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The effect of various temperature indicators on different mortality categories in a subtropical city of Brisbane, Australia

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Abstract

Background: The relationship between temperature and mortality has been explored for decades and many temperature indicators have been applied separately. However, few data are available to show how the effects of different temperature indicators on different mortality categories, particularly in a typical subtropical climate.

Objective: To assess the associations between various temperature indicators and different mortality categories in Brisbane, Australia during 1996–2004.

Methods: We applied two methods to assess the threshold and temperature indicator for each age and death groups: mean temperature and the threshold assessed from all cause mortality was used for all mortality categories; the specific temperature indicator and the threshold for each mortality category was identified separately according to the minimisation of AIC. We conducted polynomial distributed lag non-linear model to identify effect estimates in mortality with one degree of temperature increase (or decrease) above (or below) the threshold on current days and lagged effects using both methods.

Results: Akaike's Information Criterion was minimised when mean temperature was used for all non-external deaths and deaths from 75–84 years; when minimum temperature was used for deaths from 0–64 years, 65–74 years, ≥85 years, and from the respiratory diseases; when maximum temperature was used for deaths from cardiovascular diseases. The effect estimates using certain temperature indicators were similar as mean temperature both for current day and lag effects.

Conclusion: Different age groups and death categories were sensitive to different temperature indicators. However, the effect estimates from certain temperature indicators did not significantly differ from those from mean temperature.

Keywords: cardiovascular mortality; respiratory mortality; temperature; lag effect; the elderly

1. Background

The relationship between temperature and mortality has been well documented (McMichael et al., 2006). Generally, the association between temperature and mortality is V–, U– or J–shaped, with optimum temperature corresponding to the lowest point in the temperature–mortality effect curve (Curriero et al., 2002; Kalkstein and Davis, 1989). The models predominately used in the literature are generalised additive model (GAM) and generalised linear model (GLM) (McCullagh and Nelder, 1989) that allow researchers to fit models without specifying parametric relations between the dependent and independent variables (Ren & Tong, 2008).

Since the early 1970s, a lag effect of temperature on mortality has been increasingly recognised (Rogot and Blackwelder, 1970). The mortality of current day is often derived from exposure to today's temperatures and temperatures on several previous days or weeks (Anderson and Bell, 2009; Bi et al., 2008). Recently, the polynomial distributed lag model has been applied to explore the lag structure of temperature on mortality (Armstrong, 2006).

The existing literature has used different temperature indicators including mean temperature (MT) (Hajat et al., 2007), minimum temperature (T_{min}) (Michelozzi et al., 2000), maximum temperature (T_{max}) (Kim and Joh, 2006), apparent (mean, maximum, minimum) temperature (AT) (Michelozzi et al., 2000) and diurnal temperature ranges (DTR) (Kan et al., 2007). Some papers used more than one indicator in one article (Hajat et al., 2002; Medina-Ramon and Schwartz, 2007; Michelozzi et al., 2000). However, uncertainty remains as to which temperature indicator is most suitable for analysing the impact temperature on the various age groups and mortality categories. Moreover, these studies mainly focus on the cities in Europe and USA. Few data are available in cities in the Southern Hemisphere, where characteristics of climate, adaptation and sociodemographic patterns differ from those in northern countries.

The aim of this paper is to identify the relationship between certain temperature indicators and various mortality categories in Brisbane, Australia during 1996–2004. Better understanding the impact of different temperature indicators on different mortality categories will provide relevant information for developing public health programs and risk assessments in this similar environment.

2. Material and methods:

2.1 Data sources

Mortality data included daily non-external mortality from 1996 to 2004, supplied by the Office of Economic and Statistical Research of the Queensland Treasury. The causes of deaths were classified according to the International Classification of Disease, ninth version (ICD-9) before December 1996 and ICD-10 between December 1996 and December 2004 (ICD-9: 001–799 and ICD-10: A00–R99).

We divided all deaths into four age groups: 0-64 years (D_{0-64}), 65-74 years (D_{65-74}), 75-84 years (D_{75-84}), and ≥85 years (D_{85+}). Deaths from cardiovascular (CVD) (ICD-9:390–459; ICD-10:I00-I79) and respiratory diseases (RD) (ICD-9: 460–519; ICD-10: J00-J99) were examined separately.

Meteorological data of daily MT, T_{min}, T_{max} and relative humidity (RH) were obtained from the Australian Bureau of Meteorology. Air pollution data including mean daily ozone (O_3), particulate matter with aerodynamic diameters $\leq 10\mu m$ (PM_{10}) and nitrogen dioxide (NO_2)

were provided by the Queensland Environmental Protection Agency. Both meteorological and air pollution data were recorded in a central monitoring site of Brisbane.

2.3 Sensitivity analysis

Firstly, MT, T_{min}, T_{max}, AT and DT were chosen separately for deaths from D_{all}, $D_{0\text{-}64}$, $D_{65\text{-}74}$, $D_{75\text{-}84}$, D_{85+}, RD and CVD.

