature threshold (Guo et al., 2013; Lin et al., 2013; Martin et al., 2012). However, the temperature-mortality relationship varies greatly by geographic location, climate pattern and socioeconomic status (Analitis et al., 2008; Anderson and Bell, 2009; Curriero et al., 2002; Son et al., 2011).

Many previous studies examining temperature–mortality relationships focused on a single city or a small number of cities in China (Guo et al., 2011; Lan et al., 2012; Lin et al., 2011; Yang et al., 2013b). Recent multi-city studies have used a two-stage analysis approach (Analitis et al., 2008; Anderson and Bell, 2009; Armstrong et al., 2011; Martin et al., 2012; Medina-Ramon and Schwartz, 2007). In the first stage, the city-specific exposure–response relationship was estimated

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through a regression model. These estimates were then combined through a traditional meta-analysis in the second stage. However, the non-linear temperature–mortality relationship requires more sophisticated meta-analytical approaches capable of handling the multivariate nature of the summary estimates(Gasparrini et al., 2012). Multivariate meta-analysis, an approach to pooling estimates of multi-parameter associations, is useful to combine the nonlinear association of the temperature–mortality. In 2012, Gasparrini and colleagues provided detail on the use of multivariate meta-analysis within R soft ware (Gasparrini and Armstrong, 2013; Gasparrini et al., 2012).

China is the world's most populous country, with a population of over 1.35 billion. The climate differs from region to region because of the country's complex topography. In the past 100 years, the annual mean temperature increased by 0.5–0.8 °C, and will continue to increase in the next 100 years with more intense and frequent extreme weather events according to the report of the Chinese National Development and Reform Commission (Kan, 2011). In recent years, researchers have estimated the impacts of weather variation on mortality in China (Chen et al., 2013; Guo et al., 2013; Liu et al., 2013; Wang et al., 2014; Wu et al., 2013; Yang et al., 2013b), however most studies have been based on a single city or only a few cities, which do not represent the wide range of climatic, socio-demographic and cultural characteristics of China. In addition, most studies used the traditional linear threshold modeling strategy, which is based on linear assumptions of the exposure–response shape or, alternatively, only provide a partial picture of possibly complex dependencies and cannot well capture the relationship between temperature and mortality (Gasparrini et al., 2012). Therefore, a multi-city study using advanced statistical modeling techniques is warranted to provide a better understanding of the mortality risk of temperature in different regions of China and hence develop intervention strategies and adaptation planning to prevent adverse health effects of extreme temperatures.

In this study, we employed a multivariate meta-analysis to describe the temperature–mortality relationships at national and regional level in China. The findings will provide useful information to develop an effective response to the climate change projections for temperature in China.

2. Material and methods

2.1. Data collection

The China's Disease Surveillance Points system (DSPs) administrated by the Chinese Center for Disease Control and Prevention (China CDC) is a set of 161 communities (each community is a county or a set of districts of a city) chosen to be nationally representative (Zhou et al., 2010). The DSPs record all death sand population at each site and yields a nationally representative annual sample of deaths (Yang et al., 2005; Zhou et al., 2010). In order to assure enough daily death counts in model fitting of time series analysis, the current study was constrained to only 66 points when population size was over 200,000. The selected 66 communities are distributed across seven geographical regions of China: northeast China (Heilongjiang, Liaoning, Jilin), north China (Beijing, Tianjin, Hebei, Shanxi, Neimenggu), northwest China (Shanxi, Gansu, Ningxia, Xinjiang, Qinghai), east China (Jiangsu, Zhejiang, Anhui, Shandong and Shanghai), central China (Henan, Hubei, Hunan and Jiangxi), southwest China (Sichuan, Xizang, Guizhou, Yunnan and Chongqing), and south China (Fujian, Guangdong and Guangxi). The numbers of communities included in each region were 7, 8, 8, 16, 9, 11 and 7, respectively (Fig. 1). The 66 communities are home to 44.3 million inhabitants.

Fig. 1. Distribution of 66 Chinese communities included in the present study.

Community-specific daily non-accidental mortality data from 1 January 2006 through 31 December 2011 were obtained from DSPs. A death, whether it occurs at home or in a hospital must be reported to the local CDC. In both situations, the hospital or community/village doctors complete a standard death certificate. The information is then reported to China CDC through a network reporting system. Non-accidental causes of deaths were categorized using codes A00–R99 from the International Classification of Diseases 10th Revision (ICD–10).

Community-specific daily meteorological data for the same period were retrieved from the publicly accessible China National Weather Data Sharing System (http://cdc.cma.gov.cn/home.do). This dataset was compiled from national surface information-based monthly reports submitted by each province of China. Meteorological data for each community was obtained from one basic-reference surface weather observation station or automatic station. Meteorological data included daily mean temperature (T_m), maximum temperature (T_{max}), minimum temperature (T_{min}) and relative humidity (rh).

2.2. Statistical analysis

We used a two stage approach to analyze data in the present study. In the first stage, a quasi-Poisson regression model combined with Distributed Lag Non-linear Model (DLNM) was used to estimate community-specific temperature–mortality relationship. In the analysis model, the temperature–mortality association was estimated by a cross-basis function defined by a B-spline for the space of temperature. We defined natural cubic spline bases with 5 degrees of freedom (*df*) for temperature and 4 *df* for lag spaces. In the present study, to cover the tails of the distribution, we placed the 3 knots (10th–50th–90th percentiles) for temperature in the model. The knots for the lag were placed at equally-spaced values in the lag scale. The *df* for long-term trend and seasonal variation was identified as 9/year, and the *df* for relative humidity (rh) was identified as 3 days of the week were controlled using categorical variable. The initial dose–response curve suggested that cold effect last for about three weeks, so we used 21 days as the maximum lag for temperature according to previous studies (Gasparrini and Armstrong, 2013).

The multivariate meta-analysis of temperature–mortality associations requires that the temperature is measured on the same scale in all communities. However, there were different temperature ranges for the 66 communities. For example, the mean