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Adaptation to climate change: a comparative analysis of modelling methods for heat-related mortality

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Running title

Comparing adaptation modelling methods

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Abstract

Background: Multiple methods are employed for modelling adaptation when projecting the impact of climate change on heat-related mortality. The sensitivity of impacts to each is unknown because they have never been systematically compared. In addition, little is known on the relative sensitivity of impacts to "adaptation uncertainty" (i.e. the inclusion/exclusion of adaptation modelling), relative to using multiple climate models and emissions scenarios.

Objectives: (1) Compare the range in projected impacts that arises from using different adaptation modelling methods; (2) compare the range in impacts that arises from adaptation uncertainty to ranges from using multiple climate models and emissions scenarios; (3) recommend modelling method(s) to use in future impact assessments.

Methods: We estimated impacts for 2070-2099, for 14 European cities, applying six different methods for modelling adaptation; also with climate projections from five climate models, run under two emissions scenarios to explore the relative effects of climate modelling and emissions uncertainty.

Results: The range of the difference (%) in impacts between including and excluding adaptation, irrespective of climate modelling and emissions uncertainty, can be as low as 28% with one method and up to 103% with another (mean across 14 cities). In 13 of 14 cities the ranges in projected impacts due to adaptation uncertainty are larger than those associated with climate modelling and emissions uncertainty.

Conclusions: Researchers should carefully consider how to model adaptation because it is a source of uncertainty that can be greater than the uncertainty in emissions and climate modelling. We recommend absolute threshold shifts and reductions in slope.

Introduction

One of the direct public health risks posed by climate change is increased heat-related mortality and morbidity (Gosling et al. 2012; Hajat et al. 2014; Hales et al. 2014; Kingsley et al. 2016; Peng et al. 2011; Petkova et al. 2013; Petkova et al. 2016; Sheridan et al. 2012; Vardoulakis et al. 2014; Wu et al. 2014), due to increased occurrences of cardiovascular and chronic respiratory causes (Huynen and Martens 2015; Martens 1998; McMichael et al. 2006). Governments and community organisations around the world are increasingly allocating resources to prepare for a warmer future climate (Boeckmann and Rohn 2014). Central questions that should guide the decision-making process when making such investments include (1) what are the likely health impacts of possible changes? And (2) what are the interventions and programs, and scale thereof, that offer the highest probability of reducing the magnitude of any adverse impacts? Answers to these questions depend in part on the extent to which populations may adapt to future climate change.

Adaptation mechanisms may occur through autonomous adaptation, such as physiological acclimatisation and a range of behavioural adaptations such as dressing appropriately during hot weather. They may also occur through planned adaptation, such as the introduction of government subsidies to increase air conditioning installations or the introduction of heat health warning systems, and public responses through health services such as changing prescription patterns and arranging home visits. Attempts to combine both autonomous and planned adaptation to represent the whole range of adaptation mechanisms, and then factor them in to quantitative assessments of the impact of climate change on heat-related mortality by statistical modelling, are largely based on liberal assumptions on the extent to which populations will adapt (Hayhoe et al. 2004; Honda et al. 2014b; Jenkins et al. 2014; Knowlton et al. 2007; Mills et al. 2014; Zacharias et al. 2015).

The potential to adapt is supported by a growing body of evidence that shows populations across the globe are becoming less sensitive to high temperatures, e.g. see reviews by Boeckmann and Rohn (2014) and Hondula et al. (2015). However, there is variation in the magnitude of the declines in sensitivity that have been observed between studies (e.g. Bobb et al. 2014; Schwartz et al. 2015; Todd and Valleron 2015), across locations (Gasparrini et al. 2015a) and over time (Åström et al. 2016). There are also overall limits to adaptation (Smith et al. 2014; Woodward et al.) as, for example, air conditioning penetration reaches 100%, or physiological tolerance reaches biological limits. In addition, many studies neglect to unpick the factors that have driven declines in sensitivity to heat, and whether the declines are due to autonomous or planned adaptation (Petkova et al. 2014b). This precludes an understanding of what policies could help foster the most efficient adaptation practices. Multiple datasets on factors such as air conditioning penetration, human behaviour, activation of heat health warnings, and changes in health-care provision are needed to address this, but such datasets are rarely available at a sufficient temporal resolution (several decades) to elucidate the effects. The research needed to reveal these important insights will require an inter-disciplinary approach that combines quantitative and qualitative methods.

Variation in the magnitude of observed declines in sensitivity to heat has limited the ability of researchers to investigate the effects of adaptation assumptions on projections of the impact of climate change. Thus some researchers have not considered adaptation effects at all (e.g. Baccini et al. 2011; Hajat et al. 2014; Kingsley et al. 2016; Peng et al. 2011; Vardoulakis et al. 2014; Wu et al. 2014). Such an approach, however, which ignores what we refer to here as "adaptation uncertainty" (i.e. the sensitivity of impacts to including and excluding adaptation modelling respectively), is acknowledged to likely over-estimate impacts (Huang et al. 2011; Martin et al. 2011; Petkova et al. 2013).

Within this context a number of impact assessments *have* accounted for adaptation uncertainty by representing adaptation statistically in the modelling process, suggesting that impacts could be up to 30-80% (Jenkins et al. 2014; Sheridan et al. 2012) lower or more (Honda et al. 2014a) in the future with adaptation than without. Whilst the inclusion of adaptation may be considered an advantage over excluding it, because it accounts for likely autonomous and planned adaptation, it is important that the modelling methods are justified robustly with reference to empirical evidence. An arbitrary assumption that populations might adapt by 100% (Honda et al. 2014a), for instance, could lead to under-estimation of climate change impacts.

Statistical methods for modelling adaptation

A variety of different statistical methods have been used to model adaptation. Six main methods can be employed (Table 1). In all but one study, where three of the methods were applied in the Netherlands (Huynen and Martens 2015), the six methods have been applied independently and never compared quantitatively, although an interesting discussion of the methods is presented by Kinney et al. (2008). Our study is distinct from all previous work because we compare all six methods across multiple European cities and because we consider multiple assumptions in the magnitudes of potential adaptation systematically for each method. We describe the six methods here and discuss their strengths and limitations.

Two methods are based on shifting the threshold temperature of an epidemiological exposure-response function (ERF). Many different conceptualisations of threshold temperatures are presented in the literature, including minimum mortality temperatures, optimum temperatures, and other derivations related to statistical differences in relative risk between baseline and extreme conditions (see Åström et al. 2016; Honda et al. 2014b; Petitti et al. 2016). Regardless of the specific statistical definition of the threshold, in general, the risks of heat-related mortality are lowest (or lower) at the threshold whilst for temperatures higher than the threshold there is a proportionally higher risk (e.g. Baccini et al. 2008).

The "absolute threshold shift" method first defines the present-day threshold temperature in absolute terms (°C) and then increases it in the future. Assessments have assumed shifts of the ERF in the future by up to 2°C (Jenkins et al. 2014), 2.4°C (Huynen and Martens 2015), 3°C (Dessai 2003) and 4°C (Gosling et al. 2008). This is perhaps the most straightforward method, which is why it has been used most frequently in previous studies. The magnitude of shift tends to be selected arbitrarily and justified with no reference to empirical evidence from epidemiological studies.

The "relative threshold shift" method assumes "0% adaptation" when the threshold temperature in absolute terms (that is calculated originally as a percentile of the present-day daily temperature time series) is also used with the future time-series. "100% adaptation" is when the threshold temperature for the future is at the same percentile value as the present-day (the absolute value will therefore be higher in a warmer climate). The midpoint of the threshold temperatures between 0% and 100% adaptation is "50% adaptation". Previous assessments have assumed up to 50% (Zacharias et al. 2015) and 100% adaptation (Honda et al. 2014a; Honda et al. 2014b). A caveat of this method is that the magnitude of shifts employed in the studies that use this method, are based only upon changes in the threshold temperature observed in Tokyo between 1972-1994 (Honda et al. 2006).

