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Assessment of heat- and cold-related emergency department visits in cities of China and Australia: Population vulnerability and attributable burden

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ABSTRACT

Background: Non-optimal ambient temperature has detrimental impacts on mortality worldwide, but little is known about the difference in population vulnerability to non-optimal temperature and temperature-related morbidity burden between developing and developed countries.
Objectives: We estimated and compared the associations of emergency department visits (EDV) with non-optimal temperature in terms of risk trigger temperature, the average slope of exposure-risk function and attributable risk in 12 cities from China and Australia.
Methods: We modelled the associations of EDV with heat during warm season and with cold during cold season, separately, using generalized additive model. Population vulnerability within a given region was quantified with multiple risk trigger points including minimum risk temperature, increasing risk temperature and excessive risk temperature, and average coefficient of exposure-risk function. Fraction of EDV attributable to heat and cold was also calculated.
Results: We found large between- and within-country contrasts in the identified multiple risk trigger temperatures, with higher heat and cold trigger points, except excessive risk temperature, observed in Australia than in China. Heat was associated with a relative risk (RR) of 1.009 [95% confidence interval (CI):1.007, 1.011] in China, which accounted for 5.9% of EDV. Higher RR of heat was observed in Australia (1.014, 95% CI: 1.010, 1.018), responsible for 4.0% of EDV. For cold effects, the RR was similar between two countries, but the attributable fraction was higher in China (9.6%) than in Australia (1.5%).
Conclusions: Exposure to heat and cold had adverse but divergent impacts on EDV in China and Australia. Further mitigation policy efforts incorporating region-specific population vulnerability to temperature impacts are necessary in both countries.

1. Introduction

Non-optimal outdoor temperature is a well-documented hazard to human health across the globe (Gasparrini et al., 2015; Huang et al., 2011; Ye et al., 2012). Exposure to either heat or cold has been associated with increases in a wide range of cause-specific deaths and illnesses (Seltenrich, 2015; Petitti et al., 2016), but only until recently has the disease burden caused by non-optimal temperature been quantified (Gasparrini et al., 2015; Carmona et al., 2016; Yang et al., 2016). Accumulating evidence suggests that a large proportion of deaths can be attributable to non-optimal temperature in many countries (Gasparrini et al., 2015; Yang et al., 2016). However, data on morbidity attributable to non-optimal temperature are limited so far (Cheng et al., 2016; Tian et al., 2016).

It is also evident that temperature disproportionally affects populations within and between countries (Gasparrini et al., 2015; Carmona

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et al., 2016; Nordio et al., 2015), but the root causes for geographically distinct temperature impacts, especially the population vulnerability indicators such as temperature thresholds under different weather conditions and average slope of exposure-risk function, have been rarely investigated (Petitti et al., 2016). Many factors such as population density, green space coverage and socioeconomic status may play an important role in altering the population vulnerability within a region (Dang et al., 2017; Hondula and Barnett, 2014; Hondula et al., 2012), and ultimately, the overall impacts of these factors, either protective or negative, can be monitored through detecting the "turning point" (also referred to as temperature threshold or minimum mortality temperature) in temperature-health relationship (Gasparrini et al., 2015; Åström et al., 2016). However, the inconsistent methodologies employed to detect temperature threshold make it difficult to measure and compare population vulnerability and temperature-induced disease burden across regions (Petitti et al., 2016). To improve human resilience and the effectiveness of public health response mechanisms about when to issue weather warnings and to guide proper public health interventions, in addition to identifying a single temperature threshold, as in most previous studies, the investigation of other risk trigger temperatures that reflect the different severities of temperature effects is also crucial (Petitti et al., 2016). An increasing number of studies have looked into temperature and health outcomes, but most of them have focused on mortality. Additionally, few studies have specifically examined the difference in temperature impacts between developing and developed regions. Therefore, quantifying and comparing morbidity events attributable to non-optimal temperature in different settings are strongly warranted.

This paper estimated and compared the heat- and cold-related population vulnerability and attributable burden, using emergency department visits (EDV) data from multiple cities in China and Australia. It also attempted to identify multiple risk trigger temperatures, estimate the average slope of exposure-risk function, and quantify the emergency department events associated with non-optimal temperature.

