

Climate change and heat-related mortality in six cities Part 2: climate model evaluation and projected impacts from changes in the mean and variability of temperature with climate change

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Abstract Previous assessments of the impacts of climate change on heat-related mortality use the “delta method” to create temperature projection time series that are applied to temperature–mortality models to estimate future mortality impacts. The delta method means that climate model bias in the modelled present does not influence the temperature projection time series and impacts. However, the delta method assumes that climate change will result *only* in a change in the mean temperature but there is evidence that there will *also* be changes in the variability of temperature with climate change. The aim of this paper is to demonstrate the importance of considering changes in temperature variability with climate change in impacts assessments of future heat-related mortality. We investigate future heat-related mortality impacts in six cities (Boston, Budapest, Dallas, Lisbon, London and Sydney) by applying temperature projections from the UK Meteorological Office

HadCM3 climate model to the temperature–mortality models constructed and validated in Part 1. We investigate the impacts for four cases based on various combinations of mean and variability changes in temperature with climate change. The results demonstrate that higher mortality is attributed to increases in the mean *and* variability of temperature with climate change rather than with the change in mean temperature alone. This has implications for interpreting existing impacts estimates that have used the delta method. We present a novel method for the creation of temperature projection time series that includes changes in the mean and variability of temperature with climate change and is not influenced by climate model bias in the modelled present. The method should be useful for future impacts assessments. Few studies consider the implications that the limitations of the climate model may have on the heat-related mortality impacts. Here, we demonstrate the importance of considering this by conducting an evaluation of the daily and extreme temperatures from HadCM3, which demonstrates that the estimates of future heat-related mortality for Dallas and Lisbon may be overestimated due to positive climate model bias. Likewise, estimates for Boston and London may be underestimated due to negative climate model bias. Finally, we briefly consider uncertainties in the impacts associated with greenhouse gas emissions and acclimatisation. The uncertainties in the mortality impacts due to different emissions scenarios of greenhouse gases in the future varied considerably by location. Allowing for acclimatisation to an extra 2°C in mean temperatures reduced future heat-related mortality by approximately half that of no acclimatisation in each city.

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Introduction

One of the most serious threats to both human life and current lifestyles is climate change (IPCC 2007). Even if the atmospheric concentrations of greenhouse gases in the atmosphere were stabilised today, mean global temperature would continue to rise due to the unrealised effect of past climate forcing increases (Meehl et al. 2005). Future increases in greenhouse gas concentrations, from future emissions, will add to the committed warming thus leading to even higher mean global temperatures. Extremes of climate are also likely to change in the future. An increased risk of more intense, more frequent and longer-lasting heat waves in a warmer future climate are likely, and extreme events such as the European heat wave in 2003 would become more common (Meehl et al. 2007; Stott et al. 2004; Beniston and Diaz 2004).

Several studies have attempted to estimate the impacts of future climate change on heat-related mortality, and a detailed and critical review of these is provided by Gosling et al. (2008). The methods employed in these studies usually involve applying a mean climate warming to the observed present-day climate to create a temperature projection time series that can be applied to the observed present temperature–mortality relationship. The degree of climate warming is calculated as the difference between the future period and present period mean temperatures, as estimated by climate models, to give a temperature anomaly. This is commonly known as the “delta method” (Déqué 2007).

To apply the delta method, some studies use a climate model that has been run for present carbon dioxide concentrations ($1 \times \text{CO}_2$) to represent present temperatures and a model run for $2 \times \text{CO}_2$ concentrations to represent future temperatures. For example, Dessai (2003) calculated mean monthly temperature anomalies from climate simulations for the years 2040–2049 ($2 \times \text{CO}_2$) and 1981–1990 ($1 \times \text{CO}_2$) and added these to 30 years of observed climate data (1969–1998) for Lisbon, Portugal. Similarly, Guest et al. (1999) applied monthly mean changes in climate for the year 2030 relative to present ($2 \times \text{CO}_2 - 1 \times \text{CO}_2$) to temperature observations for the period 1979–1990 so that the resultant 12-year temperature projection time series was centred on 2030 (i.e. 2024–2035) for Australia’s 5 largest cities. Other climate change–health studies use the SRES (*Special Report on Emissions Scenarios*) greenhouse gas emission scenarios (Nakićenović and Swart 2000) to model present and future temperatures for the purpose of calculating temperature anomalies (McMichael et al. 2003; Hayhoe et al. 2004).

The delta method is considered a robust means of creating a temperature projection time series because climate model bias in the modelled present does not have

an influence on its creation. The main limitation of the method is that the temperature projection time series inherits the observed present variability. Therefore, the impacts presented in the studies above all assume that climate change is associated with *only* a change in the mean of the temperature distribution. Considering a theoretical temperature probability density function (PDF) defined in terms of location, shape and scale parameters, there could indeed only be a shift in the location (mean) towards warmer temperatures in future climate. However, there might also be a change in the scale (variability) of the distribution towards more variable temperatures, and also possible is a combined change in the mean and variability (Folland et al. 2001). For example, climate model simulations for the second half of the twenty-first century presented by Meehl and Tebaldi (2004) demonstrate projected increases in the mean and variability of summer-time maximum temperature associated with more intense, frequent and longer lasting heat waves.

Two arguments can be provided for excluding the impacts of climate variability on heat-related mortality. Firstly, that the changes in future temperature variability are negligible relative to the changes in the mean (Guest et al. 1999), and secondly that there are limitations on the ability of global climate models (GCMs) to represent the full complexity of observed climate variability (McMichael et al. 2003). These arguments may be justified for some regions or cities (Guest et al. 1999), but they may not hold for others (Beniston and Diaz 2004). The delta method tends to underestimate the number of extreme temperature events projected by a climate model because the expected climate change is not just a shift of the PDF (Déqué 2007; Meehl and Tebaldi 2004). Therefore, it is important to consider what the impacts associated with changing climate variability will be.

The aim of this paper is to demonstrate the importance of changing temperature variability with climate change in assessments of future heat-related mortality. Here, we present estimates of heat-related mortality resulting from climate change for six cities: Boston, Budapest, Dallas, Lisbon, London and Sydney. They are based on climate change scenarios for the 2080s (2070–2099) and the temperature–mortality (t-m) models constructed and validated in Gosling et al. (2007; hereafter referred to as Part 1). We present an analysis that quantifies the impacts for the 2080s associated with a change in the *mean* of the temperature distribution with climate change *separately* from the impacts associated with a change in the temperature *variability*. This is something previous studies have not attempted because they only consider changes in the mean temperature. To understand the outcomes of the analysis, an understanding of climate model biases and the representation of extremes is necessary, so we first include

a comprehensive and detailed evaluation of the climate model (HadCM3) from which the temperature projections are obtained. Finally, we propose a novel methodology for assessing the impacts of climate change on heat-related mortality that considers both changes in the mean and variability of the temperature distribution. Crude analyses of the uncertainties in future greenhouse gas emissions and the possibility that populations may acclimatise to warmer temperatures are briefly considered to give a preliminary indication of what the possible range of impacts could be. A more comprehensive analysis that considers the full range of uncertainty will be included in later work.

Materials and methods

This section firstly describes, briefly, the data and methods used to construct the t-m models in Part 1 (Gosling et al. 2007) that are used with climate change scenarios to estimate future heat-related mortality. Then, we describe the climate data used for the HadCM3 evaluation and the assessment of future impacts. This is followed by the methods used to conduct the HadCM3 climate model evaluation, which is important for understanding the projected impacts that follow. Then, to address the aim of this study, we describe how changes in the mean and variability of temperature with climate change are accounted for to assess future impacts on heat-related mortality in each of the six cities. This is addressed by considering four specific cases. Finally, we describe a novel method for considering changes in the mean and variability of temperature. The analyses conducted in this study are summarised in Fig. 1.

Construction of t-m models

Daily total deaths from all causes were obtained for each city and then excess mortality was calculated using a 31-day moving average. Excess mortality was used to approximate heat-related deaths. Daily maximum temperature was obtained from city-centre or airport weather stations for each city. Absolute threshold temperatures above which heat-related deaths began to occur were identified as 26°C (Boston), 28°C (Budapest), 34°C (Dallas), 28°C (Lisbon), 24°C (London) and 26°C (Sydney). The aggregate dose-response relationship between temperature and mortality was examined by grouping excess mortality into 2°C maximum temperature class intervals and calculating the number of excess deaths per day for each interval. Non-linear regression analyses were performed on the data above the city-specific thresholds to produce the t-m models. Validation techniques demonstrated that the t-m models could be used reliably to examine the potential effects of climate change on summertime heat-related mortality in the six cities.

Climate data

HadCM3 is a dynamical coupled atmosphere–ocean general circulation model (AOGCM) developed at the UK Meteorological Office Hadley Centre. Detailed descriptions are provided by Gordon et al. (2000) and Pope et al. (1999). The atmospheric component has a horizontal resolution of 2.5° latitude by 3.75° longitude, which produces a global grid of 96×72 grid boxes. This is equivalent to a surface resolution of about 417×278 km at the Equator, reducing to 295×278 km at latitude 45° (comparable to a spectral

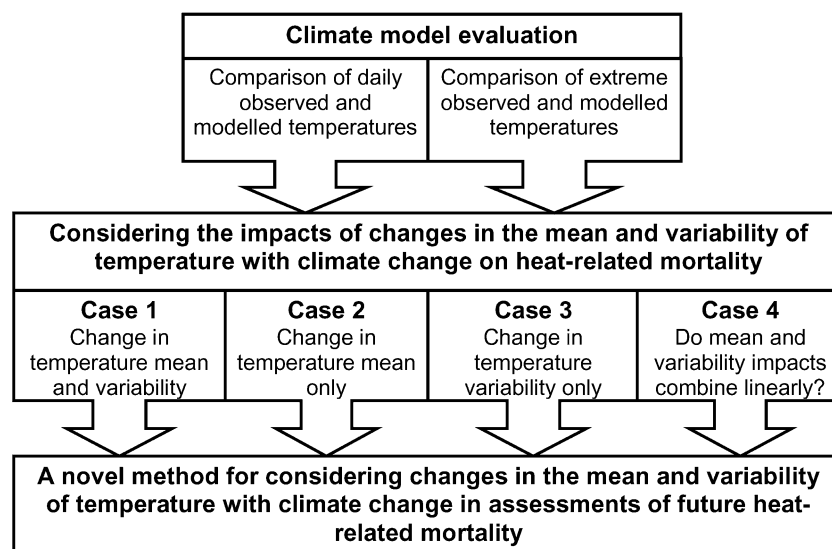


Fig. 1 Summary of analyses conducted in this study

resolution of T42). For each city, the grid box that included the location of the weather station used to calibrate the t-m models in Part 1 was identified, along with the eight surrounding grid boxes. This meant that nine grid boxes were identified and labelled A–I (see Fig. 2). Grid box ‘E’ includes the location of the weather station used to calibrate the t-m models in Part 1.