We calculated AT using the following formula:

$$AT=-2.653+0.994T+0.0153(T_{dew})^2 .$$

Where T is the air temperature and T_{dew} is the dew point temperature (Kalkstein and Valimont, 1986). AT includes mean apparent temperature, minimum apparent temperature and maximum apparent temperature depending on which T was used in the equation.

DT was calculated as:

$DT= T_{max}-T_{min}$ (Kan et al., 2007).

We compared the smoothing plots and Akaike’s Information Criterion (AIC) of the association between each temperature indicator for each mortality category using GAM models followed the method in previous studies (Hajat et al., 2002; Kim et al., 2006). We found that AIC values were much lower when mean temperature, minimum temperature and maximum temperature were used among each mortality category in the corresponding models than other temperature indicators. Thus, we selected these three temperature indicators to analyse the effect estimates in each mortality category with one degree of temperature increase (or decreases) above or below the threshold.

Secondly, the three-piece linear spline (segmented linear) function is a simpler GAM/GLM model that can be used to interpret the investigation of temperature/mortality relationships. This model divides temperature into three linear parts with hot and cold thresholds. The middle section is constrained to have a zero slope and the “V” shaped association is the special case when cold and hot thresholds are equal (Armstrong, 2006). The slopes on two sides of the minimum mortality temperature (MMT) are highly dependent on the selected threshold (Armstrong, 2006). The percent increase in mortality has often been used as the effect estimate in interregional comparisons for both hot- and cold-related mortality (The Eurowinter Group, 1997).

When each temperature indicator was applied, two types of threshold temperatures for each mortality category were explored. The threshold assessed from all cause mortality was used for all mortality categories and the specific threshold for each mortality category was identified separately according to the minimisation of AIC. We plotted the graphs of the relationship between temperature and mortality using a Poisson regression. A thin plate spline with 3 degrees of freedom was used for temperature. The initial results show that there was a V-shaped temperature-mortality relationship, and the lowest relative risk for mortality was at the temperatures between 20 °C to 30 °C. Then we used a segment spline to choose the temperature threshold, which minimised the AIC for the Poisson regression model. A similar method has been adopted in a number of previous studies (Kim et al., 2006; Chung et al., 2009, Yu et al., 2010).

2.2 Statistical analysis

The statistical analyses were based on the following equation:

$$Log(E(Death_t) =$$

$$\alpha + \beta_C(T_t - \tau_C) + \beta_H(T_t - \tau_H) + \sum_{n=1}^{b} s(conf_{tn},\ df) + \sum_{\eta=1}^{p} \gamma_{t\eta} car_{t\eta} + s(time, 7*year) \qquad [1]$$

where *t* refers to the day of the observation; *E(death$_t$)* denotes estimated daily death counts on day t; T_t is daily temperature on day t; τ_C and τ_H denote cold and hot thresholds, $\tau_C = \tau_H$ if the relationship between temperature and mortality is "V" shaped; *s*(.) denotes the smooth functions, we used thin plate regression splines (tp) available in the software of R*; conf* refers to the continuous confounders such as RH, PM_{10}, NO_2 and O_3, respectively; *car* represents categorical variables like day of the week, holidays, influenza on day *t*; α is the intercept; β and γ refer to the coefficients; df is the degrees of freedom, with three degrees of freedom for RH, air pollutants and seven degrees of freedom each year for time were used.

The polynomial distributed lag non-linear model is subject to the restriction of equation 1 as follows:

$$\beta_C(T_t - \tau_C) / \beta_H(T_t - \tau_H) = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \ldots \beta_n x_{t-n}$$

$$\beta_n = \sum_{k=O}^{d} a_k l_n{}^k , l \in [O,m] \qquad [2]$$

Where d is the degrees of freedom, l is the lags and q is the maximum number of lag days (Schwartz, 2000). To obtain flexible correlation between lag effects, we used 4 degrees of freedom polynomial to constrain the distributed lag curve (Armstrong, 2006). Sensitivity analysis showed that there were no substantial changes in results when we used 5 or 6 degrees of freedom polynomial.

The final model, as presented in equations 1 and 2, was modified accordingly to consider each of the mortality categories of interest and each of the temperature indicators (e.g. CVD and MT, CVD and T_{min}, CVD and T_{max}, and so on). The temperature indicator yielding the lowest AIC value was regarded as be the best indicator for reach of the specific age groups and mortality classifications.

Thirdly, the effect estimates among each age and death groups were identified using the polynomial distributed lag non-linear models. From the plots of the relationships between lag days and relative risks, we visualised that cold effects lasted longer than hot effects (Figure 1). In order to capture the lagged effects for all age and death categories, we selected 20 days for cold effects and 2 days for hot effects. Thus, we reported on the percent increases not only from the current day but also from the overall lag effects of 20 days for cold and 2 days for hot temperatures.

All analyses were performed in SAS 9.1 (SAS Institute Inc., Cary, NC, USA.) and R2.11.1 (The R Foundation for Statistical Computing, version 2.11.1, 2010 http://cran.r-project.org).