Temperature-mortality ERFs are typically described by linear or non-linear slopes that start from a threshold temperature. Accordingly the third adaptation modelling method reduces the slope of the ERF in the future. Huynen and Martens (2015) assumed a 10% reduction in linear slope using this method. This method is intuitive because it is plausible that populations may become less sensitive to high temperatures under climate change, which would manifest as a reduction in the slope of the ERF. However, Huynen and Martens (2015) acknowledge that the 10% decline in slope they applied is hypothetical and they do not provide empirical evidence to support it. The method is straightforward to apply to a linear ERF but considerably more complicated for a non-linear ERF.

The fourth and fifth methods combine shifts in the threshold with reductions in the slope. Huynen and Martens (2015) assumed a reduction in the slope of the ERF by 10% and combined this with absolute threshold shifts. No studies have yet combined a relative threshold shift with a reduction in slope, despite encouragement that studies should combine shifts with reductions in slope (Huang et al. 2011).

The sixth method uses "analogue ERFs", i.e. ERFs derived for locations with temperatures similar to those projected to occur in the future in the location of interest. Whilst the method has been criticised (Kinney et al. 2008) and it assumes that the underlying confounding factors that contribute to the ERF can be transferred to a different location, it is popular (Hayhoe et al. 2004; Knowlton et al. 2007; Mills et al. 2014) because it draws upon epidemiological evidence that populations in warmer/colder regions tend to be less/more sensitive to relatively higher temperatures (Davis et al. 2003).

A caveat that runs through all the methods employed in previous work is that they are not supported with reference to specific empirical evidence that confirms the magnitudes of adaptation assumed. The only exception is that the relative threshold shift method has been justified with reference to the observation that threshold temperatures can generally be estimated using the 80–85th percentile of daily maximum temperature in multiple locations in Japan (Honda et al. 2007; Honda et al. 2014b). It would of course be preferable to replicate this observation across other locations. A novel opportunity exists to develop adaptation modelling methods based upon empirical evidence of historical adaptation because a growing body of evidence shows that in some cities and countries populations are becoming less sensitive to extremes of heat (Arbuthnott et al. 2016; Astrom et al. 2013; Åström et al. 2016; Bobb et al. 2014; Gasparrini et al. 2015b; Honda et al. 2006; Schwartz et al. 2015). The mechanisms associated with, and driving this decline, are a matter of debate, but it is clear from these studies that population sensitivity to heat can and does vary over time. It is somewhat surprising therefore that there has been no significant advancement in the statistical methods used to model adaptation over the past decade – the methods used over 10 years ago are still being used now (Table 1).

Current research gaps

The application of multiple adaptation modelling methods across different climate change impact studies means that there is no clear understanding of the relative effects that each method can have on impacts. Nor is there a recommendation of what method is most appropriate for application (Huang et al. 2011). This is compounded by the general lack of rationale for the adaptation methods chosen in past studies. Some methods have been used more frequently than others, e.g. absolute threshold shifts (Table 1), perhaps because they are more straightforward to apply than some of the other methods.

The use of different Global Climate Models (also known as General Circulation Models; GCMs) and emissions scenarios in climate change impact assessments enables an evaluation of the sensitivity of the impacts to “climate model uncertainty” and “emissions uncertainty” respectively (Gosling et al. 2012; Hajat et al. 2014; Peng et al. 2011; Zacharias et al. 2015). Whilst a limited number of impact studies have included multiple GCMs, emissions scenarios and adaptation assumptions altogether in the modelling exercise to account for these three key uncertainties (Gosling et al. 2008; Petkova et al. 2016; Sheridan et al. 2012), such a holistic approach is uncommon (Huang et al. 2011). To this end little is known about the relative contributions of these three sources of uncertainty to ranges in projections of heat-related mortality impacts.

To address these important research gaps our study had three main objectives. *Firstly*, to conduct the first systematic comparison of the range in projected impacts that arises from using different adaptation modelling methods employed in previous studies; *secondly*, to compare the range in impacts that arises from adaptation uncertainty (i.e. impacts with the inclusion/exclusion of adaptation) to the ranges from climate modelling and emissions uncertainty respectively; and *thirdly*, to provide the first recommendation of one or several adaptation modelling methods to use in future impact assessments.

Materials and Methods

Experimental design

Across 14 European cities (see Table 2) we estimated the mean annual warm season (1 April to 30 September) heat-related mortality rate attributable to climate change (ΔMort-CC), under the assumption that populations will not adapt in the future, i.e. “no adaptation”. We then estimated the impacts using six different methods for modelling adaptation respectively. In both cases the impacts were estimated using climate projections from one GCM (HadGEM2-ES) that was run under a single emissions scenario (Representative Concentration Pathway (RCP) 8.5), to control for the effects of climate modelling and emissions uncertainty. We chose RCP8.5 because it is the highest of the four RCP emissions scenarios commonly used in climate modelling (Riahi et al. 2011), meaning that it should *a* *priori* enhance elucidation of the effects of modelling adaptation with different methods under a plausible emissions scenario. This approach enabled calculation of the range in impacts that arises from estimating them with adaptation and with no adaptation.

We also estimated impacts with no adaptation, using climate projections from five GCMs run under RCP8.5 to explore the effect of climate modelling uncertainty whilst controlling for adaptation and emissions uncertainty. Furthermore, we estimated impacts with HadGEM2-ES run under low (RCP2.6) and high (RCP8.5) emissions scenarios respectively to explore the effect of emissions uncertainty whilst controlling for adaptation and climate modelling uncertainty. The experimental design is summarised in Table 3.

The 14 cities were chosen because ERFs that were developed using the same methodology for each city were available (Baccini et al. 2008). This provided a consistent set of ERFs upon which to test the sensitivity of climate change impacts to adaptation assumptions.

Climate change projections

Time-series of daily maximum temperature (t_{max}), mean temperature (t_{mean}) and mean relative humidity (RH) were extracted for the 0.5°x0.5° grid cells located closest to each city, for the present-day (1981-2010) and future (2070-2099), from five GCM simulations (HadGEM2-ES GCM, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2 and NorESM1-M). This set of GCMs has been used in numerous impact assessments to demonstrate the range in impacts that can arise from climate modelling uncertainty (Warszawski et al. 2014).

Each GCM was run under RCP8.5 (high emissions) and RCP2.6 (low emissions) as these are the highest and lowest emissions scenarios commonly used in climate modelling that are available from the four RCP emissions scenarios (Riahi et al. 2011). By using the highest and lowest we were able to investigate the maximum extent to which emissions scenario choice contributes to the uncertainty in projected heat-related mortality impacts.

The climate variables were bias-corrected towards an observation-based dataset (Weedon et al. 2011), using an established method (Hempel et al. 2013), specifically designed to preserve long-term trends in temperature projections to facilitate climate change impact assessments. The GCM data could therefore be used for the present-day and future time periods in the impact assessment.

The ERFs we used (Baccini et al. 2008) required daily maximum apparent temperature (AT_{max}), so this was computed as:

$$AT_{max} = -2.653 + 0.994.t_{max} + 0.0153.(t_d)^2 \quad [1]$$

Where t_d is daily mean dew point, which was computed from RH and t_{mean} following Tetens (1930). For Barcelona, daily mean apparent temperature (AT_{mean}) had to be calculated because the ERF for Barcelona required this instead of AT_{max}. Therefore we calculated daily AT_{mean} by replacing t_{max} with t_{mean} in [1].

Heat-related mortality estimation

We applied city-specific linear ERFs derived from Baccini et al. (2008) for each of the 14 cities. The ERFs describe linear relationships between daily AT_{max} (AT_{mean} for Barcelona) and daily heat-related mortality in terms of Relative Risk (RR). RRs were reported by Baccini et al. (2008) as a percentage change in mortality per 1°C above the city-specific threshold temperature. We converted the RRs to RR ratios from:

$$\text{percentage change} = (RR - 1)*100 \quad [2]$$

β, the concentration-response factor (CRF, the estimated slope of the linear relation between AT_{max} (AT_{mean} for Barcelona) and daily heat-related mortality) was derived from:

$$RR = \exp^{\beta \Delta T} \qquad [3]$$

Where ΔT is a 1°C change in daily AT_{max} (AT_{mean} for Barcelona) above the threshold temperature. The RRs, CRFs and threshold temperatures for each city are displayed in Table 2.