For the evaluation of HadCM3, modelled surface air temperature from the first member of an ensemble of climate simulations using HadCM3 was used for comparison with observational data. An ensemble mean can reduce noise in the simulations, but the individual GCM response was used for the evaluation. This was to maintain consistency with the HadCM3 projections later applied to the t-m models, which are individual responses not ensemble means. A simulation was undertaken with twentieth century forcings, including natural (solar and volcanic) and anthropogenic (greenhouse gases, sulphate aerosols and ozone). It is hereafter referred to as ABW (the “all bells and whistles” simulation). The model was run for nearly 140 years but only 30 years (1961–1990) are presented here. ABW has previously been used for detection and attribution analysis (Stott et al. 2004; Tett et al. 2002) and the evaluation of HadCM3 global mean surface air temperature (Stott et al. 2000), arctic sea-ice changes (Gregory et al. 2002) and arctic river discharges (Wu et al. 2005).

Two observational data sets were obtained for the evaluation of HadCM3: (1) daily Tmax for the weather stations described in Part 1 for the period 1961–1990, hereafter referred to as point observations; and (2) global daily gridded land-only surface Tmax observations for the period 1961–1990 (Caesar et al. 2006), hereafter referred to as gridded observations. The gridded observations were compiled from 2,936 point observations and share the same horizontal resolution as HadCM3. To be consistent with the HadCM3 output, all data for 29 February and the 31st day of each month were omitted from the observational records.

To assess the impacts on heat-related mortality of changes in the mean and variability of temperature with climate change, modelled daily temperatures for the periods 1961–1990 and 2070–2099 were obtained from HadCM3 for the SRES A2 and B2 scenarios (Nakićenović and Swart 2000).

HadCM3 model evaluation

To evaluate the modelling capabilities of HadCM3, modelled maximum temperatures (Tmax) from HadCM3 were compared to observational data for the 30-year period 1961–1990. We focus on summer (June–August, but December–February for Sydney) temperature because the application is towards summer mortality.

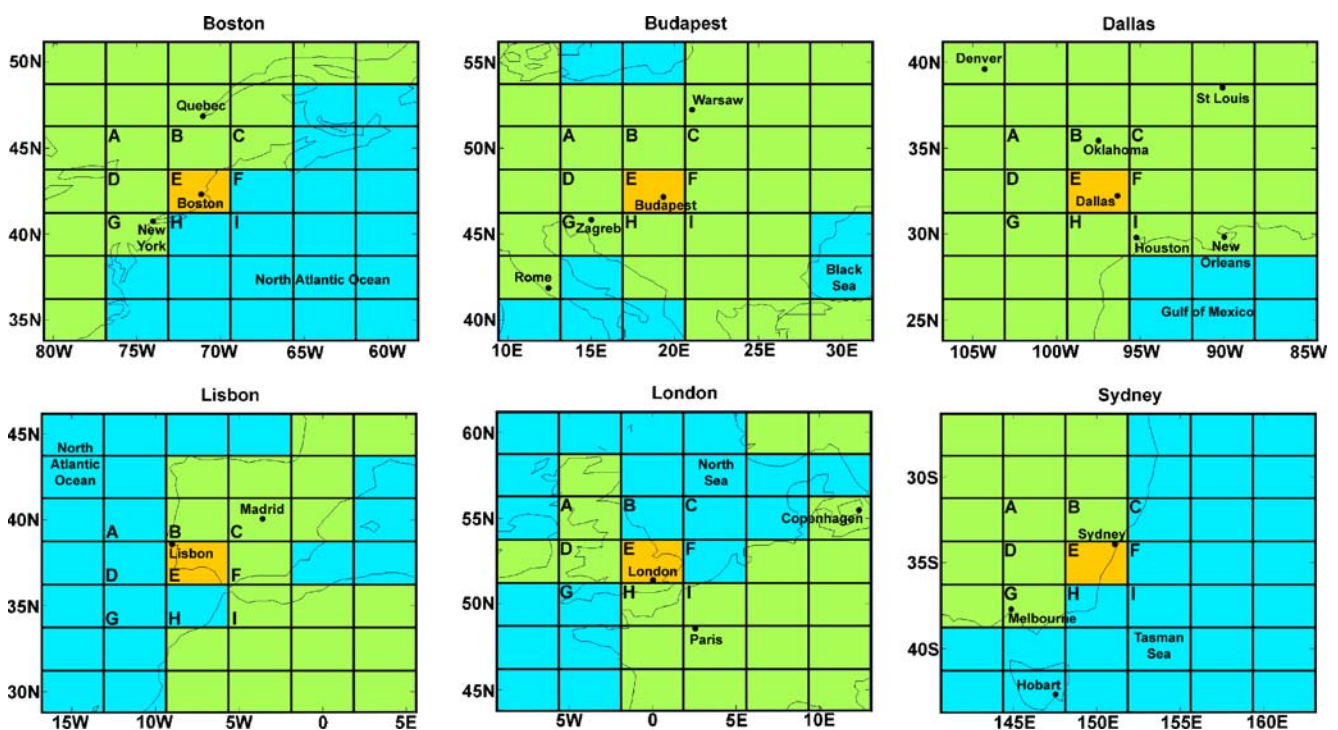


Fig. 2 Maps showing the HadCM3 grid boxes identified for each city (labelled E). The surrounding 8 grid boxes were also identified and labelled A–D and F–I. Green grid boxes indicate HadCM3 considers the grid box to be over land and blue over the ocean

HadCM3 model evaluation: comparison of daily observed and modelled temperatures

Three commonly computed statistics to compare observed to modelled values are the correlation coefficient (r), the root mean square error (RMSE) and the index of agreement (d) (Willmott 1981; Brazell et al. 1993; Salzmann et al. 2007). r is a measure of the covariability between observed and modelled values and the RMSE is a measure of the mean difference between observed and modelled values. r and RMSE indicate different components of model error indicated by d , which is sensitive to differences between observed and modelled means, as well as to changes in proportionality. d is dimensionless and has the range 0.0–1.0; 0.0 indicates complete disagreement between observed and modelled values and 1.0 indicates the observed and modelled values are identical. RMSE and d are calculated by Eq. (1) and Eq. (2), respectively:

$$RMSE = \left[n^{-1} \sum_{i=1}^n (P_i - O_i)^2 \right]^{0.5} \tag{1}$$

$$d = 1.0 - \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \right] \tag{2}$$

Where

- n total observations
- P_i model value
- O_i observed value
- \bar{O} mean of observed values

For each city grid box (E), the three statistics were computed for the daily summertime ($n=90$) 30-year means (1961–1990) of daily Tmax. This was also performed for up to eight surrounding grid boxes (A, B, C, D, F, G, H, I) that were not located over the ocean, to examine spatial variation in the statistics. Further comparisons were made between the point observations (grid box E) and the mean of all nine grid boxes (or less than nine if some grid boxes were considered ocean) from ABW. Similarly, the mean of all nine grid boxes from gridded observations were compared to the mean of all nine grid boxes from ABW.

HadCM3 model evaluation — comparison of extreme observed and modelled temperatures

We compared the occurrence of modelled extreme temperatures with observed extreme temperatures in two ways.

Firstly, we examined the average numbers of days per year that maximum daily temperatures were exceeded in the

daily time series (1961–1990, summer, $n=2,700$) of ABW, gridded observations, and point observations, respectively. The average number of days was limited to 14 because this should include the extreme temperatures associated with heat wave events as well as moderately warm temperatures that might still be associated with increases in mortality. The purpose of this is to demonstrate whether there are differences between the observed and modelled representation of extreme temperatures, regardless of whether they occur on consecutive days.

Secondly, we performed an extreme value analysis. The Gumbel distribution (Gumbel 1958) has reliably been used in meteorology, climatology and hydrology to predict rare extremes of temperature, precipitation, wind speed and streamflow (Meehl et al. 2000; Wilks 1995). The Gumbel cumulative distribution function (CDF) is given by Eq. (3).

$$F(x) = \exp \left\{ - \exp \left(- \frac{x - \xi}{\alpha} \right) \right\} \tag{3}$$

where ξ is a location parameter that represents the overall position of the distribution and α is a scale parameter that characterises the spread of the distribution. Gumbel distributions were fitted to the annual maxima of summer Tmax (1961–1990) for ABW, gridded observations and point observations for each city grid box (E). The parameters were estimated by maximum likelihood. The return levels associated with the return periods (T) up to 30 years, were then calculated by inverting the fitted Gumbel distribution. This gives a temperature (X) that is expected to be exceeded once every T years; see Eq. (4). The delta method (Coles 2001; not the same as the delta method used for producing temperature projections discussed in the Introduction) was applied to estimate the 95% confidence intervals for the return levels. This method constructs a symmetric interval based on the covariance matrix of the estimated parameters.

$$X_T = \xi - \hat{\alpha} \ln \left[- \ln \left(1 - \frac{1}{T} \right) \right] \tag{4}$$

Considering the impacts of changes in the mean and variability of temperature with climate change on heat-related mortality

Using a scenario-based approach the burden of heat-related mortality attributable to climate change can be calculated by Eq. (5) (adapted from Kovats et al. 2003):

$$A_D = D[CLIMATE CHANGE SCENARIO] - D[BASELINE CLIMATE \text{ e.g. } 1961 - 1990] \tag{5}$$

Where

- A_D burden of heat-related mortality attributable to climate change
 D heat-related mortality calculated by the t-m model for the daily temperature time series in the square brackets

This assumes that nothing changes in the future world except the climate. We used this approach to estimate the future burden of heat-related mortality attributable to climate change for each of the six cities. This meant that the impacts of factors such as population growth, ageing and socioeconomic development on the mortality estimates were excluded. Therefore, we assumed that the demographic structure of the population remained unchanged in the future. All impacts are presented as death rates (per 100,000) rather than absolute number of heat-related deaths because of this. It also assumes stationarity of the temperature–mortality relationship in the future. Although this approach is simplistic, it is useful because it separates out the contribution of climate from these other factors that determine the burden (Hayhoe et al. 2004; Kovats et al. 2003). This is particularly useful for demonstrating the impacts associated with changes in the mean and variability of temperature with climate change.

The baseline climate period that heat-related mortality was calculated for is hereafter referred to as ‘present’ and was taken as 1961–1990. Heat-related mortality burdens were also calculated under climate change scenarios, hereafter referred to as ‘future’: 2070–2099. We selected two climate change scenarios driven by HadCM3: the A2 and B2 SRES (Nakićenović and Swart 2000) emission scenarios, for the city grid boxes (E).

To consider the impacts of changes in the mean and variability of temperature with climate change on heat-related mortality we investigated the impacts in four cases. The cases were based on various combinations of location (mean) and scale (variability) changes in temperature with climate change and are summarised in Table 1.