3. Results

3.1 Descriptive information for Brisbane data

In total, there were 53,316 deaths (22,805 CVD and 4,625 RD) registered in the study population. 82% of total deaths were the elderly aged over 65 years and 33.3% of them were aged over 85 years. During the study period, the MT, T_{min}, T_{max} and RH were 20.1°C, 15.4°C, 25.2°C, and 72.5%, respectively. The mean daily average concentrations of PM_{10}, NO_2 and O_3 were 16.6 μg/m^3, 12.1 ppb and 11.3 ppb, respectively (Table 1). The correlations between MT, T_{min} and T_{max} were statistically significant ($p<0.05$) and relatively strong (Spearman correlation coefficients (r) = 0.75-0.95) (Table 2).

3.2 The sensitivity analyses for temperature indicators and thresholds.

Among all of the temperature indicators, AIC was minimised when MT fitted for D_{all} and $D_{75\text{-}84}$ with the temperature threshold at 24 °C. T_{min} was suitable for $D_{0\text{-}64}$, D_{85+}, $D_{65\text{-}74}$ and RD. There were two turning points for the groups of $D_{0\text{-}64}$ and D_{85+}, (hot thresholds were 20°C and 23°C, and cold thresholds were 18°C and 21 °C, respectively). The thresholds for both $D_{65\text{-}74}$ and RD were 24°C and 22 °C, respectively. T_{max} was the best thermal indicator for CVD with 27 °C as the cold threshold and 30 °C as the hot threshold. AT and DT were not found to be the most suitable for any of the mortality or age categories (Table 3).

3.3 The comparison of effect estimates

In general, there were similar results when using the comparison of temperature indicators across various age and death categories. However, the cold effects on $D_{0\text{-}64}$ were different, neither for the hot effects on $D_{65\text{-}74}$ (Tables 4 & 5).

Regardless of the temperature indicators, the cold effects on D_{85+} and CVD were higher than those on D_{all}. For the group of D_{85+}, the percent increases in mortality associated with one degree increment of mean temperature and minimum temperature were 2.5% (95% CI: 1.9%, 3.1%) and 3.0% (95% CI: 2.4%, 3.7%) on current day, respectively, and 3.9% (95% CI: 1.9%, 6.0%) and 3.3% (95% CI: 1.8%, 4.9%) on 20-day lags, respectively; for the group of CVD, the percent increases in mortality associated with one degree increment of mean temperature and maximum temperature were 3.1% (95% CI: 2.5%, 3.8%) and 4.3% (95% CI: 3.3%, 5.3%) on current day, respectively, and 3.5% (95% CI: 0.9%, 6.1%) and 7.7% (95% CI: 5.4%, 10.1%) on 20-day lags, respectively.

For the hot temperature, the effect estimates were significantly higher in the mortality of D_{85+}. The overall two days' effect associated with mean temperature and minimum temperature were 5.4% (95% CI: 1.4%, 9.5%) and 22.9% (95% CI: 10.5%, 36.8%) increases in mortality, respectively).

4. Discussion

In this study, we conducted a comprehensive sensitivity analysis for selecting temperature indicators of mortality. We found that different temperature indicators were suitable for different age groups and death categories. MT is a better indicator for D_{all}. Furthermore, different age and mortality categories were sensitive to different temperature indicators. Young ages (D_{0-64}), old ages (D_{65-74}), and very old (D_{85+}) groups and RD were more sensitive to T_{min}, while the group of CVD was more sensitive to T_{max}. MT experiences through all day and all night (Hajat et al., 2002), and total deaths also happened at any time through the whole day. The compromise of the thermoregulation system with age and pre-existing diseases make the elderly more vulnerable to certain temperature stress (Stafoggia et al., 2008) and correspondingly, the optimal temperatures in each subpopulation may vary.

There are controversial results in selecting optimum temperature indicators. *Gouvia et al.* (2003) compared model likelihoods of maximum, minimum and mean temperature, which suggested that mean temperature was a better predictor of both hot and cold related mortality.

Some researchers also think mean temperature is a more accurate predictor than the maximum and minimum temperature since mean temperature goes through the whole day and night (McMichael et al., 2008; The Eurowinter Group, 1997).

Another study found a constant result where minimum temperature was more closely associated with hot effects may possibly indicate that little relief is available to persons under elevated night-time temperature, while maximum temperature was more closely associated with cold effects to capture days that are consistently cold (Kinney et al., 2008). In heat wave studies some literature used both minimum and maximum temperature in one model because the differences between minimum and maximum are very small on heat wave days (Filleul et al., 2006). However, *Díaz J, et al.* (2004) found that the maximum temperature was more closely correlated with mortality than minimum temperature in extreme cold climate events in Madrid.

Several studies have used the effects of DTR on mortality to explore the variation of daily temperature risk (Kan et al., 2007; Revich and Shaposhnikov, 2008). Recently, some indicators combined air temperature and other weather metrics to take into account physical stress experienced on days with extreme temperature and other indices (Kalkstein and Valimont, 1986; Stafoggia et al., 2009). Apparent temperature considered air temperature and dew point temperature together and some researchers regard it as a better estimate of the experienced temperature in comparison to air temperatures alone (Epstein and Moran, 2006). However, these indicators are not frequently used in temperature/mortality research and need to be further evident in future studies.