2. Methods

2.1. Data collection

This study included six cities (Beijing, Shanghai, Guangzhou, Hefei, Jinan, Hangzhou) from China and six cities (Brisbane, Cairns, Mackay, Mount Isa, Rockhampton, Townsville) from Queensland, Australia (Supplementary Fig. S1). These cities were selected because they are located in northern and southern hemispheres, and developing and developed countries, with diverse characteristics such as climate and socioeconomic development. We obtained daily time series data on EDV and weather variables for each city in different periods between 2010 and 2015. The details of these data were partly described in previous studies (Chen et al., 2017; Xu et al., 2017), with additionally longer time series in China and more cities in Australia analysed for this study. Description of the data is shown in the appendix (see Supplemental Material, p.2). Considering the broad influence of temperature on disease spectrum (Seltenrich, 2015; Petitti et al., 2016), we used all-cause EDV for analysis to reflect the strength of overall temperature impacts. Mean daily temperature was chosen as the exposure index (Guo et al., 2014; Gasparrini et al., 2015).

2.2. Statistical analysis

2.2.1. Stage-I: exposure-response relationships with cold and heat

Within each city we estimated the association between EDV and temperature using generalized additive model (GAM). To minimize the confounding effects of season-related factors on the strength of association, we restricted the analysis of cold to the cold season, and analysis of heat to warm season (Petitti et al., 2016). Heat or cold stress that occurs in other period was believed to be sporadic, within the category of short-term temperature variability such as sudden temperature changes or deviations within several days (Cheng et al., 2017; Guo et al., 2016). As China and Australia are located in different hemispheres, the definitions of warm and cold seasons are exactly opposite. May to September was considered the warm season in China and the cold season in Australia, and November to March the cold season in China and the warm season in Australia (Ma et al., 2015; Li et al., 2017; Tong et al., 2015; Guo, 2017; Cheng et al., 2016; William et al., 2013; Barnett et al., 2005).

Separate quasi-Poisson GAM was used to examine relationships of EDV with heat during warm season, and with cold during cold season. Since there is convincing evidence that heat effects on acute health events occur immediately and persist within 24 h (Bhaskaran et al., 2012; Guo, 2017), and modelling the association of EDV with the current day's temperature produced the best model fit in all cities as judged by the lowest value of generalized cross-validation (GCV) score, the heat-EDV relationship was examined for the current day (lag 0). But the association with cold was examined over the lag of 27 days (lag 0–27) considering the delayed and long-lasting cold effects (Zhao et al., 2017). The used GAM took the form:

$$\log(EDV) = \alpha + \mathrm{s}(Tem, k = 4) + s(DTR, k = 4) + \mathrm{year} + \mathrm{month} + \mathrm{ns(day)} + \mathrm{dow} \quad (1)$$

where EDV is the observed daily counts of emergency department visits; α is the intercept; s() is the fitted thin-plate regression spline with k-1 degrees of freedom for the temperature (cold or heat) (Petitti et al., 2016), as well as for an independent risk factor - diurnal temperature range, which was calculated as the difference between the maximum and minimum temperature within a day (Cheng et al., 2014). Other confounding factors were also controlled for, including between-year variation with "year" as the factor term, between- and within-month variations with "month" as the factor term and natural cubic spline (ns) for the "day" of each month, and day of week with "dow" as the categorical variable.

This model parameter setting was in line with many previous studies (Petitti et al., 2016; Tong et al., 2015), and model fit was also validated by the lowest generalized cross-validation (GCV) value, and approximately normal and random distribution of model residuals over time for most regions included.

We slightly modified the methods proposed by Curriero et al. (2002), Gasparrini et al. (2015), and Petitti et al. (2016), and identified three different risk trigger temperatures at which weather-health warning system and intervention measures may be activated or triggered (Box 1). Briefly, minimum risk temperature (MRT), increasing risk temperature (IRT), and excess risk temperature (ERT), respectively reflecting various risk levels under different weather conditions, were defined and detected based on the fitted exposure-response curves (Petitti et al., 2016). It is worth noting that the risk within temperature range towards the extremes of heat and cold was not considered at this stage, because in reality under extreme weather conditions some regions might have already taken protective measures or there were relatively fewer health events, causing non-significant or decreased risk. Therefore, the exposure-risk association estimation and identification of different risk trigger points had the potential of important implications for practice prevention against adverse weather conditions (Petitti et al., 2016).

2.2.2. Stage-II: average slope of temperature-risk association

To quantify and compare the risk of heat or cold across the whole temperature distribution under study, the slope of exposure-response curve above or below MRT was estimated, instead of previously commonly used approach investigating the temperature effects at single or several cut-offs of temperature distribution such as 99th vs 90th for heat or 10th vs 25th for cold (Ban et al., 2017; Chen et al., 2013). In present study piece-wise linear quasi-Poisson regression model was