Daily heat-related mortality for each city was then calculated from the city-specific ERFs, for the present-day (1981-2010) and future (2070-2099) respectively. For the present-day and future we first calculated the daily attributable fraction, AF, which is the fraction of the mortality burden attributable to the risk factor ΔX (daily AT_{max} (AT_{mean} for Barcelona) above the threshold temperature), for the exposed population. Following previous studies, it was assumed that the whole population at the threshold temperature is exposed (Huynen and Martens 2015; Knowlton et al. 2007; Schwartz et al. 2015; Vardoulakis et al. 2014):

$$AF = 1 - \exp^{-\beta . \Delta X} \qquad [4]$$

The AF was multiplied by the baseline daily mortality rate (y_0, Table 2) and the exposed population (Pop, Table 2)to yield the absolute number of daily heat-related deaths (*Mort*) for the present-day and future respectively, using an established method (Hajat et al. 2014; Huynen and Martens 2015; Knowlton et al. 2007; Peng et al. 2011; Petkova et al. 2013; Schwartz et al. 2015; Vardoulakis et al. 2014; Wu et al. 2014), as:

$$Mort = y_0.\mathrm{AF}.\mathrm{Pop}/100{,}000 \qquad [5]$$

Mort was calculated only for the warm season (1 April to 30 September) because the ERFs were derived for these months only (Baccini et al. 2008). ΔMort-CC was then calculated by converting *Mort* into a mortality rate (per 100,000, using Pop) and then subtracting it for the present-day time period from the estimate for the future time period.

We did not change y_0 and Pop between time periods, in line with previous studies (e.g. Gosling et al. 2012; Petkova et al. 2013; Wu et al. 2014) because estimation of ΔMort-CC as a rate instead of absolute deaths facilitates comparisons across GCMs, emissions scenarios, different cities, and different methods for modelling adaptation. Application of population projection scenarios (e.g. the shared socio-economic pathways; SSPs; O'Neill et al. (2014)) would yield different absolute numbers of deaths between population scenarios but not different estimates of ΔMort-CC.

Modelling adaptation

We investigated the sensitivity of ΔMort-CC to the six main adaptation modelling methods we discussed earlier. ΔMort-CC was estimated for each of the 14 cities for each method separately (Table 3).

Absolute threshold shifts in the ERF of 1, 2, 3 and 4°C respectively, were investigated to cover the range of shifts employed in past studies that use this method (Dessai 2003; Gosling et al. 2008; Huynen and Martens 2015; Jenkins et al. 2014).

For relative threshold shifts we shifted the ERFs by 25, 50, 75 and 100% respectively, as this covers the range of values used in past studies (Honda et al. 2014a; Honda et al. 2014b; Zacharias et al. 2015).

We reduced the slope of the ERF by 5, 10, 15, 20 and 25%, respectively. 10% was chosen in line with Huynen and Martens (2015) but as no other study has used this method we also considered reductions of up to 25% to provide an indication of what might result from other assumed selected reductions in slope.

Absolute threshold shifts (1, 2, 3 and 4°C) and relative threshold shifts (25, 50, 75 and 100%) were respectively combined with reductions in the slope of the ERF (5, 10, 15, 20 and 25%).

Previous studies have paired locations for the analogue ERF method by comparing mean annual temperatures (Knowlton et al. 2007), mean summer temperatures (Hayhoe et al. 2004), or maximum summer temperatures (Mills et al. 2014) between present-day and future time periods for multiple locations, but this does not account for the whole statistical distribution of temperatures. This is a significant limitation because it is the extremes of temperature, as well as the mean, which are important for heat-related mortality.

Therefore we developed a more advanced approach that better accounts for the shapes of the temperature distributions between two cities. We created analogue city pairs based on the projected probability distribution functions (PDFs) of warm season daily AT_{max}. The best "match" for each city's future climate was determined by a comparison of the nonparametric Kolmogorov-Smirnov (K-S) test statistic (Massey 1951) between present-day and future temperature distributions. The K-S test statistic is a measure of the maximum distance between two continuous distribution functions. For 13 cities (Barcelona was excluded here because it was the only city not to use AT_{max} in its ERF), the city whose present-day distribution that had the lowest test statistic when compared to an individual city's future distribution was selected as a match. For example, the projected climate of London was found to be most similar to that of present-day Milan (out of the 12 possible options) (Figure 1, Table S1), and thus ΔMort-CC for London was computed using the London climate change projections as input to the Milan ERF.

Results

Comparison of impacts between adaptation modelling methods

Figure 2 shows the range in ΔMort-CC impacts (per 100,000) for each city that result from including and excluding adaptation, and Figure 3 shows the difference (%) in impacts between including and excluding adaptation, for each adaptation modelling method. These two figures show that there are large contrasts in the ranges of impacts between the different adaptation modelling methods.

The contrasts are brought out in Table 4, which shows, as a mean across all 14 cities, the range of the difference (%) in impacts between including and excluding adaptation. The ranges are 49% (absolute threshold shift), 94% (relative threshold shift), 28% (reduction in slope of the ERF), 68% (absolute threshold shift combined with a reduction in slope of the ERF), 103% (relative threshold shift combined with a reduction in slope of the ERF) and 76% (analogue ERF).

Combining a relative threshold shift with a reduction in the ERF is associated with the largest ranges in impacts across all the methods, for all cities except Valencia. Relative threshold shifts are associated with the second largest ranges in impacts. For example, with relative threshold shifts of 50% (100%), ΔMort-CC declines from 84, 79, 72 and 77 deaths per 100,000 respectively under no adaptation, to 43 (6), 41 (9), 29 (0) and 37 (3) with adaptation, for Athens, Budapest, Milan and Rome, respectively (Figure 2). In terms of the difference (%) in impacts between including and excluding adaptation (Figure 3), these are equivalent to 49% (93%), 48% (89%), 60% (100%) and 52% (96%) respectively (Figure 3). In 5 cities a relative threshold shift of 100% results in ΔMort-CC reaching zero (London, Milan, Paris, Stockholm, Turin), i.e. climate change has no effect on heat-related mortality with adaptation.

Across the methods we considered, the smallest ranges in impacts are with reducing the slope of the ERF. For all cities, the differences in impacts between adaptation and no adaptation are smaller than 40% when the slope is reduced by the maximum amount we considered (25% reduction in slope; see Figure 3).

The methods we investigated generally have similar effects on ΔMort-CC across cities, i.e. increasing the thresholds in the increments we considered from 0-4°C and 0-100%, and reducing the slope by 0-25% respectively, are all associated with broadly linear declines in ΔMort-CC as the magnitude of assumed adaptation increases (Figure 2). The analogue ERF method, however, results in more disparate estimates of ΔMort-CC. There are large differences between adaptation and no adaptation for some cities. For Ljubljana and London, ΔMort-CC is 36 and 19 deaths per 100,000 (no adaptation) and 2 and 6 deaths per 100,000 (with adaptation), respectively (Figure 2). This is equivalent to differences of 94% (Ljubljana) and 68% (London) between adaptation and no adaptation (Figure 3). However, for other cities the use of analogue ERFs results in greater ΔMort-CC with adaptation than without, e.g. for Stockholm, Turin and Valencia where ΔMort-CC is 16, 11 and 13 deaths per 100,000 without adaptation and 20, 20 and 92 with adaptation, respectively (Figure 2).

Comparison of adaptation, emissions and climate modelling uncertainty

Table 5 shows the effects of adaptation, emissions and climate modelling uncertainties on projected impacts. It compares the largest range in impacts from all the adaptation modelling methods we investigated with the range in impacts from using two emissions scenarios without adaptation, and the range in impacts with 5 GCMs with one emissions scenario without adaptation respectively. The range in impacts that arises from adaptation modelling uncertainty is greater than the range that arises due to emissions uncertainty for every city. It is also greater than the range due to climate modelling uncertainty for 13 out of 14 cities. These differences are considerable in some cases, e.g. for Athens, Budapest and Rome, the ranges due to adaptation uncertainty are 88, 80 and 80 whilst for climate modelling uncertainty they are 46, 57 and 45 deaths per 100,000 respectively.