Different temperature indicators have been used in literature and no uniform criteria has been selected to identify which indicator is superior to others. In practice, researchers seem to be not as concerned about which temperature indicators are used when analysing the temperature effects on mortality (Bhaskaran et al., 2009; Hajat and Kosatsky, 2010), and usually applied the same temperature indicator and threshold for all age groups and death categories, which are easily interpreted and compared. In this research confirmed this practice that the similar results were identified when using a single MT with the threshold of 24 °C for all age and deaths groups compared to those using optimum temperatures with thresholds selected by minimising AIC for each age or death group. A recent publication has focused on the exploration of the best temperature indicators for mortality in the US cities (Barnett et al., 2010). They found that no one temperature measure was superior to others which is consistent with ours. One possible reason for this is that MT, T_{min} and T_{max} are highly related to each other and the association between temperature and mortality was relatively small (Barnett et al., 2010).

This research has several strengths. Firstly, we selected a wide range of temperature indicators to examine the impact of temperature on mortality categories and age groups. Secondly, we considered lag effects when assessing the percent increases in mortality with one-degree change of different temperature indicators. Thirdly, in modelling these data, we used AIC as a guide and not as a rigid optimization criterion. Based on the prior understanding and bioknowlegements, we considered both AIC and change in the estimated effect to compare alternative models (Samet et al., 1998). The balance of AIC, plot, model diagnosis, prior understanding and biological judgement provides a better way to choose the appropriate indicators.

However, two limitations should also be acknowledged. Firstly, the data we used was collected from one city and thus cannot be used to generalise. Secondly, because of the limitation of the data available, we could not address all issues in measures of temperature indicators, such as other temperature indicators (e.g. Steadman index=-0.52+1.04*Temperature-0.65*Wind speed (Kunst et al., 1994)).

The results from this study may contribute to research from existing articles where different temperature indicators can be compared. In addition, future relevant studies can choose temperature indicators based on practical concerns (e.g. least amount of missing data or best spatial coverage of study areas). Future studies might also explore the same research focus from multiple cities.

5. Conclusions

In summary, different age and mortality categories were sensitive to different temperature indicators. The effect estimates were similar to those using the MT with one threshold for all age and death groups.

List of abbreviations

AIC: Akaike's Information Criterion; AT: apparent temperature; $D_{0\text{-}64}$: deaths aged less than 65; $D_{65\text{-}74}$: deaths aged from 65 to 74; $D_{75\text{-}84}$: deaths aged from 75 to 84; D_{85+}: deaths aged 85 and over; D_{all}: deaths from all ages; CVD: cardiovascular deaths; T_{DEW}: dew point temperature; DF: degree of freedom; DTR: diurnal temperature range; GAM: g eneralised additive model; GLM: generalised linear model; MT: mean temperature; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with aerodynamic diameters $\leq 10\mu m$; R^2: deviance explanation rate; RD: respiratory deaths; RH: relative humidity; SD: standard deviation; T_{max}: maximum temperature; T_{min}: minimum temperature; TP: thin plate regression splines.

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Conflict of interest

We declare that we have no conflict of interest.

Authors' contributions

The first author performed all data analyses and wrote the draft. Mr. Yuming Guo contributed to major revision of the manuscript. Prof. Shilu Tong contributed to data collection, analytical protocol and the final approval of the draft. Other co-authors contributed to manuscript revision.

References

Anderson BG, Bell ML. Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiology 2009; 20: 205-13.

Armstrong B. Models for the relationship between ambient temperature and daily mortality. Epidemiology 2006; 17: 624-31.

Barnett AG, Tong S, Clements ACA. What measure of temperature is the best predictor of mortality? Environ Res 2010. Res 2010; 101:604-11.

Bhaskaran K, Hajat S, Haines A, Herrett E, Wilkinson P, Smeeth L. The effects of ambient temperature on the incidence of myocardial infarction-A systematic review. Br Med J 2009; 95: 1760-9.

Bi P, Parton KA, Wang J, Donald K. Temperature and direct effects on population health in Brisbane, 1986-1995. J Environ Health 2008; 70: 48-53.

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 155:80-87.

Díaz J, García R, Lípez Cs, Linares C, Tobías A, Prieto L. Mortality impact of extreme winter temperatures. Int J Biometeorol 2004; 49: 179-83.

Epstein Y, Moran DS. Thermal comfort and the heat stress indices. Industrial Health 2006; 44: 388-98.

Filleul L, Cassadou S, Medina S, Fabres P, Lefranc A, Eilstein D, et al. The relation between temperature, ozone, and mortality in nine French cities during the heat wave of 2003. Environ Health Perspect 2006; 114: 1344-7.

Gouveia N, Hajat S, Armstrong B. Socioeconomic differentials in the temperature-mortality relationship in Sao Paulo, Brazil. Int J Epidemiol 2003;32:390-7.

Hajat S, Kosatsky T. Heat-related mortality: a review and exploration of heterogeneity. Epidemiol Community Health 2010; 64:753-60.