A novel method for considering changes in the mean and variability of temperature with climate change in assessments of future heat-related mortality

Finally, we assessed the impacts associated with an artificial future temperature time series that included changes in the mean and variability of temperature with climate change. The time series was created as follows. Firstly, we fitted logistic distributions to the modelled (SRES A2) present temperature distribution, the present point observations distribution and the future SRES A2 distribution, respectively. We fitted a logistic distribution to all distributions for consistency and because it has larger tails than a normal distribution, which made it more appropriate to the temperature data (Mudholkar

and George 1978). Although the logistic distribution does not allow asymmetric distributions, it generally provided a better fit to the actual distributions than asymmetrical distributions such as the Gumbel distribution. The changes in the location (ξ) and scale (α) parameters between the logistic distributions for the modelled (SRES A2) present and future SRES A2 were calculated. The changes in each parameter were then added to the respective location and scale parameters estimated from the present point observations distribution. The new parameters allowed for the creation of a new artificial temperature distribution. A 30-year daily time series was sampled from the artificial distribution and represents the artificial future time series. This technique is novel because it accounts for changes in the mean and variability of temperature and removes the influence of climate model bias on the time series created. It is made simpler by the fact that the t-m models do not include lag or persistence parameters. Heat-related mortality attributable to climate change was then calculated by Eq. (10).

$$A_D = D[Artificial_{Future}] - D[O_{present}] \quad (10)$$

We also used the artificial time series to explore the impact that the uncertainty of physiological acclimatisation to warmer temperatures might have on future heat-related mortality. We considered three possible degrees of future acclimatisation: (1) no acclimatisation, (2) acclimatisation to an increase of 2°C relative to present, and (3) acclimatisation to an increase of 4°C relative to present. For no acclimatisation, it was assumed that the t-m model relationships were valid from their absolute threshold temperatures identified in Part 1. For 2°C and 4°C acclimatisation, it was assumed the threshold temperatures increased by 2°C and 4°C, respectively, for each city. However, the gradient of the relationships remained unchanged. Effectively, this was the same as ‘shifting’ the dose-response relationships by 2°C and 4°C, respectively.

Results

HadCM3 model evaluation — comparison of daily observed and modelled temperatures

Frequency distributions of daily Tmax for 1961–1990 (summer) for ABW, gridded observations and point observations, respectively, are presented in Fig. 3. Table 2 shows the descriptive statistics for these distributions. HadCM3 models more variable temperatures for Budapest, Dallas, Lisbon and Sydney than is observed. Less variable climates than observed are modelled for Boston and London. ABW for Dallas and Lisbon also present higher means than the observations. This indicates that the modelled Tmax climate for Dallas and Lisbon is more variable and warmer on average than observed. Boston and

Table 1 The four cases based on various combinations of location (mean) and scale (variability) changes in temperature with climate change used to investigate the impacts of changes in the mean and variability of temperature with climate change on heat-related mortality

Case	Rationale for analysis	Eq	Equation form	Comments
Case 1: Change in temperature mean and variability	To investigate how a change in the mean and variability of the temperature distribution with climate change impacts future heat-related mortality. Illustrate the role of uncertainty in future greenhouse gas emissions.	(6)	$A_D = D[M_{future}] - D[M_{present}]$	Attributable mortality is estimated separately for modelled temperatures from the SRES A2 and B2 emissions scenarios respectively. The present temperature time series were modelled by HadCM3 for A2 and B2. Climate model bias has an influence on the impacts.
Case 2: Change in temperature mean only	To investigate how a change in the mean temperature only, for SRES A2, impacts future heat-related mortality.	(7a)	$A_D = D[(M_{future} - M_{present}) + M_{present}] - D[M_{present}]$	To consider the effect of climate model bias in the modelled present, heat-related mortality was calculated by Eq. (7a) and Eq. (7b) respectively.
		(7b)	$A_D = D[(M_{future} - M_{present}) + O_{present}] - D[O_{present}]$	Equation (7a) means that modelled present HadCM3 bias influences the temperature projection time series, and consequently the heat-related mortality impacts.
Case 3: Change in temperature variability only	To investigate how a change in the variability of temperature only, for SRES A2, impacts future heat-related mortality.	(8)	$A_D = D[M_{future} - (M_{future} - M_{present})] - D[M_{present}]$	Equation (7b) removes the influence of climate model bias by using observed present temperatures.
Case 4: Do mean and variability impacts combine linearly?	To investigate how the impacts from the change in mean and variability of the temperature distribution with climate change (Case 1) compare with the summed individual responses to a change in the mean (Case 2) and variability (Case 3).	(9)	$\frac{\{D[M_{future}] - D[M_{present}]\}}{\{D[(M_{future} - M_{present}) + M_{present}] - D[M_{present}]\}} + \frac{\{D[M_{future}] - D[M_{present}]\}}{\{D[M_{future} - M_{present}] - D[M_{present}]\}}$	Assumes that any change in the temperature distribution that was not represented by a change in the mean associated with climate change, was due to a change in variability. Climate model bias impacts on future heat-related mortality. Equation (9) is simply Eq. (6) divided by the sum of Eq. (7a) and Eq. (8).

A_D Burden of heat-related mortality attributable to climate change, D heat-related mortality calculated by the t-m model for the daily temperature time series in the square brackets, *present* temperature time series is for the period 1961–1990, *future* temperature time series is for the period 2070–2099, O observed daily temperature from point observations, M modelled daily temperature from HadCM3

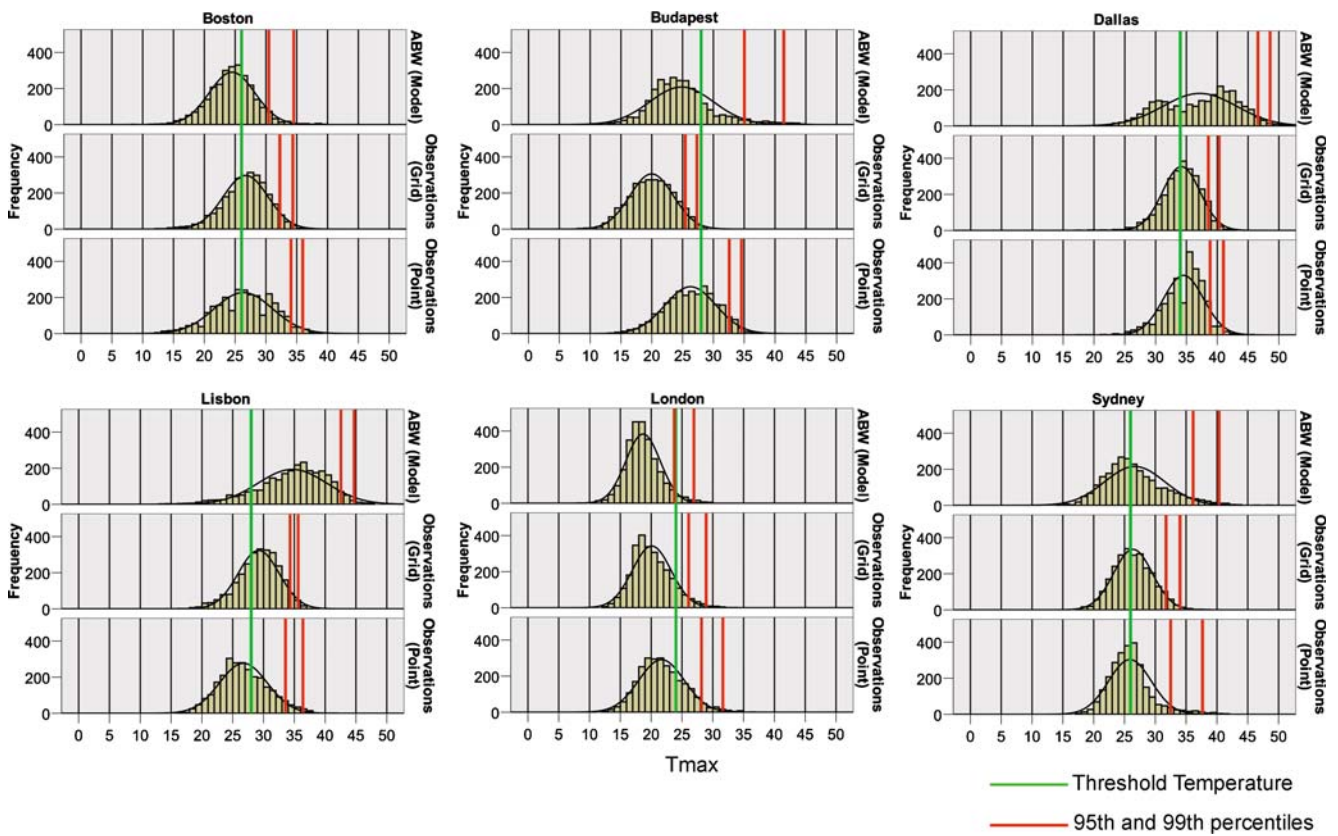


Fig. 3 Frequency distributions of daily Tmax (1961–1990; summer) for ABW, gridded observations and point observations for each city. Normal curves have been fitted to each distribution for illustrative purposes, to allow a comparison of the shapes of the distributions.

Solid continuous vertical lines (green) through all panels denote threshold temperatures. Solid vertical lines (red) on each panel denote the 95th and 99th percentiles

Table 2 Descriptive statistics of daily Tmax (°C) for ABW, gridded observations and point observations, 1961–1990 (summer) for each city grid box (E)

Source	City	Minimum	Maximum	Mean	Standard deviation	95th percentile	99th percentile
ABW	Boston	8.6	39.5	24.50	3.70	30.3	34.1
	Budapest	9.7	45.5	24.84	5.16	35.0	41.6
	Dallas	20.7	53.3	37.17	5.97	45.8	48.6
	Lisbon	13.5	48.0	34.68	5.57	42.4	44.9
	London	8.8	29.8	18.68	2.80	23.8	27.1
	Sydney	14.6	49.0	26.66	4.89	36.1	40.3
Gridded observations	Boston	12.2	37.1	26.70	3.61	32.2	34.1
	Budapest	8.5	28.9	19.97	3.52	25.6	27.4
	Dallas	18.0	42.3	34.17	3.04	38.6	40.2
	Lisbon	16.7	38.7	29.21	3.33	34.2	35.8
	London	12.1	33.2	20.08	3.14	25.9	28.8
	Sydney	17.1	38.6	26.38	3.14	31.8	34.1
Point observations	Boston	11.1	38.9	26.34	4.73	33.9	36.1
	Budapest	12.7	37.4	26.27	4.14	32.8	34.5
	Dallas	17.8	45.0	34.52	3.26	38.9	41.1
	Lisbon	16.7	41.5	26.73	3.88	33.6	36.3
	London	10.6	36.5	21.67	3.69	28.1	31.7
	Sydney	17.6	41.6	25.88	3.47	32.7	37.8

London are modelled as less variable with cooler mean Tmax. The large differences between modelled and observed Tmax for the Dallas and Lisbon city grid boxes are further highlighted in plots of the 30-year means (1961–1990) of daily Tmax (Fig. 4).