The large ranges due to adaptation uncertainty are in all but one city (Helsinki) associated with a relative threshold shift combined with a reduction in ERF slope (Table 5). However, even for Helsinki, adaptation uncertainty still results in a magnitude of impact that falls outside of the distribution of impacts estimated from multiple climate models and emissions scenarios. Application of some of the other methods also results in ranges that are larger than those from climate modelling and emissions uncertainty (denoted by A_x in Figure 2) because for 12 cities A_x is greater than or equal to 2, with such cases usually involving the relative threshold shift method.

The range in impacts from using an absolute threshold shift is smaller than the range from using multiple GCMs and/or RCPs, for all cities. The ranges are larger when absolute threshold shifts are combined with reductions in ERF slope but apart from three cities (Athens, Barcelona, Valencia) the ranges are smaller than those from using multiple GCMs or RCPs.

With exception to Ljubljana and Valencia the range in impacts from using analogue ERFs is smaller than the range from using multiple GCMs and multiple RCPs, for all cities.

Discussion

Application of linear ERFs

We used city-specific ERFs that describe *linear* relationships between daily apparent temperature and mortality in the form of a slope. They were derived from a set of *non-linear* curves developed from a flexible parametric approach presented by Baccini et al. (2008) (their Figure 1). Baccini et al. (2008) summarised their non-linear relationships by two linear terms constrained to join at a common point (the city-specific thresholds). They obtained the thresholds by the maximum likelihood approach proposed by Muggeo (2003) so that a linear slope above the threshold was used as an effect estimate for each city. These were used as the ERFs in our study. As others have noted (Kingsley et al. 2016), the summarised association between mortality and temperature per increment in temperature (1°C in this case) differs depending on where along the exposure–response curve one starts, for nonlinear exposure–response relationships like those defined by Baccini et al. (2008). For a highly non-linear curve, the strength of the temperature-mortality response might be higher further along the curve where its gradient is larger (i.e. at higher temperatures) than it might be closer to the threshold where the gradient is lower. Baccini et al. (2008) started from the threshold temperature when computing their effect estimates, so if their curves were highly non-linear, it would be fair to assume that we under-estimated the climate change effects of temperature on heat-related mortality. However, visual inspection of the curves presented by Baccini et al. (2008) suggests that the curves are broadly linear beyond the threshold temperatures. Therefore we did not calculate climate change impacts with non-linear ERFs.

A goal of our paper is to provide a point of reference to the sensitivity of climate change impacts to different adaptation modelling methods, for researchers conducting climate change impact assessments for heat-related mortality. Considering that almost all previous assessments use linear ERFs derived from estimates of RR for an increase in temperature above a specific value (Baccini et al. 2011; Hajat et al. 2014; Peng et al. 2011; Petkova et al. 2013; Schwartz et al. 2015; Vardoulakis et al. 2014; Wu et al. 2014) we also used linear

ERFs because it is likely that future studies will also do so. Thus our conclusions should be readily interpretable by the community. This is another reason why we did not calculate impacts with non-linear ERFs. In addition, the application of linear ERFs makes it straightforward to apply simple changes in slope and location to represent adaptation. The potential gains of using non-linear associations would be outweighed by the increased complexity in implementing adaptation options.

The algorithm described by Muggeo (2003) and used by Baccini et al. (2008) for the threshold temperature estimation can be unstable. This means the linear relationship we used can be sensitive to the threshold. We did not investigate the sensitivity of our estimated impacts to this because our goal was to demonstrate the sensitivity of impacts to adaptation methods. The drawback of this algorithm may be accounted for by using different starting points for each temperature and lag structure when running the algorithm (Rodopoulou et al. 2015).

Our projected impacts are not only a function of the projected climate, but also of the baseline mortality rate, which appears in Equation (5). The sensitivity of impacts to baseline mortality values has been noted by others (Baccini et al. 2011). We controlled for this in our experimental design by holding the baseline mortality rate constant between present and future periods, in line with others (e.g. Gosling et al. 2012; Peng et al. 2011; Petkova et al. 2013; Wu et al. 2014), to isolate the effects of climate model, emissions, and adaptation modelling uncertainties on the impact estimates. Changing the baseline mortality rates between future and present would affect the projected absolute number of deaths, since some future deaths would be attributable to changes in the baseline mortality rate, but it would not affect the mortality rates *attributable to climate change* (ΔMort-CC).

Some studies have calculated the baseline mortality rate from either daily mortality excluding deaths attributable to temperature (Hajat et al. 2014), or mortality on non-heatwave days (Peng et al. 2011; Wu et al. 2014). This means that the baseline mortality rate is representative of the mortality rate of the exposed population at the threshold temperature. Others have calculated the baseline mortality rate from the total number of deaths (Baccini et al. 2011; Huynen and Martens 2015; Petkova et al. 2013; Schwartz et al. 2015; Vardoulakis et al. 2014), which means it is representative of the whole exposed population year-round (i.e. at the threshold temperature and temperatures above this). We employed the last approach, simply because it is more commonly adopted, but we acknowledge that it would be useful in future work to investigate quantitatively the effect of calculating the baseline mortality rate with different methods.

Impacts are highly sensitive to adaptation modelling methods

Our *first* objective was to compare the range in projected impacts that arises from using different adaptation modelling methods. All previous assessments of the impacts of climate change on heat-related mortality have modelled adaptation with only one method (e.g. Hayhoe et al. 2004; Honda et al. 2014b; Jenkins et al. 2014; Knowlton et al. 2007; Mills et al. 2014; Zacharias et al. 2015), excluded it altogether (e.g. Baccini et al. 2011; Hajat et al. 2014; Kingsley et al. 2016; Peng et al. 2011; Vardoulakis et al. 2014; Wu et al. 2014), or in one case provided a comparison of impacts using only a subset of the range of modelling methods available (Huynen and Martens 2015). Here, for the first time, we have used multiple adaptation modelling methods with different assumed magnitudes of adaptation and shown that the ranges in projected impacts varies significantly according to what adaptation modelling method is employed.

This significant sensitivity is well illustrated with an example. Electing to model adaptation with a 4°C absolute threshold shift for Milan would suggest that the least effect climate change will have on heat-related mortality is an *additional* 44 heat-related deaths (per 100,000) each year than in the present day (Figure 2). However, modelling adaptation with a different method (relative threshold shift with a reduction in ERF slope) suggests that there will be 2 (per 100,000) *fewer* deaths each year with climate change than in the present-day. This magnitude of impact is only observed if this specific adaptation modelling method is applied. Such an effect does not occur with any of the other adaptation modelling methods. Nor does it occur under a low emissions (RCP2.6) scenario or when multiple GCMs are considered without adaptation, where the least effect climate change will have on heat-related mortality is an additional 17 and 31 annual heat-related deaths (per 100,000) respectively.

To this end our results highlight that forthcoming studies need to carefully consider what methods they use to model adaptation because we have shown the range in projected impacts is highly sensitive to what adaptation modelling method is employed.

We observed that increases in the magnitude of each adaptation modelling method (apart from analogue ERF) generally had linear effects on ΔMort-CC that were similar across cities (Figure 2). This suggests that the sensitivity of projected heat-related mortality impacts to adaptation modelling method is likely to hold for other cities across the globe.

Comparing uncertainty from adaptation uncertainty with that from climate modelling and emissions

Our *second* objective was to compare the range in impacts that arises from adaptation uncertainty to the ranges from climate modelling and emissions uncertainty respectively. We found that adaptation modelling uncertainty results in large ranges of projected heat-related mortality impacts. In 13 out of 14 cities it results in ranges that are larger than those caused by both climate modelling and emissions uncertainty respectively. This is largely as a result of modelling adaptation with relative threshold shifts. When other methods are used the ranges are still large but typically smaller than those from climate modelling and emissions uncertainty. Our results confirm other studies that have shown large differences in impacts between adaptation and no adaptation cases (e.g. Honda et al. 2014a; Jenkins et al. 2014; Petkova et al. 2016; Sheridan et al. 2012) but here we have provided additional understanding by specifically showing that adaptation uncertainty can have a greater effect on heat-related mortality rates attributable to climate than climate modelling and emissions uncertainty.