Hajat S, Kovats RS, Atkinson RW, Haines A. Impact of hot temperatures on death in London: a time series approach. J Epidemiol Community Health 2002; 56: 367-372.

Hajat S, Kovats RS, Lachowycz K. Heat-related and cold-related deaths in England and Wales: who is at risk? Occup Environ Med 2007; 64: 93-100.

Kalkstein LS, Davis RE. Weather and human mortality: an evaluation of demographic and interregional responses in the United States. Ann Assoc Am Geogr 1989; 79: 44-64.

Kalkstein LS, Valimont KM. An evaluation of summer discomfort in the United-States using a relative climatological index. JAMA 1986; 67: 842 -8.

Kan H, London SJ, Chen H, Song G, Chen G, Jiang L, et al. Diurnal temperature range and daily mortality in Shanghai, China. Environ Res 2007; 103: 424-31.

Kim H, Ha JS, Park J. High temperature, heat index, and mortality in 6 major cities in South Korea. Arch Environ Occup Health 2006; 61: 265-70.

Kim Y, Joh S. A vulnerability study of the low-income elderly in the context of high temperature and mortality in Seoul, Korea. Sci Total Environ 2006; 371: 82-8.

Kinney PL, O'Neill MS, Bell ML, Schwartz J. Approaches for estimating effects of climate change on heat-related deaths: challenges and opportunities. Environmental science & policy 2008; 11: 87-96.

Kunst AE, Groenhof F, Mackenbach JP. The association between two windchill indices and daily mortality variations in the Netherlands. Am J Public Health 1994; 84:1738-42.

McCullagh P, Nelder J. Generalized linear models. 2nd ed. New York, NY: Chapman and Hall, Inc,1989.

McMichael AJ, Wilkinson P, Kovats RS, Pattenden S, Hajat S, Armstrong B, et al. International study of temperature, heat and urban mortality: the 'ISOTHURM' project. Int J Epidemiology 2008; 37: 1121-31.

McMichael AJ, Woodruff RE, Hales S. Climate change and human health: present and future risks. Lancet 2006; 367: 859-69.

Medina-Ramon M, Schwartz J. Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. Occup Environ Med 2007; 64: 827-33.

Michelozzi P, Fano V, Forastiere F, Barca A, Kalkstein LS, Perucci CA. Weather conditions and elderly mortality in Rome during summer. Bull World Met Org 2000; 49: 348-55.

Ren C, Tong, S. Health effects of ambient air pollution–recent research development and contemporary methodological challenges. Environmental Health 2008; 7: 56-65.

Revich B, Shaposhnikov D. Temperature-induced excess mortality in Moscow, Russia. Int J Biometeorol 2008; 52:367-74.

Rogot E, Blackwelder WC. Associations of cardiovascular mortality with weather in Memphis, Tennessee. Public Health Reports 1970; 85: 25-40.

Samet J, Zeger S, Kelsall J, Xu J, Kalkstein L. Does Weather Confound or Modify the Association of Particulate Air Pollution with Mortality?: An Analysis of the Philadelphia Data, 1973-1980. Environ Res 1998; 77: 9-19.

Schwartz J. The Distributed Lag between Air Pollution and Daily Deaths. Epidemiology 2000; 11: 320-6.

Stafoggia M, Forastiere F, Agostini D, Caranci N, de'Donato F, Demaria M, et al. Factors affecting in-hospital heat-related mortality: a multi-city case-crossover analysis. J Epidemiol Community Health 2008; 62: 209-15.

Stafoggia M, Forastiere F, Michelozzi P, Perucci CA. Summer temperature-related mortality: effect modification by previous winter mortality. Epidemiology 2009; 20: 575-583.

The Eurowinter Group. Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe. The Eurowinter Group. Lancet 1997; 349: 1341-6.

Yu W, Vaneckova P, Mengersen K, Pan X, Tong S. Is the association between temperature and mortality modified by age, gender and socio-economic status? Sci Total Environ 2010; 408: 3513-8.

Table 1. Characteristics of daily mortality, weather condition and air pollutants in Brisbane between 1996 and 2004 (n=3,274 days).

			Percentile			
	Mean(SD)	Minimum	25%	50%	75%	Maximum
No. of daily deaths						
Total (non-external)	16.6 (4.5)	1	14	16	20	43
0-64	3.1 (1.6)	1	2	3	4	12
65-74	3.0 (1.6)	1	2	3	4	11
75-84	5.4 (2.4)	1	4	5	7	18
≥85	5.6 (2.6)	1	4	5	7	23
CVD	6.9 (3.0)	0	5	7	9	31
RD	1.4(1.3)	0	0	1	2	8
Meteorological measures						
24-h MT (°C)	20.1 (4.0)	9.8	16.8	20.5	23.4	31.9
T_{min} (°C)	15.4	1.6	11.8	16.0	19.4	28.1
T_{max} (°C)	25.2 (3.5)	11.8	22.6	22.3	27.9	25.3
RH (%)	72.5 (10.8)	23.8	67.1	73.6	79.6	98.4
Air pollutant concentration						
PM_{10} (µg/m^3)	16.6 (7.9)	2.1	12.1	15.3	19.3	162.1
NO_2 (ppb)	12.1 (5.8)	2.0	8	11	16	35.8
O_3 (ppb)	11.3 (4.8)	0	8	11	14	45

Abbreviations: PM_{10}: particulate matter with an aerodynamic diameter less than 10 µm; NO_2: nitrogen dioxide; O_3: ozone; SD: standard deviation; RD respiratory deaths; CVD: cardiovascular deaths; MT: daily mean temperature; T_{max}: daily maximum temperature; T_{min}: daily minimum temperature.

