Environmental Pollution xxx (2015) 1–8

Contents lists available at ScienceDirect

Environmental Pollution

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

Projecting future temperature-related mortality in three largest Australian cities

Yuming Guo [a, *], Shanshan Li [a], De Li Liu [b], Dong Chen [c], Gail Williams [a], Shilu Tong [d]

[a] Division of Epidemiology and Biostatistics, School of Public Health, The University of Queensland, Queensland 4006, Australia
[b] NSW Department of Industry, Skills and Regional Development, WaggaWagga Agricultural Institute, New South Wales 2650, WaggaWagga, Australia
[c] Ecosystem Sciences, CSIRO, Melbourne, Victoria 3190, Australia
[d] School of Public Health and Social Work, Queensland University of Technology, Brisbane, Queensland 4059, Australia

ARTICLE INFO

Article history:
Received 30 May 2015
Received in revised form
3 August 2015
Accepted 15 September 2015
Available online xxx

Keywords:
Climate change
Temperature
Mortality
Projection

ABSTRACT

We estimated net annual temperature-related mortality in Brisbane, Sydney and Melbourne in Australia using 62 global climate model projections under three IPPC SRES CO_2 emission scenarios (A2, A1B and B1). In all cities, all scenarios resulted in increases in summer temperature-related deaths for future decades, and decreases in winter temperature-related deaths. However, Brisbane and Sydney will increase the net annual temperature-related deaths in the future, while a slight decrease will happen in Melbourne. Additionally, temperature-related mortality will largely increase beyond the summer (including January, February, March, November and December) in Brisbane and Sydney, while temperature-related mortality will largely decrease beyond the winter in Melbourne. In conclusion, temperature increases for Australia are expected to result in a decreased burden of cold-related mortality and an increased burden of heat-related mortality, but the balance of these differences varied by city. In particular, the seasonal patterns in temperature-related deaths will be shifted.

1. Background

Climate change is the greatest global health challenge in the 21st century, as it will directly or indirectly affect most populations (Costello et al., 2009). A number of future climate change scenarios have been developed by the Intergovernmental Panel on Climate Change (IPCC) (Nakicenovic et al., 2000). These scenarios have shown that global average temperature will undoubtedly increase, but the magnitude of temperature increases will vary with region. It has projected that the frequency, intensity and duration of heat waves will increase, and unstable weather patterns will also likely occur in the coming decades (IPCC, 2007). Therefore, projecting the future temperature-related mortality has become a matter of increasing public health significance (Gasparrini et al., 2015a, 2015b).

Both hot and cold temperatures increase the risk of mortality (Stafoggia et al., 2006). Thus the temperature-mortality relations usually have a J-, V- or U-shape (Guo et al., 2014, 2013b), which means that increased temperatures should reduce cold-related mortality, while heat-related mortality will increase as climate change progresses. So, the increased mortality in warm seasons might be offset by decreased mortality in cold seasons. Therefore, it is urgent to assess the net impact of climate change-related mortality risks.

Some studies have projected temperature-related mortality for specific seasons (e.g., winter or summer separately) under future climate change scenarios (Dessai, 2003; Doyon et al., 2008; Hayhoe et al., 2004; Knowlton et al., 2007; McMichael, 2003). However, only few studies have considered whether the rise in heat-related mortality would be compensated by the reduction of cold-related deaths (Ballester et al., 2011; Doyon et al., 2008; Li et al., 2013; Martin et al., 2012). Also, most of these studies used a linear function to project temperature-related mortality, which may lead to no precise outcomes because the true temperature–mortality relationship is non-linear (Guo et al., 2011).

Australia is located in southern hemisphere and its average temperature has risen by about 0.7 °C from 1910 to 1999, with most of this increase occurring after 1950. It is projected that temperature will increase by 0.5 °C–2.0 °C by 2030 and by 1.0 °C–6.0 °C by 2070 (McMichael, 2003). However, no study has projected the future temperature–mortality relationship after taking into

* Corresponding author. Division of Epidemiology and Biostatistics, School of Public Health, The University of Queensland, Brisbane, Queensland 4006, Australia.
E-mail address: y.guo1@uq.edu.au (Y. Guo).

http://dx.doi.org/10.1016/j.envpol.2015.09.041
0269-7491/

account the non-linear feature of the temperature-mortality pattern, trade off of cold- and heat-related mortality. Also, no study has considered the seasonal change in temperature-related mortality.

Therefore, this study aimed to assess the baseline non-linear relation between temperature and mortality, and project the future temperature-related mortality in three biggest Australian cities – Brisbane, Sydney and Melbourne as urban areas are particularly vulnerable to heat because of high concentrations of susceptible people and the urban heat island effect (Huang et al., 2011). These three cities have different climatic patterns (Brisbane, subtropical; Sydney, temperate climate; and Melbourne, moderate oceanic climate). In this study, we used 62 downscaled global climate models (GCMs) under three SRES CO_2 emissions scenarios (A2, A1B and B1) (Supplemental material Table S1 for names of GCMS).