The correlation coefficients (r), root mean square errors (RMSE) and indices of agreement (d) for the modelled and observed Tmax illustrated in Fig. 4 are presented in Table 3. Table 3 demonstrates that, for each city, the highest index of agreement between ABW and point observations occurs when ABW temperatures *not* located in the city grid box (E) are compared with the point observations. It is interesting that, based on this statistic, GCM grid boxes that might not be considered representative of the city due

to their distance from it, are more similar to the temperatures observed in the city than those from the grid boxes actually situated over the city. The version of the Hadley Centre model used in this study does not include an explicit representation of urban effects. The coarse model resolution of HadCM3 and exclusion of resolved urban processes mean that only orography and/or land-sea distributions are portrayed at the grid box level in the region of an actual city. This contributes to general regional features of simulated climate in the vicinity of actual cities. The observation that simulated temperatures for some grid boxes near actual cities have some correspondence to the temperatures observed at the city weather station highlights that the weather is largely a product of dynamical scale

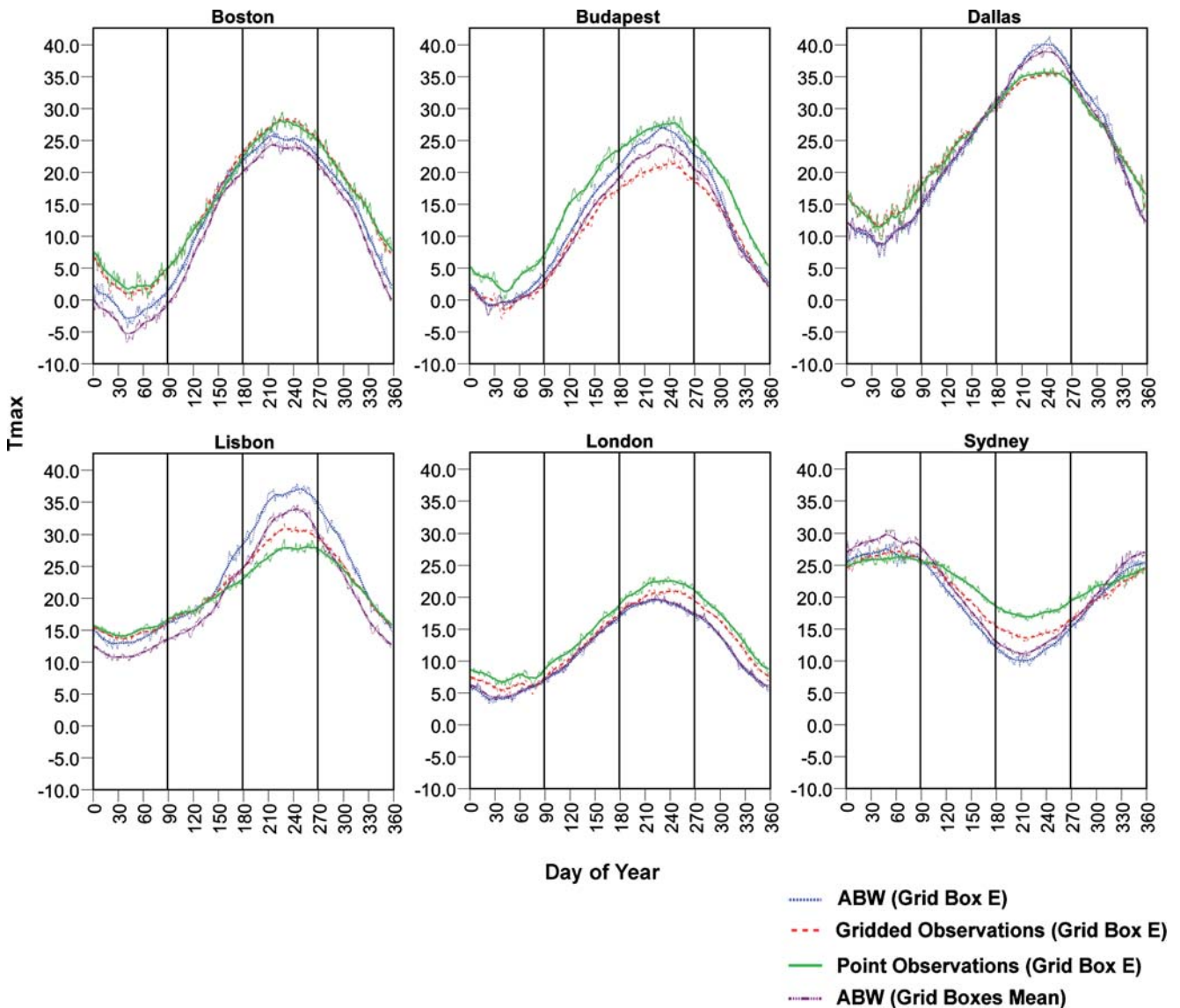


Fig. 4 The 30-year means (1961–1990) of daily Tmax (°C), for grid box E, for ABW, gridded observations, and point observations. The mean Tmax for grid boxes A–I (if not over ocean) from ABW is also shown (denoted *Grid Boxes Mean*). Vertical lines divide year (1

December to 30 November) into four seasons. For illustrative purposes only, *bold lines* denote filtered (20-day running mean) Tmax, so that the annual Tmax cycle can be separated from the inter-annual variability

Table 3 Correlation coefficients (r), RMSE ($^{\circ}\text{C}$), and indices of agreement (d) for the 30-year means (1961–1990; summer) of daily Tmax ($^{\circ}\text{C}$) between ABW and gridded observations, and ABW and point observations

		Boston		Budapest		Dallas		Lisbon		London		Sydney	
		ABW & Obs (Grid)	ABW & Obs (Point)	ABW & Obs (Grid)	ABW & Obs (Point)	ABW & Obs (Grid)	ABW & Obs (Point)	ABW & Obs (Grid)	ABW & Obs (Point)	ABW & Obs (Grid)	ABW & Obs (Point)	ABW & Obs (Grid)	ABW & Obs (Point)
A	r	0.73	0.71	0.55	0.59	0.81	0.83	–	–	0.17 ^b	0.26 ^a	0.40	0.12 ^b
	RMSE	3.48	4.71	2.68	6.51	2.14	1.53	–	–	1.30	4.97	2.32	6.79
	d	0.51	0.43	0.50	0.30	0.75	0.85	–	–	0.45	0.27	0.42	0.12
B	r	0.72	0.66	0.54	0.56	0.93	0.91	0.83	0.84	–	–	0.24 ^a	0.01 ^b
	RMSE	2.41	6.09	3.01	6.63	3.80	3.39	2.37	2.42	–	–	1.63	1.97
	d	0.61	0.36	0.45	0.30	0.63	0.63	0.81	0.77	–	–	0.42	0.28
C	r	0.73	0.68	0.65	0.68	0.88	0.90	0.94	0.88	–	–	–	–
	RMSE	1.66	3.98	1.66	5.02	5.38	3.65	2.59	2.68	–	–	–	–
	d	0.75	0.48	0.65	0.38	0.41	0.59	0.83	0.76	–	–	–	–
D	r	0.72	0.70	0.72	0.73	0.74	0.75	–	–	0.34	0.39	0.49	0.21 ^a
	RMSE	3.42	4.07	1.05	7.08	2.60	1.99	–	–	1.16	3.58	3.10	5.18
	d	0.48	0.47	0.84	0.29	0.49	0.68	–	–	0.54	0.34	0.39	0.15
E	r	0.71	0.68	0.84	0.84	0.92	0.91	0.93	0.87	0.48	0.50	0.23 ^a	–0.04 ^b
	RMSE	2.45	2.21	4.97	1.74	3.46	3.20	5.59	8.09	1.67	3.15	1.11	1.33
	d	0.60	0.64	0.35	0.76	0.61	0.63	0.43	0.28	0.54	0.39	0.53	0.31
F	r	–	–	0.81	0.82	0.90	0.92	0.67	0.51	–	–	–	–
	RMSE	–	–	1.91	3.36	4.72	3.42	2.29	4.19	–	–	–	–
	d	–	–	0.65	0.52	0.37	0.58	0.77	0.43	–	–	–	–
G	r	0.76	0.74	0.92	0.85	0.58	0.57	–	–	–	–	0.50	0.19 ^b
	RMSE	1.98	1.38	3.77	2.42	2.32	2.52	–	–	–	–	1.62	1.23
	d	0.67	0.82	0.51	0.66	0.38	0.52	–	–	–	–	0.61	0.45
H	r	–	–	0.91	0.82	0.86	0.87	–	–	0.61	0.60	–	–
	RMSE	–	–	4.43	1.75	2.56	2.32	–	–	1.45	1.45	–	–
	d	–	–	0.46	0.80	0.61	0.69	–	–	0.64	0.62	–	–
I	r	–	–	0.86	0.78	0.87	0.90	0.94	0.84	0.45	0.44	–	–
	RMSE	–	–	3.65	1.83	3.54	1.98	8.42	10.75	2.04	1.71	–	–
	d	–	–	0.48	0.77	0.32	0.74	0.32	0.22	0.52	0.54	–	–
Mean	r	0.80	0.75	0.87	0.84	0.90	0.90	0.96	0.87	0.47	0.47	0.44	0.13 ^b
	RMSE	2.46	3.40	1.47	3.82	3.29	2.43	2.68	4.68	1.48	2.92	1.39	3.04
	d	0.61	0.53	0.77	0.48	0.51	0.69	0.76	0.46	0.55	0.40	0.55	0.23

Values were calculated for each grid box (A–I). Note the point observations are only located in grid box E. “–” denotes the grid box is located over ocean. All correlations are significant at the 99% confidence level unless otherwise stated (^a correlation is significant at the 95% confidence level; ^b correlation is not significant at the 95% confidence level)

interactions in the real climate system that are captured to some extent in the HadCM3 model simulation. Actual local urban effects are likely secondary for such regional climate features, but could make a bigger difference to local climate. This finding could be used to justify selecting a grid box other than E to represent future city temperatures. However, for consistency within this study and with previous studies we selected grid box E for each city.

HadCM3 model evaluation — comparison of extreme observed and modelled temperatures

Figure 5 illustrates the average numbers of days per year that maximum daily temperatures were exceeded in ABW,

gridded observations and point observations, respectively, for each city. The temperatures occurring up to 14 days per year are over 6°C higher for ABW than observations for Dallas and Lisbon. The cooler than observed modelled climates of Boston and London can also be seen. The return levels estimated from the extreme values analysis are presented in Fig. 6. With the exception of London, it can be inferred from Fig. 6 that, beyond the 10-year return period, return levels of annual Tmax maxima are higher for ABW than the observations. This is most prominent for Dallas and Lisbon. The result is unsurprising given that we previously demonstrated increased Tmax variability for ABW relative to the observations for these two cities.