Table 2. Spearman correlation coefficients (*r*) between mean, maximum and minimum temperatures in Brisbane during 1996-2004.

coefficients	*MT*	T_{max}	T_{min}
MT	1.00		
T_{max}	0.91*	1.00	
T_{min}	0.95*	0.75*	1.00

Abbreviations: MT: daily mean temperature; T_{max}: daily maximum temperature; T_{min}: daily minimum temperature.

Table 3. Certain temperature indicators and turning point with the lowest AIC for different death categories and age groups in Brisbane from 1996-2004*.

Temperature indicator	variables	Threshold (°C)
Mean	D_{all}	24
Mean	D_{75-84}	24
Minimum	D_{0-64}	18, 20
Minimum	D_{65-74}	24
Minimum	D_{85+}	21, 23
Minimum	RD	22
Maximum	CVD	27, 30

Abbreviations: D_{all}: deaths of all ages; D_{0-64}: deaths aged below 65 years; D_{65-74}: deaths aged from 65 to 74 years; D_{75-84}: deaths aged from 75 to 84 years; D_{85+}: deaths aged 85 years and over; CVD: deaths from cardiovascular diseases; RD: deaths from respiratory diseases.

Table 4. The current day effect of temperature indicators on different death categories and age groups associated with 1°C decrease in cold days or 1°C increase in hot days.

Category	Cold % increase with 1°C decrease (95% CI)		Heat % increase with 1°C increase (95% CI)	
	MT (24°C)	Other indicators[#]	MT (24°C)	Other indicators[#]
D_{all}	0.1 (-0.5, 0.8)	0.1 (-0.5, 0.8) (MT, 24)	4.7 (3.1, 6.4)	4.7 (3.1, 6.4) (MT, 24)
D_{0-64}	0.6 (-0.5, 1.8)	0.7 (-0.2, 1.7) (T_{min},18)	5.0 (1.5, 8.6)	3.4 (0.0, 6.8) (T_{min}, 20)
D_{65-74}	1.1(0.2, 2.1)	0.9 (0.1, 1.8) (T_{min},24)	3.1(-0.8,7.3)	15.6 (-1.8, 37.3) (T_{min}, 24)
D_{75-84}	0.0 (-1.1, 1.2)	0.0 (-1.1, 1.2) (MT, 24)	3.9(1.0, 6.9)	3.9(1.0, 6.9) (MT, 24)
D_{85+}	2.5 (1.9, 3.1)	3.0 (2.4, 3.7) (T_{min}, 21)	7.2 (4.3, 10.2)	9.3 (1.7, 17.0) (T_{min}, 23)
RD	5.7 (4.2, 6.9)	3.6 (2.0, 5.3) (T_{min}, 22)	9.0(2.2, 15.9)	7.8 (-4.0, 19.5) (T_{min}, 22)
CVD	3.1 (2.5, 3.8)	4.3(3.3, 5.3) (T_{max}, 27)	4.3 (1.2, 7.4)	1.7(-2.2, 5.6) (T_{max}, 30)

[#] The temperature indicator and threshold selected for each catergories with lowest AIC.

Abbreviations: D_{all}: deaths of all ages; D_{0-64}: deaths aged below 65 years; D_{65-74}: deaths aged from 65 to 74 years; D_{75-84}: deaths aged from 75 to 84 years; D_{85+}: deaths aged 85 years and over; CVD: deaths from cardiovascular diseases; RD: deaths from respiratory diseases; MT: mean temperature; T_{min}: minimum temperature; T_{max}: maximum temperature.

Table 5. The overall lagged effect of temperature indicators on different death categories and age groups associated with 1°C decrease in cold days (20 days) or 1°C increase in hot days(2 days).