Recommended adaptation modelling methods for future assessments

Our *third* objective was to recommend one or several methods to use in future impact assessments. Our results lead us to advise that future assessments should carefully consider the plausibility of the adaptation modelling methods they employ when projecting heat-related mortality.

Absolute threshold shifts are a popular method for modelling adaptation in impact studies but they have always been shifted by between 1-4°C without being informed by epidemiological evidence of observed threshold shifts (Dessai 2003; Gosling et al. 2008; Huynen and Martens 2015; Jenkins et al. 2014). However, there is now growing evidence to support the magnitude of these shifts. Absolute threshold temperatures increased by 1.5-3°C between 1972-1994 in Tokyo (Honda et al. 2006), by around 10°C between 1901-2009 in Stockholm (Åström et al. 2016) and by 0.7°C from 1968–1981 to1996–2009 in France (Todd and Valleron 2015). Although observed increases in thresholds vary between studies, have occurred over different time periods, and thresholds have decreased in a limited number of locations (Miron et al. 2007), we argue that it is reasonable in light of the epidemiological evidence to assume that ERFs might shift by between 1-4°C in the future. Thus we recommend this method for application in future impact studies. However, we also encourage further epidemiological studies that investigate the magnitude of historical shifts in absolute threshold temperatures and in addition improved empirical assessment of the factors that drive such shifts in sensitivity and their associated costs.

Users of the relative threshold method (Honda et al. 2014a; Honda et al. 2014b; Zacharias et al. 2015) justify its application with reference to the observation that threshold temperatures can generally be estimated using the 80–85th percentile of daily maximum temperature in multiple locations in Japan (Honda et al. 2007; Honda et al. 2014b). However, relative thresholds can vary over time (Åström et al. 2016) and between countries (Gasparrini et al. 2015a), which questions the rationale behind this method. The method has also been criticised for its inappropriateness for projecting climate change impacts because the relative threshold may not be a valid proxy for the absolute threshold in the future (Åström et al. 2016). In addition, referring to "100% adaptation" (Honda et al. 2014a) is somewhat misleading because we have shown that climate change still causes an increase in heat-related mortality compared to present-day under this assumption. This is because the shape *and* location of the future temperature distribution changes but a relative threshold shift of 100% does not entirely account for the change in shape. In light of these limitations the method should be applied with caution and relative threshold shifts of 100% should be carefully considered with respect to their plausibility.

Our results confirm criticisms that impacts based on the analogue ERF method may be biased if social, economic, and demographic characteristics related to mortality differ greatly between city pairs (Huang et al. 2011). Application of this method in our study did not always have the effect of reducing mortality relative to no adaptation (e.g. for Milan, Stockholm, Turin, Valencia, and Zurich). One reason for this is that the method is sensitive to the “matching” of one city to another – some matches were better than others. Another reason is the cities were matched based only upon their daily AT_{max} distributions and not the socio-economic characteristics that contribute to the thresholds and slopes of the city-specific ERFs (Baccini et al. 2008). The method might work well for locations that share similar socio-economic characteristics but not otherwise. Therefore we recommend that future impact studies consider whether it is plausible to apply the analogue ERF method when taking into account similarities and differences between the socio-economic characteristics of the different locations under investigation.

We are aware of only one impact study that has modelled adaptation by reducing the slope of the ERF (Huynen and Martens 2015), which is surprising considering the growing body of epidemiological evidence that generally shows a decreasing sensitivity to heat over time (Barnett 2007; Bobb et al. 2014; Gasparrini et al. 2015a; Guo et al. 2012; Ha and Kim 2013; Petkova et al. 2014a; Schwartz et al. 2015; Sheridan et al. 2008). Along with others (Huang et al. 2011), we therefore see this method as showing significant potential for application in impact studies.

Overall, we recommend that future impact studies model adaptation by absolute threshold shifts and reductions in ERF slope. This should, however, not be done arbitrarily. We suggest that researchers first check the validity of the magnitude of adaptation assumed by exploring the evidence for, and magnitude of, historical adaptation in the chosen location of investigation. This should yield quantification of shifts in the threshold temperature and declines in slope over the historical period. The analysis should be performed using as long a time-series of daily data that is possible, ideally spanning around 100 years because the most compelling evidence for adaptation over the historical period is from studies that have analysed datasets of this length (Arbuthnott et al. 2016; Astrom et al. 2013; Carson et al. 2006; Ha and Kim 2013; Petkova et al. 2014a). If adaptation is not observed over the historical period and/or there is a lack of available data, then it should not be assumed that future adaptation is impossible. Rather, the reasons for this should be investigated and adaptation modelling should be undertaken. We recommend applying a shift in absolute threshold between 1-4°C in such cases because this is broadly within the range of shifts in threshold temperature observed for some locations (Åström et al. 2016; Honda et al. 2006; Todd and Valleron 2015). However, the results should be interpreted within the knowledge that historical adaptation has not occurred and/or there was not enough available data to observe it. Analysis of historical trends in adaptation will indicate whether both the threshold and slope have changed over time, or whether only one has. This in turn should inform which method to use in the climate change impact assessment.

We assumed in our comparison that the methods employed in previous studies for particular locations could readily be transferred to different locations. Previous studies that have used these methods have also made this assumption. Apart from the analogue ERF method, which we have shown may not be a plausible method for some locations, our results suggest no reason why the methods cannot be applied to locations that are different from where they have been used previously. However, as we have already noted, when using these methods for a new location, researchers should check the validity of the assumed magnitude of adaptation, by exploring historical adaptation trends for that location.Whilst our recommendation is based upon an analysis of existing methods we also encourage the development of new methods for modelling adaptation across large populations. These might include shifts and declines in slope where the magnitudes vary seasonally or inter-annually, to reflect the lead-in times that typify decreasing sensitivity to heat over the historical period (Arbuthnott et al. 2016; Petkova et al. 2016). It would also be worthwhile to attempt to separate the beneficial effects of autonomous adaptation from planned adaptation (Petkova et al. 2014b) because all the methods we employed combine the two together. In practical terms, it is likely that the two mechanisms will operate at different magnitudes, heterogeneously across locations, and at different spatial and temporal scales.

Conclusions

To the best of our knowledge, we have conducted the first climate change impact assessment for heat-related mortality that systematically compares projections using the six main methods for modelling adaptation that have been employed in previous studies.

We found that on average across all 14 cities, the range of the difference (%) in impacts between including and excluding adaptation, independent of climate modelling and emissions uncertainty, can be as low as 28% with one method (reduction in slope of the ERF) and up to 103% with another (relative threshold shift combined with a reduction in slope of the ERF). Furthermore, we have shown that in 13 of the 14 cities the ranges in projected impacts due to adaptation uncertainty are larger than those associated with climate modelling and emissions uncertainty.

Therefore we strongly encourage an advancement beyond the prevailing methodological approach adopted in most impact studies, which has traditionally focussed on accounting for climate modelling and/or emissions uncertainties at the expense of ignoring adaptation (e.g. Baccini et al. 2011; Hajat et al. 2014; Kingsley et al. 2016; Peng et al. 2011; Vardoulakis et al. 2014; Wu et al. 2014). This status quo has developed from an inherent assumption that the most important uncertainties to account for are climate modelling and emissions uncertainty, as they have been shown to result in large ranges in impacts (e.g. Gosling et al. 2012; Hajat et al. 2014; Peng et al. 2011; Zacharias et al. 2015). Our results are in stark contrast to this.

Therefore researchers should carefully consider how to model adaptation. We call for a move towards impact assessments that explicitly report the range in impacts from using multiple GCMs, emissions scenarios *and* different adaptation assumptions, to provide a more comprehensive assessment of uncertainty. This will in turn provide policy- and decision-makers with a more holistic picture of potential climate change impacts. Ideally, this will help decision-makers adopt the appropriate scale and combination of different investments and interventions required for effective adaptation to climate change.

We treated adaptation in a purely statistical sense, without consideration of the specific programs, strategies and behavioural changes that are ultimately driving the adaptation assumptions we applied. More thorough and widespread evaluation of intervention measures will be paramount in closing this loop (Boeckmann and Rohn 2014). Therefore in parallel to our recommendations for future research we acknowledge that more evidence should be generated on the costs and effectiveness of the large array of adaptation mechanisms that underlay the modelling assumptions we applied here, from individual, technological to health system levels. This would enable policy- and decision-makers to focus on the most cost-effective interventions and researchers to base their adaptation methods on more robust data.