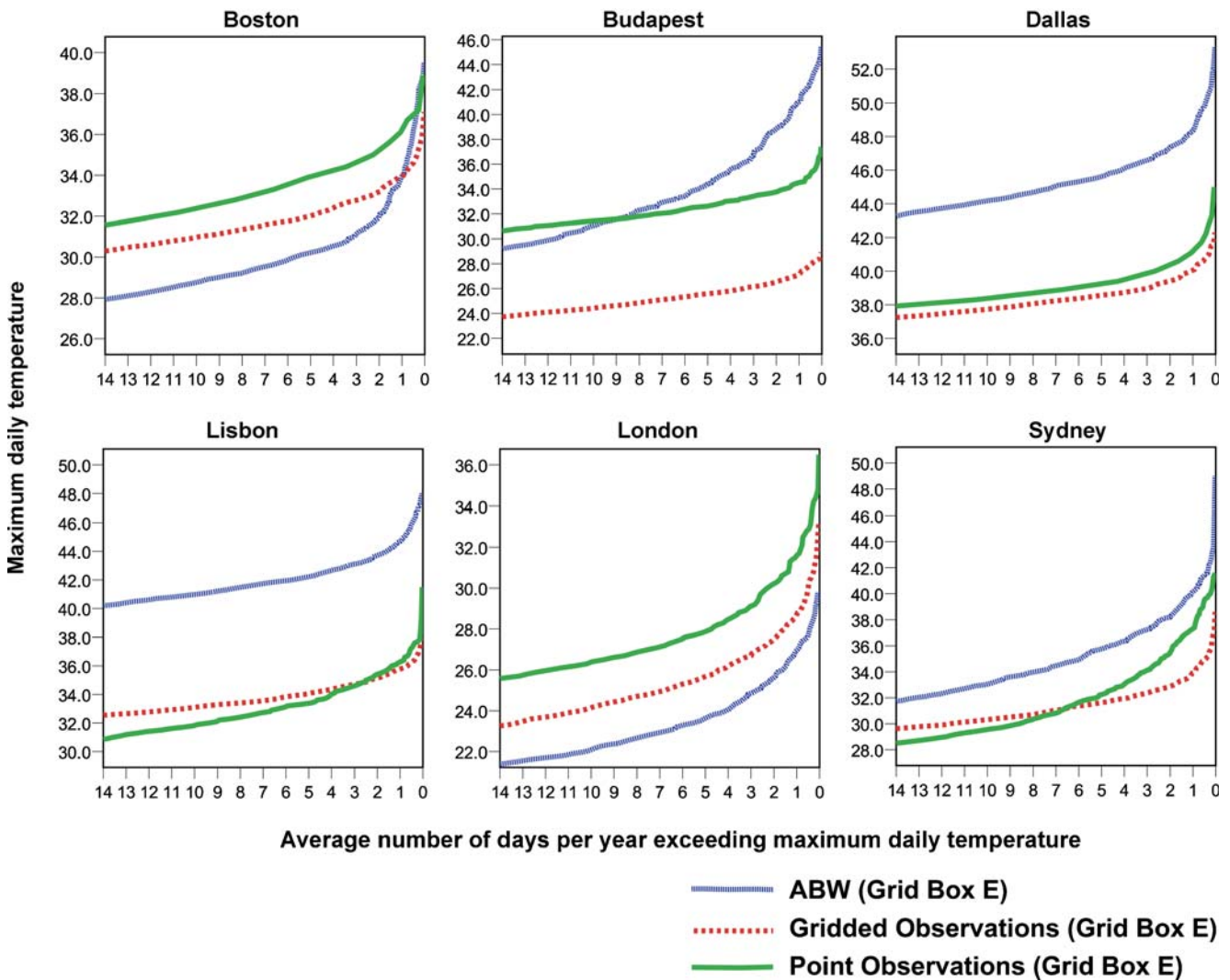


Fig. 5 The average numbers of days per year (summer only) maximum daily temperatures (°C) were exceeded

Considering the impacts of changes in the mean and variability of temperature with climate change on heat-related mortality

Four cases based on various combinations of mean and variability changes in temperature with climate change were defined to examine the potential impacts of climate change on heat related mortality. Regarding Case 1, Table 4 presents estimates of heat-related mortality arising from a change in the mean *and* variability of temperature. Estimates are greater under the SRES A2 scenario than SRES B2, but the magnitudes of the difference vary across cities because of differences in warming projected between the SRES A2 and B2 scenarios for each city (Fig. 7). Note that the climate model bias influences the temperature projection time series and consequently the impacts.

Also displayed in Table 4 are the results for Case 2, when mortality was estimated due to a change in mean

temperature *only*. The change in mean temperature from HadCM3 present A2 to HadCM3 future A2 was calculated and applied to the modelled present (Eq. (7a)) and observed present (Eq. (7b)) respectively. The influence of present HadCM3 model bias on the temperature projection time series, and so consequently on the mortality impacts, is removed in the latter. The result is that for some cities (e.g. Lisbon) the mortality estimates are very different between the two. Similarly for London and Boston, when the influence of a cooler than observed modelled present was removed, the estimated mortality was greater.

Mortality attributable to climate change was lower for Case 2 (when the A2 temperature anomaly was applied to the HadCM3 present) than Case 1, for all the cities except Dallas. Hence, more deaths were attributed to changes in the mean *and* variability of temperature with climate change than with the change in mean alone (except for Dallas).

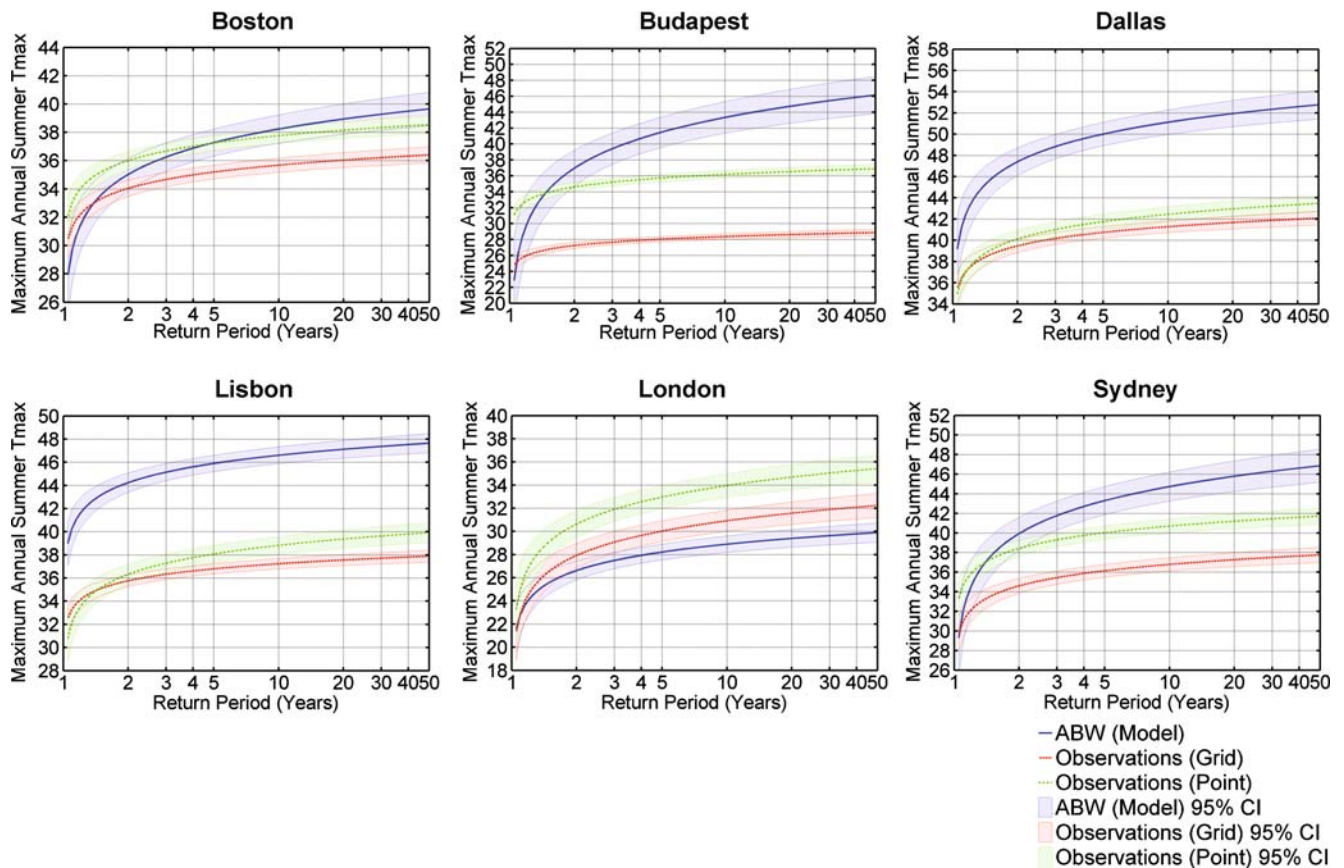


Fig. 6 The return levels (y-axis) of Tmax (°C) for ABW, gridded observations and point observations. The return period (x-axis) up to 50 years is shown on a log-scale

In Case 3, mortality was estimated due to a change in temperature variability *only*. Results are presented in Table 4. With the exception of London, the change in temperature variability for A2 was associated with lower mortality burdens than those associated with the change in mean temperature (Case 2). Interestingly, the change in variability reduced the number of future annual heat-related deaths relative to present for Dallas.

Case 4 compared the mortality for SRES A2 from Case 1 to the sum of the estimates from Case 2 and Case 3. Table 4 displays these estimates and the ratios calculated from Eq. (9). A ratio around 1.0 suggests the impacts of separate changes in the mean and variability of temperature combine linearly to impact on heat-related mortality. This appeared to be true for Budapest, Dallas, Lisbon and Sydney. However, the ratios were 3.0 and 1.9 for Boston and London, respectively. This implies that, for these cities, changes in the mean and variability of temperature with climate change have a combined impact on heat-related mortality that is greater than the sum of the individual changes in temperature mean and variability alone.

A novel method for considering changes in the mean and variability of temperature with climate change in assessments of future heat-related mortality

Figure 8 presents the PDFs of the logistic distributions and their parameters that were fitted to the HadCM3 present and future A2 temperature distributions, and to the point observations. Also shown are the PDFs of the artificial distributions and the distributions of the time series that were sampled from them. The logistic fits generally fit the data well, although they were unable to represent the skewness in some of the Lisbon and London distributions. Unlike in Case 1, the resultant temperature projection time series is not influenced by climate model bias in the modelled present.

The estimates of future heat-related mortality, allowing different degrees of acclimatisation under the artificial time series are presented in Table 5. Allowing for acclimatisation of 2°C reduced future heat-related mortality by approximately half that of no acclimatisation in each city.