Category	Cold (20 days overall) % increase with 1°C decrease (95% CI)		Heat (2 days overall) % increase with 1°C increase (95% CI)	
	MT (24°C)	Other indicators[#]	MT (24°C)	Other indicators[#]
D_{all}	2.0 (0.7, 3.3)	2.0 (0.7, 3.3)(MT, 24)	3.2(0.9, 5.6)	3.2(0.9, 5.6) (MT, 24)
$D_{0\text{-}64}$	-1.4 (-3.8, 1.0)	0.5 (-1.4, 2.4) (T_{min}, 18)	3.2 (-1.9, 8.5)	2.8 (-1.4, 7.2) (T_{min}, 20)
$D_{65\text{-}74}$	2.3(-0.5, 5.2)	0.3 (-2.1, 2.8) (T_{min}, 24)	3.8 (-3.4, 11.5)	-0.7 (-11.1, 10.8) (T_{min}, 24)
$D_{75\text{-}84}$	0.9 (-0.4, 6.2)	0.9 (-0.4, 6.2) (MT, 24)	1.7(-1.2, 4.5)	1.7(-1.2, 4.5) (MT, 24)
D_{85+}	3.9 (1.9, 6.0)	3.3 (1.8, 4.9) (T_{min}, 21)	5.4 (1.4, 9.5)	22.9 (10.5, 36.8) (T_{min}, 23)
RD	4.1 (-1.6, 10.1)	3.4 (-0.0, 6.9) (T_{min}, 22)	3.7 (-1.4, 9.1)	3.8 (-9.7, 19.3) (T_{min}, 22)
CVD	3.5 (0.9, 6.1)	7.7(5.4, 10.1) (T_{max}, 27)	4.1 (0.3, 8.1)	3.1 (0.2, 6.1) (T_{max}, 30)

[#] The temperature indicator with threshold selected for each categories with lowest AIC. Abbreviations: D_{all}: deaths of all ages; $D_{0\text{-}64}$: deaths aged below 65 years; $D_{65\text{-}74}$: deaths aged from 65 to 74 years; $D_{75\text{-}84}$: deaths aged from 75 to 84 years; D_{85+}: deaths aged over 85 years; CVD: deaths from cardiovascular diseases; RD: deaths from respiratory diseases; MT: mean temperature; T_{min}: minimum temperature; T_{max}: maximum temperature. The value in the Parentheses is the temperature indicator and the corresponding threshold.

Figure 1. The polynomial distributed lag non-linear model (df=4) for mean temperature and different temperature indicators among different age and death groups. Left: cold and right: hot.