2. Methods

Firstly, we estimated the city-specific temperature–response relationship in Brisbane, Sydney, and Melbourne in Australia. Secondly, we modelled daily temperatures using 62 downscaled global climate models and three emissions scenarios (A2, A1B and B1) based on outputs from the IPCC Fourth Assessment report. Thirdly, we combined the baseline temperature–mortality relationship and future climate change scenarios to estimate future daily temperature-related mortality. We calculated future cold-related and heat-related mortality, and net annual changes, respectively. Finally, we computed monthly changes in the future temperature-related mortality compared with the baseline monthly temperature-related mortality.

2.1. Historical data collection

We collected historical data on daily non-accidental deaths in Brisbane, Sydney, and Melbourne between 1988 and 2009 from Australian Bureau of Statistics. Non-accidental deaths were coded by ICD-9 codes (0–799.9 before 2004) and ICD-10 codes (A00-R99 after 2004). We collected population data from Australian Bureau of Statistics. Daily data on maximum temperature and relative humidity were collected from Australian Bureau of Meteorology. The stations were located at the urban city of the three studied cities.

2.2. Baseline temperature–mortality relationship

A Poisson regression model with distributed lag non-linear model was used to estimate the city-specific association between daily maximum temperature and mortality. The city-specific Poisson time series model is given as the following:

$$Y_t \sim \text{Poisson}(\mu t), log(\mu_t) = \alpha + \beta T_{t,l} + \boldsymbol{\mu} RH_{t,l} + NS(time, df) + \lambda \text{DOW}_t + \text{offset}(\text{LOGPOP}), \quad (1)$$

where Y_t is the observed daily death count on day t; α is the intercept; $T_{t,l}$ is a matrix of variables obtained by distributed lag non-linear model for daily maximum temperature, $\boldsymbol{\beta}$ is vector of coefficients for $T_{t,l}$, and l is the lag days; $RH_{t,l}$ is a matrix of variables obtained by distributed lag non-linear model for daily relative humidity, $\boldsymbol{\mu}$ is vector of coefficients for $RH_{t,l}$. $NS(time, df)$ is natural cubic spline of time, and df is degree of freedom per year for time, which was used to control for long-term trend and seasonality. DOW_t is a categorical variable for day of the week, and λ is vector of coefficients. The LOGPOP is log scaled population, which was modelled using an offset.

We used a natural cubic spline with 4 degrees of freedom for daily maximum temperature (Gasparrini et al., 2010) to examine the non-linear temperature–mortality relationship (Guo et al., 2011), and 4 degrees of freedom natural cubic spline was used for lags up to 10 days, as our sensitivity analyses showed that these degrees of freedom and 10 days' lag can fully capture the temperature–mortality relationship. A natural cubic spline with 7 degrees of freedom per year for time was used to control for long-term trends and seasonal patterns in mortality (Daniels et al., 2000). We controlled for relative humidity using the same distributed lag non-linear model as temperature.

2.3. Climate scenarios

The daily climate projections during 2000–2100 were obtained as the following. Daily climate variables of solar radiation, maximum temperature, minimum temperature and rainfall were downscaled by the approach described by Liu and Zuo (2012). The method combines spatial downscaling of monthly climate projections from archived monthly GCM data to specific site using an inverse interpolation method and bias corrections, and generated daily climate projections for the site using a modified version of WGEN (Richardson and Wright, 1984). Historical climate data required in the downscaling procedure are SILO patched point dataset downloaded at http://www.longpaddock.qld.gov.au/silo/ppd/index.php, while the monthly GCMs projections for radiation, maximum and minimum temperature and rainfall were downloaded from IPCC archived GCM data at PCMDI (http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php). All GCMs available under the A1B, A2 and B1 emission scenarios were used for this study, resulting in 62 projected scenarios for each site. In this study, future daily maximum temperature was used to project the future temperature-related mortality, while we assume that other climatic variables (e.g., humidity, rainfall and solar radiation) change little.

2.4. Projecting future temperature-related mortality

We projected future temperature-related mortality impacts by combining projected future daily maximum temperature and the baseline temperature–mortality relationship. The non-linear temperature–mortality relationship was not destroyed in this study. For any day with maximum temperature higher than the threshold (ie, minimum-mortality temperature), the change in mortality was calculated relative to that at the threshold temperature for the heat effect. For any day with maximum temperature lower than the threshold temperature, the change in mortality was calculated relative to that at the threshold for the cold effect. The minimum-mortality temperatures were 28 °C in Brisbane, 25 °C in Sydney and 26 °C in Melbourne. We computed city-specific daily additional deaths as:

$$\Delta Mortality = Y_b \times ERC \times POP \quad (2)$$

where:

$\Delta Mortality$ is daily temperature-related additional deaths;
Y_b is baseline daily mortality rate (per 100,000 population);
ERC is percentage change in mortality for a specified change in temperature, derived from model [1]; and
POP is population. We assumed the population in the future are the same as the baseline period, which can make the changed mortality only due to temperature itself but not the increased population.