Table 4 The table is divided according to the 4 Cases, described in "Materials and Methods"

City	Heat-related mortality (present)		Heat-related mortality (future)		Heat-related mortality attributed to climate change	
	A2 (modelled)	B2 (modelled)	Temperature mean and variability changes for A2	Temperature mean and variability changes for B2	Temperature mean and variability changes for A2	Temperature mean and variability changes for B2
Case 1						
Boston	2.0 (1.2, 3.4)	1.9 (1.1, 3.1)	142.5 (85.6, 237.0)	33.1 (19.9, 55.1)	140.4 (84.3, 233.6)	31.3 (18.8, 52.0)
Budapest	5.4 (1.3, 10.1)	5.0 (1.2, 9.5)	73.4 (23.5, 130.2)	48.0 (14.9, 85.7)	68.0 (22.2, 120.0)	42.9 (13.7, 76.2)
Dallas	19.2 (11.9, 31.0)	18.6 (11.5, 30.1)	145.0 (90.0, 233.6)	94.9 (58.8, 153.0)	125.8 (78.1, 202.6)	76.3 (47.3, 123.0)
Lisbon	327.7 (187.7, 568.9)	317.0 (181.6, 550.3)	7637.2 (4381.0, 13294.7)	4230.7 (2426.6, 7364.5)	7309.5 (4193.3, 12725.8)	3913.7 (2245.0, 6814.2)
London	0.3 (0.0, 0.7)	0.3 (0.0, 0.7)	6.9 (2.8, 14.8)	2.3 (0.8, 5.3)	6.7 (2.8, 14.0)	2.1 (0.7, 4.6)
Sydney	2.5 (1.6, 4.0)	2.6 (1.6, 4.1)	9.9 (6.2, 15.4)	9.4 (5.9, 14.6)	7.4 (4.7, 11.4)	6.8 (4.3, 10.5)
Case 2	A2 (modelled)	Point observations	Mean temperature change only applied to modelled present A2	Mean temperature change only applied to present point observations	Mean temperature change only applied to modelled present A2	Mean temperature change only applied to present point observations
Boston	2.0 (1.2, 3.4)	3.1 (1.9, 5.2)	37.8 (22.7, 62.9)	79.2 (47.6, 131.8)	35.8 (21.5, 59.6)	76.1 (45.7, 126.6)
Budapest	5.4 (1.3, 10.1)	5.4 (0.7, 10.8)	49.4 (14.6, 88.9)	61.7 (18.7, 110.6)	43.9 (13.3, 78.8)	56.2 (18.0, 99.8)
Dallas	19.2 (11.9, 31.0)	1.4 (0.9, 2.3)	211.3 (131.5, 339.8)	38.7 (23.9, 62.6)	192.2 (119.6, 308.8)	37.2 (23.0, 60.3)
Lisbon	327.7 (187.7, 568.9)	4.6 (2.7, 7.1)	7280.6 (4176.2, 12674.4)	99.9 (57.2, 171.7)	6952.9 (3988.4, 12105.5)	95.2 (54.6, 164.5)
London	0.3 (0.0, 0.7)	1.8 (0.3, 4.6)	1.9 (0.3, 5.1)	8.9 (3.0, 20.4)	1.7 (0.3, 4.4)	7.1 (2.6, 15.8)
Sydney	2.5 (1.6, 4.0)	1.6 (1.0, 2.6)	8.7 (5.5, 13.6)	7.1 (4.4, 11.2)	6.2 (3.9, 9.7)	5.5 (3.4, 8.6)
Case 3	A2 (modelled)		Variability temperature change only applied to present A2	Variability temperature change only applied to present A2	Variability temperature change only applied to present A2	Variability temperature change only applied to present A2
Boston	2.0 (1.2, 3.4)		12.3 (7.4, 20.5)	10.3 (6.2, 17.1)	10.3 (6.2, 17.1)	10.3 (6.2, 17.1)
Budapest	5.4 (1.3, 10.1)		12.3 (3.3, 22.6)	6.9 (2.0, 12.5)	6.9 (2.0, 12.5)	6.9 (2.0, 12.5)
Dallas	19.2 (11.9, 31.0)		10.1 (6.2, 16.3)	-9.1 (-5.7, -14.7)	-9.1 (-5.7, -14.7)	-9.1 (-5.7, -14.7)
Lisbon	327.7 (187.7, 568.9)		357.7 (204.9, 621.2)	30.0 (17.2, 52.3)	30.0 (17.2, 52.3)	30.0 (17.2, 52.3)
London	0.3 (0.0, 0.7)		2.2 (0.9, 4.8)	1.9 (0.8, 4.0)	1.9 (0.8, 4.0)	1.9 (0.8, 4.0)
Sydney	2.5 (1.6, 4.0)		3.2 (2.0, 5.0)	0.7 (0.4, 1.0)	0.7 (0.4, 1.0)	0.7 (0.4, 1.0)
Case 4	Future mortality due to a change in temperature mean and variability (A2)	Future mortality due to a change in temperature mean and variability (A2)	Future mortality due to the summed impacts of a change in temperature mean and variability separately (A2)	Ratio from Eq. (9)		
Boston	140.4 (84.3, 233.6)	46.1 (27.7, 76.7)	46.1 (27.7, 76.7)	3.0		
Budapest	68.0 (22.2, 120.0)	50.8 (15.3, 91.3)	50.8 (15.3, 91.3)	1.3		
Dallas	125.8 (78.1, 202.6)	183.1 (113.9, 294.1)	183.1 (113.9, 294.1)	0.7		
Lisbon	7309.5 (4193.3, 12725.8)	6982.9 (4005.6, 12157.8)	6982.9 (4005.6, 12157.8)	1.0		
London	6.7 (2.8, 14.0)	3.6 (1.1, 8.4)	3.6 (1.1, 8.4)	1.9		
Sydney	7.4 (4.7, 11.4)	6.9 (4.3, 10.7)	6.9 (4.3, 10.7)	1.1		

The present climate is either represented by point observations or modelled by HadCM3 [A2(modelled) and B2(modelled), which are simulations of the present climate from the same simulation used for the future A2 and B2 projections, respectively]. Cases 1–3 show mean summer heat-related mortality rates (per 100,000) in the present (1961–1990), future (2070–2099), and attributable to climate change, as calculated by Eqs. (6–8). Case 4 shows summer heat-related mortality rates (per 100,000) attributed to climate change for the future, according to the HadCM3 SRES A2 scenario; the 3rd column presents mortality rates for a climate change associated with a combined change in the location and scale of the temperature distribution (i.e. as calculated from Eq. (6)); the 4th column presents mortality rates calculated by summing the impacts estimated from separate changes in the location and scale of the temperature distribution from Case 2 and Case 3 (i.e. Eq. (7a) + Eq. (8)), and the 5th column presents the ratio calculated from Eq. (9)

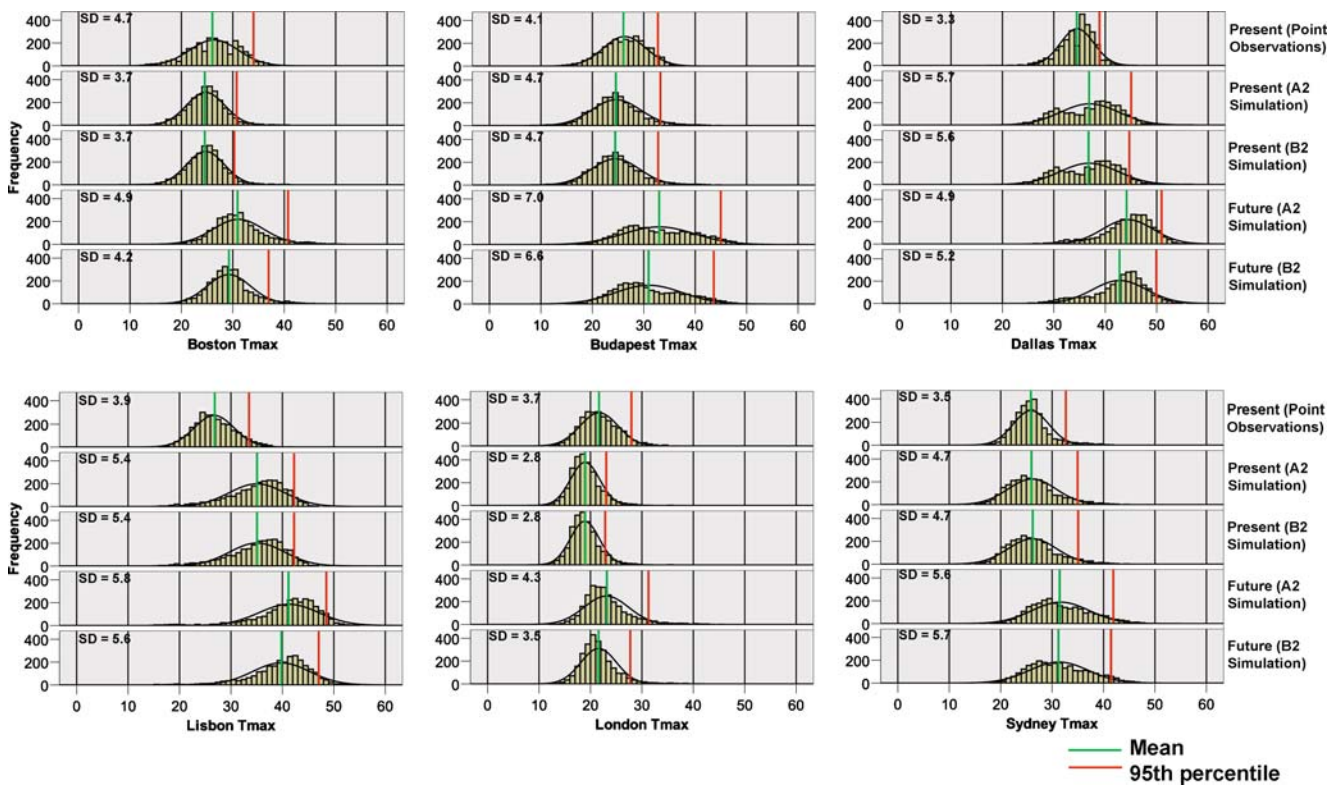


Fig. 7 Frequency distributions of daily Tmax (summer) for present point observations, HadCM3 present A2, HadCM3 present B2, HadCM3 future A2, and HadCM3 future B2. The standard deviation (SD) is labelled for each distribution. *Green vertical lines* denote the

mean, *red* the value of the 95th percentile. Normal curves have been fitted to each distribution for illustrative purposes, to allow a comparison of the shapes of the distributions

Discussion

HadCM3 model evaluation

An important inclusion in this study has been a climate model evaluation which highlights several important issues concerned with using global climate models (GCMs) such as HadCM3 to assess the impacts of climate change on heat-related mortality. These issues are discussed and are generally applicable to other climate change impacts assessments that incorporate data from GCMs.

Figure 2 illustrates that there are differences in the spatial scale at which temperatures are represented between the point observations and HadCM3 modelled temperatures. The temperatures from the GCM are representative of the entire grid box, but the point observations are only representative of the location surrounding the weather station from which the observations were made. Therefore, the grid box temperatures are not exactly representative of the conditions experienced by the populations in each city. However, strictly, neither are the point observations. For example, the point observations for Boston, Dallas and London are from airport weather stations, which may be some distance from where the majority of deaths occur.