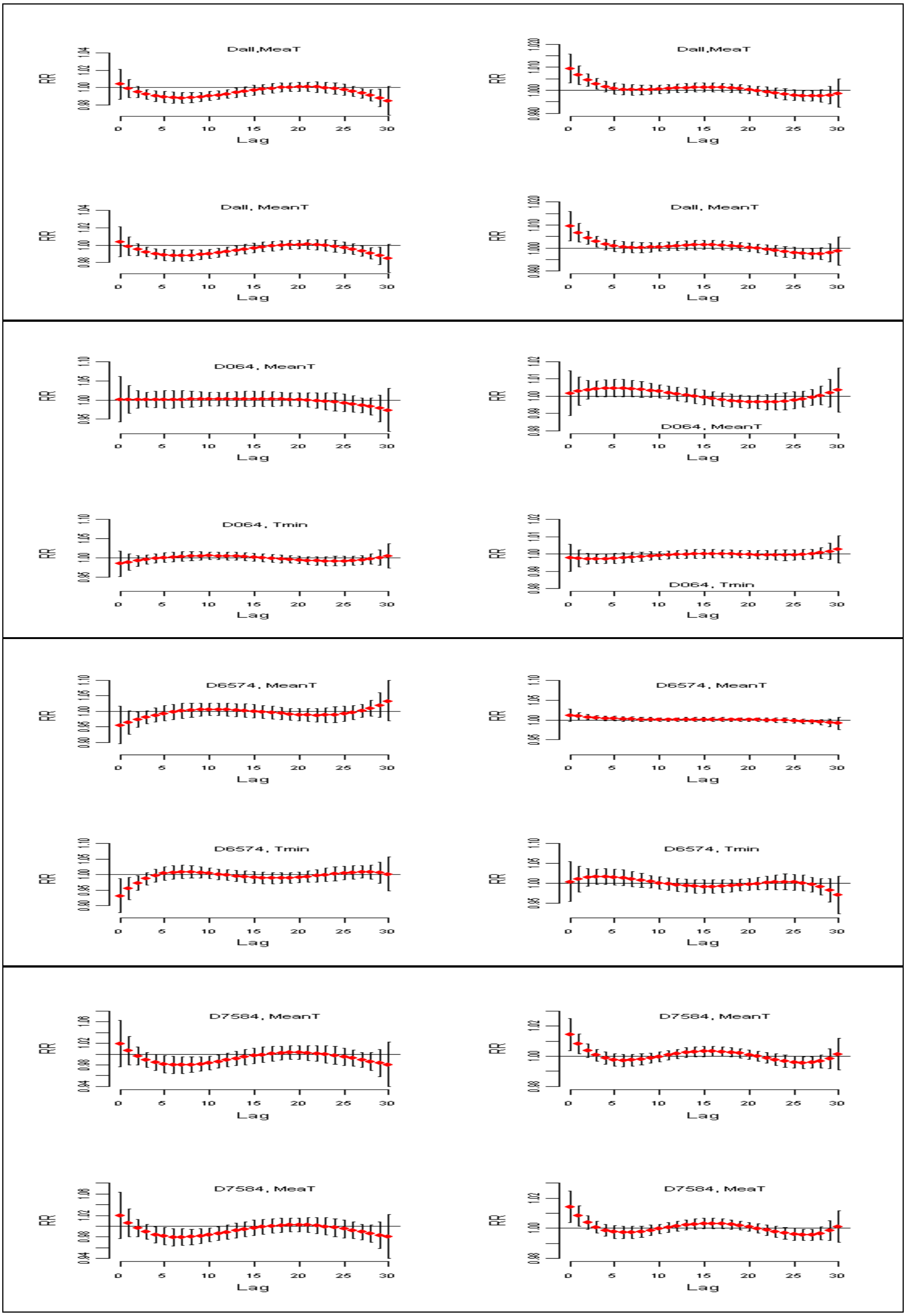
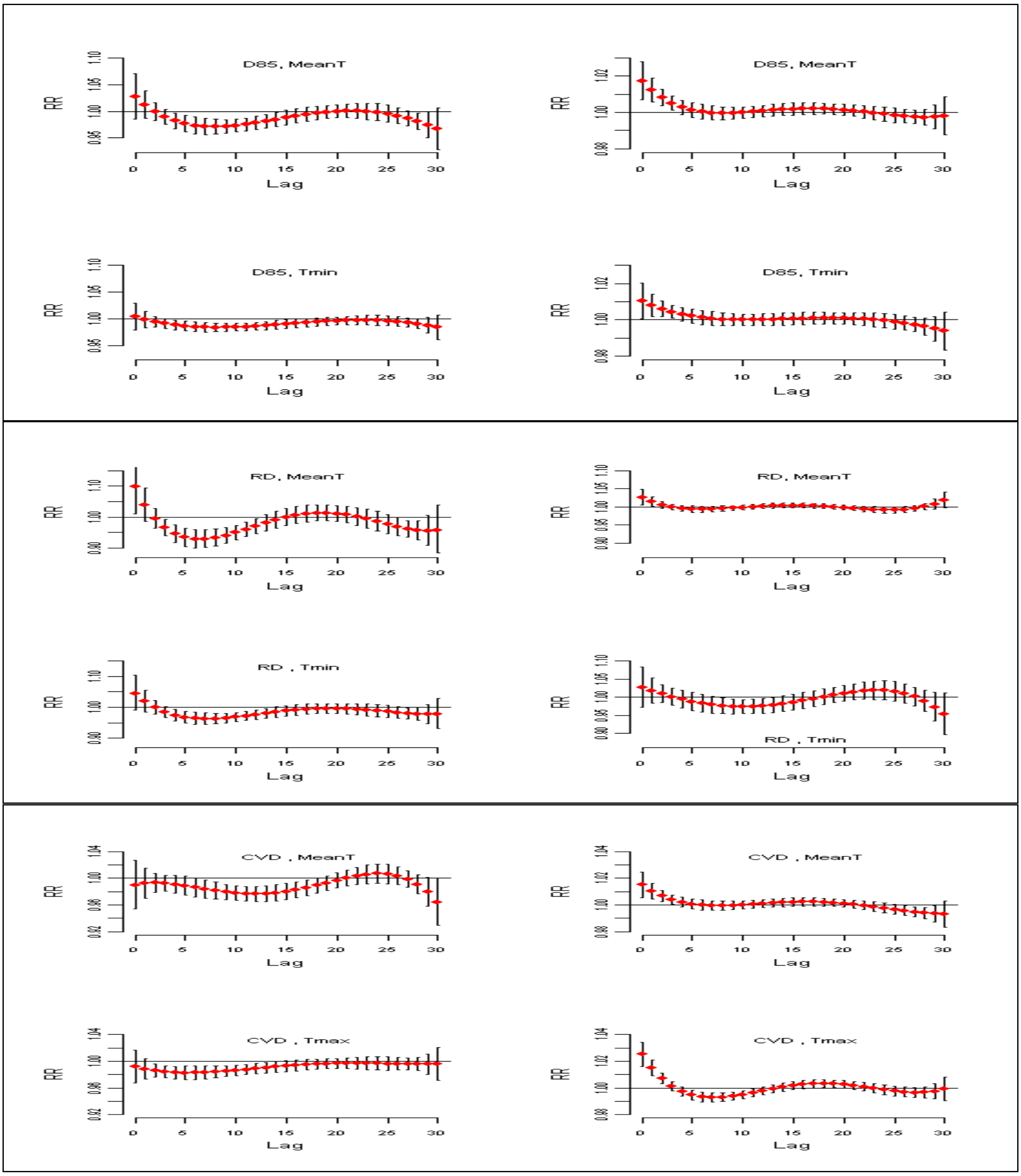


Figure 1. The polynomial distributed lag non-linear model (df=4) for mean temperature and different temperature indicators among different age and death groups. Left: cold and right: hot (Cont'd).



Abbreviations: D_{all}: deaths of all ages; D_{064}: deaths aged below 65 years; D_{6574}: deaths aged from 65 to 74 years; D_{7584}: deaths aged from 75 to 84 years; D_{85+}: deaths aged 85 years and over; CVD: deaths from cardiovascular diseases; RD: deaths from respiratory diseases; MT: mean temperature; T_{min}: minimum temperature; T_{max}: maximum temperature. The value in the Parentheses is the temperature indicator and the corresponding threshold.