Figures

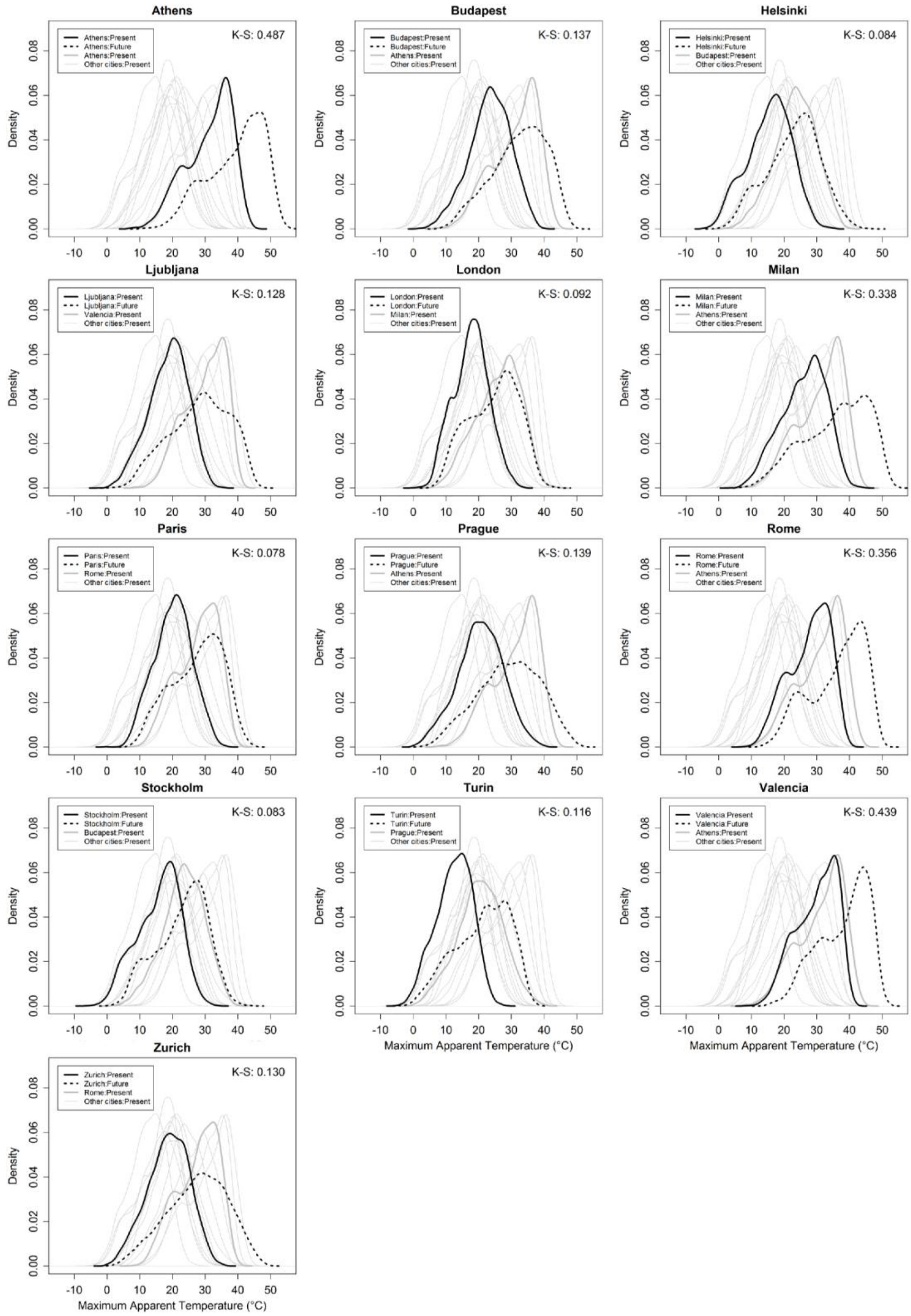

Figure 1. PDFs of present-day AT_{max} distributions for each city (solid black line), the future distribution under climate change as simulated by HadGEM2-ES under RCP8.5 for the same

city (dashed black line) and all other cities (solid thin grey lines), and for the same city the distribution for the city that under climate change is best matched to it (solid thick grey line) according to the K-S statistic (displayed in the top right of each panel; K-S statistics for all possible matches are displayed in Table S1).

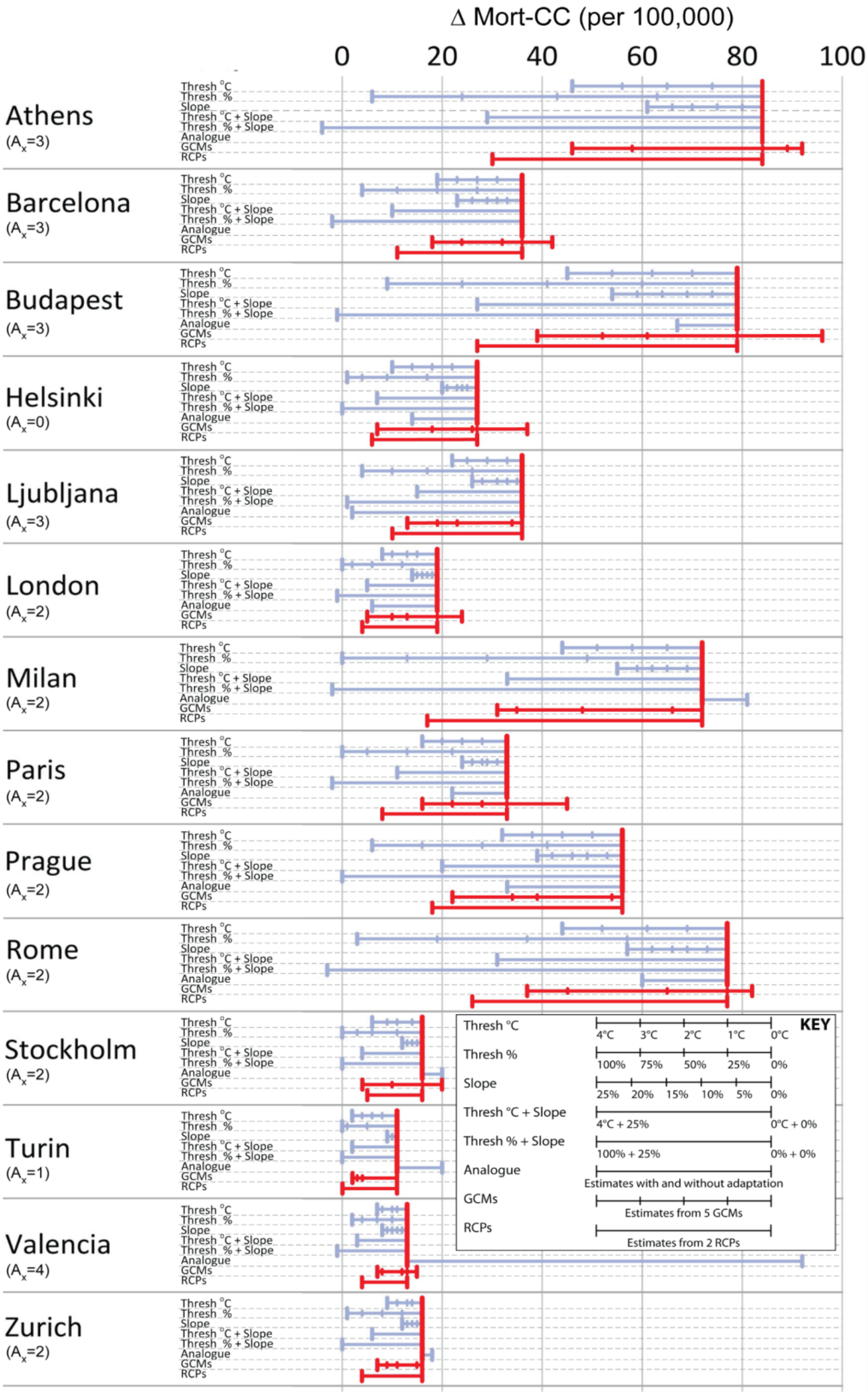

Figure 2. Mean annual warm season heat-related mortality rates (per 100,000) attributable to climate change (ΔMort-CC) for 2070-2099, using climate change projections from HadGEM2-ES run under RCP8.5, when different adaptation modelling methods are applied.