Some studies address the issue of spatial representativeness by applying downscaled data from climate models. Statistical downscaling uses statistical relationships to convert the large-scale projections from a GCM grid box to fine scales. Statistical downscaling has been applied in assessments of heat-related mortality by Hayhoe et al. (2004) and McMichael et al. (2003). Dynamical downscaling uses a dynamic model similar in formulation to a global GCM but with greater resolution and covering only a limited region. The dynamic model is then forced at its lateral boundaries using results from the coarse scale GCM. Dynamical downscaling does not rely on the central assumption of most statistical downscaling, that the downscaling relationship derived for the present day will also hold in the future. However, it is computationally demanding. Dynamically downscaled data has been used by Dessai (2003) to assess the impacts of climate change on heat-related mortality. Studies by Donaldson et al. (2001) and Guest et al. (1999) chose not to apply any downscaling to the GCM temperatures, as we have done. It is important to understand that the choice of whether to apply downscaling and/or which method of downscaling is selected will have an influence on the final impacts. No studies have examined this for heat-related mortality,

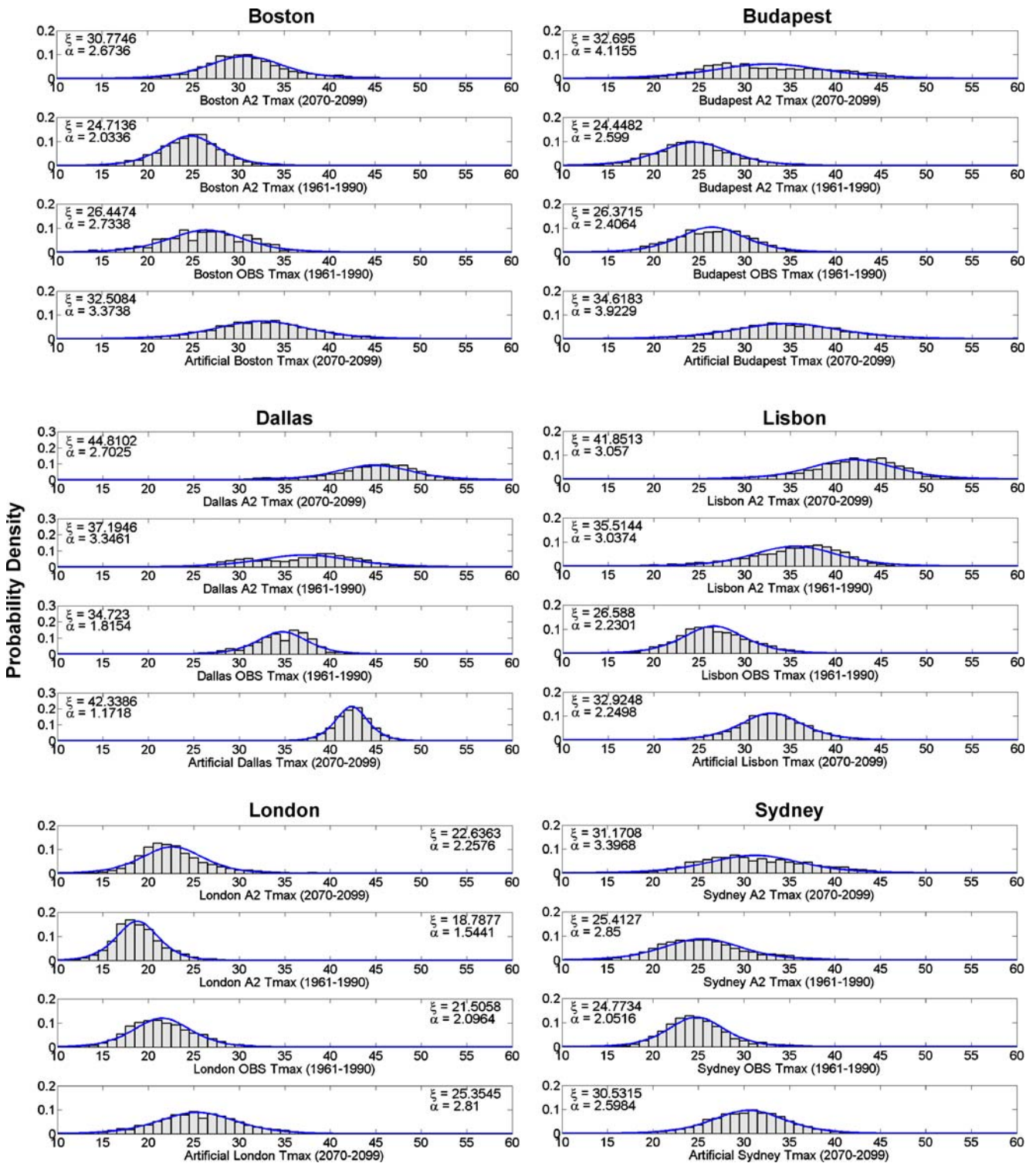


Fig. 8 Distributions of HadCM3 future A2 (*top panels*), HadCM3 present A2 (*2nd panels*), and point observations (*3rd panels*), for each city. Logistic PDFs that were fitted to these distributions are overlaid

and the parameters of the PDFs are presented in each panel. *Bottom panels* display the artificial PDF and its parameters, underlain with the distribution sampled from the PDF

although crop yield and tree range studies demonstrate significant differences in impacts dependent upon whether GCM or dynamically downscaled data is used (Kueppers et al. 2005; Tsvetinskaya et al. 2003; Mearns et al. 2001).

It should be understood that GCMs have not been designed for simulating local climates when validating GCM output on a local scale such as here (Huth et al. 2000). Nevertheless, several studies have compared GCM

output with observations at individual stations (Palutikof et al. 1997; Schubert 1998) as we did with the point observations, or with area averaged observations as we did with the gridded observations, but there remains debate as to which approach should be given preference (Huth et al. 2000; Skelly and Henderson-Sellers 1996).

For grid box E, the indices of agreement for Lisbon, London and Sydney were higher for the ABW-gridded observation pairs than the ABW-point observation pairs. An advantage of the gridded observations is that they represent surface temperatures at the same spatial resolution as the GCM. This might explain the differences in *d* for these three cities. This result means that it could have been beneficial to calibrate the t-m models from gridded observations or ABW temperatures rather than point observations for these cities. However, this would raise the question of whether the gridded observations and/or ABW temperatures are more representative of the conditions experienced by the populations living in the cities than the point observations.

Figures 5 and 6 demonstrated that extreme temperatures were generally more common in the simulated present climate than in the observed climate. Such discrepancies between observed and modelled extremes are common. Kjellström et al. (2007) found that ten RCMs generally underestimated (overestimated) maximum daily temperatures in northern (southern) Europe during summer for the period 1961–1990. Huth et al. (2000) presented similar findings to ours for eight stations in south Moravia (Czech Republic). Heat waves simulated by the ECHAM3 GCM were too long, appeared later in the year and peaked at higher temperatures than observed. In light of the results, the study concluded that climate model evaluations should be conducted prior to estimating future impacts due to climate change. Here, we have demonstrated the importance of this for heat-related mortality.

The role of climate model bias

We did not specifically calculate an estimate for the climate model bias in the modelled present for each city. Instead, we used the results from the frequency distribution plots and extreme values analysis to demonstrate that the modelled present was warmer and more extreme for Dallas and Lisbon. Climate model bias in the modelled present needs to be considered when assessing the impacts of climate change. It is perhaps for this reason that previous assessments use the delta method to create temperature projection time series that can be used to estimate future health impacts. The influence of climate model bias in the modelled present is removed because the modelled temperature anomaly (mean future–mean present) is added to the present observations rather than the modelled present.

Table 5 Mean summer heat-related mortality rates (per 100,000) estimated from point observations (1961–1990) and from the artificially created temperature projection time series (2070–2099)

City	Heat-related mortality (present)			Heat-related mortality attributed to climate change		
	Artificial time series derived from A2			Artificial time series derived from A2		
	No acclimatisation	Acclimatisation (2°C)	Acclimatisation (4°C)	No acclimatisation	Acclimatisation (2°C)	Acclimatisation (4°C)
Boston	3.1 (1.9, 5.2)	353.9 (212.5, 588.8)	191.5 (115.0, 318.7)	101.5 (61.0, 168.9)	350.8 (210.6, 583.6)	188.4 (113.1, 313.5)
Budapest	5.4 (0.7, 10.8)	98.5 (31.9, 174.2)	69.5 (22.0, 123.6)	47.7 (14.6, 85.4)	93.0 (31.2, 163.4)	64.0 (21.2, 112.8)
Dallas	1.4 (0.9, 2.3)	33.7 (20.8, 54.6)	15.0 (9.2, 24.3)	6.2 (3.8, 10.1)	32.3 (19.9, 52.3)	13.5 (8.3, 22.0)
Lisbon	4.6 (2.7, 7.1)	561.2 (322.1, 974.0)	257.2 (147.6, 445.4)	115.2 (66.1, 198.6)	556.6 (319.5, 966.9)	252.5 (144.9, 438.3)
London	1.8 (0.3, 4.6)	12.5 (4.9, 27.1)	6.8 (2.5, 15.3)	3.6 (1.2, 8.2)	10.7 (4.6, 22.5)	5.0 (2.1, 10.7)
Sydney	1.6 (1.0, 2.6)	6.7 (4.2, 10.6)	4.3 (2.6, 6.8)	2.5 (1.6, 4.1)	5.1 (3.2, 8.0)	2.6 (1.6, 4.2)

The associated mortality rates attributable to climate change [calculated by Eq. (10)] are also shown. Assumptions of varying degrees of acclimatisation are included

Case 2 demonstrated that the mortality burdens due to climate change for Dallas and Lisbon were far greater when the temperature projection time series were created by adding the anomalies to the modelled present, i.e. present model bias was not removed [Eq. (7a)]. Similarly, for Boston and London, which exhibited negative present model biases, the burdens were far less when present model bias was not accounted for. If the burdens are expressed as percentage changes from the present estimates, then the differences in the impacts between accounting for bias and not accounting for bias can be up to 1,600% (Dallas).

Although the delta method is useful because the climate model bias in the modelled present is unable to influence the magnitude of the impacts, it is not without its limitations. Biases in model simulations of the present may be present in the simulations of future conditions, for example due to differences caused by not fully representing mountain heights (Doherty and Mearns 1999). Biases may also be present in future projections if local feedbacks (e.g. cloud feedbacks) are strongly dependent on the mean climate state of the model (Williams et al. 2001). The delta method does not account for this and justifies the need for climate model evaluation in impact studies, so that the results can be interpreted accordingly. For example, considering the results of the climate model evaluation it should be noted that all estimates of future heat-related mortality for Dallas and Lisbon may be overestimated due to positive model bias. Likewise, estimates for Boston and London may be underestimated due to negative model bias. This is likely to be compounded by the use of mortality absolute threshold temperatures because, in a simulated climate with a positive bias, there will be more days when temperatures exceed the threshold temperature than for a simulation with negative or no bias. This could be an issue with other climate models. For example, Kjellström et al. (2007) validated ten RCMs and found that biases were larger in the 95th/5th percentiles of daily temperature than the corresponding biases in the median, meaning that the biases generally increased towards the tails of the probability distributions. A possible solution to this would be to define relative thresholds that are based on the 95th percentile of summer maximum temperature, for example. In such a case, the threshold temperature would be relatively higher in a climate simulated with positive model bias than in a climate with no model bias.