Also displayed is ΔMort-CC with climate change projections from five GCMs run under RCP8.5 with no adaptation (“GCMs”), and ΔMort-CC with climate change projections from HadGEM2-ES run under two emissions scenarios (RCP2.6 and RCP8.5) with no adaptation (“RCPs”). Blue lines and whiskers denote where impacts have been estimated with adaptation modelling methods employed and red lines and whiskers with no adaptation. A_x denotes the number of adaptation modelling methods that have a range which is greater than or equal to the range for GCMs and/or RCPs. The ranges are quantitatively summarised in Table 4.

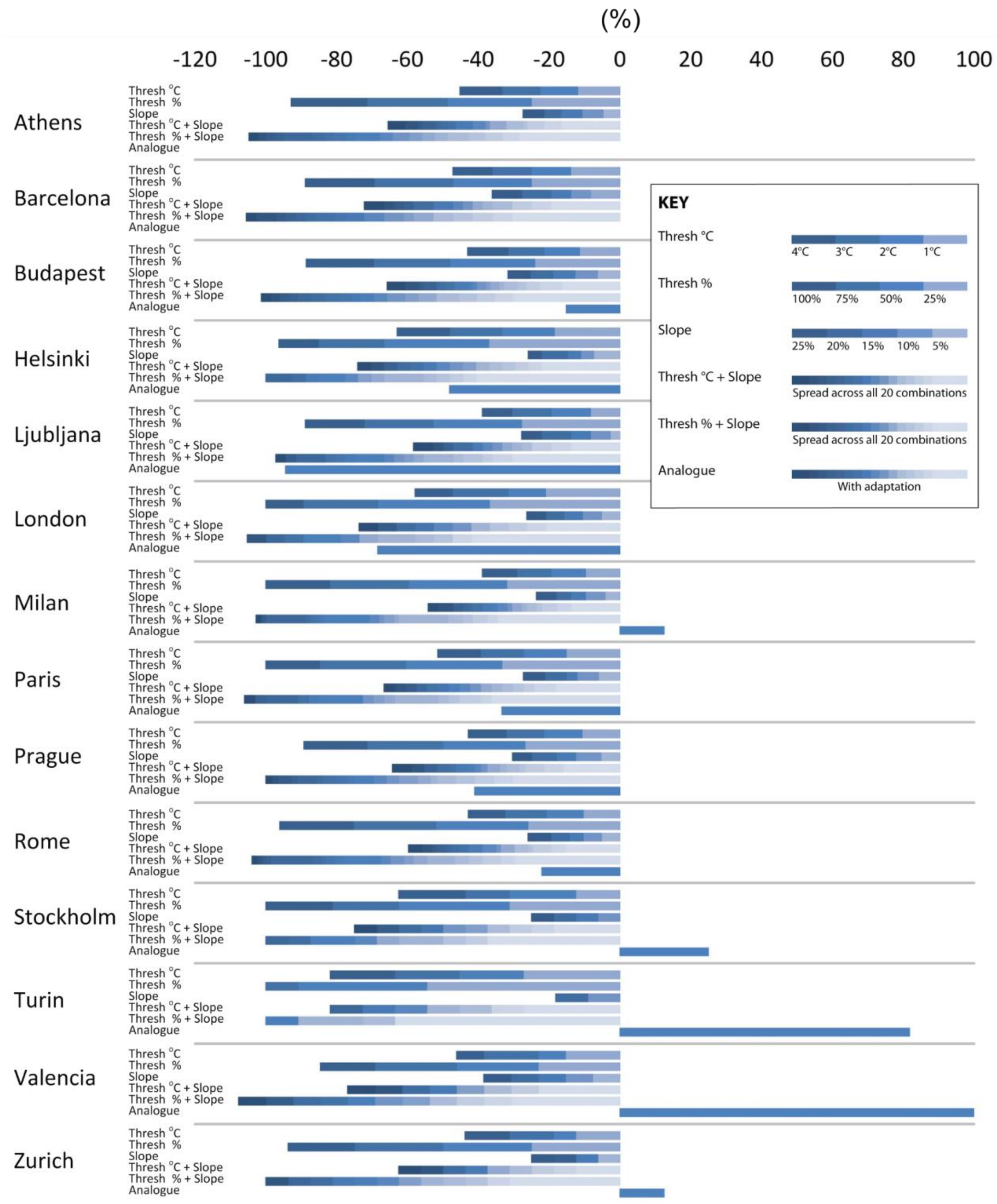

Figure 3. Differences (%) between estimating ΔMort-CC with each adaptation modelling method and with no adaptation. All estimates are for 2070-2099, with climate change projections from the HadGEM2-ES GCM run under RCP8.5. The axis labels are the same as in Figure 2. Notes: this is not a stacked bar graph – values should be read from the left (right)

of each box if they are left (right) of 0. No analogue projection is available for Athens because the city was its own match in the comparison of current and future temperature distributions; no analogue projection is available for Barcelona because a different exposure variable was used for projections for Barcelona than the other study cities.

Tables

Table 1. Summary of statistical methods used to model adaptation in climate change impact assessments for heat-related mortality.

Method	Summary	Strengths	Limitations	Studies that use the method
Absolute threshold shift.	The absolute threshold temperature is shifted to a higher value under climate change, between 2-4°C.	Straightforward to apply.	Magnitude of shift is arbitrarily defined without reference to epidemiological evidence.	Dessai (2003) Gosling et al. (2008) Huynen and Martens (2015) Jenkins et al. (2014)
Relative threshold shift.	The threshold, when defined as a percentile of the temperature distribution, is the same percentile under climate change as it is in the present (100% adaptation).	Straightforward to apply and supported by some (limited) empirical evidence.	Informed by evidence from only a single empirical study (Honda et al. 2006).	Honda et al. (2014a) Honda et al. (2014b) Zacharias et al. (2015)
Reduction in slope of the exposure response function (ERF).	The slope of the ERF is reduced under climate change, by up to 10%.	Straightforward to apply.	Magnitude of slope reduction is arbitrary and not straightforward to apply to non-linear ERFs.	Huynen and Martens (2015)
Combined absolute threshold shift with reduction in slope of the ERF.	The absolute threshold temperature is shifted to a higher value under climate and at the same time the slope of the ERF is reduced.	Intuitive because it assumes that both the threshold and sensitivity to increasing heat will change under climate change.	Magnitude of shift and slope reduction is arbitrary and not straightforward to apply to non-linear ERFs.	Huynen and Martens (2015)
Combined relative threshold shift with reduction in slope of the ERF.	The relative threshold temperature is shifted to a higher value under climate and at the same time the slope of the ERF is reduced.	Intuitive because it assumes that both the threshold and sensitivity to increasing heat will change under climate change.	Magnitude of shift and slope reduction is arbitrary and not straightforward to apply to non-linear ERFs.	Recommended by Huang et al. (2011) but not yet used in a climate change impact assessment.
Analogue ERFs.	Use ERFs for locations with present temperatures similar to those projected to occur in the location of interest under climate change.	Qualitatively informed by epidemiological evidence that populations in warmer/colder regions tend to be less/more sensitive to relatively higher temperatures (Davis et al. 2003).	Assumes that the underlying confounding factors that contribute to the ERF can be transferred to a different location.	Hayhoe et al. (2004) Knowlton et al. (2007) Mills et al. (2014)

Table 2. Components of the ERFs applied in this study, which are based upon model estimates derived by Baccini et al. (2008).

City	Threshold temperature (°C)	Total population	Baseline daily mortality rate (per 100,000)	Relative Risk (RR)	Concentration Response Factor (CRF)
Athens	32.7	3188305	2.12	1.0554	0.054
Barcelona	22.4	1512971	2.37	1.0156	0.015
Budapest	22.8	1797222	3.95	1.0174	0.017
Helsinki	23.6	955143	1.79	1.0372	0.037
Ljubljana	21.5	263290	2.39	1.0134	0.013
London	23.9	6796900	2.19	1.0154	0.015
Milan	31.8	1304942	2.02	1.0429	0.042
Paris	24.1	6161393	1.88	1.0244	0.024
Prague	22	1183900	2.95	1.0191	0.019
Rome	30.3	2812573	1.88	1.0525	0.051
Stockholm	21.7	1173183	2.38	1.0117	0.012
Turin	27	901010	2.12	1.0332	0.033
Valencia	28.2	739004	1.98	1.0056	0.006
Zurich	21.8	990000	1.17	1.0137	0.014

Table 3. Summary of the experimental design, showing the adaptation modelling methods compared and the GCMs and emissions scenarios used.

Rationale:	**Range in impacts from adaptation uncertainty, controlling for climate modelling and emissions uncertainty**							**Range in impacts from climate modelling uncertainty, controlling for adaptation and emissions uncertainty**	**Range in impacts from emissions uncertainty, controlling for adaptation and climate modelling uncertainty**
GCMs:	HadGEM2-ES							HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2, NorESM1-M	HadGEM2-ES
Emissions scenarios:	RCP8.5							RCP8.5	RCP2.6, RCP8.5
No. of climate model simulations:	1	1	1	1	1	1	1	5	2
Adaptation modelling method:	No adaptation	Absolute threshold shift (“Thresh °C”)	Relative threshold shift (“Thresh %”)	Reduction in slope of the ERF (“Slope”)	Combined absolute threshold shift with reduction in ERF slope (“Thresh °C + Sens”)	Combined relative threshold shift with reduction in ERF slope (“Thresh % + Sens”)	Analogue ERFs (“Analogue”)	No adaptation	No adaptation
Magnitude of adaptation investigated:	None	1°C	25%	5%	All 20 possible combinations	All 20 possible combinations	Use ERF from analogue city	None	None
		2°C	50%	10%					
		3°C	75%	15%					
		4°C	100%	20%					
				25%					

Table 4. Statistical ranges (maximum minus minimum values of the distribution) of the differences (%) between estimating ΔMort-CC with the upper limit of each adaptation modelling method (shown in parentheses) and with no adaptation. The values describe the width of each bar in Figure 3.

City	Absolute threshold shift (Thresh °C = 4°C)	Relative threshold shift (Thresh % = 100%)	Reduction in the slope of the ERF (Slope = 25%)	Absolute threshold shift combined with reduction in slope of ERF (Thresh °C + Sens = 4°C+ 25%)	Relative threshold shift combined with reduction in slope of ERF (Thresh % + Sens = 100% + 25%)	Analogue ERF (Analogue)
Athens	44	93	27	66	105	0
Barcelona	48	89	36	72	106	0
Budapest	42	89	32	66	101	15
Helsinki	61	96	26	74	100	48
Ljubljana	40	89	28	58	97	94
London	58	100	26	74	105	68
Milan	37	100	24	54	103	13
Paris	51	100	27	67	106	33
Prague	43	89	30	64	100	41
Rome	42	96	26	60	104	22
Stockholm	62	100	25	75	100	25
Turin	79	100	18	82	100	82
Valencia	45	85	38	77	108	608
Zurich	40	94	25	63	100	13
Mean	**49**	**94**	**28**	**68**	**103**	**76** [a]

a The mean is 35 if the result 608 for Valencia is removed.

Table 5. Statistical ranges (maximum minus minimum values of the impact distribution) and spread (minimum to maximum values that constitute the range, in parentheses) of ΔMort-CC impacts (per 100,000) due to adaptation modelling uncertainty (calculated from the largest range in impacts from all the adaptation modelling methods investigated), climate modelling uncertainty (spread and range for 5 GCMs with no adaptation) and emissions uncertainty (spread and range for two RCPs with one GCM and with no adaptation). The range values describe the width of each bar in Figure 2.

City	Range in impacts due to adaptation modelling uncertainty [a]	Adaptation modelling method that results in largest spread	Range in impacts due to climate modelling uncertainty	Range in impacts due to emissions uncertainty
Athens	88 (-4 – 84)	Thresh % + Slope	46 (46 – 92)	54 (30 – 84)
Barcelona	38 (-2 – 36)	Thresh % + Slope	24 (18 – 42)	25 (11 – 36)
Budapest	80 (-1 – 79)	Thresh % + Slope	57 (39 – 96)	52 (27 – 79)
Helsinki	27 (0 – 27)	Thresh % + Slope	30 (7 – 37) [b]	21 (6 – 27)
Ljubljana	35 (1 – 36)	Thresh % + Slope	23 (13 – 36)	26 (10 – 36)
London	20 (-1 – 19)	Thresh % + Slope	19 (5 – 24)	15 (4 – 19)
Milan	74 (-2 – 72)	Thresh % + Slope	41 (31 – 72)	55 (17 – 72)
Paris	35 (-2 – 33)	Thresh % + Slope	29 (16 – 45)	25 (8 – 33)
Prague	56 (0 – 56)	Thresh % + Slope	34 (22 – 56)	38 (18 – 56)
Rome	80 (-3 – 77)	Thresh % + Slope	45 (37 – 82)	51 (26 – 77)
Stockholm	16 (0 – 16)	Thresh % + Slope	16 (4 – 20)	11 (5 – 16)
Turin	11 (0 – 11)	Thresh % + Slope	9 (2 – 11)	11 (0 – 11)
Valencia	79 (13 – 92)	Analogue	8 (7 – 15)	9 (4 – 13)
Zurich	16 (0 – 16)	Thresh % + Slope	9 (7 – 16)	12 (4 – 16)

a Negative values denote that fewer deaths occur in the future with climate change than in the present-day.

b The range due to either GCM or emissions uncertainty is smaller than the range due to adaptation modelling uncertainty.

Supplemental Material

		Future AT_{max} Distributions												
		Athens	Budapest	Helsinki	Ljubljana	London	Milan	Paris	Prague	Rome	Stockholm	Turin	Valencia	Zurich
Present AT_{max} Distributions	Athens	0.487	0.137	0.434	0.165	0.354	0.338	0.200	0.139	0.356	0.441	0.479	0.439	0.194
	Budapest	0.703	0.497	0.084	0.312	0.136	0.592	0.293	0.342	0.628	0.083	0.155	0.678	0.283
	Dublin	0.916	0.804	0.520	0.680	0.579	0.825	0.673	0.699	0.868	0.542	0.456	0.922	0.664
	Helsinki	0.870	0.742	0.413	0.600	0.480	0.765	0.586	0.620	0.795	0.436	0.347	0.875	0.576
	Ljubljana	0.823	0.678	0.293	0.517	0.379	0.724	0.504	0.535	0.745	0.320	0.228	0.828	0.493
	London	0.854	0.720	0.377	0.575	0.451	0.751	0.561	0.595	0.776	0.402	0.305	0.858	0.550
	Milan	0.637	0.363	0.160	0.191	0.092	0.515	0.137	0.226	0.551	0.144	0.222	0.595	0.161
	Paris	0.785	0.628	0.236	0.466	0.328	0.683	0.454	0.484	0.711	0.262	0.177	0.784	0.443
	Prague	0.742	0.575	0.171	0.411	0.266	0.639	0.395	0.424	0.673	0.199	0.116	0.738	0.382
	Rome	0.617	0.317	0.270	0.164	0.167	0.492	0.078	0.198	0.527	0.253	0.310	0.573	0.130
	Stockholm	0.876	0.750	0.412	0.606	0.485	0.773	0.592	0.628	0.804	0.438	0.341	0.882	0.581
	Turin	0.950	0.848	0.587	0.726	0.632	0.867	0.721	0.748	0.911	0.605	0.523	0.955	0.713
	Valencia	0.566	0.229	0.372	0.128	0.282	0.422	0.130	0.145	0.452	0.372	0.413	0.520	0.140
	Zurich	0.805	0.660	0.276	0.501	0.364	0.705	0.489	0.521	0.729	0.303	0.213	0.809	0.478

Table S1. K-S statistics between present and future warm season daily AT_{max} distributions for each city. The best match for each city is shaded.

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