Another limitation of the delta method is that the temperature projection time series inherently has the same variability as the observed climate. Hence it assumes that climate variability does not change in the future. Relatively speaking, a 1°C change in the standard deviation of the temperature distribution under climate change will have a greater impact on the frequency of an extreme temperature

than a 1°C change in the mean of the distribution (Meehl et al. 2000). Therefore, it is important to consider the impacts associated with changes in the mean *and* variability of temperature with climate change.

Considering the impacts of changes in the mean and variability of temperature with climate change on heat-related mortality

Unlike previous climate change-heat-related mortality assessments, we considered the role of changing temperature variability. The importance of temperature variability can be highlighted by comparing the impacts estimated in Case 2 (change in temperature mean applied to modelled present) to Case 1. More deaths were attributed to changes in the mean *and* variability of temperature with climate change (Case 1), than due to the change in mean alone (Case 2) except for Dallas, i.e., with the exception of Dallas, the other cities presented increases in future temperature variability that were associated with increases in future mortality. The results from Case 3 support this by showing that increases in variability were associated with increases in mortality. Interestingly, the change in variability reduced the number of future annual heat-related deaths relative to present for Dallas. This is likely due to Dallas being the only city where the future HadCM3 A2 variability was lower than the present HadCM3 A2 variability (note standard deviations in Fig. 7).

With the exception of London, the changes in temperature variability only (Case 3) were associated with lower mortality burdens than those associated with changes in mean temperature only (Case 2). The results demonstrate that, if changes in temperature variability are ignored, it is likely that the full impacts of changing temperatures with climate change on heat-related mortality are not represented. However, the impacts associated with changes in variability are generally lower than those associated with changes in the mean climate. Nevertheless, this does not justify the exclusion of temperature variability in future impact studies.

A novel method for considering changes in the mean and variability of temperature with climate change in assessments of future heat-related mortality

Although the methodology for estimating impacts in Case 1 considers changes in both the mean and variability of temperature, climate model bias in the modelled present has an influence on the impact estimates. A solution to this could be to sum the separate impacts associated with changes in the mean and variability of temperature, respectively (when climate model bias in the modelled present is removed, as in Case 2). However, Case 4

demonstrated that this may not replicate the impacts estimated in Case 1 because the separate impacts do not necessarily combine linearly. These limitations provided the rationale for describing a novel method for considering changes in the mean and variability of temperature with climate change in assessments of future heat-related mortality.

The method we applied to create a temperature projection time series removed the influence of climate model bias in the modelled present on the mortality estimates, whilst at the same time allowing for projected changes in mean and variability of temperature. However, it should be understood that had different distributions been fitted to the temperature distributions, the sampled artificial temperature projection time series would have been slightly different. This would mean the mortality estimates would also be slightly different to those presented here. Furthermore, random samples were taken from the artificial distributions to produce the artificial time series. Again, the final impacts would be slightly different if a new random sample was taken.

By comparing the mortality estimates from this method with those of Case 1, the influence of climate model bias in the modelled present when considering changes in the mean and variability of temperature on the impacts is clear. For example, Dallas and Lisbon were the two cities with the greatest positive bias. Future mortality estimates in Case 1 were 125.8 and 7,309.5 (per 100,000), respectively, but when the influence of model present bias was removed by using the novel methodology we present, the estimates reduced to 32.3 and 556.6, respectively. Likewise, Boston and London exhibited negative model biases. Case 1 mortality estimates were 140.4 and 6.7, respectively, and estimates using the novel methodology were around two times greater at 350.8 and 10.7, respectively.

Consideration of emissions and acclimatisation uncertainties

The differences in warming projected between the SRES A2 and B2 scenarios (Fig. 7) meant that the magnitude of the impacts between each scenario differed for each city. For example, for Boston the impacts under the A2 scenario were around 78% greater than the impacts under the B2 scenario. For Sydney, the impacts were only around 8% greater for A2 than B2. This demonstrates the importance of examining the impacts for temperatures at high resolution spatial scales rather than, for example, using mean global temperatures. Guest et al. (1999) observed large differences between the impacts for a low and high climate change scenario across five Australian cities. Mortality was around 69% greater for the high scenario for the total of all five cities, but at the individual city level the difference could be as little as 10%.

By applying the novel methodology we presented, we considered the possibility that populations may acclimatise to warmer temperatures in the future. There is much debate as to how acclimatisation should be modelled (Gosling et al. 2008). An approximation of the inherent acclimatisation trend can be removed from historical time series data by regression techniques prior to modelling the temperature–mortality relationships (Davis et al. 2004). A limitation of removing the trend is that it does not attempt to model future acclimatisation per se, rather it provides an objective projection that has controlled for historical acclimatisation. Another method involves the use of ‘surrogate’ cities (Knowlton et al. 2007; National Assessment Synthesis Team 2000; Kalkstein and Greene 1997) whose present climate best approximates the estimated climate of a target city as expressed by climate model projections; for example, assuming in the future that New York’s population will have the same dose–response relationship as Atlanta’s. This method receives the most criticism because it inherently assumes stationarity of temperature–mortality relationships by using past ones to represent future ones. Furthermore, it does not account for unique place-based characteristics of cities that are related to mortality (Smoyer 1993). We adopted a method that involved increasing the threshold temperature with time (Dessai 2003; Honda et al. 1998). The gradient of the temperature–mortality relationship remains unchanged, so the dose–response curve is simply ‘shifted’. It is possible that the gradient of the relationship might change in the future, but this was not considered. Honda et al. (1998) presented empirical evidence that the threshold temperature could be up to 5°C higher in regions in Japan where the mean climate was 2°C warmer. However, this was based on observations between cities with different climates over the period 1972–1990. Unfortunately, there is no long-term evidence for a single location to indicate how much dose–response relationships may be ‘shifted’. We decided upon shifting the curves by 2°C and 4°C, respectively, because these bounded the acclimatisation assumptions of a previous study (Dessai 2003), namely that a population may acclimatise to an extra 1°C relative to present every three decades. Also, we considered the shifts as realistic because they are within the range of the geographical variation of observed threshold temperatures identified in Part 1.

The potential health benefits of acclimatisation vary. Dessai (2003) estimated that acclimatisation to an extra 3°C reduced summer heat-related mortality by about 70% by the 2080s for Lisbon, relative to no acclimatisation. We estimated a similar reduction for Lisbon, 80% relative to no acclimatisation assuming that the population acclimatised to an extra 4°C. The other cities in our assessment also presented reductions around 80% assuming acclimatisation to 4°C, although the reductions were smaller in Budapest at

about 55%. Knowlton et al. (2007) present reductions of 25% by the 2050s relative to no acclimatisation for the New York City region. The study used the ‘surrogate’ city method to model acclimatisation. The different methods available for modelling acclimatisation mean that it is difficult to objectively compare results across studies. To some extent, the results are dependent upon the method chosen.

Comparisons with previous assessments

It is simpler to compare the results from this study with other studies by assuming no acclimatisation. We use the estimates from Case 2 (Eq. (7b)) for comparison because previous assessments only consider changes in mean temperature with climate change. McMichael et al. (2003) estimated that heat-related mortality amongst people aged over 65 years would increase by 149% by the 2050s relative to 1997–1999 for Sydney. The estimates were based on a high climate change scenario from the ECHAM4 model and assumed no demographic changes. Our estimate for Sydney was greater at 344%, but this was for the 2080s when the climate was more extreme than during the 2050s. Dessai (2003) estimated that heat-related mortality would increase by 3,816% (PROMES climate model) and 1,106% (HadRM2 climate model) in Lisbon by the 2080s relative to 1969–1998 for a scenario that involved the doubling of carbon dioxide concentrations from present levels. Demographic changes were included. The increase estimated in our study was around 2,070%. Large increases have also been estimated by Hayhoe et al. (2004) for Los Angeles. Heat-related mortality increased by about 1,616% relative to 1961–1990 based on temperatures from HadCM3 driven by the SRES A1Fi scenario, and assuming acclimatisation and no demographic changes. Donaldson et al. (2001) estimated that UK total heat-related mortality would increase by 350% by the 2080s relative to 1961–1990 under the HadCM2 climate model driven by a medium-high climate change scenario and assuming no demographic changes. This compares to our estimate of 394%. It is likely that the results are similar because the medium-high scenario applied by Donaldson et al. (2001) corresponds to the SRES A2 scenario we applied. Also, although we use a newer version, both the GCMs were developed at the same modelling centre (Meteorological Office Hadley Centre) and have broadly similar climate sensitivities and patterns of temperature response. Furthermore, neither study assumes demographic changes. The differences between our estimates and those from the other assessments cited above may be explained by a number of factors. For example, the selections of climate change scenarios, the climate model used, whether demographic changes were considered and whether downscaling was applied to the temperature data.

Although our city-specific results are in general agreement with the other studies cited above, it is important to acknowledge that there are considerable differences in the impacts projected between the six cities. Some of these differences are due to climate model biases (e.g. Lisbon, discussed previously) but some are also due to the sensitivity of the temperature-mortality relationships derived in Part 1. For example, Dallas presents a strong climate model bias comparable to that of Lisbon, but the sensitivity of the temperature–mortality relationship is weaker for Dallas. Therefore, the impacts are less severe in Dallas than in Lisbon. Furthermore, a certain amount of the differences will be due to variations in the relative extents of warming projected for each city.

Conclusions

We have illustrated the importance of considering changing temperature variability with climate change in assessments of the impacts of climate change on heat-related mortality. Our results demonstrate that higher mortality is attributed to increases in the mean *and* variability of temperature with climate change than with the change in mean temperature alone. This has implications for interpreting existing impacts estimates that have used the delta method to create temperature projection time series. The impacts may be underestimated because they do not consider the role of changing temperature variability with climate change. Therefore, we recommend that future assessments consider changes in the mean and variability of temperature. The novel method we have presented allows temperature projection time series that include changes in the mean and variability of temperature to be created. The method is robust because it avoids climate model bias in the modelled present influencing the final temperature projection time series.

A key consideration has been that of climate model bias, i.e. whether the model systematically projects warmer or cooler temperatures than observed. We demonstrated that the differences in the mortality impacts between accounting for bias and not accounting for bias can be up to 1,600%. A recommendation for future health impacts assessments is to conduct climate model evaluations so that the impacts can be placed within the context of the climate model’s abilities to represent the present and future climate. However, it must be acknowledged that future estimates of mortality are not solely GCM-dependent, but also dependent upon the observed data and methods used to calibrate the climate–health relationships (Gosling et al. 2007).

The uncertainty in the mortality impacts due to different emissions scenarios of greenhouse gases in the future varied considerably by location. Whether future populations

will acclimatise to warmer temperatures in the future is another important uncertainty that needs to be considered. Allowing for acclimatisation of 2°C reduced future heat-related mortality by approximately half compared to that of no acclimatisation in each city. However, a key question is by how much will populations acclimatise in the future? Questions such as this, uncertainty associated with emissions scenarios, the roles of the mean and variability of temperature with climate change and climate model evaluation, are factors that should be considered in future climate change heat-related mortality impacts assessments. This will facilitate a better understanding of the potential impacts, which can be used to assist policy-making decisions.

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